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Embodied and Disembodied Technical Change: A Multi-Factorial Analysis of German Firms*

By *Hariolf Grupp*, Karlsruhe
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Introduction

Disembodied and embodied technical progress (capital investment in innovative goods) seem to be clear-cut theoretical concepts in traditional economic theory. However, the innovative evolution of firms is described as a quite complex phenomenon in positive economics. In this empirical approach, major determinants of innovation and their interrelation are analysed using regression and factorial analyses for 240 German firms. Apart from the analysis of patents and research and development expenditures, the appropriation of disembodied technical progress along with embodied progress is considered in order to get a concise picture of innovation. It is found that firms follow a distinctly different pattern in this respect, but the embodied and the disembodied parts of innovative sources cannot be measured by the usual proxies as is suggested in theory. Rather the innovative patterns can be derived from different arrays of indicators. Size and industry effects seem to be weak determinants in innovation as industry branches are quite heterogeneous. A proper distinction between firms absorbing disembodied and embodied change seems to be more important.

1. Theoretical frame of analysis

The measurement of embodied versus disembodied technical change is a demanding task for both economic theory and applied econometrics. If real world statistical variables are used as operational concepts in order to analyse innovation issues and the results are interpreted as if theoretical constructs, e.g. for technical progress in production functions, had been used, the problem of statistical adequation or correspondence between statistical indicators and theory formation must be

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solved.[1] Innovation research, in particular, has to cope with the problem of measuring complex issues which are – hopefully – well-defined, but in reality scarcely observable. Furthermore, a formal innovation theory differentiating between embodied and disembodied components, which can directly be checked by empirical observations, does not exist. Hence the aim of this contribution is to demonstrate that measuring innovation activities needs a set of proxy variables to give an adequate picture of the various aspects of the innovation process. In distinction to other papers on this subject and because of space limitations, we put emphasis on the construction and definition of adequate variables, their interrelation and their shortcomings, but use simple, mostly descriptive statistics and non-sophisticated econometric models.

Measuring innovation activities is not an aim in itself. The aim is to either explain the innovation process using its economic or technological determinants, or to show its economic (or technological) effects. In reality, determinants and effects are part of an interdependent process. We seek to explain innovation activities by such determinants as firm size, technological and sectoral factors for a set of 240 individual German firms observing their technology appropriation. For inferential statistics we need theory-based hypotheses and simple models. In the *microeconomic neoclassical approach,* profit maximising is the main underlying assumption. Oversimplified, the innovation case is dealt with in terms of market structure. The early models[2] have been more and more refined, i.e. by introducing dynamics, uncertainty (i.e. Kamien and Schwartz [1982]), or interdependency as in the game theoretic approach.[3] Another theoretical line, heterogeneous in itself, is the *institutionalist* or *evolutionary approach,* which explains technological change by certain rules of behaviour (i.e. Nelson and Winter [1982]), institutions and the interdependency between technology, economy and society (i.e. Dosi [1988]), Freeman [1982]). The disadvantage of this school of economic thought is that no formal mathematical framework is provided which can be taken as the starting point for statistical measurement.

Empirical innovation research is sometimes poorly based on theory with the danger of (unknown) adequation errors. We argue that proper operational concepts will show that the innovation process is too complex to be expressed by a single mathematical relation, even if this were a complex one.[4] Therefore, we use a less-

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1 For a general discussion of the statistical adequation of mental constructs see Menges [1974]. A definition of the terms 'operational concepts' and 'constructs' can be found in Machlup [1960].

2 The pioneering work has been done by Arrow [1962]. For a review see Grupp [1998].

3 I.e. Scherer [1967a], Dasgupta and Stiglitz [1980a,b], Reinganum [1981, 1982], Levin and Reiss [1984, 1988].

4 The following studies, for instance, discuss the use of patents versus R&D expenditures as innovation indicators: Mueller [1966], Pavitt [1982, 1985], Scherer [1983], Bound et al. [1984], Greif [1985], Schmoch et al. [1988], Grupp [1994b, 1995, 1998], Grupp and Schwitalla [1989], Griliches [1988, 1990]. See also the handbook edited by Stoneman (1995). In a

formalised model which lets enough room for various statistical representations: 'There exists no measure of innovation that permits readily interpretable cross-industry comparisons. Moreover, the value of an innovation is difficult to assess, (...)' (Cohen and Levin [1989], p. 1062).

In Section 2 we introduce the statistical model, the variables and the data. In Section 3 we describe how the inputs relate to each other and in Section 4 we attempt to explain the various innovation proxies suitable for empirical measurement by a latent structural model, factorial analysis.

Innovations are taken as the results of problem solving processes. Thereby typical patterns are observed. Inspired by evolutionary models (i.e. Dosi, loc. cit), empirical research has to differentiate between the *intersectoral determinants* of technological change that are responsible for different patterns of innovation in different branches. They consist in *technological opportunities, appropriability* and *market incentives*. The *appropriability* of the innovation rents depends on the sort of technology prevailing in the sector. That means, how easily can it be kept secret, protected by patents or how soon can it be introduced to the market. *Market incentives* result from the size and growth of demand, from income elasticities and changes in relative factor prices. On the one hand, these incentives influence the extent and direction of technological change within a technological paradigm, on the other hand, the search for new paradigms is stimulated. Competition nurtures the discovery process.[5] In Section 5 we attempt to clarify some of these sectoral disparities.

Intrasectoral determinants are responsible for *individual innovation behaviour* within the sectoral innovation pattern. Apart from their size, firms are different with respect to their *technological performance* and to their *innovation strategies*. The *technological performance* depends on the firm's own accumulated technological knowledge as well as the general diffusion of technological knowledge. *Innovation strategies* are also closely connected with *firm size, governance* and *ownership*. The very nature of technology may promote a certain size of firm and thus the type of industrial structure. For instance, the tendency towards automatic production leads to large firms which take advantage of scale effects, whereas the use of micro-electronic control mechanisms favours the smaller specialised firms, sometimes managed by the owner, which produce small series in a rather flexible way.[6] In Section 6 the size effects of innovative activities are investigated. Finally, market competition rewards the successfully innovating firm and thus leads to firm growth, while correspondingly punishing the less successful. Our data allow only an analysis of short-term success variables (Section 7).

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review Cohen and Levin summarise the situation as follows (1989, p. 1061): 'Equations have been loosely specified; the data have often been inadequate to analyse the questions at hand; and, until recently, the econometric techniques employed were rather primitive.'

5 See von Hayek [1978].

6 For a firm and sectoral typology according to the prevailing technology see Pavitt et al. [1987].

Principally, an innovating firm can make strategic choices between intramural research and development (R&D), external R&D by contracts to other firms, or public laboratories and technical consultancies, but may also adopt a new technology by paying fees for know-how (royalties). It always results in a *disembodied* technology.

When measuring innovation and its effects, one should also take account for the *investment-embodied* technology. In economic policy and analysis, investment is often considered as a proxy for the medium-term capacity planning of firms. But investments in modern equipment modernize production: it is an investment into the future of the firm. Thus investment is an important adjunct to the innovation process as it partly covers industries which *use* technology advances for improved production or as intermediate products. Investments of innovating companies may include investments in technology-intensive equipment, advanced materials or components. The capital inputs to the innovation process are sometimes equated with the term *indirect technology inputs.* The relative importance of indirect to direct inputs varies widely among companies due to differences in the product composition of output.

There is an increasing amount of literature which points to the importance of investments as an innovation variable. While classical economists such as Smith, Ricardo and Marx regarded technical progress as largely embodied, disembodied technical progress was defined and estimated by Solow [1957] using a time trend. Subsequently, Solow [1959] defined and estimated capital embodied technical progress using vintage production functions. The same author [1961] compared the significance of disembodied and embodied technical progress, while Intrilligator [1965] improved this approach by estimating the two factors jointly rather than separately, and by adding progress embodied in improved quality of labour as well as in improved quality of capital. He [ibid., p. 69] concludes that it is evident that neither embodied nor disembodied technical progress can be considered alone. They must be treated simultaneously. All these works are based on US data.

Nevertheless, subsequent post-war progress statistics mostly emphasised disembodied technology and the production of knowledge so that investment in new machinery has progressively lost its central position in the empirical analysis of technical change (Evangelista [1996], p. 139). Very recently, however, the empirical study of embodied change seems to have regained its place.[7]

In this paper, we distinctly model both capital-embodied and disembodied technical change as innovative sources, i.e., as inputs. Further we differentiate, with respect to appropriability, between protected disembodied sources and imitation or adoption. Our entities of observation are individual firms which we may group according to size and industry sectors.

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7 See Scott [1988], Amendola et al. [1993], Harhoff and Licht et al. [1996] and Evangelista [1996] among others.

2. Statistical model, variable description and data sources

In a new attempt to clarify the empirical significance of disembodied versus embodied technical change on the micro level, we start from an array of innovation variables *without* the usual theoretical construction of embodied and disembodied progress. By use of a latent structural model, factorial analysis, we want to check whether this distinction of two disjoint progress factors is meaningful. Backhaus et al. [1990] characterize factor analysis as a structure-revealing statistical method, suitable for our task.

The vector of proxy variables x is explained by a vector of 'factors' f and a disturbing term u:

$$x = \Lambda f^* + u^* .$$

Λ represents the parameter matrix called 'factor loadings'. The latent variables (*) are not observable in empirical measurement. The point of interest is whether f^* corresponds to the theoretical concepts of embodied and disembodied technical change.

In Section V we interpret the latent variables f^* as a linear combination f° of the observed proxy variables:

$$f^\circ = Wx ,$$

whereby W is the (s, p)-dimensional factor score matrix if we have s factors and p observed proxy variables. By help of the composed innovation measure f° we reconsider the size hypothesis (Section 6).

The starting point for a largely exploring output measurement in Section 7 is a further development of a concept known as knowledge production (summarised by Griliches [1995]). The knowledge production function can be represented in the following way:

$$\log Y = a(t) + \beta(\log X) + \gamma(\log K) + u(t)$$

where Y is some measure of output of the firm, X is a measure of embodied technical change, K is a measure of cumulated knowledge or research "capital" (disembodied), $a(t)$ represents other determinants which affect output and vary over time while u reflects all other random fluctuations in output. Certainly, this is just a first approximation to a considerably more complex relationship (Griliches, loc. cit., p. 55).

From the logarithmic form we arrive at the growth equation

$$d\log Y/dt = a + \sigma(E/Y) + \rho(D/Y) + du/dt$$

where the term $\gamma(d\log K)/dt$ is replaced by using the definitions $\rho = dY/dK = \gamma(Y/K)$ and $D = dK/dt$ for the net investment in disembodied capital, and similarly E = dX / dt for the net investment in embodied capital.

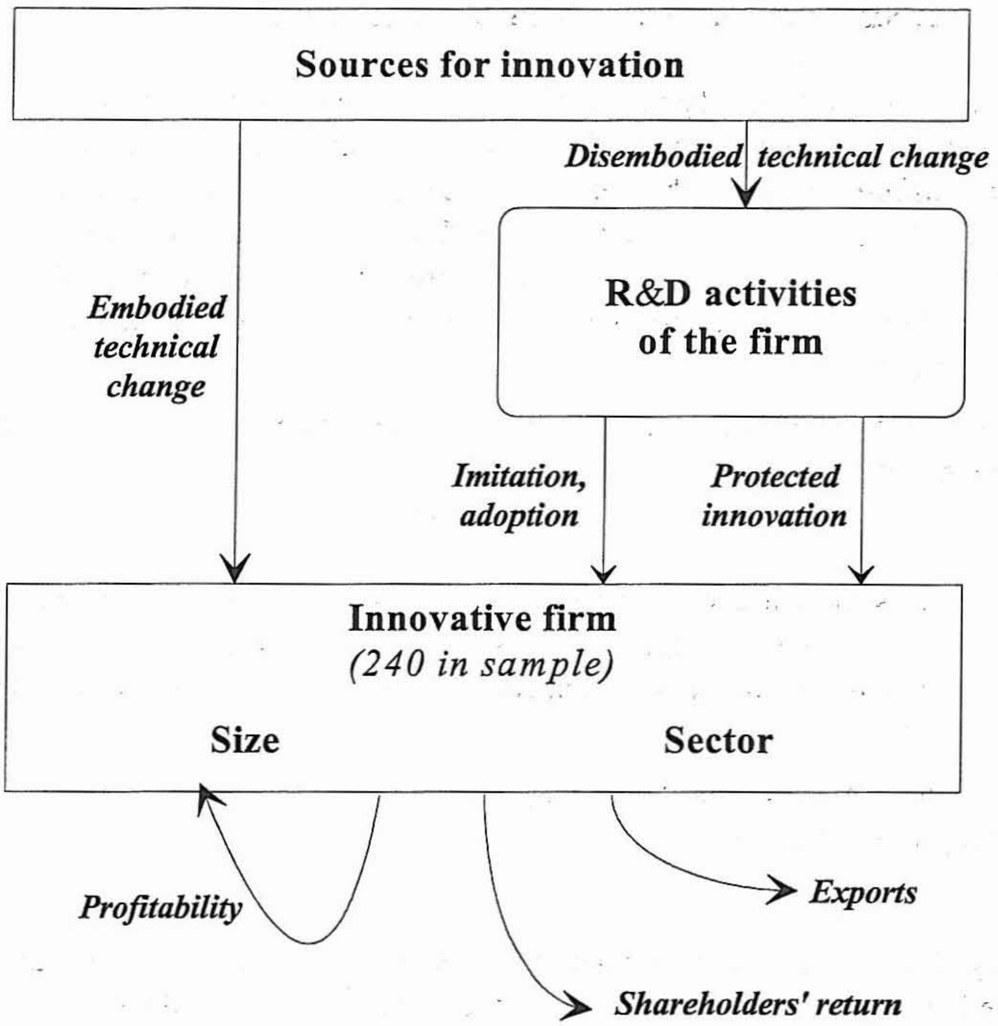

Figure 1: Simple sketch of the innovation variables.

The variables used are described below and sketched in Figure 1. Figure 1 does not intend to establish innovation as a linear process, but rather wants to highlight the basic differentiations under scrutiny in the empirical analysis. It was possible to collect data on R&D expenditures, patent applications, investments and shareholders' equity (as a source of external finance) as innovation variables, operating results, returns and export shares as output variables, as well as sales, employment, fixed assets, tangible fixed assets and the balance sheet total as alternative size variables. These variables are also used in combination to arrive at size-independent indices. Codes for variables are listed in the Appendix.

The *annual reports of large companies* are the main source of data[8] for this study. We were able for the first time to take advantage of the new German Accounting and Reporting Law according to the 4^{th} and 7^{th} EU Directives. From

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[8] For a detailed description of the data, see the list of variables in the appendix. The data base was compiled by B. Schwitalla. The data were not only used for this paper but also for previous work, see Grupp [1996b].

1987 on, large[9] corporations (Kapitalgesellschaften) must publish their company reports in a very detailed way in the official newspaper 'Bundesanzeiger' not later than nine months after the end of the business year. Another novelty is that they must comment on their involvement in R&D. Unfortunately, it is up to the company whether it reports only descriptively or quantitatively. Overall, 270 firms could be identified which gave quantitative information on R&D in their 1987 annual reports. 236 firms revealed their *R&D expenditure*, but only 108 firms their *R&D personnel*. As we wanted to use as much information on firms' innovation behaviour as possible, and as we did not accept missing data in our further analysis we dropped R&D personnel as an innovation variable and estimated corresponding R&D expenditures by branch averages for those branches with enough companies reporting on both items. This leaves us with 240 firms. Apart from the R&D data, diverse other data like *investment, labour and capital intensity* and those balance items representing *firm size* could be extracted.

It would be proper to include investments in new machinery only. Such a variable is not contained in our data source, but rather gross investment. We know, however, from a careful analysis of investment strategies of larger German firms in the same year by Littkemann [1995], that about 66 per cent of gross investments concern tangible fixed assets and therein 68 per cent technical apparatus and machinery.

The annual report data were supplemented by domestic patent data. *Patent applications* to the German *or* the European Patent Office (only if the destination country was West Germany; i.e. domestic applications on the 'European route') with the priority date between January 1985 and June 1988 were taken from the *PATDPA data base*. For a stronger temporal correlation, it would have been better to use data of a later period, but those were not available at the time of data compilation. Because of the discontinuity of patent applications, a period of 3.5 years was chosen and a yearly average was calculated. From the 240 firms, 34 firms had not applied for patents; we treat these zero cases with special attention. All other variables have no zero cases.[10]

From the construction of the sample it is clear that this is not a random sample of West German companies. It includes only companies with an active R&D and – among these – most of them with a business strategy that allow for an application of at least one patent in 3.5 years. It is representative of West German innovation-intensive firms, is weak in sectors where little or no technological innovation takes

9 Companies are defined as large when two of the following conditions are fulfilled: Sales > DM 32 million, balance sheet total > DM 15.5 million or employees > 250. See Hilke [1991, p. 14].

10 I.e., only for the patent variable, we observe some zero cases. In addition to the statistical investigations discussed in this article we performed several additional analyses with censored models the results of which are available from the authors on request. As the principle results remain unchanged we do not report on these in detail.

place, and it is heavily biased towards the manufacturing sector. By disaggregating the companies according to industrial sectors and comparing the total R&D expenditures from official sources (see next Section), we conclude that the sample covers 61.6 per cent of total R&D expenditures of German firms. The degree of representation in terms of turnover and employment is – for the reasons given above – considerably lower and somewhat below 30 per cent. Thus, the sample is clearly oriented towards larger enterprises and towards R&D-intensive firms.[11]

On the level as exposed in table 1, the R&D intensities in our sample and official statistics compare well in terms of the rank order of sectors (see figure 2).[12] As our sample is biased towards larger and towards R&D-intensive firms, R&D intensities are generally higher.

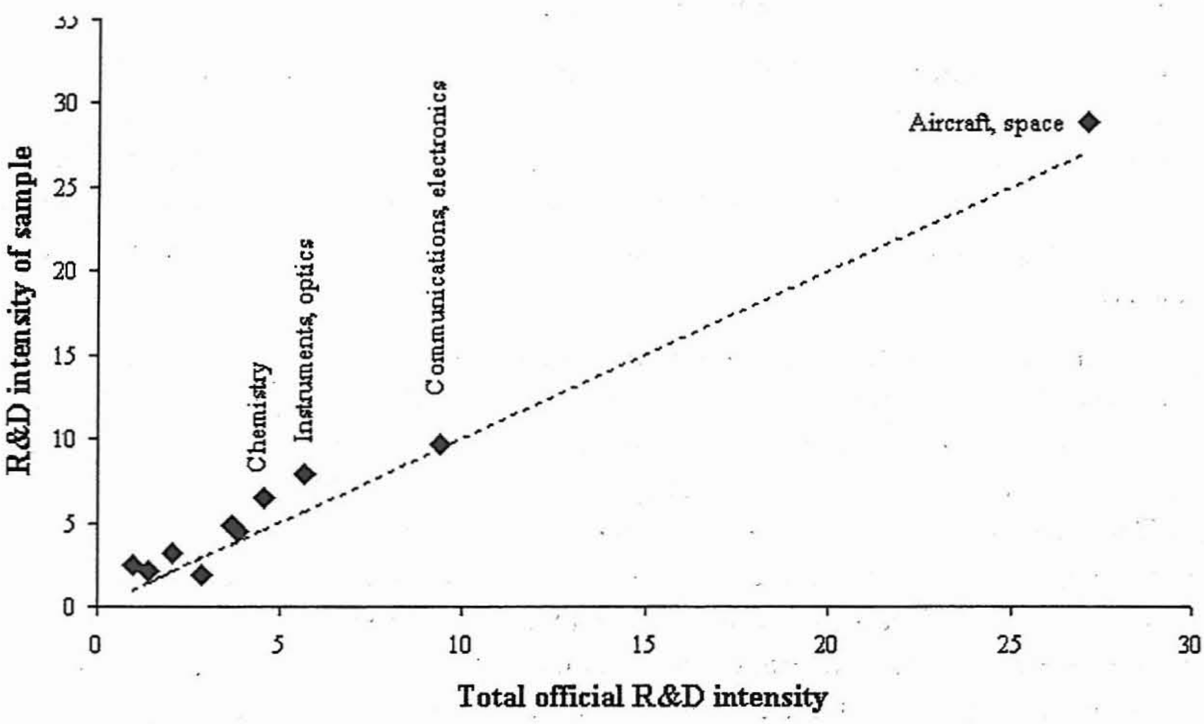

Figure 2: Degree of representation of the sample.

[11] From a later innovation survey we know that in West Germany firms with R&D activities above 1000 employeses account by number for much a smaller share than in our sample (Harhoff, Licht et al. [1996]). However, as the R&D-intensity distribution is highly skewed due to the presence of very large enterprise, we arrive at roughly comparable results, see Section 3. Our R&D-intensity distribution is unimodal and skewed to the left and thus conforms with Cohen and Klepper [1992] for the United States. The cumulative size distribution is as follows: 49 firms (20 per cent) employ more than 5000 persons, 38 per cent more than 2000, 54 per cent more than 1000, 75 per cent more than 500. The small and medium-sized companies in the narrow sense with less than 500 employees account for 25 per cent (61 firms).

[12] The Spearman rank coefficient is significant at the 0.1 level.

3. Measuring innovation activities by single indicators

The more established indicator variables for innovation, i.e. R&D expenditures and patent applications, were used in order to describe innovation activities on the firm and branch level. In table 1, the 240 firms were reclassified according to 16 narrower and five broader branches, and R&D and patent intensities, respectively, were calculated. The branch selection is motivated by the desire to be as disaggregated as possible without arriving at empty or weakly populated subsectors. This means the innovation data were weighted by size indicators sales and R&D, respectively. Variable codes are explained in the Appendix. Also given is an index for sector heterogeneity which compares the weighted branch average with the standard deviation of the unweighted means.

The indicators give an impression of the ranking of sectors to which we are accustomed. The sectors aircraft and space, the pharmaceutical industry and the electronic industry are especially R&D-intensive (compare also Figure 2). But when using the patent indicator, differences in 'innovativeness' are no longer as clear-cut. The aircraft and space and the electronics industry lose their leading places. Extremely high patenting is observed in the motor vehicles parts industry, whereas it is extremely low in motor vehicles manufacturing itself.

When comparing the innovativeness measured by the R&D indicator on the branch level with the index for sector heterogeneity, the high R&D intensity of some firms in seemingly less innovative sectors is striking. This is true especially for the chemical and the machinery sector. Apart from the small aircraft and space industry, which does not 'fit' into the vehicles sector, the sectoral definition for chemistry is much too wide to measure technological issues. Sectors are often quite heterogeneous.[13] The leading firms in the chemical industry in our sample are specialised in the development of rocket fuels and nuclear materials. The leading firms in the other machinery sector work on nuclear apparatus, are military-oriented, deliver high technology investment equipment (e.g., vacuum process technology for the semi-conductor industry or laser and digital technology for the production of printing machines). R&D-intensive firms in other sectors like 'scientific and professional instruments and optical industry' and 'motor vehicles parts', endow their goods to a great deal with micro-electronic components.

It has often been suggested that the patent-to-R&D relationship is different for different industrial sectors. The reasons for different sectoral behaviour originate from technology-specific input-output relations and sectorally different propensities to patent once an invention has been made. There are also firm-specific determinants such as the firm size or the individual technology base already accumu-

13 See Scherer [1982] for a matrix of industries and technologies. Sectors here were defined according to SYPRO, the official German industry classification system. The disaggregation level here is 16 branches. Also, consideration of technological spillovers blurs the sector analyses, see, e.g. Grupp [1996a, 1998].

Table 1

Innovation index numbers for 16 branches of the West German industry

	Sector	*n*	R&D intensity (R&DESa)	Sector hetero-geneity	Official R&D intensity*	Patent intensity (PAR&DE)	Sector hetero-geneity
1	**Chemical industry**	55	6.5	1.2	4.6	570	0.7
	11 Chemistry, oil processing, nuclear materials	41	5.7	1.2	–	637	0.6
	12 Pharmaceutical ind.	14	17.1	0.4	–	294	0.7
2	**Materials processing**	32	2.5	0.6	–	615	1.4
	21 Synthetic goods production	9	1.9	0.8	2.9	485	2.6
	22 Stone, clay, ceramics, glass	10	3.2	0.5	2.1	974	0.9
	23 Metal, steel	8	2.5	0.6	1.0	513	1.2
	24 Paper, wood	5	2.1	0.5	1.4	975	0.5
3	**Machinery**	61	4.8	0.7	3.7	659	2.1
	31 Tools machinery	9	4.6	0.4	–	222	10.7
	32 Machinery for food and chemical industries	11	4.2	0.5	–	984	0.9
	33 Other machinery	41	4.9	0.7	–	681	1.8
4	**Vehicles**	20	5.9	1.7	–	198	2.3
	41 Motor vehicles	8	4.3	0.7	} 3.9	177	1.3
	42 Motor vehicles parts	7	6.9	0.3		1091	0.5
	43 Aircraft and space	5	28.8	0.3	27.1	119	0.4
5	**Electrical industry**	49	9.1	0.4	–	336	0.9
	51 Communications equipment, electronic devices	28	11.7	0.3	} 9.4	374	0.9
	52 Other electronic electrical industries	14	6.8	0.4		582	0.8
	53 Office machines, computers	7	6.5	0.6	–	69	1.7
	Scientific and profes-sional instruments, optical industry	13	7.9	0.7	5.7	360	1.5
	Manufacturing industry	230	6.7	0.9	4.5	383	2.1
	Non-manufacturing sectors	10	2.3	2.2	–	248	2.1
	All businesses	240	6.6	0.9	–	383	2.1

Source: Calculations based on the databases PATDPA and FORKAT and on firms' annual reports from Bundesanzeiger 1988, nos. 42- 244, and 1989, nos. 1 – 86;
* Echterhoff-Severitt et al. (1990, p. 66) for official data.

lated. In Table 1, average patent-to-R&D relationships are shown for some industries and sub-branches.

Based on the average of all firms, 393 patent applications resulted from DM 1000 million of R&D expenditures or, alternatively, one patent application required 'factor costs' of around DM 2.6 million spent on R&D. One thousand R&D employees achieved an output of 64 patent applications per year, or one patent application needed the yearly labour input of 16 R&D employees. There are large differences in the patent application rates between sectors, as well as within sectors. The patent application rates are extremely low in the office machines and computer industry, the aerospace industry, the motor vehicle manufacturing industry and the pharmaceutical industry. The patent application output in relation to R&D is very high in the sectors stone, clay, ceramics and glass, other and chemical machinery, chemical industry and traditional electrical industry. The patent application rate is extremely high in the motor vehicles' parts industry.

Apart from the motor vehicles industry, strong differences within a sector exist also in the electrical and electronics industry. The patent application rate is lower in the communications equipment and electronic devices industry than in the more traditional electrical industry. The reason is a larger dependency on science and software in the communications and electronic industry than in the electrical industry.

Thus we have ample evidence that the appropriability conditions differ considerably across industries. Specifically, we have shown with Table 1 that the effectiveness of protecting the outcomes of R&D projects and thus the innovation rents vary across industries. In some industries patent application is actually not very effective in satisfying appropriation and is replaced by secrecy, 'head starts' and alert marketing. Thus the early work of Scherer [1965, 1983] and others on appropriability and market structure still leaves us with a paradox concerning the role of innovation protection.

Some firms probably take a decision not to apply for patents since this requires some kind of disclosure of the firms' R&D details (concerning the contents of the successful invention, its principle aims, its potential application and so forth) and can limit confidentiality. A two-part model for statistical analysis seems to be appropriate: First the binary qualitative choice is analysed as to whether firms seek patent protection and accept disclosure or not (probit model). Secondly, those firms which go for patents have to decide on the number of R&D projects they want to disclose and protect (OLS model).[14]

We test against firm size, sectors, R&D intensity as well as investment and export share. Literature is full of hints that patent applications are related to inno-

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14 Regressions for single sectors in order to obtain marginal relationships were not calculated, as the samples for some sectors were too small. As we suspected a great deal of heteroscedasticity, t-statistics was checked on the basis of robust standard errors.

vative exports.[15] We also include a variable for financial capability. Preferable for internal funds is cash flow, see Cohen [1995, p. 198], a variable which is unfortunately missing for many companies in our sample. As larger firms typical for our sample appear to finance their R&D through equity (loc. cit., p. 199), i.e. by external sources, unlike smaller firms (see Goodacre and Tonks [1995, p. 302]), we think shareholders' equity is an adequate variable.

Table 2

Two-part explanation of patenting (*t* values of coefficients in brackets)

Variable	Heckman selection	Total patents
n	240 (34 obs with PA = 0)	206 (PA > 0)
R&DESa	0.042 (1.52)	–1.453 (–0.17)
InvSa	0.035 (1.13)	3.623 (0.30)
EquBST	–0.000 (–0.02)	1.895 (0.62)
ExS	0.000 (0.02)	1.900 (0.82)
BST	0.001 (2.38)**	–
Larges	–	422.9 (3.14)***
Smalls	–	23.4 (0.22)
Chemical	–1.442 (0.15)	309.7 (2.04)**
Materls	0.389 (0.70)	93.6 (0.55)
Machine	0.813 (0.42)	41.1 (0.30)
Electro	0.273 (0.79)	203.1 (1.49)
Constant	0.640 (0.52)	–0.34 (0.73)
Mills Lambda	–591 (–1.37)	
Wald Chi^2	37.3 ***	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

From a two-step Heckman selection model (table 2) we learn, that none of the proposed variables explains the propensity to patent (yes or no), but only the size of the firms, here measured as the Balance Sheet Total (BST).[16] Regarding the most significant coefficients to explain the number of patents of those firms that seek patent protection of their inventions, some small, maybe technology-based start-ups, and definitely larger firms generally do better in patenting.[17] Sector-spe-

15 See e.g., Griliches [1990], Grupp [1995a], Pavitt [1985] and Schmoch et al. [1988].

16 For the reasons of this choice see Section 6.

17 The coefficient for the small firms is not significant, but positive. For R&D intensity and concentration, see Cohen [1995], pp. 192.

cific secrecy (non-patenting) is not observed as sectors are so heterogeneous in technology. However, the chemistry sector largely enhances the *amount* of patenting for those firms that decided to seek protection. If we control for firm size, financing patents is not a feature of its own, but of course, for smaller companies, it is a more general problem.

We find no correlation between R&D and patenting. From a technological point of view, *patent output* may be insignificant when R&D involves a lot of basic research (see Grupp [1994, 1996a,b] for a treatment of the science base of technology). Patenting is also obsolete when *software development* and the *integration of systems* consume the larger part of R&D efforts as in the computer and the telecommunications industry. Low patenting arises when the *developing and testing of prototypes* and *design* play a larger role, e.g. in the motor vehicles industry. R&D for *military goods* also leads to different ways of protection. But these determinants are not represented in size or industry structures.

The sectoral analysis of patent applications gives an impression of the various types of innovation activities. It becomes clear that describing innovative activities one-dimensionally by R&D – although this is very common – gives only a special view on innovation, being different from the patent approach. R&D expenditures include experimental development, applied research and basic research, whereas patent applications represent appropriation of rents in more market-directed product *development*. As patent applications per R&D vary across firms by size, patent applications and R&D indicators should be used complementarily rather than substitutively. The substitutive use of patent applications should not happen on a sectoral, but rather, on a subsectoral or market (product) or firm level.

4. Relations between innovation indicators by factorial analysis

So far, innovation activities have been measured by the most common single indicators. The aim of this Section is to explore the relation between different innovation indicators in terms of a latent structural model. In Table 3, as the usual first step in factor analysis, correlation coefficients have been computed for the innovation indicators used in the above probit model but normalised differently: R&D expenditures per sales (R&DESa), R&D labour intensity (R&DEm), patent intensity (PASa), patent labour intensity (PAEm), gross investment per sales (Inv Sa), gross investment per employment (InvEm), gross investment per R&D (InvR&D) and equity ratio (EquBST).

Although the firms of the sample cover very different branches, there is a very good correlation between some innovation indicators. In each row and column there is at least one very good correlation with the exception of equity (as a proxy for financing innovation). Our results are consistent with studies by Scherer

[1982], and Acs and Audretsch [1988] for the US economy, who also calculated correlation coefficients for R&D and patents.[18] The correlations in table 3 are likewise strong between indicators for investment and R&D.

Table 3

Correlation coefficients of innovation indicators for industrial firms
(n = 240; significance levels as in Table 2)

Indicator	R&DESa	R&DEm	PASa	PAEm	InvSa	InvEm	InvR&D	EquBST
R&DESa	1.00							
R&DEm	0.67***	1.00						
PASa	0.29***	0.05	1.00					
PAEm	0.25*	0.11	0.90***	1.00				
InvSa	0.24***	0.04	0.11*	0.09	1.00			
InvEm	–0.01	0.09	–0.12*	0.00	0.61***	1.00		
InvR&D	–0.37***	–0.26***	–0.24***	–0.20***	0.37***	0.50***	1.00	
EquBST	–0.09	–0.05	–0.05	0.01	–0.02	0.08	0.03	1.00

Source: Annual Reports from Bundesanzeiger 1988, nos. 42–244, and 1989, nos. 1–86; database PATDPA

The use of factorial analysis is a proper statistical concept to test for the theoretical construct of innovative strength which is a latent, multi-facet variable which cannot be observed directly, but is strongly related to several directly measurable determinants. The operational concept then is to collect as many innovation variables as possible (in this case: eight) representing the various aspects of innovation activities and to extract one or a few latent variables, so-called factors, by explorative factor analysis, which is / are characteristic for the different kinds of innovative activity. In this way the complexity of innovation proxies is well-covered and at the same time reduced to few essential aspects, as in innovation theory. Factor analysis techniques are more frequently applied in the social sciences than in economics. Since the studies by Blackman et al. [1973] and by Schlegelmilch [1988] factor analysis has come into more frequent use in order to measure innovation activities.[19]

In the following, innovation factors for the 240 firms are extracted from the eight innovation indicators displayed in Table 3. Both sales and employment are intentionally used for size standardisation. Bartlett's test of sphericity is highly significant (< 0.1 %), so it appears unlikely that the correlation matrix (Table 3) is an

18 There is also a sampling effect because of some zero observations for the patent indicator; see the Heckman model in Section 3.

19 Very recent applications of factorial analysis in innovation studies, one of them being the Italian innovation survey, can be found in Evangelista [1996].

identity. The Kaiser-Meyer-Olkin measure (see Kaiser [1974]) of sampling adequacy is acceptable but not marvellous, therefore, a principal factor analysis was carried out. According to the Kaiser criterion, two factors with an eigenvalue >1 were extracted.[20] Table 4 presents the unrotated[21] loadings, which represent the correlation coefficients between variables and factors.

Table 4

Factor loadings and shares of variance of the innovation factors

Variables	**Factor 1** Disembodied innovation activity	**Factor 2** Embodied innovation activity	Communality
R&DESa	**0.705**	0.269	0.570
R&DEm	**0.529**	0.199	0.319
PASa	**0.766**	0.186	0.621
PAEm	**0.740**	0.242	0.606
InvSa	–0.049	**0.870**	0.760
InvEm	–0.286	**0.838**	0.784
InvR&D	–0.633	**0.524**	0.675
EquBST	–0.117	0.015	0.014
Sum			4.349
Eigenvalues	2.409	1.838	
Share of total variance	30.1 %	24.2 %	
Share of commulative variance	30.1 %	54.3 %	

As R&D expenditures reflect mainly intramural innovation activities, and R&D personnel exclusively so, and patent applications refer mainly to product innovations, the first factor is interpreted as *disembodied innovation activity* according to the variables with high loadings. The second factor has a high loading due to the investment variables. Hence, it is assumed to represent *investment-embodied innovation activity.*

Apart from the factor loadings, Table 4 contains shares of variance of the two innovation factors. The communalities express the share of variance of the innova-

20 A third factor with an eigenvalue slightly above 1 could not be interpreted in a meaningful way and does not load any variable > 0.6. It is not always a good criterion to include all factors > 1, see Backhaus et al. [1990], p. 91; therefore, the third factor was dropped.

21 A varimax rotation did not lead to essentially different loadings.

tion factors which they have in common with the variance of the respective indicator variables. Hence, the variable *InvEm,* which has the highest communality value, is explained best by the two innovation factors. The unexplained variance reflects indicator-specific factors as well as measurement errors. The unexplained variance does not contradict the concept of two latent innovation factors, as there is rarely an economic or technological indicator that reflects a latent variable better. The empirical analysis thus confirms the theoretical notion of *two principle types of innovation* activity, disembodied and embodied technical change. But these theoretical concepts of technical change *cannot* be observed by *single proxy variables,* respectively, but only as a linear combination of some of these.

5. Measuring sectoral innovation activities by factor scores

Factor analysis does not only allow the identification of latent variables and the estimation of their values but also provides indications of the specific components of the variables and their proximity to the latent variables. Factor scores were calculated for all the firms and aggregated in order to compare the innovation activities of different sectors.[22] The factor scores are standardised variables with mean *0* and standard deviation *1.* They serve as index values for disembodied and for embodied innovation activity. Table 5 presents the rankings of the industrial sectors with respect to both innovation factors. Sectors with positive values show above average, sectors with negative values below average innovation activities.

With respect to *disembodied innovation activity,* the top positions[23] are held by the *pharmaceutical industry, aircraft and space industry, motor vehicle parts, communications equipment, chemistry* and *electronic devices.* The aircraft and space industry does not dominate to the same extent when compared with its ranking by the R&D indicator alone (Table 1). This results among other things from its low patent application activities as already reported above. In contrast to this, the motor vehicle parts producing industry achieves a very high ranking according to the factor analytic index due to its high patenting. The *lower ranking* of the software-intensive sectors *office machines and computers* and *tools machinery* is also the result of considering low patent numbers when extracting the latent innovation variable.

However, when considering the investment-embodied factor, these sectors appear to be especially innovative with respect to buying new technology and introducing new production processes, thus shifting the production function.

22 The matrix of factor scores, W, need not to be estimated in case of a principle component analysis.

23 The term 'top position' should be understood only within the sectors of this particular sample, because sectors like the textile or the food industry are missing in the sample (since not enough companies meet the required publication conditions, see Section 1).

Table 5

Factor loadings and shares of variance of the innovation factors

	Sector	Disembodied innovation activity (factor 1)	Embodied innovation activity (factor 2)
1	**Chemical industry**	**0.36**	**0.05**
	11 Chemistry, oil processing, nuclear mat.	0.25	0.08
	12 Pharmaceutical ind.	1.10	–0.17
2	**Materials processing**	**–0.89**	**–0.02**
	21 Synthetic goods production	–1.56	0.76
	22 Stone, clay, ceramics, glass	–0.57	0.14
	23 Metal, steel	–0.74	–0.57
	24 Paper, wood	–1.00	–0.92
3	**Machinery**	**–0.19**	**–0.18**
	31 Tools machinery	–1.00	–0.17
	32 Machinery for wood and chemical ind.	–0.19	–0.05
	33 Other machinery	–0.11	–0.21
4	**Vehicles**	0.53	–0.14
	41 Motor vehicles	–0.99	–0.07
	42 Motor vehicles parts	0.48	–0.20
	43 Aircraft and space	1.12	–0.48
5	**Electrical industry**	**0.31**	**0.19**
	51 Communication equipm., electric devices	0.55	0.24
	52 Other electronic and electrical industries	0.18	–0.05
	53 Office machines, computers	–1.07	0.52
	Scientific and professional instruments, optical industry	–0.13	–0.38
	Manufactury industry	0.01	0.00
	Non-manufacturing sector	–1.83	–0.19
	All businesses	0.00	0.00

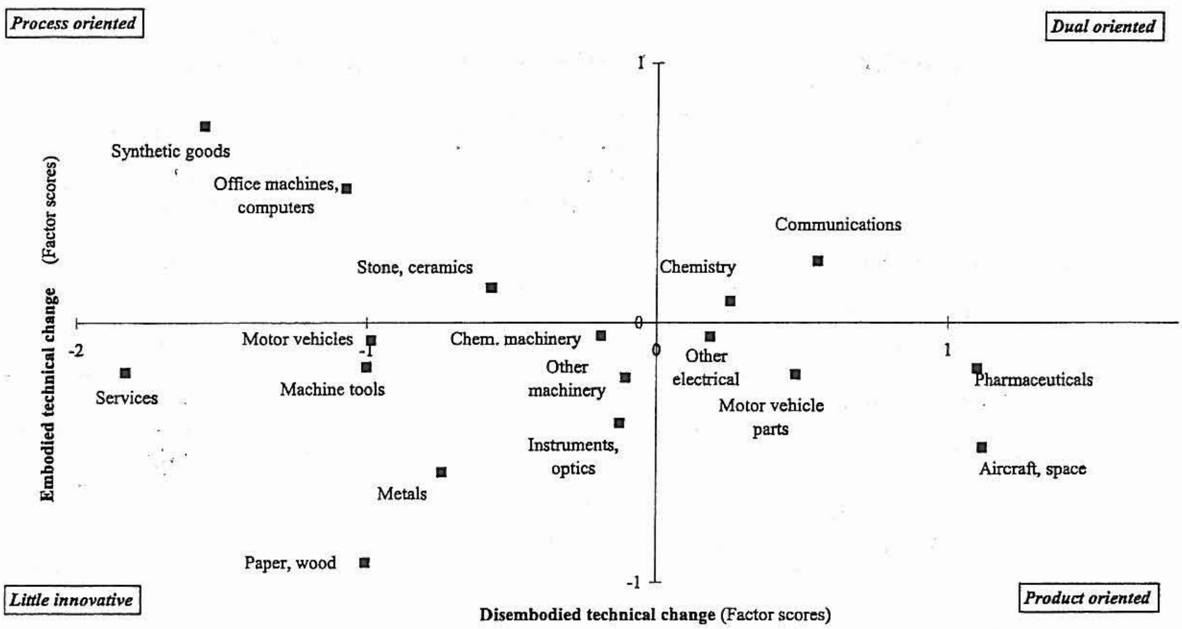

Figure 3: Sector's position towards embodied and disembodied technical change.

The positions of the *office machinery industry* and the *producers of synthetic goods* demonstrate that measuring innovativeness using only indicators of disembodied innovation activities is heavily biased. While these sectors rank last with respect to the innovation factor 1, they take front places when the process-oriented innovation factor serves as a yardstick. As Table 5 and Figure 3 clearly indicate, *chemistry* and *communications equipment and electronic devices* are the only sectors to develop above-average activities in both latent innovation dimensions which means they are dually oriented towards both embodied and disembodied innovation. On the other hand, some sectors (in particular *metal and steel* and *paper and wood)* show below-average innovation activities in both respects.

The factor scores of the latter sectors correspond to Pavitt's [1984] postulated features for the group of *supplier-dominated firms.* These firms are, in general, small and stem from traditional industries. Innovations mostly refer to new processes which are developed and produced by the suppliers of equipment and materials. The other sectors also show typical patterns which resemble Pavitt's sectoral industry classification. The scientific and *professional instruments and optical industry* and the *motor vehicle parts* industry belong to the group of *specialised equipment suppliers* with emphasis on product innovations (more likely by factor-1-type of technical change). For the *science-based firms,* a high degree of in-house R&D as well as the use of high-tech production equipment is becoming ever more necessary. This category of firm may be reflected in the dual positions of the pharmaceutical industry and communications equipment and electronic devices. Motor vehicle manufacturers are typical for the group of *scale-intensive firms* which show a high proportion of embodied technical change.

Sectoral and technological influences on innovation activities were implicitly assumed when innovation activities were measured separately for each sector. A relation to firm size was also implicitly established by calculating relative innovation indicators. In the following Sections, the relations between innovation and firm size is examined, and special attention is paid to an adequate correspondence of different indicators of firm size.

6. Explaining innovation activities by firm size

The firm size hypothesis, which can be interpreted as a sub-species of the Neo-Schumpeter hypothesis, or which is sometimes seen as a hypothesis of its own and then attributed to Galbraith [1952], proposes a relation between firm size and innovation efforts. The type of relation between our latent – and more balanced – innovation indicators and different size indicators will be examined in the following. Indicators expressing firm size are the traditional sales (*Sa*) and employment (*Em*) indicators. Furthermore three balance sheet items representing different categories of firms' assets are introduced as size variables. They are the balance sheet total (*BST*), fixed assets (*FA*) and tangible fixed assets (*TFA*).

As this is an empirical investigation, we cannot review the vast literature on the size hypothesis in innovation. Suffice to follow two handbook contributions (Cohen and Levin [1989] and Cohen [1995]). These conclude that the advantage of larger firms may not be due to size per se but may arise from common characteristics, namely the appropriability conditions and limited firm growth due to innovation. There seems to be a consensus now that size has little effect on innovation. The many empirical findings to the contrary are flawed by the single-indicator approach, non-random samples, or because the importance of the size variables is minute both in terms of variance explained and magnitude of coefficients. Cohen and Levin [1989, p. 1069] consider the empirical research on size and innovation as *inconclusive* and suggest to move to more complete models of technological change [loc.cit., p. 1078].[24] It is thus demanding to examine in how far the two latent innovation indicators we propose here are explained by size.

As the various size variables may produce multicollinearities we test them one by one in an OLS model with industry dummies. For the sake of brevity, this is not reported here in detail.[25] We can infer that only size as measured by tangible fixed assets may influence the embodied part of innovation.[26] All other size rela-

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24 Earlier work, i.e. Scherer [1965, 1967b] and Levin et al. [1985], has shown that market structure and technological opportunities as well as appropriability compete with each other in order to explain innovation activities. Others [Pavitt et al., 1987, Acs and Audretsch, 1988] explicitly stated that the distribution of firm size and innovational strength are simultaneously determined by technological opportunities and appropriability.

25 For details, see Schwitalla [1993, pp. 213].

26 Significance level is about 2 %, the coefficients are very small.

tions are insignificant, in particular those for the disembodied part. Only the vehicles branch with its very few very large car manufacturers is so ill-composed that disembodied change is affected. If we drop this branch the results remain largely unchanged.

The general tendency of these findings does not spotlight the innovation activities of larger firms. We emphasise the fragility of this issue in industrial economics but the *size hypothesis cannot* be rigorously *rejected* because of a weak influence of the assets indicator. The *balance sheet total indicator* can be seen as a relatively *'neutral' size indicator*, which is neither biased towards personnel, nor towards establishments and which does not so much depend on business cycles. Thus, the balance sheet total seems to be a more adequate yardstick for the measurement of innovation activities in relation to firm size than the more usual size variables of sales and employment. Based on the results for this 'neutral' size indicator, we confirm for our sample there are *neither advantages nor disadvantages in innovation on the part of large firms.*

The new findings show that differences in innovation activities due to firm size are highly dependent on the selective choice of indicators. Different innovation indicators correspond to different aspects and qualities of innovation activities. Therefore, we would like to draw attention to another question that has been raised by Pavitt et al. [1987] and that seems to be more important than merely discovering quantitative size effects. The question is *what are the different kinds of innovation activities of small and large firms?* These authors discuss that firm size and technology have to be seen as an interdependent relationship and that the quality of innovations differs between small and large companies in terms of a division of labour (see also Cohen [1995], p. 197). These qualitative aspects of innovation activities are reflected by interfirm differences in innovation behaviour. The following last Section, before we conclude, is devoted to these interfirm differences and thus the short-term consequences of innovative activities.

7. Short-term consequences of firm's choice between embodied and disembodied technical change

This paper is focussing on the roles of embodied vis-à-vis disembodied technical change. The new data set exploited does not presently allow for long-term observations. Work is in progress to prepare similar cross-section data for subsequent years and to derive panel data of German firms since 1987 overcoming artefacts from unification. However, for this paper we can only deal with short-term effects of innovation. The point is made here that while medium-term welfare effects have every right to be in the centre of innovation literature (see, e.g. van Reenen [1996] on wage effects in British firms occurring four or more years after innovation), the discussion of possible short-term detrimental effects on innovation may be a concern for a firm's decision. The literature is full of claims that innovation is hampered by 'short-sightedness'. Can we contribute to the understanding of short-term consequences of innovation?

If we want to test the knowledge production function (see Section II), we do not have a direct measure of production output available in firms' annual reports. As an output indicator, the sales variable may be used, which is, apart from changes in stocks, almost identical with the gross value added product.[27] But more variables can be taken from the firms' reports.

First, we are interested in the short-term *profitability* of firms. As a variable, cash flow seems to be appropriate. However, often cash flow is considered as a measure of internal financial capability, i.e. liquidity, and thus as a measure of *future* profitability of innovative investment (see Cohen [1995], p. 198). We prefer to start from the trading result (operating result), i.e. either net profit or loss. We are well aware that these data may be subject to the vagaries of accounting procedures (van Reenen [1996], p. 205). On the other hand, a favourable profit-turnover ratio (or net operating margin) is always an indication of competitiveness (Hanusch and Hierl [1992]). This variable is important for firm's management, but probably less so for the shareholders. So we add shareholders' equity return on the agenda of potentially interesting short-term effects.

International technological competition is becoming an increasingly important issue. However, there is no straightforward answer to the question of what defines technological competitiveness abroad. Most contributions measure the export shares despite ongoing internationalisation of firms. Most German companies are oriented towards important segments of international markets and try to compete with foreign rivals in offering better (innovative) products. It is, therefore, interesting to know to which extent the operating margins are sensitive to turnover abroad (this information is also part of the balance sheet).

We apply a two-step Heckman selection model to investigate which innovators are at all profitable in the year of the innovative activity measured by the two latent variables (factors). In the second step we analyse by the knowledge production model to what extent profits, returns on sales, shareholders' equity return and exports are determined by innovation or else.[28] This constitutes a first exploratory approach to tackle short-term effects and is scoping in character. A more in-depth investigation would need panel data.

None of the sector and size dummies explains why some firms are not profitable (OR ≤ 0). We have 43 such firms. They face one common feature: they significantly relate on disembodied innovation but less so on investment-embodied sources. We offer two explanations: First, for the accounting systems, R&D expen-

27 Sales are also used as an output measure in order to estimate the R&D productivity of West German pharmaceutical firms by Brockhoff [1970].

28 For variable names see the appendix. A full Heckman model with or without robust errors did produce inferior results in any case.

Table 6: **Two-step Heckman selection regression of short-term effects of innovation (*t* value of coefficients in brackets; significance level as in Table 2)**

Variable ***n* (uncensored)**	**Selection** **240**	**ln OR** **(197)**	**ln (RetSa)** **(197)**	**ln (RetEqu)** **(197)**	**ln (ExS)** **(197)**
Dis TP	–0.141 (–1.77)*	0.035 (0.27)	–0.143 (–1.31)	-0.271 (-2.60)***	0.197 (2.56)**
Emb TP	0.177 (1.59)	0.376 (2.02)**	0.110 (0.92)	–0.014 (–0.09)	–0.045 (–0.36)
Chemind	0.379 (1.07)	0.058 (0.12)	0.352 (1.09)	0.333 (0.82)	–0.636 (–1.87)*
Materls	0.102 (0.25)	–0.842 (–1.60)	–0.019 (–0.06)	–0.032 (–0.08)	–0.403 (–1.13)
Machine	–0.283 (–0.91)	–0.733 (–1.36)	0.299 (0.86)	–0.008 (–0.02)	0.297 (0.82)
Electro	–0.431 (–1.41)	–0.909 (–1.46)	–0.161 (0.40)	–0.376 (–0.75)	–0.320 (–0.77)
Larges	0.057 (0.17)				
Medium	–0.375 (–1.16)				
Medsme	–0.166 (-0.50)				
Smalls	0.174 (0.52)				
Constant	3.726 (0.00)***	2.920 (4.05)***	–3.639 (–7.87)***	–2.360 (–4.12)***	–0.424 (–0.88)
Mills Lambda	–	1.010 (0.47)	0.705 (0.51)	1.702 (1.00)	–1.436 (–1.01)
Wald Chi^2	–	25.14**	21.67**	23.81**	26.83***

ditures are *costs* and are thus directly related to the operating result. Secondly, R&D projects are risky and some are not successful. If innovative steps are achieved by embodied sources, the firm profits from a *successfully achieved* innovation of other firms (compare also Haid and Weigand [1999]). Large companies test their investment goods insofar as these are new and take deliberate decisions *what* to purchase. The investment-embodied innovation strategy explains higher profits on an absolute level (i.e. of the larger firms), but if we try to explain the *relative amount* of returns of the 197 profitable companies, both innovation indicators (as well as sector and size dummies) fail to offer an explanation. This result may be disappointing, but we are concerned here with short-term growth – our findings contribute nothing to medium-term growth and they relate to individual firms, not to welfare effects of industry branches, spillover or the whole economy.

A different snapshot is possible if we look at the equity returns. As we definitely do not observe multicollinearities (the variance inflation factors are around 1), it is again *disembodied* technical change which significantly reduces shareholders' value. This seems to be the other coin of the same medal: if a firm relies on disembodied, risky innovation, the propensity to be not profitable in the short run is higher, and on the other hand, those who are profitable reduce shareholders' equity return. Gugler et al. [1998] note that standard q-theories of investment assume that managers maximize shareholders wealth, and thus embodied progress is desirable up to the point where its return equals the firm's cost of capital. This is not the case for disembodied progress. A firm does not always have free choices which pathway to innovation between embodied and disembodied sources to go. To the extent it has, the short-term consequences do not point in the same direction.

In international competition and as far as the companies are exporting their innovative goods, those relying on disembodied innovation are the *more* successful. It may well be that embodied technology sourcing is still more limited to national environments. If a company in an 'innovation race' competes largely with foreign rivals, it seems to rely more on internal R&D and patenting (factor 1). But here again, we analyse short-term effects and do not want to expand the scoping part of this study too much. Suffice it to say that differentiation of the two dimensions of innovation matters in terms of profitability.

8. Concluding remarks

In this paper, the major determinants of innovation and their interrelations are analysed using regression and factorial analyses for 240 West German firms based on a new set of data from 1987. The empirical analysis starting from theory-based models throws new light on economic phenomena associated with innovation to which not enough attention has been paid either by economic theory or by applied economics or econometrics. After decades of emphasis on disembodied technical change we think the simultaneous re-integration of embodied sources of innovation in economic analysis is in place. Yet both sources of innovation may not be measured by two simple proxy variables, but need an array of indicators.

Naturally, in the analyses, the special situation in only one 'national system of innovation' was captured which may have typical features for Central Europe, but not for other triad regions. Also, the survey represents a cross section in the late eighties before the unification of Germany. It is not clear, how the German situation compares to other economies in the nineties. There is a need for more such treatise, to find out which findings are specific to a national endowment and which have general validity for the economics of innovation.

In conclusion, we put forward the argument that empirical innovation research is prepared to measure many aspects of technical change if the measurement procedures and indicators are based on well adequated theoretical constructs and, in particular, give attention to embodied versus disembodied technical progress. Although the modern innovation theories are very complex, there are ways to explore the interplay of technological opportunities, appropriability, market incentives and competition quantitatively.

Appendix: List of Variables

BST	Balance Sheet Total
Chemind	Chemical industry incl. pharmaceutics and oil proc.
DisTP	Disembodied technical progress from factor scores (factor 1)
Electro	Electrics and electronic industries, office machines, computers
Em	Employment
EmbTP	Embodied technical progress from factor scores (factor 2)
Equ	Shareholders' (total) equity
EquBST	Ratio of equity to total assets (Equ / BST)
Ex	Turnover abroad, i.e. all direct supplies of goods and services to a consignee abroad plus the deliveries to German export houses
ExS	Export share (Ex / Sa)
FA	Fixed Assets
Inv	Gross capital formation (investment)
InvEm	Gross investment per employee *(Inv / Em)*
InvR&D	Gross investment per R&D *(Inv / R&DE)*
InvSa	Gross investment per sales *(Inv / Sa)*
Larges	Firms with more than 2000 employees
Machinery	Machinery other than electrical
Materls	Material processing industries (Resins, ceramics, metals etc.)
Medium	Firms with between 1000 and 1999 employees
Medsme	Medium-sized firm with between 500 and 999 employees
OR	Operating results (i.e., net profit or loss)

PA	Domestic patent applications in West Germany
PAEm	Patent applications per employee (*PA / Em*)
PAR&DE	Patent application per DM 1000 million R&D expenditures (*PA / R&DE*)
PASa	Patent applications per year and DM million sales (*PA / Sa*)
R&DE	R&D expenditures
R&DESa	R&D intensity (*R&DE / Sa*)
R&DEm	R&D labour intensity (*R&DE / Em*)
RetEqu	Shareholders' equity return (OR / Equ)
RetSa	Returns on sales (OR / Sa)
Sa	Sales (turnover) for sold products and services
Smalls	Firms below 499 employees
TFA	Tangible fixed assets
Vehicles	Motor vehicles, pacts, aircraft, spaces

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