THE EFFECT OF STRATEGIC TECHNOLOGY ALLIANCES ON COMPANY PERFORMANCE

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Strategic technology partnering between firms has become a growing subject of interest to both companies experimenting with this mode of economic organization and researchers from a wide variety of academic disciplines. In this study an effort is made to measure the effect of strategic technology partnering on companies engaged in such joint efforts. A study of the relevant literature on interfirm cooperation generates some basic understanding of this phenomenon, after which the empirical analysis is expanded with linear structural modeling of a number of relevant explanatory variables setting strategic partnering in a more complex environment.

INTRODUCTION

Strategic technology partnering is the establishment of cooperative agreements aimed at joint innovative efforts or technology transfer that can have a lasting effect on the product-market positioning of participating companies. The 1980s witnessed a growth in this phenomenon at an unprecedented scale, see for instance Chesnais (1988), Haklisch (1986), Hagedoorn and Schakenraad (1990a and b), Hladik (1988), Hertig and Morris (1988) and Mytelka (1991). This increase has been attributed to the present rapid changes in technological development, the necessity of quick preemption strategies, complexities and uncertainties surrounding technological developments, and the necessity for large firms to monitor a wide spectrum of technologies. Moreover, firms increasingly compete in world markets where strategic alliances can be part of global competitive strategies. In order to comprehend the consequences of interfim cooperation the analysis has to go beyond the mere description of trends in alliance formation and of company strategies. For a closer assessment one has to analyze the economic effects of strategic technology alliances on the companies involved.

We assume that strategic partnering is pursued by companies because they expect a positive economic results. Correspondingly, the central question to be investigated in this paper is: to what extent does interfim strategic technology partnering affect the profitability of companies engaged in such joint efforts?

In the following section we review the literature related to partnering between companies, the economic effects of joint ventures, joint R & D and equity investment, and mergers and acquisitions. The issue of possible increased economic performance through strategic technology partnering is further developed with empirical research. The statistical procedure used in this study is linear structural modeling (LISREL), an exponent of the so-called general linear model. The model includes assumed interrelations among a number of explanatory variables. The sample of companies to be studied covers European, American, and Japanese firms operating in

Key words: Strategic alliances, international competition, company performance
three compound industrial sectors: information technologies and electronics, mechanical engineering, and process industries. In the final section of this paper we will discuss the results of our research and place them in a broader perspective of the dynamics of technological change. In that context industry development, innovative capabilities of firms, cooperation strategies and industry specificities present a complex picture against which the relation between strategic technology alliances and corporate performance has to be interpreted.

THE ECONOMIC EFFECTS OF COOPERATION—SOME ELEMENTS OF ECONOMIC ANALYSES

In Berg, Duncan and Friedman (1982), as far as we know the only comprehensive study in which corporate performance is related to interfirm cooperation, the effect of joint venture activity on profitability is measured with cross-firm and cross-industry empirical tests. In the cross-firm analysis the authors expect ambiguous short-term effects and an overall positive, but insignificant long-term effect on profitability. Short-term negative effects are expected for knowledge-acquisition oriented joint ventures because of the investments involved. Production and marketing joint ventures are supposed to have positive short-term influences. Berg et al. also mention market power increase as an important aspect of joint ventures leading to increased profit margins. Efficiency gains, such as operational efficiency, are also likely to raise profitability, but Berg et al. doubt whether these effects can be measured. Results from their regression analysis show that joint venture activity tends to have a significant negative impact on profitability in chemicals and (mechanical) engineering but insignificant effects in the resource-processing sector. No significant long-term effects of joint venture activity on profitability were found in any industrial sector. In the cross-industry analysis of 19 industry groups the dependent variable is the industry-average after-tax rate of return on investment. Potential influences of the following cause variables were examined: size of the firm, the rate of capital stock increase in a given industry, mean R & D intensity, and two joint venture indices, one for knowledge-acquisition inclined joint ventures and one for other joint ventures. The results demonstrate that all variables are significantly different from zero at the 0.05 level or better. R & D oriented joint ventures produce a negative impact on industry-average rate of return, whereas non-R & D driven joint ventures on average have a positive impact on rates of return.

As so little is known about the economic effects of cooperation at company level we turn to results from both somewhat older research and recent measurement of the effects of mergers and take-overs on the companies involved. Such an exercise can lead to some insights on the economic benefits of joint activities at a related although more intermediate level of economic governance.

In what could be referred to as the common sense understanding of the effects of mergers and take-overs it is clear that the economic rationale of both mergers and take-overs is found in the improvement of the economic performance of the combined partners in an enlarged economic entity. Apart from growth in economic control, which some would emphasize, the long-term effects of a merger or take-over should be found in synergy effects through economies of scale and/or scope leading to gains in turnover, rationalization of production, improved innovative performance and decreasing costs of control for the combined companies. Compared with the added results of separate companies in a premerger situation, the postmerger or take-over results of these synergy effects are anticipated to exceed the earlier economic performance and cause an increase in profit margins. In particular in so-called 'event studies' on stock market valuation of take-overs and mergers we can find some scattered evidence of improved economic performance through corporate mergers. However, as Caves (1989) and Scherer (1988) report, many studies also suggest that the value of the bidder's shares frequently falls after the take-over or merger.

In addition to event studies there is substantial ex post evidence on the effects of mergers and acquisitions which suggests that acquirers realized diminishing economic results after the take-over, with substantial negative effects on the profitability of acquired business units. Meeks (1977) provides an overview of some of the older European and U.S. studies on the subject from
the early fifties to the late sixties. Only a few studies show an improved performance of companies after a merger, most studies detect an unfavorable or an indecisive relationship between mergers and economic performance. Meeks' own research on 200 acquisitions in the U.K. during the second half of the sixties and early seventies suggests that in general mergers demonstrate a decline in profitability. Mueller (1986a) reports on approximately 800 mergers from the late seventies in advanced capitalist countries in Europe and the United States. His study shows that mergers have had negative or but little effect on profits of the companies involved. In Mueller (1986b, 1989) we see comparable results for subsequent research on the effects of mergers on company performance. Ravenscraft and Scherer (1986) found that on average acquisitions and mergers made by over 450 U.S. companies during the late sixties and the early seventies did not lead to an increase of market shares and profitability but instead they found declining performances for most companies. In Ravenscraft and Scherer (1987) it is reported that take-overs did slightly worse than their industry peers at the time of acquisition, but results were clearly poorer after about 10 years from take-over. Almost identical outcomes on the decline of post-merger profitability are reported in Ravenscraft and Scherer (1989). Recent research by Cosh et al. (1989) on a sample of nearly 140 mergers in the U.K. during the eighties reveals that on the whole mergers have not been very successful in terms of the improvement of profitability. For Japan, where until recently take-overs were a relatively unknown phenomenon, Odagiri and Hase (1989) found a growing number of Japanese firms engaging in merger and acquisitions. However, they found no evidence that in general mergers and acquisitions improved profitability or growth significantly. Porter (1987) pays attention to a number of alternative mechanisms for company diversification such as acquisition, joint ventures and start-ups. If one accepts that the rate of divestment of new acquisitions by companies within a few years after they have been made is a relevant indicator of the success or failure, the outcomes of Porter's study are remarkable. About 75 per cent of all 'unrelated acquisitions' in the sample were divested after a few years and so were about 60 per cent of the 'acquisitions in entirely new industries'. For 'joint ventures in new fields' and start-ups the rate of divestment is somewhat lower with about 50 per cent and over 40 per cent respectively. Although the rate of failure for joint ventures and start-ups is also significant and their relative importance should not be exaggerated, it is obvious that these mechanisms could be relatively successful if compared with take-overs. Worth mentioning in that context is a study by Link and Bauer (1989) which reveals that mergers have become less important mechanisms for acquiring and developing new technologies whereas the popularity of cooperative research has grown considerably.

The above generates some serious doubts about the across-the-board positive effects on companies participating in mergers or take-overs whereas the effects of interfirm partnering, for instance through strategic technology alliances, could be more positive. If companies would gradually become aware of the disappointing results of conglomerate and unrelated acquisitions or mergers cooperative activities might become more important as a mechanism for the thorough scanning of partners without the far reaching effects as with instant integration.

THE MODEL, DATA AND RESULTS

A general framework for the explanation of the relation between strategic alliances and economic performance

In order to improve our understanding of the effects of strategic technology alliances on corporate performance we developed a path model which places strategic technology alliances, i.e., external linkages of firms, in a wider set of interrelated factors. Figure 1 shows the general explanatory framework in the form of a path diagram where an arrow indicates an assumed direct effect from one factor on another. A brace suggests there is a relation that we do not want to investigate further. For the analysis of this path model and the interrelated factors we apply a specialized approach of the more generic form of path analysis which was developed by Jöreskog (1977) who labeled it linear structural relations modelling (LISREL). In spite of the title of our article which indicates a bivariate relationship it is necessary to adopt this bivariate
relationship in a (multivariate) LISREL model. Since a number of relationships can be two-way we postulated a number of reciprocal relations in the model, but none of them appeared significant. We reran the models on different data-sets, see Hagedoorn and Schakenraad (1991) which revealed a number of general results. Specifics about path analysis and the choice of model are discussed extensively in Appendix 1.

In the simplified explanatory framework as set out above the economic performance by companies depends on five basic (groups of) factors.

— The economic performance of the firm is represented by its net income to sales ratio or profit rate, indicated as PR. We use the average share of net income in total sales over the years 1984–88. This indicator has certain drawbacks, in particular it is sensitive to the degree of vertical integration or sectoral differences, see Davis and Kay (1990) and Ansoff and McDonnell (1990). As our sample has only manufacturing and no service companies and as we control for industry differences we have been able to substantially meet the shortcomings that this indicator generally has.

— We study three broad industrial sectors. The information technologies and electronics (IT) sector comprises firms of which key activities lie in one or more of the following fields: microelectronics, computers, industrial automation, telecommunications, instrumentation, consumer electronics and heavy electrical equipment. The mechanical engineering (ME) field covers automotive, aviation, and defense companies. Oil- and (petro)chemicals corporations, chemicals, pharmaceuticals, and food and beverages producers are classified as process industries (PI).

— In this paper the country of origin of the corporation plays also an important role. We focus on European, American, and Japanese companies that build the three major economic blocks that together form the so-called TRIAD (Ohmae, 1985). EC and EFTA-based companies are regarded as European firms.¹

— The size of firm during the period 1980–86 is measured by weighing two indicators, the first being the log₁₀ of average worldwide employment, the second one is the log₁₀ of average turnover. Logarithms are taken to correct potential disturbing influences of a small number of extremely large companies. Factor analysis is applied to the indicators in order to derive the principal factor, the factor that accounts for the greatest part of the covariance of the indicators.

¹ The countries from the European Free Trade Association (EFTA) are: Austria, Switzerland, Finland, Iceland, Sweden, and Norway. The EC-member countries are: Belgium, Denmark, Federal Republic of Germany, France, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, and the United Kingdom.
factor-scores of the companies on the principal factor are used to arrive at a new variable called SIZE.

- The innovativeness of the firm is assessed by its patent intensity (PATINT), i.e., the total number of assigned U.S. patents set against the firm’s average turnover over the years 1982–86. The use of U.S. patents as a reliable metric of innovativeness of international companies is widely accepted in the literature, see Patel and Pavitt (1991) for brief discussion. Unfortunately, we could not apply R & D intensity for our sample because this information is missing for a large number of European and Japanese companies.

- The phenomenon of strategic partnering and technology cooperation will be dealt with by measuring three variables. The intensity or the weight of strategic partnering (WSPART) is defined as the natural logarithm of the following ratio: the firm’s total number of strategic linkages (dyads) over the period 1980–87, set against the natural logarithm of average turnover over the years 1982–86. In order to count the total number of dyads of a firm, all alliances were split up in the following way. An alliance between two partners (A and B) gives one dyad (A-B); a project with three partners, called A, B and C, results in three different dyads (A-B, A-C and B-C), etcetera.

To examine the content of a strategic link, we define the technology-to-market ratio (T/M) as being the log10 of the ratio between the firm’s total number of prevailing R & D inclined strategic linkages and its total number of predominantly ‘market-related’ strategic linkages. By taking the log10 form we accomplish that zero is a neutral score indicating equal weight for the technology and the market aspects of strategic cooperation. A positive value marks an inclination towards ‘pure’ technology cooperation; negative scores indicate a dominance of motives primarily related to market access and influencing the market structure.

The variable pertaining to the direction of the firm’s external linkages is the generation to attraction ratio. This ratio (G/A) is the log10 of the ratio between the total number of ‘generative’ strategic linkages and the firm’s total number of ‘absorptive’ or ‘attractive’ linkages. The term ‘generation to attraction’ ratio suggests some kind of flow. It can therefore only be computed on the basis of directed linkages. Approximately one-third of all strategic linkages that we registered are found to be directed in one way or another. As directed links we regard strategic equity investments, strategic second-sourcing arrangements and research contracts. Other strategic alliances having unidirectional technology flows are for instance joint ventures with OEM contracts, or the joint improvement of technology that one partner has originally developed. The generation to attraction ratio allows to find ‘generators’, i.e., firms that, within the context of directed strategic links, supply technology. On the other hand, ‘attractors’ are firms that generally speaking award contract research, make equity investments, or join technological developments started by others.

The main source for our empirical research is the Cooperative Agreements and Technology Indicators (CATI) information system. This data bank is a relational data base which provides information on nearly 10,000 cooperative agreements involving some 3500 different parent companies. Systematic collection of interfirm alliances started in 1987. If available, many sources from earlier years were consulted enabling us to take a retrospective view. In order to collect interfirm alliances we consulted various sources, of which the most important are newspaper and journal articles, books dealing with the subject, and in particular specialized journals which report on business events. Company annual reports, the Financial Times’ Industrial Companies Yearbooks and Dun & Bradstreet’s ‘Who Owns Whom’ provide information about dissolved equity ventures and investments, as well as ventures that we did not register when surveying alliances.

This method of information gathering which we might call ‘literature-based alliance counting’ has its drawbacks and limitations:

- in general we have only come to know those arrangements that are made public by the companies themselves
- newspaper and journals reports are likely to be incomplete, especially when they go back in history and/or regard firms from countries outside the scope of the journal; furthermore, in earlier years some journals simply did not exist whereas existing periodicals might grasp the collaboration subject less thoroughly
- a low profile of small firms without well-
established names is likely to have their collaborative links excluded

— some journals emphasize fashionable items, such as superconductivity or HDTV, while interest for 'outdated' topics such as solar and wind energy seems to fade away

— the fact that most articles we consulted are written in English probably causes some bias and distortion, too

— another problem is that information about the dissolution of agreements is not systematically published; this is in particular true for licensing and customer–supplier relationships, on the other hand, research contracts and joint product developments have often disclosed time schedules, equity joint ventures and divestments are published rather systematically in specialized journals

— one final problem is that the number of customer–supplier relations and licensing agreements is subject to a fierce underestimation due to the fact that these more casual agreements are little reported publicly, even in the professional literature.

All together these handicaps in the first place lead to a skewed distribution in the distribution of modes of cooperation, followed by some geographic—i.e., Anglo-Saxon—bias. Next, we have to reckon with a possible underestimation of certain technological fields not belonging and finally, there is some overrepresentation of large firms.

Despite these shortcomings, which are largely unsolvable even in a situation of extensive and large-scale data-collection, we think we have been able to produce a clear picture of the joint efforts of many companies. This enables us to perform empirical research which goes beyond case studies or general statements. Some of the weaknesses of the data base can easily be evaded, as done in this paper, by focusing on the more reliable parts, such as strategic alliances (see Appendix 2).

The data bank also contains information on each agreement and some information on companies participating in these agreements. The first entity is the interfirm cooperative agreement. We define cooperative agreements as common interests between independent (industrial) partners which are not connected through (majority) ownership. In the CATI data base only those interfirm agreements are being collected, that contain some arrangements for transferring technology or joint research. Joint research pacts second-sourcing and licensing agreements are clear-cut examples. We also collected information on joint ventures in which new technology is received from at least one of the partners, or joint ventures having a R & D program. Mere production or marketing joint ventures are excluded. In other words, our analysis is primarily related to technology cooperation. We are discussing those forms of cooperation and agreements for which a combined innovative activity or an exchange of technology is at least part of the agreement. Consequently, partnerships that regulate the sharing of production facilities, the setting of standards, collusive behavior in price-setting and raising entry barriers are omitted, although all of these may be side effects of interfirm cooperation.  

The assumed interrelations of the variables

The versatility of LISREL with respect to the specification of cause and effect variables is one reason for its use, see Appendix 1. As a consequence, the interrelations of all variables in the model need clarification about their strength and direction. In the effect matrix, see Table 1, we indicate the expected direct effects of a number of variables on each other. The anticipated effects that we mention are due to either logical association, established knowledge in the literature, chronological consistency, or a combination of these. We will discuss the plausibility of such a direct effect for each potential relation in the effect matrix. The effect matrix does not include sectoral and national particularities (SECTOR and TRIAD) as effect variables because these are treated as exogenous variables.

Sector-specific circumstances

The intensity of strategic partnering is not independent of sectoral features. Cross-sectoral research shows that the number of strategic technology alliances is far from uniformly distributed over technological fields. Also, differences in profitability and patent intensity

2 More extensive description of the data bank can be obtained from the authors.
of industries are well established stylized facts. From recent studies on the relation between market structure and innovation we learn that technological opportunities differ with industries and these technological opportunities largely explain differences in innovative performance, see for instance Cohen and Levin (1989) and Hagedoorn (1989).

Differences due to the nationality of the firm

‘National’ differences in patenting behavior can be anticipated. For instance, an indirect measure of the growing technical competence of Japanese companies can be found in their sharply rising number of assigned U.S. patents.

In the literature on strategic partnering the role of the ‘Triad’ is stressed to emphasize that cooperation between companies takes place not only within blocks but also between blocks of the Triad (Ohmae, 1985). However, it would be misleading to suggest a uniform distribution of alliances across these blocks. A first exploration of our own data shows indeed a skewed distribution. In the present research we present the results of a cross-firm, multivariate analysis which can tell whether for instance Japanese firms are generally less inclined to cooperation strategies than their European and American competitors.

We also assume a differentiation of profit rates for European, American, and Japanese companies. Japanese companies are expected to have relatively lower rates of profits than for instance U.S. firms. Possible explanations deal with currency issues, different attitudes with respect to dividends and profits, the Japanese preoccupation with growth strategies, short-run profit maximizing behavior of U.S. firms, and the almost absence of a highly profitable pharmaceuticals industry in Japan.

The effects of size of the firm on innovation and patent intensity, cooperation and profitability

We expect a direct effect of size on the intensity of strategic partnering. Berg et al. (1982) found that size of the firm has a positive effect on joint venture participation. This correlation can simply be explained by better and more opportunities to seek external linkages for instance through economies of scope. Large firms may also be attractive or even indispensable partners. However, small high-tech firms are likely to possess desirable characteristics as a partner as well. Therefore, for at least a number of sectors
we expect some J-shaped relation between size and strategic partnering as found in Hagedoorn and Schakenraad (1990c). Concerning the size of companies and innovation a direct effect of size of companies is assumed. However, a number of qualifications are necessary for this effect, see for instance Hagedoorn (1989). In the classical Schumpeterian and Galbraithian theory research output (patent-intensity) increases more than proportionally with firm size. The classical counter-argument is provided by Bain (1956), who stated that small companies were more innovation-efficient, whereas larger firms suffer from ‘creative backwardness’. Others, for instance Freeman (1982), mention industry-specific circumstances with a positive relationship between size and innovation in R & D intensive industries and/or industries where economies of scale are decisive, for instance pharmaceutical, aerospace, vehicles. Widely accepted is the view by Scherer (1965) that both R & D input and output (patents) tend to rise less than proportionally once a threshold has been passed, which leads to an ‘inverted U-shape’ distribution of size and innovation. Empirical studies by Mansfield (1984), Philips (1971), and Mueller (1986a) support this view of nonlinearity, usually with the exception of the chemical industry where a linear relationship is found. Some qualifications are found in Scherer (1984), where it is stated that there are diminishing returns in the relation between firm size and patent-activity.

Recent contributions stress the relevance of technological opportunities as an intermediary factor, see Kamien and Schwartz (1982) and Cohen and Levin (1989). Dosi (1984) stresses the dynamic relation between innovation, market structure and size of firms. His hypotheses suggest that the degree of innovativeness is a positive function of the technological opportunities in industries, whereas market concentration is a positive function of past innovativeness and a negative function of technological opportunity, with innovativeness being a positive function of firm size. This makes the relation between size of firms and innovation dependent on the intersectoral pattern of technological opportunities. Following this Pavitt, Robinson, and Townsend (1987) suggest a general U-shaped relation between size and innovation with considerable variation among sectors.

Despite some effect of decreasing propensity to patent with increasing firm size, see Schmoolker (1966), Pavitt et al. (1987), Soete (1979), we still expect a direct effect of the size of companies on their patent intensity. A direct effect of size of companies on profitability of companies is not anticipated. A number of surveys of older and more recent studies suggest that there is no general relation between both variables, see Schmalensee (1989), Devine et al. (1986), Hay and Morris (1979), an exception is found in Berg et al. (1982).

The effect of patenting on cooperation and profitability

We assume that innovative firms are attractive partners for strategic partnering. Therefore, patent intensity of companies is expected to affect the intensity of strategic alliances of companies in the years 1980–87. A direct effect of patent intensity in the years 1982–86 on the intensity of strategic alliances from 1980–87 is possible as most of these alliances have been formed since 1984. This expectation of a high correlation between patent intensity and the intensity of alliances is based on a number of characteristics of interfirm cooperation. In Hagedoorn (1993) and Hagedoorn and Schakenraad (1990c) it is found that technological complementarity of partners, concrete development of innovations and the need for technology monitoring are important motives for forming strategic alliances. Therefore technologically capable companies are to achieve a higher degree of ‘courtship’ than less innovative companies. Such an assumption is supported by e.g. the work of Hladik (1985; 1988) who found that positive effects on successful cooperation in joint ventures and the occurrence of cooperation are amongst other things related to the similarity of partners with respect to technical assets. Link and Bauer (1989) report that the more innovative an industry the larger the funds for cooperative endeavors.

We expect patent intensity of firms in the years 1982–86 to have a moderately positive effect on the rate of profit for companies in the years 1984–88. Patent intensity is an indicator of innovativeness which is expected to generate ‘Schumpeterian’ short-term monopoly-rents that
raise the rate of profit for the innovating company, see Scherer (1984).

**The effect of strategic alliances on innovation and patenting**

In theory the degree of cooperation should affect the innovativeness of large groups of companies as improving innovative performance is to be seen as one of the major objectives of strategic interfirm collaboration. However, most of the alliances in our data bank have been forged since the mid-eighties and with an average period of 2 years for patent approval the periodization for both variables prohibits a testing of such a direct effect.

**The relation between strategic alliances and rate of profit**

It is expected that a high intensity of strategic partnering, in particular for 'attractors' during 1980–87, is transformed into an increase of turnover with a time-lag of 1–4 years. Through alliances companies acquire new skills, have access to new markets and improve their overall performance which generates a growth in turnover.

Concerning possible effects of profit rate on collaboration we recall that within the present analysis we do not expect any effect of profit rate on other variables, also because the different time intervals do hardly allow for such relations.

**Results**

For the empirical investigation of the effects of the variables discussed above we apply a sample comprising 346 corporations from the U.S.A., Japan and Europe in information technologies and electronics, mechanical engineering and process industries which have achieved minimum average annual sales of $1,000 million over the years 1982–86, see Appendix 3 for the distribution of sub-populations in the sample.

The LISREL path diagrams are shown in Figures 2A and 2B. The data reveal the following:

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3 We present two path diagrams because one cannot specify all dummy variables in a single model as this would generate perfect linear dependencies. Dummy variables and dummy

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- Patent intensive, i.e., innovative corporations, are heavily involved in strategic partnering.
- Information technology firms have a higher cooperation intensity, while process industries have lower inclination to cooperate. Patent intensity (PATINT) acts as an intermediary variable between sectors (IT, PI) and cooperation intensity (WSPART).
- It is clear that U.S. firms are on average larger and moreover, they are definitely not more inclined to strategic cooperative strategies than the Japanese and European. Although Europe, the U.S.A. and Japan have different average strategic partnering intensities, this relationship dissolves at the multivariate level when controlling for the intervening variable of size. Our 'Triad' sample of largest enterprises comprises Japanese firms that are on average smaller and this is precisely the explanation for the lower Japanese cooperation intensity.
- European firms are more 'absorption'-oriented. An interesting finding is that Japanese firms, contrary to popular beliefs, on average appear to have more 'generative' strategic linkages, rather than 'absorptive' linkages.

An interesting point to be discussed somewhat more extensively is the effect of firm size on the intensity of strategic partnering and technology cooperation. The estimated equations all show that the intensity of strategic partnering, as measured through the firm's weighted number of linkages, tends to rise with the average size of companies. So, despite our attempt to reduce the large firm bias, larger firm size is still associated with higher strategic partnering rates. In other words, firm size reflects the degree to which firms actively seek and find external opportunities in strategic linkages. We think a codings are included to measure sectoral and 'Triadic' features. In the path diagrams normal lines represent direct effects that are found to be significantly different from zero at the 0.05 level. The estimated coefficients on the effects are put next to the lines. If indirect effects can be computed, the total effects are placed in between brackets. Since our purpose is to generate a parsimonious, yet statistically acceptable overall model, we may be forced to include some insignificant effects, or effects 'marginally significant' at the 0.10 level; these effects are indicated with dashed lines. Finally, for each effect variable the multiple determination coefficient or $R^2$ will be presented. Insignificant $R^2$ are placed in between brackets (0.05 level).
number of factors can explain this strong positive effect of size on cooperation intensity:

— size of firms partly reflects their degree of diversification which broadens their basis for potential cooperation with other firms,
— absolute size can be considered a relevant proxy of barriers to entry as a large number of strategic alliances will be foreclosed to smaller firms due to economies of scale in R & D and capital intensity of the ventures,
— forging alliances takes substantial administrative, organizational and monitoring support, the support of a staff for these particular activities is usually only available to large firms,
— if size is already related to an existing high network density self-enforcing dynamics of cooperation can easily create new opportunities for new linkages,
— technological development is frequently characterized by certain absolute ‘thresholds’ in terms of a minimum level of expenses and other inputs, cooperation will lower these thresholds for individual partners, although not necessarily proportionally; for many small firms these thresholds, together with some of the other barriers mentioned above, will still set substantial restraints for their chances of benefitting from cooperation with larger firms or even entering these agreements,
— although firms of all sizes will occasionally be engaged in a process of restructuring, in particular large firms are more suited to channel their restructuring activities through joint ventures and other forms of interfirm cooperation, and finally
— large multinational firms with a number of international production sites and research centers are more likely to be involved in all kinds of ‘multidomestic’ partnerships than less geographically spread firms.

Table 2 summarizes the findings from LISREL path diagrams for separate economic blocks and industrial branches. The conclusions are as follows:

— there is a general and strong tendency for the intensity of strategic partnering to increase with size of firm—the larger the firm, the more it ‘absorbs’, this holds in particular for European information technology firms and Japanese process industries
— for European and Japanese firms in information technology and all process industries, a high patent intensity produces a strong positive impact on the propensity to establish strategic alliances
— U.S. corporations in information technology and mechanical engineering that are heavily involved in strategic partnering are more inclined towards R & D cooperation
— European information technology firms heavily involved in strategic partnering are inclined to engage more in attracting than in generating technological knowledge through their alliances
— as far as the relation between strategic technology partnering and profitability is concerned disaggregated analyses show some divergent patterns:
  • the generation to attraction ratio influences profitability in particular for U.S. mechanical engineering firms,
  • for European and American process industries there is a positive association between R & D-driven cooperation and profitability.

CONCLUSIONS

It is obvious that statistical research can capture only particular features of complex phenomena such as the one studied in this paper. Our research generates no straightforward relations between strategic technology partnering and company performance, but we have been able to improve our understanding of the effects of strategic technology alliances.

Regarding the relation between firm size and strategic partnering and profitability, and some ‘Schumpeterian’ issues on the influence of firm size on innovation, we found no general significant direct effects of size on profitability. Also, quite in accordance with some of the theoretical contributions that we briefly mentioned, different types of industries show divergent relations between size and innovation.

It appears that in contrast with the impact of the extent and intensity of cooperation, there is evidence that the content and direction of strategic linkages do significantly influence profitability in several industrial branches. The results indicate that companies attracting technology through their alliances and companies concentrating on
R & D cooperation have significant higher rates of profit. In other words, the use made of strategic technology alliances appears to be more relevant to improving corporate performance than just having alliances or being in the core of a network. In our opinion these results clearly qualify earlier findings on the effect of cooperation on profitability reported above. One particular generalization to be made is that the intensity of strategic partnering tends to
Table 2. Summary of findings from LISREL analyses of economic blocks and industrial branches

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<td>ME 0 (+) 0 0 0 0 0 0 0 0 + 0 0</td>
<td>PI 0 0 0 0 0 0 0 0 0 + + 0</td>
<td></td>
</tr>
<tr>
<td>ALL all 0 + 0 0 0 0 0 0 0 0 + + 0</td>
<td>IT 0 (+) 0 0 (+) 0 0 0 (+) 0 0 0 0 + 0 0</td>
<td>ME 0 0 0 0 0 0 0 0 0 0 + 0 0</td>
<td>PI 0 + 0 0 0 0 0 0 0 + + 0</td>
<td></td>
</tr>
</tbody>
</table>

0 = no relation
+ = significant positive relation (0.05 level)
(+) = marginally significant positive relation (0.10 level)
− = significant negative relation (0.05 level)
(−) = marginally significant negative relation (0.10 level)
rise with the increasing size of companies. In other words, firm size reflects the degree to which firms actively seek and find external opportunities in strategic linkages.

Although our present analysis does not show a direct impact of strategic alliances on economic performance, it certainly does not demonstrate as negative results as found in the research on mergers and acquisitions. It should be stressed that in general the R & D inclination of a firm's strategic linkages, and the firm's patent intensity all are associated with high economic performance. Differences in technological opportunities play a decisive role in explaining the R & D inclination of strategic partnering and patent intensity of firms. Such findings can be interpreted in analogy to the analysis of the effects of market structure and firm size on innovation where 'technological opportunities' were found to be a decisive intermediary variable. Apparently the crucial relation between strategic technology partnering and profitability of firms is of an indirect character which can to a large extent be explained by the differentiation of firms and sectors with regard to these technological opportunities.

APPENDIX 1: A GENERAL NOTE ON LISREL AND PATH ANALYSIS

LISREL is a general computer program for estimating parameters in a set of linear equations. It may be used for the analysis of causal models with multiple indicators of latent variables or factors and reciprocal causation in nonrecursive models. Specific arrangements can be made for time series analysis and multi-sample comparisons, see Jöreskog (1977) and Jöreskog and Sörbom (1977). Generally speaking one should compare LISREL to path analysis rather than making a separate comparison with factor or regression analysis. In fact, a LISREL specification may include both (elements of) regression as well as factor equations. LISREL is a very versatile approach that may be used for the analysis of causal models with multiple indicators of latent variables, reciprocal causation, measurement errors, correlated errors to name but a few. In traditional path analysis the validity of the method was based on a set of very restrictive assumptions, such as variables are measured without error, residuals are not intercorrelated, the causal flow is unidirectional. LISREL is a more sophisticated and more general way of analyzing causal relations. We did not adopt regression analysis with a measure of performance for the following reasons:

— Multicollinearity may lead to difficulties in assessing the significance of the effect of parameters and of the model as a whole, the higher the intercorrelations, the larger the standard errors of the parameters. In general, this reduces the number of statistically significant parameters. It may even turn out that none of them is significant. From a technical point of view, of course, it is always possible to circumvent problems arising from multicollinearity by using factor analysis (or principal component analysis) in order to create a set of fully independent cause variables. Theoretical notions and the way in which theoretical concepts are measured may block such solutions. Therefore, it is preferable to use a model that allows greater flexibility with respect to the specification of cause variables.

— A potential statistical problem in multiple regression is heteroscedasticity. The effect of heteroscedasticity is to reduce the precision of the estimated relationship: the standard error of the parameter increases thereby weakening the significance. LISREL breaks the error term in two parts, a disturbance term which indicates the effect of variables not in the equation, and a measurement error term which specifies random measurement errors. This splitting up of the error term provides a possible corrective for heteroscedasticity.

— In multiple regression no distinction is made in direct and indirect effects. LISREL offers the possibility to decompose a total effect into direct and indirect effects.

In the measurement part of the model LISREL offers a data reduction technique comparable with factor analysis. The measurement model specifies the relations between 'unobserved' or latent variables known as factors in factor analysis, or constructs, and 'observed' or manifest variables, also called indicators. Two equations describe this model. The relation between endogenous latent constructs and their indicators is written as:
\[
\begin{align*}
\mathbf{y} &= \mathbf{\Lambda}_y \mathbf{\eta} + \mathbf{\epsilon} \\
\mathbf{\eta} &= \mathbf{B} \mathbf{\eta} + \mathbf{\Gamma} \mathbf{\xi} + \mathbf{\zeta}
\end{align*}
\]

where:
\( \mathbf{y} \) = a vector of \( p \) indicators of \( m \) endogenous variables
\( \mathbf{\Lambda}_y \) = a matrix of coefficients, or loadings, of the \( p \) indicators on the \( m \) endogenous variables
\( \mathbf{\epsilon} \) = a vector of errors of measurement of \( \mathbf{y} \)

In the LISREL terminology, exogenous variables act only as independent variables; whereas endogenous variables are dependent variables, or act as both dependent as well as independent variables. In LISREL, endogenous variables are designated as \( \eta \)'s, and exogenous variables as \( \xi \)'s.

The relation between exogenous latent constructs and their indicators is then written as equation (2):
\[
\mathbf{x} = \mathbf{\Lambda}_x \mathbf{\xi} + \mathbf{\delta}
\]

where:
\( \mathbf{x} \) = a vector of \( q \) indicators of \( n \) exogenous variables
\( \mathbf{\Lambda}_x \) = a matrix of coefficients, or loadings, of the \( q \) indicators on the \( n \) exogenous variables
\( \mathbf{\delta} \) = a vector of errors of measurement of \( \mathbf{x} \)

The lambda (\( \Lambda \)) matrices in equations (1) and (2) correspond to the pattern matrix in factor analysis, giving the factor loadings or direct contributions of a latent variable to explain the variance of a variable.

The structural equations part of the model, which is presented in (3), refers to relations among exogenous (\( \xi \)) and endogenous (\( \eta \)) variables.

\[
\mathbf{\eta} = \mathbf{B} \mathbf{\eta} + \mathbf{\Gamma} \mathbf{\xi} + \mathbf{\zeta}
\]

where:
\( \mathbf{\eta} \) = a vector of \( m \) endogenous variables
\( \mathbf{B} \) = a coefficient matrix representing the direct effects of \( m \) endogenous variables on each other
\( \mathbf{\Gamma} \) = a matrix of coefficients of the effects of \( n \) exogenous variables on \( m \) endogenous variables
\( \mathbf{\xi} \) = a vector of \( n \) exogenous variables
\( \mathbf{\zeta} \) = a vector of \( m \) residuals giving errors in the equations

When inspecting equations (1), (2) and (3) a total of four matrices of coefficients can be distinguished: \( \mathbf{\Lambda}_y, \mathbf{\Lambda}_x, \mathbf{B}, \) and \( \mathbf{\Gamma} \). Furthermore, we have to deal with four covariance matrices. One of them is the covariance matrix of the latent exogenous variables called \( \Phi \). The remaining relate to residuals and measurement errors, viz. \( \Psi \) which is the covariance matrix of the residuals \( \xi \), and \( \Theta_e \) and \( \Theta_\varepsilon \), the covariance matrices of the errors of measurement of \( \mathbf{y} \) and \( \mathbf{x} \), successively.

There are three kinds of elements in the eight matrices of coefficients and covariance or parameters of the model:
- fixed parameters that have been assigned given values
- constrained parameters that are unknown but equal to one or more other parameters,
- free parameters, that are also unknown but not constrained to be equal to any other parameter.

Finally, the assumptions under which the model holds are:
- \( \mathbf{\epsilon} \) is uncorrelated with \( \mathbf{\eta} \)
- \( \mathbf{\delta} \) is uncorrelated with \( \mathbf{\xi} \)
- \( \mathbf{\zeta} \) is uncorrelated with \( \mathbf{\xi} \)
- \( \mathbf{\xi}, \mathbf{\epsilon}, \text{and} \mathbf{\delta} \) are mutually uncorrelated
- the diagonal elements of \( \mathbf{B} \) are zero

On the basis of these assumptions the covariance matrix of the observed variables (\( \Sigma \)) is a function of the eight matrices of coefficients and covariance mentioned above. If we list the \( \mathbf{y} \) variables first, and then the \( \mathbf{x} \) variables, the implied covariance matrix of the observed variables can be written as:

\[
\begin{bmatrix}
\Sigma_{yy} & \Sigma_{yx} \\
\Sigma_{xy} & \Sigma_{xx}
\end{bmatrix}
\]

It can be shown that \( \Sigma \) can be calculated as (5), see Hayduk (1987) for detailed calculations:

\[
\begin{bmatrix}
\Lambda_y (I - \mathbf{\Gamma}^\top \mathbf{\Phi} \mathbf{\Gamma} + \Psi) (I - \mathbf{\Gamma}^\top \mathbf{\Phi} \mathbf{\Gamma})^{-1} \Lambda'_y + \Theta_e \Lambda_y (I - \mathbf{\Gamma}^\top \mathbf{\Phi} \mathbf{\Gamma})^{-1} \mathbf{\Phi} \Lambda'_y \\
\Lambda_x (I - \mathbf{\Gamma}^\top \mathbf{\Phi} \mathbf{\Gamma})^{-1} \Lambda'_x + \Theta_e \Lambda_x (I - \mathbf{\Gamma}^\top \mathbf{\Phi} \mathbf{\Gamma})^{-1} \mathbf{\Phi} \Lambda'_x
\end{bmatrix}
\]

For instance, the lower right element of (4) can be written as:

\[
\Sigma_{xx} = \text{cov} (\mathbf{x}, \mathbf{x}) = \text{cov} (\Lambda_x \mathbf{\xi} + \mathbf{\delta}, \Lambda_x \mathbf{\xi} + \mathbf{\delta}) = \text{cov} (\Lambda_x \mathbf{\xi}, \Lambda_x \mathbf{\xi}) + \text{cov} (\Lambda_x \mathbf{\xi}, \mathbf{\delta}) + \text{cov} (\mathbf{\delta}, \Lambda_x \mathbf{\xi}) + \text{cov} (\mathbf{\delta}, \mathbf{\delta})
\]

\[
= \Lambda_x \text{cov} (\mathbf{\xi}, \mathbf{\xi}) \Lambda'_x + \Lambda_x \text{cov} (\mathbf{\xi}, \mathbf{\delta}) + \mathbf{\delta} \text{cov} (\Lambda_x \mathbf{\xi}, \mathbf{\delta}) + \text{cov} (\mathbf{\delta}, \mathbf{\delta})
\]
\[ \text{cov}(\delta, \xi) \Lambda_x' + \text{cov}(\delta, \delta) = \Lambda_x \Phi \Lambda_x' + \Theta_{\delta} \]

To arrive at estimates of elements of the matrices Jöreskog (1977) suggests three iterative methods: unweighted least squares (ULS), general least squares (GLS), and maximum likelihood (ML) estimation, using starting values produced by either the specification of instrumental variables or a two-stage least squares (TSLS) method. In this study the ML estimator will be applied.

The LISREL program should solve the parameters from information supplied by the observed covariance matrix, which can also be a correlation matrix. However, the problem of identification might block a unique solution for the values of the parameters. Identification refers to whether or not the set of parameters is uniquely determined by the observed data. If there is more than one way to calculate a particular parameter, which in general will lead to different values, the coefficient is not identified. A necessary condition for solving unknowns in equations is that the number of unknowns should be equal or less than the number of distinct equations. In other words, the degrees of freedom should be equal or larger than zero. Since there are \( n(n+1) \) equations in the case of \( n \) observed variables, a necessary condition for identification is found in Equation (6),

\[ S \leq \frac{1}{2} n (n + 1) \] (6)

where \( S \) is the number of unknown elements. There are also rules for sufficient conditions for identification, but their formulation is rather complex. A first rule of thumb is that, if the model is identified, the input matrix is almost certainly positive definite. Further information is provided by Saris and Stronkhorst (1984), Hayduk (1987), Gujarati (1988), and the work of Jöreskog (1977) and Jöreskog and Sörbom (1977).

Once procedures for testing identification have been followed, the significance of both model and parameters can be assessed. The program gives a number of indicators for the goodness of fit of the measurement model and structural model, the model as a whole, and the individual parameters.

Dividing an estimated parameter by its standard error yields a critical ratio which has an approximate \( z \)-distribution. These critical ratios are labeled as \( t \)-values. Small \( t \)-values indicate that the coefficients associated with them may be deleted, thereby arriving at a more parsimonious model. Tables of normal probabilities can be used to create confidence intervals of any desired accuracy. Absolute \( t \)-values of 1.96 and higher indicate a 95 percent confidence interval for the corresponding population parameter which means that we can reject the null hypothesis of a zero parameter. With respect to the interpretation of the parameters, we can say that they represent the direct effect of a one unit change of the cause, when all other variables are held constant. However, we should not only concentrate on the direct effects between variables when we interpret a LISREL solution or a path diagram, but also compute the indirect effects, for computation of indirect effects between variables, see for example Saris and Stronkhorst (1984). The total effect of a cause on an effect variable, then, is defined as the sum of direct and indirect effects.

In order to check whether the endogenous variables in the model have sufficiently been accounted for, we report the squared multiple correlation coefficient for each endogenous variable. This coefficient is also known as the coefficient of determination \( (R^2) \).

The overall fit of the model will be judged by the well-known chi-square \( (\chi^2) \) measure. It is computed on the basis of differences between observed and predicted values, in this case being covariances or correlations. Given comparable degrees of freedom, relatively small \( \chi^2 \) values indicate that the model closely fits the observed data, while relatively large values point out that the model is empirically inadequate. To be used as a test statistic all observed variables should have a multinormal distribution and the size of the sample must be fairly large. Since we want to test the differences between the observed and predicted \( \Sigma \), and find a model acceptable if no real difference exists, \( P \) values below 0.05 reject the model. This principle differs radically from the analysis of crosstabulations where we use \( \chi^2 \) to test significant relationships between nominal variables. Here, a \( P \) value of 0.05 and below indicates a significant relationship.

It has to be stressed that LISREL requires endogenous variables to be measured at least on an interval scale. For ordinal variables, specific correlation coefficients can be used to reflect the strength of their relationships. The specification of
variables of the nominal level is also possible if two conditions hold:
— they are specified as exogenous, coded dummy variables, LISREL is then only concerned with conditional distributions for given x,
— all exogenous variables are manifest, i.e., each exogenous variable is measured by one single indicator without specifying error of measurement, see Hayduk (1987).

If there are nominal variables, their values can be used to create groups in a multisample LISREL analysis. One can check whether model specifications for one subgroup also result in a significant model for the other data sets, or whether the same parameters differ significantly in different subsets. This approach is particularly useful in comparing experimental and control groups. In the present research aimed at the explanation of the economic performance of companies, we could, for instance, check the suitability of a model in one particular branch for other branches. The first problem, however, is the absence of a clear reference branch. Should we depart from the chemical industry, or from electronics, or from some kind of average model for all branches? A second problem is that we do not have a priori knowledge with respect to intersectoral differences in relations among causes and effects. The conclusion is that designing of parsimonious, LISREL models with acceptable fits for separate branches is preferred to multisampling LISREL. Results of these separate analyses can be compared in order to achieve a multisectoral analysis.

APPENDIX 2: ORGANIZATIONAL MODES OF INTERFIRM COOPERATION, THEIR UNDERLYING MOTIVES, AND A DEFINITION OF STRATEGIC ALLIANCES

As primary modes of cooperation we distinguish between joint ventures and research corporations, joint R & D agreements, technology exchange agreements, direct investment, customer-supplier relations and one-directional technology flows. All these modes of cooperation have different impacts on the character of technology sharing, the organizational context and the possible economic consequences for participating companies (see Contractor and Lorange, 1988; Hagedoorn, 1990). We refer to joint ventures and research corporations as combinations of the economic interests of at least two separate companies in a 'distinct' firm; profits and losses are usually shared according to equity investment. Joint R & D refers to joint research pacts and joint development agreements which establish joint undertaking of R & D projects with shared resources. Technology exchange agreements cover technology sharing agreements, cross-licensing and mutual second-sourcing of existing technologies. Some equity investments can be seen as a form of cooperation between companies which in the long run could affect the technological performance of at least one 'partner'. Minority stakes, especially those by a large company in a smaller 'high tech' company, can be understood as a case of cooperation, in particular if such minority sharing is coupled with research contracts. Under customer-supplier relationships we have joined those categories of agreements through which contract-mediated collaboration in either production or research is established. These customer-supplier relationships can be divided into a number of forms of partnership such as coproduction contracts, co-makership relationships, and research contracts that regulate R & D cooperation in which one partner, usually a large company, contracts another company, frequently a small specialized R & D firm, to perform particular research projects. Finally, there are unilateral technology flows such as second-sourcing and licensing agreements.

We also have to make a distinction between cooperative agreements which are aimed at the strategic, long-term perspective of the product market positions of the companies involved and cost-economizing agreements which we think are more associated with the control of either transaction costs or operating costs of companies. In case both strategic and cost-economizing arguments appear possible, either because it is not feasible to differentiate between the cost or the strategic argument or because partners can be expected to have alternating motives as a consequence of the character of the agreement, we consider such agreements of a mixed character. Although there is no strict correlation between organizational modes of cooperation and their strategic or cost-economizing content, we think some modes of cooperation are more strategically motivated whereas others tend to be more oriented towards cost-economizing. We esti-
mate that e.g., R & D joint ventures, research corporations joint R & D agreements and equity investments are for over 85 percent strategically motivated (see Hagedoorn and Schakenraad, 1990b). Compared with this only a small portion of the technology exchange agreements, one-dimensional technology flows and customer–supplier relationships are strategically motivated, with the exception of a subgroup within the latter mode, i.e., research contracts, which we expect to be at least partly strategically motivated.

In our assessment of the strategic implications of cooperative agreements between companies each agreement is valued according to its strategic or cost economizing content. We also distinguish two broad groups of motives:
— motives directly related to basic and applied research;
— motives directly related to market access and structure of the market.

This distinction enables us to select strategic alliances and next, determine the content of each strategic alliance: whether it is predominantly research oriented, or primarily market oriented. We call this R & D/Market dichotomy the 'technology to market ratio', designated as T/M.

A detailed overview of the 'scoring procedure' can be obtained from the authors, see also Hagedoorn (1993) and Hagedoorn and Schakenraad (1990c).

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