# Partnerships between Software Firms: Is There Value from Complementarities?

**Lucia S. Gao and Bala Iyer**

***University of Massachusetts Boston, Babson College***

***lucia.silva-gao@umb.edu, biyer@babson.edu***

## Abstract

*In network-type industries companies can explore the existence of complementarities in different ways to create value and competitive advantage.*

*Gao and Iyer (2006) introduce a new methodology, based on the software stack, and show that there is value in mergers and acquisitions between companies that produce complementary components of network systems. We apply the same methodology to a sample of Alliances and find that even though there is value in Alliances between companies that produce in adjacent layers of the stack, abnormal returns are higher when both participants produce on the same layer of the stack.*

## 1. Introduction

In network-type industries, particularly industries in information technology and communications, decision-making and strategy are shaped by the existence of complementarities and network effects. Some of the most prominent and successful companies in these industries follow a strategy of pursuing alliances, acquisitions and strategic investments in businesses that are complementary to their own core business.

Traditionally, companies form strategic alliances to share resources, coordinate joint promotions, share production facilities, or develop new products or technologies [21,24,26]. In the software industry, companies form strategic research partnerships, joint product development, technology licensing and marketing and distribution agreements [40].

Complementary network systems are defined by the existence of different components that have to be used together and may require different technologies. These technologies may be independently developed by different firms. Each firm may possess a technology that has a much greater value when combined with those of the other firms to form a complementary system. Gao, Kulatilaka and Lin [18] discuss the use of coordination mechanisms in the development of new technologies in complementary network systems. They show that the development efforts of complementary technologies are lower in the absence of coordination and discuss the use of mergers and acquisitions, equity investments and licensing as mechanisms to coordinate efforts. They illustrate with the example of how several companies have used different coordination mechanisms and conclude that no single mechanism provides a universal solution and that the appropriate mechanisms may evolve over time.

In a study applied the Mergers and Acquisitions (M&As) in the software industry, Gao and Iyer [17] provide evidence that there is value in M&As involving firms that produce complementary components of network systems. They define complementary components as products classified in adjacent layers of the software stack and show that abnormal returns around the date of the announcement of the M&As are higher if acquirer and target produce on adjacent layers and lower if they produce on the same layer or in layers further apart on the stack.

This paper extends the study by Gao and Iyer [17] to Alliances in the software industry. We use the same methodology to test if there is value in alliances between companies that produce complementary components of a network system.

Applying the event studies methodology, we find that alliances between companies that produce in the same layer earn higher abnormal returns, but as the distance on the stack increases abnormal returns decrease. This result proves that there is some value in alliances between companies that produce in adjacent layers of the stack, even though alliances between companies that produce on the same layer seem to earn higher abnormal returns.

## 2. Complementarities in Software Markets and the "Stack"

Software markets present special dynamics that distinguish them from conventional markets. The existence of direct and indirect externalities creates incentives for companies to expand market shares and to aim to connect to some degree with producers of complementary products.

In our work we deal with the theoretical architecture of the software industry which is the designer's version of the various components that constitutes the products within the industry and their relationships. Designers of complex artifacts look for a modular product architecture such that the overall design tasks are manageable. An espoused architecture (like a product architecture [47]) is the scheme by which the function of a product is assigned to its components. As a result, it specifies the arrangement of the functional parameters and the specification of the interfaces (design rules) among the interacting components. Given this specification of the modules and the design rules for integrating modules into larger system, firms can work within the parameters of a specific module while the design rules help to coordinate across them. The espoused industry architecture is often presented as an analog of the software stack.

In our paper, we propose that the espoused stack has five layers. Here is the reasoning behind it. At the lowest level we have the hardware layer. This layer provides a core service called processing or computing and several peripheral services to manage devices like storage, printing and device management. To get the hardware to provide these services at the appropriate time, we have the systems software. This layer includes the operating system and other utilities that make the hardware layer more efficient. As we chronicle the history of computing, the next layer that emerged was the application layer. This layer was the one that provided the actual services that users needed. In the enterprise setting, this would include accounting software, inventory management, transaction processing etc. As these applications were developed as and when needed, they would run on preferred operating systems. For example, much of the financial services industry developed applications that ran on the Unix operating system. Most of the decision support software applications were built to run on the Windows operating environment. This meant that within any medium to large size companies there were applications running on multiple operating systems and could not share information across these applications. This led to the creation of a new layer within the industry called the middleware layer. This layer provided products that allowed application to exchange information across operating systems. The final layer that we present in this paper is the service layer. When organizations purchased packaged software to meet their needs, these packages required installation and customization and seldom ran out of the box. This resulted in the creation of the service layer. Companies operating in this layer would install and customize packaged software and in many cases created interoperability across application packages.

In markets characterized by systems-based competition in which customers must purchase bundles of products, often from multiple vendors, value is derived from complementary products. In simple terms, a complementary product is one that enhances the value of another product when the two of them are used together by end-users [35,36]. For example, in the software industry database products and operating systems are complementary. A database product cannot even be used without an operating system; thus, the existence of operating systems increases the value of the database product. Similarly, the existence of database products drives the sales of hardware and operating systems.

The desire to exploit complementarities to derive competitive advantages and create and appropriate value motivates a number of managerial decisions. These decisions include those that lead to mergers and acquisitions, alliance formation, standards creation, and product introductions.

Companies that produce highly complementary components may want to merge or vertically integrate if customers value a more reliable systems integration supplied by a single provider [17] or if they want to quickly gain market share in the complementary market. Companies also make acquisitions in a complementary market with the purpose of foreclosing competitors in that market. The "winner takes all" nature of software economics gives firms that achieve major platform status massive profit pools from which to invest in adjacent software categories.

Based on the resource-based views of the firm [14,41], the use of complementary factors of production across multiple business units should lead to production-side synergies, economies of scope and improved firm performance [12]. For example, software firms that reuse the same software code in multiple software products should gain economies of scope in software development and perform better than software firms that write new code for each new product. Moreover, the firm can leverage their complementary assets - sales force, customer support departments, installed base, and their understanding of customer requirements [45,19].

Companies can form alliances and standards committees to facilitate tighter integration at a strategic or technological level. Interoperability among products occurs when the products can utilize each others' published application program interfaces (APIs). The interfaces are the result of negotiations among companies. These negotiations are sometimes public and are conducted in standards committees and are sometimes private. Both public and private negotiations involve the sharing of varying levels of company confidential information, which leads to the formation of alliances.

Companies can also use either their installed base, or the installed base of complementary components, to leverage and promote growth through product introductions. Firms developing products can choose to participate in developing and marketing complementary products or they may allow third-party developers to provide them. Firms can actively engage in making sure that complementary products are interoperable, or they can rely upon their customers to do that. Historically, large firms have developed complementary products in-house to ensure that the product interfaces are properly utilized and incremental profits appropriated [43].

Related products can also exploit consumption side synergies. When a set of products serve the needs of the same customer base, and the value of the set of products to the consumer is greater than the sum of the value of each product in isolation, the set is said to offer consumption-side synergies. There are three types of consumption-side synergies: shopping cart and search cost savings, demand variance reduction [1] , and product value in-learning and in-use [3].

A firm's performance depends upon its internal capabilities and knowledge resources [8,46] and its ability to access critical complementary resources from other firms within its ecosystem [22]. Firms exploit their own, existing knowledge and explore others' knowledge to generate new knowledge [10,33,37] while sustaining their competitive advantage through their ability to reconfigure their knowledgebase [30,25,46].

Software is a setting that calls for knowledge interdependence between firms to achieve product interoperability [44], where a network of relationships is key for a software firm's success [6].

Inter-firm alliances are relationships that are governed by formal mechanisms of resource pooling and value appropriations [23]. These include license-sharing agreements, joint ventures, research consortia, joint R&D activities, and other activities governed by the formal agreements. Firms create interconnections for many reasons, such as access to financial capital, specialized knowledge, complementary assets, technical capabilities and new marketing channels [38]. For such reasons and others, firms form relationships with other firms and such moves create the network of relationships that act as the backdrop for competition and value delivery in this industry.

Dyer, Gale and Singh [13] defend that when a company estimates that a collaboration's outcome is highly or moderately uncertain, it should enter into an alliance rather than acquirer. An alliance will limit the firm's exposure since it has to invest less money and time than it would in an acquisition. The company can sink more into the partnership if it starts showing results, and even buy the firm eventually. Otherwise, the company can withdraw from the alliance in case the results are not the expected.

Gao and Iyer [17] study the value of mergers and acquisitions in complementary network systems. They apply the concept of software stack to define a measure of complementarity between components of network systems. The stack is defined by the following layers: Hardware, Systems Software, Middleware Software, Applications Software and Services, as shown in Figure1. Each of these components is layered above the other, and communicates through more or less standard interfaces, with closer layers being more related to each other than layers that are further apart on the stack. Software developers usually focus on one or a few layers of the stack and rely on other developers to provide the requisite functionality in other layers.

We use the same methodology to investigate if there is value creation in Alliances between producers of complementary components of network systems. Formally, the hypothesis we test is:

*Hypothesis: There is value in alliances between companies that produce in adjacent layers of the software stack.*

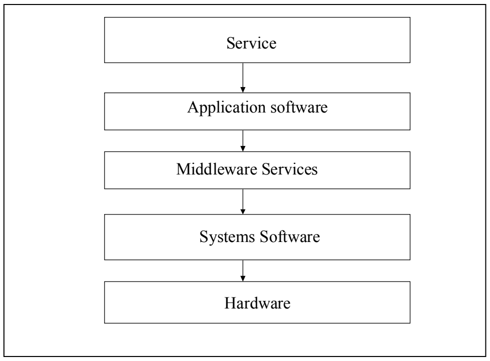


***Figure 1 – The stack***

# 3. Relevant Literature in Alliances

Alliances between firms can be used to avoid the rigidity of mergers and acquisitions and to gain access to knowledge and skills otherwise not available. Alliances can help firms to conserve resources, share risks, gain information, access complementary resources, reduce product development costs, and improve technological capabilities [14,29,20,25,39].

A number of event studies document positive and significant announcement returns related to the formation of strategic alliances and joint ventures. McConnell and Nantell [34] find significant wealth gains from Joint Ventures, and conclude that their results support the hypothesis that synergy between companies is a source of gain. In a study of strategic non-equity alliances between high-tech firms, Chan, Kensinger, Keown, and Martin [7] find a day 0 return of 1.12%. Koh and Vankatraman [28] find two-day average abnormal returns of 0.87%, in a sample of Joint Ventures in information technology. They also show that Joint Ventures have a greater impact then other forms of alliances.

Previous papers have pointed several factors to explain the distribution of gains in alliances. Joint ventures are almost always associated to positive stock market reactions [34,28].

Alliances are also more valuable when the creation or the transfer of knowledge is involved. Investments and outputs in R&D are subjected to severe moral hazard and adverse selection problems because of the inability of the parties to observe actions and accurately assess the value of the output [2]. The costs of knowledge transfer can be particularly high for innovative projects, for example involving new product creation or new technology development. Because of the contractual flexibility involved, to enter into alliances is more cost effective than M&As, when knowledge transfer is necessary [7]. Therefore, alliances that involve knowledge transfer may offer participants greater value than other types of alliances, in which contracts are more easily written and enforced.

Chan, Kensinger, Keown, and Martin [7] do not find more value for alliances involving R&D projects than those involving existing know/how, technologies or products. However, in a multivariate analysis, they conclude that alliances involving the transfer or the pooling of a technology are better valued when the partners are in the same industry than a non-technical alliance. The opposite happened for alliances between partners of a different industry. They also find that alliances in high tech industries are more valuable (significant abnormal return of 1.12%,) than those in low tech industries (insignificant abnormal return of 0.10 %).

There is some evidence that smaller firms earn higher returns in alliances and this is especially relevant for small entrepreneurial firms in the advent of new technologies. However, there is also some ambiguity in prior research. In some cases, much of the economic value created by the alliance is appropriated by the larger partner. McConnell and Nantell [34] find that investors in the smaller firm, on average, receive larger abnormal returns, but the absolute gains in shareholder value for both partners are more or less equivalent. Also Chan, Kensinger, Keown, and Martin [7] conclude that while smaller partners experience larger abnormal returns than larger partners, the magnitudes of the absolute gains are roughly equal. In contrast, in an analysis of 60 non-equity alliances from the information technology sector, Koh and Venkatraman [28] find that on average, the smaller partner gains more than the larger partner. Das, Sen, and Sengupta [11] also find cumulative abnormal returns to be larger for smaller partners.

There is also some ambiguity concerning the financial status of the participant. Lerner and Merges [31] find that the greater the financial resources of the technological partner, the fewer the control rights allocated to the financing firm and the lower the value of the partnership to this firm. However, Das, Sen, and Sengupta [11] observe that the profitability of firms entering strategic alliances is negatively correlated with abnormal returns attributable to alliance announcements. A possible explanation is that cash– stretched firms are in a greater need of inter-firm collaboration. However, Campart and Pfister [5], in a study applied to the pharmaceutical industry, find that abnormal returns are increasing with profitability. They argue that more profitable firms have increased bargaining power and should be in a better position to appropriate a larger share of the surplus generated through the partnership.

## 4. Empirical Design and Sample

We use the Stack Distance Index (*STACK_DISTANCE*) presented by Gao and Iyer [17] to measure the relationship between both participants in the alliance. The index is defined as the weighted sum of a coefficient that represents the distance on the stack between two different layers or industry segments. The weights are equal to the product of the percentage of sales of each firm in the corresponding layer. The index is computed as:

$$STACK\_DISTANCE = \sum_{i=1}^{L}\sum_{j=1}^{L} P_{Ai}P_{Tj}d_{ij}$$

where,

*STACK_DISTANCE* denotes Stack Distance Index,
$L$ is the number of layers of the stack,
$P_{Ai}$ is the percentage of sales of the acquirer in layer $i$ of the stack,
$P_{Tj}$ is the percentage of sales of the target in layer $j$ of the stack,
$d_{ij}$ is a coefficient that assumes different values according to the distance on the stack between layer $i$ and layer $j$,
and $\sum_{i=1}^{L}\sum_{j=1}^{L} P_{Ai}P_{Tj} = 1$ .

We define the coefficient $d_{ij}$ to assume the values 1, 2, 3, 4 and 5, if both participants focus on the same layer, one layer apart, two layers apart, three layers apart or four layers apart.

Intuitively, the index is a simple measure of the distance between two companies when classified according to the layers of the software stack. For example, if both companies have all of their sales in the same layer then the index is equal to 1. If one of the companies produces only hardware and the other produces only applications software, the index is equal to 4.

The *STACK_DISTANCE* index suffers the same validity problems that Robins and Wiersema (2003) discuss for the concentric index. They argue that the index is sensitive to features of portfolio composition that can create significant ambiguities. In our case, the *STACK_DISTANCE* index may overestimate the distance between two companies when both of them are highly diversified in the different layers of the stack. [1]

In parallel to the analysis using the *STACK_DISTANCE* index, we conduct the analysis using a variable defined as the distance on the stack between both participants when classified according to their specific roles in the alliance. To construct this measure we asked a third party to classify the role of each of the participants in the alliance according to the layers of the stack. The variable assumes values equal to 1, 2, 3, 4 or 5 if participants are on the same layer of the stack or 1, 2, 3 or 4 layers apart. This construct serves to purposes: to investigate if investors take into account only the part of the company that is involved in the alliance or, otherwise, the overall activity of the company (as it is considered in the *STACK_DISTANCE* index); and as a robustness test to the results obtained using the *STACK_DISTANCE* index.

We study the value of alliances in which either the participants produce on the same or on different layers of the stack. For this purpose, the standard event studies methodology is used. This methodology is based on the assumption that share prices are simply the present value of expected future cash flows to shareholders and that any changes in the company's prospects are immediately reflected in its stock price. We measure the effect of the announcement of alliances on stock prices. [2] Abnormal returns are calculated for a three-day window centered on the announcement date of the alliance, using a market model estimated from 231 to 31 days before the announcement date. We use the Equally Weighted Market Index from CRPS as the benchmark to compute expected returns.

We obtain the initial sample from the Joint Ventures and Alliances Database from Securities Data Company (SDC, a product from Thomson Financial[3]). We select all alliances with announcement dates between 1999 and 2002 and require both the acquirer and the target to have a primary SIC code classified as either software, hardware, communications or services in information technology, and at least one of the sides to have one industry segment with an SIC

[1] In our sample 71.5% of the companies have more than 50% of total sales concentrated in one of the layers of stack.

[2] A detailed exposition of the event studies methodology can be found in Brown and Warner [4] and MacKinlay [32].

[3] www.thomson.com/financial/financial.jsp

classification as software. [4] Other requirements for selection are that (1) both participants are public firms, (2) both participants are listed on the CRSP and on the Compustat databases during the event windows and (3) there are at least 75 trading days during the estimation period window. For simplification, we select alliances in which there are only two participants.

For a smaller number of firms, we obtain data from the International Data Corporation (IDC, www.idc.com) that provides enough information to classify sales on the five-layer stack. The IDC market classification allows the classification of sales as systems software, middleware software, applications software and services. Our initial sample from SDC was comprised of 1064 alliances. After applying the requirements and merging the sample from SDC with the information obtained from IDC, our sample yields 103 alliances. There are no Joint Ventures in our final sample.

To exclude the effect of firm and transaction characteristics we consider the following control variables:

- *Firm's Size*. Consistent with prior studies [34,28,7,11] we control for the size of the firm by using the logarithm of the market value of the firm at the time of the announcement of the alliance. We obtained the market value of equity (MVE) from CRSP as equal to the number of shares outstanding times the price two days prior to the announcement of the transaction.

- *Technical Alliance*. Alliances are classified as technical if they involve the possible pooling or transfer of technology, Licensing, Research and Development and technology transfer agreements [7,28,11].

- *Relative Size Smaller/Larger participant*. We investigate if there is value in alliances between smaller partners and larger companies.

- *Lead.* Larger firms can be expected to have more bargaining power than smaller firms. However, smaller firms may have access to proprietary technology, which increases their bargaining power.

- *Participants Tobin q*. There is evidence that profitability is negatively correlated with abnormal returns around the announcement date of the alliance. A possible explanation is that firms with poor performance or cash-stretched firms are in greater need of inter-firm collaboration [11]. Tobin's q is defined as the ratio of the value of book assets plus market equity minus book equity to the value of book assets.

- *Participants Leverage*. We investigate the relationship between leverage and abnormal returns. Firms that have higher leverage may be rewarded by pursuing strategies of forming alliances instead of acquiring other companies or investing in R&D. Leverage is calculated as the ratio of the firm's debt (long-term + short-term + preferred stock) to the firm's book value of common equity.

From Compustat we retrieve values for book assets, market equity, book equity, sales, earning before interest, taxes and depreciation, long-term debt, debt in current liabilities and preferred stock – redemption value.

Table 1 presents the structure and statistics of our sample. About 75.7% of the alliances in our sample are technical alliances. We classify alliances as technical only if they exclusively involve technical agreements. In a few cases the alliances involved both technical and marketing agreements. [5]

**Table 1: Summary statistics for the sample of Alliances per year and Alliance Type**

| Year | Freq. | Perc. | Marketing | Exclusively Technical | Percentage Technical |
|---|---|---|---|---|---|
| 1999 | 26 | 25.2% | 5 | 21 | 80.8% |
| 2000 | 39 | 37.9% | 9 | 30 | 76.9% |
| 2001 | 9 | 8.7% | 4 | 5 | 55.6% |
| 2002 | 29 | 28.2% | 7 | 22 | 75.9% |
| All | 103 | 100.0% | 25 | 78 | 75.7% |

[4] We limit our sample to alliances announced until the end of 2002 because we do not have data from IDC for more recent years. We benchmark abnormal returns to a market index, and consequently the fact that our sample includes data from the 1999-2000 bubble should not significantly affect our results.

[5] For example, in an Alliance announced in 02/09/1999, "Amkor Technology Inc (ATI) and Synopsys Inc (SI) formed a strategic alliance to provide joint marketing and library licensing services in the United States. "

**Table 2: Mean of Proportions of Sales in each of the layers of the Stack - calculated using data from IDC and Compustat Segments**

| | Hard. | Soft. | Sys. | Mid. | Appl. | Serv. |
|---|---|---|---|---|---|---|
| All Years N=206 | 13.200 | 86.800 | 16.962 | 14.799 | 52.536 | 2.499 |
| 1999 N=52 | 13.958 | 86.042 | 14.346 | 12.097 | 56.899 | 2.700 |
| 2000 N=78 | 8.597 | 91.403 | 20.340 | 15.313 | 53.417 | 2.328 |
| 2001 N=18 | 17.962 | 82.038 | 3.786 | 23.055 | 54.026 | 1.170 |
| 2001 N=58 | 17.235 | 82.765% | 18.852 | 13.969 | 46.975 | 2.960 |

**Table 3: Function of each of the participants in the Alliance as classified by layer of the stack**

| | No.Alliances | Proportion |
|---|---|---|
| Hardware/Systems | 1 | 1.0% |
| Hardware/Middleware | 1 | 1.0% |
| Hardware/Applications | 15 | 14.6% |
| Hardware/Services | 3 | 2.9% |
| Sytems/Systems | 0 | 0.0% |
| Sytems/Middleware | 3 | 2.9% |
| Sytems/Applications | 6 | 5.8% |
| Sytems/Services | 1 | 1.0% |
| Middleware/Middleware | 3 | 2.9% |
| Middleware/Applications | 19 | 18.4% |
| Middleware/Services | 6 | 5.8% |
| Applications/Applications | 22 | 21.4% |
| Applications/Services | 23 | 22.3% |
| Services/Services | 0 | 0.0% |
| No. of Alliances | 103 | 100.0% |

Table 6 (in Appendix) presents descriptive statistics for the sample, considering all the variables included in our analysis. We construct the measure of the distance between both participants on the stacks using the *STACK_DISTANCE* from Gao and Iyer [17]. Because this index considers the overall activity of the company, we also test if the results are improved when we construct a measure based only on the activities of the company that are involved in the alliance. For this purpose, we asked a third party to classify each of the participants in our sample of alliances on a stack layer according to their role in the alliance, base on the "Deal Text" provided by IDC. [6] Table 3 describes the role of each participant in the alliance as classified by layer of the stack. Almost half of the alliances in our sample involve both participants providing applications, or one providing applications and the other services.

## 5. Results

The values obtained for abnormal returns are consistent with the findings of previous research. Average cumulative abnormal returns around the announcement dates of alliances for the entire sample are 1.794% and significant *(*t-*stat.* = *2.917,* p < *0.01)*. In Table 4, we also present abnormal returns when we group alliances according to the distance on the stack between both participants (as classified considering the specific role of companies in the alliance). We find that abnormal returns are higher when alliances involve participants either on the same layer of the stack or on adjacent layers. When participants are on the same layer of the stack abnormal returns are equal to 3.457% *(*t-*stat.* = *2.705,* p < *0.01)* and abnormal returns are 2.016% *(t-stat.* = *2.136,* p < *0.05)* when alliances are classified on adjacent layers. For larger distances abnormal returns are close to zero and statistically insignificant.

Based on information obtained from IDC on market classification, software sales are classified as systems software, middleware software or applications software. IDC also provides information for sales on services. From the Industry Segments database in Compustat we obtain sales for hardware. For each transaction, the *STACK_DISTANCE* index is calculated. We then run cross-sectional regressions of abnormal returns on the *STACK_DISTANCE* index and on the measure of distance between participants when considering their role in the alliance.

The results of are presented in Table 5. In accordance with the results obtained in previous papers, we find an inverse relationship between abnormal returns around the announcement of the alliance and the size of the participant.

[6] For example, IBM has activity in all the five layers of the stack but in one of the alliances in our sample, the company provides only applications.

**Table 4: Abnormal returns and distance on the stack between participants**

| | All sample | D=1,2 | D=3,4,5 |
|---|---|---|---|
| N | 206 | 142 | 64 |
| ACAR | 1.794% | 2.524% | 0.177% |
| t-stat | 2.917*** | 3.324*** | 0.170 |

*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

| | D=1 | D=2 | D=3 | D=4 | D=5 |
|---|---|---|---|---|---|
| N | 50 | 92 | 24 | 34 | 6 |
| ACAR | 3.457% | 2.016% | 0.586% | -0.240% | 0.897% |
| t-stat | 2.705*** | 2.136** | 0.357 | -0.160 | 0.323 |

*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

*Notes*: Alliances are classified according to the role of each participant with reference to the layers of the stack. If D=1, then the role or each of the participants is classified on the same layer. If D=2,3,4,5, the role or each of the participants is classified 1,2,3,4 layers apart.

**Table 5: Cross-sectional regression, ACARs in Alliances**

| | Model (1) | Mode (2) | Model (3) | Model (4) |
|---|---|---|---|---|
| Intercept | 0.116<br>(2.381)*** | 0.113<br>(2.386)*** | 0.116<br>(2.853)*** | 0.111<br>(2.828)*** |
| *STACK_ DISTANCE* | -0.0169<br>(-1.979)** | | -0.018<br>(-2.092)** | |
| Alliance Distance | | -0.012<br>(-2.104)** | | -0.011<br>(-2.056)** |
| Log(MV) | -0.004<br>(-1.179) | -0.004<br>( -1.325) | -0.004<br>( -1.521) | -0.004<br>(-1.739)* |
| Log (Relative Size) | 0.003<br>(0.879) | 0.003<br>(0.842) | | |
| Lead | 0.009<br>(0.5905 ) | 0.009<br>( 0.622) | | |
| Technical | 0.047<br>( 3.7178)*** | 0.044<br>( 3.545)*** | 0.049<br>(3.982)*** | 0.046<br>( 3.783)*** |
| Tobin Q | -0.003<br>(-2.954)*** | -0.003<br>( -2.813)*** | -0.003<br>( -2.817)*** | -0.003<br>(-2.620)*** |
| Leverage | -0.010<br>( -1.332) | -0.012<br>( -1.423) | | |
| *R^2* | 0.148 | 0.149 | 0.1383 | 0.1385 |
| *F-statistic* | 4.847 | 4.935 | 7.945 | 8.039 |
| *N* | 206 | 206 | 206 | 206 |

*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

*Notes*: In Model (1) and Model (3) the independent variable is the *STACK_DISTANCE*, as defined in Gao and Iyer (2006). In Model (2) and Model (4) the independent variable is *Alliance Distance*, defined as the distance on the stack between both participants according to their specific role in the alliance. This variable assumes values 1, 2, 3, 4, 5 if participants are on the same layer of the stack or 1, 2, 3 and 4 layers apart.

We also find an inverse relation between abnormal returns and profitability (t-*stat.* = *2.817,* p < *0.01)*. Technical Alliances earn significantly higher abnormal returns when compared with non-technical alliances (t-*stat.* = *3.982,* p < *0.01)*. The other control variables – Relative Size, Lead and Leverage – are insignificant in explaining abnormal returns in our sample.

We find a significant inverse relationship between abnormal returns and our independent variable – both in the case when we use the *STACK_DISTANCE* (t-*stat.* = *-2.092,* p < *0.05)* and when we define the distance between the role of both participants in the alliance and use the variable *Alliance Distance* (t-*stat.* = *-2.056,* p < *0.05)*. Even though there is a slight increase in the $R^2$ and F-statistic, a measure that takes into account only the part of the company that will be involved in the alliance does not significantly improve the results. It seems that the market is rewarding the alliance based on the overall activity of the company. The results obtained using the variable *Alliance Distance* also contribute for the robustness of the results obtained using the *STACK_DISTANCE* index.

We conclude that alliances have the largest value when both participants produce on the same layer of the stack, and the value decreases has the distance on the stack between participants increases.

## 6. Discussion and Conclusion

Our results are different from those obtained by Gao and Iyer [17] for a sample of M&As. Gao and Iyer [17] obtain higher abnormal returns when acquirers and targets produce on adjacent layer of the stack and lower when both parts are on the same layer. Our results are in the opposite direction: we find higher abnormal returns when companies enter into alliances with other companies that have the largest proportion of sales in the same layer of the stack, and lower abnormal returns when companies are in adjacent layers of the stack.

The conclusion that alliances between similar firms have higher value is consistent with results from previous papers. Chan, Kensinger, Keown, and Martin [7] find that technical alliances involving firms in the same industry earn higher abnormal returns. They find that alliances between firms in the same three-digit SIC code produce higher abnormal returns than alliances between firms in unrelated industries. They provide evidence that the greater wealth impact in these alliances can be attributed to a transfer or pooling of complementary technology. For alliances between firms in the same industry, technical alliances (licensing, research and development and technology transfer) produce higher abnormal returns. For these alliances, abnormal returns are 3.5%, while for non-technical alliances abnormal returns are 1.02%.

Previous literature explains why alliances between similar firms are more valuable. Alliances are often viewed as a mechanism for reducing the organizational inefficiencies associated with M&As [48]. While these "hybrid organizational forms" or "network organizations" do involve a mutual commitment that goes beyond the usual market transactions, they also have less impact on the operations of participant firms than have M&As. Participants can easily bring the partnership to a halt, while the costs of divestitures are much higher. Chan, Kensinger, Keown, and Martin [7] conclude that alliances add the most value because they allow companies to maintain the focus of their business while making use of complementary technical skills of complementary firms. They justify that alliances that involve the pooling or transfer of technical knowledge tend to produce larger wealth effects than marketing alliances.

While other papers have studied the value of alliances and M&As according to strategies of concentration versus diversification in one industry, our paper and Gao and Iyer [17] study the effect of concentration in one layer of the stack versus diversification along different layers of the stack as a way to capture value from complementarities. Ultimately, companies acquire, merge and enter into alliances with the purpose of achieving higher growth rates. The strategy is then either to reach for complementary products in adjacent layers of the stack, or to create scale effects and realize synergies in the same layer of the stack.

A key challenge that companies face when they acquire other companies is the technical integration of their products. The value of M&As between software companies depends on how easy it is to technically integrate the products of both companies. There is value creation only if potential synergies and complementarities are realized. Synergies represent the antecedent potential for value creation that may or not be realized. Very often the outcome of mergers between similar software companies is not very successful because these companies have problems with the technical integration of the software products. In practice the integration may take time or not happen at all.

While products that are in different layers of the stack were very often developed to work together, most often products that are in the same layer of the stack were not developed with the purpose of being integrated. Hence, when products occupy complementary layers of the stack they are already interoperable in most instances. Gao and Iyer [17] hypothesize that even though technical integration between products of similar companies may be difficult, when products are in different layers of the software stack they may already be working together as complementary components of a network system and companies may want to internalize the value of complementary network externalities through M&As. They argue that the lower uncertainty on the interoperability between products that are within different layers of the stack may justify their results. For example, when EMC acquired Documentum in 2003, that company was offering software that run on many operating system platforms but was most closely tied to EMC’s storage hardware. Documentum offered enterprise document management software for managing unstructured content. With the purchase of Documentum, EMC planned to offer an integrated system, including the infrastructure and the software layer.

On the other hand, alliances allow firms to incorporate new knowledge and experiment without the commitment of M&As. An alliance will limit the firm's exposure, when compared to M&As, since it has to invest less money and time, and it is much easier for the firm to withdraw from the alliance in case of failure. Therefore, alliances are a more viable mechanism for companies to exploit consumption side synergies and create interoperability between their products, since the cost is much smaller in case of difficulty in technically integrating their products.

Alliances also permit firms to form multiple partnerships and increase the scope of their activity and learning. In industries characterized by constant innovation and product change it may be better for companies to form alliances, rather than merge, to obtain economies of scale and offer more reliable integrate products to their customers. The possibility of being associated with several companies may extend the customers’ base compared with being highly integrated with only one partner.

Therefore, the choice of alliances versus mergers is a consequence of the flexibility of this form of organization and some of the characteristics of the software industry. When there is uncertainty regarding the technical integration of products and when there is standardization, firms may prefer to be loosely coupled than to be highly integrated.

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## APPENDIX

### Table 6: Descriptive statistics for the sample

***Correlations***

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 4 | 1 | -0.09 | -0.13 | -0.09 | 0.14 | -0.08 | 0.23 | -0.22 | -0.04 |
| 2 | -0.09 | 1 | 0.39 | 0.14 | 0.14 | 0.00 | 0.24 | -0.04 | 0.12 |
| 3 | -0.13 | 0.39 | 1 | 0.15 | 0.08 | 0.00 | 0.13 | 0.07 | -0.03 |
| 4 | -0.09 | 0.14 | 0.15 | 1 | 0.12 | 0.48 | 0.12 | 0.14 | 0.13 |
| 5 | 0.14 | 0.14 | 0.08 | 0.12 | 1 | 0.00 | 0.29 | -0.13 | 0.28 |
| 6 | -0.08 | 0.00 | 0.00 | 0.48 | 0.00 | 1 | 0.00 | 0.19 | 0.26 |
| 7 | 0.23 | 0.24 | 0.13 | 0.12 | 0.29 | 0.00 | 1 | -0.02 | 0.06 |
| 8 | -0.22 | -0.04 | 0.07 | 0.14 | -0.13 | 0.19 | -0.02 | 1 | -0.28 |
| 9 | -0.04 | 0.12 | -0.03 | 0.13 | 0.28 | 0.26 | 0.06 | -0.28 | 1 |

***Descriptive Statistics***

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Mean | 0.02 | 2.19 | 2.29 | 62 | 185 |
| STD | 0.09 | 0.72 | 1.09 | 112,314 | 526 |
| Min. | -0.22 | 1 | 1 | 47 | 1.00 |
| Max. | 0.27 | 4 | 5 | 521,163 | 3,946 |
| N | 206 | 206 | 206 | 206 | 206 |

***(continuation of Descriptive Statistics)***

| | 6 | 7 | 8 | 9 |
|---|---|---|---|---|
| Mean | 0.50 | 0.35 | 5.15 | 0.82 |
| STD | 0.50 | 0.48 | 5.69 | 0.89 |
| Min. | 0.00 | 0.00 | 0.04 | -2.27 |
| Max. | 1.00 | 1.00 | 38.11 | 5.68 |
| N | 206 | 206 | 206 | 206 |

Variables:
1. Accumulative Abnormal Returns (ACAR)
2. Stack Distance Index
3. Alliance Distance
4. Market Value (MV) – in millions of dollars
5. Relative Size
6. Lead
7. Technical Alliance (Dummy Variable)
8. Tobin q
9. Leverage