How Information from a Strategic Alliance Network Relates to Future Acquisition Performance in the Biotechnology and Pharmaceutical Industries

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Honors Thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University.

Duke University
Durham, North Carolina
2008

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Acknowledgments

The author would like to thank Henry Grabowski for his priceless support and feedback during this project. The author is also extremely grateful for the help and guidance from Michelle Connolly and Ed Tower, as well as his Economics 198S and 199S classes' comments and patience.

Abstract

Acquisitions in the pharmaceutical and biotechnology field have been fueled by a variety of factors ranging from riding strong equity markets to lucid managerial hubris. In all cases, asymmetric information, specifically the moral hazard problem between acquiring and target firms, played large roles in the final value of any acquisition; target firms inherently had better valuations of their worth than acquiring firms. To mitigate this, firms actively engage in learning activities that include forming strategic alliances. Efficient markets will recognize advantageous relationships. This study investigates whether learning effects from strategic alliances helped to remedy this moral hazard problem by investigating how various alliance metrics affected acquiring firms' short-term cumulative abnormal returns and daily stock return volatility for acquisitions in 1998-2004. Evidence was discovered that acquiring firms that were more central figures in an alliance network and engaged in a prior alliance with their target company tended to realize greater short-term cumulative abnormal stock returns. In addition, more central firms tended to realize less daily stock return volatility on the date of the acquisition. In contrast, firms with more third-party shared alliances tended to realize less short-term cumulative abnormal stock returns and greater daily stock return volatility.

I. Introduction

Would William Faulkner take offense if his quote, "[Man's] tragedy is the impossibility – or at least the tremendous difficulty – of communication," was used to describe the economic nature of acquisitions?[1] Acquiring companies must attempt to value a target firm appropriately, many times relying on prior acquisition and industry experience to infer what the correct metric is. Naturally the target firm has more knowledge of its own value than the acquiring firm, and it could very well be in its best interest to withhold information that may decrease its worth. Inherent in mergers and acquisitions is the problem of information asymmetry; the target firm knows more about its assets and liabilities than the acquiring firm. This research will aim to improve the knowledge on how strategic alliances attempt to mitigate the asymmetric information problem between acquiring and target companies by studying the market's ability to incorporate alliance network information about the acquiring firm.

Merging is a specious act for many acquiring companies; Andrade et al. notes that the majority of firms do not realize any positive returns (Andrade, Mitchell, & Stafford, 2001). It is perplexing that while many firms see merging as a way to achieve economies of scale or realize synergies, merger waves are still one of the ten unsolved puzzles in finance (Brealey & Myers, 2003). It is therefore relevant to continue to study mergers and acquisitions,

[1] The terms "mergers" and "acquisitions" are used interchangeably even though there is a distinction between the two. Acquisitions typically refer to a company buying another company while mergers involve the combination of two or more companies into one larger company. In either case, cash or equity payments can occur, and there are similar management integration issues in each. For this study, the term "merger" will be used for verbal relief of "acquisition".

especially in the biotechnology industry where there are large fixed and variable costs for operating and undertaking research and development.

Present relationships between biotech and pharmaceutical firms stem from two initial responses to the genetic revolution.[2] Pharmaceuticals either developed narrow strategies and advanced biotech research internally, or nurtured broad biotech capabilities and obtained the necessary technologies through acquisition (Galambos & Sturchio, 1998).[3] The decision to use one or the other has been dependent on numerous firm and market factors. While the decision on what type of relationship firms should engage in is not examined in this paper, it is worthy to note that the amount of money dedicated to acquisitions is substantial. In 2004, approximately $32.91 billion were invested in M&A activity between US acquiring and target pharmabiotech companies.[4] This is a significant amount in an industry whose total market size was roughly $270 billion in 2004.[5]

Research has shown that alliances tend to create value (Chan, Kensinger, Keown, & Martin, 1997), yet there has been some disagreement as to what drives this value.[6] Alliances

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[2] The term pharmabiotech will be used throughout this proposal to indicate the pharmaceutical and biotech industries. For rigorous definition, pharmaceuticals and biotechnology firms are classified under the Standard Industrial Classification (SIC) system as having SIC Codes 2833-2836.

[3] The terms "broad" and "narrow" refer to the breadth of R&D efforts in relation to how many different therapeutic classes they span. For example, a firm with "broad" strategies may have interests in liver growth-factors as well as transcriptomes in stem cells, while "narrow" strategies entail focusing on select therapeutic classes.

[4] Data taken from Thomson Financial.

[5] Frost and Sullivan Healthcare Industry Report for 2004.

[6] Value-creation in this context refers to a stock-price increase with no wealth transfer between allied partners. One plausible explanation for the value-creation is that alliances are more cost-effective than an integrated firm (Jensen & Meckling, 1991). However, the facilitation of organizational learning is the most commonly cited reason for value-creation though (Anand & Khanna, 2000).

provide avenues for organizational learning, whereby both parties are exposed to skills and knowledge from the other party (Anand & Khanna, 2000). In addition, firms learn how to handle the collaboration process more efficiently; future collaborations will be a function of previous collaborations (Arino & de la Torre, 1998). Finally, firms learn skills concerning how to manage alliances, which influence the success of future alliances (Anand & Khanna, 2000). Research has been able to generalize further to state that engaging in alliances generates organizational learning effects that are applicable to mergers and acquisitions (Porrini, 2004). Our research will aim to quantify, or at the least aid in the understanding of the learning effects of alliances as they pertain to mergers and acquisitions. The methodology is discussed in more detail in Section 4, but we will examine how the learning effects generated in an alliance network impact the short-term profitability and the riskiness of a pharmabiotech acquisition. Our specific hypotheses are presented in Section 3.

Alliances on average seem to be beneficial to both parties, but it should also seem apparent that not all alliances are created equally. It is plausible that in some alliances there will be an unequal transfer of proprietary information to one firm (Khanna, Gulati, & Nohria, 1998). The receiving firm could potentially use this information out of the context of the alliance in an opportunistic fashion. If a firm has been exposed to this type of behavior, they could be overly cautious in disclosing information in future alliances, thereby significantly decreasing the learning effects of that alliance. We develop a method to deal with this problem by postulating that firms who engage in this detrimental activity won't have a significant number of alliances with reputable firms. We define reputation using a measure of eigenvector centrality, which is consistent with the theory that central figures within a

network are generally considered more reputable (Podolny, 1993).[7] In addition to centrality, we use the idea of proximity to define the relative relationship between parties. The proximity idea takes into account whether there was a previous alliances between the two parties and number of shared third parties (Robinson & Stuart, 2006).[8]

For the sake of clarity, the idea that eigenvector centrality is consistent with reputability will be discussed. One of the best examples of eigenvector centrality can be found in Google's PageRank algorithm, which is used to rank websites with respect to a search string. As explained on their website, "Votes cast by pages that are themselves "important" weigh more heavily and help to make other pages "important."[9] This is analogous to the way that more central alliance figures have a higher reputation by themselves being connected to other highly central firms. Moreover, when a firm forms an alliance with a more reputable company, the said firm's centrality measure will increase. This idea of centrality will be important for determining how certain alliances with more reputable firms influence a subsequent acquisition.

The question of what constitutes a successful alliance can be answered in a number of fashions. When an alliance is announced, a portion of the firm's future activities are revealed to investors, potentially along with future financial gains, which could ease investor's uncertainty. Stock return volatility has historically been used as a proxy for uncertainty, and

[7] Eigenvector centrality is a concept in graph theory that allows one to examine the connectivity of a node not only by the sheer number of connections it has, but also by the number of connections that the connected nodes have. A paper by David Robinson and Tony Stuart of the Fuqua Business School gives a good account of the calculation (Robinson & Stuart, 2006). The methodology is elaborated in Section 4.

[8] This will be elaborated on in the empirical methodology section, but the idea of proximity has its roots in graph theory in a similar fashion to centrality. The Robinson and Stuart paper gives a good account of this also.

[9] A full explanation of Google's PageRank™ technology can be found at http://www.google.com/technology/.

examining the effects of pharmabiotech alliances on the stock return volatility following the announcement of an acquisition could give insight into how the market judges the learning effects of certain alliances. Specific literature involving the study of alliances across industries in a different time period than this study found that stock return volatility increased for marketing alliances, but did not for technological alliances (Das, Sen, & Sengupta, 1998).[10] Regardless of how the market reacted to the announcement of the alliance, learning effects should have accrued in various degrees.[11] In this study we will examine the relationship between alliances and acquisition stock return volatility in the pharmabiotech field.

Acquiring a firm has the potential to be a risky endeavor due not only to the valuation problems, but to the post-acquisition integration issues as well. It has been shown however, that prior acquisition experience affects acquisition performance positively (Hayward, 2002). In our study we will not be controlling for prior acquisition experience, but we will be taking into account the heterogeneity of acquisitions.[12] To this effect, we will also be looking at how CAPM coefficients change from pre-acquisition to post-acquisition, and whether or not this can indicate overall riskiness. Given that we are focusing on short-term profitability and riskiness, we will not be examining post-acquisition integration issues.

[10] The results of their study are not as important as the verification the paper gives to the methodology of studying volatility following alliances. It is important to remember that the effects of alliances and acquisitions are very industry specific and a cross-sectional analysis, like theirs, may produce different results.

[11] Chan et al. (1997) discovered that strategic alliances, on average, generated positive wealth effects. These positive experiences will generate varying degrees of learning effects.

[12] Heterogeneity in this sense refers to how an acquisition was financed, and whether or not the acquisition was for a company involved in the same therapeutic class.

This study will build on the work previously done by Higgins and Rodriguez (2006) and Danzon et al. (2006) whereby alliances were shown to have effects on the short-term abnormal returns of a merger. We intend to support previous literature that alliances help to mitigate the asymmetric information problem and build upon the work to show that positive learning effects influence not only short-term acquisition gains, but also decrease market uncertainty about these acquisitions.

The remainder of this paper is constructed as follows. Section II presents a review of the literature, Section III details our theoretical framework, Section IV provides an overview of our empirical specifications, Section V presents the results of our empirical analysis, and Section VI provides our conclusion.

II. Literature Review

There is a litany of papers that are devoted to looking at the profitability of mergers and acquisitions. Authors employ different time frames, different samples, and use slightly different metrics (some variation of event-study methodology), to come up with a bastion of heterogeneous conclusions. Andrade, Mitchell, and Stafford (2001) provide a comprehensive review of the empirical landscape, and indicate that the reasons for mergers and acquisitions appear to be time and industry dependent. Since the release of Jensen and Ruback`s paper (1983), which documented that mergers do create value for the combined firm with the majority of the value being allocated to the target firm, there have been multiple industry-orientated merger and acquisition analyses. For the specific relationship between mergers, alliances, and other determinants in the pharmabiotech industry, Higgins and Rodriguez

(2006) showed that prior access to information about a target firm through an alliance was positively associated with an acquirer's returns. This paper is important because it delves into the current number of determinants that researchers are using to assess the short-term profitability of mergers. Porrini (2004) found similar results across different industries, that acquisition performance was correlated with prior-alliances between acquirer and target. There are also a number of additional and different variants that influence merger performance. Danzon, Epstein, and Nicholson (2005) examined the broad effect of mergers on various metrics of performance in the pharmaceutical and biotech space.

The value-creation process of mergers and acquisitions has been fairly detailed, with explanations ranging from the monopoly theory of acquisitions (Eckbo, 1992; Ravenscraft and Scherer, 1987), the potential for synergies (Bradley et al., 1988) economies of scale (Ravenscraft and Scherer, 1989; Houston et al., 2001), additional market power (Anand and Singh, 1997; Baker and Bresnehan, 1985; Barton and Sherman, 1984) to increasing the effectiveness of assets (Capron, 1999). The majority of the research concludes that the value created for the acquiring firms' shareholders is essentially zero (Andrade et al., 2001). As Andrade et al. (2001) postulate, if the fundamental reasons for merging could be accounted for, there might be a more efficient way of distinguishing those mergers that are based on sound reasoning and those that are based on bad reasoning (managerial hubris, empire building, etc...). If the literature on acquisitions and mergers tells us nothing else, it screams that a decision process for a firm to merge or acquire is highly individualistic, and generalizing across time, industry, or even motive can prove spurious.

Danzon et. al (2004) delve into the most detail regarding determinants of mergers. Notably, they account for a firm's propensity to merge and find that firms with a high

propensity to merge underwent a lower growth in sales, employees and R&D irrespective of whether or not they merged. The study also accounted for the inherent differences in pharmaceutical and biotech firms' cost and production functions. Large firms were found to merge as a response to lacking product pipelines and looming patent expirations, but it was shown that merging was not an effective response. Smaller biotech firms were also found to merge primarily as a response to financial distress. The study was somewhat myopic in that it only looked at three years following the merger and therefore it is difficult to determine what the long-term profitability effects are.

A significant drawback to these studies is that they offer no consensus on what type of metric should be employed to value an acquisition. The debate between book and market-based metrics continues to cause polarization, but we feel that given the nature of the pharmabiotech industry, relying on market-based metrics will allow us to skirt the issue that many of these biotech firms have negative cash flows and substantial burn rates, making accounting data impractical to use.[13]

Danzon et al. (2005) provided the most comprehensive work regarding alliances in the pharmabiotech industry. They conclude that products born out of an alliance have a greater probability of success. Their results also confirm the learning-curve hypothesis that we will carry forth in our research.[14]

[13] A firm's burn rate measures how quickly a company is depleting its capital. It is tantamount to continuous negative cash flows and is usually expressed in cash outflow per month.

[14] The learning effects model we rely on states that experience is positively correlated with future performance. One could then define the learning curve to state that performance is a monotonically increasing function of experience. There is some literature, by Haleblian and Finkelstein (1999) and others, that states performance may be a U-shaped function of experience, meaning inexperienced firms may detrimentally generalize prior

The effects of alliances and joint ventures have been well chronicled in the literature. A paper that is particularly relevant to our research is Das et. al (1998), whereby researchers used event-study methodology to examine the abnormal returns and variance of returns for technological and marketing alliances. They found that technological alliances produced greater abnormal returns than marketing alliances, and that marketing alliances had higher stock return variance than technological alliances. An interesting conclusion they found was that on the whole, the equity markets were indifferent to the announcement of strategic alliances; any abnormal returns were found to be statistically insignificant. This is in contrast to Chan et. al (1997), who did find positive responses from capital markets overall. A point of contention for Das et. al (1998) is that similar to mergers and acquisitions, alliances are very industry-specific, and generalizing across industries using cross-sectional data may prove inconclusive. Again, we endeavor to confirm that alliances within the pharmabiotech industry generate value through the creation of learning effects, and show that there is a relationship between alliances and acquisitions.

Porrini (2004) examines the relationship between manufacturing acquisitions and alliances during a prolonged period of nine years across a variety of industries. He finds that an acquiring company can gain target-specific information and learning-experience, both of which may prove resourceful during a subsequent acquisition, from a prior alliance. Also important to our study are the control variables he accounts for, specifically: SIC relatedness, aggregate acquisition experience of acquiring and target, change in sales, and method of payment. It is worthy to note that our data set will be comprised solely of pharmaceutical and

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experience to future activities. The model we will employ assumes that performance is a monotonically increasing function with respect to experience.

biotech companies and while we share similar preliminary hypotheses such as positive relatedness between acquisition performance and prior alliance between acquirer and target, his paper does not delve into a study of market uncertainty of an acquisition as measured by stock return volatility. In addition, his sole dependent variable is returns-on-assets (ROA), which is effective at measuring how efficient a management team produces after-tax profits using given assets. However, we are more interested in the expected value of an acquisition as appropriated by the market.[15]

It is important to mention another article that develops a Capital Asset Pricing Model (CAPM) for studying mergers, which will be modified to fit our particular research.[16] Davidson, Garrison, and Henderson (1987) published a method for assessing the change of alphas and betas in a merger between two parties. The researchers begin by creating a pre-merger portfolio of the two firms, and comparing the alphas and betas before the merger to the alphas and betas post-merger. In their study the researchers were trying to shed light on the idea of a merger synergy, as represented by a change in the CAPM coefficients, and they did find evidence to suggest that nonconglomerate mergers, mergers between two parties with similar businesses, were synergistic. What we take away from this is not the results, per se, but rather the motivation to study the change in CAPM coefficients over different events.

[15] It is worthwhile, again, to note here that the literature takes two sides to the debate on whether to use book values or market values for measuring the success of a merger. In the biotechnology industry, and other industries with the prevalence of negative cash flows, market values are considered to be a more tractable measure of a firm's performance.

[16] The CAPM model used as a basis for Davidson et al.'s work is based on the model published by William Sharpe (Sharpe, 1964). In this model, the excess return of a company over the risk-free rate (taken to be the interest rate of a short-maturity US Treasury bill) is linearly related to the non-diversifiable risk of the market, represented by the beta.

We shall adapt their methodology to look at how an acquisition could influence a change in CAPM coefficients. The empirical methodology behind this is presented in Section 4.

The literature provides a firm groundwork to build upon, yet leaves room for our addition to the field. This study will uniquely distinguish itself by trying to *quantify* the relationship between pharmabiotech acquisitions and alliances through the study of stock return volatility in hopes of providing useful information as to how the market perceives certain acquisitions. In addition, we will examine alliances with a more network driven model, accounting for different types of alliances, and the alliance network as a whole.

III. Theoretical Framework

The theoretical foundation for our work will revolve around the existing theory based in managerial decision making. Undertaking mergers or acquisitions can be a firm's response to internal distress, an aggressive move towards potential gains, a defensive move against industry-related shocks, market-related shocks, macroeconomic effects, and many other exogenous variables. Nonetheless, acquisitions are considered by many to be a value-adding or at the least, a value-preserving event. There have been documented wealth effects from mergers, wealth that was created, not redistributed among different groups of stakeholders (bond-holders to stock-holders for example). In the pharmaceutical and biotech industry, where there is thought to be the potential for economies of scale and scope, acquisitions are perceived as a way for a firm to grow R&D externally, enter a new market without the burden of expanding internally, acquire complementary drugs and technologies, and achieve

synergies.[17] There are also anticompetitive motivations to merge, which are frequently regulated against, but nonetheless include: the ability to eliminate a competing product, eliminate a drug in a competitor`s pipeline, and gain monopolistic market power.

There are specific motivations in the pharmaceutical and biotech fields to merge or acquire target firms, most notably the ability to gain additional bargaining power with insurance companies and pharmacy benefit managers (PBM), the ability to continue to consolidate, and the outsourcing of R&D (Burns, Nicholson, & Evans, 2005). There have also been industry shocks that may have been contributing causes for mergers. The Waxman-Hatch Act of 1984 increased generic competition in the industry, forcing many firms to rely more heavily on blockbuster drugs. This added focus helped to catalyze a wave of mergers and acquisitions. Also, the rise of managed care in the 1990s brought cost-containment to the forefront, forcing some to merge or acquire in the hopes of reducing expenses.

Mergers and acquisitions tend to occur in waves, and the pharmabiotech industry is no different. According to one source, beginning in the late 1980s large firms merged primarily to cut fixed costs. The second wave began approximately in 1994 and continued throughout 1997, where mergers were used by companies to leap-frog into higher market shares.[18] Finally the third wave of mergers, from 1998 onward, has been characterized by the desire to keep a full product-pipeline, and maintain optimistic growth figures. In conjunction, Pharmaceuticals began utilizing alliances with biotech firms to increase their R&D potential and replace their product pipeline. It is this third wave that we are most interested in.

[17] Synergistic behavior can be defined as "positive return endeavors" (Davidson, Garrison, & Henderson, 1987).

[18] Obtained from Business Insights report on "Pharmaceutical M&A: The Third Wave" (1999).

The empirical findings researchers have discovered reinforce the theoretical findings, for the most part. Positive learning experiences, such as worthwhile alliances, have a positive effect on acquisition returns. Firms with a low Tobin Q, low product pipeline, and low cash flow, in essence firms that are in distress, have a higher propensity to merge (Danzon, Nicholson, & Pereira, 2005).[19] Firms that have previous experience merging with companies of the same therapeutic class as themselves, on average realize increased returns. Firms that have a distressed research program, evident by diminished patent lives or lacking product-pipeline, will also have a higher propensity to merge (Danzon et al., 2005).

Our research will aim to build on the empirical findings by examining more closely the relationship between alliances and acquisitions. Our hypotheses are explicitly outlined below.

Hypothesis 1: The acquiring firm's short-term profitability will be positively related with a prior alliance between acquiring and target firms.

Hypothesis 2: The acquiring firm's short-term profitability will be positively related with the centrality score of the acquiring company.

Hypothesis 3: The acquiring firm's short-term stock return volatility will be negatively related with prior alliance between acquiring and target firms.

Hypothesis 4: The acquiring firm's short-term stock return volatility will be negatively related with the centrality score of the acquiring company.

[19] Tobin's Q can be defined as a ratio between the market value of a company and its asset value. The value of a firm's assets is usually measured by the replacement cost of its assets. A high Q ratio could indicate that a firm is overvalued.

Hypothesis 5: It is not clear *a priori* whether the number of shared third-party alliances will influence cumulative abnormal returns and short-term stock return volatility in a positive or negative fashion. According to the majority of the literature, the number of shared third-party alliances is another metric for a firm's embeddedness within a network, and hence this variable may mirror the effects of a firm's centrality score. However, it may well be the case that shared third-party alliances will act in the opposite fashion, in essence acting as a proxy for a measure of competition, unbiased learning effects, or an unknown variant that will affect cumulative abnormal returns and short-term return volatility in a negative manner

Hypothesis 6: Acquisitions will on average be perceived as risky, meaning the CAPM coefficients of acquiring companies will rise following an acquisition. This will either be the result of an increase in the debt-to-equity ratio or the market's perception of increased risk.

Our hypothesis is that a prior alliance with a target company, and other advantageous alliance network arrangements, will have a positive effect on the acquirer shareholder's value, and specifically, alliances with greater learning effects will have a more pronounced effect on shareholder value. This value will be realized not only through the stock returns, but in additional market certainty about the future plans of the acquiring company following an acquisition.

IV. Empirical Specifications

This section will step through the analysis of the data, beginning with a discussion of how the data was acquired. Our initial set of acquiring firms was determined by performing

an acquisition search of the Securities Data Company (SDC) database using the SIC codes 2834-2836 for the years 1998-2004. Acquisitions were then filtered to ensure that only appropriate transactions were included.[20] Section 3 of the data appendix includes additional details on the screening process. After our set of acquisitions was finalized, The Center for Research in Security Prices (CRSP) database, Thomson Datastream, and Yahoo! Finance were used to obtain stock price data for each acquiring company. In addition, we obtained daily S&P 500 returns for each of the acquisitions. Firm specific information was acquired using COMPUSTAT and checked against publically available documents (10-K, annual reports, etc.) when ambiguity arose. Alliance data were obtained from Recombinant Capital, and when available, cross-checked with alliance data from the SDC database. Next, we obtained intraday stock return data for 65 of the 100 acquiring firms on the day of their acquisition using the New York Stock Exchange Trade and Quote database (NYSE TAQ).[21] Finally, the CRSP was used again to obtain daily stock return data for these 65 acquisitions for 1800 to 10 days prior to the acquisition in order to calculate average daily stock return volatility.

The remainder of this section will be composed in the following manner. First, the event-study method used to obtain the cumulative abnormal returns for the acquiring companies will be discussed. Then the methods used to calculate the centrality and proximity

[20] Transactions that were not acquisitions, such as stock buybacks, were not included. In addition, the manual filtering process weeded out mergers of equals, such as the merger between GlaxoWellcome and SmithKline Beecham in 2000. Moreover, transactions that were classified as acquisitions but were really small undisclosed equity purchases or minority stakes of the target company were excluded. For example, GlaxoSmithKline's purchase of an undisclosed minority stake in Replidyne in June 2003 was not included in the final dataset. Consult Section 3 of the Data Appendix for further details.

[21] 65 firms out of the 100 firms were used because the NYSE TAQ only contains intraday pricing data for securities listed on the NYSE and the American Stock Exchange (AMEX).

measures will be detailed. Following this, the GARCH volatility model used to generate predicted daily volatility will be presented, as well as the methods used to calculate realized daily stock return volatility and average daily stock return volatility. Finally, the CAPM model, as it relates to this study, will be discussed.

a. Event Study Methodology

The event-study methodology used to capture short-term abnormal returns is based upon using OLS multivariate regression methods for time series data. In short, an event-study measures the effect of a given event, in this case an acquisition, on the normal returns of financial data. We used historical stock prices and the CAPM model to estimate a normal return for the event window, and then compared this normal return to the actual return we witnessed. The difference between the two was considered the effect. Both a three and five event-study window were used to control for any conflicting events. The realized return during this window was constructed from adjusted closing stock prices obtained from CRSP, Thomson Financial, and Yahoo! Finance.[22] In our model to judge the effect of alliance network information on the short-term profitability of the acquiring company, the dependent variable was cumulative abnormal returns for the acquiring firm. The independent firm-specific variables included: difference in log sales, log market cap, log R&D expenditures, log transaction value, method of payment, SIC relatedness, and a number of alliance-specific variables. The difference in log sales variable was created by subtracting the log sales of the

[22] Daily returns will be expressed as, $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$. P_t represents the adjusted closing price of the stock at time *t*. The adjusted closing price takes into account any cash dividends or stock splits that may have occurred between time *t-1* and time *t*.

acquiring company in the year of the acquisition by the log sales of the acquiring company in the year prior to the acquisition.

b. Centrality and Proximity Construction

The methodology for constructing the centrality measurement will now be discussed. Eigenvector centrality is a concept in graph theory that allows one to examine the connectivity of a node not only by the sheer number of connections it has, but also by the number of connections that the connected nodes have. In the context of this research, alliances between firms will be represented in an adjacency matrix. One can solve the eigenvector equation for this adjacency matrix, and use the i^{th} entry of the eigenvector associated with the highest eigenvalue to determine the centrality measure. Higher centrality scores proxy for more reputable firms; more reputable firms have higher centrality scores. A paper by David Robinson and Tony Stuart of the Fuqua Business School gives a good account of the calculation (Robinson & Stuart, 2006), and we summarize it below.

Let our adjacency matrix, which is comprised of both the alliances of the acquiring firm and the alliances of the target firm, be denoted $A_{i,j}$. This is a symmetric matrix comprised of elements of the set $\{0, 1\}$, with each $A_{i,i}$ entry equal to zero. For the i^{th} firm, the centrality will be the sum of all the centralities of the firms connected to it multiplied by a proportionality constant. We can represent this as, $x_i = \frac{1}{\lambda}\sum_{j=1}^{N} A_{i,j}x_j$. This can be rewritten in vector notation to read, $\mathbf{x} = \frac{1}{\lambda}\mathbf{A}\mathbf{x}$, where **x** is an Nx1 column vector and **A** is an NxN symmetric matrix. This readily transforms into the archetypal eigenvector equation,

$\mathbf{Ax} = \lambda\mathbf{x}$. One can solve this equation by diagonalizing the adjacency matrix, or by first determining the eigenvalues, through the following method.

$\mathbf{Ax} = \lambda\mathbf{x}$ can be rewritten as follows, $(\mathbf{A} - \mathbf{I}\lambda)\mathbf{x} = \mathbf{0}$. In order for this to have a non-trivial solution, meaning for the null-space of $\mathbf{A} - \mathbf{I}\lambda$ to be comprised of more than the empty set, $\mathbf{A} - \mathbf{I}\lambda$ must be a singular matrix, which occurs if and only if the determinant of this matrix is equal to zero. Therefore one can solve, $\det(\mathbf{A} - \lambda\mathbf{I}) = \mathbf{0}$, by solving its corresponding characteristic equation, which will return the eigenvalues. The adjacency matrix is a real positive NxN matrix, and as such, the Perron-Frobenius theorem applies. This theorem allows one to focus on the eigenvalue with the largest magnitude. From this eigenvalue, denoted λ_0, the corresponding eigenvector can be found by examining the null set solutions to $(\lambda_0\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{0}$. The i^{th} component of the eigenvector **x** is the centrality measure for the i^{th} firm.

The proximity scores are computed by looking at the number of shared third-party alliances between the acquiring and target companies. If company A is acquiring company B, and both had a separate alliance with company C, it would be possible for company A to consult with company C about the integrity of company B. This type of learning may be more unbiased than the information obtained from a direct contact with company B. A firm's proximity score is then the sum of all of these shared third-parties. In notation if company *i* acquired company *j* then this proximity score would be, $P_i = \sum_k x_{i,k} x_{j,k}$ for all *k* shared third-party alliances. Including this proximity score may correct for any upward omitted variable bias present in the learning effects captured by the centrality and prior alliance variables.

c. GARCH Volatility Model

The most appropriate parametric model to use for studying the effects of stock return volatility during the acquisition event-window is the generalized autoregressive conditional heteroskedastic (GARCH) model.[23] To compare the effects of alliances on acquisition volatility, we will compare the realized volatility of acquiring firms against the predicted volatility and a number of alliance-specific variables. To begin, the canonical GARCH model is presented below.

$$r_t = a_0 + a_1 * r_{t-1} + e_t$$
$$e_t \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = b_0 + b_1 * e_{t-1}^2 + c_1 * \sigma_{t-1}^2$$

In the auto-regressive model, the variable "*r*" represents returns at a given time, and the variable "*e*" represents the residual return at a given time. The residuals are normally distributed with mean zero and a variance that is time-dependent. The GARCH model is a standard GARCH(1, 1) model, which means there are one-period lag effects for the squared residuals and the variances.

d. Realized and Average Volatility Construction

In order to properly test the GARCH model, realized daily return variances had to be calculated for each acquisition. The daily return variances are a function of the intraday returns for a stock, and data for acquiring firms was obtained from the NYSE Trade and Quote Database (TAQ). The variation in trading frequency across the set of firms brings

[23] The GARCH model was first published by Professor Tim Bollerslev in 1986. The work can be found under: Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31*, 307-327.

forth the econometric question of whether there will be a bias in the returns for some companies due to the presence of serial correlation from non-synchronous trading. This autocorrelation has been documented by several researchers, including Kadlec and Patterson (1999). When comparing across firms, stocks that trade with a higher frequency will seem to have returns that lead returns to stocks that trade with a lower frequency. This may induce a one-period lagged cross-correlation across stocks, causing bias. Andersen and Bollerslev (1997) correct for this problem by using five-minute intraday returns. This window allows for firms that trade at different frequencies to have comparable agility in adjusting to market-moving information. Once five-minute returns were calculated, the daily variance was computed using the following estimator.

$$s_t^2 = \sum_{i=1}^{N} r_{n,t}^2$$

$E[s_t^2] = \sigma_t^2$, where N refers to the number of five-minute intraday returns in a

$s_t = \sqrt{s_t^2}$

trading day.

As can be proven, s_t^2 is an unbiased estimator for the daily variance, and the square root of this estimator is an unbiased estimator for the daily volatility. To judge the effectiveness of our parametric volatility models, we regressed the predicted daily volatility on the realized volatility using OLS methods and Gauss-Markov assumptions with the following model, $\ln(s_t) = \alpha + \beta \ln(\hat{\sigma}_t) + e_t$, where s_t is the realized daily stock return volatility and $\hat{\sigma}_t$ is the square root of the predicted daily stock return variance generated from the GARCH(1,1) model. If our predictions are unbiased, than the estimated alpha and beta should be 0 and 1 respectively.

The average daily stock return volatility was calculated using daily stock returns from the CRSP database. The unbiased sample variance of daily returns was first computed using the following formula, $\bar{\sigma}^2 = \frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})^2$, where *n* represents the number of daily stock return observations. This is readily identified as the formula for a sample variance, and the unbiased sample standard deviation, the average daily volatility, is simply, $\bar{\sigma} = \sqrt{\bar{\sigma}^2} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})^2}$. This measure of average daily stock return volatility was compared against the realized daily stock return volatility on the date of an acquisition.

To estimate the effects of the alliance network on volatility, the following model was estimated using OLS methods where s_t is the realized daily stock return volatility and $\hat{\sigma}_t$ is the square root of the predicted daily stock return variance generated from the GARCH(1,1) model:

$$\ln(s_t) = \beta_0 + \beta_1 \ln(\hat{\sigma}_t) + \beta_2 prioralliance + \beta_3 centralityscore + \beta_4 sharedalliances + \upsilon_i$$
$$\upsilon_i \sim N(0, \delta^2)$$

e. CAPM

In order to test our hypothesis surrounding the change in CAPM coefficients, the alphas and betas, after an acquisition, the following empirical methodology was utilized. Although our model was substantively different, the core ideas follow from previous work done by Davidson, Garrison, and Henderson (1987). We will begin with a review of the basic CAPM model, as developed by Sharpe in his 1964 paper, and then progress to show how we adapt this model for our use.

At its most fundamental level, the Capital Asset Pricing Model (CAPM) attempts to describe the relationship between asset returns and risk. An asset's risk can be quantified as the standard deviation of an asset's return over a period of time. Risk defined in this manner will be represented as:

$$Var(r_i - r_f) = E[(r_i - r_f)^2]$$
$$\sigma_i = \sqrt{Var(r_i - r_f)}$$
r_i = Return for asset i
r_f = Return for risk - free asset

Two types of risk need to be distinguished first. The non-diversifiable risk, or the systematic risk of an asset, is the risk associated with the entire market of these assets that cannot be diversified away by holding other assets of the same class. The other type of risk is the idiosyncratic risk, which can be lowered through diversification. We will constrain our thinking to equities, and when we do, we notice from the properties of variances, that if an investor holds a portfolio of two equally risky equities with equivalent returns, and these two equities are not perfectly correlated, that the overall portfolio variance is smaller than the individual asset's variance.[24] This motivates the idea of a market portfolio, which can be

[24] A brief mathematical argument for diversification will be presented now. Imagine a risk-averse investor, meaning that given a set of assets with equivalent expected rates of return, this given investor would prefer to hold the asset with the least risk, the lowest variance σ^2. Imagine there are 2 assets in this class, each with an expected return, $E(R_i)$. A weighted portfolio of these two assets would have an expected return of, $E[R_p] = w_1 E[R_1] + w_2 E[R_2]$. We assume no short-selling of these assets, meaning $0 \le w_i \le 1$. For tractability, assume that $R_1 = R_2 = R$, and therefore $w_2 = 1 - w_1$. Therefore the expected return of the portfolio would simply be R. The variance of the portfolio can be represented as follows, $Var(R_p) = w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\rho_{1,2}\sigma_1\sigma_2 = w_1^2\sigma_1^2 + (1-w_1)^2\sigma_2^2 + 2w_1(1-w_1)\rho_{1,2}\sigma_1\sigma_2$. Now for arguments sake, assume that $\sigma_1^2 = \sigma_2^2 = \sigma^2$. Then, $Var(R_p) = \sigma^2(w_1^2 + (1-w_1)^2 + 2w_1(1-w_1)\rho_{1,2})$. As one increases the number of assets held that aren't

thought of as the portfolio that has the highest Sharpe ratio on the efficient frontier.[25] In effect holding the market portfolio allows one to maximize the diversification of risk. The CAPM accounts for the amount of risk in a given asset that can't be diversified away. The model can be stated as follows, $E(R_i) - R_f = \beta_{i,m}(E(R_m) - R_f)$. In theoretical terms, the market portfolio should be a weighted-portfolio of all the available assets. However this is impractical for empirical applications. Instead, a market proxy such as the S&P 500 index is used. Our analysis deals with the returns to equities, and the S&P 500 index is comprised of the 500 largest companies by market capitalization, weighted according to each one's market capitalization.[26] It is therefore the most accessible market portfolio proxy for us to use.

The reason behind calling this model a "pricing model" is as follows. Under this model, only non-diversifiable risk is rewarded. This is derived because this model relates the

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perfectly correlated with each other, $\rho_{i,j} \neq 1$, the overall variance of the portfolio decreases. For our example, let $w_1 = w_2 = 0.5$. Then, $Var(R_p) = \sigma^2(0.5 + 0.5\rho_{1,2})$. Our investor notices that if the two assets are perfectly positively correlated, than the portfolio variance is simply the variance of one of the individual assets. If the two assets are perfectly uncorrelated, meaning $\rho_{1,2} = 0$, then $Var(R_p) = 0.5\sigma^2$. Finally, if the two assets are perfectly negatively correlated, $\rho_{1,2} = -1$, then $Var(R_p) = 0$. The principle of diversification entails that, even if a group of assets share equivalent expected rates of return and risks, as long as they are not perfectly positively correlated with each other, one can achieve the same expected rate of return with the smallest risk by holding the entire set. Holding the entire set, or the "market" portfolio, minimizes risk. Hopefully this motivates the general notion behind diversification. For a more detailed analysis of modern portfolio theory, one can consult the textbook "Modern Portfolio Theory and Investment Analysis" by Elton, Gruber, Brown, and Goetzmann (2006).

[25] The efficient frontier, also known as "The Markowitz Frontier", is a set of all assets that have the highest return for a given level of risk. The Sharpe ratio is a reward-to-risk ratio defined as, $\frac{E[R - R_f]}{\sqrt{Var(R - R_f)}}$.

[26] The market capitalization of a firm is defined as the number of outstanding shares a company has multiplied by the stock price. It is interesting to note that presently the S&P 500 does not use the number of outstanding shares of a company in calculating market capitalization but utilizes the number of floating shares, or the number of shares that are publically available for trading. The float is an estimated number with some degree of subjecti

riskiness of a given asset to the riskiness of the market portfolio, and calculates the appropriate rate of return that would be required to compensate the investor for holding this risky asset. We have shown already that the market portfolio has only one kind of risk, systematic or non-diversifiable risk.

The CAPM equation is estimated by using ordinary least-squares (OLS) linear regression techniques over a given time period. The beta coefficient follows from the OLS definition of the slope coefficient in a simple linear regression. It is as follows, $\hat{\beta}_{i,m} = \frac{\sum_{T}(R_{i,t} - \overline{R}_i)(R_{m,t} - \overline{R}_m)}{\sum_{T}(R_{m,t} - \overline{R}_m)^2}$. The summations are taken with respect to the representative time intervals. For our purposes, returns will be expressed as daily returns and calculated as the continuously compounded return between time periods *t-1* and *t*.[27]

Using the CAPM model, one can estimate ex-ante what the required rate of return will be for an asset in a given time period given its exposure to market risk. The estimated CAPM model used for predicting an asset's return in time *t* is:

$$\hat{R}_{i,t} = R_{f,t} + \hat{\beta}_{i,m}(R_{m,t} - R_{f,t})$$

The measure of a stock price's excess return over the required rate of return predicted by the CAPM model is called Jensen's alpha. The alpha can be thought as the persistent

[27] Daily returns will be expressed as, $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$. P_t represents the adjusted closing price of the stock at time *t*. The adjusted closing price takes into account any cash dividends or stock splits that may have occurred between time *t-1* and time *t*.

contribution to an asset's return not accounted for by the CAPM equation. We can express the CAPM with the alpha term as follows:

$$E(R_i) - R_f = \alpha_i + \beta_{i,m}(E(R_m) - R_f)$$

Again, this equation can be estimated using OLS techniques with the alpha analogous to the intercept coefficient in a simple linear regression.

To refresh, we will be looking at the change in alphas and betas of the acquiring company from before to after an acquisition between the acquiring and target company. For calculating the alphas and betas before the acquisition, we will use the following formula, $R_{i,t} - R_{f,t} = \alpha_{i,BA} + \beta_{i,m,BA}(R_{m,t} - R_{f,t})$. The time period used will be 180 days to 60 days prior to acquisition.[28] For calculating the alphas and betas after the acquisition, the following formula will be used, $R_{i,t} - R_{f,t} = \alpha_{i,AA} + \beta_{i,m,AA}(R_{m,t} - R_{f,t})$. The time period used will be 60 day to 200 days after an acquisition. The before-after change in alphas and betas for acquisitions will be calculated as [$\Delta\alpha_{i,A} = \alpha_{i,AA} - \alpha_{i,BA}$, $\Delta\beta_{i,A} = \beta_{i,AA} - \beta_{i,BA}$]. We aim to investigate how the CAPM coefficients are affected by any given acquisition.

V. Empirical Analysis

Our data set is comprised of 100 acquisitions in the pharmabiotech industry from 1998 to 2004. For each of these acquisitions data was collected on specifics relating to the transaction and to the acquiring firm. Table 1 highlights the important independent variables

[28] Davidson et al. (1987) provide support for using 180 to 60 days prior to a merger.

that were used in the regression of cumulative abnormal returns versus alliance information. Logarithmic transformations were used to normalize the data when needed.

Table 1: Summary Statistics for Acquiring Firms and Transaction

Variable	Obs.	Mean	Std. Dev.	Min	Max
Cumulative Abnormal Returns	100	0.87%	11.73%	-23.00%	73.00%
Log Sales in Year of Acquisition	100	4.033	3.328	-4.490	13.090
Log Sales One Year Prior to Acquisition	100	3.852	2.955	-4.710	10.770
Log Market Cap in Year of Acquisition	100	6.683	2.116	2.048	11.724
Log Transaction Value	100	3.416	2.244	-1.427	9.735
Log R&D Expense in Year of Acquisition	100	3.347	2.272	-2.120	9.207
Relatedness	100	0.590	0.494	0.000	1.000
Method of Payment	100				
Stock	**Percent**	60.0%			
Hybrid		18.6%			
Cash		21.4%			

The cumulative abnormal returns were constructed using event-study methodology and a window of -2 to +2 days with respect to the acquisition. Historical stock returns were regressed upon S&P 500 returns to predict normal returns for the window. Realized daily returns were then compared to normal returns to generate daily abnormal returns. Abnormal returns were then summed across the event window to create cumulative abnormal returns. For method of payment, hybrid represents a payment of both stock and cash.

The mean cumulative abnormal return was 0.87%, yet the p-value under the null hypothesis that these cumulative abnormal returns were insignificant was 0.4958. For robustness, a three-day window was also examined and similar results were obtained. This supports the claim by Andrade et al. (2001) that acquiring firms, on average, don't realize positive returns.

The acquiring alliance information was gathered using the Recombinant Capital Database and cross-checked against the SDC database. Alliances were screened based on acquiring and target firms, and on average, each acquiring company engaged in approximately 17 alliances with a biotech. When reported, the average size of the alliances

for the acquiring firms was $102.53 million, the average equity stake in the alliance was $9.13 million, and the average royalty payments were $0.23 million. Table 2 presents aggregate summary statistics for the alliance data, while Table 3 presents the relevant summary statistics for the acquiring firms. Table 4 presents summary statistics for the average number of alliances by alliance type.

Table 2: Summary Statistics for Alliance Data

	Obs	Mean	Standard Deviation	t-statistic	Min	Max
Total Alliances in Entire Network	2174	7.85	27.69	13.23	0	6777
Centrality Values	2174	0.01	0.02		0	0.33
Acquisition/Target Sub-Group						
Total Alliances within Acq/Target SubGroup	172	36.15	83.16	5.70	0	677
Total Pharma-Biotech Alliances	172	17.19	49.46	4.58	450	1
Total Alliances with Royalties	172	7.41	16.24	6.02	0	96
Total Alliances with Equity Payments	172	4.10	10.34	5.23	0	80
Number of Shared Third-Party Alliances	97	7.30	13.70		0.00	98

All of the variables in the acquisition/target sub-group, except for number of shared third-party alliances, were constructed for both acquiring and target firms. While there are 100 acquisitions in question, some acquiring firms engaged in multiple transactions, and some target firms were acquiring firms in prior transactions.

Table 3: Summary Statistics for Acquiring Firm's Alliance Data

	Obs	Mean	Standard Deviation	t-statistic	Min	Max
Prior Alliance	100	0.21	0.41	5.13	0.00	1.00
Centrality Score	97	0.06	0.07	7.53	0.00	0.33
Shared Alliances	97	7.30	13.70	5.25	0.00	98.00

Table 4: Alliance Data by Type of Alliance

	Type of Alliance					
	Development	Co-Development	Co-Marketing	Co-Promotion	Collaboration	Cross-License
Mean	8.80	1.74	0.45	1.72	5.97	0.48
	Joint Venture	Manufacturing	Marketing	Research	Sub-License	Supply
Mean	1.37	1.35	0.06	8.92	0.37	3.77

In many cases, an alliance was classified under multiple listings; alliance types are not mutually exclusive. For example, a research alliance could also be classified as a development alliance in some instances.

One take-away from examining these numbers is that the aggregate average of development, research, and co-development alliances is 19.5 per firm, which accounts for approximately 56% of all alliances in our dataset. This is not surprising given the intense focus on R&D in the pharmabiotech industry.

As discussed in Robinson and Stuart (2006) and others, the construction of a network of alliances is substantively important in and of itself. To this end, we used the universe of Recombinant Capital alliances generated by the acquiring and target companies to investigate the centrality and proximity makeup of the alliance network. A graphical representation of the alliance adjacency matrix is presented below in Figure 1. A key takeaway is that the overall network is fairly centralized, with the largest companies, as denoted by market capitalization, occupying the most central roles, and consequentially having the highest centrality scores. Presented in Table 5 are the top twenty centrality scores shown alongside the top 20 firms with the most total alliances. While the two groups are extremely similar, the centrality scores have embedded in them not only the sheer aggregate number of alliances, but also the reputability of these alliances.

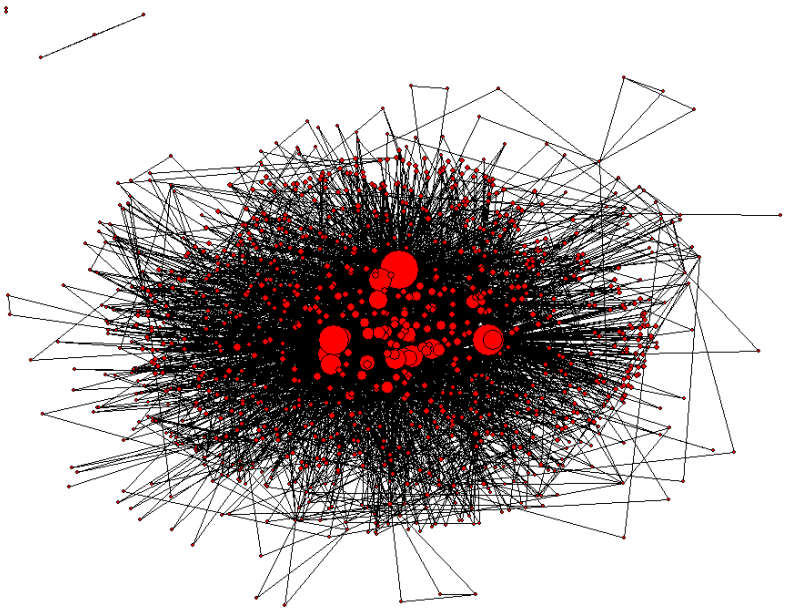

Figure 1: Network Graph of Alliances – The circles are prescribed by their centrality score; the more central figures, on average, have higher centrality scores. The key abstraction from this diagram is that the network is fairly centralized. We observe outlying firms forming more alliances with central figures than with other outliers. The graph was constructed using UCINET 6 and our adjacency matrix.

Table 5: Centrality Scores and Total Alliances for the Top 20 Firms

	Centrality
GlaxoSmithKline	0.3328
Merck	0.2738
Roche	0.2440
Chiron	0.1881
Lilly	0.1854
Amgen	0.1800
Genzyme	0.1710
Bayer	0.1690
Pharmacia	0.1589
Elan	0.1473
Serono	0.1465
Genentech	0.1431
MedImmune	0.1384
Biogen	0.1196
Medarex	0.1134
Baxter	0.1129
Corixa	0.0936
MGI Pharma	0.0908
SmithKline	0.0902
Abbott	0.0829

	Total Alliances
GlaxoSmithKline	677
Merck	430
Roche	385
SmithKline	326
Chiron	294
Lilly	265
Genzyme	263
Amgen	227
Elan	222
Bayer	220
Pharmacia	201
Merck Serono	171
MedImmune	152
Serono	150
Cambridge Biotech	139
Biogen	129
Abgenix	121
Genentech	118
Baxter	113
Cetus	109

An important note should be made regarding the construction of the adjacency matrix, as it is obvious both GlaxoSmithKline and SmithKline are members of the above table. In this analysis we assumed the learning effects acquired by a firm are not necessarily lost after a merger occurs. In the case of GlaxoWellcome and SmithKline, a merger of equals, the combined company will be able to harness the learning effects of both companies. In the data, there is certainly overlap in alliances between GlaxoSmithKline and SmithKline, but we are treating both as two entirely separate entities. Each set of alliances is truncated at the time of the respective acquisition in order to isolate the total amount of alliance knowledge available for use in the acquisition, and therefore the table above is not for any given time period.

In addition to centrality measures, proximity scores were calculated for acquiring-target pairs. As defined previously, the proximity score is the number of shared alliances

between the acquiring and target firms. On average, acquiring and target companies had approximately 7 alliances with shared third-parties.

Overall, an analysis of our alliance data shows that the pharmabiotech industry is a highly relational industry with a culture for forming alliances. Given the high risks of the industry, it is not surprising that firms tend to spread that risk out over a broad set of alliances. Given this risk-diffusing behavior, we examined the change in CAPM coefficients from before to after an acquisition for acquiring firms to help determine if the market perceives pharmabiotech acquisitions as a risk-abating maneuver. The summary statistics for the CAPM coefficients are presented below in Table 6.

Table 6: CAPM Coefficients of Acquiring Firms

	Mean	Std. Dev	|t|	p-value
Before Beta	0.9494 ***	0.935	9.840	0.000
After Beta	1.0004 ***	0.862	10.700	0.000
Before Alpha	-0.0001	0.007	0.090	0.929
After Alpha	0.0004	0.004	0.950	0.347
Confidence Interval for Difference in Pre-Post Beta Coefficient				
Point Estimate	0.0510	[-0.1509 , 0.2529]		

Stock prices were obtained from CRSP, Datastream, and Yahoo! Finance. The risk-free rates used in the CAPM equations were the average rates of the three-month U.S. Treasury bill over the course of each acquiring firm's dataset.

The statistic of interest is the difference between the post-pre CAPM coefficients. The point-estimate for the difference in beta was determined to be 0.0510 while the difference in alpha was 0.0005. The difference in beta was not statistically significant at the 5% level, as is evident by a 95% confidence interval of [-0.1509, 0.2529]. The difference in alpha was also not statistically significant at the 5% level. The beta coefficient exhibited a statistically insignificant increase, and therefore we can offer no conclusion based on this cursory

examination as to whether an acquisition is perceived on average to cause a firm to have an increased exposure to market risk. To answer one of our fundamental questions, does the market recognize the learning effects inherent within alliances, we examined the volatility of stock returns, specifically on the date of a pharmabiotech acquisition.

The realized volatilities of stock returns for the acquiring companies were obtained for a subset of our larger group, as intraday returns data was only available for 65 of the initial 100 firms. The summary statistics for the realized stock return volatility are presented below in Table 7.

Table 7: Summary Statistics for Acquiring Firm's Daily Stock Return Volatility on Acquisition Date

	Obs	Mean	Std. Dev.	Min	Max
Realized Daily Return Volatility	65	7.56%	12.98%	0.09%	100.07%

Using the daily stock returns of these 65 acquiring companies, we constructed average daily volatilities using past returns. As discussed previously, data was obtained for 1800 days to 10 days prior to the acquisition. The summary statistics are presented below in Table 8.

Table 8: Summary Statistics for Average Daily Stock Return Volatility for Acquiring Firm

	Obs	Mean	Std. Dev.	Min	Max
Average Daily Return Volatility	65	4.97%	1.98%	1.88%	10.47%

A two-sample t-test assuming unequal variances was used to determine if there was a statistical difference between the average and the realized daily stock return volatility. Assuming a two-sided alternative hypothesis, the p-value reported was 11.72%. Therefore while we can't reject the hypothesis that the difference is zero, the results are hardly conclusive that the stock return volatility on the date of the acquisition was well-determined

by historical averages. A more robust model was needed that could account for the wide-swings in daily volatility To this end, a GARCH(1,1) was constructed for each acquiring firm using past daily stock returns.

As explained in the previous section, the variable of interest from the GARCH model was the conditional variance estimate. Daily stock returns were compiled, when available, from 1800 trading days to 10 trading days prior to the acquisition. A GARCH(1,1) model was then constructed for each of the 65 available firms. Using OLS methods, the logarithm of realized volatility was then regressed against the logarithm of predicted volatility obtained from the GARCH model. The logarithm transformation was used to normalize the distribution of realized and predicted volatility. The results are presented below in Table 9.

Table 9: Regression Results for Log-Realized Volatility vs. Log-Predicted Volatility

Log of Realized Volatility	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
Log of Predicted Volatility	1.33	0.18	7.34	0.00	0.97	1.69
Constant	1.01	0.57	1.76	0.08	-0.14	2.15
R-squared	0.35					
Observations	64					

The key takeaway from Table 8 is the magnitude of the coefficient on Log of Predicted Volatility. It is greater than one. This was expected given that the volatility prediction was ignorant of the future acquisition, and riskiness inherent with it.

The 35% R-squared is acceptable given this is a 10-day ex-ante prediction of log-volatility for the day of acquisition. When alliance-related variables are included in the regression, there are a couple of important items to note. The regression is first presented below in Table 10.

Table 10: Regression Results of Log-Realized Volatility vs. Log-Predicted Volatility and Alliance Variables

Log of Realized Volatility	Coef.		Robust Std. Err.	t	P>t	[95% Conf.	Interval]
Log of Predicted Volatility	1.24	***	0.27	4.51	0.00	0.69	1.79
Shared Alliances	0.01	***	0.00	2.80	0.01	0.00	0.02
Centrality Score	-2.34	*	1.39	-1.69	0.10	-5.12	0.43
Prior Alliance	-0.11		0.21	-0.55	0.59	-0.53	0.30
Constant	0.81		0.76	1.06	0.29	-0.71	2.32
R-squared	0.37						
Observations	64						
Significant at 10%-*, 5%-**, 1%-*** level							
F-test on Shared Alliances, Centrality Score, Prior Alliance = 0							
F(3,59)	**2.98**			Prob > F	**0.0384**		

The key takeaways from Table 9 are the signs on the alliance variables, and the fact that the shared alliances and centrality score coefficients were significant at the 1% and 10% level, respectively.

While the coefficient for log-predicted volatility does decrease from 1.33 to 1.24 when alliance variables are added, the change isn't statistically significant. More importantly, the coefficient on shared alliances is statistically significant at the 1% level. On another note, the constant would now be judged as statistically insignificant from zero even at the 29% level. In addition, the signs on the prior alliance coefficient and the centrality score coefficient are as we expected. An interpretation of the above coefficients is as follows. The presence of a prior alliance is predicted to decrease realized volatility 11%. Therefore if all else is equal, if the realized volatility of a firm without a prior alliance is 7.56%, this same firm's realized volatility would be predicted to decrease by 0.83% to 6.73% if it did have a prior alliance. Given the results of the F-test on the joint null hypothesis that the alliance variables are insignificant, we have to reject the null at the 5% level. The presence of a prior alliance should be indicative of learning effects, and while the coefficient is statistically insignificant, the negative coefficient has the expected sign. One potential interpretation of this result is that while the GARCH model under-predicts the realized volatility, which

appears reasonable given the model is ignorant of the inherent riskiness of an acquisition, we have a firm's centrality score and the learning effects present in a prior alliance working to dampen the adjusted prediction. Since a firm's centrality score is a proxy for the entirety of the firm's knowledge, the aggregate size of this stock works to propitiate the market's uncertainty while the more relevant, the more up-to-date knowledge of the firm's interaction with the target company, inherent in the prior alliance variable, works to correct or adjust this somewhat lagged stock of information. For robustness sake, a regression was run without shared alliances, in which case the coefficients on prior alliance and shared alliance became insignificant and larger in magnitude. The results of this regression are presented below in Table 11. Including shared alliance helped to abate this upward omitted variable bias.

Table 11: Regression Results of Log-Realized vs. Log-Predicted and Alliance Variables, excluding Shared Alliances

Log of Realized Volatility	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
Log of Predicted Volatility	1.22 ***	0.28	4.36	0.00	0.66	1.78
Prior Alliance	-0.07	0.21	-0.33	0.74	-0.48	0.34
Centrality Score	-0.90	1.31	-0.68	0.50	-3.52	1.73
Constant	0.75	0.77	0.96	0.34	-0.80	2.29
R-squared	0.35					
Observations	64					

Significant at 10%-*, 5%-**, 1%-*** level

None of these results are conclusive with regard to the idea that alliance specific data has a significant impact on an acquisition's ability to influence stock return volatility. Yet it is illustrative. The R-squared increased slightly when alliance data was included, but the more interesting result is that the centrality score and the number of shared alliances were statistically significant in helping to explain the realized volatility. While we can't rule out

the notion that these variables are subject to omitted variable bias, it appears the learning effects associated with alliances are related to realized volatility.

In conjunction with the study of how alliances are related to the volatility of an acquisition, the short-term profitability of an acquisition, as measured by event-study returns of an acquisition, was regressed on various firm specific, transaction-specific, and alliance-specific characteristics to determine what effects different alliances had on an acquisition's short-term profitability. The cumulative abnormal returns were from the five-day event-study window.

The model utilized was:

$$CAR_i = \mathbf{FS_i} \cdot \boldsymbol{\beta_1} + \mathbf{TS_i} \cdot \boldsymbol{\beta_2} + \delta_1 centscore_i + \delta_2 sharedalliances_i + \delta_3 prioralliance_i + \upsilon_i$$
$$\upsilon_i \sim N(0, \sigma^2)$$

Firm-specific characteristics included: difference in log sales between the year of the acquisition and the prior year, log market capitalization in the year of acquisition, and log R&D in the year of acquisition. The transaction-specific characteristics included: log transaction value, SIC relatedness of acquiring and target firms, and whether the transaction was cash financed. Variables that induced multicollinearity problems in the model were dropped from the regression. See section two of the data appendix for the pair-wise correlation matrix and explanation. Initially OLS methods were used, but due to the presence of outliers and heteroskedasticity in the error term, robust-regression methods were used to increase the precision of the estimates. For these reasons, the robust-regression results are presented below in Table 12.

Table 12: Regression Results for Cumulative Abnormal Returns

Dependent Variable: Cumulative Abnormal Returns for Acquiring Firm

	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Difference in Sales	-0.031 *	0.018	-1.750	0.091	-0.067	0.005
Log Market Cap	-0.008	0.007	-1.100	0.280	-0.024	0.007
Log R&D	-0.023 ***	0.008	-2.930	0.007	-0.039	-0.007
Log Transaction Value	0.013 *	0.007	1.800	0.083	-0.002	0.028
Prior Alliance	0.097 ***	0.021	4.660	0.000	0.055	0.140
Centrality Score	0.633 ***	0.181	3.490	0.002	0.261	1.004
Shared Alliances	-0.014 ***	0.003	-5.280	0.000	-0.019	-0.009
Cash Financed	-0.033 *	0.016	-2.000	0.056	-0.066	0.001
Relatedness	-0.021	0.018	-1.210	0.235	-0.057	0.015
Constant	0.111 ***	0.031	3.580	0.001	0.048	0.175
Observations		97				
Adjusted R-squared		68.86%				

Significant at 10%-*, 5%-**, 1%-*** level

The difference in sales variable was constructed by taking the difference between log-sales in the year of the acquisition minus the log-sales in the year prior to the acquisition. This variable was utilized to help proxy for firms that may have had disparaging sales trends.

A number of items should be pointed out. The difference in log sales coefficient could be the result of self-selection, which is given credence by the discovery of Higgins and Rodriguez (2006) that firms with decreasing sales tend to have a higher probability of engaging in an acquisition to supplement their R&D efforts. Given these firms' disparaging sales figures and their high propensity to acquire, they could act in a somewhat more thoughtful manner when selecting appropriate targets, and hence be subjected to better short-term results. Another postulate could be that the market doesn't reward those acquisitions that are undertaken with less necessity. The coefficient on log R&D expenditures is also significant at the 1% level, and again the explanation for this is likely similar to the explanation for the difference in log sales; firms that have decreasing R&D expenditures may have a higher necessity to undertake an acquisition, and hence the market may not reward acquisitions that are undertaken with less necessity. Also consistent with the findings of

Higgins and Rodriguez (2006), but not with the majority of the literature, was that stock financed acquisitions tended to produce higher cumulative abnormal returns on average than cash financed acquisitions; the coefficient on cash financed was -0.033 and statistically significant at the 10% level.

The coefficient on prior alliance, 0.097, was significant at the 1% level and confirmed our hypothesis that acquiring firms who engaged in a previous alliance with their target realized better cumulative abnormal returns. This is consistent with the findings of Higgins and Rodriguez (2006) and others. The coefficient of the centrality score, 0.633, is also significant at the 1% level and confirmed our hypothesis that firms with a higher reputation within the alliance network realized greater cumulative abnormal returns. This result gives credence to the learning effects model that firms with more reputable experiences have accrued more knowledge that may be applicable in navigating a successful acquisition. Finally, the most interesting result is the coefficient on shared alliances, which is negative and significant at the 1% level. The interpretation of this coefficient is that increasing the number of shared alliances by one unit tends to, on average, decrease predicted cumulative abnormal returns by 0.014. This result is intriguing. The literature on alliance networks discusses the notion of being embedded within a network as an important trait in mitigating information asymmetries, but the literature does not find that different notions of network integration correspond to different types of effects. For example, in Robinson and Stuart (2006), centrality and proximity have the same type of effects on overall network learning.

VI. Conclusion

In this study, we argue that the alliance network between acquiring and target pharmaceutical and biotechnology firms has an impact on the future acquisition between firms, in terms of the acquiring firm's short-term profitability and on how the market perceives the marginal riskiness of the transaction. Our findings were illustrative of the fact that firms with more involvement in the alliance network, in terms of the number of overall alliances and the reputability of those alliances, tended to experience higher cumulative abnormal stock returns and lower stock return volatility. In addition, firms that engaged in a prior alliance with their target company experienced greater cumulative abnormal returns, evidence that the learning effects gained during a prior alliance with the target were applicable in the future acquisition. However, we found cursory evidence that the number of shared alliances acted in an opposing manner to the centrality and prior alliance effects. It is plausible that the shared alliances are accounting for the level of competition amongst potential buyers for any given target company.

Not discounting any additional, undiscovered effects, if a given target company has many potential suitors, the acquiring company would need to increase its offer amount to account for the fact that there are other firms with a similar valuation of the target. If an acquiring company has knowledge of these potential suitors, then they would perhaps need to pay a slight premium to discourage those with similar valuations of the target company from bidding. The higher premium could have an impact on the abnormal stock returns. Also, because the acquiring company could have been forced to increase their offer amount due to the presence of additional competitors, the market might have viewed this gaming as disadvantageous to the long-term health of the acquiring firm and consequentially regarded

the transaction as riskier. In this light, the statistically significant results of the shared alliance variable from the volatility and cumulative abnormal returns provide evidence that this may be the case. However, this conclusion should be regarded with caution as the shared alliances could have potentially been acting as a proxy for undetermined effects.

There is also the possibility that the prior alliance learning effects could have been tainted by the agenda of the target company. While our model attempted to show how learning effects, as a whole, mitigated the moral hazard problem in an acquisition, the target firm may have had an alternative reason for exaggerating its capacities, financial situation, or development status in a certain alliance. Therefore, the information learned from a prior alliance may have been somewhat biased. In this context, it is possible that shared alliances were helping to assuage this bias. The acquiring firm's learning effects from third parties about the target could have acted as a smoothing agent to the biased learning effects obtained directly from the prior alliance. However, this explanation would be more credible if we had observed statistically significant interaction terms between the shared alliance and prior alliance variables; in additional regressions this interaction term was statistically insignificant. The competition explanation for the effect of shared alliances appears more credible, yet again, we can't discount the possibility that the variable is acting as a proxy for an undetermined effect.

These results should be examined with caution however, as there is undoubtedly self-selection bias; firms who chose to engage in an acquisition may have experienced higher cumulative abnormal stock returns or lower stock return volatility. Higgins and Rodriguez (2006) provide evidence that R&D intensity is not statistically related to cumulative abnormal returns, yet the statistical significance we observe on R&D expenditures could be

the result of the endogeneity associated with the self-selection. The question could be raised as to how much *a priori* knowledge a given firm had regarding its predicted short-term acquisition profitability being a function of its alliance network involvement, but restraint should be used when drawing any causal relationships.

While we discovered two suggestive results that acquisitions were indeed risky endeavors, the upward movement of the CAPM beta coefficients in conjunction with the realized stock returns volatility being higher than the predicted volatility on the day of the acquisition , these are by no means conclusive measures to indicate that acquisitions are risky. Both of these movements were shown to be statistically insignificant. Nevertheless, there is inherent uncertainty involved in any financial transaction between two parties, even if both groups are subjected to perfect information. The large majority of the literature agrees that acquisitions on average are risky. What we have aimed to illustrate is that information regarding how parties are situated within a learning environment, in this case an alliance network, can be helpful in shedding light on how various transactions fair better than others.

This study certainly could be enhanced by effectively controlling for the propensity to acquire a target company. One solution would be to observe how the alliance network evolves over time, and then estimate the probability that a given firm will engage in an alliance given past firm-specific and alliance information. A similar method could be employed to control for the endogeneity of an acquisition. Other studies, such as Higgins and Rodriguez (2006), have found that controlling for this type of endogeneity is important, yet it is not immediately clear as to whether this type of endogeneity would affect the influence of the alliance network on certain learning effects that would be applicable in a future transaction. Nonetheless, controlling for this would be important in strengthening our results.

Future work needs to be undertaken to determine what the exact effect shared third-party alliances have on pharmabiotech informational learning. It is not immediately clear that shared third-party alliances should act in an opposing manner to the most relevant acquisition specific information, information gleaned from a prior alliance. We cannot discount the possibility that the true effect of these shared alliances is negligible, and that the variable is capturing some other undetermined effect. To this end, more robust experiments need to be carried out where the effect of shared third-party alliances, perhaps over time, can be parsed out more effectively.

Data Appendix

The following items are included in the appendix for robustness and the benefit of the reader:

Section 1 – List of Acquiring and Target Companies

Section 2 – Correlation Matrix for Regressors in Cumulative Abnormal Returns Regression

Section 3 – Discussion of Screening Process for Acquisitions

Section 1: List of Acquiring and Target Companies – If the firms have changed company names since their acquisitions, the current name is presented in parenthesis. List sorted by announcement date.

Acquirer Name (Current Name)	Target Name	Announcement Date
Elan Corp PLC	Neurex Corp	4/29/1998
Ligand Pharmaceuticals Inc	Marathon Pharmaceuticals LLC	5/11/1998
Techne Corp	Genzyme General	6/23/1998
Urogen Corp, (Via Pharmaceuticals)	Baxter Healthcare	7/8/1998
Genetic Vectors Inc	BioQuest Inc	8/5/1998
MegaBios Corp (Urigen Pharmaceuticals)	GeneMedicine Inc	10/26/1998
Peptide Therapeutics Group PLC (Acambis PLC)	Oravax Inc	11/11/1998
SafeScience Inc (Glycogenesis Inc)	PHYTOpharmaceuticals	12/1/1998
Serologicals Corp	Bayer-Pentex Blood Protein Bus	12/2/1998
Corixa Corp	Anergen Inc	12/14/1998
Pharmacia & Upjohn Inc	Miravant Medical Technologies	1/19/1999
Cantab Pharmaceuticals PLC	ImmuLogic Pharm	2/2/1999
Strategic Diagnostics Inc	HTI Bio-Products Inc	3/1/1999
Strategic Diagnostics Inc	Atlantic Antibodies	5/12/1999
Roche Holding AG	Genentech Inc	6/3/1999
Ligand Pharmaceuticals Inc	X-Ceptor Therapeutics Inc	7/1/1999
Novavax Inc	Dyncorp	8/11/1999
Creative BioMolecules Inc	Reprogenesis Inc	2/15/2000
Incara Pharmaceuticals Corp	Aeolus Pharmaceuticals Inc	3/31/2000
Qiagen NV	Operon Technologies Inc	6/13/2000
Invitrogen Corp	Life Technologies Inc (Dexter)	7/9/2000
Cephalon Inc	Anesta Corp	7/17/2000
Chiron Corp	PathoGenesis Corp	8/14/2000
Elan Corp PLC	Targeted Genetics Corp	8/16/2000
Antigenics Inc	Aquila Biopharmaceuticals Inc	8/21/2000
BresaGen Ltd	CytoGenesis Inc	8/29/2000
Exelixis Inc	Agritope Inc	9/7/2000
Human Genome Sciences Inc	Principia Pharmaceutical Corp	9/8/2000
Genzyme Corp	GelTex Pharmaceuticals Inc	9/11/2000
Corixa Corp	Coulter Pharmaceuticals Inc	10/16/2000
Amgen Inc	Kinetix Pharmaceuticals Inc	10/16/2000
MediGene AG	NeuroVir Therapeutics Inc	11/9/2000
BioTransplant Inc	Eligix Inc	12/11/2000
Trinity Biotech PLC	Bartels Inc (Intracel Corp)	12/18/2000
Biota Holdings Ltd	NuMax Pharmaceuticals Inc	5/21/2001
CSL Ltd	Nabi Inc	6/25/2001
Cell Genesys Inc	Calydon Inc	8/2/2001
MedImmune Inc	Aviron	12/3/2001
Amgen Inc	Immunex Corp	12/17/2001
Genencor International Inc	Enzyme Bio-System Ltd (CPC Int)	2/5/2002
CytRx Corp	Global Genomics Capital Inc	2/11/2002
Qiagen NV	Xeragon Inc	4/18/2002
ISTA Pharmaceuticals Inc	AcSentient Inc	5/3/2002
Merck & Co Inc	Gliatech Inc	5/9/2002
Immunomedics Inc	IBC Pharmaceuticals LLC	5/24/2002
Novozymes A/S	InterBio	7/2/2002
Medarex Inc	Corixa Corp	8/8/2002
NaPro BioTherapeutics Inc (Tapestry Pharmaceuticals)	Pangene Corp	1/24/2003
Invitrogen Corp	PanVera	2/4/2003
Serologicals Corp	Chemicon International Inc	2/11/2003

Section 1 (continued): List of Acquiring and Target Companies – If the firms have changed company names since their acquisitions, the current name is presented in parenthesis. List sorted by announcement date.

Acquirer Name (Current Name)	Target Name	Announcement Date
Hemispherx BioPharma Inc	Interferon	3/12/2003
GenVec Inc	Diacrin Inc	4/15/2003
ICN Pharmaceuticals Inc (Valeant Pharmaceuticals International)	Ribapharm Inc	6/2/2003
IDEC Pharmaceuticals Corp	Biogen Inc	6/20/2003
Novozymes A/S	Roots Inc	6/23/2003
Vencor International Inc	AccuDx Inc	6/30/2003
PPD Inc	Eminent Research Systems Inc	7/16/2003
ArQule Inc	Cyclis Pharmaceuticals Inc	7/17/2003
Hycor Biomedical Inc	Stratagene Holding Corp	7/24/2003
Inveresk Research Group Inc	PharmaResearch Corp	7/29/2003
Genta Inc	Salus Therapeutics Inc	8/14/2003
Acambis PLC	Berna Products Corp	8/28/2003
CalbaTech Inc	Molecula Research Labs LLC	10/1/2003
Diamond International Group (Organetix)	Organetix Inc	10/24/2003
Invitrogen Corp	Sequitur Inc	11/4/2003
Genome Therapeutics Corp (Oscient Pharmaceuticals)	Genesoft Inc	11/17/2003
Eli Lilly & Co	Applied Molecular Evolution	11/21/2003
CSL Ltd	Aventis Behring LLC	12/8/2003
Genaissance Pharmaceuticals	Lark Technologies Inc	12/19/2003
PacificHealth Laboratories Inc	STRONG Research Corp	12/22/2003
Keryx Biopharmaceuticals Inc	ACCESS Oncology Inc	1/7/2004
Bioniche Life Sciences Inc	AB Technology Inc	1/10/2004
Merck & Co Inc	Aton Pharma Inc	2/23/2004
Enzo Biochem Inc	Oragen Corp	2/26/2004
Virbac SA	Antigenics Inc	3/18/2004
Invitrogen Corp	Protometrix Inc	4/2/2004
QT 5 Inc (Addison Davis Diagnostics)	Xact Aid Inc	4/13/2004
Trinity Biotech PLC	Fitzgerald Industries Intl Inc	4/20/2004
AGT Biosciences Ltd (ChemGenex)	ChemGenex Therapeutics Inc	4/26/2004
NanoDynamics Inc	MetaMateria Partners LLC	5/3/2004
Benitec Ltd	Avocel Inc	5/16/2004
Bio-America Inc	Novocure Inc	5/26/2004
VI Technologies Inc	Panacos Pharmaceuticals Inc	6/2/2004
Chromos Molecular Systems Inc	CellExSys Inc	6/21/2004
Serologicals Corp	AltaGen Biosciences Inc	6/30/2004
Chiron Corp	Sagres Discovery	7/6/2004
Distributed Diagnostics Inc	Real Radiology Inc	7/7/2004
Neurobiological Technologies	Empire Pharmaceuticals Inc	7/15/2004
Antigenics Inc	Mojave Therapeutics Inc	7/30/2004
Enhance Biotech Inc	Ardent Pharmaceuticals Inc	8/12/2004
MGI PHARMA Inc	Zycos Inc	8/25/2004
Chiron Corp	Prion Solutions Inc	8/31/2004
Serono International SA	ZymoGenetics Inc	9/8/2004
Exelixis Inc	X-Ceptor Therapeutics Inc	9/28/2004
PharmaFrontiers Corp (Opexa Therapeutics Inc)	Opexa Pharmaceuticals Inc	10/8/2004
Moliris Corp	Mycobis Corp	10/22/2004
Nutra Pharma Corp	Portage Biomed LLC	11/9/2004
Kyorin Pharmaceutical Co Ltd	ActivX Biosciences Inc	12/1/2004
Guilford Pharmaceuticals Inc (MGI GP, Inc)	ProQuest Pharma Inc	12/2/2004
GlaxoSmithKline PLC	Corixa Corp	12/13/2004

Section 2: Correlation Table for Potential Variables in Cumulative Abnormal Returns Regression

	Shared Alliance	Total Alliances	Total Drug-Biotech Alliances	Centrality Score	Total R&D Alliances	Equity Payment	Royalty Payment
Shared Alliance	1.00						
Total Alliances	0.61	1.00					
Total Drug-Biotech Alliances	0.61	**0.97**	1.00				
Centrality Score	0.60	**0.97**	**0.91**	1.00			
Total R&D Alliances	0.62	**0.98**	**0.95**	**0.97**	1.00		
Equity Payment	0.68	**0.92**	**0.92**	**0.90**	**0.93**	1.00	
Royalty Payment	0.65	**0.91**	**0.87**	**0.92**	**0.91**	**0.92**	1.00
Method of Payment	-0.13	-0.01	-0.06	-0.03	0.00	-0.08	-0.07
Relatedness	0.07	0.10	0.03	0.10	0.11	0.09	0.04
Log Market Cap	-0.01	0.46	0.43	0.49	0.45	0.39	0.39
Log R&D	0.07	0.20	0.14	0.27	0.22	0.21	0.29
Log Transaction Value	0.41	0.16	0.08	0.27	0.18	0.14	0.26
Prior Alliance	0.25	0.16	0.12	0.19	0.16	0.18	0.23
Difference in Sales	0.00	-0.08	-0.08	-0.07	-0.08	-0.07	-0.09
Centrality*Total Alliances	0.62	**0.95**	**0.98**	**0.88**	**0.94**	**0.88**	0.82
Prior*Shared Alliances	0.71	0.34	0.32	0.36	0.34	0.41	0.50

	Method of Payment	Relatedness	Log Market Cap	Log R&D	Log Transaction Value	Prior Alliance	Difference in Sales
Method of Payment	1.00						
Relatedness	-0.06	1.00					
Log Market Cap	0.00	0.24	1.00				
Log R&D	0.08	-0.11	0.79	1.00			
Log Transaction Value	-0.09	0.12	0.41	0.49	1.00		
Prior Alliance	0.15	-0.07	0.07	0.31	0.22	1.00	
Difference in Sales	-0.06	0.18	0.14	0.02	0.11	-0.04	1.00
Centrality*Total	-0.03	0.04	0.39	0.11	0.04	0.08	-0.09
Prior*Shared Alliances	-0.01	-0.04	0.00	0.21	0.37	0.51	-0.05

	Centrality*Total Alliances	Prior*Shared Alliances
Centrality*Total	1.00	
Prior*Shared Alliances	0.28	1.00

This correlation matrix highlights variables that caused issues of multicollinearity in the regression of cumulative abnormal returns. In initial regressions, all of the above variables were included, but due to the pair-wise correlations, the lack of additional explanatory power when they were included, and abnormally high standard errors on the coefficients, the following variables were removed from the final regression: Total Alliances, Total Drug-Biotech Alliances, Total R&D Alliances, Equity Payment, Royalty Payment, Centrality*Total Alliances, Prior*Shared Alliances.

Section 3: Discussion of Screening Process for Acquisitions

The final set of 100 acquisitions was determined by a multi-stage process. Initially, the Securities Data Corporation (SDC) Platinum database was queried in the following manner. Acquisitions were screened to be between 1998 and 2004, the acquiring company had to be a pharmaceutical or biotech firm, and the target company had to be a biotech firm. In addition the acquiring firm needed to be a publically traded company at the time of the transaction, but the target firm could be either a public or a private company. This initial query identified 168 potential transactions, and automatically screened against mergers of equals. Besides the list of acquiring and target companies, we were interested in the reported value of the transaction and the method of payment. Of the 168 transactions identified, 131 provided this information. Following this, publically available accounting data was collected on these 131 transactions. Standard & Poor's COMPUSTAT database was used in conjunction with SEC 10-K and other public filings to collect accounting data, specifically: R&D expenditure in the year of the acquisition, total sales for the year of the acquisition, total sales for the year prior to the acquisition, total sales for two years prior to an acquisition, and the market capitalization in the year of the acquisition. Due to the initial filtering process, almost all of this accounting data was easily found. However, only 84 acquiring firms had data for total sales two years prior to an acquisition. Partly because of this reason, this piece of data was not incorporated into our model. Next, daily stock data was collected for each of the firms. The Center for Research in Security Prices (CRSP), Thomson Datastream, and Yahoo! Finance were used to identify daily adjusted stock prices for all but 22 transactions. These 22 firms were largely traded on foreign exchanges where historical stock data was not easily obtained. The remaining 109 transactions were checked to ensure that there were no egregious errors in their stock price reporting, and that there were sufficient observations for

each acquiring company. Observations were obtained for -433 to +28 trading days from an acquisition. This range was the result of selecting a window that would maximize the number of firms with sufficient observations, and also provide enough observations without sacrificing appreciable power in the regressions. In a few cases, CRSP reported negative adjusted closing prices, and/or reported stock prices that were off by an order of magnitude. These errors were manually screened against and corrected. For negative adjusted closing price error, the sign was reversed. For the order of magnitude error, the stock price was manually compared against previous and future closing prices, and when available, the error was corrected by using an alternative source. If an alternative source was not available, a subjective decision to align the order of magnitude of the stock price to previous ones was made. Of the 109 transactions, 100 contained sufficient observations and were relatively error-free.

Bibliography

Anand, B. N., & Khanna, T. (2000). Do Firms Learn to Create Value? The Case of Alliances. *Strategic Management Journal, 21*, 295-315.

Anand, J., & Singh, H. (1997). Asset Redeployment, Acquisitions and Corporate Strategy in Declining Industries. *Strategic Management Journal, 18*, 99--118.

Andersen, T. G., & Bollerslev, T. (1997). Heterogeneous Information Arrivals and Return Volatility Dynamics: Uncovering the Long-Run in High Frequency Returns. *Journal of Finance, 52*, 975-1005.

Andrade, G., Mitchell, M., & Stafford, E. (2001). New Evidence and Perspectives on Mergers. *The Journal of Econnomic Perspectives, 15*(2), 103-120.

Arino, A., & de la Torre, J. (1998). Learning from failure: Towards an evolutionary model of collaborative ventures. *Organizational Science, 9*, 306-325.

Barton, D. M., & Sherman, R. (1984). The Price and Profit Effects of Horizontal Merger: A Case Study. *The Journal of Industrial Economics, 33*(2), 165--177.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31*, 307-327.

Bollerslev, T., Andersen, T. G., Diebod, F. X., & Ebens, H. (2001). The Distribution of Realized Stock Return Volatility. *Journal of Financial Economics, 61*, 43-76.

Brealey, R. A., & Myers, S. C. (2003). *Principles of Corporate Finance* (7 ed.). Boston: McGraw-Hill.

Burns, L. R., Nicholson, S., & Evans, J. (2005). Mergers, acquisitions, and the advantages of scale in the pharmaceutical sector. In L. R. Burns (Ed.), *The Business of Health Care Innovation*.

Capron, L. (1999). The Long-Term Performance of Horizontal Acquisitions. *Strategic Management Journal, 20*(11), 987--1018.

Chan, S. h., Kensinger, J. W., Keown, A. J., & Martin, J. D. (1997). Do strategic alliances create value? *Journal of Financial Economics, 46*, 199-221.

Cockburn, I., & Henderson, R. (2001). Scale and Scope in Drug Development: Unpacking the Advantages of Size in Pharmaceutical Research. *Journal of Health Economics, 20*(6), 1033-1057.

Danzon, P., Epstein, A., & Nicholson, S. (2004, June). Mergers and Acquisitions in The Pharmaceutical and Biotech Industries. *NBER Working Paper*, from http://www.nber.org/papers/w10536

Danzon, P. M., Nicholson, S., & Pereira, N. S. (2005). Productivity in Pharmaceutical-Biotechnology R&D: The Role of Experience and Alliances. *Journal of Health Economics, 24*(2), 317-339.

Das, S., Sen, P. K., & Sengupta, S. (1998). Impact of Strategic Alliances on Firm Valuation. *Academy of Management Journal, 41*(1), 27-41.

Davidson, W. N., Garrison, S. H., & Henderson, G. V. (1987). Examining Merger Synergy With The Capital Asset Pricing Model. *The Financial Review, 22*(2), 233-247.

Eckbo, B. E. (1992). Mergers and the Value of Antitrust Deterrence. *The Journal of Finance, 47*(3), 1005--1029.

Galambos, L., & Sturchio, J. L. (1998). Pharmaceutical Firms and the Transition to Biotechnology: A Study in Strategic Innovation. *The Business History Review, 72*(2), 250-278.

Haleblian, J., & Finkelstein, S. (1999). The Influence of Organizational Acquisition Experience on Acquisition Performance: A Behavioral Learning Perspective. *Administrative Science Quarterly, 44*(1), 29-56.

Hayward, M. L. A. (2002). When do firms learn from their acquisition experience? Evidence from 1990-1995. *Strategic Management Journal, 23*, 21-39.

Higgins, M., & Rodriguez, D. (2006). The outsourcing of R&D through acquisitions in the pharmaceutical industry. *Journal of Financial Economics, 80*, 351-383.

Jensen, M., & Meckling, W. (1991). Specific and general knowledge, and organizational structure. In L. Werin & H. Wijkander (Eds.), *Main Currents in Contract Economics*. Oxford: Blackwell Publishers.

Kadlec, G. B., & Patterson, D. M. (1999). A transactions data analysis of nonsynchronous trading. *Review of Financial Studies, 12*(3), 609-630.

Khanna, T. R., Gulati, R., & Nohria, N. (1998). The dynamics of learning alliances: Competition, cooperation and relative scope. *Strategic Management Journal, 19*, 193-210.

Mueller, D. C. (1985). Mergers and Market Share. *The Review of Economics and Statistics, 67*(2), 259--267.

Podolny, J. M. (1993). A Status-Based Model of Market Competition. *The American Journal of Sociology, 98*(4), 829-872.

Porrini, P. (2004). Can a Previous Alliance Between an Acquirer and a Target Affect Acquisition Performance? *Journal of Management, 30*(4), 545-562.

Ravenscraft, D. J., & Scherer, F. M. (1987). Life After Takeover. *The Journal of Industrial Economics, 36*(2), 147--156.

Robinson, D. T., & Stuart, T. E. (2002). Financial Contracting in Biotech Strategic Alliances. *Columbia University Working Paper*.

Robinson, D. T., & Stuart, T. E. (2006). Network Effects in the Governance of Strategic Alliances in Biotechnology. *Journal of Law, Economics, and Organization, 23*(1), 242-273.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *Journal of Finance, 19*(September 1964), 425-442.

Zakoian, J.-M. (2002). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control, 18*(5), 931-955.