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TIIVISTELMÄ

Tämä tutkimus tarkastelee Suomen yrityskauppoja vuosina 1994–1999. Tutkimuksessa analysoidaan erityisesti yrityskauppojen syntyyn vaikuttaneita tekijöitä. Näissä tekijöissä kiinnitetään erityinen huomio uuden teknologian tuottamiseen ja hyödyntämiseen. Tutkimuksessa testataan empiirisesti, vaikuttavatko yrityksen hallussa olevat innovaatiot yrityskaupan syntymisen todennäköisyyteen. Kaupan syntymistä analysoidaan tuolloin sekä ostavan että myynnin kohteena olevan yrityksen kannalta.

Tutkimuksessa havaitaan, että innovatiivisuus vaikuttaa yrityskauppojen syntymiseen prosessiteollisuudessa[1] hyvin eri tavalla kuin muussa teollisuudessa. Prosessiteollisuudessa, jossa yrityskoko on suuri ja jossa kaikki markkinoilla olevat yritykset ovat tehneet merkittäviä kiinteitä investointeja, pyrkimys kuroa umpeen tehokkuuseroja – jotka aiheutuvat esimerkiksi innovaation hallussapidosta ja niiden soveltamisesta – voi johtaa yrityskauppoihin. Muussa teollisuudessa yritysten vahvuudet voivat vaihdella merkittävästikin. On suuria yrityksiä, joiden asema tuotemarkkinoilla on vahva, ja toisaalta sellaisia yrityksiä, joilta puuttuu edellytyksiä kaupallistaa innovaatioita tai viedä kaupallistettuja innovaatioita suurille markkinoille. Niinpä on ilmeistä, että muussa teollisuudessa se epäsymmetria, joka liittyy edellytyksiin hyödyntää innovaatiota, voi johtaa yrityskauppoihin.

Keskeisen tutkimustuloksen mukaan innovaatiot lisäävät sen tapahtuman todennäköisyyttä, että prosessiteollisuuden yritys ostaa toisen yrityksen. Toisaalta innovatiivinen prosessiteollisuuden yritys ei kovin todennäköisesti tule muiden yritysten ostamaksi. Nämä tulokset saatiin, vaikka käytetty VTT:n keräämä innovaatiotiedosto, SFINNO, sisältää lähinnä vain merkittäviä tuoteinnovaatioita. Tutkimustulokset viittaavat siihen, että prosessiteollisuudessa tehokas yritys tyypillisesti ostaa tehottomamman yrityksen, eikä päinvastoin.

Muussa kuin prosessiteollisuudessa taas yrityksen hallussa oleva innovaatio lisää todennäköisyyttä, että yritys tulee toisen yrityksen ostamaksi. Vastaavasti taas innovatiivisuus ei lisää yrityksen halukkuutta ostaa muita yrityksiä. Nämä tulokset viittaavat siihen, että sel-

[1] Prosessiteollisuuteen on luettu elintarviketeollisuus, tekstiilien valmistus, puu- ja paperiteollisuus, kustantaminen ja painaminen, öljy- ym. tuotteiden valmistus, muiden kemikaalien kuin lääkeaineiden valmistus, kumi- ja muovituotteiden valmistus, ei-metallisten mineraalituotteiden valmistus, perusmetallien valmistus, sähkö-, kaasu- ja lämpöhuolto sekä veden puhdistus ja jakelu.

laiset yritykset, joiden asema markkinoilla on vahva tai joilla on muuta suhteellista etua innovatiivisiin yrityksiin nähden, ostavat innovatiivisia yrityksiä.

Edellä esitettyjä johtopäätöstä vahvistaa myös estimointitulos, jonka mukaan muussa kuin prosessiteollisuudessa ostotapahtuman jälkeen markkinoille tuodut innovaatiot lisäävät yritysoston todennäköisyyttä. Prosessiteollisuudessa taas tätä vaikutusta ei havaittu. Tämä viittaakin siihen, että muilla kuin prosessiteollisuuden toimialoilla yritykset ostavat myös sellaisia yrityksiä, joilla on hallussa keskeneräisiä innovaatioita, joita ei ole vielä tuotu markkinoille.

PRAFACE

This project is ordered and funded by Tekes, the National Technology Agency. The aim of the study was to analyse the motives of mergers and acquisitions and empirically test whether mergers and acquisitions were used as means to transfer technology. The report was written by Eero Lehto from Labour Institute for Economic Research and Olavi Lehtoranta from Statistics Finland. We are grateful for the contribution of Markus Koskenlinna and Ari Mikkelä who supervised the work at Tekes. We would also like to thank Reija Lilja from Labour Institute for Economic Research for her comments.

The innovation data set for this study was provided by VTT, Group for Technology. In this project we also exerted an extra effort to gather the data on mergers and acquisitions. The rest of the data set was obtained from Statistics Finland. We are grateful to Paul Dillinghan for checking the English language.

Helsinki, March 2002
Eero Lehto and Olavi Lehtoranta

1. INTRODUCTION

In this study we analyse ownership changes as a means to transfer technology. More closely, we empirically test whether the possession of innovations affects the likelihood that a firm is acquired or that it acquires another firm.

One may say quite generally that in mergers and acquisitions (M&A) the arranged interaction between the factors of production owned and controlled by various firms changes. With new technology, new assets (at least in the form of knowledge) emerge, and the optimal use of old assets, as well as the expertise of human capital in relation to the firm's assets, may change. As a consequence of this, new complementarity or synergy gains arise between the assets and labour in the possession of different firms. This creates dynamics by which all the forms in which the firms are in touch with each other – contractual and non-contractual – change in time. Now and again the arisen potentiality for synergy gains can be internalised through M&As. But in the case of the utilization of knowledge, is it possible that the firms do not react to the new challenges, which emerge with the changing environment, but only revise the forms of collaboration and check the appropriate division of work between self-making and external sourcing of knowledge? For what purpose is M&A needed then? M&A can evidently be used as a means to transfer knowledge in such a situation in which collaborative schemes do not work. To answer this question more specifically one must specify the functions of the firm and the ownership and also discuss more closely the degree of imperfection of the information which the firms face.

By ownership we mean the entitlement to that income stream which accrues from the assets in the firm's possession. Ownership gives the owner the right to combine tangible and intangible assets in his possession and control the actions of the hired labour concerning these assets so that the income stream accrued from all of it is maximal. The existence of a firm as an institution and the role of ownership is understood most naturally in such a world in which all the ongoing business cannot be handled contractually. As noticed by Williamson (1975) and (1985), many contingencies relevant to the contractual relationship are actually unpredictable – or too complex to understand or articulate – for trading parties. The authority to perform tasks in the unspecified contingencies – that cannot be handled contractually – is imposed on the owners – or on the manager – of the firm. This is regarded as one of the main functions of the firm and also a reason for the existence of firms as decision power allocating institutions (see Hart, 1995). In this sense, the existence of the firm is already proof of such a world in which imperfect information deters from handling all situations contractually.

Picturing the limits of contractual mechanisms and non-contractual mechanisms other than M&As helps in understanding the functions of ownership and reasons for changes in ownership structure. In contractual arrangements – as in cooperation – unobservability of true actions or some other type of imperfection in information often create such restrictions that lead to efficiency losses. This pushes firms toward non-contractual arrangements like bargaining or auctioning. But if the losses associated with these arrangements are also great enough, maybe M&A is then used to carry out the tasks at hand.

As concerns M&A, it usually means a break in which the boundaries of in-house activities – usually the production of an acquiring or a merging firm – enlarge but, simultaneously, the same acquiring firm externally sources some of the target firm's strategic assets. The terms for M&A can be determined in the market. It is possible that several potential sellers and buyers are involved in the trade.

Let us take a closer look at the production of knowledge. In the production of technology the information concerning the firms' true actions and the real outcome of actions are typically more or less imperfect. This especially concerns R&D activity, and so the firms involved in R&D co-operation face welfare-deteriorating constraints in such contractual arrangements as licenses, R&D agreements and joint ventures.[2] If it is difficult to verify the outcome of R&D actions, it also becomes difficult to share the outcomes of R&D contractually. This encourages firms to deal in technology (or knowledge) through non-contractual mechanisms, or alternatively, to give up external sourcing and internalize technology procurement.

Insofar as new technology is the motivator of M&A, M&A can be regarded as one of the non-contractual instruments to source technology externally. Which party – the acquirer or the acquired firm – receives knowledge capital depends on the case in question. In ad-

[2] According to an innovation survey of Statistics Finland in 1996, R&D co-operation between competitors has been infrequent. Co-operative parties were rather located in different industries of the vertically integrated structure, by which the costs of moral hazard were diminished.

dition, in M&A the borders of self-making, as concerns both innovation activity and the production itself, may change. No doubt the further development of technology and its commercialization are moved to that unit which is formed as a result of M&A. The terms of this change are often determined in the market with many potential buyers and sellers. All in all, one can say that in M&A not only the scope of self-making but also of trade-off between self-making and external sourcing is redefined. Therefore, the trade-off between external sourcing of knowledge and internalization – which is empirically analysed by Teece (1986), Pisano (1990) and Veuglers and Cassiman (1999) – is also valid in explaining the use of M&As as means of knowledge transfers. We would also like to remark in this context that despite M&A firms do not necessarily give up their own R&D on any occasion.

In theoretical modelling, the shaping of ownership structures has been explained by the property rights approach (see Hart, 1995)[3]. Related to this, such studies as Aghion and Tirole (1994), which focuses on R&D investments, also offer some insight into that mechanism which determines the optimal ownership structure for research activity. Aghion and Tirole (1994) considered, for example, a case in which imperfect information makes an innovation (to be produced) ex-ante noncontractible, and so technology should be produced either in-house (an integration) or then by a specialized unit itself after which the producer and a customer (who utilizes the innovation) bargain over the outcome of R&D. These studies specify rather the optimum in a steady state than the dynamics by which the optimal arrangement changes. But the central perception in this approach, which stresses that the various practices associated with R&D are very much shaped by the non-contractible nature of R&D activities, is also valid in explaining why technology transfer is implemented through a change in ownership.

In our previous study (Lehto and Lehtoranta, 2002) we found two basic cases in which M&A is used as a means to transfer technology. These cases are

[3] In Hart's (1995) and Hart's and Moore's (1990) models the incentives to invest in human capital are sensitive to ownership structure. By optimal adjustment of ownership structure – which determines whether transactions are carried within the firm or through the market – the investments can be induced to settle as close as possible to optimal.

1. The firm is specialized in producing an innovation. Owing to its weak presence in the product market, this firm is, however, merged or acquired by such a firm that possesses the complementary assets which are necessary in utilizing the innovation. We have argued that in these situations M&A comes into the picture most likely when the input of the inventing firm is required in the commercialisation of an innovation after M&A. Through M&A the market failure regarding the inventing firm's actual post-trade effort is diluted.

2. Entry to production is costly. Two firms are equally established in the product market. One firm is more effective than the other because of past investments in R&D. The markets of the two firms concerned do not overlap each other completely, however. An opportunity then arises to transfer technology from an efficient firm to an inefficient firm.

In the first case, one firm is specialized in R&D before M&A occurs. The acquired firm's weakness is related to the deficiency of such complementary assets as distribution channels, expertise in commercialization and brand name. The entry costs associated with the production itself can be modest. By M&A, R&D in the commercialization phase is integrated to occur in the merging or acquiring firm. This pattern presupposes that the firms involved in trade are heterogeneous. So, as Teece (1986) and Pisano (1990) have noticed, the new entrants typically have a relative advantage in R&D, while the established firms who have invested in production, distribution channels and brand name may have a relative advantage in commercialization. Having this heterogeneity, contractual or non-contractual bilateral arrangements concerning R&D are easily rejected because the inventing firm first likes to invent and after that sell the innovation in the market (as noticed by Radnor (1991)). In this mechanism, the invention is sold to the highest-paying buyer through M&A, and not as fixed-price trade, if the original invention must be further developed by both firms as shown in Lehto (2002a) and (2002b). It is really commonly noticed that the innovation process includes several phases. Acs and Audretsch (1990) describe the innovation as a process which begins with a basic idea and ends up with the introduction of a new product or process to the market place.[4] The imperfect nature of in-

[4] Choi (1999), who considered licensing of technology, also assumed that the start-up firm's input is needed in the commercialization phase.

formation, however, often makes it impossible to define ex-ante what products and what portion of arisen income streams are generated by the innovation concerned. The problem of ill-definition is still aggravated, if the innovation is not ready at the trading date, for example, and if some commercialization effort must still be exerted. Imperfections in information can thus rule out licensing and other contractual mechanisms. M&A then becomes a real option and the motive for M&A could then be to confirm the target firm's incentives to exert commercialization effort in the latter phases of the innovation process.[5] Similarly, Aghion and Tirole (1994) saw that by ownership arrangements one can affect the incentives to exert R&D effort.

Licensing is seen as an appropriate instrument to transfer technology in the second case mentioned above. Gallini and Winter (1985) and Katz and Shapiro (1985) have shown that under quite general conditions it pays the more efficient firm to grant a license to the inefficient firm despite the possible tightening of competition in the product market. If the outcome of an innovation is not a contractible variable, licensing is, however, ruled out. But through M&A the efficient process can still be transferred for the use of an inefficient firm.

The knowledge which is transferred from one firm to another can be either in a tacit or in a codified form as is emphasized by Kogut and Zander (1992) and Spender (1996).[6] Insofar as knowledge is in the tacit form, typically embodied in human capital, the likelihood of M&A as an instrument to transfer technology is increased at the expense of contractual means in both the cases considered above. It is also possible that in the contractual arrangement the receiver of the knowledge cannot be safeguarded against the hazard of expropriation (see Pisano, 1990), which arises when the deliverer sells the contracted knowledge to rivals. This problem is also overcome, if the deliverer of the knowledge becomes an owner in the acquiring firm.

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[5] It is evident that assuming the innovation process as a chain-linked model (see Palmberg et al. 1999) which includes the interaction and feedback loops between research and marketing would not change our conclusion in this matter. In any case, more emphasis is set on the commercialization in the latter phases of the whole process.

[6] See also the discussion in Hämäläinen and Schienstock (2001).

In the previous paper (Lehto and Lehtoranta, 2002) we found that the increment of R&D stock, given the firm's scale, increased the acquiring propensity in all the industries, also in industries other than the processing industries (the non-processing industries). We interpreted this to indicate, contrary to the findings of Blonigen and Taylor (2000), that those firms who buy technology also invest in R&D themselves. This is explained by the fact that a firm's own R&D strengthens the firm's 'absorptive capacity' to utilize the delivered knowledge, as well as to take advantage of that knowledge which spills over, as suggested by Cohen and Levinthal (1990) (see also and Kim and Dahlman, 1992). Secondly, it is evident that the firms who invest in R&D have, in any case, a natural advantage in the exploitation of high technology, and if the results of their own R&D have not been satisfactory, those firms are inclined to buy technology. Also, this may explain why a firm's own R&D seems to confirm the propensity to obtain new knowledge through M&As.

We also discovered (in Lehto and Lehtoranta, 2002) that heavy investments in R&D increase the probability of becoming a target of acquisition in the non-processing industries, whereas in the processing industries the R&D stock, given the firm's scale, had no impact on the likelihood that a firm was acquired. But it contributed positively to the likelihood that a firm acquired. This was seen to verify our hypothesis about the direction of technology transfers in heavily investing processing industries.

In this study we focus on the impacts of success in innovation activity on the likelihood that a firm is acquired or that a firm acquires. Our data set is much larger than that in the previous study in which the required information about a firm's R&D stock restricted the size of the data set. The data set covers the major innovations which have been commercialized. We believe that the observed transfers of the possessed innovations, associated with M&A, can still precede further stages of commercialization or measures by which the new product is brought to the big market.

We still consider the behaviour in the processing industries and in the non-processing industries separately. Owing to high entry costs in the processing industries, all the firms in those industries can be considered as incumbents. In such industries it is typical that an efficient incumbent who possesses a process innovation buys an inefficient rival. The pure process innovations for a firm's own use are, however, poorly represented in the available data available. Owing to this, the evidence that technology transfers are also used in the processing industry to bridge up a gap in the efficiency between two firms may remain scarce. Despite this, we still expect to find some evidence of this. Related to this, we expect that in the processing industries a firm who possesses an innovation will not become a target for M&A.

We expect that in the non-processing industries an innovation in a firm's possession positively contributes to the probability that the firm is acquired. This result would be in line with our previous findings. Because the innovation in the firm's possession tells us that the firm has been successful, the firm's need to source technology externally cannot be expected to be so urgent as in the case of failure in R&D. Therefore, we do not expect that an innovation in such a firm's possession – which operates in the non-processing industries – necessarily increases the propensity to acquire.

In the literature there are no empirical studies which have investigated the link from materialized innovations to M&As. Previous studies have tended to analyse empirically how a firm's R&D is related to mergers and acquisitions (see Granstrand and Sjölander (1990), Blonigen and Taylor (2000)). By and large, we expect that the results of this study confirm the conclusion of our previous study (see Lehto and Lehtoranta, 2002) and produce new results which let us picture more accurately M&A as a mechanism to transfer technology.

2. DATA

The coverage

We have restricted the analysis to the 1994–1999 period (for lagging regressors 1989–1999) and to the manufacturing industries (SIC 1–37), construction (45), wholesale and commission trade (51), transport, storage and communications (60–64), computer and related activities (72), research and development (73), business and management consultancy, holdings (741), technical consultancy and analysis (742, 743), advertising (744) and other social or personal services (90–93) in Finland.

Innovations

The innovation data of this study is the Sfinno database compiled by the VTT Group for Technology Studies. This data has been collected by means of three main sources: expert opinion, a review of trade and technical journals and a special study of large firms.[7] The Sfinno data covers the major innovations. The innovation is included in the data set, if

1) the innovation is a technologically new or significantly enchanced product from the firm's perspective;

2) the innovation has been commercialised for the market by a business firm;

3) the domestic firm (a firm operating in Finland) has played a relevant role in the development of innovation.

Pure process innovations which do not lead to new products are excluded from the Sfinno data. Because product and process innovations are interrelated and a product innovation can later be used to renew a process, the process innovations are not, however, ignored altogether.

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[7] A closer description of this data is given in Palmberg et al. (1999) and in Leppälahti (2001).

To identify the firm and its SIC-code and to define the firm's turnover, the innovation data was linked with the Business Register of Statistics Finland. At this stage, the data includes 486 new innovations which were introduced in 1994–1998 and 272 new innovations which were introduced in the years 1989–1993. This latter information from the years 1989–1993 is useful, because the lagged variables of innovations introduced are also used as explanatory factors. Linking this data then with the Financial Statements Data of Statistics Finland – to obtain debt and profit information – the number of new innovations from the years 1994 –1998 dropped to 477 and in the years 1989–1993 to 265. So, although at this stage the number of firms reduced roughly by one third, the number of innovations hardly decreased at all. Table 1 includes annual information of new innovations by industry.

Table 1. Number of new major innovations by industry

SIC95	89 - 93	1994	1995	1996	1997	1998	94 - 98	%	N of firms 94 - 98	N of firms 1998
food, beverages and tobacco	31	4	9	7	8	6	34	0.4	8391	1462
textiles, textile products and leather	2	2	0	3	1	1	7	0.1	10756	1419
Wood products	3	2	2	1	1	1	7	0.1	11709	1837
Pulp, paper and paper products	6	1	0	4	4	3	12	1.2	981	188
Printing and publishing	0	1	0	0	1	1	3	0.0	12323	2436
Oil, chemicals, rubber and plastic	21	5	11	2	9	7	34	0.8	4399	875
Other non-metallic mineral products	0	1	1	3	0	0	5	0.1	3815	659
Basic metals and metal products	31	6	5	7	4	8	30	0.2	18903	3399
Machinery and equipment	27	17	16	18	15	17	83	0.6	14472	2303
Electrical and optical equipment	47	13	13	29	25	12	92	1.3	7186	1393
Transport equipment	4	1	2	0	4	1	8	0.2	3474	622
Other manufacturing	0	0	0	1	0	3	4	0.0	10318	1600
Electricity, gas and water supply	5	0	2	0	1	3	6	0.2	3663	797
Construction	0	1	0	2	1	1	5	0.0	98450	16196
Wholesale trade	15	11	3	11	8	6	39	0.1	70066	13711
Transport	1	0	0	0	0	0	0	0.0	70808	8499
Telecommunication	0	1	0	1	2	2	6	0.4	1695	352
Computer services, r&d	30	7	10	10	14	5	46	0.3	13380	2923
Other business services	42	6	6	15	17	10	54	0.1	82247	15933
Other services	0	1	0	0	0	1	2	0.0	46178	4855
ALL	265	80	80	114	115	88	477	0.1	493214	81459

In estimating the models concerning the probabilities that a firm acquires or is acquired – the dummy which tells whether the firm has introduced a new innovation in the year in question or not – turns out to be a better explanatory factor than the firm's annual number of new innovations. Table 2 describes the number of innovating firms by industry.

Table 2. Number of firms who have introduced at least one new major innovation by industry

	89 - 93	1994	1995	1996	1997	1998	94 - 98	%	N of firms 94 - 98	N of firms 1998
SIC95										
food, beverages and tobacco	25	4	8	7	7	6	32	0.4	8391	1462
textiles, textile products and leather	2	2	0	3	1	1	7	0.1	10756	1419
Wood products	3	2	2	1	1	1	7	0.1	11709	1837
Pulp, paper and paper products	6	1	0	3	3	3	10	1.0	981	188
Printing and publishing	0	1	0	0	1	1	3	0.0	12323	2436
Oil, chemicals, rubber and plastic	15	5	10	2	9	6	32	0.7	4399	875
Other non-metallic mineral products	0	1	1	3	0	0	5	0.1	3815	659
Basic metals and metal products	24	5	5	6	4	6	26	0.1	18903	3399
Machinery and equipment	25	17	14	17	14	17	79	0.5	14472	2303
Electrical and optical equipment	42	11	11	21	17	11	71	1.0	7186	1393
Transport equipment	4	1	2	0	4	1	8	0.2	3474	622
Other manufacturing	0	0	0	1	0	3	4	0.0	10318	1600
Electricity, gas and water supply	4	0	1	0	1	2	4	0.1	3663	797
Construction	0	1	0	2	1	1	5	0.0	98450	16196
Wholesale trade	15	11	3	11	7	6	38	0.1	70066	13711
Transport	1	0	0	0	0	0	0	0.0	70808	8499
Telecommunication	0	1	0	1	1	2	5	0.3	1695	352
Computer services, r&d	30	7	10	10	13	5	45	0.3	13380	2923
Other business services	33	6	5	13	17	9	50	0.1	82247	15933
Other services	0	1	0	0	0	1	2	0.0	46178	4855
ALL	229	77	72	101	101	82	433	0.1	493214	81459

One can see from Tables 1 and 2 that among various industries innovativeness (the column with the % label) is highest in the electrical and optical industry and in the paper industry. In the paper industry the high number is explained by the huge size of the firms concerned. Other fairly innovative industries are the food industry, the chemical industry and the machinery and equipment industries. But even such service industries as computer services and other business services have introduced fairly many new innovations. The number of major innovations is very small compared with the total number of all firms in the market. Annually, only 0.1 percent of firms bring a new innovation to the market. During a longer time interval the share of innovating firms is, however, much higher.

Mergers and acquisitions

The data concerning mergers and acquisitions is the same as in Lehto and Lehtoranta (2002), in which the characteristics of the M&A data are described in detail. M&A data is compiled from two sources. The first source is the M&A data of the tax authorities and the National Board of Patents and Registers over the 1994–1999 period. That data can be found in the Business Register of Statistics Finland. The second source is the data of the magazine "Talouselämä".

The data collected by the magazine include the name of the buying firm, the name of the target firm, the amount of the sales turnover and personnel in the target businesses having a turnover of more than FIM 2 million. We have taken into account only domestic acquirers and domestic targets. Those acquisitions in which foreign firms purchase business units locating abroad and belonging to a Finnish group of enterprises are excluded. If a firm sells only a part of its business, which is quite common, the selling firm or its parent firm will have been recorded as the target firm, with the exception of the situation when the target unit is clearly in a different branch of industry or locates abroad. If a firm or an independent entity of a larger firm is outsourced – through a management buy-out or other means – the new firm is registered in our data as an acquirer.

Table 3. Number of mergers and acquisitions by industry

SIC95	1994	1995	1996	1997	1998	1999	ALL	%	N of firms 94 - 99	N of firms 1999
food, beverages and tobacco	28	30	28	20	16	12	134	1.4	9820	1429
textiles, textile products and leather	2	2	10	5	4	8	31	0.3	12108	1352
Wood products	10	10	8	7	17	14	66	0.5	13472	1763
Pulp, paper and paper products	9	8	11	20	15	9	72	6.2	1165	184
Printing and publishing	19	22	29	35	30	35	170	1.2	14713	2390
Oil, chemicals, rubber and plastic	13	19	29	23	29	24	137	2.6	5263	864
Other non-metallic mineral products	6	8	7	11	8	10	50	1.1	4463	648
Basic metals and metal products	12	24	24	24	21	23	128	0.6	22234	3331
Machinery and equipment	17	19	20	29	37	42	164	1.0	16756	2284
Electrical and optical equipment	10	21	13	12	18	23	97	1.1	8578	1392
Transport equipment	2	4	2	5	4	6	23	0.6	4091	617
Other manufacturing	4	6	7	8	9	8	42	0.4	11873	1555
Electricity, gas and water supply	15	14	15	12	19	16	91	2.0	4459	796
Construction	36	26	52	47	57	55	273	0.2	114959	16509
Wholesale trade	62	73	90	80	89	130	524	0.6	83204	13138
Transport	27	57	41	28	37	15	205	0.3	79537	8729
Telecommunication	1	0	5	5	5	9	25	1.2	2041	346
Computer services, r&d	23	28	23	19	38	60	191	1.2	16349	2969
Other business services	97	112	115	121	115	120	680	0.7	98087	15840
Other services	20	14	14	10	8	19	85	0.2	51000	4822
ALL	413	497	543	521	576	638	3188	0.6	574172	80958

The data set on mergers and acquisitions and target firms is linked with the other data compiled so far (which is constructed from the innovation data, the Business Register and the Financial Statements Data of Statistics Finland). We have assumed that the data set on mergers and acquisitions and target firms covers all the relevant events in Finland.

When we analyse the fact that a firm acquires, we are interested in explaining the annual number of purchases of each firm. The data on M&A is then count data with zeros or some positive integers. In most cases, the value of this positive number is one. Table 3 indicates the number of mergers and acquisitions by industry. These numbers also include acquisitions in which the Finnish firm acquires a foreign target. From Table 3 one sees that M&As are quite infrequent in Finland. The average number of acquisitions per firm was annually only 0.6 percent in the years 1994–1999. But during a longer period of time this figure was, of course, higher.

It must be noticed that in our previous study (see Lehto and Lehtoranta, 2002), the R&D panel restricted the size of the data set to the extent that the number of M&As dropped to 1880. The data set of this study thus includes 1308 more M&As than those in our previous study.

In analysing the probability that a firm (or an entity which is part of the firm) is purchased by another firm, the explained variable is the dummy which gets a value of one in that year in which the firm is purchased. Otherwise, the value is zero. Table 4 describes the number of targets by industry.

One can see from Table 4 that the total number of targets in M&As in the years 1994–1999 is 1300 and so much less than the respective number of mergers and acquisitions in Table 3. In the data of Table 4 foreign targets are excluded, but all the Finnish targets – even if the acquirer is a foreign firm – are included.

Table 4. Number of target firms by industry

	1994	1995	1996	1997	1998	1999	ALL	%	N of firms 94 - 99	N of firms 1999
SIC95										
food, beverages and tobacco	10	11	11	4	9	3	48	0.5	9820	1429
textiles, textile products and leather	6	0	3	3	6	8	26	0.2	12108	1352
Wood products	6	3	5	8	11	5	38	0.3	13472	1763
Pulp, paper and paper products	0	2	7	3	2	2	16	1.4	1165	184
Printing and publishing	13	14	9	21	15	7	79	0.5	14713	2390
Oil, chemicals, rubber and plastic	5	10	12	8	11	6	52	1.0	5263	864
Other non-metallic mineral products	4	4	1	3	3	4	19	0.4	4463	648
Basic metals and metal products	7	7	10	10	20	15	69	0.3	22234	3331
Machinery and equipment	9	11	13	8	22	16	79	0.5	16756	2284
Electrical and optical equipment	8	14	7	7	17	15	68	0.8	8578	1392
Transport equipment	4	2	2	6	5	0	19	0.5	4091	617
Other manufacturing	1	0	3	3	9	4	20	0.2	11873	1555
Electricity, gas and water supply	12	2	5	4	16	5	44	1.0	4459	796
Construction	16	7	6	9	22	23	83	0.1	114959	16509
Wholesale trade	34	20	21	27	75	30	207	0.2	83204	13138
Transport	15	18	19	11	29	8	100	0.1	79537	8729
Telecommunication	2	2	3	5	9	6	27	1.3	2041	346
Computer services, r&d	6	12	10	19	35	33	115	0.7	16349	2969
Other business services	18	28	15	17	44	25	147	0.1	98087	15840
Other services	16	5	3	3	5	12	44	0.1	51000	4822
ALL	192	172	165	179	365	227	1300	0.2	574172	80958

There are several reasons which explain the difference between these figures. First, on those rare occasions in which the number of targets in a year is more than one – for example, when more than one independent entity of a large firm is purchased during the same year – the value of the variable concerned in Table 4 is, however, only one. Secondly, Finnish firms have evidently been more active buyers abroad than foreign firms in Finland. The exclusion of foreign targets and foreign buyers may then generate a gap between comparable figures. Thirdly, on average, it has been more difficult to identify and link a target firm than a purchasing firm to the Business Register and especially to Financial Statements Data of Statistics Finland. In fact, linking the M&A data with the Financial Statements Data dropped the number of mergers and acquisitions in 1994–1999 from 3234 to 3188, but the number of target firms from 2022 to 1300. The data set considered in this study is, however, larger than that in our previous study (see Lehto and Lehtoranta, 2002) and so the total number of target firms has increased from a total of only 709 to 1300.

3. THE METHOD AND THE MODEL

3.1. Method

The firm as an acquirer – negative binomial model

When we study how a firm behaves as an acquirer, we use as the dependent variable the number of purchases per firm. To overcome some deficiency of the Poisson regression in the analysis of the acquisition behaviour, we use negative binomial count dependent variable models developed by Hausman et al. (1984).[8] The M&A decision of the firm concerned is contingent on the characteristics of the other potential purchasers, as well as on the characteristics of all potential target firms. In the M&A decision the purchaser must meet certain criteria in relation to the target firm. For these reasons, it is natural to stress "between firms" variation and estimate the random effects model. Obtaining estimators from the panel data, the random effects apply to the dispersion parameter, which is randomly distributed and the same for all elements in the same group (firm). A more detailed description of the negative binomial random effects model is given in Hausman et al. (1984). (See also Stata Reference Manual Release 7 (2001), Volume 4, Stata Press, College Station, Texas, pp. 393–394, and Lehto and Lehtoranta (2002).)

The firm as a target – logit model

The random effects model is also suitable when we consider the likelihood that a firm is acquired by another firm. In our modified data firms appear as a target at most once a year. This makes it natural to analyse the contingency that a firm is sold either with a probit or with a logit model. Qualitatively, the results obtained in terms of estimated coefficients and their standard deviations from both models are similar. We chose to use the

[8] Traditionally, counts have been presumed to follow a Poisson distribution. However, the Poisson distribution assumes that the mean and variance are equal, but this is typically not the case with the count data. Alternatives to the Poisson, such as the negative binomial distribution, often provide better models of variation among the counts that are overdispersed, that is, the variance is larger than the mean.

logit-likelihood function to estimate the random effects panel data model. (The method is described more closely in Lehto and Lehtoranta, 2002.)

3.2 The explanatory variables

The likelihood of M&As is explained by the firm's possession of innovations, the number of innovators in the same industry, the log of fixed-price turnover, the log of debt ratio and profit ratio (or log of profit ratio).

The innovation variable

We use different specifications for the innovations in the firm's possession. We may focus on the introduction of an innovation in each year or, alternatively, on a variable which tells whether a firm has introduced a new innovation during some time interval which includes several years.

We expect that in the processing industries the possession of an innovation encourages a firm to acquire. The possession of an innovation would then also affect rather negatively the likelihood that a firm is acquired by another firm. These effects do not, however, come out necessarily in our data set, which covers process innovations quite poorly.

In the non-processing industries the possession of an innovation would, instead, increase the likelihood that the others buy such a firm. Previously (in Lehto and Lehtoranta, 2002) we obtained a result according to which in the non-processing industries the firm which has heavily invested in R&D is more eager to purchase another firm than an average firm. We interpreted this result to indicate that R&D does not only increase the firm's knowledge capital but its capacity to absorb the knowledge of other firms. In the innovation context of this paper, this result has no relevance. So, we expect that in the non-processing industries the possession of an innovation tells us that a firm has been successful in its R&D and therefore has little reason to buy technology by purchasing another firm.

The number of innovations in the possession of other firms in the same industry

The firms whose SIC code is the same at the two-digit level are specified as belonging to the same industry. We construct a variable which gives the number of innovators in the same industry. The other firm is then classified as being an innovator, if the innovation variable concerned has a value of one, instead of being zero in the year in question. If the relevant innovation variable, for example, takes into account the innovations introduced between the current year and three years previously, the number of other innovators then gives the number of those other firms in the industry for which the value of this innovation variable has been one in the year concerned.

Focusing on the number of innovators, we aim at capturing that impact which arises when the number of potential buyers or sellers change. Matching is then affected. For example, when the number of innovators increases it is easier for the potential purchaser to find such an innovation which corresponds to the needs of the purchaser. But the bargaining situation is also then affected. Because we cannot separately specify the number of potential targets and buyers (as Pisano, 1990), the expected sign of the number of innovators on the explained likelihoods – insofar as the change in bargaining position is concerned – is ambiguous

In the processing industries innovators evidently buy inefficient, non-innovating firms. Then the high number of other innovators tells us that there are many other willing buyers, too, and that there are perhaps not so many appropriate target firms. In explaining the likelihood that one firm acquires another firm, the sign of the variable concerned is then expected to be negative, whereas, in explaining the probability that a firm is acquired, the sign of the variable concerned is rather expected to be positive.

In the non-processing industries unlucky firms (whose position in the product market is strong) buy innovating targets. The high number of other innovators in the same industry then tells that there are a lot of appropriate targets. We therefore expect that in the non-processing industries the great number of innovators will, in any case, positively affect the probability that one firm acquires another firm. It would then be logical to expect that the impact of this variable on the probability that a firm is acquired is negative. But taking into account the possible matching effect and the fact that the number of innovators is very small in our data set, the high number of innovators in the industry may then tell us that there is also a great number of such firms who have invested in R&D but have not succeeded in inventing major innovations. Therefore the number of other innovators in the same industry may also increase the probability that a firm is acquired in the non-processing industries.

The volume of turnover

The fixed-price turnover describes the scale of operations. Our previous study (Lehto and Lehtoranta, 2002) already showed that the larger a firm is, the more likely it is that the firm will acquire another firm. The larger resources to buy and, presumably, the greater number of opportunities to find appropriate targets have an effect in this direction. Because, in our data, a target can also mean an independent entity of a larger firm, the scale variable is also assumed to have a positive effect on the probability that a firm becomes a target in M&A. We found the impact of the turnover on the explained likelihood to be rather log-linear.

Debt ratio

In *line* with the results obtained in our previous study (see Lehto and Lehtoranta, 2002) we expect that indebtedness – in logarithms – reduces the firm's attractiveness as a target and also the firm's propensity to buy another firm.

Profit ratio

It is sensible to expect that the profit ratio has a similar effect on the explained probabilities as the debt ratio.

Test statistics

The Wald Test tests whether the parameters of the model are jointly zero. The quadratic form of the test statistics has chi-squared distribution. The degrees of freedom are reported in parentheses and the related p-value is reported below the test statistics.

We also report a likelihood-ratio test obtained in the estimation of the negative binomial model. This test compares the panel estimator with the pooled estimator (i.e. negative binomial estimator with constant dispersion). According to the zero hypothesis, the panel estimator is not different from the pooled estimator. This statistic also follows chi-squared distribution.

In the context of logit analysis the relevance of the panel-level variation is also tested. Let σ_v denote the standard deviation of the panel-level error term. We then test with a likelihood-ratio test to see whether $\rho = \frac{\sigma_v^{\ 2}}{\sigma_v^{\ 2} + 1}$, labelled rho, deviates from zero. If rho is zero, the panel-level variance component is unimportant, and the panel-level estimator is not different from the pooled estimator. This test statistic is also reported.

4. THE RESULTS[9]

We found that the dummy variable which only tells whether the firm has innovated or not explained M&As better than the number of annually introduced innovations. As innovation variables we used either index-variables, which measure whether the firm has innovated during a given time interval or not, or variables which tell the exact year of the newly introduced innovation. We first estimated the models which include the innovation dummy which has a value of one, if the firm has innovated during the years from t-1 to t-5 or then from t to t-3.[10] Otherwise, the value of the dummy is zero.

We considered both the likelihood that a firm acquires and that a firm is acquired in all industries. The estimation results are reported in Tables A1 and A2 of the Appendix A. The results do not elicit any clear influence from success in innovation activity to M&As. There is, however, some weak evidence that innovation in a firm's possession encourages the firm to purchase another firm. The positive sign of the turnover and negative sign associated with the debt ratio, in regressions concerning the likelihood that a firm is acquired (Table A1) and that a firm acquires (Table A2), correspond to expectations. The impact of the profit ratio was not different from zero. This result is not reported. As concerns the impact of the number of other innovative firms in the regressions concerned, our expectations are ambiguous. Because this number, to a certain extent, describes the number of both potential buyers and potential sellers, the positive sign that was discovered can be interpreted as reflecting primarily the matching effect.

Analysing the processing industries and the non-processing industries (other industries) separately gives a more accurate picture of the role of technology transfers in M&A activity. We first consider the likelihood that a firm is acquired. In Table 5 we report some results obtained from the data which is divided into processing and other industries. It turns out that in the non-processing industries firms which have innovated within three years

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[9] The descriptive statistics of the variables and the data which is used in various regressions are reported in the Appendix B.

[10] Using a dummy for the time interval (from t to t-3), we also included a dummy for the year 1999, because the innovation data includes only a few innovations which have been introduced in the year 1999, and because we do not want to drop the year 1999 from our analysis.

are purchased by others. The same kind of result is also obtained when the likelihood that a firm is acquired is explained by the innovation dummy, which has value of one, if the firm has innovated within 5 years, current year excluded (see Table A3 in the Appendix A). The results reported in Table 5 and A3 also show that in the processing industries the other firms are not interested in buying an innovative firm. The positive sign of the volume of a firm's turnover and the negative sign of the debt ratio correspond to our expectations. In the non-processing industries the number of other innovative firms seems to have a positive impact on the explained likelihood. This hints to the fact that this explanatory factor primarily describes the number of potential buyers of innovations. In the processing industries this impact was not significantly different from zero.

Table 5

The probability of ownership changes for the target firm. Random effects firm level Logit model for the panel data. Dependent variable: ownership changes (=1), does not change (=0)., 1994–1999

Regressor	*Contemporary Other industries*	*Lagged Other industries*	*Contemporary Processing industries*	*Lagged Processing industries*
Constant	-14.263*	-12.107*	-11.842*	-11.494*
	(0.270)	(0.151)	(0.406)	(0.448)
Innovation dummy from t	0.582*	0.413*	-0.458	-0.379
to t-3	(0.216)	(0.181)	(0.336)	(0.341)
Dummy, 1999=1	0.159	-0.043	-0.276	-0.289
	(0.085)	(0.088)	(0.174)	(0.183)
Log Turnover	0.834*	0.709*	0.693*	0.668*
	(0.020)	(0.015)	(0.031)	(0.034)
Number of other innovative	0.148*	0.018*	-0.014	-0.013
firms in an industry	(0.003)	(0.002)	(0.011)	(0.011)
Log Debt Ratio	-0.232*	-0.112*	-0.245*	-0.118
	(0.047)	(0.052)	(0.090)	(0.112)
Log likelihood	-5603	-4775	-1512	-1264
Wald chi(2)	1780	2705	524	409
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LR test of rho = 0	157	33	18	13
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
Number of firms	143328	113645	15073	12218
Number of observations	515982	366992	58190	43003

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level. Innovation dummy is not lagged in 'lagged version' of the model.

We also experimented by using the profit ratio as an explanator. In the non-processing industries the profit ratio had no impact on the probability concerned. But in the processing industries this impact turned out to be negative. The results of this regression are reported in Table A4.

In Table 6 we report the estimation results from the regression in which the firm's propensity to acquire another firm is analysed. The explained variable is the count of purchases. The results indicate that in industries other than the processing industries innovative firms are no longer interested in buying other firms. This result corresponds to our expectations. In the processing industry the firm who possesses an innovation is inclined to buy another firm. In Table A5 we report estimation results from the model in which the innovation dummy takes into account the introduction of new innovations since t-5, the current year excluded. In the processing industries the innovation variable no longer has a positive impact. This shows that the innovations introduced during the current year may have a decisive role. Perhaps in the processing industries the transfer of production experience is also a part of technology transfer from an efficient firm to an inefficient firm. Then the results obtained by Cabral and Leiblein (2001), which indicate that production experience associated primarily with the most recent technology is adopted by others, may explain why in the processing industry technology transfers in the form of M&A are linked with the latest innovations.

We can conclude that the results reported in Tables 5, 6, A3, and A5 verify our previous findings about the direction of technology transfers. In other industries the target firm's knowledge capital is transferred to the use of the purchasing firm, and in the processing industries the direction of transfer is reverse.

Table 6

Acquisition propensity estimates. Random effects negative binomial firm-level model.
Dependent variable = the number of acquisitions per firm in each year, 1994–1999.

Regressor	*Contemporary Other industries*	*Lagged Other industries*	*Contemporary Processing industries*	*Lagged Processing industries*
Constant	-9.834*	-9.542*	-8.908*	-9.120*
	(0.154)	(0.168)	(0.322)	(0.361)
Innovation dummy from t to	0.059	0.195	0.426*	0.419*
t-3	(0.143)	(0.149)	(0.190)	(0.213)
Dummy, 1999 = 1	0.161*	0.036	-0.062	-0.093
	(0.057)	(0.062)	(0.110)	(0.121)
Log Turnover	0.803*	0.757*	0.761*	0.755*
	(0.013)	(0.014)	(0.024)	(0.027)
Number of other innovative	0.019*	0.016*	-0.022*	-0.029*
firms in an industry	(0.002)	(0.002)	(0.009)	(0.010)
Log debt ratio	-0.072*	-0.102*	-0.046	-0.173
	(0.037)	(0.043)	(0.083)	(0.095)
Log likelihood	-9967	-8151	-2424	-1934
Wald chi(2)	4175	3340	1071	863
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LR test vs. Pooled	715	551	151	132
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
Number of firms	143328	113645	15073	12218
Number of observations	515982	366692	58190	43003

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level.
Innovation dummy is not lagged in 'lagged version' of the model.

The firm's scale has a positive impact on the acquiring propensity considered (in the models of Table 6). The result is not surprising and is in line with previous results (see Blonigen and Taylor, 2000) and also some other studies which analyse rather the propensity of collaborate (Torbett, 2001). This result is also very robust and it holds in all the models considered. The negative sign of the debt ratio also corresponds to our expectations and similar result is also obtained by Blonigen and Taylor (2000), Tremblay and Tremblay (1998) and Jensen (1998). The number of other innovative firms affects the likelihood that a firm acquires another firm negatively in the processing industries and positively in other industries as we have expected (see Tables 6 and A5).

We have also experimented with the impact of the profit ratio. The effect was not different from zero when the likelihood that a firm will acquire is explained. For some firms the profit ratio is negative. Omitting these observations and taking the logs of the profit ratio, however, we obtain a positive impact. The estimation results of the model, which includes the log of the profit ratio, are reported in Table A6 in Appendix A. After inclusion of the profit ratio (in log form), the negative impact associated with the debt ratio dilutes or disappears.

Table 7

The probability of ownership changes for the target firm. Random effects firm level Logit model for the panel data. Dependent variable: ownership changes (=1), does not change (=0), 1994–1999.

Regressor	*Contemporary Other industries*	*Lagged other industries*	*Contemporary Processing industries*	*Lagged Processing industries*
Constant	-14.293*	-12.168*	-11.858*	-11.509*
	(0.269)	(0.151)	(0.408)	(0.450)
New innovation during t	0.039	-0.338	-0.657	-0.629
	(0.351)	(0.362)	(0.521)	(0.527)
New innovation during t-1	-0.678	-0.700	-0.465	-0.381
	(0.393)	(0.376)	(0.485)	(0.487)
New innovation during t-2	0.438	0.480	0.179	0.229
	(0.312)	(0.291)	(0.441)	(0.441)
New innovation during t-3	0.541	0.553	-0.257	-0.209
	(0.321)	(0.297)	(0.520)	(0.521)
Dummy, 1999=1	0.151	-0.058	-0.284	-0.297
	(0.086)	(0.088)	(0.175)	(0.184)
Log Turnover	0.838*	0.716*	0.694*	0.669*
	(0.020)	(0.015)	(0.031)	(0.034)
Number of other innovative	0.015*	0.018*	-0.015	-0.014
firms in an industry	(0.003)	(0.002)	(0.011)	(0.114)
Log Debt Ratio	-0.233*	-0.117*	-0.246*	-0.117
	(0.047)	(0.052)	(0.091)	(0.112)
Log likelihood	-5603	-4772	-1511	-1263
Wald chi(2)	1803	2694	526	410
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LR test of rho = 0	152	32	18	13
(p-value)		(0.000)	(0.000)	(0.000)
Number of firms	143328	113645	15073	12218
Number of observations	515982	366692	58190	43003

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level. Innovation dummy is not lagged in 'lagged version' of the model.

Let us then consider more closely the lag structure of the innovation effect. Instead of one composite index, we use as explanators the introduction date of new innovations. The value of these variables is one, if a firm has introduced one or several innovations in the year concerned. Otherwise the value of the innovation variable concerned is zero. In constructing the variable which gives the number of other innovative firms, the other firm is classified as being innovative in the year concerned, if it has introduced an innovation during any of those years which are taken into account in the model's innovation variables.

The results reported in Table 7 tell us that the impact associated with the separate years at which innovation is introduced is rather weak. We have presumed that the p-value should be less than 5 percent in order that the impact concerned can be considered significantly different from zero. Using this criterion, all the effects associated with separate dates are zero in both the processing and in the non-processing industries. If the p-value criterion is raised to the 10 percent level, some impacts in the estimation – which uses the data from industries other than the processing industries – become different from zero. The innovation introduced during the previous year then has a negative impact and innovations introduced three years ago have a positive impact. In the lagged regression the innovations introduced two years ago also have a positive effect on the likelihood that a firm is acquired in the non-processing industries. We also estimated a model which includes the innovations introduced four and five years ago in addition. But these variables have no significant impact even at a 10 percent significance level.

Let us then consider the lag structure in the models which explain the likelihood that a firm acquires. The results from the negative binomial regression are reported in Table 8. Surprisingly, the innovation variable lagged with three years has a positive impact in the non-processing industries, although the impact associated with the respective composite index has only zero impact (see Table 6). That a current innovation has a positive impact on the likelihood that a firm acquires another firm in the processing industries could already have been expected on the basis of the estimation results presented in Tables 6 and A5.

The inclusion of innovation variables lagged with 4 and 5 years changes the results in some respects. In the non-processing industries the innovation which was introduced 5 years earlier seems to have a negative impact on the acquisition probability concerned. These results are not reported.

Table 8

Acquisition propensity estimates. Random effects negative binomial firm-level model.
Dependent variable = the number of acquisitions per firm in each year, 1994–1999.

Regressor	*Contemporary Other industries*	*Lagged Other industries*	*Contemporary Processing industries*	*Lagged Processing industries*
Constant	-9.843*	-9.551*	-8.950*	-9.137*
	(0.154)	(0.169)	(0.322)	(0.359)
New innovation during t	-0.201	-0.226	0.427*	0.384
	(0.212)	(0.217)	(0.186)	(0.200)
New innovation during t-1	-0.133	-0.048	0.151	0.249
	(0.198)	(0.207)	(0.193)	(0.203)
New innovation during t-2	-0.022	-0.022	-0.169	-0.107
	(0.188)	(0.197)	(0.217)	(0.220)
New innovation during t-3	0.148	0.407*	0.338	0.406
	(0.176)	(0.180)	(0.215)	(0.219)
Dummy, 1999=1	0.153*	0.022	-0.036	-0.080
	(0.058)	(0.063)	(0.111)	(0.122)
Log Turnover	0.804*	0.760*	0.762*	0.755*
	(0.013)	(0.014)	(0.024)	(0.027)
Number of other innovative	0.019*	0.016*	-0.024*	-0.029*
firms in an industry	(0.002)	(0.002)	(0.009)	(0.010)
Log Debt Ratio	-0.073*	-0.104*	-0.048	-0.175
	(0.037)	(0.043)	(0.083)	(0.095)
Log likelihood	-9966	-8149	-2422	-1932
Wald chi(2)	4190	3343	1090	875
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LR test vs. Pooled	702	548	152	136
(p-value)		(0.000)	(0.000)	(0.000)
Number of firms	143328	113645	15073	12218
Number of observations	515982	366692	58190	43003

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level. Innovation dummy is not lagged in 'lagged version' of the model.

Next, we also take into account the leading years for the innovations introduced. Again, in constructing the variable for the number of other innovating firms, only those dates are taken into account which are included to the dates of the model's innovation variables. Because there are only few innovations in the data which have been introduced during 1999 and because we will also explain current M&As by innovations which are introduced two years after M&A, we restrict the time period to cover only the years 1996, 1995 and 1994. In Table 9 we have reported the results of the estimation in which the likelihood that a firm acquires another firm is explained by innovations whose introduction date varies from a three year lag to a two year lead. We obtained a result according to which in the non-processing industries an innovation which is introduced two years after M&A has a positive impact on the likelihood of acquisition. This result hints that in industries other than the processing industries firms have also bought such targets that possess such unfinished innovations which become mature only after M&A. In the processing industries this phenomenon does not exist. There an innovation which precedes M&A by two or three years has a weakly positive influence on the explained likelihood. These results confirm our hypothesis about the direction of technology transfers associated with M&A in various industries.

Table 9

Acquisition propensity estimates. Random effects negative binomial firm-level model.
Dependent variable = the number of acquisitions per firm in each year, 1994–1996.

Regressor	*Contemporary Other industries*	*Lagged Other industries*	*Contemporary Processing industries*	*Lagged Processing industries*
Constant	-9.683*	-9.520*	-8.393*	-8.312*
	(0.226)	(0.264)	(0.540)	(0.541)
New innovation during t+2	0.781*	0.894*	0.211	0.245
	(0.259)	(0.286)	(0.289)	(0.305)
New innovation during t+1	0.362	0.493	-0.361	-0.294
	(0.267)	(281)	(0.345)	(0.370)
New innovation during t	-0.012	-0.189	0.093	0.251
	(0.295)	(0.312)	(0.325)	(0.332)
New innovation during t-1	-0.258	-0.203	0.210	0.262
	(0.352)	(0.363)	(0.280)	(0.283)
New innovation during t-2	-0.334	-0.388	0.504	0.529
	(0.349)	(0.357)	(0.304)	(0.314)
New innovation during t-3	0.070	0.342*	0.549	0.534
	(0.311)	(0.310)	(0.305)	(0.318)
Log Turnover	0.831*	0.805*	0.733*	0.691*
	(0.019)	(0.021)	(0.031)	(0.035)
Number of other innovative	0.011*	0.006*	-0.007	0.001
firms in an industry	(0.002)	(0.003)	(0.007)	(0.009)
Log Debt Ratio	-0.077	-0.257*	-0.048	-0.075
	(0.057)	(0.069)	(0.117)	(0.147)
Log likelihood	-4599	-3316	-1212	-931
Wald chi(2)	2169	1592	722	514
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LR test vs. Pooled	263	185	30	27
(p-value)		(0.000)	(0.000)	(0.000)
Number of firms	116859	84721	12691	9553
Number of observations	268489	151975	29868	17663

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level. Innovation dummy is not lagged in 'lagged version' of the model.

5. CONCLUSIONS

With this study we step into an area where there is hardly any other empirical studies. We have analysed whether innovations in a firm's possession increase the firm's propensity to buy other firms and, on the other hand, whether this possession attracts other firms to buy the firm concerned. All in all, our study handles a case in which M&As are used as a means to transfer technology in the form of innovations. The results confirm the conclusions obtained in our previous study (see Lehto and Lehtoranta, 2002). Considering the data which covers most industries, the results are blurred by the fact that in some industries technology is transferred from the purchaser to the selling firms, and in some other industries the knowledge streams to the opposite direction. Dividing the data into the processing industries and the non-processing industries gives clearer results. It turns out that in the heavily investing processing industries, where the firm size is also greater than in the non-processing industries, those firms who possess innovations buy such firms who possess no more innovations than the average. This lets us conclude that in the processing industries the efficient firms buy inefficient firms. We obtained this result although the data primarily includes remarkable product innovations.

In the non-processing industries the target firms turn out to be innovators. These firms are purchased by such firms who do not possess more innovations than the average firms. This result is supplemented by a discovery which tells us that in the non-processing industries the purchasing firm tends to introduce a new innovation two years after the acquisition. This refers to the fact that such firms are also purchased that possess unfinished innovations. All in all, it looks as if in the non-processing industries those firms whose strength lies in its incumbency in other areas than in innovative activity buy innovative firms.

We also obtained an interesting result according to which the number of innovative firms in the same industry tends to increase both the likelihood that a firm acquires and is acquired in the non-processing industries. Maybe this indicates that the existence of numerous potential sellers and buyers of innovations in the market makes it easier for buyers to find appropriate targets, which also increases the likelihood that an innovative firm is purchased by some other firm. In the processing industries the number of innovative firms in the industry has, however, a negative impact on the acquiring propensity. This shows that the increase in the number of other innovators – which weakens buyers and strengthens the seller's bargaining power – makes it more difficult for a buyer to find an appropriate target at a reasonable price.

Appendix A. Supplementary results

Table A1

The probability of ownership changes for the target firm in all industries. Random effects firm level logit model for the panel data. Dependent variable: ownership changes (=1), does not change (=0), 1994–1999.

Regressor	*Contemporary*	*Lagged*	*Contemporary*	*Lagged*
Constant	-13.895*	-13.421*	-13.851*	-13.392*
	(0.229)	(0.250)	(0.228)	(0.250)
Innovation dummy from t-1	0.106	0.211		
to t-5	(0.186)	(0.188)		
Innovation dummy from t			0.240	0.291
to t-3			(0.185)	(0.189)
Dummy, 1999 = 1			0.071	-0.074
			(0.076)	(0.081)
Log Turnover	0.815*	0.779*	0.814*	0.778*
	(0.017)	(0.019)	(0.017)	(0.018)
Number of other innovative	0.013*	0.016*	0.011*	0.016*
Firms in an industry	(0.002)	(0.002)	(0.002)	(0.003)
Log Debt Ratio	-0.232*	-0.124*	-0.234*	-0.132*
	(0.042)	(0.050)	(0.042)	(0.050)
Log likelihood	-7131	-6032	-7138	-6034
Wald chi(2)	2348	1839	2349	1839
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LR test of rho = 0	176	129	177	128
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
Number of firms	157872	125673	157872	125673
Number of observations	574172	410250	574172	410250

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level. Innovation dummy is not lagged in 'lagged version' of the model.

Table A2

Acquisition propensity estimates in all the industries. Random effects negative binomial firm-level model. Dependent variable = the number of acquisitions per firm in each year, 1994–1999.

Regressor	*Contemporary*	*Lagged*	*Contemporary*	*Lagged*
Constant	-9.735*	-9.469*	-9.744*	-9.451*
	(0.136)	(0.148)	(0.136)	(0.148)
Innovation dummy from t-1	0.041	0.125		
to t-5	(0.121)	(0.124)		
Innovation dummy from t			0.154	0.277*
to t-3			(0.114)	(0.121)
Dummy, 1999 = 1			0.114	0.006
			(0.051)	(0.055)
Log Turnover	0.797*	0.752*	0.796*	0.750*
	(0.011)	(0.012)	(0.011)	(0.012)
Number of other innovative	0.016*	0.014*	0.016*	0.014*
firms in an industry	(0.002)	(0.002)	(0.002)	(0.002)
Log Debt Ratio	-0.069*	-0.117*	-0.071*	-0.120*
	(0.034)	(0.038)	(0.034)	(0.038)
Log likelihood	-12410	-10255	-12415	-10256
Wald chi(2)	5487	44578	5459	4431
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LR test vs. Pooled	853	685	856	690
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
Number of firms	157872	125673	157872	125673
Number of observations	574172	410250	574172	410250

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level. Innovation dummy is not lagged in ‘lagged version’ of the model.

Table A3

The probability of ownership changes for the target firm. Random effects firm level Logit model for the panel data. Dependent variable: ownership changes (=1), does not change (=0), 1994–1999.

Regressor	*Contemporary Other industries*	*Lagged other industries*	*Contemporary Processing industries*	*Lagged Processing industries*
Constant	-14.293*	-12.112*	-11.921*	-11.589*
	(0.271)	(0.151)	(0.408)	(0.449)
Innovation dummy from t-1	0.461*	0.412*	-0.609	-0.527
to t-5	(0.217)	(0.176)	(0.341)	(0.343)
Log Turnover	0.833*	0.707*	0.698*	0.672*
	(0.020)	(0.015)	(0.031)	(0.034)
Number of other innovative	0.017*	0.018*	-0.015	-0.010
firms in an industry	(0.002)	(0.002)	(0.010)	(0.010)
Log Debt Ratio	-0.230*	-0.106	-0.235*	-0.102
	(0.047)	(0.052)	(0.091)	(0.112)
Log likelihood	-5595	-4772	-1511	-1265
Wald chi(2)	1778	2705	521	408
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LR test of rho = 0	156	33	18	13
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
Number of firms	143328	113645	15073	12218
Number of observations	515982	366692	58190	43003

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level. Innovation dummy is not lagged in 'lagged version' of the model.

Table A4

The probability of ownership changes for the target firm in the processing industries. Random effects firm level logit model for the panel data. Dependent variable: ownership changes (=1), does not change (=0), 1994–1999.

Regressor	Contemporary	Contemporary
Constant	-11.921*	- 11.841*
	(0.409)	(0.407)
Innovation dummy from t-1	-0.610	
to t-5	(0.342)	
Innovation dummy from t		-0.458
to t-3		(0.336)
Dummy, 1999 = 1		-0.280
		(0.175)
Log Turnover	0.698*	0.693*
	(0.342)	(0.031)
Number of other innovative	-0.015	-0.015
firms in an industry	(0.010)	(0.011)
Log Debt Ratio	-0.238*	-0.248*
	(0.091)	(0.091)
Profit ratio	-0.015*	-0.016*
	(0.007)	(0.007)
Log likelihood	-1510	-1510
Wald chi(2)	519	523
(p-value)	(0.000)	(0.000)
LR test of rho = 0	18	18
(p-value)	(0.000)	(0.000)
Number of firms	15052	15052
Number of observations	57928	57928

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level. Innovation dummy is not lagged in 'lagged version' of the model.

Table A5

Acquisition propensity estimates. Random effects negative binomial firm-level model. Dependent variable = the number of acquisitions per firm in each year, 1994–1999.

Regressor	*Contemporary Other industries*	*Lagged Other industries*	*Contemporary Processing industries*	*Lagged Processing industries*
Constant	-9.798*	-9.540*	-9.011*	-9.228*
	(0.154)	(0.169)	(0.322)	(0.360)
Innovation dummy from t-1	0.058	0.129	0.108	0.164
to t-5	(0.154)	(0.158)	(0.194)	(0.204)
Log Turnover	0.800*	0.756*	0.768*	0.765*
	(0.013)	(0.014)	(0.024)	(0.027)
Number of other innovative	0.019*	0.016*	-0.022*	-0.029*
firms in an industry	(0.002)	(0.002)	(0.008)	(0.009)
Log debt ratio	-0.069	-0.099*	-0.052	-0.165
	(0.037)	(0.043)	(0.083)	(0.094)
Log likelihood	-9961	-8147	-2426	-1936
Wald chi(2)	4194	3364	1081	864
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LR test vs. Pooled	712	549	150	131
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
Number of firms	143328	113645	15073	12218
Number of observations	515982	366692	58190	43003

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level. Innovation dummy is not lagged in 'lagged version' of the model.

Table A6

Acquisition propensity estimates. Random effects negative binomial firm-level model. Dependent variable = the number of acquisitions per firm in each year, 1994–1999.

Regressor	*Contemporary Other industries*	*Lagged Other industries*	*Contemporary Processing industries*	*Lagged Processing industries*
Constant	-9.852*	-9.582*	-8.646*	-9.065*
	(0.167)	(0.183)	(0.351)	(0.389)
Innovation dummy from t	0.029	0.104	0.409*	0.361
to t-3	(0.157)	(0.172)	(0.190)	(0.213)
Dummy, 1999 = 1	0.132*	0.049	-0.029	-0.095
	(0.063)	(0.068)	(0.115)	(0.123)
Log Turnover	0.884*	0.817*	0.768*	0.755*
	(0.015)	(0.016)	(0.026)	(0.028)
Number of other innovative	0.015*	0.013*	-0.020*	-0.025*
firms in an industry	(0.002)	(0.002)	(0.009)	(0.010)
Log debt ratio	0.039	-0.025	0.057	-0.122
	(0.042)	(0.048)	(0.092)	(0.103)
Log profit ratio	0.275*	0.206*	0.159*	0.039
	(0.031)	(0.033)	(0.062)	(0.064)
Log likelihood	-8422	-6802	-2232	-1838
Wald chi(2)	3803	3068	988	813
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LR test vs. Pooled	536	398	143	121
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
Number of firms	138021	109765	14207	11621
Number of observations	464572	332208	50822	38022

Notes: Standard deviations are in parentheses. * Significant at the 5 percent significance level. Innovation dummy is not lagged in 'lagged version' of the model.

Appendix B. The descriptive statistics

We use the following abbreviations for the names of the variables:
Target = dummy for being a target
Npurch = the number of purchased firms
Inn3 = Innovation dummy from t to t-3
Lturn = Log Turnover
Ldebt = Log debt ratio
Nothers = Number of other innovative firms in an industry
d99 = Dummy, 1999 = 1
lprof = log profit ratio
inn t = an innovation introduced in the current year
inn t-1 = an innovation introduced one year earlier
inn t-2 = an innovation introduced two years earlier
inn t-3 = an innovation introduced three years earlier

Table B1. All industries, statistics of the data set of the model in table A2 column 3

574172 observations

Variable	Mean	Std. Dev.	Min	Max
Npurch	.0055523	.111125	0	26
fitted	-4.3305	1.321847	-9.881164	4.732369
d99	.1409996	.3480214	0	1
inn3	.0026978	.0518703	0	1
lturn	6.488244	1.622331	-.123015	17.64955
Nothers	11.81813	12.81731	0	57
ldebt	-.5524602	1.028267	-8.906054	9.668208

covariance matrix

	Npurch	fitted	d99	inn3	lturn	Nothers	ldebt
Npurch	1.0000						
fitted	0.1356	1.0000					
d99	0.0085	0.1111	1.0000				
inn3	0.1016	0.1160	0.0021	1.0000			
lturn	0.1350	0.9851	0.0721	0.1065	1.0000		
Nothers	0.0159	0.2007	0.0521	0.0378	0.0416	1.0000	
Ldebt	-0.0049	-0.0317	-0.0429	0.0019	0.0317	-0.0396	1.0000

Table B2. Other industries, Statistics of the data set of the model in Table 2, Column 1

Number of observations = 515982

Variable	Mean	Std. Dev.	Min	Max
Npurch	.0047308	.1048408	0	26
Fitted	-4.36769	1.298032	-9.973523	4.744054
d99	.1401018	.3470929	0	1
inn3	.0023295	.0482091	0	1
lturn	6.430432	1.557626	-.123015	17.58183
Nothers	12.49624	13.17986	0	57
ldebt	-.5575855	1.034516	-8.906054	9.668208

Covariance matrix:

	Npurch	fitted	d99	inn3	lturn	Nothers	ldebt
Npurch	1.0000						
Fitted	0.1185	1.0000					
d99	0.0091	0.1312	1.0000				
inn3	0.0745	0.0984	0.0020	1.0000			
lturn	0.1178	0.9768	0.0768	0.0910	1.0000		
Nothers	0.0218	0.2594	0.0601	0.0439	0.0601	1.0000	
Ldebt	-0.0034	-0.0380	-0.0413	0.0025	0.0310	-0.0428	1.0000

Table B3. Processing industries, Statistics of the data set of the model in Table 2, Column 3

58190 observations

Variable	Mean	Std. Dev.	Min	Max
Npurch	.0128373	.1559627	0	8
Fitted	-3.699661	1.553793	-9.475522	4.890186
d99	.1489603	.3560524	0	1
inn3	.0059632	.076992	0	1
lturn	7.000868	2.040623	-.123015	17.64955
Nothers	5.805173	6.362186	0	22
ldebt	-.5070132	.9699153	-7.955074	6.684612

covariance matrix

	Npurch	fitted	d99	inn3	lturn	Nothers	ldebt
Npurch	1.0000						
fitted	0.2099	1.0000					
d99	0.0046	0.0309	1.0000				
inn3	0.2011	0.1821	0.0014	1.0000			
lturn	0.2057	0.9945	0.0397	0.1654	1.0000		
Nothers	0.0056	-0.0202	-0.0389	0.0456	0.0780	1.0000	
ldebt	-0.0171	-0.0062	-0.0585	-0.0034	0.0273	0.0534	1.0000

Table B4. Other industries, Statistics of the data set of the model in Table 1, Column 1

515982 observations

Variable	Mean	Std. Dev.	Min	Max
target	.0019225	.0438047	0	1
fitted	-8.56369	1.349808	-14.78656	1.354314
d99	.1401018	.3470929	0	1
inn3	.0023295	.0482091	0	1
lturn	6.430432	1.557626	-.123015	17.58183
Nothers	12.49624	13.17986	0	57
ldebt	-.5575855	1.034516	-8.906054	9.668208

covariance matrix

	target	fitted	d99	inn3	lturn	Nothers	ldebt
target	1.0000						
fitted	0.0977	1.0000					
d99	0.0069	0.1311	1.0000				
inn3	0.0484	0.1143	0.0020	1.0000			
lturn	0.0967	0.9704	0.0768	0.0910	1.0000		
Nothers	0.0171	0.2135	0.0601	0.0439	0.0601	1.0000	
ldebt	-0.0049	-0.1557	-0.0413	0.0025	0.0310	-0.0428	1.0000

Table B5. Other industries, Statistics of the data set of the model in Table A6, Column 1

464572 observations

Variable	Mean	Std. Dev.	Min	Max
Npurch	.0043718	.1000259	0	26
fitted	-4.407149	1.300993	-15.66289	5.653796
d99	.1366096	.3434351	0	1
inn3	.0020169	.0448648	0	1
lturn	6.457957	1.539179	-.123015	17.58183
Nothers	12.22916	13.21987	0	57
ldebt	-.5824468	1.025408	-8.906054	9.342541
lprof	-1.625485	1.08701	-37.13045	6.662174

Covariance matrix

	Npurch	fitted	d99	inn3	lturn	Nothers	ldebt	lprof
Npurch	1.0000							
fitted	0.1217	1.0000						
d99	0.0086	0.1138	1.0000					
inn3	0.0714	0.1005	0.0020	1.0000				
lturn	0.1183	0.9686	0.0892	0.0933	1.0000			
Nothers	0.0189	0.2033	0.0595	0.0431	0.0735	1.0000		
ldebt	-0.0022	0.0425	-0.0440	0.0018	0.0310	-0.0530	1.0000	
lprof	-0.0230	-0.2182	-0.0967	-0.0211	-0.4040	-0.1324	-0.0477	1.0000

Table B6. Other industries, Statistics of the data set of the model in Table 3, Column 1

515982 observations

Variable	Mean	Std. Dev.	Min	Max
target	.0019225	.0438047	0	1
fitted	-8.562789	1.354904	-14.82414	1.154819
d99	.1401018	.3470929	0	1
inn t	.0006609	.025699	0	1
inn t-1	.0007345	.0270921	0	1
inn t-2	.0006841	.026147	0	1
inn t-3	.0006008	.0245038	0	1
lturn	6.430432	1.557626	-.123015	17.58183
Nothers	12.49624	13.17986	0	57
ldebt	-.5575855	1.034516	-8.906054	9.668208

covariance matrix

	target	fitted	d99	inn t	inn t-1	inn t-2	inn t-3	lturn	Nothers	debt
target	1.0000									
fitted	0.0973	1.0000								
d99	0.0069	0.1290	1.0000							
inn t	0.0264	0.0558	-0.0086	1.0000						
inn t-1	0.0200	0.0483	0.0014	0.1273	1.0000					
inn t-2	0.0361	0.0677	0.0052	0.1089	0.1334	1.0000				
inn t-3	0.0386	0.0671	0.0067	0.0886	0.1103	0.1294	1.0000			
lturn	0.0967	0.9702	0.0768	0.0540	0.0583	0.0584	0.0560	1.0000		
Nothers	0.0171	0.2154	0.0601	0.0234	0.0244	0.0240	0.0229	0.0601	1.0000	
ldebt	-0.0049	-0.1561	-0.0413	0.0010	0.0017	0.0014	-0.0000	0.0310	-0.0428	1.0000

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