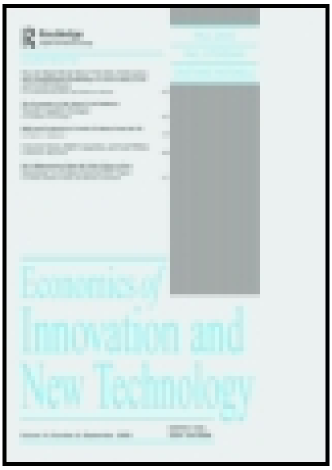

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Innovation and skills from a sectoral perspective: a linked employer-employee analysis

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Innovation and skills from a sectoral perspective: a linked employer–employee analysis

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Science and engineering skills as well as management and leadership skills are often referred to as sources of innovative activities within companies. Broken down into sectoral innovation patterns, this article examines the role of formal education, actual occupation and work experience in the innovation performance in manufacturing firms within a probit model. It uses unique micro data for Germany (LIAB) that contain information about corporate innovation activities and the qualification of employees in terms of formal education, actual professional status and work experience. We find clear differences in the human capital endowment between sectors according to the Pavitt classification. Sectors with a high share of highly skilled employees engage in above average product innovation (specialised suppliers and science-based industries). However, according to our estimation results, across as well as within these sectors a large share of highly skilled employees does not substantially increase the probability of a firm being innovative.

Keywords: innovation; human capital; qualification; sectoral innovation system

JEL Classification: O31; J24

1. Introduction

Education, R&D and innovation rank very high in today's policy agendas. Frequently cited in this context is the Lisbon strategy of the EU. Although the originally ambiguous goals have been revised (European Commission 2005), the agenda is still recognised as a political milestone in support of the knowledge-based economy. One of the most influential policy measures implemented in the EU strategy is the improvement of human capital formation, especially with respect to tertiary education. This strategy is explicitly based on the assumption of the innovation enhancing impact of human capital.

Indeed, on the macro level there is evidence indicating a positive correlation between a country's human capital endowment and technological change (Dakhli and De Clercq 2003; Benhabib and Spiegel 2005). However, how to interpret this correlation is far from obvious. First, on the macro level ecological fallacies might occur since the correlation

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between human capital and innovation is measured on a very aggregate level. And even if it is shown that skill level has a strong impact on innovativeness the aggregate perspective does not tell us *how* this impact works. Secondly, the applied measures of technological change are ambiguous. Usually, studies rely on total factor productivity, number of patents or innovation input measures like R&D expenditures. These concepts exhibit only weak relationships to actual innovation activities within an economy. Thirdly, it is questionable whether the positive correlation represents a unidirectional causal effect of human capital on innovation. Rather, certain strands of literature propose a complementary relationship. The literature on skill-biased technological change confirms that technological innovation might cause skill upgrading (Acemoglu 1998; Autor, Levy, and Murnane 2003). Other reasons for requiring more educated workers are the acceleration pace of technical progress (Bartel and Lichtenberg 1987; Violante 2002) and the general purpose nature of recent technology changes (Aghion, Howitt, and Violante 2002).

Thus, macro analysis provides a picture of the relationship between skills and innovation that is far from clear. It seems necessary to switch from the macro to the firm level to analyse the link in more detail. The firm level approach enables a more precise understanding of the mechanisms behind the aggregate correlation between skills and innovation. In our analysis, this was first realised by the application of a framework of sectoral innovation regimes. The sectoral perspective allows analysis of differing human capital requirements according to several innovation regimes (Pavitt 1984; Malerba 2005). Secondly, we were able to distinguish between basic types of innovation qualities to meet the essential distinction between imitation and frontier innovation and its differing human capital requirements (Krueger and Kumar 2004; Vandenbussche, Aghion, and Meghir 2006; Aghion 2008). Furthermore, we measured innovation activities directly and addressed the endogeneity problem.

Surprisingly, few empirical studies focus on the question of how skills affect the actual innovation output of firms. Recently, Leiponen (2000, 2005) and Vinding (2006) estimated the impact of skills on innovation on the firm level. Leiponen analyses the complementarities between employee skills and firm innovation activities for manufacturing firms in Finland, and finds that technical skills are the key enabling factor of profitable innovations. However, Vinding (2006) in a micro-econometric study for Denmark comes to a different conclusion as he shows that the share of highly educated employees is not necessarily positively related to firms' ability to innovate.

There are two reasons that justify the refinement of these studies. First, the studies do not adequately distinguish between different innovation regimes and innovation qualities. We suppose that different sectoral innovation regimes as well as innovation qualities require different types of human capital. Neglecting these differences might bias estimation results. Secondly, the main human capital measure applied seems to be insufficient. Vinding as well as Leiponen calculate the human capital endowment via formal qualification (share of employees with a higher education or a technical degree), not via the occupation held in the firm. As Spitz-Oener (2006) and Green, Felstead, and Gallie (2003) show it is more reliable to apply narrowly defined occupational information than formal qualification of employees even if this very advanced measure might also suffer from some codification errors. In our paper, we made use of alternative micro data for Germany, a linked employer–employee data set, which allowed us to consider precisely defined records on the actual occupations of employees instead of their formal qualifications.

The article is organised as follows. Chapter 2 presents the theoretical considerations. These are followed by the introduction of the econometric model and by the data, both laid out in Chapter 3. Finally, estimation results are presented (Chapter 4) and conclusions drawn (Chapter 5).

2. Theoretical considerations

Endogenous growth theory presents the strong significance of human capital for innovation and economic growth at the macro level (Aghion and Howitt 1998). The link between human capital and innovation, however, remains unconsidered here. Overall, the theoretical literature has not much to offer regarding the mechanisms linking skills and innovation at firm level. As a result, we based our empirical study on theoretical considerations stemming from the broader field of 'innovation studies'.[1] This brought us closer to our particular perspective in our empirical study, namely, innovations at firm level.

In the field of 'innovation studies', one first of all encounters the work of Schumpeter who in his 'Theory of Economic Development' explains the emergence of innovations focusing on the importance of entrepreneurial efforts.[2] This documents the importance of individual capabilities. Schumpeter's interest in innovation was, however, at least in his early work, aimed at identifying radical innovation as a driving force of economic development.

Going further, the systemic innovation theory teaches us that today innovation is an interactive process that largely involves inter-personal as well as inter-organisational learning (Kline and Rosenberg 1986). Lundvall picks up this perspective and develops it further in the context of the 'learning economy' (Lundvall and Johnson 1994). Later on, he states that there are two ways in which higher education has an impact on innovation: on the one hand, higher education graduates can operate as basic innovators, for instance, by inventing and developing new technologies; on the other hand, they might serve as second stage innovators, who rather exploit technological progress and ensure the 'equilibrium' between technological change and daily business. According to this differentiation, he concludes that engineers and scientists are particularly active as basic innovators while people with a management or social sciences degree are important as second stage innovators (Lundvall 2007). When referring to human capital as an important determinant of innovation, one has to recognise that human capital is made up not only of technical knowledge acquired by people, but also of personal skills, and individual expertise that people develop during professional life and bring into firms' innovation activities. This idea originated with Polanyi (1966) and has been further developed and referred to in the literature as the tacit and codified dimension of knowledge (Cowan, David, and Foray 2000; Foray 2004, 2007). For creative work like innovation activities, one can assume that tacit knowledge matters, this should therefore also be reflected in an empirical study.

Summing up, one important component of human capital is the formal qualification, and as indicated above, especially higher (tertiary) education qualifications. Furthermore, tacit knowledge matters, which only develops over time. Accordingly, we formulated our first hypothesis as follows.

> *H*1: The higher the human capital endowment in terms of engineers, scientists and managers as well as in terms of work experience, the higher the company's innovation propensity.

Beyond the focus on qualification and experience as an input for innovation, the theoretical literature also implies that the degree of human capital requirement differs among sectors.

The theoretical concept of a 'sectoral innovation system' starts from the idea that industries are not homogenous regarding their innovation processes. Instead, sectors largely differ with respect to their innovation regimes. Malerba (2005) explains that sectoral innovation systems differ according to the (1) knowledge and technological domain, (2) actors and networks as well as (3) institutions. As regards the first aspect, he refers to qualification (human capital) by saying that ‘the knowledge base has been embodied in skilled personnel . . .’ (390), and a sector’s innovation process differs with respect to human capital input.

In principle, one could assume that every single industry has its own sectoral innovation system, but in order to reduce complexity (and for empirical feasibility) it made sense for us to look at broader industry categories.[3] With respect to the topic of this article it was most suitable to refer to the sectors introduced by Pavitt (1984, 343) which express ‘considerable variety in the sources, nature and uses of innovation’. Pavitt’s classification does not directly refer to differences in type or intensity of human capital among industries. However, the criteria used to classify sectors (especially the aspect of ‘internal sources of innovation’) strongly imply that sectors have different skill requirements.[4] Accordingly, we distinguish between the following industry classes:

(1) *Science-based* industries are characterised by much organised R&D with a strong link to university or other publicly funded basic research. These industries, obviously, require high-level science and engineering skills. Examples of science-based industries are the chemical and electronics industries.
(2) *Specialised suppliers* operate in close relationships with customers. Firms in this category focus strongly on product innovations and require interactive learning skills, vocational skills, practical development skills and the capacity to develop highly client specific solutions. A typical example within this sector would be a machinery company.
(3) *Scale intensive* industries are made up of production intensive companies with rather simple production, and often with mass products. Innovation is mostly process oriented. R&D activities predominantly serve internal purposes. Economies of scale require managers with cross-functional skills, specialists in product design and development skills as well as a qualified workforce that is able to adapt new technologies. Examples in this sector would be manufacturers of transport equipment and the steel industry.
(4) *Supplier dominated* industries tend to be oriented towards process innovation. Operators in this category are mostly defined in terms of their professional skills, design, brand and advertising. Technological innovations, however, mainly come from outside these companies. In-house R&D and engineering capabilities are considered to be weak. An example in this sector would be the textile industry.

According to Pavitt (1984), the science-based industries and the specialised suppliers serve the rest of the economy with new technology. Scale intensive industries mostly take over and adapt external technology while supplier dominated industries hardly fulfil their own development activities. With respect to human capital, we formulated the following hypothesis:

> *H*2: The higher the original innovation activity of a sector, the stronger the importance of a highly qualified workforce.

Before turning to the empirical analysis, it should be pointed out that product innovation can appear in mainly two different qualities: on the one hand, new products can be produced through further development or imitation of existing products; and on the other hand, firms sometimes produce true frontier innovations that lead to market novelty products (Aghion 2008; Krueger and Kumar 2004).

3. Model and data

3.1. Econometric model

Besides bivariate descriptive analysis, the hypotheses were tested on the basis of a micro-econometric probit model, since the firm's innovation activity as dependent variable is measured by a binary variable. The innovation variable was regressed on variables representing the firm's human capital endowment in terms of qualification and experience. In order to avoid regression biases due to the problem of omitted variables, almost every central impact on the innovation behaviour of the firm, in addition to the primary interest – level of qualification – had to be included in the estimation. In accordance with the empirical literature's focus on determinants of innovation activity the following exogenous variables were taken into account:[5]

- *R&D activities:* According to the traditional 'science push model' of innovation, R&D is a central source of innovation. This one-dimensional perspective has since been extended; however, we still had to assume that enterprises are particularly innovative if they employ resources for the development of new products.
- *Firm size:* If an enterprise is large, this is assumed to facilitate the innovation activity due to more favourable conditions to finance innovations, the availability of real and human capital resources, and the exploitation of scale effects.[6]
- *Export intensity:* Firms selling their products on foreign markets are subject to global competition forces – survival when competition is strong should require persistent innovation efforts.
- *Profitability:* The financing of innovation activities predominantly comes from internal firm resources since banks are usually reluctant to provide capital for risky projects like innovation. Accordingly, a profitable firm will be more likely to generate the monetary resources needed for innovations.
- *Equipment:* A sufficient technological standard is a precondition for the feasibility of elaborate innovation types. Moreover, the technical equipment complements the absorptive abilities of an enterprise. Hence, a high level of technology should promote the innovation propensity of firms.
- *Further training:* This variable concerns whether the firm invests in the further education of its employees. In the sense of life-long-learning, such activities add to the knowledge and capabilities of the workforce, and are associated with a positive impact on the innovation behaviour of the firm.
- *Age of the firm:* That a firm has been operational for many years might indicate the ability to meet market challenges sufficiently, thus ample adaptation capacities could be expected of such a firm. From this point of view the age of a firm should be positively correlated to its innovation activities. However, one reason for the emergence of enterprises might be that existing (older) firms will resist radical types of innovations – for example, due to path dependencies. Therefore, the impact of the age of the firm is not clear cut.
- *East-location:* Due to regional distinctions resulting from the transition period, a dummy is included controlling for an unexplained 'East-effect', thereby expecting a lower innovativeness of firms located in the Eastern part of Germany.
- *Foreign ownership:* In order to control for different access to non-market knowledge flows, a dummy variable measuring majority foreign ownership is implemented. Due to the easier import of advanced technology from its multinational enterprise group, a foreign-owned firm should have advantages in innovation processes.

Thus, the estimation equation had the following general form:

$$y_i^* = \alpha + \beta \mathrm{HK}_i + \gamma' \mathrm{X}_i + \varepsilon_i$$
$$\text{With } y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases} \text{ and } \varepsilon \sim N(0,1), \tag{1}$$

where y_i denoted our binary outcome, which took the value of one if firm i was active in product innovation, y^* was a latent variable. HK was our qualification variable, denoting the share of highly-qualified employees in terms of formal education or, alternatively, occupational characteristics. Thus, β measured the effect of qualification on innovation. γ' denoted a vector of coefficients for the above described exogenous control variables in X_i, α represented the constant, and ε denoted the error term. The estimations were limited to the manufacturing sector (without construction) and to firms with at least 10 employees.[7] The model was estimated for the entire sample and separately for each of the four sub-samples according to the Pavitt categories.

3.2. Data

The analysis was carried out on the basis of the linked-employer–employee data set (LIAB), provided by the Institut für Arbeitsmarkt- und Berufsforschung Nuremberg, Germany.[8] The data set contained firm-level data from the IAB-Betriebspanel, an annual panel survey of about 15,000 German firms, and individual data of the employees working in the panel firms. The individual statistics covered all the workers who were registered in the national social insurance system. For the purposes of this article, the LIAB data set was particularly useful since the firm-level data about innovation activity and other relevant firm characteristics could be combined with exact information on the qualification level of the firms' employees. Hence, the question of how the qualification level of a firm's workforce affects its innovation activity could be appropriately addressed. A particular advantage of using this data set was that it contained rich information about the qualification structure. Qualification can be measured not only in terms of formal education (higher education degrees), but also in terms of the actual occupational status of the employee in the firm. So, the data allowed precise detection of the actual qualification level.

As regards innovation, we did not use proxy variables like R&D, patents or the like, but referred to direct measures of product innovations. The innovation variable stemming from the panel survey was binary coded.[9] A value of one was assigned if the firm was engaged in product innovation. Three categories of innovation qualities were distinguished in the data set:

(1) Improvement of an existing product (*improvement*);
(2) Introduction of a product that in general already exists in the market, but is new to the firm (*new product*);
(3) Creation of a market novelty (*market novelty*).

These three qualities could be separated as such: (1) and (2) represent innovations that are mostly incremental or imitating and (3) stands for frontier innovations. The aggregate variable *product innovation* was set to one if at least one of the three types of product innovation was realised. The collection of innovation data is governed by the international standards of innovation surveys provided in the 'Oslo Manual' (OECD 2005). Product innovations are subject to the survey every 3 years. Process innovations are not subject to the survey so far.[10]

The qualification variable was based on occupational status, which was reported in the LIAB employees' statistics. According to the typology of Blossfeld (1985), an employee is classified as highly qualified if he or she performs a job as an engineer, scientist or manager. These occupations usually require formal education at the tertiary level. Alternatively, formal education (higher education degree) was used as the qualification variable.[11] The second variable that arose from the LIAB was experience. To measure differences in work experience, three categories of job tenure within the firm were distinguished (up to 1 year, 1–5 years, and more than 5 years).

The control variables as mentioned above were taken from the panel survey, this meant that the information given was based on each firm's self-assessment. Firm size was measured by the logarithm of the number of employees. Export intensity was defined as the share of sales abroad. The variable 'further training' was the ratio of further training participants to the number of employees in each firm. The remaining control variables were implemented as dummy variables. The R&D variable was set to one if the firm was engaged in R&D activities or cooperation. If the firm rated its profitability as at least 'good' the corresponding dummy was set to one. Due to a lack of differentiation, the age of the firm had to be implemented as binary variable, too. A value of one was assigned if the enterprise was founded before 1990. Foreign ownership was set to one if the majority of the firm was owned by foreigners. The value one was assigned to the equipment dummy, if the firm rated its technological level as 'state of the art'. The 'East' dummy was, of course, one if the firm was located in the area of the former GDR.

The probit estimation was performed for the most recent year available – 2004. After the exclusion of non-manufacturing firms, firms with less than 10 employees and firms with missing values, 1307 observations remained in the sample. The data about innovation activities referred to the period of 2 years preceding the survey, which was carried out in June 2004. The exogenous variables related to 2002, that is, the year before the innovation data.[12]

The implementation of lagged variables was necessary to address the problem of endogeneity. Because innovation may itself lead to adjustments of the production system, the exogenous variables should measure the inputs before innovation took place. The use of a lagged model meets – at least to some degree – the problem of causality.

4. Empirical results

4.1. Descriptive analysis

Regarding innovation activities in the four sectoral groups, we can confirm the innovation patterns described by Pavitt (1984). Science-based industries and specialised suppliers make up 84 and 77% of product innovators, respectively, whereas supplier dominated and scale intensive industries only account for 55 and 67%, respectively (Table 1). The same pattern is found for the different types of innovation. Market novelties especially are primarily developed within the group of science-based industries. Among companies in the supplier dominated sector, only 5% develop market novelties, whereas 30% of companies in the science-based sectors are active in this field.

A similar picture arises from the qualification structure (Table 2, first row). The share of employees with tertiary education ranges between 5 and 15%. Supplier dominated and scale intensive industries employ relatively few formally high-qualified employees, whereas specialised suppliers and science-based industries employ more people with a higher education degree (12 and 15%, respectively). According to the occupational status (Table 2, second row), the share of highly qualified employees (engineers, scientists and managers) ranges

Table 1. Share of innovative firms (%) by sector and innovation quality.

Type of innovation	Sector			
	Supplier dominated industries	Scale intensive industries	Specialised suppliers	Science-based industries
Product innovation	54.7	67.2	77.3	83.8
Improvement	52.2	64.6	73.1	79.1
New product	16.4	25.1	32.0	32.4
Market novelty	4.7	11.8	19.1	29.1
Sample size	232	618	309	148

Source: LIAB 2001–2004.

Table 2. Share of highly qualified and experienced employees as a percentage of all employees.

Qualification indicator	Sector			
	Supplier dominated industries	Scale intensive industries	Specialised suppliers	Science-based industries
Highly qualified – measured by formal education	5.1	7.0	11.9	15.1
Highly qualified – measured by occupational status	4.3	5.7	9.6	11.1
Experience (>5 year tenure)	60.9	59.7	55.2	58.1

Source: LIAB 2001–2004.

between 4 and 11%.[13] The highest share of highly qualified employees arises in industries that are active in product innovation at a level above the average for the whole industrial spectrum.

However, with respect to work experience the descriptive findings are rather different. The innovation-intensive sectors who serve the economy with original innovations (science-based industries and specialised goods suppliers) seem to employ workers with somewhat less tenure on average.

We now look at the qualification structure of innovative and non-innovative firms within the Pavitt categories (Table 3). For the low innovation sectors (supplier dominated and scale intensive industries), the level of employment of highly-qualified people in companies not engaged in innovation is the same as that of or only slightly higher than that of companies that are active in product innovation. Remarkable differences arise among innovators and non-innovators in specialised suppliers and science-based industries. In both sectoral groups, the level of qualification is obviously higher for innovators than for non-innovators.[14] Furthermore, across all sectors the share of qualified personnel is higher among innovators performing more radical innovations, that is ‘market novelties’. Thus, there is some descriptive evidence that qualification is more important in companies concerned with original innovations than in low innovation sectors that mostly take over and adapt external technology or, indeed, hardly fulfil their own development activities.

Overall, these results are also confirmed in terms of work experience (Table 4). Regarding product innovations in general, substantial differences between innovators and non-innovators only occur in innovation intensive sectors. Here, innovators are characterised by a considerably higher share of employees with work experience over 5 years. However, with respect to the various innovation qualities an exception of this general rule

Table 3. Sector-specific share of highly qualified employees (occupational status) according to innovators, non-innovators and innovation quality.

	Sector							
Type of innovation	Supplier dominated industries		Scale intensive industries		Specialised suppliers		Science-based industries	
Innovation (yes/no)	yes	no	yes	no	yes	no	yes	no
Product innovation	4.0	4.7	5.7	5.6	10.4	6.7	11.5	9.2
Improvement	4.0	4.6	5.7	5.5	10.8	6.4	11.3	10.3
New product	4.4	4.3	5.9	5.6	10.8	9.0	10.2	11.6
Market novelty	6.8	4.2	6.3	5.6	14.0	8.6	12.5	10.5

Source: LIAB 2001–2004.

Table 4. Sector-specific share of experienced employees (>5 year tenure) according to innovators, non-innovators and innovation quality.

	Sector							
Type of innovation	Supplier dominated industries		Scale intensive industries		Specialised suppliers		Science-based industries	
Innovation (yes/no)	yes	no	yes	no	yes	no	yes	no
Product innovation	60.0	62.0	59.3	60.6	56.4	51.0	59.4	51.4
Improvement	60.4	61.6	59.1	60.8	56.3	52.1	59.4	53.4
New product	55.4	62.0	56.6	60.8	57.7	54.0	62.7	55.9
Market novelty	48.5	61.5	54.7	60.4	51.9	56.0	57.6	58.3

Source: LIAB 2001–2004.

shows up. Across all the sectors, firms engaged in the most radical type of innovation, that is, market novelty, typically employ workers with less experience. The interpretation of this surprising result needs to take into account the correlation between work experience measured in terms of tenure and the age of the firms involved. The simple explanation may be that radical innovations are frequently performed by young firms.

To sum up, descriptive evidence supports $H1$ and $H2$ with regard to the qualification variable. First, firms with a higher innovation propensity are characterised by a higher share of qualified employees. Secondly, the sectoral assumption that the higher the original innovation activity of a sector, the stronger the importance of a highly qualified workforce is confirmed. In terms of work experience, the evidence for these hypotheses is somewhat weaker.

One can assume that the higher share of qualified employees, especially among innovators in the group of specialised suppliers and science-based industries, is an expression of the fact that these firms employ more R&D personnel than others. Thus, as a further step we look at the differences in the share of highly qualified employees according to the R&D participation of firms (Table 5). Apart from in the supplier dominated industries, the share of highly qualified employees is higher in firms with their own R&D activities compared with firms without R&D activities. This effect is especially visible in the group of specialised suppliers (12.4 vs. 5.7%).

Obviously, a high share of highly qualified employees and R&D activities are interconnected. Therefore, the regression analyses were also run with an interaction term of human capital and R&D, expecting a positive impact on innovation.

Table 5. Sector-specific share of highly qualified employees (occupational status) according to R&D activity.

	Sector			
R&D participation	Supplier dominated industries	Scale intensive industries	Specialised suppliers	Science-based industries
R&D existent	4.2	6.5	12.4	12.3
R&D non-existent	4.3	5.0	5.7	9.1

Source: LIAB 2001–2004.

4.2. Estimation results

We first ran the regression analysis with the full sample (Table 6). When qualification and R&D are included without the interaction term (Model I), the qualification and experience variables do not turn out to be significant.[15] Other commonly estimated effects stemming from R&D activity, firm size and export intensity appear to be significant with the anticipated positive direction of influence. Furthermore, the two dummies for the science-based and the specialised supplier industries have a significant positive impact on the probability of a firm's product innovation activity that corresponds to our expectations.[16]

When we include an interaction term of qualification and R&D (Model II), the qualification variable turns out to be significant, but with a negative sign; whereas the interaction

Table 6. Regression results of the probit estimation without interaction between R&D and qualification (Model I) and with interaction term (Model II) – full sample.

	Model I		Model II	
Dependent variable: product innovation	Coefficient	z-value	Coefficient	z-value
Highly qualified (occupational status)	−0.938	−1.61	−2.2565***	−2.82
R&D activities	1.201***	11.85	0.9711***	7.14
Interaction (R&D∗highly qualified)	–	–	3.2868**	2.41
Job tenure maximum 1 year	0.621	1.38	0.5893	1.31
Job tenure 1–5 years	0.292	1.51	0.2505	1.29
Job tenure >5 years	–	–	–	–
Firm size	0.187***	4.76	0.1963***	4.95
Export intensity	0.941***	4.62	0.9516***	4.63
Profitability	0.138	1.55	0.1497*	1.65
Equipment	0.019	0.19	0.0068	0.07
Further training	0.150	0.66	0.1304	0.57
Age of the firm	0.021	0.19	0.0243	0.22
East	0.046	0.45	0.0562	0.55
Foreignness	0.015	0.11	−0.0005	−0.00
Scale intensive industry	0.063	0.56	0.0646	0.58
Specialised supplier	0.230*	1.70	0.2118	1.56
Science-based industry	0.311*	1.75	0.3195*	1.78
Supplier dominated industry	–	–	–	–
Constant	−1.293***	−5.10	−1.2436***	−4.88
Sample size	1307		1307	
LR-Test	410.96***		417.78***	
McFadden R2	0.255		0.259	

Source: LIAB 2001–2004.
*10% significance level.
**5% significance level.
***1% significance level.

term exhibits a significantly positive impact. This means that if R&D and qualification occur together in a firm, they clearly have a positive impact on the firm's propensity to carry out a product innovation. The negative sign of the qualification variable implies that the presence of a significant number of highly qualified personnel in a firm without R&D hinder innovation. This seemingly surprising result might, however, be explained by some of the firms in the sample having a high share of qualified people (engineers, scientists and managers), but not engaging in any product innovation activity. The other human capital variable, work experience measured via job tenure, is found not to affect the propensity to product innovation.

Table 7. Regression results of the probit estimation of Model II (with interaction term).

	Sample			
	Supplier dominated industries	Scale intensive industries	Specialised suppliers	Science-based industries
Dependent variable: product innovation	Coefficient (z-value)	Coefficient (z-value)	Coefficient (z-value)	Coefficient (z-value)
Highly qualified (occupational status)	−1.7072	−1.9408	−2.6019*	−1.6265
	(−0.92)	(−1.45)	(−1.66)	(−0.70)
R&D activities	1.5566***	0.8332***	0.8402***	1.1902**
	(3.57)	(4.24)	(2.71)	(2.04)
Interaction (R&D∗highly qualified)	1.5856	3.5061	4.1660*	6.5115
	(0.22)	(1.40)	(1.80)	(1.18)
Job tenure max. 1 year	−0.1666	0.8692	1.2513	−4.5096*
	(−0.17)	(1.37)	(1.17)	(−1.71)
Job tenure 1–5 years	0.8625*	0.4721*	−0.2133	−0.8964
	(1.76)	(1.64)	(−0.51)	(−1.42)
Job tenure >5 years	–	–	–	–
Firm size	0.1705*	0.2032***	0.2928***	0.1913
	(1.67)	(3.69)	(2.98)	(1.37)
Export intensity	1.9098***	1.2821***	0.7381*	−0.5538
	(3.19)	(3.96)	(1.78)	(−0.89)
Profitability	0.1181	0.1527	0.1748	0.3375
	(0.55)	(1.21)	(0.87)	(0.98)
Equipment	−0.0898	−0.0831	0.0146	0.3287
	(−0.38)	(−0.62)	(0.07)	(0.85)
Further training	2.0535**	−0.0103	0.0589	−0.5668
	(2.41)	(−0.03)	(0.12)	(−0.77)
Age of the firm	−0.0780	0.1726	−0.2492	0.2349
	(−0.28)	(1.13)	(−1.03)	(0.58)
East	−0.1017	0.1454	0.0245	0.4897
	(−0.42)	(1.02)	(0.10)	(1.21)
Foreignness	−0.1920	0.1510	−0.3559	0.6049
	(−0.51)	(0.73)	(−1.09)	(1.27)
Constant	−1.4308**	−1.4101***	−1.0296*	−0.4630
	(−2.06)	(−4.10)	(−1.87)	(−0.49)
Sample size	232	618	309	148
LR-Test	90.12**	176.85***	95.29*	47.74
McFadden R2	0.282	0.226	0.288	0.364

Source: LIAB 2001–2004.
Note: z-values in parentheses.
*10% significance level.
**5% significance level.
***1% significance level.

As laid out in the discussion of the descriptive analysis, the correlation between qualification and sectoral innovation patterns is quite high. Thus, the impact of the human capital variable could possibly be covered by the dummy variables for the Pavitt categories.[17] In order to control for this, we ran the regressions separately for sectoral sub-samples according to Pavitt's industry categories (Table 7). But here again, the qualification variable does not appear to have a significantly positive (basic) effect. The interaction term exhibits a significantly positive impact only in the specialised suppliers group, while the basic effect of qualification is significantly negative in this group. This finding might be related to the fact that in specialised supplier firms, the R&D and production activities are closely connected (for example, the production of special equipment in small batches or even as single units according to a particular customer order). A similar picture arises if the dependent innovation variable is disaggregated into the three qualities of product innovations: improvement, new product or market novelty (Tables 8 and 9).

Table 8. Regression results of the probit estimation – coefficients for the qualification variable only (Model I).

	Dependent variable					
	Improvement		New product		Market novelty	
Sample	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Entire Sample	−0.7747	−1.33	−0.1836	−0.36	1.0788*	1.94
Supplier dominated	−0.8389	−0.46	−0.2792	−0.13	4.0116	1.45
Scale intensive	−0.8564	−0.78	−0.0722	−0.07	0.8908	0.72
Specialised suppliers	−0.0795	−0.07	0.5712	0.67	1.2654	1.33
Science-based	−1.2852	−0.88	−0.3261	−0.26	1.1706	1.12

Source: LIAB 2001–2004.
*10% significance level.

Table 9. Regression results of the probit estimation – coefficients for qualification variable and interaction term only (Model II).

	Dependent variable					
	Improvement		New product		Market novelty	
Sample	Highly qualified	Interaction R&D/qualified	Highly qualified	Interaction R&D/qualified	Highly qualified	Interaction R&D/qualified
Entire sample	−1.9197**	2.5374**	−0.4526	0.3918	−0.0881	1.4975
	(−2.36)	(2.03)	(−0.52)	(0,38)	(−0.08)	(1.16)
Supplier dominated	−1.1430	4.1388	−1.9867	8.9289*	4.5066	−3.8882
	(−0.61)	(0.59)	(−0.81)	(1.68)	(1.55)	(−0.51)
Scale intensive industry	−1.8769	3.3249	−0.8122	1.3358	0.4073	0.7617
	(−1.38)	(1.34)	(−0.53)	(0.66)	(0.20)	(0.31)
Specialised suppliers	−1.6026	2.9326	−0.6944	1.6565	−4.3317	6.4348*
	(−1.02)	(1.33)	(−0.40)	(0.85)	(−1.22)	(1.74)
Science-based industry	−2.8216	2.2744	0.4588	−1.0829	−2.2426	3.8202
	(−1.04)	(0.67)	(0.19)	(−0.38)	(−0.66)	(1.07)

Source: LIAB 2001–2004.
Note: z-values in parentheses.
*10% significance level.
**5% significance level.

Table 10. Regression results of the probit estimation without R&D activities and without R&D activities, firm size and export intensity – full sample.

	Without R&D activities		Without R&D activities, firm size & export intensity	
Dependent variable: product innovation	Coefficient	z-value	Coefficient	z-value
Highly qualified (occupational status)	0.101	0.547	1.050*	0.545
R&D activities	–	–	–	–
Interaction (R&D∗highly qualified)	–	–	–	–
Job tenure max. 1 year	0.549	0.430	−0.425	0.412
Job tenure 1–5 years	0.426**	0.186	0.183	0.177
Job tenure >5 years	–	–	–	–
Firm size	0.284***	0.037	–	–
Export intensity	1.276***	0.190	–	–
Profitability	0.071	0.084	0.087	0.079
Equipment	0.082	0.090	0.162*	0.085
Further training	0.092	0.210	0.169	0.198
Age of the firm	0.027	0.102	0.104	0.097
East	0.021	0.094	−0.342***	0.086
Foreignness	0.002	0.133	0.423***	0.123
Scale intensive industry	0.139	0.106	0.307***	0,101
Specialised supplier	0.407***	0.127	0.567***	0.121
Science-based industry	0.452***	0.166	0.731***	0.158
Supplier dominated industry	–	–	–	–
Constant	−1.598***	0.239	−0.088	0.171
Sample size	1307		1307	
LR-Test	254.7		106.2	
McFadden R2	0.158		0.066	

Source: LIAB 2001–2004.
*10% significance level.
**5% significance level.
***1% significance level.

Table 11. Pavitt taxonomy (manufacturing industry).

Category	International Standard Industrial Classification of all Economic Activities, Revision 3 (1990) ISIC (Rev. 3)
Supplier dominated industries	Agriculture (01); Forestry (02); Fishing (05); Textiles (17); Clothing (18); Leather and footwear (19); Wood & products of wood and cork (20); Pulp, paper & paper products (21); Printing & publishing (22); Furniture, miscellaneous manufacturing, recycling (36–37).
Scale intensive industries	Mining and quarrying (10–14); Food, drink & tobacco (15–16); Mineral oil refining, coke & nuclear fuel (23); Rubber & plastics (25); Non-metallic mineral products (26); Basic metals (27); Fabricated metal products (28); Motor vehicles (34); Building and repairing of ships and boats (351); Aircraft and spacecraft (353); Railroad equipment and transport equipment n.e.c. (352+359); Electricity, gas and water supply (40–41).
Specialised suppliers	Mechanical engineering (29); Office machinery (30); Insulated wire (313); Electronic valves and tubes (321); Telecommunication equipment (322); Scientific instruments (331); Other instruments (33–331).
Science-based industries	Chemicals (24); Other electrical machinery & apparatus (31–313); Radio and television receivers (323).

Source: Robinson et al. (2003).

If we look at the work experience variable, the sectoral disaggregated estimations only validate small effects. For the science-based industries, the share of employees with no experience (job tenure less than 1 year) seems to discourage innovation activities. In the low innovation sectors, product developments are intensified by a large share of workers with a medium experience level. Overall, however, the estimations do not reveal a noticeable effect of worker experience on the innovation propensity of firms.[18]

Altogether the regressions do not prove a significant impact of human capital on the innovation activities of firms. The result is in sharp contrast to our hypotheses and to the descriptive evidence. Two possible explanations might shed light on these unexpected findings.

From an econometric point of view, the correlation of human capital with other implemented exogenous variables might depress the significance of the qualification coefficient. Indeed, if we re-estimate model I without the most significant variable – R&D activities – the qualification coefficient becomes positive but still insignificant (Table 10, left column). If we additionally drop the very significant variables of firm size and export intensity,

Table 12. Description of regression variables.

Variable	Scale	Year of reference	Description
Endogenous variables			
Product innovation	0/1	2002–2004	At least one product innovation took place (improvement, new product or market novelty)
Improvement	0/1	2002–2004	At least one existing product was improved
New product	0/1	2002–2004	At least one product was introduced that existed in general, but was new to the firm
Market novelty	0/1	2002–2004	At least one product was introduced that was not only new to the firm, but new to the entire market of the firm
Exogenous variables			
Highly qualified (occupational status)	%	2002	Share of engineers, scientists and managers within the firm
R&D activities	0/1	2004	Engagement in R&D activities or cooperation
Job tenure max. 1 year	%	2002	Share of employees with max. 1 year job tenure (in % of total employees)
Job tenure 1–5 years	%	2002	Share of employees with 1–5 years' job tenure (in % of total employees)
Firm size	log	2002	Log. number of employees
Export intensity	%	2002	Share of sales abroad
Profitability	0/1	2002	At least 'good' profitability (Assessment better than 3 on a range of 1–5)
Equipment	0/1	2002	At least 'good' technological standard (Assessment better than 3 on a range of 1–5)
Further training	%	2001	Share of employees that received further training (in % of total employees)
Age of the firm	0/1	2002	Firm foundation before 1990
East	0/1	2002	Firm located in East-Germany
Foreignness	0/1	2002	Majority of firm owned by foreigners
Scale intensive industry	0/1	2002	According to Pavitt (1984) and Robinson et al. (2003), see Table 11.
Specialised suppliers	0/1	2002	
Science-based industry	0/1	2002	

qualification turns out to be significant with the right sign (Table 10, right column). But the explanatory power of the reduced model is far behind the full model; thus, we cannot reject the full model in order to obtain results giving significant human capital effects. Nonetheless, the technical problem of correlation indicates an important real-world issue. Typically, innovators are characterised by R&D activities, remarkable size, high export intensity and human capital. So, complementarities between these factors might exist. Since the coefficient of human capital becomes insignificant after controlling for R&D, firm size and exports, the driving difference between innovators and non-innovators is not human capital endowment but the most structural factors.

The second explanation draws on measurement aspects. In our model, human capital is operationalised in terms of quantity, that is, the number of highly qualified employees. It might be argued though that the qualitative characteristics could be more important than quantitative ones. Although the quantity of high-skilled employees differs only slightly between innovators and non-innovators, highly qualified staff could differ in terms of their specific discipline, university background and respective imparted knowledge and skills. However, if we distinguish between basic skill groups (engineering vs. managerial skills) and re-estimate the model separately for these groups the results remain unchanged. The regressions do not confirm a robust impact of human capital on innovation activities – neither for engineers nor for managers. Nevertheless, there might be other dimensions of human capital quality that we are not able to measure and, therefore, the quality vs. quantity explanation of our unexpected findings might still be valid.

5. Conclusions

The bivariate descriptive analysis reveals clear differences with respect to the share of highly qualified employees between sectors distinguished according to the classical innovation patterns described by Pavitt. Sectors with a high share of highly qualified employees are characterised by product innovation activities clearly above average (specialised suppliers and science-based industries). Furthermore, within the sectoral groups qualification seems to be particularly important for companies that are engaged in frontier innovations. Thus, the descriptive findings support our hypotheses in terms of qualification. With respect to the dimension of work experience, the outcome is somewhat weaker.

However, the multivariate regression results for the tested specifications do not reveal significantly positive coefficients for the qualification variables. In line with the Vinding's outcome (2006), the high share of qualified employees as such is not a sufficient condition to enhance the propensity of product innovation at the firm level. Nevertheless, the findings suggest that qualification drives innovation when the qualified people focus on innovative activities (R&D) – indicated by the significantly positive sign of the interaction term.

We offer two explanations for these mixed results. First, the positive correlation between qualification on the one side and R&D activities, firm size and export intensity on the other side reduces the effect of qualification in the multivariate estimations as compared with the bivariate analysis. Secondly, we suppose that the qualitative aspects of human capital matter more than the quantitative ones we used in the regressions.

Further research should address the question of whether there are qualitative rather than quantitative aspects determining a firms' innovative performance. In other words, the impact of human capital on innovation might be quite sophisticated, and even 'occupation' as the more precise measure might cover specific individual skills and functions that matter for innovation. Moreover, to estimate the actual effect of human capital it is necessary to disentangle the effects of skills, R&D, firm size and exports. However, this is no trivial task and would require more comprehensive information about firms, especially with respect to the longitudinal dimension.

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Notes

1. For an insightful discussion of 'innovation studies' as a discipline, see Fagerberg and Verspagen (2006).
2. According to Fagerberg and Verspagen (2006), the 'Schumpeter crowd' carries much weight in the field of 'innovation studies'.
3. For a recent overview of industry classifications in general, see, for example, Peneder (2003).
4. The assignment of industries (three digit level) to the four Pavitt categories based on International Standard Industrial Classification of All Economic Activities, Revision 3 (1990), is shown in Table 11.
5. A more detailed discussion of the variables selected here can be found in Günther and Gebhardt (2005); Gottschalk and Janz (2003) and Rammer et al. (2005).
6. This assumption originally dates back to Schumpeter who argues that innovative activity is positively related to size. Although some empirical studies indicate that a linear relationship cannot clearly be confirmed (Gottschalk and Janz 2003), there seems to be a consensus about the positive relationship (Acs and Audretsch 1988; Brouwer and Kleinknecht 1996; Vinding 2006).
7. Innovations in the other sectors – in particular regarding the service industries – are difficult to identify and factors driving innovation cannot be easily determined (Hempel 2003). Under these conditions, an estimation runs the risk of neglecting factors that have substantial impacts on innovation behavior, the estimation coefficients will therefore be biased.
8. This study uses the Cross-sectional model of the Linked-Employer-Employee data (LIAB) (Years 2001–2004) from the IAB. Data access was provided via on-site use at the Research Data Centre (FDZ) of German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and/or remote data access. For a description of the data set see Alda (2005) and Alda and Herrlinger (2005).
9. A detailed description of endogenous and exogenous variables is given in the Table 12.
10. Information on organisational innovations, related to management, labor organisation, quality control, and so on, is available. But since organisational innovations follow a different logic, especially in the sectoral perspective (Lam 2005), we excluded them from our analysis.
11. As can be seen in chapter 4, the qualification variable based on occupational status is a more suitable concept since the operationalisation via formal education includes employees with a tertiary degree who are performing occupations that are not classified as highly qualified.
12. Due to data availability, only the further training variable referred to 2001. The R&D variable values were taken from 2004 because earlier surveys did not contain information about R&D cooperation.
13. As indicated above (footnote 12), there are employees with tertiary degrees who are not working in positions that are classified as highly qualified. This is shown by the fact that the share of highly-qualified employees measured by formal education is higher than the share of highly qualified employees measured by occupational status (Table 2).
14. Within the science-based industries one exception occurs: the share of highly-qualified employees in companies who upgrade their product range ('new product') is lower than that in companies not engaged in this type of innovation.
15. For all estimations, we present the coefficients for the linear relationship of the underlying latent variable. The coefficients indicate the sign and significance of influence, but are not interpretable in terms of magnitude.

16. The use of regular industry dummies instead of Pavitt sectors does not change the results.
17. In Vinding (2006), the human capital variable becomes insignificant when the differences between Pavitt sectors are controlled for.
18. The results for the experience effect innovation qualities are not displayed. As stated, but for a few exceptions, no significant effects could be found.

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