ANALYZING COMPLEMENTARITIES USING SOFTWARE STACKS FOR SOFTWARE INDUSTRY ACQUISITIONS

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ABSTRACT

The existence of product complementarities is especially relevant in network-type industries, such as information technology and communications, where systems of complementary components made by different manufacturers have to be assembled. Relying on the characteristics of software markets and drawing on the *economic theory of complementarity*, this paper investigates how *complementarity* creates value in mergers and acquisitions between software companies. We introduce and empirically validate the *software stack*. In a sample of mergers and acquisitions, in which either the acquirer or the target is a software firm, we find values of abnormal returns consistent with previous results. However, when we use the concept of stack, we find an inverse curvilinear relationship between abnormal returns and the distance between acquirers and targets in various layers of the stack.

Keywords. Complementarities, empirical methods, event study, mergers and acquisitions, product complementarities, software stack, technology firms, theory development, value creation.

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1. Introduction

Over the last five years, the software industry has seen a large number of *mergers and acquisitions* (M&As). Some analysts see the recent spate of takeover activity as marking the onset of an era of consolidation within a maturing industry. Perhaps the most important reason why software companies merge is to achieve higher rates of growth. In the 1990s companies were showing high growth rates, but the economic slowdown and the existence of too many software companies dramatically cut growth. One of the ways, and probably the quickest one, that companies can use to grow, is by acquiring other software firms. However, the realization of value through mergers in software markets is not straightforward.

Software markets present special dynamics that distinguish them from conventional markets. Very often, mergers between similar companies are not successful, at least in the short term. M&As add value when firms correctly explore opportunities by taking into consideration the characteristics of the software industry.

In a recent businessweek article[1], it is estimated that annual M&A activity in 2005 was in excess of $75 billion and the enterprise application market alone, between January 2004 and March 2005, saw $30 billion being spent in acquisitions. Given that acquisition activities are averaging several billion dollars over the last several years, are companies deriving any value from this activity? While prior research has shown that acquirers do not get much value from a market evaluation perspective, our research reexamines these acquisitions and asks the following question: is the existence of network effects between acquirers and targets a source of value creation in mergers and acquisitions? We use *economic theory of complementarity* and, in

[1] http://www.businessweek.com/technology/tech_stats/ma050923.htm

particular, a software concept called stacks to explain potential value creation in the software sector.

This study explores value creation using M&As and shows how companies can use *software stack*s as a way to create value. Using a three-layer stack, defined by the layers hardware, software and services, we find that mergers in which acquirers and targets produce in the same layer of the stack earn smaller abnormal returns than acquisitions in which acquirers and targets produce in different layers. However, the results are not statistically robust. When we extend the study to a more detailed definition of the stack, the significance of the results is improved. These results empirically validate the existence of the stack and show that complementarity is a source of value creation in M&As between software companies.

2. Characteristics of software markets

Software markets are different from conventional markets. The existence of network effects [17, 18, 26, 46] -- the idea that a product's valuation is higher for larger installed bases of consumers -- is a reason for managers to place significant effort in expanding market shares.

In network-type industries, two or more components made by different manufacturers using different technologies may have to be used together, and systems have to be interoperable. Network effects across markets result in higher valuation for products with larger complementary markets and create incentives for producers of a particular good to enter the markets for complements.

Within the software industry, companies deliver products that interoperate with complementary product components from other companies to deliver business value. When success is determined by a set of complementors to a product, this phenomenon is referred to as network effects-based or system-based competition. These network effects can be derived from two sources: the degree of acceptance and adoption by customers and the availability of supporting software modules. The first source is direct or customer network effects and the second is complementary or indirect network effects. Network effects have been widely discussed both in the economics literature [17, 18, 26, 46] and within the information systems economics literature [3, 13, 22, 29, 54, 58].

Compatibility is also an important issue to the users. The number of network users reflects long-term market stability and consumers prefer firms with large installed bases. An established standard provides access to a larger network composed of firms complying with that standard. Consequently, standards are a source of network effects [27]. Competition in these markets differs significantly from competition in conventional markets. An understanding of the factors that may influence market dominance is critical for competition in markets with network effects. It can be very difficult for new companies to compete with established competitors in the presence of network effects [28]. When consumers place a great value on the size of the installed base, the best product or service does not always win [44].

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. 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. Many markets that are subject to network externalities are also characterized by having multiple sides [41, 44]. In multi-sided markets, consumers benefit not from using both complementary products separately but from interacting with consumers of complementary products through a common platform. Providing both components may offer opportunities for the firm to enhance exchange benefits.

Companies can use either their installed base, or the installed base of complementary components, to leverage and promote growth. Companies may acquire with the intent of quickly gaining market share. In some cases the purpose is to acquire the installed base of an old technology and then gradually replace it with the company's own technology. In other cases, companies make acquisitions in a complementary market with the purpose of foreclosing competitors in that market. The “winner takes all” nature of software economics has given firms that have achieved major platform status massive profit pools from which to invest in adjacent software categories.

However, companies may face difficulties with the technical integration of the software products. In theory they have a completely integrated product the day after the announcement of a merger, but in practice integration may take much longer. In some cases some products may be abandoned. If the product complementarity is a motive for the acquisition but companies fail to integrate products, the potential synergies are not realized and underperformance will occur when compared with the price paid for the acquisition.

3. Role of complementarities

In network-type industries, particularly the information technology industries, decision-making and strategy are shaped by the existence of complementarities and network effects [42, 57].

The theoretical foundations of this paper are the economic theory of complementarities and the literature on network economics. The economic theory of complementarities focuses on the super-additive value of combining activities. Activities are complements if increasing (doing more of) one of them increases the returns of (doing more of) the other. This means that marginal returns in one activity vary with the level of variables in the other activity, for example prices. Milgrom and Roberts [35] formalize this 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). In their paper, they 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.”

Foundational theoretical models where products and services are subject to network effects were introduced in Farrell and Saloner [18] and Katz and Shapiro [26]. Network effects are defined by the benefits of having a larger number of consumers purchasing compatible products. *Direct network effects* stem from the benefits from having a large installed base where standardized products provide access to larger physical networks. This direct effect is relevant, for example, in applications software such as word-processing and spreadsheets, where users have the need to share files. Another benefit from a larger installed base is the indirect effect of an enhanced provision of complementary goods. This effect, in which complementary products benefit from the installed base of the complement, is usually referred as *indirect network effects*. One of the benefits of having a large installed base in hardware is the incentive for stronger competition in the complementary market for software. This paper focuses on indirect network effects. Furthermore, this paper builds on the aforementioned literature on complementarity to investigate its role in M&As between producers of complementary components of network systems. Formally, the hypothesis to be tested is:

- **Main Hypothesis (Complementary Network Effects and M&A Value Creation Hypothesis).** *The existence of complementary network effects between acquirers and targets is a source of value creation in mergers and acquisitions.*

There is no generally accepted empirical measure of complementarity. Current measures of complementarity are either difficult to operationalize, or imprecise in defining the value of product complementarity, or require information for which data is not readily available. Sudaram, et al. [48] operationalize the concept of strategic substitutes and complements in a competitive interactions context. They study announcement effects of R&D spending. The concept of strategic substitutes and complements was introduced by Bulow, et al. [8]. The difference between strategic and conventional complements is that a change in a strategic variable (price in price competition, quantity in quantity competition, advertising, etc.) will raise the competitor's marginal profits instead of total profits. To implement the idea of strategic substitutes and complements empirically, Sudaram, et al. (1996) propose a measure obtained by computing the coefficient of correlation between a firm's marginal profits (change of the profits relative to changes in own output) and the change in the competitor's output. When this measure is positive (negative) firms compete in strategic complements (substitutes). However, the application of this methodology will not distinguish between the value of realizing direct network effects from the increase in the consumer base and the value of product complementarity.

Some other studies use detailed data about software markets to study the effect of product complementarity. For example, Cottrell and Koput [13] estimate the effects of software provision on the valuation of hardware in the early microcomputer industry and conclude that there is a positive relationship between software variety and price. Network effects explain the dependency of the price of a hardware platform on the size of the installed based and on the variety of software available. Cottrell and Nault [14] find little evidence of benefits from economies of scope in production, but conclude that there are benefits from economies of scope in consumption. Their study is focused on the variety and integration of application categories into products. Gallaugher and Wang [22] empirically test several key factors influencing software pricing, including network externalities and cross-market complementarities. In a study applied to web servers, they find a positive relationship between market share and price and that firms with a larger share of the browser market enjoy higher server prices. They conclude that firms that are able to capture market share for one product enjoy benefits in terms of market share and price for the complement. In a study applied to computer spreadsheets, Brynjolfsson and Kemerer [7] find that prices significantly increase with the installed consumer base and products that adhere to a dominant standard exhibit higher prices. This study is related to, and empirically tests, some of the predictions of models that study the internalization of complementarity effects and network externalities in investments in networks.

Several papers study the effect of integration between complements, starting with Cournot (1838). There are a vast number of papers that study the effects of integration or specialization when there is the possibility of interoperability and standardization [12, 17, 19]. In general, the results suggest that consumers prefer to purchase from separate producers if there is standardization and from integrated producers if not.

3.1. Constructing a measure of complementarity

We propose a measure of complementarity between two firms based on the structure of the *software stack*. This measure takes into account the positioning of companies in different segments of the software industry. The industrial organization of the software industry can be structured according to an approach imported from the software architecture, commonly designated as the "*software stack*".

The software stack. One of the most common approaches in software architecture is a layered view of the architecture. Layering reflects a division of the software into units, generally called virtual machines, where each unit provides a cohesive set of services that other software programs can utilize without knowing how these services were implemented [4]. These units, or layers, should interact with each other according to a strict ordering relation. These relations are usually represented as a stack, in which each layer is allowed to use only the nearest layer or any layer further apart, but higher layers can only use the facilities of lower layers. Lower layers are usually built using knowledge of the computers, communications channels, distribution mechanisms, process dispatchers, etc. and are independent of the applications that may run on them. Higher layers use the facilities of lower layers and are more independent of the hardware in which they work, because the existence of lower layers permit them to do so. This means that higher layers don't have to change if there is a change on the computing platform or environment. A change in a lower layer that does not affect the interface used will require no change in higher layers. Also, a change in a higher layer that does not change the facilities required will not affect lower layers.

Software developers focus on one or a few layers of the stack and rely on other developers to provide the requisite functionality in other layers. Software architecture of a program or computing system provides a description of the system as a sum of parts, or sub-systems, and how those parts relate and interoperate with each other. These sub-systems carry out some cohesive set of functionality that can be executed independently and are loosely coupled to the rest of the system.

The software activity as a whole can be organized in a similar way. The *software stack* divides the software activity into layers that are complementary to each other, as depicted in Figure 1. As explained by Lou Gerstner, former CEO of IBM, most companies specialize on one or few layers and rely on other companies to offer the complementary components [23]. 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.

This organization of the software industry has important implications for the structure of the industry competition. Each layer depends on the layers below, that are complementary, and integration requires coordination among suppliers. Competition occurs at each layer, with the suppliers in lower layers trying to provide at that layer for a wider range of suppliers in layers above. This creates some pressure on suppliers within lower layers to integrate with suppliers in higher layers. In software markets, the main underlying factor for success has been the ability of companies to establish platforms with high levels of integration and high associated switching costs for users. Standardization allows competition at the level of the different components of the system. However, dominant firms may have to establish standards and initially engage in standards competition. A new entrant can compete by introducing a new architectural layer that spans two or more previously incompatible dominant architectures [53].

One of the consequences of stacks is that different layers within the stack can develop at different speeds. The details of each layer are hidden from the layers above and below a given layer. Another consequence of stacks within an industry is that different firms can supply different layers of the stack, resulting in divided technical leadership [6]. A third consequence is that customers and firms can experiment with alternative designs at a significantly lower cost than they could in the absence of layered modularity. This has been referred to as *combinatorial innovation* [51]. The idea is that every now and then a set of standardized parts or components comes along, triggering a wave of experimentation by innovators who tinker with the many combinations of these components. The result: a wealth of new systems built on the newly-available components or by recombining existing components. Some of these systems are novel even to the designer of the component.

Even though the stack is common knowledge within the software industry and software companies devise their strategies based on the stack, there is little empirical work that proves its existence. We claim that, if the *software stack* can be the structure of a reliable measure of complementarity between firms in network systems, we can provide evidence on its validity as the structure of the organization of the software industry.

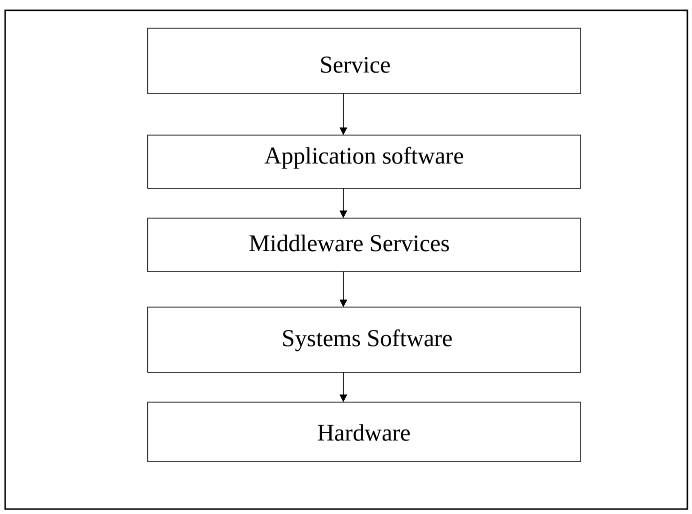

Figure 1 – The stack

The stack distance index. We propose a measure of concentration and diversification based on the software stack. This measure is an adaptation of the Herfindahl index and the concentric index, used extensively in the strategic management literature. The Herfindahl index is generally defined as the sum of the squared market shares of firms within one industry and measures the degree of concentration of a specific industry. The concentric index is in itself an adaptation of the Herfindahl index and is widely used to measure relatedness in corporate portfolios of multi-business firms or between business units of a firm [16, 37, 38, 42]. The concentric index is equal to the weighted sum of a coefficient that assumes mechanically imposed and pre-established values 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. One of the major problems associated with the concentric index, based on the way it is generally constructed, is that it imposes strong assumptions based on SIC codes. That procedure assumes that industries are homogenous within each SIC category, and that different levels of SIC codes, at the 2, 3 and 4-digit level, reflect an increasing scale of relatedness. To alleviate this problem, Davis and Thomas [16] and Robins and Wiersema [42], estimate the coefficient that measures relatedness.

We define the *stack distance index* (*STACK_DISTANCE*) 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 formally computed as:

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

where *STACK_DISTANCE* denotes stack difference index,

L is the number of layers of the stack,

P_{Ai} is the percentage of sales of the acquirer in layer i of the stack,

P_{Tj} is the percentage of sales of the target in layer j of the stack,

d_{ij} is a coefficient that assumes different values according to the distance on the stack between layer i and layer j, and,

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

The construction of the *STACK_DISTANCE* index captures two important features that define the difference between two software companies: it takes into account the positioning of companies in the different segments of the software industry; and it considers the spectrum of activities in which both firms are engaged to construct a measure that relates the focus of each company.

As an example, consider the reduced two-layer stack Hardware/Software. Define d_{ij} equal to 0 if industry segments are classified in the same layer of the stack, and equal to 1 if industry segments are classified one layer apart, that is,

$$d_{ij} = \begin{cases} 0 & i = j \\ 1 & i \neq j \end{cases}$$

The value of the index is equal to:

$$STACK\_DISTANCE = ACQ_{HW} * TARGET_{HW} * 0 + ACQ_{HW} * TARGET_{SW} * 1 + ACQ_{SW} * TARGET_{HW} * 1 + ACQ_{SW} * TARGET_{SW} * 0$$

where *ACQ_HW* and *ACQ_SW* are the *proportion of sales of the acquirer in hardware* and *proportion of sales of the acquirer in software* and $TARGET_{HW}$ and $TARGET_{SW}$ are the *proportion of sales of the target in hardware* and *proportion of sales of the target in software*.

If both the acquirer and target are exclusively software firms, the value of the index is equal to 0 (i.e., the distance between both firms on the stack is 0). If the acquirer is exclusively a software firm and the target is exclusively a hardware firm, the value of the index is 1 (i.e., both firms are one layer apart on the stack). If the acquirer is exclusively a software firm, the value of the index increases with the percentage of sales of the target in hardware (i.e., the more hardware the target produces the larger is the distance between the acquirer and target). The way the index is defined, in this particular case, it generates values that are between 0 and 1, where 1 is the largest possible distance on the stack between acquirer and target. In general, the value of the index has a minimum equal to the minimum value that d_{ij} assumes, and that corresponds to the cases when $i=j$, and a maximum value equal to the largest d_{ij}, which defines the largest distance between two layers of the stack. The *STACK_DISTANCE* index is simply the weighted average of the distances between the different layers of the stack in which two different companies have activity.

4. Empirical Design and Methodology

The objective of the empirical work is to study the effects of concentration/diversification around the layers of the stack in M&As between companies in complementary network systems. To measure concentration and diversification on the stack, we use either the *STACK_DISTANCE* index, described in the previous section, or a simpler variation of that index that measures concentration on the same layer. This variation of the index is used when the data available do not provide enough information to allocate firms on a five-layer stack, but instead on a reduced three-layer stack, defined by the layers Hardware, Software and Services.

This measure of concentration is defined as:

$$CONCENTRATION\_STACK = ACQ_{HW} * TARGET_{HW} + ACQ_{SW} * TARGET_{SW} + ACQ_{SERV} * TARGET_{SERV}$$

where ACQ_{HW}, ACQ_{SW} and ACQ_{SERV} are the *proportion of sales of the acquirer in hardware*, *proportion of sales of the acquirer in software* and *proportion of sales of the acquirer in services* and $TARGET_{HW}$, $TARGET_{SW}$ and $TARGET_{SERV}$ are the *proportion of sales of the target* *in hardware*, *proportion of sales of the target in software* and *proportion of sales of the target in services*.

Robins and Wiersema [43] discuss the validity of the concentric index as an indicator of portfolio relatedness. They argue that the index is sensitive to features of portfolio composition that can create significant ambiguities, and that these ambiguities are associated with the way the measure is constructed. They show that dominant business focus and the number of businesses in a corporate portfolio introduce variability in the concentric index. Based on these criticisms, they suggest that the value of the concentric index may be driven by features of portfolio composition that are not linked to the concepts and measures that are intended to be captured.

In this paper, the concentration index is higher not only for higher levels of similarity between the portfolios of companies but also if both companies being compared have very diversified portfolios.[2] In this way the results might be driven by the fact that both sides of the transaction hold highly diversified portfolios, rather than by a measure of concentration or dispersion on the stack resulting from the acquisition.

Robins and Wiersema (2003) suggest sensitivity analysis as a way to evaluate the validity of findings. Sensitivity analysis is important when there are portfolio features that may introduce ambiguities in the meaning of the measure and have significant implications in the interpretation of the results. To test the consistency of our results, we repeat the analysis after

[2] Consider the following examples: Case 1: Acquirer has 90% of sales in Software, 9% in Hardware and 1% in Services, Target has 50% of sales in Software and 50% in Hardware. The concentration measure is 0.495.
Case 2: Acquirer has 33% of sales in Software, 33% in Hardware and 34% in Services, Target has 33% of sales in Software, 33% in Hardware and 34% in Services. The concentration measure is 0.3334.
However intuition suggests that the concentration measure in Case 2 should be higher than in Case 1.

excluding all observations in which both sides of the transaction have activity in more than one layer of the stack. [3]

To test whether complementary network effects create value in M&As, we study abnormal returns around the announcement dates, in a sample of firms in industries characterized by the existence of network effects. Both our methodology and our dependent variable (market value) have been used in prior studies [10, 47]. It is important to note that our notion of value has been widely described and used in the literature [5, 9, 30, 33, 49, 52]. This work takes into consideration potential value as opposed to realized value [11, 15]. Specifically, we select mergers in which both acquirer and target are mainly information technology firms and at least one of the sides produces software. Sales are obtained for each firm, and allocated through the layers of the stack. The *STACK_DISTANCE* index or the concentration measure is then constructed for each transaction.

We compute abnormal returns for acquirers, targets, and combined acquirer/target firms. The analysis is based mostly on the combined abnormal returns, which incorporate the total effects of the strategic motivations that lead to the merger or acquisition. Combined abnormal returns reflect the changes in value in the resulting merged firm or in the value of portfolios of diversified investors.

According to the theoretical foundations of this paper, the existence of complementarities between acquirers and targets of M&As is a source of value creation. Also, the definition of the *software stack* implies that there are stronger complementary relations between companies that produce in closer layers of the stack. We investigate if abnormal returns are higher for M&As of

[3] We did also construct an alternative measure of concentration, which accommodates the cases in which both sides hold diversified portfolios. However, the results obtained were not statistically significant. This measure is defined as: $CONCENTRATION\_STACK = 2 - [\text{Abs}(ACQ_{HW} - TARGET_{HW}) + \text{Abs}(ACQ_{SW} - TARGET_{SW}) + \text{Abs}(ACQSERV - TARGETSERV)]$

companies that have activity classified in closer layers of the stack, when compared with companies that have activities classified in the same layer of the stack or in layers that are further away.

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

- *Method of payment is cash.* There is strong evidence in the M&As literature that cash transactions earn higher abnormal returns for public firms than other methods of payment, particularly when the payment is made with equity. Travlos [50] and others show that acquisitions of public firms paid for with equity earn lower abnormal returns than acquisitions paid for with cash. Asquith, et al. [2], Huang and Walking [25] and Yook [55] provide evidence that stock deals are associated with significant negative results for acquirers while cash deals are zero or slightly positive. The common explanation for the different value effects of mergers financed with cash or equity is that the announcement period reaction for the acquirer to a stock-financed transaction represents a combination of a merger or acquisition announcement and an equity issue announcement. Myers and Majluf [40] show that equity issues are a signal that the market is overvaluing a company. Travlos [50] also points out that firms with poor results generally pay with equity.
- *Transaction Value.* The size of the transaction is related to the size of the target and the percentage of the company that is acquired. We expected that abnormal returns increase with the transaction value.

- *Percentage of Target Acquired*. There are different implications for M&As with different degrees of integration. The percentage of the target acquired can be a proxy for the degree of integration. Zaheer, et al.[56] argue that the performance of acquisitions is related to appropriately matching the type of relatedness with the degree of integration. They provide evidence, using a survey study, that business similarity and product complementarity are associated with negative performance when integration is low and become more valuable as the degree of integration increases.
- *Acquirer's Equity Value or Acquirer's Market Value.* Market Value is defined as the sum of market value of equity, long-term debt, debt in current liabilities, and the liquidating value of preferred stock. Moeller, et al. [36] found that announcement abnormal returns are higher for smaller acquirers, regardless of the form of financing and whether the acquired firm is public or private. One of the reasons associated with this result is that managers of larger firms may be more prone to hubris.
- *Acquirer's Tobin q.* 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. Lang, et al. [32] and Servaes [45] found that acquirers with higher Tobin q have higher announcement abnormal returns. They also found that returns are higher when targets have lower q ratios. These results indicate that the value of acquisitions is higher if targets are performing poorly and acquirers are performing well. A low Tobin's q ratio for the target can also be a sign that the firm is under-priced.

- *Acquirer's Leverage*. Maloney, et al. [34] found that higher leverage bidders have higher abnormal returns. 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.
- *Acquirer's Cash Flows*. Hartford [24] shows that firms with excess cash are more likely to make poor acquisitions. Agency theory predicts an inverse relationship between cash flows and abnormal returns.
- *Relative Size of Target on Acquirer*. Asquith, et al. [2] show that abnormal returns for acquirers increase in the ratio of the target's equity capitalization to the acquirer's equity capitalization. The inclusion of this variable allows the model to adjust for the impact of an acquisition on the equity market capitalization of the acquiring firm. Abnormal returns should increase with the relative size of target on acquirer if a dollar spent on acquisitions has the same return, regardless of the size of the acquisition.
- *Year*. We also include a dummy variable for the year and control for possible industry or economic shocks that happened in a particular year.

The sample includes only public firms, both acquirers or targets. Fuller, et al. [21] show that abnormal returns are higher when targets are private firms or subsidiaries, rather than public firms. The final model selected includes only the significant variables that explain abnormal returns in these samples.

5. Data

The sample of acquisitions is obtained from the Mergers and Acquisitions Database in Securities Data Company (SDC, a product from Thomson Financial www.thomson.com/financial/financial.jsp). We select all transactions with announcement dates between 1999 and 2004 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) the transaction is complete, (2) the transaction is not a stock repurchase, (3) both the acquirer and the target are public firms, (4) both the acquirer and the target are listed on the CRSP and on the Compustat (on both a consolidated and an industry-segment basis) databases during the event windows and (5) there are at least 75 trading days during the estimation period window.   These requirements yielded a sample of 193 M&As.

The information necessary to classify firms according to the layers of the *software stack* comes from two sources. From the Compustat Industry Segment database we obtain the primary four-digit SIC codes for each segment reported by the company in the year previous to the announcement date of the transaction. For a small sub-sample, we obtain data from the International Data Corporation (IDC, www.idc.com) that provides enough information to classify sales on the five-layer stack. The IDC market classification allows the classification of sales as systems software, middleware software, applications software and services. The sub-sample with data from IDC comprises 45 M&As.

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. From Compustat we also retrieved 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. The classification of firms according to SIC codes was also imported from Compustat. *Market value* is defined as the sum of MVE, long-term debt, debt in current liabilities, and the liquidating value of preferred stock. *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. *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. The classification of sales as Hardware, Software and Services is based on the Compustat Industry Segment database. Table 1 presents the structure and statistics of our sample. More of half of our sample consists of M&As with announcement dates in 1999 (27.46%) and 2000 (24.35%). From 2001 to 2004 the number of M&As is substantially smaller, as a consequence of the economic slowdown.

Table 1: Summary Statistics for the sample

Yearly distribution and characteristics of transactions

Year	Frequency	Percentage	Average Transaction Value ($millions)	Cash (%)
1999	53	27.46	697	37.74
2000	47	24.35	1658	27.66
2001	37	19.17	175	24.32
2002	24	12.44	253	58.33
2003	23	11.92	773	47.83
2004	9	4.66	210	55.56
All	193	100	747	37.31

Industry/segment distribution of firms

	Acquirer	Target
Primary SIC Hardware (%)	17.10	14.51
Primary SIC Software (%)	64.25	60.62
Primary SIC Services (%)	18.65	24.87
Largest sales Hardware (% no. firms)	23.32	19.17
Largest sales Software (% no. firms)	58.03	64.77
Largest sales Services (% no. firms)	18.65	16.06
Average Sales Hardware ($millions)	2001	323
Average Sales Software ($millions)	1711	76
Average Sales Services ($millions)	643	36

Firm Characteristics

	Acquirer	Target
Market Value (mean, $millions)	35,845	1,384
Tobin's q (mean)	6.07	3.61
Leverage (mean)	2.91	0.06

6. Empirical results and discussion

The values of abnormal returns obtained for M&As are consistent with the findings of previous research. The results for the calculations of abnormal returns in the M&As sample are presented in Table 2. Our computations show significant average cumulative announcement abnormal returns for acquirers of -2.74% (t-stat. = -5.064, $p < 0.01$) and for targets of 28.89% (t-stat. = 39.951, $p < 0.01$). In most previous papers, abnormal returns for acquirers are zero or negative and abnormal returns for targets are large. The evidence suggests that gains on mergers are limited to target shareholders. These results are in accordance with the results obtained in recent papers [1, 20, 31, 39].

7.1.Analysis based on a three-layer stack

Using the three-layer stack, defined by the layers Hardware, Software and Services, we find that mergers in which acquirers and targets have primary SIC codes in the same layer of the stack earn smaller abnormal returns than acquisitions in which acquirers and targets have primary SIC in different layers of the stack. This conclusion is true for abnormal returns for both acquirers, targets and combined. However, the difference tests based on t-tests for equality of means are significant at the 10% level only for acquirers (t-stat. = -1.739, $p < 0.10$) and combined firms (t-stat. = -1.701, $p < 0.10$) and insignificant for targets (t-stat. = -0.259, $p > 0.10$). We repeated the same analysis comparing abnormal returns from acquisitions in which acquirers and targets have the largest proportions of sales in the same layer. We conclude that abnormal returns for acquirers are significantly higher, at 10% level, when acquirers and targets produce mostly in different layers (t-stat. = -1.942, $p < 0.10$). However, although we can also find higher abnormal returns for targets and combined abnormal returns when both sides have highest percentage of sales in different layers, difference tests based on t-tests for equality of means are still insignificant. Therefore, it seems that the results obtained using the three-layer stack do not fully explain abnormal returns obtained in M&As in software.

To determine the relation between concentration on a layer of the stack and abnormal returns after controlling for other variables that might affect abnormal returns obtained by acquirers and targets, we ran cross-sectional regressions of individual cumulative abnormal returns on a measure of concentration on layers of the stack.

From the Industry Segment database in Compustat (see Table 6 for descriptive statistics), we classified a firm's activity on a three-layer stack, as Hardware, Software or Services. In this case, we use the *CONCENTRATION_STACK* measure instead of the *STACK_DISTANCE* index, since the maximum distance between software and other activities can only be one layer apart and most of the activity in the sample is in software.

Table 2 - Announcement ACARs sorted by concentration in stack layers, payment form

	ACAR Acquirer	ACAR Target	ACAR Combined	No. Observations
All transactions	-2.74%***	28.89%***	0.54%	193
	(-5.064)	(39.951)	(0.870)	
Cash transactions	0.79%	42.86%***	3.38%***	72
	(0.643)	(37.209)	(4.017)	
Stock, mixed and other considerations	-4.84%***	20.57%***	-1.15%**	121
	(-6.892)	(21.753)	(-2.000)	
Acquirer/Target primary SIC in same layer (1)	-4.11%***	28.18%***	-0.84%	96
	(-4.447)	(27.563)	(-0.063)	
Acquirer/Target primary SIC in different layers (2)	-1.38%***	29.59%***	1.89%	97
	(-2.719)	(28.933)	(1.290)	
Difference tests (1) –(2)	-2.12%*	-2.19%	-2.25%*	
	(-1.739)	(-0.259)	(-1.701)	
Maximum proportion of sales same layer (3)	-4.01%***	28.27%***	-0.29%	112
	(-5.042)	(29.149)	(0.271)	
Maximum proportion of sales different layers (4)	-0.98%*	29.74%***	1.67%	81
	(-1.889)	(27.392)	(1.024)	
Difference tests (3) –(4)	-3.03%*	-1.47%	-1.96%	
	(-1.942)	(-0.2835)	(-1.223)	

*Notes***:** Abnormal returns are calculated for a three-day window centered on the announcement date of the merger and calculated from a market model estimated from 231 to 31 days before the announcement date. *Average Cumulative Abnormal Returns* (ACAR) are the sum of abnormal returns in the three-day window. The group Cash transactions includes transactions paid with at least 90% cash. The group Stock, mixed and other considerations is defined as transactions paid with stock, with a mix of cash and stock in which cash represents less than 90% of the payment, and other forms of payment. Primary SIC codes are classified according to the three-layer stack: Hardware, Software and Services. *t*-statistics for abnormal returns are shown below each parameter estimate in parentheses. The significance levels for the independent variables are given by: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

Table 3 reports the behavior of abnormal returns for acquirers and targets, and combined abnormal returns, as a function of concentration on the three-layer stack. In each case, the base model without the *CONCENTRATION_STACK* variable (1) and the complete model with the *CONCENTRATION_STACK* variable (2) are presented. Acquirers' abnormal returns and combined abnormal returns are significantly higher at a 10% level when investments are made in a different layer of the stack. However, there is no statistically significant relation between targets abnormal returns and *CONCENTRATION_STACK* variable (*t*-stat. = -0.7347, $p > 0.10$).

The low level of significance obtained for the results suggests that the concentration or diversification on the three-layer stack explains little of the variation of abnormal returns in M&As in the software industry. To test if the *software stack* characterizes the industrial organization of the software industry, and can be the structure of a measure of complementarity between different software companies, we repeat the analysis using the five-layer stack.

Table 3 - Cross-sectional regression, ACARs in M&As, entire sample

Variable	Combined (1)	Combined (2)	Acquirer (1)	Acquirer (2)	Target (1)	Target (2)
CONSTANT	0.0953*	0.1273**	0.0302	0.0574	0.0276	0.0352
	(1.894)	(2.3965)	(0.6667)	(1.1992)	(0.3016)	(0.3812)
CONCENTRATION_STACK		-0.0292*		-0.0279*		-0.0417
		(-1.7956)		(-1.7068)		(-0.7347)
PAYMENT_CASH	0.0622***	0.0609***	0.0643***	0.063***	0.2618***	0.2599***
	(3.824)	(3.7574)	(3.9294)	(3.8654)	(4.803)	(4.757)
ACQ_MV	-0.0083**	-0.0093***	-0.0055*	-0.0064**		
	(-2.4805)	(-2.7722)	(-1.7744)	(-2.0265)		
PROPORTION_TARGET/ACQ	0.0378***	0.0355**				
	(2.586)	(2.436)				
PCT_ACQUIRED					0.0018**	0.002**
					(1.9905)	(2.1062)
R^2	0.1332	0.1045	0.0775	0.0915	0.1158	0.1184
F-statistic	9.677	8.149	7.981	6.345	12.18	8.283
N	193	193	193	193	193	193

*Notes***:** Abnormal returns are calculated for a three-day window centered on the announcement date of the merger from a market model estimated from 231 to 31 days before the announcement date. The following control variables were introduced in the model (and some later dropped): *Method of payment is cash (PAYMENT_CASH), Transaction Value (VALUE), Percentage of Target Acquired (PCT_ACQUIRED), Acquirer's Equity Value ACQ_MVE, Acquirer's Market Value (ACQ_MV), Acquirer's Tobin q (ACQ_TOBINQ), Acquirer's Leverage (ACQ_LEVRG), Acquirer's cash-flow (ACQ_CF), Relative Size Target/Acquirer (PROPORTION_TARGET/ACQ)*, *Year* (*YEAR*) and *Concentration on the stack* (*CONCENTRATION_STACK*). *PAYMENT_CASH* is a dummy variable equal to one if the method of payment is at least 90% cash. *PROPORTION_TARGET/ACQ* is the ratio of the equity values of target and acquirer. *CONCENTRATION_STACK* is the sum of the product of proportions of sales for acquirer and target in the same layer of the three-layer stack. t-statistics are reported below each coefficient in parentheses. The significance levels for the independent variables are given by: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

7.2. Analysis based on a five-layer stack

Based on information obtained from the IDC on market classification (see Table 7 for descriptive statistics), 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.

The results are presented in Table 4. Model 1 shows the results of the regressions before introducing the *software stack* related variable. Subsequently, we experimented with several measures to establish a valid relationship between abnormal returns and concentration or diversification on layers of the stack. We next explain the steps we followed in the context of four additional models.

Model 2: Abnormal Returns ~ Concentration Measure + Control Variables. We start by studying the behavior of abnormal returns, if there is concentration on the same layer of the stack. We used a similar measure as in the previous analysis but this measure is based on a more detailed classification of layers. What was previously coarsely classified as software is here more finely classified as systems software, middleware software or applications software. Model 2 shows that abnormal returns are decreasing with concentration in the same layer of the stack (t-stat. = -1.7804, $p < 0.10$). This result brings some robustness to the results of the analysis with the three-layer stack and supports the conclusion that investment in complementary layers of the stack creates value in M&As.

Model 3: Abnormal Returns ~ *STACK_DISTANCE* + Control Variables. Next, we study the behavior of abnormal returns as a function of the *STACK_DISTANCE* index. The *STACK_DISTANCE* index is defined as in section 3.1 and the coefficient d_{ij} assume the values

1, 2, 3, 4 and 5, if acquirer and target focus on the same layer, one layer apart, two layers apart, three layers apart or four layers apart. This measure considers not only the effect of having both companies producing in the same layer of the stack but also how far apart they are. However, the *STACK_DISTANCE* index is not significant in explaining abnormal returns in M&As (*t*-stat. = -0.4039, $p > 0.10$).

Model 4: Abnormal Returns ~ *STACK_DISTANCE* + *STACK_DISTANCE* ^2 + Control Variables. When we introduce the squared *STACK_DISTANCE* index variable in the model, both the *STACK_DISTANCE* index (*t*-stat. = 2.1312, $p < 0.05$) and the squared *STACK_DISTANCE* index (*t*-stat. = -2.3019, $p < 0.05$) are significant in explaining abnormal returns. Furthermore, the coefficient on the squared *STACK_DISTANCE* index variable is negative. This result points to a negative curvilinear relation between the *STACK_DISTANCE* index and abnormal returns. Abnormal returns are smaller for small values of the *STACK_DISTANCE* index, increase as the index increases, and then decrease again as the index reaches higher values.

The results show that abnormal returns are higher when acquirers and targets produce products in adjacent layers of the *software stack*, and are smaller when they produce in the same layer or in layers that are further apart. We interpret this as evidence for complementarity as a source of value creation in M&As.

Furthermore, the statistical significance of this result is improve relatively to that of the analysis with a three-layer stack, and we conclude that a more detailed definition of the *software stack* explains more of the variation of abnormal returns in M&As between software companies than the three-layer stack.

Model 5: Abnormal Returns ~ Measure of Concentration+ One Layer Distance + Two-Layer Distance + Three-Layer Distance + Four-Layer Distance + Control Variables. To better understand the relationship between abnormal returns and the *STACK_DISTANCE* index, we break the *STACK_DISTANCE* index in its different components and construct separated variables for concentration and investment in one, two, three or four layers apart. The variable for investment in the same layer of the stack is defined in the same way as the measure *CONCENTRATION_STACK*. The variable *ONE_LAYER_DISTANCE* is obtained by adding the product of proportions of sales of acquirer and target on adjacent layers of the stack. The variables *TWO_LAYER_DISTANCE, THREE_LAYER_DISTANCE* and *FOUR_LAYER_DISTANCE* are constructed in the same way, but considering proportions of sales two, three and four layers apart. By definition, the sum of these five variables adds to one, as do the weights in the *STACK_DISTANCE* index. For these reason, the construction of Model 5 implies the existence of some problems and calls for caution in the interpretation of the results.

The results obtained are in accordance with the conclusions of the previous models. The coefficient for same layer is -0.0779, indicating an inverse relation between abnormal returns and concentration on the stack. However, this coefficient is not statistically significant (*t*-stat. = -0.0779, $p > 0.10$). The coefficient for *ONE_LAYER_DISTANCE* is 0.0134, providing evidence of gains in acquisitions in adjacent layers. Both the coefficient for *TWO_LAYER_DISTANCE* and the coefficient for *THREE_LAYER_DISTANCE* are negative and the second is smaller than the former, demonstrating that as the distance between acquirers and targets on the stack increases abnormal returns decrease. However, these coefficients are not statistically significant.

However, Model 5 exhibits multicollinearity. We test for the equality of the coefficients and obtain significance for the difference between the coefficients of same-layer and one-layer distance, and the coefficients of one-layer distance and three-layer distance.

Even though the individual correlations between the variables do not seem to be extremely high (see Table 5), the lack of statistical significance for the coefficients, and higher values of R^2, which increased from 0.2356 in Model 4 to 0.3994 in Model 5, suggest multicolinearity. Because we cannot solve this problem by eliminating variables from our model, we test for the equality of the coefficients of the variables. We obtain significance for the difference between the coefficients of *CONCENTRATION_STACK* and *ONE_LAYER_DISTANCE*, and the coefficients of *ONE_LAYER_DISTANCE* and *THREE_LAYER_DISTANCE* (see details in Notes below Table 4).

Table 4 - Cross-sectional regression, ACARs for M&As, IDC sub-sample

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
CONSTANT	-0.0046	0.0092	0.0056	-0.0935*	0.0468
	(-0.3793)	(0.6545)	(0.1997)	(-1.8479)	(0.00442)
PROPORTION_TARGET/ACQ	0.1069**	0.1168***	0.1027**	0.1067*	0.0901**
	(2.5736)	(2.8548)	(2.3797)	(2.5923)	(2.2943)
STACK_DISTANCE			-0.0044	0.0919**	
			(-0.4039)	(2.1312)	
STACK_DISTANCE^2				-0.0195**	
				(-2.3019)	
CONCENTRATION_STACK		-0.0429*			-0.0779
		(-1.7804)			(-0.0738)
ONE_LAYER_DISTANCE					0.0134
					(0.0127)
TWO_LAYER_DISTANCE					-0.0301
					(-0.0284)
THREE_LAYER_DISTANCE					-0.1232
					(-0.1158)
FOUR_LAYER_DISTANCE					-0.0875
					(-0.0825)
R^2	0.1335	0.1943	0.1368	0.2356	0.3994
F-statistic	6.623	5.064	3.329	4.213	4.212
N	45	45	45	45	45

*Notes***:** Abnormal returns are calculated for a three-day window centered on the announcement date of the merger from a market model estimated from 231 to 31 days before the announcement date. The following control variables were introduced in the model (and some later dropped): *Method of payment is cash (PAYMENT_CASH), Transaction Value (VALUE), Percentage of Target Acquired (PCT_ACQUIRED), Acquirer's Equity Value ACQ_MVE, Acquirer's Market Value (ACQ_MV), Acquirer's Tobin q (ACQ_TOBINQ), Acquirer's Leverage (ACQ_LEVRG), Acquirer's cash-flow (ACQ_CF), Relative Size Target/Acquirer (PROPORTION_TARGET/ACQ), Year* (*YEAR*) and *Concentration on the stack* (*CONCENTRATION_STACK*). *PAYMENT_ CASH* is a dummy variable equal to one if the method of payment is at least 90% cash. *PROPORTION_TARGET/ ACQ* is the ratio of the equity values of target and acquirer. *CONCENTRATION_STACK* is the sum of the product of proportions of sales for acquirer and target in the same layer of the three-layer stack. The *STACK_DISTANCE* Index is the sum of the product of proportion of sales for acquirer and target in each of the layers of the five-layer stack, either in the same layer or in different layers, multiplied by a coefficient that defines the distance on the stack for each pair of considered layers. t-statistics reported below for each coefficient are in parentheses. Significance levels for the independent variables are given by: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.10$.

In Model 3 and Model 4 the coefficients for *STACK_ DISTANCE* are: 1 for the same layer, 2 for one layer distance, 3 for two layers distance, 4 for three layers distance and 5 for four layers distance. In Model 5, *CONCENTRATION_STACK* is the sum of the product of proportions of sales in same layers of the stack. *ONE_LAYER_DISTANCE* is obtained by adding the product of proportions of sales of acquirer and target on adjacent layers of the stack. *TWO_LAYER_DISTANCE, THREE_LAYER_DISTANCE* and *FOUR_LAYER_DISTANCE* are constructed in the same way, but considering proportions of sales two, three and four layers apart.

We also tested the equality of the coefficients in Model 5 using an F-test, with the following results: Same-layer and one-layer distance: F = 7.90; one-layer distance and two-layer distance: F =0.50; one-layer distance and three-layer distance: F = 3.79
One-layer distance and Four-layer distance: F = 0.56. We reject the null hypothesis that the coefficients are the same for the variables "same-layer distance" and "one-layer distance" and the coefficients for the variables "one-layer distance" and "three-layer distance." We cannot reject the null hypothesis that the coefficients for the variables "one-layer distance" and "two-layer distance" and the coefficients for the variables "one-layer distance" and "four-layer distance are equal.

Table 5 – Correlation between variables that result from the partition of the *STACK_DISTANCE* index

	CONCENTRATION _STACK	*ONE_LAYER _DISTANCE*	*TWO_LAYER _DISTANCE*	*THREE_LAYER _DISTANCE*	*FOUR_LAYE R_DISTANCE*
CONCENTRATION_STACK	1				
ONE_LAYER_DISTANCE	-0.5752	1			
TWO_LAYER_DISTANCE	-0.3175	-0.2240	1		
THREE_LAYER_DISTANCE	-0.4441	-0.2197	0.0407	1	
FOUR_LAYER_DISTANCE	-0.1292	-0.1330	-0.0851	-0.0810	1

We repeat the analysis after eliminating observations in which both sides of the acquisition have activity in more than one layer of the stack and did not find significant changes in the results. In most of our sample, at least one of the sides of the acquisitions has activity in only one layer of the stack. Overall, the results show some robustness in providing evidence of an inverse curvilinear relationship between abnormal returns and the *STACK_DISTANCE* index and validate the hypothesis that there is value in M&As between components of complementary networks.

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. 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. When products are complements, in the sense that they can be coupled, integration may not always be easy, but when products are already working as complementary components on the provision of a product, integration is not an uncertainty. In many cases, companies are already partners before they merge. These facts provide some explanations for the results of our analysis.

EMC[4], a company with core business traditionally in large data-storage computers has been using acquisitions to move into data-storage software, products that help companies store information and manage it more easily and efficiently. EMC's strategy can be justified by two major motivations: to complement the core business of the company, which is storage hardware, and to gain competitive advantage relatively to IBM, its major competitor. But while EMC's strategy has been generally well received, mergers such as the one between Stellent[5] and Optika, two firms positioned in the middleware layer of the *software stack*, did not get a very favorable market reaction. The companies justified their integration as a strategy to expand their portfolio of products and services and to obtain economies of scope but the market viewed the transaction as a movement towards consolidation and there were doubts about the technical integration of their products. As a result, both companies showed cumulative abnormal returns in the three days surrounding the announcement of the merger around –10%.

When the products are highly complementary, companies may want to integrate if customers value more reliable systems integration made possible by a single provider. Tight integration may also allow companies to compete at the level of systems and establish winning standards. Therefore, the choice of the organizational form in which companies should integrate depends on how to effectively realize the value of synergies and complementarities. When complementary products are already working together as components of a network system, through a common platform, the value of synergies is already realized and companies may want to internalize it. M&As, allowing firms to hold equity stakes in complementary companies, may also lead to the realization of value from the internalization of complementary network externalities.

[4]www.emc.com

1. Conclusions

The results provide evidence that there is value in M&As involving firms that have complementary components of network systems. We find that M&As between companies that are in adjacent layers earn higher abnormal returns than M&As between companies which are in the same layer or in layers further apart on the stack. By definition, layers of the *software stack* that are closer together exhibit stronger complementaries. We interpret these results as evidence that complementarity is a source of value creation in M&As. Technical integration between products of similar companies may be difficult, but 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. This provides some evidence that there is value in equity participation between firms that are complementary components of a network system.

A limitation of this work is in our operationalization of complementarities. In this paper we used the concept of *software stacks* to group products into the various layers and assumed complementarities between layers. We also treated each layer in aggregate and computed 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. A report writer is a perfect complement to a database management system. Similarly, an application development toolkit is a complement to the database management system or even a web server. In our analysis, these products appear within the

[5] www.stellent.com

same layer of the stack and, hence, are not treated as complements. We consider our approach as a first step, where we grouped the products into espoused software layers and treated adjacent layers as complementarity layers. A second option would be to treat each product as an independent unit or layer and compute a complementarity score between it and every other product on the market. Since we have the data on all products sold to the various markets, we can compute complementarity based on the co-occurrence of products within bundles sold to customers. We call this mapping of the products as the *emergent stack* (since it is based on market behavior and not theoretical assumptions) as apposed to the espoused stack used in this paper. Having done this computation, we will analyze the M&A data using the emergent stack. For example, when a company makes an acquisition, we will determine the products in the portfolio of the acquirer and the acquired and then compute complementarity scores between all of them and see if our results hold. We plan to do this as part of future work.

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Table 6: Descriptive statistics for the sample from COMPUSTAT

	1	2	3	4	5	6	7	8	9	10
1. CARS_COMBINED	1.0000									
2. VALUE	-0.0469	1.0000								
3. PAYMENT_CASH	0.1960	-0.1092	1.0000							
4. PCT_ACQUIRED	-0.0320	0.0575	-0.1810	1.0000						
5. ACQ_MVE	-0.0684	0.0653	0.2635	-0.5245	1.0000					
6. PROPORTION_TARGET/ACQ	0.2342	0.1006	-0.1125	-0.0054	-0.1449	1.0000				
7. ACQ_TOBINQ	-0.1527	0.2730	-0.0967	-0.0790	0.1419	0.0077	1.0000			
8. ACQ_LEVRG	0.0570	-0.0266	-0.0571	0.0300	-0.0319	-0.0071	-0.0302	1.0000		
9. ACQ_CF	-0.0140	-0.0268	0.2535	-0.0908	0.1657	-0.0687	-0.5772	0.0231	1.0000	
10. CONCENTRATION_STACK	-0.1123	0.0481	-0.0919	0.2512	-0.2269	-0.0099	0.1485	0.0564	-0.0483	1.0000
Mean	0.0054	747	0.3731	89.2254	40,546,921	0.2486	6.0684	2.9253	-0.2890	0.5165
SD	0.0081	140	0.0349	2.0815	7,441,479	0.0407	0.8217	2.4550	0.1122	0.0340
N=193										

Table 7: Descriptive statistics for the sample from IDC

	1	2	3	4	5	6	7	8	9	10	11
1. CARS_COMBINED	1.0000										
2. VALUE	0.0837	1.0000									
3. PAYMENT_CASH	-0.1859	0.0494	1.0000								
4. PCT_ACQUIRED	0.1401	-0.0239	-0.3140	1.0000							
5. ACQ_MVE	-0.2030	0.0631	0.3890	-0.8653	1.0000						
6. PROPORTION_TARGET/ACQ	0.3094	0.1531	-0.4223	0.1305	-0.2005	1.0000					
7. ACQ_TOBINQ	-0.0336	0.2686	-0.1099	-0.1084	0.1475	-0.0990	1.0000				
8. ACQ_LEVRG	0.0858	-0.0597	-0.1573	0.0774	-0.0817	-0.1045	-0.0524	1.0000			
9. ACQ_CF	-0.0669	-0.0792	0.2799	-0.1652	0.1889	-0.0908	-0.8061	0.0349	1.0000		
10. STACK_DISTANCE	-0.0939	0.0097	0.0972	-0.2250	0.4036	-0.1871	0.2584	-0.0058	-0.1419	1.0000	
11. STACK_DISTANCE ^2	-0.1750	-0.0400	0.0964	-0.1817	0.3459	-0.1868	0.2190	-0.0360	-0.1152	0.9719	1.0000
Mean	0.0083	827	0.5349	83.7634	90,463,702	0.1343	7.3585	0.7115	-0.2937	2.2085	5.8108
SD	0.0111	292	0.0770	5.6586	23,722,309	0.0331	2.4321	0.6321	0.3336	0.1491	0.7660
N=45											

BRIEF BIOS OF THE AUTHORS

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