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Learning in Dynamic Inter-firm Networks: The Efficacy of Multiple Contacts*

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Abstract

This paper examines the relevance of both efficiency-based and learning-based network behaviour in the context of inter-firm partnering. The effect of these different forms of network behaviour on company performance is analyzed for companies in the international computer industry. Strategies associated with learning through so-called exploratory networks appear to generate a greater impact on technological performance in a dynamic environment than efficiency strategies through exploitative networks.

Descriptors: networks, learning, technological performance

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Introduction

The objective of this paper is to evaluate the behaviour of companies in the context of their specific network-ties with other companies in a dynamic industrial network setting. We expect particular network behaviours to enable some companies to develop new knowledge that allows them to achieve higher performance than other network players. Our research follows some recent developments in academic work on networks (Burt 1992 a and b; Freeman 1979; Powell et al. 1996; Walker et al. 1997) where the attention paid to the strategic behaviour of network players coincides with a refocusing of research from the traditional laboratory setting or a purely theoretical approach to empirical research. This increase in empirical network analysis affects the current management and organization literature that focuses on the effect of inter-company networks on company performance. According to some, the practical and strategic implications of recent empirical network analysis might even go as far as offering '... a manual for those wishing to optimize their instrumental networks ...' (Andrews 1995: 355) in a concrete business setting. However, our contribution has not only practical implications. The main research questions guiding our empirical analysis are based on the theoretical understanding of two different perspectives on the network behaviour of companies.

In the following, we will refer to these two different network perspectives as alternative approaches, where efficiency and learning are placed in the context of strategic players who are using networks to improve their own performance

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vis à vis other players. The expected higher performance of strategic players, then, is linked to their ability to access information about rewarding opportunities through network behaviour that is based on either maximum efficiency in setting up network-ties or based on learning through multiple contacts with a number of companies. This debate about the rationale of networks, the role of information and their effect on performance clearly fits in the tradition of social network analysis influenced by the seminal work of Granovetter (1973), where 'weak ties' in networks serve as bridges that can help to transfer information from one group of players to another.

One of the implications of our critical evaluation of modern network analysis is that we will qualify some of its instrumentalist suggestions. In our opinion, concrete advice based on applied network analysis in a market environment can easily lead to some misleading suggestions for the network strategies of companies, unless proper attention is paid to the environmental and behavioural conditions of networks. The main point we are making below is that in a dynamic environment, learning through multiple contacts with some quasi-redundancy, will be more effective than following strict maximizing rules for the efficiency of networks, for instance through a preference for so-called non-redundant contacts. This discussion of different forms of rationality in network behaviour, that we refer to as efficiency-based network behaviour versus learning-based network behaviour, returns to the classical discussion on the role of improved information flows through increasing contacts that come with higher 'gregariousness' (Erbe 1962). Under conditions of increased gregariousness, which implies an increasing number of contacts between participants, the flow of information also increases. This approach emphasizes improved information flows through repeated ties with a number of partners, instead of efficiency improvement by means of non-redundant contacts.

Following suggestions by, among others, Burkhardt and Brass (1990), this paper focuses on the level of inter-organizational networks, more in particular on companies, their interrelationships, and their performance in terms of their learning achievements through networks. Traditionally, network analysis was mainly applied to study inter-personal networks, however, recent contributions to the study of inter-organizational relationships have introduced a network perspective, using standard network measures, to understand the development of groups of companies and individual companies in a competitive environment. Comparing different forms of networking behaviour, we complement this recent research in which the diversity in the network portfolio of companies, through their range of ties to other companies, is placed at the centre of empirical research (Burt 1992a and b; Duysters and Vanhaverbeke 1996; Gulati 1995a; Mowery et al. 1997; Powell et al. 1996; Walker et al. 1997; Zaheer and Zaheer 1997). More specifically, we will analyze the inter-firm networks of strategic technology alliances through which companies acquire and develop R&D-related knowledge that will help them to differentiate their technological performance from other companies.

In the next section, we first explore the theoretical background of network analysis from both an efficiency and a learning perspective, leading to the basic hypotheses to be tested in this paper. In the following section, we explain the general model and the set of variables used in this study and report on the data set and population of companies studied. We chose the international computer industry to analyze the effect of different network strategies on the technological performance of companies. After reporting on the results of our investigation, we discuss our findings and draw some conclusions in terms of the possible implications of different network behaviours for learning and the technological performance of companies.

Theoretical Perspectives on Inter-firm Networks

An Efficiency Perspective on Networks

Social network analysis has been developed through various models using laboratory settings, scenarios and small number experiments. Many of these models feature some rather strong, assumptions about the efficiency of maximizing behaviour by network players. These assumptions show a remarkable resemblance to the economic 'textbook' maximizing understanding of economic subjects with perfect knowledge and complete information about market transactions. As in economic theory, there is a recent increase in the number of advanced, theoretical studies that focus on the role of incomplete information (Willer 1992).

Translated to companies and their networks, such 'textbook' examples of maximizing assumptions still found in a large part of social network analysis are:

- companies (players) in a network setting are expected to have complete and accurate information about all network linkage.
- companies comprehend and apply the principles of network power, which implies that they are very selective and efficient in choosing partners (see, e.g., Leik 1992).

Given these maximizing or efficiency assumptions, it is not necessarily rational or valuable for a company to simply increase the number of its 'dyadic' linkages within an existing network. Being linked to companies that carry interesting information, and that play a crucial role in an overall set of network linkages, is expected to be more valuable than just being part of a dense network. In other words, there is diminishing utility of added linkages in general, whereas there is an increasing utility for adding the 'right' kind of linkages.

Based on such behavioural assumptions, participants with a low network participation will prefer to add new links to their existing network, whereas central players choose to delete as many duplicating links as possible. Linking up to well-positioned companies with a high 'network status' is also thought to be more valuable than just being linked to others in a network of whatever density. This strategic manipulation of network linkages, through which major players change the potential of their position, is a crucial element in most contributions to the theory of network analysis (Leik 1992).

In organization- and management-related studies of networks, these past developments in network theory have stimulated a further search for improved network analysis that should go beyond a straightforward evaluation of network positioning (Salancik 1995). Apart from theoretical research on the implications of different network structures for the interactions within networks, empirical research related to recent developments in network theory concentrates on the individual company perspective, with some network positions generating better access to information and better results, with fewer constraints than others.

The recent work by Burt (1992 a, b) is one of the more influential contributions, which is also a good example of the current efficiency-based approach in network analysis. Central to this approach is the already well accepted idea in 'traditional' network analysis that the size of a specific network of a strategic player as such is not very important for the adequate transfer of information. What really counts is the number of non-redundant contacts, because it is assumed that redundant contacts carry the same information. By definition, dense networks involve a considerable degree of interaction between companies and many of these interactions are expected to be redundant and inefficient.

The argument is taken further by stressing that strategic players (companies) should aim at having non-redundant contacts or 'structural holes' that are additive and not merely overlapping. A strategic player can create an efficient network by focusing resources on the maintenance of 'bridge ties' that overarch structural holes with as little redundancy as possible. In standard network analysis terminology this implies that the structural equivalence of strategic players in the network (the degree of interaction with the same players) and the cohesion in strategic players' networks (the connectivity of players) should be limited, if they are to benefit from their contacts. In addition, linking up to other players that have a high degree of network status, as they are well positioned in the network, is important for the transfer of information.

In terms of the current social network terminology, the implications of an efficiency framework for understanding the benefits for strategic players are as follows:

- It is beneficial for companies to get access to existing information through a limited number of diverse contacts (bridges), avoiding dense inefficient networks. This line of reasoning is based on classical arguments such as, for instance, those found in Granovetter (1973), where the importance of so-called 'weak ties' are demonstrated, because they serve as bridges that can help to transfer information from one group of social players to another.
- Companies should avoid duplicating existing contacts; they should create well-informed and selective linkages that generate so-called structural auton-

omy and that exercise control over rewarding opportunities (structural equivalence should be small). According to Burt (1992a), for example, the lower the number of structurally equivalent firms that a company faces, the more effective is a firm's network strategy.

- Having access to information and being linked to others with high network status makes a company a suitable partner for others (network status should be high). This is in line with the arguments of Podolny (1994) and Podolny and Baron (1996), who argue that the status of players in a network is an important factor in the network performance of companies.

The technical implications of the above, in terms of the variables for network analysis, are discussed in the section 'Methodology and Data'.

A Learning Perspective on Networks

An alternative approach for understanding network behaviour, that we would like to put forward here, assumes that companies experiment with and learn from their contacts, without following strict rules of efficiency maximization. This learning approach shares a number of aspects of its criticism of efficiency assumptions with behavioural theory (Simon 1956, 1987; Cyert and March 1964) and evolutionary economics (Nelson and Winter 1982). A central element in these alternative approaches is the concept of 'bounded rationality', with companies demonstrating a satisficing behaviour under conditions of imperfect knowledge. Also, the attention for topics such as routinized behaviour and learning runs contrary to more orthodox approaches that explain the behaviour of companies in the light of efficiency and rational choices that lead to an optimization of decision rules.

This approach also parallels some of the work in evolutionary economics that stresses the positive effect of learning behaviour on company performance in a dynamic context. For instance, Silverberg and Verspagen (1994, 1996) found that, in a world of technological change, firms do not necessarily demonstrate short-term optimal, efficient behaviour. Instead, a long-term, learning-oriented behaviour was found to generate higher returns. Allen's (1988) analysis also shows that, in a dynamic economic environment, learning through various contacts pays off, as this behaviour can outperform short-term maximizing behaviour that only concentrates on the efficiency of information transfer in existing contacts. This attention paid to the importance of learning, particularly in a dynamic, technologically sophisticated, environment is reflected in a growing body of literature on alliances, learning and industry development (e.g. Ciborra 1991; Osborn and Hagedoorn 1997; Oster 1992; Powell et al. 1996).

Also, the literature on the learning behaviour of companies (and individuals) reveals that a dynamic environment with frequently changing conditions encourages continuous learning by companies. Environmental change and exposure to new ideas is expected to extend the existing knowledge base of companies, improve their existing learning capabilities and, more in particular, improve their technological capabilities (Cohen and Levinthal 1989; March 1991). As suggested by, amongst others, Barkema and Vermeulen (1998), cooperation between companies in changing environments helps companies to learn different ways of doing things; it generates new ideas and new practices that create incentives for innovative behaviour that further enhances their technological capabilities.

To continue along this line of argument, we suggest that, in a dynamic environment, with rapid technological development or frequent structural changes in the market, the relevance of continuous learning by companies increases. In the case of rapid technological change, there is immanent uncertainty about future technological development (Dosi et al. 1988). It will be difficult for companies to assess which company or group of companies will be the first to master and develop new technologies, or who will be the main carriers of new innovations. This lack of clarity regarding the role of major players seems to be present particularly in advanced sectors, where new designs are frequently developed by new players (Wade 1996). Research so far also suggests that the introduction of new designs fosters new market niches occupied by a mixture of older companies and new ones, where the role of new players remains somewhat unclear for some time (Dosi et al. 1988; Duysters 1996, Hagedoorn 1989; Sahal 1981). Concentrating only on those companies that can provide information on existing, fully developed, technologies might result in missing unexpected opportunities. Entering into a relationship with a well-established player with a high network status and technological credibility is important for the transfer of established knowledge, but this is not necessarily relevant in the quest for new knowledge that is central to new technological developments.

This kind of argument also applies to structural changes in the market, where entry from new companies, international competitors and diversifying companies can change the competitive space for an existing group of companies. The efficiency of information transfer through bridges in existing networks and avoiding duplication of contacts will become less relevant within these changing market environments (Yamaguchi 1994).

For learning behaviour in inter-firm networks in an environment of technological change, it seems much more important for companies to build a relationship with various players with whom they can jointly develop new technological knowledge. A number of studies reveal that multiple contacts over a number of years can help companies build inter-organizational trust (Gulati 1995b; Heide and Miner 1992; Kogut 1989; Nooteboom et al. 1997; Saxton 1997). This literature suggests that shared experiences with several contacts encourages companies to add new dimensions to their collaboration. Joint technological development can certainly be seen as an important aspect of further collaboration between companies, which also exposes the partners to new ideas, enhances their innovative behaviour and improves their technological capabilities.

The argument we are making boils down to the following: in a dynamic environment characterized by technological change and 'openness' of markets, continuous learning, even through seemingly redundant network contacts is preferable to efficiency-based behaviour. Dynamic environments require intensive, exploratory learning (Dodgson 1993; March 1991) for which companies can use a diversity of links to particular companies without maximizing the efficiency of their overall network ties. In a dynamic environment, the current network status of companies is not an accurate predictor of their potential future influence and the network itself fluctuates, such that there is no clear definition, even, of the set of potential partners. Learning-based behaviour implies that, under conditions of change, the value of a particular tie or number of ties, between players might be unknown or difficult to estimate at the start of the collaboration. In searching for valuable contacts, reducing redundancy is not a priority if companies intend to learn from a variety of sources through the network in which they are operating. For instance, Gomes-Casseres (1996) points at the positive effect that the intentional duplication of contacts between participants in networks might have for improving their learning capabilities. Over time, a successful tie-up might develop information that was unknown at its initial stage. The value of the information and the value of the process of exploratory learning that goes with establishing different tie-ups to other companies cannot be estimated beforehand. Also, it is impossible to gauge in advance exactly which network pattern would generate the highest returns for a company. In-depth studies of the importance of multiple ties in high-tech industries, such as the computer industry, can be found in Duysters and Vanhaverbeke (1996), Gomes-Casseres (1996), and Hagedoorn et al. (2001). These studies demonstrate the relevance of these multiple ties, not just for information transfer, but particularly for joint learning experiences regarding new technologies and new opportunities.

Based on our understanding of these alternative network perspectives, presented above, we formulate two basic hypotheses that will guide our research:

H1: In a dynamic environment, there is a positive relationship between the degree to which companies demonstrate a learning-based network behaviour and their performance.

H2: In a dynamic environment, efficiency-based network behaviour by companies is expected to have no effect on their performance.

These hypotheses could also be related to a set of sub-hypotheses, in terms of the different operationalizations of network behaviour and the expected effects, and their signs, as presented in Table 1, below. However, unless the particular statistical indicator is clarified, see the next section, some technical aspects of measuring network variables make it somewhat difficult to explain the expected effects and their values. Therefore, we prefer to test two basic hypotheses in the statistical analysis by using a set of several network indicators.

Methodology and Data

Population

In the following, we will study the effects of efficiency-based behaviour and learning-based behaviour on company performance in the context of networks of strategic technology alliances, with joint R&D and other shared innovative efforts. These strategic technology alliances, through which companies acquire R&D-related knowledge, are expected to help them differentiate their technological performance from other companies. The relevance of this topic, as for instance demonstrated by the growing importance of strategic technology alliances as a major element in the external linkages of companies, has been documented in many publications. See Hagedoorn (1996) and Osborn and Hagedoorn (1997) for an overview of the literature.

Given the emphasis on 'technology' alliances, their effect will not be related to economic performance in general, but to the technological performance of companies. However, this technological performance of companies is expected to be dependent not only on the networking characteristics of companies, but also on some firm-specific characteristics or endogenous capabilities. In that context, one has to think of the size of companies that captures scale and scope effects and R&D efforts that might generate technological performance differentials.

Our empirical analysis covers the industrial, technological and networking activity of companies operating in the international computer industry. There are 88 companies in our analysis (see Appendix 2), these companies represent over 80 percent of the sales of the worldwide computer industry. There are several reasons for choosing this particular industry and its network of strategic technology alliances. The computer industry is known to be a high-tech sector that creates a dynamic environment for companies (OECD 1992). It is a large, competitive and technologically advanced sector with a high R&D intensity of over 10 percent (OECD 1997). It is an industry where one finds a large number of strategic technology alliances that play an important role in the competitive strategies of companies (see, amongst others, Duysters and Hagedoorn 1998; Gomes-Casseres 1996; Hagedoorn and Schakenraad 1992; Mytelka 1991). It is also a sector with a diverse population of companies such as diversified companies, specialized suppliers, new entrants and 'older' established companies (Duysters 1996; Duysters and Hagedoorn 1995; Gartner Group 1994).

Dependent Variable

In this study, *technological performance* is measured by taking the 1993 patent intensity of companies, i.e. the number of computer patents divided by the size (computer revenues) of the company, as the innovative output indicator. As with so many other measures, this patent indicator is subject to a debate regarding its usefulness (Cohen and Levin 1989; Griliches 1990;

Archibugi 1992). However, it may be one of the more appropriate indicators that enables us to compare the technological performance and technological learning of companies (Acs and Audretsch 1989; Aspden 1983; Cantwell and Hodson 1991; Patel and Pavitt 1991, 1995; Pavitt 1988). It is important to note that the dependent variable measures the technological capabilities and performance of individual companies that are affected, amongst other things, by strategic technology alliances. This indicator does not measure joint patenting activities, as it reflects the technological performance of each individual company in the population. As such, this indicator is particularly relevant for our study of the networks of strategic technology alliances which can be expected to influence the technological learning capabilities of companies. See also Powell and Brantley (1992), who describe patents as 'signals' of technological competencies and learning capabilities of companies in inter-firm networks.

Network Measures and Variables

As mentioned in the above, strategic technology alliances between companies are taken as the measure of ties in our analysis. These ties are symmetric. To account for repeated ties, multiple, separate alliances between the same partners are counted separately. Networks of these ties are measured for the complete period of the analysis (1986-1992). The main indicators of a particular network behaviour are standard network measures, such as density, bridge ties, structural equivalence, and status. In other words, we stay as close as possible to conventional network analysis. See also Appendix 1 for additional information on these measures.

The variable measuring *multiple contacts* concerns the number of contacts with the same partners. From a learning perspective, having multiple links with a variety of partners increases the probability that companies will develop new capabilities. From a traditional network analysis perspective, however, having multiple links with the same partners is of little relevance, if not inefficient. For this measure ('multiple contacts'), we divide the degree centrality (C_D) of a firm by the number of its partners to express this relative redundancy. The degree centrality (C_D) is a rather straightforward measure of centrality, which is equal to the total number of direct links of that particular player to all the other players.

The maintenance of *bridge ties*, that overarch structural holes with as little redundancy as possible, is measured by means of two indicators: betweenness centrality (C_B) and degree centrality (C_D). The importance of bridge ties as such is measured by the betweenness centrality (C_B). Betweenness refers to the number of times a player is located on the shortest geodesic path between two other players. The expression geodesic path is used to denote the shortest path between two points in the network. If a certain player is directly linked to two other players who are not directly linked to each other, then the first actor is said to be 'between' the other players. In an information network, a company that has a high degree of betweenness centrality has the potential to control the flows of information between those other companies (Freeman 1979; Knoke and Kuklinski 1982). From an efficiency perspective, the number of bridge ties is more important than the total number of links at a firm's disposal. Therefore, we divided the betweenness centrality (C_B) by the degree centrality (C_D) to arrive at a relative measure ('bridges').

The *structural equivalence* of firms measures the degree of interaction with the same players. Firms are referred to as a structural equivalent if they have identical ties to all other firms in the network ('structural equivalence'). According to Burt (1992a), the lower the number of structural equivalent firms that a company faces, the more effective a firm's network behaviour will be. In this paper, we use a standard structural equivalence measure of the number of identical contacts. Following Wasserman and Faust (1994) we assume that there will be no loss of information by combining the two (or more) structurally equivalent actors into a single subset.

Network status is defined as the degree to which a company has alliances with powerful companies in terms of their network position, indicated by the Bonacich eigenvalue centrality measure (C_E) (Bonacich 1972). In this measure, the centrality of each firm is determined by the centrality of the firms to which it is connected (Borgatti et al. 1992). The normalized eigenvector that is used in our study is calculated as the scaled eigenvalue centrality divided by the maximum possible difference. A high score on this variable ('network status') means that a company is associated with a relatively large number of powerful partners in terms of their centrality in the network. This seems to be particularly important for an efficiency perspective.

Table 1 presents an overview of the expected relationship between each of these variables regarding network efficiency and the technological performance of companies. In the statistical analysis, given the way they are operationalized and measured, we expect two efficiency variables ('bridges' and 'structural equivalence') to be negatively related to performance, when viewed from an efficiency perspective. It should be clear that this negative relationship is due to the specifics of the measurement of these variables. The assumed negative relationship does not indicate a normative appreciation. To help arrange the material clearly, we designed these variables in such a way that, for an efficiency strategy, the expected sign in the analysis would be negative, due to the conversion of values.

For efficiency-based behaviour, 'network status' is expected to be positively related to performance. 'Multiple contacts' is irrelevant from an efficiency perspective, whereas, from a learning perspective, this variable is expected

Table 1
The Expected Effect* of Network Variables on the Technological Performance of Companies From the Perspective of Efficiency Behaviour and Learning Behaviour in a Dynamic Environment

Variables	Efficiency	Learning
Multiple contacts	Irrelevant	Positive*
Bridges	Negative*	Irrelevant
Structural equivalence	Negative*	Irrelevant
Network status	Positive*	Irrelevant

* negative and positive effects refer primarily to the expected non-normative, statistical relationships.

to be the network variable that is positively related to performance. From the perspective of learning behaviour, the effects of the other variables are predicted to be statistically irrelevant.

Control Variables

Apart from these network variables, we expect the *size* of companies to have an effect on their patent activity. In the classical Schumpeterian argument, the patent activity of companies — an indicator of their technological performance — increases more than proportionally with firm size. The main arguments are: the growing importance of science-based industries, innovation as a major source of competition, and economies of scale and scope. The classical counter-argument is provided by Bain (1956), who stated that small companies are more innovation-efficient, whereas larger firms suffer from 'creative backwardness'. Scherer's (1965 and 1984a) view is also widely accepted, i.e. that the patent activity of companies tends to rise less than proportionally, once a certain threshold has been passed. Empirical studies by Mansfield (1984) and Mueller (1986) support this view of non-linearity. See also Cohen and Levin (1989) for a review of the literature on the effect of company size on their innovative output.

The size of companies is measured by taking the average sector-specific (i.e. computer) revenues of companies (Size). As we take the natural logarithm of size, we also take into account, as suggested by the literature, the diminishing effect of size on patenting activity.

The R&D activity of companies — the ratio of computer-related R&D spending to computer revenues — is taken as a second control variable ('R&D intensity'). We expect an effect of R&D on patent activity as research efforts will (at least partly) be transformed into patents. Also, internal R&D is important, as it can be seen as the 'ticket of admission to an information network' (Mowery and Rosenberg 1989), and, as such, it is expected to affect both the network properties of companies and their learning through alliances (Mowery and Rosenberg 1989; Powell and Brantley 1992).

The relation between R&D and patents has been studied extensively. In Kamien and Schwartz' (1982) well-known survey, it is stated that '... without much doubt, on average, a direct relation between innovational effort and innovational output exists' (Kamien and Schwartz 1982: 57). However, it is added that other factors can influence the transformation, so that the relation may not be linear. In studies by Bound et al. (1984), Scherer (1984a), and Hausman et al. (1984), it is mentioned that patenting output decreases gradually with an increase of R&D expenditures. By using the ratio of R&D expenditures to the logarithm of size, we take this decreasing effect into account.

Finally, given the technological leadership of US companies in the international computer industry, we include a US dummy as a dichotomous control variable.

Data Sources

Data for the size of companies and their R&D expenditures is taken from the Gartner Group's annual Yardstick: the top 100 computer hardware companies, worldwide, that published data up to 1992. The Yardstick, *Top-100 Worldwide* was an authoritative statistical review of the computer industry. Data in the *Yardstick* was updated annually through surveys and research by Gartner Group consultants and analysts. The *Yardstick* contains calendar year information, as opposed to information based upon fiscal years, which allows us to make better comparisons between companies. The Gartner group (1994) estimates that their sample of the leading 100 computer companies accounts for over 90 percent of the worldwide market. The firms in our sample cover more than 90 percent of the revenues presented in the Gartner Group sample. This implies that our sample accounts for more than 80 percent of the total computer industry.

The data on patents for the dependent variable (technological performance) was taken from the US Patent and Trademark Office database (US Department of Commerce). We took the number of patents in the SIC code 357 (computer and office equipment) for which firms had applied, which not only covers computers in a narrow sense, but also includes peripheral equipment, such as storage devices and terminals. Although this US data could imply a bias in favour of US companies and against non-US firms, the group of non-US companies in this study represents a group of innovative and rather large firms that are known to have taken out patents, worldwide. Furthermore, the innovation literature suggests several other reasons for using 'taking out US patents' as an indicator. Frequently mentioned reasons are the importance of the US market, the 'real' patent protection offered by US authorities, and the level of technological sophistication of the US market, which makes it almost compulsory for non-US companies to file patents in the United States. See Patel and Pavitt (1991) for a discussion on the use of US patent data.

The data on strategic technology alliances was obtained from the MERIT-CATI data bank on cooperative technology agreements. The most important data sources for this databank are a large number of international and specialized trade and technology journals for each sector and for many fields of technology. The database contains information on each cooperative agreement and some information on companies participating in these agreements. Cooperative agreements are defined as the establishment of common interests between independent (industrial) partner, i.e. partners who are not connected through (majority) ownership. The transfer of technology or the undertaking of joint research is considered to be crucial for these arrangements. Strategic technology alliances take the form of contractual agreements (such as R&D pacts) or equity joint ventures. For the purpose of the present analysis, information is used regarding the industrial sectors and fields of technology and the year of establishment of the strategic technology alliances. Additional information on this data bank can be found in Hagedoorn (1993) and

Hagedoorn and Schakenraad (1994), or it can be obtained from the authors.
Data for the independent variables in the analysis covers a 7-year period (1986-1992), during which the number of annually made alliances was growing at an unprecedented rate (Hagedoorn 1996). This development led to a large number of alliances forming a population of sufficient size. The population of alliances in the analysis is based on the total number of alliances of companies in the computer industry established during the period 1986-1992.
For the dependent variable, we take its value in 1993. This implies that we introduce a time lag, of, on average, four years, for the joint innovative input, such as joint R&D projects, to materialize into innovative output, i.e. patents. Research on such time lags (Scherer 1984b; Pakes and Griliches 1984) suggests that, on average, an invention leads to patents after about two and a half years, although there is substantial variation. If we include the process of R&D itself, and the additional time that joint projects can be expected to take, then an average time lag of four years appears to be a valid estimate.
As companies are the major carriers of technological change in this network environment, the dynamics of the environment do not only reflect structural changes in the market, but also technological changes that come with the entry of new players into the network and into the industrial environment. Many of these new players are relatively small and 'unknown' firms, or diversified companies that have a major interest in other industries. This particular aspect of a dynamic environment is relevant in the current context, because 64 percent of the 88 companies in the analysis entered the overall network during the second half of the period (1989-1992). See Appendix 2 for the list of companies.
Finally, there are several reasons why we chose to analyze one particular population of companies, instead of comparing different sectors. First, the objective of this exercise is to compare efficiency and learning behaviour under conditions brought about by a dynamic network environment. Second, within one particular network environment, we can control for a large number of industry effects, such as differences in economies of scale and economies of scope, alternating business-cycle effects and differences in the propensity to patent. In particular, the differences in propensity to patent is crucial. If we were to undertake an analysis in which we compared different networking strategies in, for example, a dynamic and a static environment, using patents as an indicator of technological performance, the comparison would be troublesome. In the MERIT-CATI data set, sectors such as the steel industry and the auto industry would qualify as mature, static environments with a large enough number of strategic technology alliances with a stable number of partnering companies. However, previous research (e.g. Arundel and Kabla 1998; Mansfield 1986) indicates that patents are poor indicators of technological performance in these industries, making the exercise rather useless.Third, by concentrating on one network environment, we follow the example of many recent empirical network analyses (Duysters and

Vanhaverbeke 1996; Human and Provan 1997; Powell et al. 1996; Walker et al. 1997; Zaheer and Zaheer 1997), that each of them studies a particular sector or a specific network of companies.

Results

To measure the effect of different kinds of network behaviour, we apply standard ordinary least square regression. Table 2 lists the mean and standard deviations for the variables in the analysis. In order to detect possible multicollinearity, we not only analyzed the correlation between the variables (see Table 3), but also regressed each independent variable on all the other independent variables. This method is often described as the most preferred method of assessing multicollinearity (see Lewis-Beck 1993). The advantage over the frequent practice of examining bivariate correlations among the independent variables is that it takes into account the relationship between all independent variables and an independent variable. As noted in Lewis-Beck (1993: 52) '... it is possible, for instance, to find no large bivariate correlations, although one of the independent variables is a nearly perfect linear combination of the remaining independent variables ...'. This test showed that no significant multicollinearity was detected, as none of the other regressions used for checking multicollinearity in the analysis produces R^2 s above 0.7. R^2s close to 1.0 are considered to reveal a high degree of multicollinearity (Lewis-Beck 1993).

Table 2 Means and Standard Deviations for Variables in the Analysis of the Effect of Network Caracteristics on the Technological Performance of Companies (n = 88)

Variable	Mean	Standard Deviation
Multiple contacts	0.3711	0.8929
Bridges	0.5010	0.3538
Structural Equivalence	0.8714	0.2970
Network status	5.8327	12.1543
Size	13.7028	1.3022
US dummy	0.6591	0.4767
R&D intensity	0.0717	0.0404

Table 3 Pearson Correlation Coefficients (n = 88)

	Multiple Contacts	Bridges	Structural Equivalence	Network Status	Size	US Dummy	R&D Intensity
Multiple contacts	1.000						
Bridges	–0.036	1.000					
Structural equivalence	–0.066	0.170	1.000				
Network status	0.462**	–0.132	0.057	1.000			
Size	0.234*	0.138	0.066	0.440**	1.000		
US dummy	–0.161	–0.023	–0.072	–0.026	–0.352**	1.000	
R&D intensity	0.295**	–0.167	–0.071	0.228*	0.198	0.124	1.000

* Correlation is significant at the 0.05 level (2-tailed) ** Correlation is significant at the 0.01 level (2-tailed)

Table 4 presents the analysis for this population of computer companies. According to the F value and the R^2 value, the model is significant. All

Table 4
The Effect of Network Characteristics on the Technological Performance of Companies in the International Computer Industry (n = 88)

Variable	Beta	T
Constant		0.53
Multiple contacts	0.582	3.22*
Bridges	–0.050	–0.31
Structural equivalence	0.106	0.68
Network status	0.167	0.85
Size	–0.095	–0.50
US dummy	–0.140	–0.02
R&D intensity	–0.004	–0.81

* $p < 0.01$; $R^2 = 0.47$ Adj $R^2 = 0.31$
Std Er = 0.026 F = 2.95 Sign. F = 0.023

variables that would support an efficiency perspective are insignificant, which supports Hypothesis 2. As predicted by Hypothesis 1, the only important variable from a learning perspective, 'multiple contacts', has a positive effect and is highly significant.

The control variables (size, R&D intensity and the dummy for US companies) appear to have no significant impact on the patent intensity of these computer companies. The (insignificant) negative effect of size that was measured appears to support some research in the neo-Schumpeterian tradition, as mentioned above. The same applies to the insignificant effect of R&D intensity on technological performance. The results for both these variables suggest a possible non-linear relationship between size, R&D intensity and patent output.

We also undertook several additional analyses. First, we looked separately at contractual agreements to see whether the form of organization of an alliance might have an effect on our findings. This exercise generated results similar to those obtained for the general population of strategic technology alliances. As such, this is not so surprising, because contractual agreements account for over 75 percent of these alliances (Hagedoorn 1996). Given the small number of equity joint ventures in the sample, it was not possible to run the analysis, also for this particular form of partnering.

Second, we also weighted the age of the alliances in the analysis, assuming that, for example, 7-year old alliances from 1986 might have had a smaller effect on the technological performance of companies in 1993, than alliances that were only two or three years old. This correction for the weight of alliances turned out to have no effect. This can be explained by the fact that the growth of newly made alliances during the early nineties was at least twice as high as that during the mid-eighties. This growth pattern, with a large presence of later alliances, dominates any exercise that considers correcting for the age of strategic technology alliances.

Third, we also considered the possible interaction effects between multiple contacts (relevant for a learning perspective) and the other three network variables (relevant for an efficiency perspective) on the dependent variable. However, none of these interactions had a significant effect on the technological performance of companies.

Discussion and Conclusions

Our findings suggest a number of important implications for understanding different forms of network rationality in a dynamic network environment. In such an environment, a network rationality based on learning-based behaviour seems to become important, as indicated by the effect of this behaviour on the higher technological performance of companies. A dynamic environment, characterized by market structural changes that accompany technological development, appears to induce companies to learn as much as possible from a number of 'trusted' sources. With this learning-based behaviour, companies do not necessarily maximize their linkages in terms of being most effective in producing results with little waste of effort. Given the unstable environment they are facing, companies appear to concentrate much more on achieving the desired results as such. As for networks of strategic technology alliances, these desired results are given in terms of technological performance, for which learning as much as possible, even through multiplication of contacts, appears to yield positive results. The multiplication of contacts between the same companies will usually take place over a period of a number of years. Therefore, our findings also support earlier research that stresses the relevance, for understanding networks, of looking at the history of partnerships between companies, see Gulati (1995a, b).

Our findings complement the recent research of Walker et al. (1997) who conclude that contributions such as Burt (1992a) are probably most relevant in the context of analyzing networks of standard market transactions. Walker et al. (1997) apply the concept of social capital to develop their understanding of the durability of embedded networks of cooperating firms; networks that, nevertheless, allow the entry of new players. Although there are differences from a learning perspective, the results regarding the importance of both of them increasing relationships in another dynamic environment (biotechnology) are quite similar to our findings.

It is also important to note that our analysis does not reject the idea that efficiency behaviour in building a network of strategic technology alliances could still be instrumental for companies, if they want to learn from partners in a static environment. Then, efficiency, in terms of concentrating both on alliances with primary contacts and with companies that have higher network status, while overarching structural holes with as little redundancy as possible, could generate significantly higher performance for companies that follow such a policy. To put it differently, it is still possible that in a static environment, higher company performance will be associated with efficient network positioning, in the sense that there is non-redundancy and higher selectivity in contacts with other companies. However, as mentioned in the above, there are some serious methodological problems in comparing network strategies and technological performance in a dynamic network environment with a static environment, using the same measure for technological performance. Our current analysis is limited to one network environment and we can only speculate about the possible relevance of efficiency behaviour in a static network environment.

The distinction between efficiency and learning-based behaviour in the context of networking can also be linked to a further refinement of different forms of learning, such as explorative and exploitative learning. Exploratory learning or non-routinized learning involves changes in company routines and experimentation with new alternatives (see, e.g., Dodgson 1993; March 1991), which, if successful, does change the nature of company competencies and increases their innovative performance. In a dynamic environment, with changes in both players and technologies, exploratory learning becomes important, not only in terms of the endogenous capabilities of companies, but also in terms of learning, when the relevance of the knowledge of partners is unclear in advance. Under these circumstances, dense patterns of interaction, with repeated contacts and continuous flows of information, as in exploratory learning-based networks, start to count. Exploitative learning, on the other hand, is characterized as routinized learning which only adds to the existing knowledge and competencies of a firm, without changing the nature of its activities. This could suggest that, if companies build networks in a static context, in which they have accurate information about the existing capabilities of their network linkages, they can add capabilities to their own performance, but the improvement will be in line which what could be expected. Hence, efficiency or exploitative network behaviour can still be beneficial in a static environment.

As far as network status, in terms of existing network power, is concerned, our research suggests that this aspect of network performance is not very relevant in a dynamic environment. From a learning perspective, it can be argued that status derived from existing network positioning is probably not so germane in a dynamic context. Having repeated ties with a group of companies, including those companies that still have to demonstrate their value, probably has a higher learning potential than linking up to companies that are well established in terms of being connected to other, historically, powerful companies.

Finally, it is obvious that the current analysis has its limitations in terms of the degree to which we can generalize its outcomes, in particular to static environments. However, the results for this particular dynamic industry are quite significant, not only statistically, but also because we study a large and important network environment. Future studies of other networks might provide further insight into the rationality that lies behind both efficiency and exploitative forms of network strategies, as well as exploratory and learning strategies. The current contribution already strongly suggests that alternative forms of networking behaviour and network configurations, based on different perceptions of rational behaviour and learning, can also generate different results in terms of the technological performance of companies.

Appendix 1

Brief Technical Description of Standard Network Measures

Degree centrality:

$$C_D(Pk) = \sum_{i=l}^{n} a(p_i, p_k)$$

$a(P_i,P_K)$ =1 if P_i and P_K are connected directly, and 0 otherwise.

Betweeness centrality:

$$C_B(p_k) = \sum_{l}^{n} \sum_{j}^{n} \frac{g_{ij}(p_k)}{g_{ij}}$$

n represents the number of points in the network, g_{ij} represents the number of geodesic paths linking p_i and p_j that contain p_k.

Structural equivalence:
Given an adjacency matrix, or a set of adjacency matrices for different relations, a correlation matrix can be formed by the following procedure. A profile vector is formed for a vertex *i* by concatenating the *i*th row in every adjacency matrix. The *i,j*th element of the correlation matrix is the Pearson correlation coefficient of the profile vectors of *i* and *j*. This (square, symmetric) matrix is called the first correlation matrix.
The procedure can be performed iteratively on the correlation matrix until convergence takes place. Each entry is now 1 or –1. This matrix is used to split the data into two blocks, such that members of the same blocks are positively correlated, and members of different blocks are negatively correlated.
CONCOR, a widely applied block modelling algorithm, uses the technique mentioned above to split the initial data into two blocks. Successive splits are then applied to the separate blocks. At each iteration, all blocks are submitted to the analysis. However, blocks containing two vertices are not split. Consequently *n*-partitions of the binary tree can produce up to 2*n* blocks (see Borgatti et al. 1992).

Network status indicated by a normalized eigenvector:
Given an adjacency matrix *A,* the centrality of vertex *i* (denoted *ci*) is given by ci = $\alpha \sum Aijcj$ where α is a parameter. The centrality of each vertex is therefore determined by the centrality of the vertices to which it is connected. The parameter α is required to give the equations a non-trivial solution and is therefore the reciprocal of an eigenvalue. The normalized eigenvector centrality is the scaled eigenvector centrality divided by the maximum difference, expressed as a percentage (see Borgatti et al. 1992).

Appendix 2

List of 88 Companies in the Network Analysis of the International Computer Industry

3Com	Lexmark	Texas Instruments*
Acer Corp.*	Lockheed	Toshiba*
Alps Electric	Mannesman	Unisys
Amdahl	Matsushita*	Wang
Apple*	Maxtor	Wyse*
AST Research*	Memorex-Telex*	Xerox
AT&T*	Mitac	Quantum
BASF – Comparex	Mitsubishi	Gateway
Canon	Motorola*	Packard-Bell
Cisco Systems	NEC*	EMC
Commodore	Nihon Unisys*	Synoptics
Compaq*	Northern Telecom	Cabletron
CompuAdd	NTT	Micropolis
Computer Vision	Oki	Tektronix*
Conner	Olivetti*	Cadence
Control Data Corp.	Philips*	Sequent*
Cray Research*	Quantum	Mentor Graphics
Data General	Racal	National Computer
Dell	Ricoh	Systems
Digital Equipment Co.*	Seagate	QMS
Escom	Seiko Epson	Exabyte
Fujitsu*	Siemens*	Telxon
Groupe Bull*	Silicon Graphics*	Gerber Scientific
Hewlett-Packard*	Sony*	Digital Communications
Hitachi*	Storage	Recognition Equipment
IBM*	Stratus*	Banctec
Intel*	Sun Microsystems*	NET
Intergraph	Tandem*	Genicom
Kaufhof	Tandy*	Zeos
		Network Systems
		General DataComm

* marks a company that was already active in the network during the period 1986–1988.

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