Working Paper

EDUCATION AND INNOVATIVE CAPABILITIES

Aija Leiponen

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Preface

This new research project at IIASA is concerned with modeling technological and organisational change; the broader economic developments that are associated with technological change, both as cause and effect; the processes by which economic agents -- first of all, business firms -- acquire and develop the capabilities to generate, imitate and adopt technological and organisational innovations; and the aggregate dynamics -- at the levels of single industries and whole economies -- engendered by the interactions among agents which are heterogeneous in their innovative abilities, behavioural rules and expectations. The central purpose is to develop stronger theory and better modeling techniques. However, the basic philosophy is that such theoretical and modeling work is most fruitful when attention is paid to the known empirical details of the phenomena the work aims to address: therefore, a considerable effort is put into a better understanding of the `stylized facts' concerning corporate organisation routines and strategy; industrial evolution and the `demography' of firms; patterns of macroeconomic growth and trade.

From a modeling perspective, over the last decade considerable progress has been made on various techniques of dynamic modeling. Some of this work has employed ordinary differential and difference equations, and some of it stochastic equations. A number of efforts have taken advantage of the growing power of simulation techniques. Others have employed more traditional mathematics. As a result of this theoretical work, the toolkit for modeling technological and economic dynamics is significantly richer than it was a decade ago.

During the same period, there have been major advances in the empirical understanding. There are now many more detailed technological histories available. Much more is known about the similarities and differencers of technical advance in different fields and industries and there is some understanding of the key variables that lie behind those differences. A number of studies have provided rich information about how industry structure co-evolves with technology. In addition to empirical work at the technology or sector level, the last decade has also seen a great deal of empirical research on productivity growth and measured technical advance at the level of whole economies. A considerable body of empirical research now exists on the facts that seem associated with different rates of productivity growth across the range of nations, with the dynamics of convergence and divergence in the levels and rates of growth of income in different countries, with the diverse national institutional arrangements in which technological change is embedded.

As a result of this recent empirical work, the questions that successful theory and useful modeling techniques ought to address now are much more clearly defined. The theoretical work described above often has been undertaken in appreciation of certain stylized facts that needed to be explained. The list of these `facts' is indeed very long, ranging from the microeconomic evidence concerning for example dynamic increasing returns in learning activities or the persistence of particular sets of problem-solving routines within business firms; the industry-level evidence on entry, exit and size-distributions -- approximately log-normal; all the way to the evidence regarding the time-series properties of major economic aggregates. However, the connection between the theoretical work and the empirical phenomena has so far not been very close. The philosophy of this project is that the chances of developing powerful new theory and useful new analytical techniques can be greatly enhanced by performing the work in an environment where scholars who understand the empirical phenomena provide questions and challenges for the theorists and their work.

In particular, the project is meant to pursue an `evolutionary' interpretation of technological and economic dynamics modeling, first, the processes by which individual agents and organisations learn, search, adapt; second, the economic analogues of `natural selection' by which interactive environments -- often markets -- winnow out a population whose members have different attributes and behavioural traits; and, third, the collective emergence of statistical patterns, regularities and higher-level structures as the aggregate outcomes of the two former processes.

Together with a group of researchers located permanently at IIASA, the project coordinates multiple research efforts undertaken in several institutions around the world, organises workshops and provides a venue of scientific discussion among scholars working on evolutionary modeling, computer simulation and non-linear dynamical systems. The research will focus upon the following three major areas:

1. Learning Processes and Organisational Competence.
2. Technological and Industrial Dynamics
3. Innovation, Competition and Macrodynamics

Abstract

This study investigates the role of capabilities, acquired through education and on the job learning, in innovation. It is argued that education enhances learning and innovation because it provides employees with communication and interaction skills, and, more importantly, with abilities to receive, understand and utilize relevant knowledge, and solve problems. These dynamic capabilities are one of the sources of innovation.

A dataset of 333 Finnish manufacturing firms is used to estimate the factors that influence the probability of making product and process innovations, and incremental product improvements. The period of study is 1987-91. The estimations suggest that competences and skills acquired through education and work experience are important for innovation. Different types of innovation turn out to be affected by different competences. General level of education is important for product innovation. Technical skills are relevant for both innovation and incremental improvement of products, whereas firm-specific work experience comes into play with incremental product improvements and process innovation. However, process innovation seems to be determined mainly by firm size, instead of competences or industry-specific factors. This suggests that the life cycle stage may be related to the type of innovation undertaken.

According to the estimations there are considerable lags involved with the effects of competences on innovation. However, longer time series would be needed to evaluate the underlying dynamics properly.

Key words: Innovation, education, competences

1 Introduction

This paper examines the factors that influence the innovativeness of firms. The question is fundamental for understanding economic development, because innovation is one of its most important driving forces. The aim of the study is to shed light on the roles of education and on the job learning in innovation.

Several determinants of innovation have been identified in previous studies, notably firm size, market structure, technological opportunity and appropriability of returns to innovation (Cohen 1995). Internal characteristics of firms have not been analyzed very thoroughly within industrial economics. In addition to the size of the business unit, financial position (i.a. Kamien and Schwartz 1978) and degree of diversification (Nelson 1959) have been suggested as potential factors. The so called integrated models of innovation (Rothwell 1992) emphasize the internal linkages between R&D, manufacturing and marketing, while the national innovation systems approach (Lundvall 1992) focuses on the external linkages like user-producer relations.

More recently, firm-specific dynamic capabilities of firms have been suggested as a key factor in innovation (e.g. Teece and Pisano 1994). The problem with incorporating dynamic capabilities in empirical analysis is, however, that their measurement is next to impossible, as they are to a large extent organizational and internally developed through collective learning. Nevertheless, it would be a step forward to come up with proxies for the *rate* of accumulation of capabilities, even if the knowledge *stock* as such does not yield for measurement. The fundamental causal relationships behind innovation are difficult to trace, but understanding the process of innovation and knowledge accumulation would be an improvement. The purpose of this study is to move in this direction.

Accumulated capabilities have been considered mainly in case studies (see ICC 1994 for some). Arising from this line of research, Henderson and Cockburn (1996) are able to illuminate with some more generality the innovation processes in drug industry, in particular the roles of economies of scale and scope and internal spillovers. Within more traditional empirical industrial economics, studies by Cohen and Klepper (1992) and Klepper (1996) are exceptional in that they develop explicit models of firms with innovative expertise, albeit randomly distributed. They argue that expertise, together with the size of the firm, determines the composition of research and development (R&D) and direction of innovative activities. However, the work by Cohen and Klepper aims at explaining the distribution of R&D activities in industries. Instead, this study uses competence measures to explain innovation *outcomes.* Moreover, the dataset at hand allows for analyzing innovation across manufacturing industries, not only in small samples of firms in specific industries.

Cohen (1995) describes the supply of trained engineers as a macroeconomic factor of innovation. In contrast, here it is maintained that skills and competences in a firm are not only a macroeconomic factor but at least limitedly a decision variable. Nor are innovative capabilities randomly allocated among firms. Employment strategy, e.g. how many engineers and scientists, and how well educated workers to employ, has a substantial bearing on the innovative outcome, if properly aligned with the overall knowledge and innovation strategy, and the organizational constraints. For instance, competences have implications for how technological opportunities are perceived, and for the efficiency, productivity, and profitability of R&D.

The novelty of the work at hand is to estimate the effects of the employees' acquired competences on innovation. To my knowledge, this has not been explicitly done previously. A companion paper (Leiponen 1996a) found that innovating firms tend to have more highly educated employees, and especially more of those with a post-graduate degree. Now it is investigated, whether educational competences affect the propensity to innovate even when controlling for other factors like firm size, market share and industry effects. This is done via probit analysis, by estimating the factors that influence the probability of innovation.

The next section discusses the role of education and work experience in accumulating innovative capabilities. Section 3 presents the data, and section 4 the empirical model. Estimation results of the basic model are discussed in section 5. In section 6 the principal components of competence variables are computed and applied in the probit analysis. Conclusions are drawn in section 7.

2 Education and Work Experience in the Accumulation of Innovative Capabilities

2.1 Innovation Models

The traditional approach to innovation emphasizes research and development activities (R&D) as the engine of innovation, giving rise to the so called linear, or technology-push, model of innovation. Linearity arises from the conception of innovation as a process characterized by a knowledge production function. R&D function is a black box, where the firm allocates resources -- scientists, engineers and equipment -- in the hope of getting innovations as an output.

Later research has rejected this simplistic view and replaced it with more complex descriptions of the innovation process, where R&D still has a central role, but linkages between activities within the firm, and between the firm and its environment, are considered as well. Manufacturing, marketing, customers and suppliers interact with R&D, and they are crucial as sources of knowledge and ideas, and as users of innovations. The latest generation of innovation models, according to Rothwell (1992), is the Systems Integration and Networking model (SIN), which, along the lines of the chain-linked model (Kline and Rosenberg 1986), emphasizes the system of linkages within the firm and with leading-edge customers, but also with suppliers, and other firms in terms of horizontal collaboration in R&D and marketing. This kind of an internal innovation system requires great flexibility and communication ability from the organization. As success is largely based on the speed of development, efficient adaptation and rapid learning become critical capabilities.

2.2 Learning, Education and Innovation

The linkages are important for innovation because they enable communication and interaction between individuals, subunits and the environment. Some evidence of the importance of internal and external integration has been presented by Henderson (1994, with Cockburn 1994) and Iansiti and Clark (1994). Without tapping into the critical external sources of knowledge, the firm loses touch with the developments in the industry, which may lead to serious competitive disadvantage. Cohen and Levinthal (1989) coined the term *absorptive capacity* to describe the ability to recognize the value of new information, assimilate it, and apply it. Absorptive capacity enables the firm to keep track of the technological change in the market. On the other hand, internal integration enables the flows of knowledge and ideas, which are essential, because the organizational innovative capability arises largely from the interactions between people with diverse knowledge structures. Organizational capacity for novel linkages and associations, that is, innovations, is beyond the capabilities of any one individual (Cohen and Levinthal 1990). Hence, communication, integration and diversity of knowledge are key elements of the organizational innovative capability.

The building of such an organizational capacity is a slow and path-dependent process, because it involves gradual evolution of interactive routines to operate, cooperate and communicate. Learning is a local and cumulative process, which builds on the existing knowledge base. It is easier to learn in directions in which the employees already possess prior knowledge and skills. Formal education provides a broad base of general knowledge. Hence

(1) *education constitutes a basis for learning on the job.*

Effective interaction necessitates a sufficient base of shared knowledge. The communicating parties have to share at least the codes of communication and some knowledge of the substance in order to be able to interact. Thus,

(2) *education provides shared knowledge and communication codes.*

The importance of integration of knowledge and effective communication and interaction implies that the capabilities of *all* members of the organization are relevant for the accumulation of organizational knowledge, not only of those working in research or product development. Consequently,

(3) *high general level of education improves innovative performance.*

It has been emphasized, that the bulk of dynamic capabilities are strategic and firm-specific by nature, and therefore they must be internally developed (Teece and Pisano 1994). There are no markets for strategic capabilities, partly because they are valuable only in a specific organizational context. Integration of new employees into the organization takes rather a long time, and the availability of dynamic competences through consulting, joint ventures, mergers etc. is limited, even though these measures are regularly taken by firms and should not be completely overlooked either. Nevertheless, it is argued here that employing highly educated people is beneficial for the *rates* of learning, interacting, and assimilating both external and internal information. Therefore, education has an important role in the accumulation of strategic organizational knowledge through learning and problem-solving, and ultimately, innovation, but *there are significant lags* in the effects, because of the time-intensive process of organizational learning. This, together with the "lemmas" (1) - (3), gives rise to the first hypothesis:

H1: High level of general education facilitates innovation, but with significant lags.

However, the effects of education vary in different industries. For instance, rapidly changing, technology intensive sectors are more dependent both on technical skills and absorptive capacities. Therefore, it is important to account for sectoral differences in patterns of technological change and knowledge intensity.

2.3 Product and Process Innovation Capabilities

Product life cycle (PLC) literature asserts that the type of innovation carried out in firms is related to the stage in the PLC (e.g. Klepper 1996, Anderson and Tushman 1990). The early stages of the cycle are characterized by variation and experimentation with product designs. Later, as the *dominant design* emerges, firms gradually shift from product to process innovation. Process innovation is necessary in order to reap the productivity possibilities inherent with the production technology, because competition shifts towards prices and costs, instead of product features and differentiation.

However, PLC has been criticized because it does not apply very well in many industries, except for consumer durables like automobiles and televisions (Malerba and Orsenigo 1996). Products with systemic characteristics do not fit in the model, and the sequence of product innovations followed by process innovations does not hold in many capital intensive industries, nor in industries with customized demand, like machine tools. Further, it is often difficult to identify the emergence of any dominant design. Some industries employ technologies which do not support a lock-in to a specific design, and hence product modifications appear continuously. Also, the assertion that after the major breakthrough there is a stream of new entrants does not apply necessarily, in some cases the industry may be quite concentrated right from the beginning.

Cohen and Klepper (1996) have generalized the PLC idea to the type of innovation being a function of the *size* of the firm. They theorize that big firms are able to spread the costs of process innovation over larger output. Because there are only very limited markets for process innovation, large firms benefit more from innovation. This may explain why large firms are more likely to engage in process innovation.

Skills and capabilities required in different types of innovation have not been thoroughly analyzed. Malerba and Orsenigo (1996) have made a preliminary attempt to characterize competences and innovative activity under different technological regimes, following Pavitt's taxonomy (1984) (see table 1). Malerba and Orsenigo suggest, that the nature of technological change in each regime is associated with specific modes of learning and innovation. This has ramifications for the competence requirements. They observe that science-based and scale-intensive industries are likely to do both product and process innovations. However, their modes of knowledge accumulation differ radically; science-based industries engage in learning by searching and therefore are dependent on very advanced and diversified competences, whereas scale-intensive industries are more dependent on learning by doing and by using, and their specific competences are related to production and engineering. In the third taxonomic group, specialized suppliers, the dominant mode of innovation is incremental product innovation, making use of technical competences in product development, engineering and design. Finally, in the supplier R&D dominated industries, learning by doing and by using are the focal modes of knowledge accumulation, and incremental changes in processes are the key innovation activity.

Table 1. Pavitt's taxonomy of industries with competence implications

Group	Type of products (industries)	Modes of innovation and/or learning	Key competences
Science-based	Electronical Chemical (electronics, chemical, oil & coal)	Product and process innovation R&D Learning by searching	Advanced and diversified competences
Scale-intensive	Bulk materials Assembly (food, base metals, metal products, vehicles, glass & stone)	Process and product innovations R&D, Learning by doing and by using	Production and engineering competences
Specialized suppliers	Machinery	Incremental product innovation	Development, engineering and design competences
Supplier dominated industries	Traditional manufactures (textiles, clothes, wood, paper, printing & publishing, furniture)	Process innovation, incremental improvements Learning by doing and by using	Technology adoption rate

To sum up, incremental changes in products and processes rely on internal learning, while for product innovation, scientific or technical knowledge from R&D and external sources is very important. This leads to the conjecture that product innovation is more dependent on technical/scientific competences, whereas process innovation and incremental product improvement rely more on the experience accumulated in production.

H2: Technical/scientific competences are necessary for product innovation.

H3: Incremental innovation of products and processes depends on firm-specific work experience.

There exists a tradeoff between inward- and outward-directed capabilities. The larger the degree of shared knowledge among the members of a group, the easier it is for them to communicate. However, this may happen to the detriment of external communication. For instance, it has been observed, that external communication with other project groups decreases with group tenure (Cohen and Levinthal 1990). Novelty is necessary for continuous learning, also at the employee level: continuous learning by interacting depends to some extent on the new capabilities, skills and insights. Either novelty is created through training and external communication, or through recruiting altogether new employees. Bringing new tacit knowledge in the process of interaction necessitates the latter. Therefore, the accumulation of innovative capabilities is a concave function of tenure. Taking into account the importance of internal learning in incremental innovation, it is hypothesized that:

H3b: Incremental innovation of products and processes is a concave function of firm-specific work experience.

3 The Empirical Model

The returns to investment in innovative activities arise from the income streams generated by new or improved products and better cost efficiency with upgraded methods of production. The costs of innovation include, in addition to the direct R&D expenditures, indirect switching costs from introduction and adoption of new products and processes, and marketing costs from launching new products.

The cost of innovation depends on the accumulated knowledge, i.e. past R&D and organizational knowledge created through learning. This makes innovation a dynamic and path-dependent process. Moreover, learning rate, a manifestation of dynamic competences, has an impact on the adoption costs.

The hypothesis is that competences acquired via schooling and/or work-experience increase the net benefit from innovation, leading to better profitability of innovative activities and greater propensity to innovate. First, more competent employees are more efficient in developing new products and processes. Second, they learn faster both to use new technologies, and to produce and sell new products, which diminishes the adoption, introduction and adjustment costs.

Innovations are realized if the difference in profit $\pi_i^I - \pi_i^N$ in case the firm i innovates (I) or does not innovate (N), exceeds the innovation costs C_i^I involved. The returns and costs are functions of a set of explanatory variables x_i. The net benefit from innovation is then

(1) $$I_i = \pi_i^I - \pi_i^N - C_i^I = \beta' x_i + \varepsilon_i$$

where β is a vector of coefficients, and ε is an IID white noise error term.

Profitability of innovation is unobservable, as there are no data concerning the income streams generated by new products and processes. It is only observed whether the firm innovates or not. Nonetheless, we do have data on variables that are assessed to influence these income streams.

Assuming normally distributed disturbances this setting gives rise to the probit model (Greene 1993). Let us define a dummy variable $\overline{I}_i$:

(2) $$\overline{I}_i = \begin{cases} 1, \\ 0, \end{cases} \text{iff} \begin{cases} I_i \geq 0 \\ I_i < 0 \end{cases}, \quad \text{i} = 1, \ldots, \text{N}$$

Then the conditional probability that $\overline{I}_i = 1$ is

(3) $$\begin{aligned} &\Pr(\overline{I}_i = 1 | x_i) = \Pr(I_i \geq 0 | x_i) \\ &= \int_{-\infty}^{\beta' x_i} \phi(t) dt = \Phi(\beta' x_i) \end{aligned}$$

where Φ denotes the standard normal distribution. The expected value of I is then

(4) $$E(I_i) = \Phi(\beta' x_i)$$

and the marginal effects of changes in explanatory variables on this expectation are

$$(5) \qquad \frac{\partial E(I_i)}{\partial x_i} = \phi(\beta' x_i)\beta$$

For dummy variables the marginal effects reported are not the slopes but the impact of the dummy on probability at mean values for other variables (cf. Greene 1993: 641).

The focus in the estimations is naturally on the stock of education and experience related competences, and with them I hope to reduce the role of firm-specific unobservable effects. In addition, some of the firm- and industry-specific factors suggested to affect innovation will be controlled for. This leads to the following general model of the probability of innovation in a firm:

Prob(innovation) = f(competences, firm characteristics, industry characteristics)

4 The Data

A firm-level dataset compiled by Statistics Finland, which combines several data sources including labor statistics, innovation survey and business statistics, is used in the empirical analysis. The 333 firms in the sample represent the whole manufacturing sector, and they are classified into 15 two-digit industries.

The innovation survey was carried out in 1991, and it concerns product innovation, product improvement, and process innovation. The firms were inquired, whether they accomplished process innovations and product improvements during the period 1989-1990. The measure of product innovation is slightly different. Product innovators include firms that launched new products in the markets between 1989-1990 and collected some sales revenue from them. This turned out to be more informative an indicator than the simple question whether the firms had made product innovations or not. In addition, another dummy was constructed for firms that innovated both products and processes, in order to characterize these “comprehensive innovators” (cf. Baldwin and Johnson 1996).

The explanatory variables include indicators of educational levels and fields of the workers in each firm, accumulated firm-specific work experience indicated by the average tenure, and a set of financial control variables and industry dummies (see table 2). A more detailed description and discussion of the data can be found in Leiponen 1996a.

Table 2. List of Variables

Vector	Variable	Definition
COMPETENCE	HCI	*Human Capital Index*, defined below (available 1987-93)
	HIGH	Share of employees with higher education degree, % (1987-93)
	POST	Number of employees with post-graduate degree (1987-93)
	TECH	Share of employees with technical or natural scientific degree, % (1987-93)
	HITECH	- " - higher technical or natural scientific degree % (1987-93)
	TEN	Average tenure in the firm, years (1987-93)
	TEN^2	Tenure squared (1987-93)
INNOVATION DUMMIES	PRODUCT	New products launched successfully between 1989-1991
	IMPROVEMENT	Significant product improvements realized between 1989 1991
	PROCESS	Process innovations realized between 1989-1991
	COMPREHENSIVE	Both product and process innovations 1989-1991
FIRM	SALES	Sales turnover, million FIM (1985-1993)
	$SALES^2$	Sales squared
	MS	Market share, % (1987-1993)
	EXPORT	Exports in proportion to sales (1989-1993)
INDUSTRY	Dummies	14 manufacturing industries, reference group being "other industries"
	Taxonomic groups	Industrial groups according to Pavitt's taxonomy of technological change

The general level of education is described by an index (HCI), constructed from the shares of employees with different educational levels. These shares are weighted with wage differences, assumed to reflect the differences in their productivity to some extent. The index is constructed in the following way:

$$HCI = \frac{(h_2 w_2 + h_3 w_3 + h_4 w_4)}{w_1}$$

where h_i denotes the share of employees with the level of education i; 1 = primary education, 2 = secondary, 3 = higher (tertiary) to 4 = post-graduate (doctoral or licentiate) degree, and w_i denotes the average wage level of the corresponding group in the firm. The index is thus the sum of the shares of employees with more than basic education, weighted by the wage differences.

Firm differences are accounted for with size (measured by sales), market power (market share) and export performance (export share). Market share is proxied by sales of the firm divided by that of its 2-digit industry. This is not exactly a correct measure for firms operating in more than one industry. It also biases downward the market power of firms dominating smaller industries within the 2-digit classes, and upward the market power of export oriented firms, since the sales include both domestic and export markets. Industry-specific effects are taken into account with dummies for either the 2-digit industries in section 5, and taxonomic groups of technological regimes in section 6.

5 Basic Estimation Results

5.1 Product Innovations

A measure of innovated products that already generate sales is used, because this guarantees that we are dealing with an economically valuable innovation. The estimation results are in table 3 below. Several specifications were estimated, and the ones reported turned out to be the most significant. Due to the problems of multicollinearity, the results are not very robust to adding too many explanatory variables in the equations.

The general level of education in 1987 (HCI87) and the growth of technical and research competences 1987-91 (ΔTECH and ΔPOST, respectively) are positively associated with the probability of successfully introducing new products in the market. The importance of the initial level of general education for innovation is in line with the conjecture that education enhances the rate of learning, which facilitates the introduction and selling of new products. Moreover, the benefits from employing educated workers appear with lags.

The importance of technical and research competences is rather intuitive, but it is interesting that the growth rates were more important than the levels. Bearing in mind the usual long lags in innovation processes, this might reflect that the firms need certain competences in order to be able to develop marketable products from the original inventions. Another interpretation is that being an innovative firm requires continuously more investment in R&D, knowledge and skills. These enable the firm to perceive opportunities related to markets and technologies, the exploiting of which necessitates more investment in internal capabilities. It is thus a self-reinforcing cycle. However, with the short time series available it is impossible to assess the underlying dynamics.

Table 3. Probability of having new products introduced in the market

	Variable	Estimate	t-statistics	Marginal effects
	Constant	-1.19*	-2.46	
COMPETENCES	HCI87	0.93*	2.19	0.34
	ΔPOST	0.13*	1.99	0.05
	ΔTECH	3.08*	2.74	0.01
FIRM	SALES	-0.001*	-3.28	-0.0003
	MS	0.37*	3.14	0.14
INDUSTRY DUMMIES	Food	0.85	1.83	0.33
	Textile	0.28	0.62	0.11
	Wood products	0.27	0.56	0.10
	Paper	0.63	1.06	0.24
	Printing & publishing	-0.59	-1.29	-0.19
	Furniture	0.67	1.23	0.26
	Chemical	0.71	1.17	0.27
	Oil & coal	1.51*	2.53	0.52
	Glass & stone	0.54	1.08	0.21
	Base metal	0.81	1.29	0.31
	Metal products	-0.19	-0.36	-0.07
	Machine	1.07*	2.12	0.40
	Electronic	1.16*	2.16	0.43
	Vehicles	1.27*	2.14	0.46
Probability at means	0.35			
Log Likelihood	-189.93			
Likelihood Ratio	77.94			
d.f.	311			

McFadden's R^2 *** = significant at the 5% level (two-tailed test)**	0.17			

Among the firm-specific factors, the most important turn out to be market share and firm size. Interestingly, market power increases the likelihood of launching new products, but size as such does not. Industry dummies are significant only in the cases of oil refining, machine, motor vehicle and electronics industries, and positively so. That is, compared to the heterogeneous base industry "other industries", these industries are significantly more likely to make product innovations.

The last column present the marginal effects as defined in equation (5). Marginal effect, or the slope, is the marginal change in the expected benefit from innovation due to change in the explanatory variable[1]. Marginal effects are calculated for an average firm, i.e. at the mean values of explanatory variables. The slope of the sales variable seems very insignificant, partly because the magnitude of the slope reflects the wide range of values of the variable. For industry dummies, the marginal effect is calculated as the impact on innovation probability of the dummy for a firm with mean values for other variables. For instance, among firms with average values for other variables, the ones in oil, electronics, machine or vehicle industries are 40-50% more likely to innovate.

5.2 Product Improvements

With respect to the probability of incremental product improvements, the initial level of higher technical competences (HITECH87) turns out to be an important factor (table 4), together with firm-specific work experience (TEN). The square of TEN is significantly negative, which supports the concavity hypothesis, i.e., that there are limits to learning on the same job.

[1] The estimates of β do not as such have an elasticity interpretation.

Market share and export share are positively associated with product improvements, possibly thanks to the incentives to upgrade that they provide. Again, firms in oil, machine and motor vehicle industries are more likely to improve their products.

Table 4. Probability of product improvements

	Variable	Estimate	t-statistics	Marginal effects
	Constant	-1.30*	-2.50	
COMPETENCES	HITECH87	4.85*	2.07	0.02
	TEN87	0.19*	2.28	0.07
	$TEN87^2$	-0.01*	-2.25	-0.004
FIRM	MS	0.19*	2.53	0.07
	EXPORT	0.66*	1.99	0.003
INDUSTRY DUMMIES	Food	0.72	1.70	0.26
	Textile	-0.09	-0.23	-0.04
	Wood product	0.41	0.94	0.16
	Paper	0.39	0.69	0.15
	Printing & publishing	-0.29	-0.67	-0.12
	Furniture	0.18	0.36	0.07
	Chemical	0.98	1.61	0.33
	Oil & coal	1.77*	2.76	0.46
	Glass & stone	0.13	0.27	0.05
	Base metal	0.90	1.45	0.31
	Metal product	-0.09	-0.19	-0.04
	Machine	2.00*	3.34	0.47
	Electronic	0.93	1.74	0.32
	Vehicles	1.56*	2.37	0.43
Probability at means	0.51			
Log Likelihood	-171.15			
Likelihood Ratio	108.11			
d.f.	313			
McFadden's R^2	0.24			
* = significant at the 5% level (two-tailed test)				

5.3 Process Innovations

The determinants of process innovations differ remarkably from those of product innovations and improvements, and there are practically no significant explanatory variables found (table 5). The logic behind and thus the determinants of process innovation appear to be quite different from both product innovation and improvement. This is reflected also in the quasi-R^2, which is clearly lower for this dependent variable.

None of the competence variables was found to be a significant determinant of process innovation. Employees with a post-graduate degree have a modest positive effect (confidence about 80%). Tenure has consistently positive and its square negative coefficients.

Table 5. Probability of process innovation

	Variable	Estimate	t-statistics	Marginal effects
	Constant	-0.51	-1.10	
COMPETENCES	POST87	0.10	1.23	0.04
	TEN87	0.10	1.39	0.04
	$TEN87^2$	-0.01	-1.54	-0.003
FIRM	SALES	0.0009*	2.18	0.0003
	$SALES^2$	-0.000	-1.53	-8.6E-09
	EXPORT	0.47	1.55	0.002
INDUSTRY DUMMIES	Food	0.28	0.68	0.10
	Textile	-0.31	-0.81	-0.12
	Wood products	0.20	0.49	0.07
	Paper	-0.52	-0.88	-0.20
	Printing & publishing	-0.13	-0.31	-0.05
	Furniture	-0.14	-0.29	-0.05
	Chemical	-0.36	-0.67	-0.14
	Oil & coal	0.54	1.10	0.18
	Glass & stone	-0.39	-0.83	-0.15
	Base metal	0.62	1.02	0.20
	Metal products	0.08	0.20	0.03
	Machine	0.34	0.85	0.12
	Electronic	0.22	0.48	0.08
	Vehicles	0.02	0.05	0.01
Probability at means	0.63			
Log Likelihood	-209.05			
Likelihood Ratio	41.01			
d.f.	312			
McFadden's R^2	0.09			
* = significant at the 5% level (two-tailed test)				

The propensity to engage in process innovation appears to be mainly related to the size of the firm, although the coefficient appears insignificant due to the wide range of possible values. This is in accordance with Cohen and Klepper (1996), who argue that the share of R&D directed to process innovation tends to rise with the size of the firm (or more precisely the business unit). Because process innovations are usually exploited internally, the bigger the firm, the more there are opportunities to benefit from innovation externalities. In line with this, the SALES variable has a positive coefficient. The negative coefficient on SALES squared suggests there are limits to the benefits from size. In addition, export share has a positive but not quite significant impact. None of the industry dummies are significant. Thus, a firm in any industry is equally likely to engage in process innovation after reaching a certain size.

5.4 Comprehensive innovation

Firms innovating both products and processes have a high initial general level of education, indicated by the significant positive coefficient on HCI87. Initial number of researchers (POST87) has a positive relation, too, but not a significant one. Comprehensive innovators tend to be relatively small, somewhat export oriented firms with some domestic market power. In this sense they remind more of product than process innovators. Among the different industries, surprisingly firms in food industry, in addition to oil and machine industries, are more likely to be this type of innovators.

To sum up, the quasi-R^2 suggests that this empirical model is more suitable for studying product innovation and improvement than process innovation, which seems to be determined mainly by other factors. Overall, competence variables are statistically significant determinants of innovation. In particular, the initial values are most significant, which lends support to the conjecture of education having effects on innovation through a time-intensive process of collective learning. Furthermore, technical competences are associated with product innovation and improvement. On the job learning, on the other hand, is important for incremental innovation.

Table 6. **Probability of both product and process innovation**

	Variable	Estimate	t-statistics	Marginal effects
	Constant	-1.83*	-3.64	
COMPETENCES	HCI87	0.91*	2.22	0.21
	POST87	0.05	1.05	0.01
FIRM	SALES	0.0004*	-2.83	-8.9E-05
	EXPORT	0.47	1.56	0.001
	MS	0.17*	2.32	0.04
INDUSTRY DUMMIES	Food	1.18*	2.50	0.41
	Textile	0.43	0.94	0.12
	Wood products	0.52	1.07	0.15
	Paper	0.90	1.51	0.30
	Printing & publishing	-0.29	-0.59	-0.06
	Furniture	0.04	0.07	0.01
	Chemical	0.70	1.16	0.22
	Oil & coal	1.43*	2.59	0.50
	Glass & stone	0.03	0.06	0.01
	Base metal	0.90	1.48	0.30
	Metal products	0.33	0.65	0.09
	Machine	1.11*	2.32	0.38
	Electronic	0.87	1.65	0.28
	Vehicles	1.06	1.89	0.36
Probability at means	0.15			
Log Likelihood	-185.77			
Likelihood Ratio	57.26			
d.f.	311			
McFadden's R^2	0.13			
* = significant at the 5% level (two-tailed test)				

6 Competence Strategies with Principal Components Approach

This section examines the typical competence strategies among firms, and how they are associated with innovation. A principal component analysis is carried out first, and the components are then used in the probit analysis. Principal components alleviate the possible problems of multicollinearity among the explanatory variables, and provide information about which competences tend to go together.

6.1 Principal Components Analysis

As table 6 reveals, the first four principal components capture 73% of the variation among firms. The first component (PRIN1) weights heavily the initial levels of higher education and both general and higher technical skills (highlighted in the table 7). Firms scoring high in the second component have long tenures, a large number of post-graduate employees, and also hire more of them. As to the technical skills, the initial level of general technical education is low, but it has been increasing rapidly in this strategy. The third component is dominated by the initial level of POST, and increases in HIGH and POST. Also the average tenure is quite strongly negatively weighted. The fourth and last one considered here is dominated by positive weight on the change in technical skills and negative one on average tenure.

Table 7. Principal Components of Competences

Variable	PRIN1 "General technical"	PRIN2 "Experience research"	PRIN3 "Dynamic research"	PRIN4 "Dynamic technical"
HIGH87	**0.58**	0.11	-0.15	0.12
HITECH87	**0.61**	-0.03	-0.12	0.17
POST87	0.24	**0.40**	**0.50**	-0.18
TECH87	**0.38**	**-0.48**	0.07	-0.09
TEN87	-0.07	**0.54**	-0.31	**-0.43**
ΔHIGH	-0.17	-0.18	**0.64**	0.15
ΔPOST	0.22	**0.39**	**0.44**	-0.01
ΔTECH	-0.12	0.34	-0.10	**0.84**
Proportion of variance	29%	17%	14%	13%
Cumulative	29%	47%	61%	73%

6.2 Probability of Innovation with Principal Components

Now the principal components are utilized in the probit analysis of innovation. Instead of industry dummies, the sectoral differences in the modes of technological change and the propensity to innovate are controlled for with dummies according to the taxonomy developed by Pavitt (1984) (see table 1). Thus we have four dummies, "the others" being the reference group again.

The four principal components all show up in a positive association with innovation, but with little statistical significance (table 8). However, the "dynamic technical" component turns out to be a significant explanator of product innovation. "General technical" component gains some significance with respect to comprehensive innovation, but not quite within the 95% confidence interval.

Table 8. Probability of innovation with principal components

Variable	Product Innovation	Process Innovation	Comprehensive Innovation	Product Improvement
INTERCEPT	-0.600	-0.12	-1.181*	-0.291
	(-1.42)	(-0.31)	(-2.79)	(-0.72)
"General technical"	0.092	0.052	0.128	0.102
	(1.15)	(0.69)	(1.75)	(1.10)
"Experienced research"	0.127	0.080	0.163	-0.005
	(1.20)	(0.74)	(1.62)	(-0.04)
"Dynamic research"	0.096	0.074	0.156	0.009
	(0.76)	(0.59)	(1.31)	(0.07)
"Dynamic technical"	0.196*	0.037	0.044	0.018
	(2.42)	(0.48)	(0.55)	(0.22)
SALES	-0.001*	0.001*	-0.0003*	0.0005
	(-3.27)	(2.14)	(-2.59)	(1.34)
MS	0.290*	-0.016	0.129*	0.115
	(2.97)	(-0.22)	(1.96)	(1.40)
EXPORT	0.502	0.456	0.603*	0.686*
	(1.78)	(1.68)	(2.20)	(2.32)
TAXONOMIC DUMMIES				
Science-based	1.055*	0.137	0.991*	0.975*
	(2.28)	(0.32)	(2.16)	(2.10)
Scale-intensive	0.592	0.075	0.795	0.247
	(1.41)	(0.19)	(1.88)	(0.59)
Specialized suppliers	1.039*	0.269	1.095*	1.842*
	(2.13)	(0.60)	(2.32)	(3.03)
Supplier dominated	0.105	-0.164	0.253	-0.188
	(0.26)	(-0.44)	(0.62)	(-0.48)
Log Likelihood	-203.87	-216.12	-196.07	-185.37
Likelihood Ratio	53.03	26.86	38.37	79.66
d.f.	319	321	319	321
McFadden's R^2	0.12	0.06	0.09	0.18
*** = significant at 5% level (two-tailed test)**				

Note: t-statistics in parentheses

As before, firm size is positively related to process innovation, and negatively to product and comprehensive innovation. For the latter types of innovation, market power is important, not size as such. Within this setup, export share becomes more significant, plausibly due to the cruder way to control for industry effects. The coefficient is within the 95% confidence interval for comprehensive innovation and product improvement, and within 90% for product and process innovation.

The taxonomic dummies appear to describe reasonably well the differential patterns of technological change among industries. Specialized suppliers and science-based firms are significantly more likely to make product innovations and improvements, and also to be comprehensive innovators. Again, process innovation is not associated with any particular technological regime.

7 Conclusions and Discussion

Competences proxied by education and tenure measures are found to be significant determinants of different types of innovation. Including the competence variables in the estimations of the probability of innovation is justified by the tests for both joint and individual significance of the coefficients.

Support is found for the hypothesis that the level of general education is positively associated with innovation, in particular product innovation, but with lags. Technical competences turned out to be important for both innovation and gradual improvement of products, as hypothesized. Furthermore, experience accumulation was significant for incremental product improvement, but not for developing completely new products. The determinants of process innovation, in addition to firm size, remain unclear. Capabilities needed therein may be internally developed to an even greater extent than those in product innovation, and the quantitative proxies used do not reflect this activity.

The importance of lagged variables is in line with our hypothesis about the dynamic process of building innovative capabilities. The significance of the *growth* of technical and research competences raises the question about a possible underlying factor, which causes both competence accumulation and innovation. However, given that the process of innovation often takes years, we cannot assess properly the dynamics behind the results. This would require longer and more detailed time series on competences and innovation inputs and outputs.

Concerning the market related factors, it seems that export oriented firms with domestic market power are the more likely to innovate. Also, the technological intensity of the industry increases the probability of product innovation, as indicated by the taxonomic dummy variables. Sectoral differences are considerable, and have to be controlled for. The nature of technological change clearly influences the type and effort of innovation undertaken, and has ramifications in terms of competence accumulation as well.

The principal component analysis revealed some typical combinations of competences prevailing in the firms. Using these components to estimate the probability of innovation lent support for the significance of both general and technical competences in product innovation. In line with the other estimations, the results suggested that product innovating firms tend to be in a very dynamic phase of evolution. This was suggested by the "dynamic technical" component which weighted tenure strongly negatively, and the change in the stock of technical competences positively.

Overall, it can be concluded that educational competences are significantly involved in the innovation process, and different competence combinations are associated with different types of innovation. The question remains, why not all firms are hiring highly educated employees, since they seem to be so useful for innovation. I maintain that acquired competences are a necessary but by no means sufficient condition for successful innovation. Unobservable factors like managerial "talent" and organizational routines affect the efficiency of employing skilled and knowledgeable workers. Acquired competences contribute to innovation indirectly via collective learning, provided that coordination and incentives are aligned with the general knowledge strategy. Nevertheless, on average they may reflect the process of knowledge accumulation.

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