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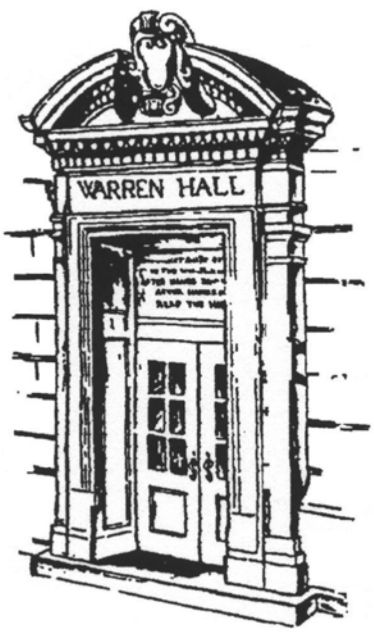

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EXPLORING THE SOURCES OF SKILL-BIASED TECHNICAL CHANGE: A FIRM PERFORMANCE PERSPECTIVE

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Exploring the Sources of Skill-Biased Technical Change: A Firm Performance Perspective

by

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Abstract

The literature on skill-biased technical change has examined the role of skills in the adoption of new technology. Here the focus is on the creation of new technology, that is, innovation. Low skill firms are hypothesized to benefit less from innovation activities, particularly collaborative research and development (R&D). In other words, skills and innovation are complementary. Complementarities associated with innovation may generate persistent differences in firm behavior and performance. Results from a panel of manufacturing firms indicate that technical skills reinforce the profitability effects of innovation and R&D collaboration. Skills, collaboration, and innovation form a system of interdependent activities.

Key words: Innovation, R&D collaboration, skills, complementarities

JEL codes: O12, O15, O31, O32, O33

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1 INTRODUCTION

The view of innovation as the main engine of long-run economic development is widespread. It seems that the social returns to innovation can be enormous, yet at the level of individual firms it is not evident that the returns to innovation investments are always positive. Teece (1986) documented this phenomenon with case studies of product innovations. He concluded that profiting from innovation depends on access to complementary capabilities, especially in marketing and distribution, without which the innovative idea cannot be profitably commercialized.

Similarly, recent literature on research joint ventures and strategic alliances has observed that, despite the proliferation of these arrangements, it is difficult to benefit from joint innovation projects (Kogut 1989; Harrigan 1988). Economic literature on research joint ventures, however, does not present insights into what might be driving the high failure rates. This paper suggests that an important but neglected factor is firms' existing base of skills and knowledge. Skills complement both internal and collaborative research and development (R&D). This argument can be viewed as a new angle to the debate on skill-biased technical change (Acemoglu 1998; Autor, Katz, and Krueger 1998; Machin and Reenen 1998), or more recently, skill-biased organizational change (Caroli and Reenen forthcoming). Most recently, Autor, Levy and Murnane (2001) provided a detailed analysis of how computers are used in firms. The findings indicate that computers substitute for routine cognitive and manual tasks and complement non-routine problem solving and interactive tasks. These effects shift the demand for labor toward highly skilled and highly educated people.

In this paper it is argued that not only adoption of technology but its successful creation is complemented by skilled employees in the firm. This is supported by cognitive studies of learning (see Cohen and Levinthal 1990, for a review). Notably, the need for skilled employees is not limited to the R&D function. The entire innovating organization benefits from upskilling. In the current environment of deregulation and globalization, competition is increasingly based on innovation, and therefore the notion of skill-biased technical change is not limited to the adoption of information technology. Upskilling may be driven by multiple facets of technical change.

This argument is in line with a recent study by Bresnahan, Brynjolfsson, and Hitt (forthcoming) that suggests that product or service innovation is an essential component in the theory of demand for skilled labor. According to case studies and surveys of managers, adoption of technology is motivated by the need to improve product and service offerings (Brynjolfsson and Hitt 1995). Also, the organizational changes identified by Brynjolfsson and Hitt (2000) as complementary to technology investment are intended to improve product and service capabilities. Clearly, innovation is involved in these recent developments. However, the empirical work by Brynjolfsson and his coauthors suffers from the lack of direct measures of innovation. The focus in the current paper is precisely on the process of innovation and its impact on the demand for skills. Broad-based innovation surveys and the employment register of the Finnish manufacturing sector enable a more detailed analysis of the nature of the relationship between skills and innovation.

The idea of complementarities related to the nature of the firm is new in neither strategic management (the notion of "synergy") nor business history (e.g., Chandler 1962). However, organizational complementarities have not been a focus of inquiry in the economic theory of the firm, until Milgrom and Roberts (1990; see also Holmström and Milgrom 1994) introduced the concept in organizational economics. Studies of technological change and innovation, on the other hand, have emphasized interactions among activities within the firm (Kline and Rosenberg 1986; Rothwell 1994) and the firm's relationship with external sources of knowledge (e.g. Levin, Cohen, and Mowery 1985; Cohen and Levinthal 1989). Essentially, organizational interactions are seen to stem from the need to combine different kinds of knowledge in the innovation process. Complementary knowledge sources are thus the basis of organizational complementarities.

Empirical studies of innovation provide evidence that the accumulation of knowledge may be a source of considerable variation in firms' behavior and performance (e.g., Geroski, Machin, and Reenen 1993; Henderson and Cockburn 1996; Klette 1996). According to Geroski et al. (1993), a firm's innovation record affects its profitability. They contend that innovation performance approximates the accumulation of knowledge capital and that this capital enables firms to continuously bring new products to market and improve productivity through process innovation. However, the fundamental factors behind differences in knowledge accumulation remain unknown. If possessing knowledge capital translates into improved market performance, and any firm can acquire knowledge, i.e., learn and innovate, then all firms facing the same opportunities should invest identically and no performance differences should be observed in the long run.

In real economies firms do perform and behave differently. I suggest that one reason why firms may make different learning investments is the combinatory characteristics of the investments. The "portfolio" of investments, collaborations, and skills may have an effect on the marginal productivity of each of the components. If the components of a firm's knowledge capital complement one another, then each is more productive in the presence of the others.

Systemic effects could also explain the persistent differences in firm performance. Firms that initially possess some components of the "knowledge system" perceive further investment to be more productive, making virtuous cycles possible. In contrast, knowledge-poor firms are less likely to recognize productive R&D investment opportunities because of the missing complementary components. Managers might be unaware of the complementarities, and creating a system of complementary skills from a nonexistent foundation is a risky, time-consuming, and expensive venture. There are thus significant adjustment costs to setting up the knowledge system. Hiring skilled employees may not be sufficient; employees also need to learn to use their skills in the organization. In fact, learning may be the key source of adjustment costs in creating the system of knowledge complementarities. The proposition that adjustment is not instantaneous despite strong positive interactions is borne out by the data used in this study: even though most firm observations are found in the extremes of "engages in all complementary activities" or "engages in no activities," as predicted by the theory, a considerable number of firms make "mistakes" and end up with mixed knowledge creation portfolios.

Knowledge accumulation processes are likely to vary across industries and sectors. Within manufacturing, investments in learning often include R&D, hiring skilled employees, on-the-job learning and training, technology licensing and other intellectual property acquisitions, collaboration with other organizations, and designing the internal organizational such that it promotes communication and provides proper incentives. There is an emerging literature that examines whether these learning investments and activities reinforce one another. In addition to the work by Brynjolfsson, Hitt, and Bresnahan, as well as that by Caroli and Van Reenen, Geroski et al. (1993) found evidence of complementarities. Specifically, external and internal sources of knowledge are complementary in that the effects of knowledge spillovers are larger and more significant for innovating firms. This finding accords with the absorptive capacity argument of Cohen and Levinthal (1989): Internal R&D facilitates absorption of knowledge spillovers. In other words, internal and external knowledge are complements. Analyzing interactions among firms' various internal knowledge assets, Helfat (1997) argued that there are economies of scope among different fields of R&D within the petroleum industry. According to her results, R&D in coal conversion depends positively on complementary R&D in refining.

This paper seeks to assess the scope of interactions among firms' skill bases, collaborative innovation activities, and innovation output in a profitability framework. In an earlier study, employees' skills were found to impact firms' profits (Leiponen 2000). Interestingly, skills interacted with one another. The positive effect of research skills on profits was conditioned by a sufficiently high level of "general" skills in the firm. Moreover, the impact of skills on profitability was larger for innovating firms than for non-innovating firms. This suggests that skills and innovation interact in determining economic performance. Here I build on these results and analyze more explicitly whether skills and accumulated knowledge complement R&D collaboration and innovation. The following section develops the hypotheses. The data are presented in section 3, and the empirical framework for estimating complementarities is developed in section 4. Section 5 discusses the empirical results and section 6 concludes.

2 HYPOTHESES

Management literature has long discussed the role of interactions related to skills and knowledge, but few robust, cross-sectional studies exist. Nevertheless, the widely accepted logic of Teece's (1986) complementary capability proposition is intuitive. Having an innovative idea is only one part of the successful development of a new product or process. To develop the idea into a well-functioning technology that can be profitably manufactured and marketed the firm needs high technical, marketing, and "integrative" competencies (Iansiti 1995; Kogut and Zander 1992). Thus, the first hypothesis to be assessed with the firm-level panel dataset is that to benefit from product and process innovation the firm must have sufficient internal competencies. In other words, a firm's skills complement innovation in its effects on profitability.

The second hypothesis concerns the profitability effects of R&D collaboration. In theoretical studies of the economics of R&D joint ventures (d'Aspremont and Jacquemin 1988; Kamien, Muller, and Zang 1992, and the literature building on these seminal works), the focus is usually on horizontal and industry-wide cooperation, and there are no additional organization costs associated with collaboration. As a result, collaboration is always socially efficient, because it enables internalizing spillovers. However, the relatively high failure rates of collaborative arrangements observed in empirical studies attest to the opposite (Harrigan 1988; Kogut 1989). Thus, in reality, R&D collaboration is costly and difficult.

Empirical studies suggest that firms engage in collaborative arrangements in order to cope with technological complexity, reduce the uncertainty and costs of R&D, capture partners' knowledge, and reduce product development time (Hagedoorn 1993; also Kogut 1988; Contractor and Lorange 1988; Coombs et al. 1996, among others). As in the theoretical literature, the reasons for *not* collaborating—costs of collaboration rather than benefits—have not been sufficiently examined, despite consistent findings that instability and less than satisfactory performance of alliances and joint ventures are common. Notable exceptions are the studies by Pisano et al. (1988) and Oxley (1997) arguing that collaboration decisions are aligned with strategies to minimize transaction costs, particularly knowledge spillover hazards. In addition, management studies by Mowery et al. (1996) and Dyer and Singh (1998) argue that the extent of overlap in the partners' knowledge bases increases the potential to generate rents. Recent theoretical literature on endogenous spillovers (Kamien and Zang 2000) also has begun to examine knowledge leakage as a strategic variable and a cost related to collaboration.

Here another explanation is proposed for why some firms are less likely than others to engage in external innovation activities. Collaborative R&D is always costly, because it entails investments of time and resources. However, the costs and benefits of collaborative projects are a function of the existence and scope of a firm's complementary internal knowledge assets. Without sufficient internal knowledge assets, a firm will not be able to internalize and effectively utilize the knowledge created or accessed through collaboration (cf. Cohen and Levinthal, 1989). Recognizing that employees' skills and their collective experience, not only R&D, are an important component of absorptive capacity positions us to analyze the relationships between internal and external knowledge sources: Internal skills and accumulated knowledge of a firm reinforce the profitability effects of collaborative R&D, i.e., collaborative R&D is hypothesized to be complementary with internal knowledge.

To summarize and formalize the hypotheses, we can specify a profit function for the firm. The firm maximizes profits with respect to skills (S), innovation (I), and R&D collaboration (C):

(1) $\max_{S,\,I,\,C}\ \Pi = f(S, I, C, \text{other firm and industry variables})$

The two hypotheses can be expressed in the following way:

(2) Π is supermodular in (S, I) and in (S, C).[2]

The profit-maximizing firm is taken here as the starting point, as opposed to productivity performance that has been the focus of most of the literature on skill-biased technical change. Indeed, an extension of this study could assess the productivity implications to create a benchmark against the skill-bias literature.

[2] See Topkis (1998).

3 DATA

The empirical analysis makes use of data from two Finnish innovation surveys, national business surveys, the register for domestic patent applications, and the employment register. The innovation survey datasets contain information about product and process innovations, R&D investments, and innovation collaboration during the periods 1989–1991 (first survey administered in 1992; see SF 1992) and 1994–1996 (second survey administered in 1997; see SF 1998).[3] Innovation and business survey questionnaires were sent to all manufacturing firms with more than one hundred employees and to a random sample stratified by size and industry for smaller firms. Response rates were about 70 percent in both innovation surveys. The patent and employment registers cover all firms.

From these sources, I constructed a panel dataset of 159 manufacturing firms over the period 1990–1996. To be included in the sample, firms must have participated in both innovation surveys and all or all but one of the annual business surveys for the period 1990–1996.[4] This construction creates some bias toward larger firms because large firms are slightly over-represented in the innovation surveys, and larger firms are both more likely to show up in the business surveys and survive over the seven-year period (Hall 1987). All manufacturing industries at the two-digit industry classification level are included (see table 1 for industry breakdown). For comparison, table 1 also provides a breakdown for the representative innovation survey sample of 1,029 firms (weights provided by Statistics Finland are used to increase representativeness of the raw data). The printing and publishing industry appears to be slightly overrepresented in the smaller panel sample, possibly due to stable industry conditions leading to a higher probability of firms surviving, while the metal products industry is underrepresented.

The period of study coincides with a sharp economic recession and subsequent recovery in Finland. This turbulence in the environment is reflected in firms' behavior and performance. Several outliers were eliminated from the dataset due to dramatic changes in

[3] Statistics Finland (SF) has adhered to the Eurostat guidelines for European Community Innovation Surveys in designing and implementing the Finnish innovation surveys.
[4] The missing observation has to be either the first or the last year.

firm size, profitability, or other variables.[5] Because of these historical events, the analysis could alternatively be interpreted as a study of the factors of rapid recovery from a considerable external shock. Some of the estimation results may be weakened by this source of noise, however.

Table 1 Industries

Industry	Dummy Variable	NACE	No. of observations in the sample	Share (%)	No. of observations in the innovation survey	Share (%)
Food	IND1	15-16	21	13.2	107	10.4
Textile	IND2	17-19	13	8.2	79	7.7
Wood	IND3	20	11	6.9	76	7.4
Paper	IND4	21	5	3.1	26	2.5
Printing, publishing	IND5	22	25	15.7	98	9.5
Oil, chemical	IND6	23-24	10	6.3	43	4.2
Plastic, rubber	IND7	25	8	5.0	47	4.6
Nonmetallic minerals	IND8	26	4	2.5	44	4.3
Primary metals	IND9	27	6	3.8	26	2.5
Metal products	IND10	28	4	2.5	97	9.4
Machines, equipment	IND11	29	25	15.7	146	14.2
Electronics	IND12	30-33	16	10.1	133	12.9
Cars, vehicles	IND13	34-35	3	1.9	54	5.2
Furniture	IND14	36	8	5.0	53	5.2
Total			159	100.0	1,029	100.0

Estimation variables are listed and described in table 2 and descriptive statistics are displayed in table 3. The data are at the level of the firm, not business group. The dependent variable, operating profit margin is derived from the business survey information. It is a rather standard profitability measure (see e.g., Geroski et al. 1993). Operating profit levels tend to vary systematically across industries, which can be sufficiently controlled for with industry level variables. An average firm in the dataset had 506 employees in 1995; 79 percent of the firms reported positive R&D expenditures that year and, on average, these R&D investing firms spent 1.8 percent of their sales revenue in R&D.[6]

[5] "Dramatic" is defined as more than 100 percent growth or 50 percent reduction in sales or number of employees, or negative three-digit profit margins.

[6] There are some problems of distinguishing zeroes from missing data in the R&D survey information. Based on information about sampling procedures, a missing observation means that R&D investment is probably

Table 2 Variables

Dependent Variable	PROFIT	Operating profit/sales
Explanatory variables		
Innovation Activities	INNO	Innovation dummy (either product or process innovations in 1989–1991 *and* either product or process innovations in 1994–1996)
	COLLAB	R&D collaboration dummy (firm collaborated with competitors, customers, suppliers or universities in 1989–1991 *and* in 1994–1996)
	RDINV*	Internal research and development investments/sales
	RDDUM	Dummy for R&D investment > 0
Skills	TECH SKILL	Share of employees with a higher technical or natural scientific degree (e.g., university engineer, master of science in chemistry)
	TECHDUM	Dummy for value of TECH SKILL higher than the mean
	PATENT*	Number of domestic patent applications
	RESEARCH*	Share of employees with a post graduate degree (licentiate, Ph.D.)
Firm	EMPLOYEES	Number of employees
	CAP-INT	Capital intensity (fixed capital/sales)
	MSHARE	Domestic market share in the two-digit industry
Industry	CONC3	Three-firm concentration ratio in the domestic two-digit industry
	INDCAP-INT	Average capital intensity in the industry
	INDPATENT	Average number of patents in the industry among patenting firms

Notes: Data are available for 1990-1996 unless otherwise indicated. Variables marked with an asterisk are used as instruments in the estimations.

Internal skills are proxied here by educational levels and fields of employees; 6.7 percent of the employees in an average firm have a higher university degree in technical or natural sciences.

According to the 1992 innovation survey data, 61 percent of firms introduced new products in the markets (with positive sales revenue), 60 percent adopted new processes, and 56 percent of firms engaged in collaborative R&D in the three years before that. In the 1997 innovation questionnaire, the wording was changed to emphasize *technological* product and process innovations and perhaps partly for this reason the share of innovating firms dropped to 37 percent for product and 40 percent for process innovators. 47 percent of firms reported collaborating with customers, suppliers, universities, or competitors.

zero but I cannot be completely certain. Because of this potential measurement error, this variable is used mainly as an instrument in the econometric analysis.

Table 3 Descriptive Statistics

	Mean	Std. Dev.	Min.	Max.	Mean for the Innovation Survey sample (1996; N=1,029, weighted)
PROFIT (%)	7.5	8.5	-24.0	42.8	6.8
EMPLOYEES	506	897.7	25	6650	98
CAP-INT (%)	16.3	15.5	0.4	142.3	13.8
MSHARE (%)	1.9	6.0	0.03	56.0	0.4
PATENT	1.4	6.1	0	54	0.3
RESEARCHER (%)	0.20	0.50	0	3.63	0.10
TECH SKILL (%)	6.7	7.5	0.0	48.0	6.4
TECHDUM	0.36	0.48	0	1	n.a.
RDDUM	0.79	0.41	0	1	0.30
RDINV (N=107) (%)	1.8	2.0	0.03	13.0	2.4 (N=400)
INNO	0.46	0.50	0	1	0.19*
COLLAB	0.34	0.48	0	1	0.22**
INDCAP-INT (%)	15.6	5.3	9.9	28.9	14.8
INDPATENT	2.8	2.4	0.0	8.9	3.7
CONC3 (%)	26.7	10.9	8.8	50.2	34.8

Notes: n.a. = not available. N = 159, year = 1995.
* Either product or process innovations in 1996.
** Collaboration in 1996.

The innovation and collaboration indicators used in the empirical analysis combine these survey variables. The INNO variable is a dummy that takes on the value 1 if the firm introduced product *or* process innovations in both 1989–1991 and 1994–1996. Hence, the innovating firm may have introduced a product innovation in 1991 and a process innovation in 1996—mixed combinations are allowed. The idea is to find the *consistent* innovators in the sample. Similarly, the COLLAB dummy variable is 1 for firms that engaged in external collaboration according to both 1992 and 1997 surveys.

Compared to the representative innovation survey sample of 1997 (1,029 firms unless otherwise indicated), as expected, the panel sample is considerably biased toward larger firms. There is also a bias toward innovating firms. This can be attributed to survivor bias, because innovative firms generally perform better economically and therefore were more likely to survive the hard times of the Finnish economy in the early 1990s. Somewhat surprisingly, however, although firms in the panel sample are much more likely to engage in R&D, their investments in R&D are smaller. This may relate to the size bias: smaller R&D performing firms are perhaps more likely to be highly R&D intensive (R&D investments per sales revenue).

Table 4 Innovator Profiles of Firms Investing in R&D

	TECHDUM	INNO	COLLAB	All R&D Investing Firms	Non R&D Firms	All Firms
PROFIT (%)	9.8	9.8	8.8	8.2	6.1	7.5
SALES (mill. FIM)	1324	1169	1494	889	197	663
EMPLOYEES	790	780	915	633	245	506
INNO	0.72	1	0.94	0.64	0.10	0.46
COLLAB	0.68	0.70	1	0.49	0.04	0.34
TECH SKILL (%)	13.5	8.8	10.2	8.1	3.9	6.7
TECHDUM	1	0.51	0.65	0.47	0.15	0.36
RDINV (%)	2.7	2.0	2.3	1.8	0	1.2
N	50	73	54	107	52	159

Notes: N = 159, Year = 1995. The three first columns present mean statistics for R&D firms, for which the respective innovation indicator is equal to 1.

To examine the relationships among variables related to innovation activities, table 4 provides a simple contingency table by displaying variable means for different kinds of R&D investing firms, non-investors, and all firms in the sample for 1995.[7] The first three data columns show means of the variables on the left for firms that invested in R&D in 1995 *and* engaged in the activity indicated at the head of the column. For example, the average sales of consistently innovating R&D active firms were FIM 1,169 million.

Table 4 presents descriptive evidence that innovation activities and competencies tend to cluster. The first observation is that technical skills concentrate in firms that engage in innovation activities.[8] Furthermore, firms that innovate tend to employ a very large number of highly educated engineers, 8.8 percent of employees compared to 8.1 percent for all R&D investing firms. Collaborating firms employ the most employees with higher technical education, 10.2 percent. The second observation is that innovating and collaborating firms, and particularly firms with high skill levels, invest more in R&D as a share of sales revenue than the larger group of all R&D investing firms. This suggests that returns to R&D investments are higher in the presence of high skills and collaboration. Third, collaboration increases firms' likelihood of innovation. 94 percent of consistently

[7] See table A3 in the appendix 1 for numbers of observations for different combinations of innovation and skill variables.
[8] Comparison with Finnish surveys of R&D personnel and investments indicates that most of these technical employees do not work in jobs directly related to R&D, but in production, sales, and other functions (SF 2000). High skill levels thus reflect the overall higher knowledge intensity of R&D performing firms.

collaborating firms also innovated consistently, against 64 percent of all R&D investing firms. Thus, either collaboration increases innovativeness or benefits to collaboration and innovation both depend on some unobserved firm characteristics such as their other knowledge assets.[9] Finally, profit margins tend to follow the same clustering pattern when compared across different groups of firms. Non-R&D-investing firms have the lowest profit margins, while R&D, collaboration, successful innovation, and high skills gradually improve the margins. However, firm size also appears to be highly correlated with the innovation and skill indicators, so controlling for that variable in the estimations is likely to be important.

Table 5 Determinants of INNO and COLLAB

Dependent variable:	INNO		COLLAB	
	Coeff.	Std. error	Coeff.	Std. error
Constant	-1.13**	0.19	-1.10**	0.20
TECH SKILL	2.49**	0.51	3.19**	0.52
EMPLOYEES	1.60**	0.25	1.61**	0.24
MSHARE	0.01	0.05	-0.10*	0.06
IND1	0.11	0.24	0.08	0.24
IND2	0.16	0.24	0.05	0.25
IND3	0.05	0.25	-0.42	0.27
IND4	0.75**	0.36	0.51	0.37
IND5	0.03	0.24	-0.38	0.25
IND6	0.57*	0.31	0.13	0.32
IND7	0.81**	0.26	0.64**	0.26
IND8	0.22	0.27	0.06	0.28
IND9	-0.02	0.40	0.33	0.38
IND10	-0.02	0.23	0.00	0.23
IND11	0.35	0.22	0.07	0.22
IND12	0.59**	0.24	0.14	0.24
IND13	0.13	0.28	-0.14	0.30
Log Likelihood	-600.90		-563.30	
McFadden's pseudo R^2	13%		15%	
% of correct predictions	72%		74%	
N	1056		1056	

Notes: Probit ML estimation. ** implies significance at the 95% level, * at the 90% level.

[9] Correlations among the original variables and among the first-differenced variables to be used in the estimation can be found in tables A1 and A2 in appendix 1.

Table 6 Determinants of R&D intensity and TECH SKILL

Dependent variable:	RDINT			TECH SKILL	
	Coeff.	Std. Error		Coeff.	Std. Error
Constant	-0.12**	0.02	Constant	-0.02	0.01
TECH SKILL	0.47**	0.05	INNO	0.02	0.01
EMPLOYEES	0.03**	0.01	COLLAB	0.05**	0.01
MSHARE	-0.01	0.01	EMPLOYEES	0.02**	0.01
IND1	0.01	0.02	MSHARE	0.000	0.004
IND2	-0.01	0.03	IND1	-0.04*	0.02
IND3	-0.01	0.03	IND2	-0.01	0.02
IND4	0.06	0.03	IND3	0.05**	0.02
IND5	-0.04	0.03	IND4	0.03	0.03
IND6	0.03	0.03	IND5	-0.03	0.02
IND7	0.06**	0.03	IND6	0.10**	0.02
IND8	0.01	0.03	IND7	0.01	0.02
IND9	0.01	0.04	IND8	0.09**	0.02
IND10	0.00	0.02	IND9	0.05	0.03
IND11	0.02	0.02	IND10	0.05**	0.02
IND12	0.03	0.02	IND11	0.08**	0.02
IND13	0.00	0.03	IND12	0.12**	0.02
			IND13	0.05**	0.02
Log likelihood	-1.22		Log likelihood	338.39	
Sigma	0.10	0.00	Sigma	0.10	0.00
N	1056		N	1056	

Notes: Tobit ML estimation. ** implies significance at the 95% level, * at the 90% level.

Tables 5 and 6 provide additional simple tests of multiple correlation between skills and innovation activities. These estimations were carried out with the larger innovation survey dataset of 1994–1996. The results indicate that skills significantly determine INNO and COLLAB. Table 6 shows results for Tobit estimations of the determinants of R&D intensity and those of technical skill levels. Firms with higher skill levels invest significantly more resources in R&D activities. Then reversing the direction of causation, technical skill levels are significantly determined by R&D collaboration. The insignificance of the INNO variable here is caused by the high multicollinearity between INNO and COLLAB.

In summary, the data in table 4 are consistent with the proposition that there are complementarities among skills and innovation activities. Higher than average skills and R&D investments are observed in firms that innovate or collaborate. Profitability also correlates with innovation activities. The simple estimation results in tables 5 and 6 demonstrate the strong mutual determination among technical skills, R&D, innovation, and

R&D collaboration, controlling for industry differences and firm size. However, these observations do not yet establish complementarity as they could be driven by unobserved heterogeneity. The next sections present an explicit test as to whether firms' skills and innovation activities are indeed complementary in terms of their effects on profitability.

4 ECONOMETRIC METHOD

The econometric model is the following:

$$(3) \qquad \Pi_{it} = \alpha'\Pi_{it-1} + \beta^{E}{}'X_{it}^{E} + \beta^{P}{}'X_{it}^{P} + \gamma'Y_{it} + \mu_i + \varepsilon_{it} + \delta_t$$

Π_{it} denotes profits for firm i in period t, $\boldsymbol{X^E_{it}}$ are the strictly exogenous industry level control variables, $\boldsymbol{X^P_{it}}$ are potentially predetermined firm-level explanatory variables, μ_i are unobserved firm-specific fixed effects, $\boldsymbol{\delta_t}$ are time dummies, and ε_i are error terms. α, β^E, β^P, and γ are the parameters to be estimated. $\boldsymbol{Y_i}$ is a vector of the interactions of the X^Ps to test for the presence of complementarities. In general, positive cross-partial derivatives of continuous X_i variables would imply complementarity. This is equivalent to the γ parameters being positive.[10]

However, in the case of binary variables such as the innovation and collaboration indicators, simple interaction terms are not the best way to empirically identify potential complementarities. In particular, then the "mixed cases" are not identified. The identification strategy used here builds on Bresnahan et al. (1999). The starting point is the definition of supermodularity (complementarity) for a two-dimensional function $f(x,y)$, where $x = \{0,1\}$ and $y = \{0,1\}$ (see Topkis 1998, 45):

$$(4) \qquad f(1,1) - f(0,1) \geq f(1,0) - f(0,0)$$

Supermodularity thus implies "increasing differences": the effect of increasing x from 0 to 1 is larger when y = 1 than when y = 0. In the estimation we can normalize $f(0,0) = 0$, and thus the empirical complementarity condition is:

$$(5) \qquad f(1,1) \geq f(0,1) + f(1,0)$$

[10] See appendix 2 for more discussion of the identification of complementarities.

Estimation will generate coefficients for mutually excluding dummies for the different combinations. Combinations include, for instance, high skill innovator ("high-high" combination), low skill innovator ("low-high"), and high skill non-innovators ("high-low"), while low skill non-innovator ("low-low") is the reference case. A result in line with the complementarity condition (5) could then be interpreted to mean that the effect of introducing innovations on profitability is greater in the presence of high skills than in the presence of low skills.

Generalized method of moments (GMM) for panel data is used for estimation in order to account for simultaneous or predetermined variables (see Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998). A dynamic model with predetermined explanatory variables leads to inconsistent estimates with such methods as fixed effects or three-stage least squares. To control for fixed effects, with which the *X*s may correlate, the model can be estimated in first differences:

$$\Delta\Pi_{it} = \alpha'\Delta\Pi_{it-1} + \beta^{E}{}'\Delta X_{it}^{E} + \beta^{P}{}'\Delta X_{it}^{P} + \gamma'\Delta Y_{it} + \Delta\varepsilon_{it} + \Delta\delta_{t} \tag{6}$$

Some of the firm-level variables are likely to be predetermined, that is, correlated with the previous period's error term, rather than strictly exogenous. Therefore, some undesirable correlation between the explanatory variables and the error terms may still remain. Instruments are used to correct for this. Values of the dependent variable lagged two or more periods are valid instruments, because the model is dynamic (AR1). The values of explanatory variables lagged one or more periods are also valid. The orthogonality conditions are:

(7) $E(\Pi_{i,t-s}\Delta\varepsilon_{it}) = 0$ for $t=3,\ldots,T$ and $s \geq 2$.

$E(X_{i,t-s}\Delta\varepsilon_{it}) = 0$ for $t=3,\ldots,T$ and $s \geq 1$.

Additionally, current exogenous variables X^E are valid instruments. Second-order serial uncorrelation of the error terms is required for the consistency of this model. The Sargan test statistic of overidentifying restrictions (stacked instrumental variables) is also reported with the results (see Arellano and Bond, 1991).

Arellano and Bover (1995) argued that first-differenced estimation loses information particularly useful with short panels. They propose a system method that estimates the level equations together with the differenced equations to increase precision. Then lagged first differences are used as instruments for the level equations, and lagged levels are used as instruments for the differenced equations.

Blundell and Bond (1998) found that the system estimator can alleviate the problem of weak instruments in cases where α is close to one. Moreover, this estimator preserves information from the level equations enabling the identification of time-invariant effects. This is essential when applied to the cross-sectional innovation variables in this study.[11] The additional moment conditions are:

(8) $E(\varepsilon_{it}\Delta\Pi_{i,t-1}) = 0$ for $t = 3,4,\dots,T$

$E(\varepsilon_{it}\Delta X_{i,t-1}) = 0$ for $t = 3,\dots,T$

The requirement for the validity of the instruments for the level equations is that they be uncorrelated with the fixed effect. Validity of these moment conditions will be tested with the Difference Sargan test, comparing the instruments for the differenced estimator with those for the system estimator.

5 ESTIMATION RESULTS

The objective of the econometric analysis is to test for complementarities among firms' skills, innovation, and collaborative R&D. Estimation results for the specification without interaction effects are shown in table 7 to provide a base case. For comparison, the model is estimated here with both the standard fixed effects method, one-step differenced GMM (Arellano and Bond, 1991) and one-step system GMM (Arellano and Bover, 1995). [12]

All specifications include a set of standard economic control variables: lagged dependent variable, size proxied by number of employees, capital intensity, market share, three-firm concentration ratio, and capital intensity in the industry. Among these, lagged profitability,

[11] Time invariant effects are "differenced" away in the difference equations, and only included in the level equations. They are instrumented with lagged *differences* of the skill variables, which are valid because they are likely to correlate with the innovation activities but not with the fixed effect.
[12] See appendix 2 for the differences between the one-step and two-step system estimators.

firm size, capital intensity, and market share are assumed to be predetermined (endogenous) variables, and they are instrumented in the differenced and system estimations. In addition, patenting intensity in the industry and full sets of year dummies are used as control variables.

Table 7 Baseline Regressions (1992–1996, N_max = 159, T = 5, N*T = 781)

	Fixed Effects		Differenced 1-Step		System 1-Step		System 1-Step	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
CONST	-1.81**	0.49	0.90	0.60	3.26**	1.38	2.26	1.83
PROFIT$_{-1}$	0.09*	0.04	0.17**	0.07	0.50**	0.06	0.44**	0.06
EMPLOYEES	-0.002**	0.001	-0.01**	0.002	-0.001*	0.001	-0.002**	0.001
CAP-INTENSITY	-0.06	0.04	-0.12**	0.04	0.05	0.03	0.03	0.03
MSHARE	15.13**	6.93	16.57**	7.56	12.68*	7.66	15.77**	7.44
CONC3	-0.02	0.03	0.01	0.03	0.05*	0.03	0.04	0.03
INDCAP-INTENSITY	-0.31**	0.10	-0.20**	0.10	-0.09	0.08	-0.05	0.09
INDPATENT	-0.31*	0.18	-0.30*	0.16	-0.12	0.13	-0.24	0.15
TECHDUM							1.01	2.02
INNO							0.76	3.47
COLLAB							3.08	4.41
1st order serial correlation (p)	-5.19	(0.00)	-4.39	(0.00)	-5.92	(0.00)	-5.66	(0.00)
2nd order serial correlation (p)	-0.97	(0.33)	-0.77	(0.44)	-0.44	(0.66)	-0.55	(0.59)
Sargan test (p)			72.3 (d.f. 68)	(0.34)	126.4 (d.f. 117)	(0.26)	126.4 (d.f. 114)	(0.20)
Difference Sargan (p)					54.1 (d.f. 49)	(0.29)		

Notes: Estimations are carried out with the DPD98 for Gauss by Arellano and Bond. Dependent variable: operating profit margin (PROFIT). Specifications include time dummies.
Instruments for the differenced equations (differenced and system estimators): Const, PROFIT(gmm), EMPLOYEES(gmm), CAP-INT (gmm), MSHARE(gmm), PATENT(gmm), RESEARCHER(gmm), TECH SKILL(gmm), CONC3, INDCAP-INT, INDPATENT. "gmm"-instruments are the stacked, overidentifying moment restrictions as in (7) above. A maximum of three lags are used.
Instruments for the level equations in the system estimator include differences of the following variables: PROFIT$_{-3}$, EMPLOYEES$_{-2}$, CAP-INT$_{-2}$, MSHARE$_{-2}$, CONC3, INDCAP-INT, INDPATENT, PATENT$_{-2}$, RES$_{-2}$, TECH SKILL$_{-2}$, RDINV$_{-2}$. Two first levels equations are omitted for lack of instruments.
** denotes significance at the 95 percent confidence level, * denotes significance at the 90 percent level.

The three estimation methods agree on most signs of the coefficients, but the levels of significance vary. The system estimator is better able to identify the dynamic process (lagged dependent variable). This lends support for the previously discussed theoretical advantages of the system estimator. The discrepancies between the results with differenced and system estimators could in principle reflect the nonstationarity of the dataset (see

Blundell and Bond 1998, 124). However, based on their Monte Carlo simulations, Blundell and Bond suggest that the Sargan test is able to detect problems related to this. In table 7 the Difference Sargan test assessing the validity of the additional moment conditions defined by (8) does not indicate these kinds of specification problems. This test will also reject in case the overidentifying moment conditions for the level equations are not valid in terms of correlation with the error terms. Hence, no specification problems are indicated vis-à-vis the system estimation method.

Also in line with Blundell and Bond's results, the one-step system estimator possibly somewhat inflates standard errors.[13] Therefore, coefficients that are significant with the one-step procedure used here are likely to be strongly statistically associated with the dependent variable, but this test may be too strict. In spite of this, Blundell and Bond recommend the one-step results instead of the efficient two-step ones, which deflate standard errors and may produce "too" significant coefficients, particularly if the data are heteroskedastic.

The last specification in table 7 using the system estimator includes the dummy variables that describe skills and innovation activities. All of these indicators have positive signs, as one would expect, but they are not close to being statistically significant. However, multicollinearity may play a role there.

The specifications in table 7 account for industry differences with three variables: concentration ratio, capital intensity, and patenting intensity. To assess their ability to control for industry-specificities the system equation was estimated with a full set of industry dummies instead of the aforementioned industry variables (see tables A4 and A5 in appendix 3). The results suggest that the three industry controls used here account better, or at least as well, for industry-specificities than do the industry dummies.[14]

Finally, to examine the performance of the instruments the model was estimated with system GMM but lagging the predetermined variables' GMM-instruments by two (employees, market share, capital intensity) and three periods (patenting and skill variables)

[13] The one-step weighting matrix is arbitrary, which can have considerable effects in finite samples.

instead of by one and two periods, respectively. This had no substantial effect on the results.

Subsequent analysis is based on the system estimator, using industry control variables instead of dummies. Fixed effects results will not be considered, because they are inconsistent for the dynamic model and cannot identify the time-invariant innovation dummy variables. The latter also applies for the differenced estimator.

5.1 Testing for Complementarities: Innovation and Skills

The specifications in the rest of the paper have exactly the same control variables and instruments as the baseline equation in table 7. Skills are measured with the dummy for high technical competencies TECHDUM. The estimation results in table 8 indicate that these competencies support the benefits of innovation. Positive profitability effects of innovation are stronger in the presence of high technical skills. The interaction term for the (1,1) combination is strong and statistically significant, implying that innovating firms with high technical skills attain a profit margin increase of almost five percentage points compared to their non-innovating, low-skill counterparts. This suggests that firms also need absorptive capacity to benefit from their *internal* innovation activities.

5.2 Collaborative R&D and Competencies

Internal skills were also hypothesized to be prerequisite to benefiting from collaborative R&D. The original absorptive capacity proposition by Cohen and Levinthal (1989) concerned the role of R&D in learning about external technological developments. The results here indicate that skills and accumulated competencies are also important in making use of external knowledge: technical skills significantly complement collaborative innovation arrangements (table 9).

[14] Time dummies interacted with industry dummies would be an even stronger test, but the estimation with thirteen dummies for four periods as explanatory variables and instruments generates too large a matrix for Gauss to handle.

Table 8 Interactions between Technical Competencies and Innovation Outcomes

	Coeff.	Std. Err.
CONST	2.55	1.89
$PROFIT_{-1}$	0.45**	0.06
EMPLOYEES	-0.002**	0.001
CAP-INT	0.05	0.04
MSHARE	14.43**	7.23
CONC3	0.04	0.04
INDCAP-INT	-0.08	0.08
INDPATENT	-0.27*	0.15
TECH SKILL high & innovator	4.96**	2.52
TECH SKILL low & innovator	1.75	4.03
TECH SKILL high & non-innovator	0.92	3.12
1^{nd} order serial correlation (p)	-5.81	(0.0)
2^{nd} order serial correlation (p)	-0.56	(0.57)
Sargan test (p), d.f. 110	105.1	(0.62)

Notes: See notes about specification and instrumentation in table 7.
One-step GMM system estimator, N*T = 781, 1992–1996.
** denotes significance at the 95 percent confidence level, * denotes significance at the 90 percent level.

Table 9 Interactions between Technical Competencies and Innovation Collaboration

	Coeff.	Std. err.
CONST	2.92*	1.67
$PROFIT_{-1}$	0.44**	0.07
EMPLOYEES	-0.002**	0.001
CAP-INT	0.04	0.04
MSHARE	14.63**	7.32
CONC3	0.04	0.03
INDCAP-INT	-0.05	0.08
INDPATENT	-0.23	0.15
TECH SKILL high & collaborator	5.61**	2.86
TECH SKILL high & non-collaborator	-1.22	3.08
TECH SKILL low & collaborator	1.39	3.48
1^{st} order serial correlation (p)	-5.61	(0.00)
2^{nd} order serial correlation (p)	-0.56	(0.58)
Sargan test (p) d.f. 110	104.49	(0.63)

Notes: The same estimation method, control variables and instruments were used as in table 7.
One-step GMM system estimator, N*T = 781, 1992–1996.
** denotes significance at the 95 percent confidence level, * denotes significance at the 90 percent level.

Table 10 examines the possibility that collaboration and innovation might complement one another as well. Indeed, estimation results are supportive of this proposition: A strongly positive interaction term is found. In fact, the negative coefficients for the mixed cases suggest that firms may be better off staying put rather than trying to innovate without collaborating, and vice versa. However, these negative coefficients are not statistically significant.

Table 10 Interactions between Innovation and Collaboration

	Coeff.	Std. err.
CONST	2.15	2.00
PROFIT-1	0.45**	0.07
EMPLOYEES	-0.003**	0.001
CAP-INTENSITY	0.04	0.04
MSHARE	15.71**	7.07
CONC3	0.04	0.03
INDCAP-INTENSITY	-0.05	0.09
INDPAT	-0.24*	0.14
Innovator & collaborator	6.86**	2.82
Innovator & non-collaborator	-2.10	9.88
Non-innovator & collaborator	-1.78	4.29
1st order serial correlation (p)	-5.69	(0.00)
2nd order serial correlation (p)	-0.55	(0.58)
Sargan test (p), d.f. 110	106.88	(0.57)

Notes: The same estimation method, control variables and instruments were used as in table 7.
One-step GMM system estimator, N*T = 781, 1992–1996.
** denotes significance at the 95 percent confidence level, * denotes significance at the 90 percent level.

5.3 Complementarity Tests

Here I provide a simple test for the complementarity hypotheses specified earlier in equations (1) and (2). It statistically tests whether the complementarity condition (5) is satisfied by the coefficients in tables 8–10. It turns out that the tests reject the complementarity hypotheses at conventional levels of significance. The standard errors on the mixed cases are prohibitively high, even though the coefficients themselves clearly align with the hypotheses. Hence, the complementarity results are not as statistically strong as the positive interaction terms suggest. It is possible that the numbers of observations for the mixed cases are too low to generate sufficiently precise estimation results.

Table 11 Complementarity Tests for Estimated Coefficients

INNO & TECH SKILL	4.96 (2.52) > 1.75 (4.03) + 0.92 (3.12)	p = 0.34
TECH SKILL & COLLAB	5.61 (2.86) > -1.22 (3.08) + 1.39 (3.48)	p = 0.16
INNO & COLLAB	6.86 (2.82) > -2.10 (9.88) – 1.78 (4.29)	p = 0.17

Note: Standard errors in parentheses.

5.4 "Systemic" Interactions among Collaborative R&D, Skills, and Innovation

The last set of estimations takes a more systemic approach and simultaneously examines interactions among the innovation, collaboration, and skill variables. In the previous subsections, firms' skill levels were found to reinforce the profitability effects of collaboration and innovation output, and innovation and collaboration were found to reinforce one another. A potential weakness of the estimation approach is that interactions are assessed separately, because the two-way interaction dummies for skills and innovation, for instance, cannot really be identified simultaneously with those for collaboration and skills.

One way to assess the nature of interactions among several variables is to construct mutually excluding dummies for all the possible combinations. However, this method aggravates the issue that when the complementarity is strong, most observations are likely to cluster into the combinations (1,1,1) and (0,0,0) leaving few observations of mixed combinations. For example, table 12 shows the number of observations for each three-way combination for the variables TECH SKILL, COLLAB, and INNO. Indeed, thirty-three firms engage in all activities exhibiting the combination (1,1,1) and sixty-four firms engage in none of the activities and thus have the combination (0,0,0). In addition, the combinations (0,1,1), (1,0,0), and (0,0,1) each receive eighteen or nineteen observations. Other combinations have very few observations—in particular, the combination of low skills, collaboration, and no innovation (0,1,0) features only one firm. Estimation based on these observations would not give reliable results.

Table 12 Observations for the Combinations of Technical Skills, Collaboration, and Innovation

	N
TECH SKILL high, COLLAB = 1, INNO = 1	33
TECH SKILL high, COLLAB = 1, INNO = 0	2
TECH SKILL high, COLLAB = 0, INNO = 1	4
TECH SKILL low, COLLAB = 1, INNO = 1	18
TECH SKILL high, COLLAB = 0, INNO = 0	19
TECH SKILL low, COLLAB = 1, INNO = 0	1
TECH SKILL low, COLLAB = 0, INNO = 1	18
TECH SKILL low, COLLAB = 0, INNO = 0	64
Total	159

To examine whether the three variables—technical skills, consistent R&D collaboration, and consistent innovation—form a mutually reinforcing system, I simplify the complementarity condition to enable identification. Here the hypothesis is that these three activities are more profitable when observed together (1,1,1) than when observed in any other combination, resulting in a kind of a condition for "systemic" effects (cf. Ichniowski et al. 1997):

$$f(1,1,1) \geq f(1,x_2,x_3) \qquad \text{where } x_i = 0 \text{ for at least some } i = 2,3.$$

$$f(1,1,1) \geq f(x_1,1,x_3) \qquad \text{where } x_i = 0 \text{ for at least some } i = 1,3. \tag{9}$$

$$f(1,1,1) \geq f(x_1,x_2,1) \qquad \text{where } x_i = 0 \text{ for at least some } i = 1,2.$$

For example, $(1,x_2,x_3)$ refers to a dummy variable for firms that have high skills but either lack INNO or COLLAB or both. Again, the reference case is (0,0,0). Table 13 presents the estimation results. The variable (1,1,1) thus refers to the combination with all four dummy variables obtaining the value of 1. In line with the hypothesis, the (1,1,1) combination has the largest and most significant coefficient. In addition, COLLAB has a positive coefficient, but is statistically insignificant. The other variables obtain insignificant negative coefficients. Thus it appears that having all three innovation characteristics does pay off quite well: firms that succeed in both hiring and retaining highly skilled employees, collaborating in R&D with other organizations, and introducing new products or processes consistently earn a boost in profit margin of an additional 7.4 percentage points. Comparing this number to results in table 10 shows that adding high TECH SKILLS to INNO and COLLAB results in an additional 0.5 percentage point benefit in terms of profit margin.

Table 13 Interactions among Technical Skills, Collaboration, and Innovation

	Coeff.	Std. err.	N
CONST	2.82	2.02	
PROFIT-1	0.42**	0.07	
EMPLOYEES	-0.003**	0.001	
CAP-INT	0.03	0.04	
MSHARE	15.84**	7.32	
CONC3	0.04	0.03	
INDCAP-INT	-0.05	0.08	
INDPAT	-0.24	0.15	
(1,1,1)	7.39**	2.82	33
TECH SKILL high, not (1,1,1)	-1.55	3.09	25
COLLAB, not (1,1,1)	3.32	5.06	56
INNO, not (1,1,1)	-0.03	3.84	41
1st order serial correlation (p)	-5.53	(0.00)	
2nd order serial correlation (p)	-0.58	(0.57)	
Sargan test (p) d.f. 109	106.45	(0.55)	

Notes: The same estimation method, control variables and instruments were used as in table 7.
One-step GMM system estimator, N*T = 781, 1992–1996.
** denotes significance at the 95 percent confidence level, * denotes significance at the 90 percent level.

Now the last column does not add up to 159 as the dummies for TECH SKILL high, COLLAB, and INNO but not (1,1,1) are not mutually excluding. They only exclude the firms with all activities present, i.e., (1,1,1).

The modified complementarity test in table 14 now requires that the coefficient on (1,1,1) is significantly larger than other dummy coefficients. This is strongly statistically supported by the result on TECHDUM: the benefits from high skills in this framework really appear through their use in innovation activities (significance 98 percent). The result on INNO is significant at the 94 percent level, while that on COLLAB is significant only at the 76 percent level.

Table 14 Tests for Systemic Effects

TECHDUM	7.39 (2.82) > -1.55 (3.12)	p = 0.02
COLLAB	7. 39 (2.82) > 3.32 (5.06)	p = 0.24
INNO	7. 39 (2.82) > -0.03 (3.84)	p = 0.06

Note: Standard errors in parentheses.

Note, however, that this approach is not, strictly speaking, based on the theory of supermodularity. The results concern only the interactions between the individual variable and the rest of the "system," not the pairwise interactions between all the elements of the system. Thus these results do not imply that profits are supermodular with respect to TECHDUM and INNO. Rather, having high skills is significantly more valuable in the presence of COLLAB and INNO.

In summary, the estimation results provide support for the hypotheses that technical competencies help firms to profit from both innovation and collaboration, and that they may be as important as R&D in building absorptive capacity. The magnitudes of the coefficients—which must be treated as suggestive at best—imply that adopting the set of complementary competencies and activities boosts the firm's profit margin by some five to seven percentage points. Thus innovation may have substantial effects on firm performance, but realization of these effects depends on complementary skills. The insignificance of the explicit complementarity tests, however, represents a caveat. Improving precision in the estimation of the mixed cases may require a larger dataset.

6 CONCLUSIONS

This paper subscribes to the view that a firm's knowledge assets affect its profitability. Knowledge is accumulated by investing in various learning processes, including internal and collaborative R&D and the hiring of skilled employees. In addition to examining the profitability effects of firm-level competence measures and innovation activities, this study explicitly focuses on the interactions among them. Identifying complementarities sheds new light on the effects of organization on firms' innovative and economic performance.

The main results are the following. First, consistent innovation alone is not a significant explanatory factor of profitability. Both technical competencies and R&D collaboration reinforce the profitability effects of innovation. Second, collaborative R&D has stronger positive economic effects when the firm possesses high technical competencies. Third, these positive interactions represent a system wherein technical skills, collaboration, and innovation reinforce one another. These results suggest that complementarities exist between competencies and innovation activities, and that the choice of how to organize innovation activities matters. In particular, the positive interaction between internal and collaborative innovation activities suggest that outsourcing R&D services is likely to have minor effects on firm performance without internal skills and R&D activities. In other words, choices related to the organization of R&D activities may be characterized by "make and buy" (Veugelers and Cassiman 1999) as opposed to the classical transaction cost question of make or buy.

A potential issue with the dataset is that performance is measured at the same time that innovation and R&D collaboration occur. The panel of profitability used in the estimation extends from 1992 to 1996 (observations from 1990 and 1991 are used as instruments), while the second innovation survey concerns the period 1994–1996. Thus all performance implications of innovation may not have yet materialized by the end of 1996. This is the reason for constructing the consistent innovation dummy for firms innovating in both 1989–1991 and 1994–1996: these firms have the "habit" of innovating successfully. Nevertheless, there may remain some timing issues in terms of the realization of the innovation returns. An additional factor for consideration is that the time period studied involved dramatic changes in the economic environment due to a recession between 1990 and 1993. This may be reflected in the results that smaller and less capital intensive firms are more profitable. Testing the predictions with a more stable dataset would be useful. Finally, the dataset may not be cross-sectionally large enough to enable sufficiently precise estimation of the "mixed cases," that is, profitability of firms that innovate but have low skills or vice versa. Despite these data concerns, relevant results emerge and may be interpreted as reflecting conditions under which firms benefit rapidly from innovation and recover from recessions in a timely manner.

This study sheds new light on the economic effects of collaborative innovation among firms. Theoretical work in the economics of research joint ventures has ignored the central role of internal skills within these arrangements. In particular, not all firms are equally capable of synthesizing knowledge from various sources. Empirical studies of the impact of collaborative innovation on firm performance are scarce and biased toward success stories. However, high failure rates of collaborative arrangements observed in the available studies suggest that it is difficult to benefit from collaboration. Findings here show that internal competencies and innovation activities complement external collaboration strategies and thus may be prerequisites of successful collaboration.

The findings have relevance for technology policy. Subsidies for R&D or promotion of consortia may disappoint unless targeted firms possess the requisite complementary skills. Policies can focus either on picking winners—in other words, supporting R&D by firms with existing high levels of skill—or on supporting the development of complementary knowledge simultaneously with innovation activities. The latter approach expands the set of potentially successful innovators in the economy. Hence, in addition to being a factor in adopting information technology, upskilling helps firms to succeed in consistent innovation and sourcing of knowledge from external partners. Skill-biased technical change may be driven by both technology adoption and technology creation.

APPENDIX 1able A1 Correlations among the Original Variables, 1995, N = 159

	SALES	EMPLOYEES	CAP-INT	MSHARE	PROFIT	PAT	RESEARCH	TECH SKILL	TECH-DUM	RD-DUM	INNO	COLLAB	IND CAP-INT	INDPAT
SALES	1													
EMPLOYEES	0.71	1												
CAP-INT	-0.01	0.04	1											
MSHARE	0.85	0.79	0.03	1										
PROFIT	-0.01	0.05	0.22	0.04	1									
PAT	0.52	0.46	-0.05	0.32	-0.06	1								
RESEARCH	0.25	0.17	0.16	0.17	0.15	0.19	1							
TECH SKILL	0.18	0.16	-0.02	0.12	0.14	0.29	0.27	1						
TECHDUM	0.17	0.19	0.01	0.20	0.18	0.25	0.25	0.71	1					
RDDUM	0.12	0.18	0.07	0.13	0.09	0.11	0.11	0.23	0.19	1				
INNO	0.19	0.28	0.12	0.22	0.25	0.17	0.13	0.26	0.27	0.41	1.00			
COLLAB	0.24	0.33	0.18	0.27	0.25	0.26	0.19	0.33	0.42	0.33	0.70	1.00		
INDCAP-INT	0.14	-0.03	0.31	0.10	0.13	-0.09	0.16	-0.08	-0.10	-0.07	-0.11	-0.17	1	
INDPAT	0.15	0.12	-0.12	0.01	0.03	0.28	0.11	0.44	0.46	0.21	0.27	0.28	-0.22	1
CONC3	0.25	0.20	0.07	0.17	0.16	0.17	0.18	0.33	0.36	0.19	0.19	0.19	0.33	0.70

Table A2 Correlations among the Differenced Variables 1992–1996, N_max = 159

	dPROF	dPROF(-1)	dEMPL-OYEES	dCAPINT	dMSHARE	dCONC3	dINDCAP-INT	dINDPAT
dPROF	1							
dPROF(-1	-0.29	1						
dEMPLOYEES	0	-0.01	1					
dCAP-INT	-0.16	0	-0.06	1				
dMSHARE	0.09	0.05	0.1	-0.03	1			
dCONC3	0.03	-0.04	-0.01	-0.13	-0.06	1		
dINDCAP-INT	-0.17	-0.03	0.01	0.21	-0.01	-0.27	1	
dINDPAT	-0.05	0.04	-0.01	-0.04	0.06	0.1	-0.04	1
TECHDUM	-0.07	0	0.05	0.06	-0.11	0.02	0.08	-0.06
COLLAB	-0.04	0	0.05	-0.01	-0.12	0.02	0	0.03
INNO	-0.04	0.01	0.02	-0.01	-0.13	0.03	0.01	0.04
RDDUM	-0.02	-0.01	0	0.04	-0.1	0.01	0.03	0.01

Note: *d* indicates first-differenced variables.

Table A3 Observations for the Different Innovator Profiles

	Innovator	Non-innovator	Collaborator	Non-collaborator	High skills	Low skills	N
Collaborator	51	3					54
Non-collaborator	22	83					105
High skills	37	21	35	23			58
Low skills	36	65	19	82			101
R&D	71	55	53	73	52	74	126
No R&D	2	31	1	32	6	27	33
N	73	86	54	105	58	101	159

APPENDIX 2

Identification of Complementarities

According to Arora (1996) there are two problems in identifying complementarities in a cross-sectional dataset. First, X_i and X_j may appear to be complements, even though they are not in reality, if each is positively related to an omitted variable. Second, X_i and X_j may appear negatively associated, even though they are complements in reality, if there is another variable, that is a complement of X_i and a substitute of X_j. Since the data on innovation outcomes here are effectively cross-sectional too, the same problems may be an issue. In particular, since the innovation outcomes are measured as dummies, which may be correlated with the unobserved characteristics, it is possible that the interaction effects are biased upward. However, this is not really different from the usual problem of omitted variables. Using the system approach mitigates this problem to the extent that the unobserved heterogeneity correlated with innovation indicators is captured by the firm fixed effect.

Apart from the fixed effect, the approach here with respect to Arora's observations is pragmatic. By instrumenting with the competence factors that correlate with innovativeness (technical and research skills, past innovation activities; see notes for table 7), I attempt to control for the "technological capability" that would otherwise confound the decisions to invest in R&D, engage in R&D collaboration, and innovate.[15] The second point raised by Arora is another case of the omitted variable problem. One scenario in which this would arise is when internal R&D activities are a substitute with external collaborative R&D, while they complement benefiting from innovation output. This is controlled for by using past investments in R&D (differenced) as an instrument for the level equation. Indeed, introducing this instrument strengthens the interaction coefficients, implying that the system might be characterized by both complementarities and substitutabilities.

Athey and Stern (1998) also discuss testing for organizational complementarities. They suggest controlling for the biases arising from unobserved heterogeneity by a system of equations approach. They propose a framework for estimating simultaneously the "adoption equations"—in this case the determination of competencies, innovation, and R&D collaboration—and the main equation of interest, here the profitability equation (1). In the current study, the panel data approach controls for unobserved firm fixed effects that is the source of bias in the cross-sectional framework discussed by Athey and Stern.

Generalized Method of Moments for Dynamic Panel Data

The two-step estimation procedure developed by Arellano and Bond (1991) is the following. The estimator

(9)
$$\hat{\delta} = (\Delta X' Z A_N Z' \Delta X)^{-1} \Delta X' Z A_N Z' \Delta \Pi$$

is used with respect to equation (1) in two stages, first utilizing an initial weights matrix

(10)
$$A_N = \left(N^{-1} \sum_{i=1}^{N} Z_i' H Z_i \right)^{-1}$$

with (T-2)×(T-2) matrix

(11)
$$H = \begin{pmatrix} 2 & -1 & 0 & \dots & 0 \\ -1 & 2 & -1 & \dots & 0 \\ 0 & -1 & 2 & \dots & 0 \\ \dots & \dots & \dots & \dots & -1 \\ 0 & 0 & 0 & -1 & 2 \end{pmatrix}$$

which is then replaced in the second step by the estimate $u_i u_i'$:

(12)
$$A_N = \left(N^{-1} \sum_{i=1}^{N} Z_i' \hat{u}_i \hat{u}_i' Z_i \right)^{-1}$$

where $u_i^{'}$ are residuals from the one-step estimation. This estimator is asymptotically efficient in its class. However, it is well known that for finite samples this estimator deflates the standard errors, especially in the presence of heteroskedasticity, which is likely to be the case here (Blundell and Bond, 1998, appendix A). Blundell and Bond recommend the one-step estimates as "empirically right," even though the estimator is inefficient.

[15] The competence and other firm level variables used here provided a reasonable prediction of innovation outcomes in Leiponen 2001

APPENDIX 3

Table A4 Baseline Regressions with Industry Dummies

	System 1-step	
	Coeff.	Std. error
CONST	2.09**	0.75
PROFIT$_{-1}$	0.44**	0.06
EMPLOYEES	-0.001	0.001
CAP-INTENSITY	0.02	0.03
MSHARE	7.22	7.41
Time dummies:		
1993	0.11	0.71
1994	1.29*	0.69
1995	1.07	0.80
1996	0.28	0.86
Industry dummies:		
IND2	1.74	1.40
IND3	-0.97	1.30
IND4	3.97**	1.92
IND5	0.57	0.70
IND6	2.63**	1.19
IND7	3.04**	1.34
IND8	1.73	3.54
IND9	1.64	2.26
IND10	0.56	1.43
IND11	1.57*	0.87
IND12	1.00	1.13
IND13	3.85	3.40
IND14	0.30	1.33
1st order serial correlation (p)	-5.69	(0.00)
2nd order serial correlation (p)	-0.51	(0.61)
Sargan test (p) d.f. 99	108.5	(0.24)

Notes: Instruments are the same as in table 7, except for the industry variables. Here industry dummies are used as instruments. One-step GMM system estimator, N*T = 781, 1992–1996.
** denotes significance at the 95 percent confidence level, * denotes significance at the 90 percent level.

Table A5 Results of Table 8 with Industry Dummies

	System 1-step	
	Coeff.	Std. error
CONST	3.26	2.19
$PROFIT_{-1}$	0.37**	0.07
EMPLOYEES	-0.002**	0.001
CAP-INTENSITY	0.002	0.03
MSHARE	6.17	6.63
TECH SKILL high & innovator	8.95**	3.50
TECH SKILL high & non-innovator	-2.20	4.31
TECH SKILL low & innovator	-1.32	4.41
Time dummies:		
1993	0.24	0.69
1994	1.49**	0.70
1995	1.32	0.86
1996	0.52	0.87
Industry dummies:		
IND2	1.08	2.04
IND3	-0.74	1.53
IND4	4.81*	2.63
IND5	0.57	1.44
IND6	1.09	3.29
IND7	-2.22	2.42
IND8	3.03	4.23
IND9	0.12	3.20
IND10	0.52	1.98
IND11	-2.35	1.83
IND12	-3.41	2.12
IND13	0.32	2.49
IND14	0.24	1.78
1^{st} order serial correlation (p)	-5.47	(0.00)
2^{nd} order serial correlation (p)	-0.59	(0.56)
Sargan test (p) d.f. 96	97.6	(0.44)

Notes: Instruments are the same as in table 7, except for the industry variables. Here industry dummies are used as instruments. One-step GMM system estimator, N*T = 781, 1992–1996.
** denotes significance at the 95 percent confidence level, * denotes significance at the 90 percent level.

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