Partnerships between Software Firms: Is There Value from Complementarities?

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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 a 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 - Gulati (1998), Harrigan (1988) and Kale, Dyer & Singh (2002). In the software industry, companies form strategic research partnerships, joint product development, technology licensing and marketing and distribution agreements - Rao and Klein (1994). Additionally, software companies pursue alliances with producers of complementary products, because it increases the value of their products.

In a study applied the Mergers and Acquisitions (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. 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 (2006) 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.

Network-type industries are defined by the existence of different components that have to be used together but may be produced by different manufacturers using different technologies. In these industries systems have to be assembled. Network effects across markets result in higher valuation for products with larger complementary markets and create incentives for producers of one good to enter the markets for complements.

Milgrom and Roberts (1995) define activities as complementary if increasing (doing more of) one of them increases the returns of (doing more of) the other - the idea in which "the whole is more than the sum of the parts" (i.e., the returns obtained from combining the activities are greater than the sum of the returns of both activities in isolation). They also explain how the concept of network effects fits this definition of complementarity and illustrate this with the example that "the gains for computer users from focusing on just one or two standards is that it eases the development of complementary products including both software (operating systems, operations software) and hardware."

There are many ways in which firms can explore complementarities in network systems to create competitive advantages and value. Companies that produce highly complementary components may want to integrate if customers value a more reliable systems integration supplied by a single provider. Gao and Iyer (2006) provide evidence that there is value in M&As between companies that produce complementary components of network systems. The bundling of different application categories into products, by promoting the standardization of commands and functional interoperability, allow combined providers to offer a better service to existing customers and to attract new customers that see value in the integration of compatible products. Providing both components may offer opportunities for the firm to enhance exchange benefits.

Gao and Iyer (2006) apply the concept of software stack to define a measure of complementarity between components of network systems. The concept of stack itself is an approach imported from the software architecture, and then applied as a way to organize the software industry by dividing it into layers that are complementary to each other. 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.

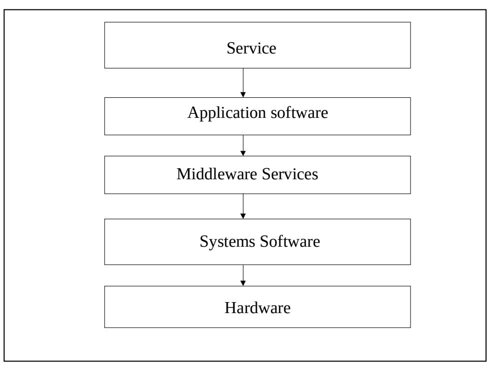

Figure 1 – The stack

Based on the economic theory of complementarities, as defined by Milgrom and Roberts (1995), and using the methodology based on the software stack presented in Gao and Iyer (2006), we investigate the role of complementarities in Alliances between producers of complementary components of network systems. Formally, the hypothesis we test is:

Hypothesis: The existence of complementary network effects between participants in an alliance is a source of value creation.

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 - Eisenhardt and Schoonhoven (1996), Kogut, (1988), Gulati (1995), Henderson and Cockburn (1994) and Powell, Koput and Smith-Doerr (1996).

A number of 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 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 (1997) find a day 0 return of 1.12%. Koh and Vankatraman (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 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 - McConnell et Nantell (1985), Woolridge and Snow (1990), Koh and Venkataraman (1991).

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 - Balakrishnan and Koza (1993). 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 - Chan, Kensinger, Keown, and Martin (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, Kensinger, Keown, and Martin (1997) do not find more value for alliances involving R&D projects and 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 - Alvarez and Barney (2001). McConnell and Nantell (1985) obtain different results. They 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 (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, Sen, and Sengupta (1998) also find cumulative abnormal returns to be larger the smaller. Kalaignanam, Shankar and Varadarajan (2006) point out that the divergent results in prior studies can be attributed to heterogeneity in the focus of alliance agreements (e.g., R&D, marketing, and licensing).

There is also some ambiguity concerning the financial status of the participant. 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, Sen, and Sengupta (1998) 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 (2002), 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 (2006) 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,

$$\text{and } \sum_{i=1}^{L}\sum_{j=1}^{L} P_{Ai} P_{Tj} = 1 .$$

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.

The objective of this paper is to 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. [1] 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 obtain the initial sample from the Joint Ventures and Alliances Database from Securities Data Company (SDC, a product from Thomson Financial www.thomson.com/ financial/financial.jsp). We select all alliances with announcement dates between 1999 and 2002 and require both the acquirer and the target

[1] A detailed exposition of the event studies methodology can be found in Brown and Warner (1980, 1985) and MacKinlay (1997)

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. [2] 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 then 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 - McConnel and Nantell (1985), Koh and Venkatraman (1991), Chan, Kensinger, Keown, and Martin (1997) and Das, Sen and Sengupta (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 of the alliance. We obtained the market value of equity (MVE) from CRSP and it is 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 - Chan, Kensinger, Keown, and Martin (1997), Koh and Venkatraman (1991) and Das, Sen and Sengupta (1998)

- *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 - Das, Sen and Sengupta (1998). 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. [3]

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 (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 IDC. [4] Table 3 describes the role of each participant in the

[2] We limit our sample to alliances announced until the end of 2002 because we do not have data from IDC for more recent years.

[3] 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. "

[4] 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.

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.

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%

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.	Middl.	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%

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 the 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 from Compustat. 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, considering their role on 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. 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 (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.

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.

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 (2.381)***	0.113 (2.386)***	0.116 (2.853)***	0.111 (2.828)***
STACK_ DISTANCE	-0.0169 (-1.979)**		-0.018 (-2.092)**	
Alliance Distance		-0.012 (-2.104)**		-0.011 (-2.056)**
Log(MV)	-0.004 (-1.179)	-0.004 (-1.325)	-0.004 (-1.521)	-0.004 (-1.739)*
Log (Relative Size)	0.003 (0.879)	0.003 (0.842)		
Lead	0.009 (0.5905)	0.009 (0.622)		
Technical	0.047 (3.7178)***	0.044 (3.545)***	0.049 (3.982)***	0.046 (3.783)***
Tobin Q	-0.003 (-2.954)***	-0.003 (-2.813)***	-0.003 (-2.817)***	-0.003 (-2.620)***
Leverage	-0.010 (-1.332)	-0.012 (-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 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.

6. Discussion and Conclusion

Our results are different from those obtained by Gao and Iyer (2006) for a sample of M&As. Gao and Iyer (2006) obtained higher abnormal returns when acquirers and targets produce on adjacent layer of the stack and lower when both parts are on the same layer. They also found that abnormal returns decrease as the distance on stack between both companies increases. Our results show 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 abnormal returns decrease as the distance on the stack between both participants increases. We conclude that there is value in alliances between complementary components of network systems, but alliances between firms that produce on the same layer of the stack earn higher abnormal returns surrounding the day of the announcement of the alliance.

The conclusion that alliances between similar firms have higher value is consistent with results from previous papers. Chan, Kensinger, Keown, and Martin (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, 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 – 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 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 (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 complementary firms. They justify that alliances that involve the pooling or transfer of technical knowledge tend to produce larger wealth effects than marketing alliances.

Gao and Iyer (2006) used the concept of software stacks to group products into the various layers and assumed complementarities between layers. Each layer is treated in aggregate and we compute its complementarity with adjacent layers. However, it is quite possible for complementarities to exist within a layer. Take, for example, the middleware layer. Within this layer, there are many products such as web servers, database management systems, report writers and application development toolkits. It is also possible that the results we obtain for our sample of alliances are capturing some of these complementarities.

The value of a merger 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. Alliances allow firms to incorporate new knowledge and experiment without the commitment of M&As. 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.

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. Companies may want to internalize the value of complementary network externalities through M&As.

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 standardization, firms may prefer to be loosely coupled than to be highly integrated. Also, the possibility of being associated with several companies may extend the customers' base compared with being highly integrated with only one partner.

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APPENDIX

Table 6: Descriptive statistics for the sample

Correlations

	1	2	3	4	5	6	7	8	9
1	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

	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

	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