Value creation using alliances within the software industry

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1. Introduction

Announcements of mergers and acquisitions (M&As) and alliances are common in the software industry. There are many reasons why companies may enter into alliances or merge. In general companies enter into M&As and alliances to grow. Growth can be internal or can involve joint actions with other firms. Important cooperative efforts with other firms often involve risky investments and tend to be organized as contracts. Alliances and joint ventures are examples of such contracts. When cooperative efforts are sufficiently complex and risky, companies may prefer to combine under common ownership and M&As. Some of the most prominent and successful companies in information technology (IT) 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 (Gulati 1998, Harrigan 1988, Kale et al. 2002). In the software industry, companies form strategic research partnerships, joint product development, technology licensing and marketing and distribution agreements (Rao and Klein 1994). Companies acquire when unified ownership and control rights permit more thorough exploitation of combined organizational resources (Yin and Shanley 2008).

We argue that there are distinct and unique reasons specific to the software industry and other network-type industries that determine the choice of mergers versus alliances and that are related to specific characteristics of these industries. In network-type industries, particularly industries such as IT and communications, decision-making and strategy are shaped by the existence of complementarities and network effects. Complementary network systems are defined by the existence of different components that must 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. These factors create incentives for companies to engage in forms of cooperation with each other.

While there are many differences between M&As and alliances on dimensions such as size, risk, duration, degree of integration, scope of overlap (whole versus part of the organization), and structural possibilities, the fundamental difference concerns ownership, since a merger or acquisition implies a controlling ownership interest whereas an alliance or joint venture does not (Yin and Shanley 2008).

In a study applied to M&As in the software industry, Gao and Iyer (2006) provide evidence that there is value in M&As involving firms that produce complementary components of network systems. Complementary components are defined as products classified in adjacent layers of the software stack, and Gao and Iyer (2006) show that abnormal returns around the date of the
announcement of the M&As are higher if acquirer and target pro-
duce on adjacent layers and lower if they produce on the same
layer or in layers further apart on the stack. In this paper we extend
the study by Gao and Iyer (2006) to alliances in the software indus-
try, and 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. Our results sug-
gest that software companies gain a larger value from alliances
when companies are in the same layer of the software stack, while
the value of M&As is larger when companies involved are in com-
plementary layers of the stack. These results and the subsequent
discussion add to the existing literature of alliances in the software
industry, in that they introduce new factors that influence the deci-
sion of pursuing alliances versus other forms of inter-firm cooper-
pation, and have practical implications for the strategic behavior of
software companies.

We have organized our paper as follows: Section 2 reviews previ-
sion literature that discusses the choice of mergers versus alli-
ances; Section 3 discusses some of the specific characteristics of
the software industry and organization; Section 4 presents the
empirical methodology used in the paper; Section 5 presents the
results; and Section 6 brings the paper to a close with some

### 2. Determinants of alliances and “merger vs. alliance” decision

Alliances and M&As are alternative forms of organization that
govern cooperative efforts between different firms. Companies in
the software and information technology industries have special
incentives to enter into inter-firm cooperation contracts. These
incentives are related to the characteristics and dynamics of the
software markets, for example the existence of network externali-
ties. Therefore, software companies have reasons to enter into alli-
ances and M&As that go beyond the general justifications currently
listed in the literature.

There are various alternative explanations and determinants for
alliances proposed in the economics and management literature.
One is the incomplete contracts-related explanation, which pre-
dicts that ownership should be allocated in order to most effi-
ciently provide marginal incentives for effort (e.g., Grossman and

Other studies explain alliance formation using resource based
theory (Contractor and Ra 2002, Das and Teng 1998, 2000; Eisen-
From a resource-based view, alliances are the outcome of
resource integration among firms that allow access to each other's
resources (Das and Teng 2000). Alliances can help firms to con-
serve resources, share risks, gain information, access complement-
ary resources, reduce product development costs, and improve
technological capabilities (Eisenhardt and Schoonhoven 1996, Ko-
et al. 1996). Tanriverdi and Venkatraman (2005) propose that eco-
omic benefits of resource combination result from both the simi-
ilarity and complementarity of two firms’ resources.

Alliances are a mechanism through which knowledge, compe-
tence and technologies are transferred between companies, and
are particularly suitable for the transfer of tacit knowledge. How-
ever, transferring information can be costly. When the cost is
low, information stickiness is low; when high, stickiness is high
(von Hippel 1994). Absorptive capacity and differences in organi-
zational types in disparate industries also play a role in facilitating
knowledge transfers between companies (Mowery et al. 1996, Gans
et al. 2002).

M&As and alliances are strategic alternatives along a continuum
of governance modes (Williamson 1991, Villalonga and McGahan
2005). While there is a vast body of literature that studies determin-
ants and the value of alliances and M&As for companies, the num-
ber of papers that study the decision of pursuing one over the other
is much smaller.

Transaction costs theorists argue that the level of environmental
uncertainty on a transaction determines the choice of M&As versus
alliances. In relatively efficient markets, neither M&As or alliances
are needed, but market imperfections raise the costs of transac-
tions, and alternatives to market transactions must therefore be
considered (Williamson 1985). Alliances between firms, when com-
pared with M&As, can be used as less expensive and more flexible
mechanism to support cooperation and knowledge transfer.

The choice between M&As and alliances involves balancing
requirements for flexibility with requirements for commitment.
Alliances have greater flexibility and allow the option to scale up
or down depending on the initial outcomes, but they provide less
control over the joint resources, which may result in governance
problems. Depending on the industry’s requirements for commit-
ment or flexibility, M&As will be preferred when unified ownership
and control rights permit more thorough exploitation of combined
organizational resources (Yin and Shalney 2008).

Prior research also suggests that a firm prefers an alliance to an
acquisition if the focal firm does not have enough information
about the other company (Balakrishnan and Koza 1993) or the
other company has assets that are inseparable from the ones the
focal company wants to acquire. Characteristics of a focal firm, as
well as environmental characteristics of the new market, together
affect the decision of the entry mode the company will select (Ko-

Wang and Zajac (2007) look at factors specific to both firms, as
opposed to those specific only to the focal firm, as well as factors
that play an important role in the decision of using an alliance ver-
sus an acquisition to combine resources. They argue that dyadic
characteristics such as resources similarities or complementarities,
combined relational capabilities and partner specific knowledge
will affect the value of using alliances and acquisitions. They find
that higher levels of resource similarity of two firms are more
likely to trigger firms to choose acquisition as the governance form
of resource combination rather than alliance. In addition, high lev-
els of resource complementarity of two firms are more likely to
trigger firms to choose alliances rather than acquisitions.

Alliances may be preferred in industries that do not require
such large investments or undergo such unpredictable periods of
change that large investments are too risky. Industry concentra-
tion may also determine the choice between M&As and alliances.
M&As are more likely where there is a relatively large number of firms
competing and numerous potential partners. In more concentrated
industries, M&As are more difficult and costly to implement, and
firms are more likely to pursue alliances (Yin and Shalney 2008).

Villalonga and McGahan (2005) argue that firms may choose a
more integrative form of governance with acquisitions when their
technological knowledge capital is highly valuable, since intangible
capital, such as firm’s technological and marketing resources, are
vulnerable to appropriation by partners in alliances.

Roberts and Liu (2001) relate alliances and acquisitions to the
evolution of a technology and the market it serves. They argue that
industry structure and critical success factors change as the under-
lying technology evolves from phase to phase, competitive press-
sures exerted on a firm vary, and companies respond by adopting
changing approaches to inter-firm collaboration. According to Rob-
erts and Liu (2001), in the first phase new technology companies
often form marketing alliances with established technology firms
and pursue an aggressive licensing strategy to gain market recog-
nition. At the same time, the proliferation of technology startups
provides an opportunity for established technology companies to
obtain new technologies or enter niche markets through acquisi-
tions or minority equity investments. Anticipating the emergence of a dominant design, companies can form standards alliances to promote their own proprietary technologies. During the transitional phase, companies with dominant designs acquire some of their competitors. During the mature phase, technology is well-defined and competition becomes intense. Companies can form technology alliances to cut R&D costs or acquire new firms with technologies that cannot be developed in-house. Companies will also enter in marketing alliances to target latent markets and expand into new geographic markets.

This paper introduces new factors that influence the decision of pursuing alliances, as well as the decision of pursuing alliances vs. M&As in the software industry. We provide evidence that these factors are related to specific characteristics of the software markets.

3. Cooperation strategy and the organizations of software markets

Software markets present special dynamics that distinguish them from conventional markets. The existence of direct and indirect externalities creates incentives for companies to expand their market share by connecting 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 constitute the products within the industry and their relationships. Designers of complex artifacts look for a modular architecture such that the overall design tasks are manageable. Complex artifacts like computer systems are composed of subcomponents that are manufactured by a group of firms specializing either in one component of the artifact or some stage of the production process of the artifact. Researchers have labeled such groups of firms as modular clusters (Baldwin and Clark 2000, Jacobides et al. 2006).

Similar insights were provided by Bresnahan (1998), who argued that the market structure of the computer industry can be best understood through the lens of divided technical leadership. It is feasible for firms to develop these complex artifacts because of the existence of an architecture that allows the various subcomponents to be produced independently while at the same time to interoperate.

Modular clusters of products in the software industry are sometimes referred to as stacks. Stacks are organized into horizontal layers, with firms within a layer producing components that can be substituted; and firms in other layers producing components that complement the ones in the first layer. Components are also modular, meaning that they have clearly defined interfaces and boundaries, making them interoperable with any component from other layers.

An espoused architecture like a product architecture (Ulrich 1995) is the scheme by which the function of a product is assigned to its components. As a result, it indicates 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.

We propose that the espoused stack has five layers, as depicted in Fig. 1. Our reasoning is as follows. 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 functions such as 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.

Looking at the history of computing, the next layer to emerge was the application one. This layer 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, providing products that enabled applications 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, seldom running out of the box. This resulted in the creation of the service layer. Companies operating in this layer would install and customize packaged software, in many cases creating 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 (Milgrom and Roberts 1988, 1995). 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 (Gao and Iyer 2006) 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 (Eisenhardt and Schoonhoven 1996, Robins and Wiersema 1995), the use of complementary factors of production across multiple business units should lead to production-side synergies, economies of scope and improved firm performance (Davis and Thomas 1993). 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 writing fresh 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 (Teece 1986, Gawer and Henderson 2005).
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 conducted in standard committees, but 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 on 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 [Sengupta 1998].

Related products can also exploit consumption-side synergies. When a set of products serves 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 (Bakos and Brynjolfson 1999), and product value in-learning and in-use (Baldwin and Clark 2000).

A firm's performance depends upon its internal capabilities and knowledge resources (Conner and Prahalad 1996, Teece et al. 1997) and its ability to access critical complementary resources from other firms within its ecosystem (Gulati and Gargiulo 1999). Firms exploit their own existing knowledge and explore others' knowledge to generate new knowledge (Cohen and Levin 1989, March 1991, Nonaka and Takeuchi 1995) while sustaining their competitive advantage through their ability to reconfigure their knowledgebase (Kogut and Zander 1992, Henderson and Cockburn 1994, Teece et al. 1997).

Software development involves a setting that calls for knowledge interdependence between firms to achieve product interoperability (Shapiro and Varian 1999). In this setting, a network of relationships is key for a software firm's success (Campbell-Kelly 2003).

Inter-firm alliances are relationships that are governed by formal mechanisms of resource pooling and value appropriations (Gulati and Singh 1998). These include license-sharing agreements, joint ventures, research consortia, joint R&D activities and other activities governed by the formal agreements. Firms create inter-connections for many reasons, such as access to financial capital, specialized knowledge, complementary assets, technical capabilities and new marketing channels (Oliver 1990). For such reasons and others, firms form relationships with other firms, creating the network of relationships that act as the backdrop for competition and value delivery in this industry.

Dyer et al. (2004) argue that when a company estimates that a collaboration's outcome is highly or moderately uncertain, it should enter into an alliance rather than acquire. 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 et al. (2008) 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.

Gao and Iyer (2006) study the value of mergers and acquisitions in complementary network systems. They apply the concept of a 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 Fig. 1. 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.

The positioning of the service layer on top of the stack in Gao and Iyer (2006) is mostly based on evidence from the practitioner world. In other papers (Cottrell and Nault 2004, West and Dedrick 2000) researchers have presented and used the stack model that includes the hardware, systems software, middleware and applications layers. Service companies have groups within them that provide support for each individual layers of the stack. As a result, in this paper, we also test the model with the services layer placed adjacent to the other layers of the stack, as represented in Fig. 2. The rationale for this representation is that, since firms can provide services to support hardware, systems, middleware or applications layers, the service layer may be equidistant from all these layers.

We investigate how value is created through alliances between software companies, and then we compare our results with the results obtained in Gao and Iyer (2006) for an informal comparison of the mechanisms of value creation in alliances versus M&As. The hypotheses to be tested are:

Hypothesis 1 (The Complementary Network Effects Hypothesis). Complementary network effects are a source of value creation in alliances in the software industry.
Hypothesis 2 (The Value Creation with Adjacent Layers of the Software Stack Hypothesis). Value creation is larger in alliances between companies that produce in adjacent layers of the software stack, when compared to alliances between companies that produce in the same layer or in layers further apart.

4. Empirical design and sample

We use the Stack Distance Index (STACK_DISTANCE) presented by Gao and Iyer (2006) to measure the relationship between both participants in the alliance. The index is computed as:

$$STACK\_DISTANCE = \sum_{i=1}^{L} \sum_{j=1}^{L} P_{1i}P_{2j}d_{ij}$$

where $STACK\_DISTANCE$ denotes Stack Distance Index, $L$ is the number of layers of the stack, $P_{1i}$ is the percentage of sales of the first participant in the alliance in layer $i$ of the stack, $P_{2j}$ is the percentage of sales of the second participant in the alliance 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 $\sum_{i=1}^{L} \sum_{j=1}^{L} P_{1i}P_{2j} = 1$.

We define the coefficient $d_{ij}$ to assume the values 1, 2, 3, 4, and 5, if both participants focus on the same layer, or on one layer apart, two layers apart, three layers apart or four layers apart. The index is defined as the sum of the coefficients that represent the distance on the stack between two different layers or industry segments, weighted by the product of the percentage of sales of each firm in the corresponding layer.

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 Robin and Wiersema (2003) discuss for the concentric index. The concentric index is an adaptation of the Herfindahl index that is widely used to measure relatedness in corporate portfolios of multi-business firms or between business units of a firm (Davis and Thomas 1993, Montgomery and Hariharan 1991, Robin and Wiersema 1995). It is computed based on the weighted average of coefficients that assume mechanically imposed and pre-established weights, according to the relations of the SIC codes of pairs of industries, where the weights are equal to the product of the percentage of sales of the firm for each of these industries. Robin and Wiersema (2003) 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 are highly diversified in the different layers of the stack.

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 (Alliance Distance). 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. This variable is defined as:

$$Alliance\_Distance = d$$

where $d = 0$ if the roles of participants in the alliance are classified in the same layer, $d = 1$ if the roles of participants in the alliance are classified in adjacent layers, $d = 2$ if the roles of participants in the alliance are classified two layers apart, $d = 3$ if the roles of participants in the alliance are classified three layers apart, $d = 4$ if the roles of participants in the alliance are classified four layers apart.

By setting the code of alliances in which participants that are classified in the same layer equal 0, we have set this case as the base case. Our construct serves two purposes: to investigate if investors take into account only the part of the company that is involved in the alliance or, conversely, 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 (Cumulative abnormal returns (CAR) 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 CRSP 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). 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 classification as software. 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. We could have broken multi-firm alliances into groups of two companies, but then we could not identify which part of the alliance is determining abnormal returns for a specific company. Multi-firm alliances represent about 10% of the number of alliances in our initial sample. We did not find significant differences between two-sided and multi-sided alliances in terms of the proportion that is technical or marketing-focused, or involve licensing agreements.

For a smaller number of firms, we obtained data from the International Data Corporation (IDC, www.idc.com) that provide enough information to classify sales on the five-layer stack. The IDC market classification enables the identification of sales in different categories, including systems software, middleware software, applications software and services. Our initial sample from IDC was comprised of 1064 alliances. After applying the requirements and merging the sample from IDC 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 (McConnell and Nantell 1985, Koh and Venkatraman 1991, Chan et al. 1997, Das et al. 1998) 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.

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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 (1985) and MacKinlay (1997).

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. There is some evidence that smaller firms earn higher returns in alliances—especially relevant for small entrepreneurial firms in the advent of new technologies. However, there is also some ambiguity in the prior research. In some cases, much of the economic value created by the alliance is appropriated by the larger partner. McConnell and Nantell (1985) 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 et al. (1997) 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 (1991) find that on average, the smaller partner gains more than the larger partner. Das et al. (1998) also find cumulative abnormal returns to be larger for smaller partners.

- **Technical alliances:** Alliances are classified as technical if they involve the possible pooling or transfer of technology, licensing, R&D and technology transfer agreements (Chan et al. 1997, Koh and Venkatraman 1991, Das et al. 1998). Alliances are also more valuable when the creation or transfer of knowledge is involved. Investments and outputs in R&D are subject 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 (Balakrishnan and Koza 1993). The costs of knowledge transfer can be particularly high for innovative projects, for example those 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 (Chan et al. 1997).

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 et al. (1997) do not find more value for alliances involving R&D projects than those involving existing knowhow, 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 in a non-technical alliance. The opposite happened for alliances between partners from different industries. They also find that alliances in high tech industries are more valuable (yielding a significant abnormal return of 1.12%), than those in low tech industries (yielding an insignificant abnormal return of 0.10%).

- **The relative sizes of smaller and larger alliance participants:** We investigate if there is value in alliances between smaller partners and larger companies. Relative size is defined by the ratio of the market value of the smallest participant to the market value of the largest participant in the alliance.

- **Larger participant:** Larger firms can be expected to have more bargaining power than smaller firms. However, smaller firms may have access to proprietary technology, increasing their bargaining power. Larger Participant is a dummy variable equal to 1 if the participant has the largest equity market value.

- **Tobin’s q of the participants:** 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 (Das et al. 1998). Lerner and Merges (1998) 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 et al. (1998) observe that 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 (2002), in a study applied to the pharmaceutical industry, find that abnormal returns increase 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. 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.

- **The alliance 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 (see Table 2).4 Table 3 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 Index from Gao and Iyer (2006). 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 SDC.5 Table 4 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 either both participants providing applications, or one providing applications and the other services.

5. Results

A number of previous event studies document positive and significant announcement returns related to the formation of strategic alliances and joint ventures. McConnell and Nantell (1985) find significant wealth gains from joint ventures, and conclude that

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4 For example, in an Alliance announced in February 9, 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.”

5 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 2
Mean of proportions of sales in the layers of the stack – calculated using data from IDC and Compustat segments.

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<th>Hardware/Systems</th>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Hardware/systems</td>
<td>1</td>
<td>1.0</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Hardware/middleware</td>
<td>1</td>
<td>1.0</td>
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</tr>
<tr>
<td>Hardware/applications</td>
<td>15</td>
<td>14.6</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Hardware/services</td>
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<td>2.9</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Systems/systems</td>
<td>0</td>
<td>0.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Systems/middleware</td>
<td>3</td>
<td>2.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Systems/applications</td>
<td>6</td>
<td>5.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Systems/services</td>
<td>1</td>
<td>1.0</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Middleware/middleware</td>
<td>3</td>
<td>2.9</td>
<td></td>
<td></td>
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<tr>
<td>Middleware/applications</td>
<td>19</td>
<td>18.4</td>
<td></td>
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<tr>
<td>MiddleWare/services</td>
<td>6</td>
<td>5.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Applications/applications</td>
<td>22</td>
<td>21.4</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>Applications/services</td>
<td>23</td>
<td>22.3</td>
<td></td>
<td></td>
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<tr>
<td>Services/services</td>
<td>0</td>
<td>0.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Number of alliances</strong></td>
<td>103</td>
<td>100.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3
Descriptive statistics for the sample.

<table>
<thead>
<tr>
<th>Correlations</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>-0.09</td>
<td>-0.13</td>
<td>-0.09</td>
<td>0.14</td>
<td>-0.08</td>
<td>0.23</td>
<td>-0.22</td>
<td>-0.04</td>
</tr>
<tr>
<td>2</td>
<td>-0.09</td>
<td>1</td>
<td>0.39</td>
<td>0.14</td>
<td>0.14</td>
<td>0.00</td>
<td>0.24</td>
<td>-0.04</td>
<td>0.12</td>
</tr>
<tr>
<td>3</td>
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<td>0.39</td>
<td>1</td>
<td>0.15</td>
<td>0.08</td>
<td>0.00</td>
<td>0.13</td>
<td>0.07</td>
<td>-0.03</td>
</tr>
<tr>
<td>4</td>
<td>-0.09</td>
<td>0.14</td>
<td>0.15</td>
<td>1</td>
<td>0.12</td>
<td>0.48</td>
<td>0.12</td>
<td>0.14</td>
<td>0.13</td>
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<tr>
<td>5</td>
<td>0.14</td>
<td>0.14</td>
<td>0.08</td>
<td>0.12</td>
<td>1</td>
<td>0.00</td>
<td>0.29</td>
<td>-0.13</td>
<td>0.28</td>
</tr>
<tr>
<td>6</td>
<td>-0.08</td>
<td>0.00</td>
<td>0.00</td>
<td>0.48</td>
<td>0.00</td>
<td>1</td>
<td>0.00</td>
<td>0.19</td>
<td>0.26</td>
</tr>
<tr>
<td>7</td>
<td>0.23</td>
<td>0.24</td>
<td>0.13</td>
<td>0.12</td>
<td>0.29</td>
<td>0.00</td>
<td>1</td>
<td>-0.02</td>
<td>0.06</td>
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<tr>
<td>8</td>
<td>-0.22</td>
<td>-0.04</td>
<td>0.07</td>
<td>0.14</td>
<td>-0.13</td>
<td>0.19</td>
<td>-0.02</td>
<td>1</td>
<td>-0.28</td>
</tr>
<tr>
<td>9</td>
<td>-0.04</td>
<td>0.12</td>
<td>-0.03</td>
<td>0.13</td>
<td>0.28</td>
<td>0.26</td>
<td>0.06</td>
<td>-0.28</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 4
Function of each of the participants in the alliance as classified by stack layer.

<table>
<thead>
<tr>
<th>Correlations</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.02</td>
<td>2.19</td>
<td>2.29</td>
<td>62</td>
<td>185</td>
<td>0.50</td>
<td>0.35</td>
<td>5.15</td>
<td>0.82</td>
</tr>
<tr>
<td>STD</td>
<td>0.09</td>
<td>0.72</td>
<td>1.09</td>
<td>112.314</td>
<td>526</td>
<td>0.50</td>
<td>0.48</td>
<td>5.69</td>
<td>0.89</td>
</tr>
<tr>
<td>Min.</td>
<td>-0.22</td>
<td>1</td>
<td>1</td>
<td>47</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
<td>-2.27</td>
</tr>
<tr>
<td>Max.</td>
<td>0.27</td>
<td>4</td>
<td>5</td>
<td>521,163</td>
<td>3946</td>
<td>1.00</td>
<td>1.00</td>
<td>38.11</td>
<td>5.68</td>
</tr>
<tr>
<td>N</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
</tr>
</tbody>
</table>

Variables: (1) Accumulative Abnormal Returns (ACAR), (2) Stack Distance Index (STACK_DISTANCE), (3) Alliance Distance, (4) market value (MV) – in millions of dollars, (5) relative size, (6) larger participant, (7) technical alliance (dummy variable), (8) Tobin’s q, and (9) leverage.

Table 5
Average Cumulative Abnormal Returns (ACAR) and distance on the stack.

<table>
<thead>
<tr>
<th>Correlations</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.02</td>
<td>2.19</td>
<td>2.29</td>
<td>62</td>
<td>185</td>
<td>0.50</td>
<td>0.35</td>
<td>5.15</td>
<td>0.82</td>
</tr>
<tr>
<td>STD</td>
<td>0.09</td>
<td>0.72</td>
<td>1.09</td>
<td>112.314</td>
<td>526</td>
<td>0.50</td>
<td>0.48</td>
<td>5.69</td>
<td>0.89</td>
</tr>
<tr>
<td>Min.</td>
<td>-0.22</td>
<td>1</td>
<td>1</td>
<td>47</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
<td>-2.27</td>
</tr>
<tr>
<td>Max.</td>
<td>0.27</td>
<td>4</td>
<td>5</td>
<td>521,163</td>
<td>3946</td>
<td>1.00</td>
<td>1.00</td>
<td>38.11</td>
<td>5.68</td>
</tr>
<tr>
<td>N</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
</tr>
</tbody>
</table>

In Table 5, we also present abnormal returns when we group alliances according to the distance on the stack between both participants (as classified by 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 would be

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 et al. (1997) find a day 0 return of 1.12%. Koh and Venkatraman (1991) 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 than other forms of alliances.

The values we 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).
are close to zero and statistically insignificant. These results support The Complementary Network Effects Hypothesis (H1) and The Value Creation with Adjacent Layers of the Software Stack Hypothesis (H2), which state that there is greater value in alliances between companies that produce in adjacent layers of the stack when compared to alliances between companies that produce in layers further apart. However, our results show larger abnormal returns in alliances between companies that produce in the same layer of the stack.

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 these regressions are presented in Table 6. In accordance with the results obtained in previous papers, we find an inverse relationship between abnormal returns and the amount of information about the alliance and the size of the participant.

We also find an inverse relationship between abnormal returns and profitability (t-stat. = -2.954, p < 0.01). Technical alliances earn significantly higher abnormal returns when compared with nontechnical alliances (t-stat. = 3.7178, p < 0.01). The other control variables—relative size, larger participant and leverage—are insignificant in explaining abnormal returns in our sample. The value of $R^2$ of the regressions is low but comparable those obtained in similar studies.

We find a significant inverse relationship between abnormal returns and our independent variable—both in the case when we use the Stack Distance Index and when we use the Alliance Distance and use the variable Alliance Distance. Even though there is a slight increase in the $R^2$ and F-statistic, a measure taking into account only the part of the company that will be involved in the alliance does not significantly improve the results. The results obtained using the variable Alliance Distance also contribute to the robustness of the results obtained using the Stack Distance.

In Model (3) and Model (4) we test if the results change when we place the layer “Services” differently on the stack. Instead of considering “Services” as the top layer, we test if it should be placed in equal distance to all other layers in the stack, as represented in Fig. 2. We modified both the Stack Distance Index and the Alliances Distance variables in order to reflect this assumption.

In Model (3) the independent variable is STACK DISTANCE SERVICES, a variation of STACK DISTANCE where the coefficient $d_{ij}$ assumes the value 1 for same layer of the stack, 2 for adjacent layers or when of one of the layers is “Services”, and 3 and 4 for two and three layers apart. In Model (4) we construct the variable that measures the distance on the stack between both participants when classified according to their specific roles in the alliance as:

$$AllianceDistanceServices = d$$

where $d = 0$ if the roles of participants in the alliance are classified in the same layer, $d = 1$ if the roles of participants in the alliance are classified in adjacent layers or if one of the participants is classified as “Services”, $d = 2$ if the roles of participants in the alliance are classified two layers apart, $d = 3$ if the roles of participants in alliance are classified three layers apart.

The coefficient of STACK DISTANCE SERVICES is statistically insignificant (t-stat. = -0.994), but the variable that proxies for distance on the stack between both participants in the alliance significantly explains abnormal returns around the date of the announcement of the alliance (t-stat. = -2.695, p < 0.01), while the values of the t-statistics, $R^2$ and F-statistic are slightly improved. The results suggest that the market perception of the value of an alliance between two software companies depends on the role of each company in the alliance and not on the overall activity of the company. The results are also stronger when we place the layer “Services” in an equidistant position to all other layers, instead of placing it as the top layer on the software stack.

We found strong support for the model that used alliance distance and weak support for the stack index. As we explain in the discussion section, this may be the result of having more accurate information about the layers involved in the transaction, enabling a clearer analysis of the alliance announcement. In the stack index computation, we compute the complementarity score for the two companies regardless of what is contained in the announcement. This may not be an accurate representation of the intent of the alliance.

---

Table 6: Cross-sectional Regression of Cumulative Abnormal Returns (CAR) on measures of distance on the stack.

<table>
<thead>
<tr>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
<th>Model (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.116</td>
<td>0.107</td>
<td>0.126</td>
</tr>
<tr>
<td>(2.381)**</td>
<td>(2.132)**</td>
<td>(2.5859)**</td>
<td>(2.397)**</td>
</tr>
<tr>
<td>STACK DISTANCE</td>
<td>-0.0169</td>
<td>-0.012</td>
<td>-2.104)**</td>
</tr>
<tr>
<td>(1.979)**</td>
<td>(1.214)**</td>
<td>(1.325)</td>
<td>(-0.994)</td>
</tr>
<tr>
<td>Alliance Distance SERVICES</td>
<td>-0.016</td>
<td>-2.695)**</td>
<td></td>
</tr>
<tr>
<td>Log (Market Value)</td>
<td>-0.004</td>
<td>-0.004</td>
<td>-0.006</td>
</tr>
<tr>
<td>(1.179)</td>
<td>(1.325)</td>
<td>(1.843)</td>
<td>(1.568)</td>
</tr>
<tr>
<td>Log (Relative Size)</td>
<td>0.003</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>(0.878)</td>
<td>(0.842)</td>
<td>(0.715)</td>
<td>(0.534)</td>
</tr>
<tr>
<td>Larger Participant</td>
<td>0.009</td>
<td>0.009</td>
<td>0.015</td>
</tr>
<tr>
<td>(0.5905)</td>
<td>(0.622)</td>
<td>(0.972)</td>
<td>(0.807)</td>
</tr>
<tr>
<td>Technical alliance</td>
<td>0.047</td>
<td>0.044</td>
<td>0.040</td>
</tr>
<tr>
<td>(3.317)**</td>
<td>(3.545)**</td>
<td>(3.334)**</td>
<td>(3.713)**</td>
</tr>
<tr>
<td>Tobin’s q</td>
<td>-0.003</td>
<td>-0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td>(2.954)**</td>
<td>(2.813)**</td>
<td>(2.846)**</td>
<td>(2.744)**</td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.010</td>
<td>-0.012</td>
<td>-0.009</td>
</tr>
<tr>
<td>(1.332)</td>
<td>(1.423)</td>
<td>(1.214)</td>
<td>(1.423)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.148</td>
<td>0.149</td>
<td>0.133</td>
</tr>
<tr>
<td>F-statistic</td>
<td>4.847</td>
<td>4.935</td>
<td>4.347</td>
</tr>
<tr>
<td>N</td>
<td>206</td>
<td>206</td>
<td>206</td>
</tr>
</tbody>
</table>

Notes: The dependent variable in the regression is Cumulative Abnormal Returns (CAR). In Model (1) the independent variable is the STACK DISTANCE, as defined in Gao and Iyer (2006). In Model (2) 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 the value of 0 if participants are classified in the same layer of the stack and 1, 2, 3, 4 if participants are 1, 2, 3 and 4 layers apart. In Model (3) the independent variable is STACK DISTANCE SERVICES, a variation of the Stack Distance Index where the layer “Services” is equidistant to all other layers. In Model (4) the independent variable is Alliance Distance Services, defined as the distance on the stack between both participants according to their specific role in the alliance. This variable assumes value 0 if participants are classified in the same layer of the stack; 1 if participants are classified one layer apart or if one of the participants is classified as services, and 2 or 3 if participants are 2 or 3 layers apart.

* p < 0.01.

** p < 0.05.

*** p < 0.10.

---

6 For example, Campart and Pfister (2002) report a value of $R^2$ of 18% in a study of abnormal returns in alliances in the pharmaceutical industry; Brooke and Oliver (2005) report a value of $R^2$ of 11% in a study investigating the source of abnormal returns in strategic alliances; Moeller et al. (2004) obtained a $R^2$ around 6% in regressions that aim to explain abnormal returns for M&As; and Fee and Thomas (2004) report $R^2$ values between 2% and 5% in a study applied to M&As.
An alternative to the models applied in this paper is the Open Systems Interconnection Reference Model (OSI) model (Zimmermann 1980). The reasons for not using the OSI model are manifold. First, it is more of a computational model and may not be fully applicable to the software industry. Second, we have limited current data on companies. Given that we use SIC codes to classify companies across layers, we have to use the same data for the OSI model. The SIC codes, however, are not granular enough to do that. Moreover, even with the simpler model that we use, we do not have enough data points in some of the layers. Finally, we believe that the current model used is an effective representation of the industry.

One possible limitation of our results is that a large proportion of alliances in our sample have at least one of the participants classified in the applications layer. In a total of 103 alliances, 85 have at least of the participants classified as “Applications”, leaving only 18 alliances in which neither of the participants is classified as “Applications”. (see Table 4). This could limit the generalization of our results to companies in other layers of the stack. In the sub-sample of companies that participate in alliances in which neither of the participants can be classified as “Applications”, the correlation coefficient between the variable Cumulative Abnormal Returns (CAR) and the variable STACK DISTANCE is −0.313 and between CAR and Alliance Distance is −0.158. For this sub-sample, Average Cumulative Abnormal Returns for the group of companies that participate in alliances in which both participants are classified in the same layer is equal to 7.05%, while for the group of companies that participate in alliances between participants in different layers, the figure is 2.53%. Six companies participate in alliances in which both participants are classified on the same layer of the stack, and 30 companies participate in alliances in different layers. These values seem to indicate that the conclusion reached for the sub-sample of alliances in which neither participant is classified as “Applications” is similar to the one obtained for the overall sample: alliance between companies in the same layer of the stack earn larger abnormal returns.

We conclude that alliances have the largest value when both participants produce on the same layer of the stack, and the value decreases as the distance on the stack between participants increases. Thus, there is value in alliances between companies that produce in either the same layer or adjacent layers of the software stack, as stated the Value Creation with Adjacent Layers of the Software Stack Hypothesis (H2). Gao and Iyer (2006) propose that layers of the software stack that are closer together exhibit stronger complementarities. Therefore, our results also support the hypothesis that the existence of complementary network effects is a source of value creation in alliances in the software industry, as stated in the Complementary Network Effects Hypothesis (H1).

6. Discussion and conclusions

Our results are different from those obtained by Gao and Iyer (2006) for a sample of M&As. Gao and Iyer (2006) 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 indicate that alliances work 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 et al. (1997) 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, R&D 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 (Williamson 1989). 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 M&As have. Participants can easily bring the partnership to a halt, while the costs of divestitures are much higher. Chan et al. (1997) 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 their alliance partner. They show that alliances involving 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 (2006) 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. Quite 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.

We found that, while products that are in different layers of the stack were very often developed to work together, most often products 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, in most instances they are already interoperable. Gao and Iyer (2006) 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, thus and companies may want to internalize the value of complementary network externalities through M&As. They argue that the lower uncertainty of interoperability between products that are within different layers of the stack may justify their results. For example, when EMC acquired Documentum in 2003, the latter was offering software that could be 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.7

As discussed in Economides (1998), the decision on compatibility vs. incompatibility between software components is a critical one. Since firms want to benefit from the externality of the total sales of all compatible firms, they desire compatibility and standardization. As a result, they produce products that are compatible between the hardware, systems, middleware and applications layer. In addition, service firms develop expertise around compatible layers to serve customers better.

While this is the case for firms operating in different parts of the ecosystem, the story is quite different when they compete within layers. As discussed in Cottrell and Koput (1998), product variety is preferred by customers to meet their diverse needs. To avoid intense competition between their products, firms try to be incompatible with other competitors, making it difficult for customers to substitute products, as shown by Pil and Cohen (2006). When such tendencies exist in the market place, it becomes hard to integrate products within a layer and easier to integrate across layers.

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 an M&A, since it has to invest less money and time, and it is much easier for the firm to withdraw from the alliance in the 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 if difficulty arises 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 and integrated products to their customers. The possibility of being associated with several companies may extend the customer base much more than being highly integrated with only one partner.

We also conclude that our operationalization of complementary network effects, defined by products in adjacent layers of the software stack, captures higher value in M&As than in alliances. That is not to say that there are no complementarities in the same layer of the stack, but our results suggest that while same-layer complementarities and synergies are valued higher through alliances, adjacent layer complementarities are more valuable in M&As. Our results also provide strong support to the stack model where the services layer is positioned adjacent to all the other layers vs. the model where the services layer is placed on top of the stack, as presented in Gao and Iyer (2006).

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

The most important limitation of this work is the small sample size. Our classification of the relationship between both participants in the alliance requires information that permits classifying the proportion of the activity of each company in the different layers of the stack. This information is not easily available and was provided to us by IDC only for the years between 1999 and 2002. It is possible that some abnormal behavior occurred during this period of “irrational exuberance”. Yet in spite of this, we are convinced that our results provide new and relevant information to the understanding of the factors that influence the decision of software companies to enter into alliances.

References


