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Communication to

European Meeting on Applied Evolutionary Economics

7 - 9 June 1999, Grenoble, France

Organised by the Institute for Energy Politics and Economics
Organisé par l'Institut d'Economie et de Politique de l'Energie /
IEPE, BP 47, 38040 Grenoble Cedex 9, France

And the INRA-Unit of Sociology and Economics of Research and Development
Et l'unité Sociologie et Economie de la Recherche Développement de l'INRA
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Determining the Innovativeness of Firms: An Evolutionary Approach Using Data Envelopment Analysis*

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JEL Classification: O31, D24, C61.
Keywords: Technological Change, Firm Behaviour, DEA.

– ABSTRACT –

Measuring technological change with conventional methods such as R&D, patent statistics or the Solow-residual faces multiple econometric and conceptual problems. This is especially true if the evolutionary nature of technological change is considered. In this paper, we apply an alternative method – the Data Envelopment Analysis – to trace localised technological change. We construct a simple model that explains the innovativeness of individual firms with respect to their past technological performance. The properties of the model will be examined using a unique data set of about 450 German manufacturing firms.

The empirical findings suggest that a firm's innovativeness is predominantly characterised by its past technological performance, emphasising the evolutionary nature of technological change. Technological trajectories in the form of different factor combinations may be identified and evaluated. Also, effects of technological paradigms may be observed. The dominance of the evolutionary component that becomes apparent in the empirical evaluation of the model implies that effects from technology transfer might have been overstated.

1. Introduction

This paper assesses the measurement of localised technical progress in firms from an evolutionary perspective. We pursue the question how an evolutionary measure of technological progress can give additional insights in vertical (efficiency-related) and horizontal (production technology-related) structures as well as in their interaction. This should shed some light on the role of the vertical evolutionary component and the role of the horizontal diversity in the process of technological development. In section 2, several common indicators of technical change are considered with respect to their ability to reflect its evolutionary and localised nature. Section 3 introduces an alternative indicator – the Data Envelopment Analysis (DEA), a non-parametric method to assess localised technical change. In Section 4, we will sketch a simple model that uses the DEA to explain a firm's innovativeness from an evolutionary perspective. This microeconomic model will be tested empirically using a data set of about 450 firms over a period of 12 years. Finally, section 5 draws some conclusions.

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2. Innovation and Technological Change: Measurement Issues

To Schumpeter we owe the renewed emphasis theoretical and empirical economics put on technical change as an engine of growth. Since then, many important contributions have been made to the research of the determinants, mechanisms and consequences of innovations. Two of the most important findings were that technical change should be treated as endogenous and that technical change is evolutionary in its nature.

a) new products

However, one problem persists: we still have no unproblematic way to measure many variables associated with this important phenomenon. For example, it is still difficult to measure technical change objectively. Any attempt will begin with the question how technical change can be defined. One possibility would be to utilise Schumpeter's famous five cases (see Schumpeter 1935) but it quickly becomes evident that such abstract things as 'new markets' or 'new production methods' are difficult to assess empirically. Hence, most researchers restrict themselves to new products. But data on new products are hard to come by and the data frequently originate in firm questionnaires, thus being not really objective, although great efforts have been made to introduce international standards and concepts (see for example OECD 1994). Notable exceptions are case studies where innovative products are identified by researching relevant journals and interviewing independent experts (see, for example, Baily/Chakrabarti 1985). But the considerable work involved and the lack of standardised data collection methods has prevented the widespread use of this approach. Further difficulties arise when innovations are considered to be endogenous. To make innovations an endogenous instead of an exogenous variable it is necessary to find variables capable to explain innovation. As a consequence, we end up trying to find variables that explain an economic phenomenon we cannot really measure objectively.

b) R&D expenditures

To solve the problem of measuring technical change or innovation directly numerous alternative approaches have been put forward which take into accounts its endogeneity. Perhaps the most popular approach within the so-called neo-Schumpeterian branch of economics has been the use of R&D expenditure data.[1] Simplified, the underlying idea is that R&D expenditures are an input that – assuming the existence of a unique algorithm – generates knowledge that determines the innovativeness of a particular firm or sector. The innovativeness is a necessary condition for technical change. Technical change then translates to productivity improvements and increased profits, which can be used to fund R&D (see Griliches 1984).

The advantage of the R&D data approach is that it – unlike qualitative indicators – is capable to reflect innovative efforts in products *and* processes. Moreover, innovations resulting from R&D efforts are estimable with respect to their expected economic value and productivity improvements from synergy effects are not a priori excluded from the analysis. R&D data is reliable and comparable over time and across countries, albeit only for the manufacturing sector (see Sirilli 1997). On the other hand, R&D data is merely an

[1] Measuring R&D personnel or expenditures for R&D personnel has similar properties and is therefore not treated separately.

approximation of investment in innovation (see Terleckyj 1980). R&D carried out in small firms with no institutional research framework is probably not accounted for. The data still depend on subjective estimations of individual firms, although efforts have been made to standardise the data collection procedures. Another problem is that the absolute figures of R&D expenditures do not reflect the effectiveness of their use. But perhaps the most important problem is that R&D expenditures are an explanatory variable to something we cannot measure – and therefore have to approximate. Consequently, it is common to test the relationship between R&D expenditures and productivity. However, productivity growth may have many sources, innovation being only one of them unless we define innovation by productivity growth itself. For example, research from universities and independent research facilities, feedback from customers and suppliers and information from competitors may contribute to the development of an innovation and finally to productivity improvements. Additionally, traditional indicators of productivity have some disturbing properties and the relationship between R&D and productivity growth is not always established easily (see, for example, Sterlacchini 1990). As a result, R&D is sometimes treated as an indicator of innovation while it is really not more than an indicator of innovative effort with a priori unknown outcome.

R&D expenditures on a yearly basis do not take into account the evolutionary nature of technical progress. To avoid this problem, it is necessary to acknowledge past and present investment in R&D. This is usually accomplished by constructing an R&D stock. The problem with R&D stocks that becomes immediately apparent is the correct rate of depreciation and deflation. There is little doubt that knowledge depreciates differently than capital. While even conventional depreciation methods do not always properly reflect the real wear and tear of machinery and other capital goods, it is more difficult to judge depreciation of knowledge. If knowledge is revolutionary and valuable it may not depreciate at all for a long time until a new superior technique is discovered. Then the depreciation is sudden and complete. Similarly, finding the correct rate of deflation is a serious problem. New products are typically not included in price indexes for several years; therefore innovations are deflated with an index in which they are not represented.[2]

c) technology spillovers

In addition to the construction of R&D capital stocks, technology spillovers can be taken into account by the use of technology matrices. This approach assumes that technology and innovation is incorporated in inputs into the production process. A simple way to measure embodied technical progress is to use a system of vertically integrated sectors (see Scherer 1982 or Kalmbach/Kurz 1986). However, for this approach input-output tables are necessary and these have very special problems on their own. The most striking problem is that they are published in intervals of several years. For the time in between we have to assume constant input coefficients, which is questionable dealing with innovations. A more sophisticated approach is to use matrices that derive producing and using sectors of innovations from direct observation of particular technologies. Of course, such matrices can be compiled only ex-post, so that little can be said about currently developing and future technologies. Without doubt, the acknowledgement of technology spillovers is a big step towards a better explanation of the innovation process. Economic relations are predominantly characterised by the exchange of goods. On the other hand the transfer of

[2] For example, Boskin et al. (1998, p. 10) state that in the US, VCRs, microwave ovens and personal computers were included one decade or more after they penetrated the market. Similarly, cellular phones were included in 1998, when there were already 47 million users.

knowledge is related to the exchange of information by human relations and, consequently, much more difficult to measure.

There remain some more fundamental problems with R&D data and production sets that deserve attention. First, R&D as an explanatory variable for productivity growth is very sensitive to sectoral disaggregation. Baumol stated as early as 1967 that there may be sectors that have inherent small potential for productivity improvements. His much-quoted example is a half-hour horn quintet, which obviously cannot become more productive in terms of labour productivity without severe consequences for quality (see Baumol 1967). The same argument applies to education. Thus, analysing R&D expenditure on the sectoral level, care must be taken not to mix such stagnant sectors with potentially progressive sectors because the return to R&D might be fundamentally incompatible. Second, even using an R&D stock to explain technical progress does not assess the true evolutionary nature of this process. Instead of learning by doing and using, learning by funding is measured (see Nelson 1980). But it seems worthwhile to point out that there are processes that will not perform faster or better if more money is thrown in. Nothing can substitute for experience – particularly not if new frontiers are explored. R&D expenditure analysis can give us great insights in properties of the innovation process but it cannot reflect the characteristics that make it similarly unique and important: the cumulativeness and irreversibility derived from the application of new techniques and products.

d) patents
Another variable frequently used for the explanation of technical progress is patenting activity. However, patents are either throughput or output of the innovation process, hence they are more or less indicators of innovative activity not so much an explanatory variable for technical progress. Their main virtue is the availability of consistent data, at least on the national level. Also, it is possible to distinguish different paths of technological evolution. These advantages are compensated by several disadvantages. The decision to apply for a patent is a microeconomic one that cannot be easily transferred on an aggregate level. Different strategies of different entrepreneurs will result in different patenting behaviour (see Scherer 1983). A firm may try to secure its technological advantage by secrecy instead of patenting. On the other hand, firms may try to patent even marginal improvements for reasons of market dominance. Patents, other than R&D expenditures, are difficult to estimate with respect to their economic value. On the other hand, marginal technical improvements may have a larger economic impact than revolutionary new products. The problem is that patents are little more than inventions while the economist is usually interested in innovations. Of course, one may argue that if the number of patents is large enough, there may be a mean value of anticipated economic importance (see Beggs 1984). An alternative approach is to use the cost for maintaining a patent as a proxy for its value (see Archibugi/Pianta 1996). However, the results are biased by cross-national and intertemporary differences in patenting costs. Additionally, patent statistics may be biased by the changing efficiency of the patent office. For example, Griliches (1990) found that the decline in US patenting activity in the 70s was caused by a contraction of the patent office's resources. The technological decline of those years was nothing but a bureaucratic mirage. Using patent applications instead of grants (see for example Grenzmann/Greif 1996) is a questionable solution because then it is no more possible to distinguish between real inventions and rejected applications. Like R&D indicators, patent statistics cannot tell us much about the evolutionary nature of technical progress. Considering the concept of localised technological progress the development of innovations depends to a good part on previously accumulated knowledge and experience. The movement along a particular path

of technological development cannot be assessed with patent statistics unless extensive technological analysis accompanies the econometric work.

e) productivity improvements
Another indicator of technical change frequently used in equilibrium theory is derived from Solow's famous aggregate production function (see Solow 1957). Introducing a time-dependent parameter into an aggregated Cobb-Douglas production function, technical change is defined as the residual representing the deviation of the growth rate of output from the growth rate of input. The necessary assumptions for this approach include the existence of a suitable and unique production function and optimising behaviour of rational (representative) agents with complete foresight. Criticism of this approach has been put forward in particular by Schumpeterian and Evolutionary economics[3]. Researchers applying the Schumpeterian or Evolutionary approach emphasise the following features:

- Localised technological change represents solutions to firm- and/or industry-specific problems based at least partly on «tacit» knowledge. This knowledge-based technological change is cumulative and leads to firm specific trajectories of development.[4]
- Firms are heterogeneous with respect to the production technique in use as well as to the relative efficiency in production. This horizontal and vertical heterogeneity is not a temporary phenomenon.
- Changes in the horizontal and vertical structures of industries are influenced mainly by firm-specific technological advances, technological spill-over effects and overall economic factors like changes in price-ratios.

As a consequence a methodology for the measurement of technological progress within this theoretical context has to meet the following requirements:

- The vertical heterogeneity of firms requires a methodology that allows for the existence of at least parametrically different production functions within one industry.
- The neo-classical smooth isoquant that represents the production possibilities at a certain point in time has to be replaced by an «accessible-practice-frontier»[5]. This frontier consists of linear parts that connect a number of «best-practice» techniques in use.

Thus, it would be possible to measure innovation in production processes reflected by the use of less input given a constant output and innovation in products which is reflected in higher monetary output given constant input.[6] We argue that such a modified approach on total factor productivity is superior to other indicators of innovation output such as patent statistics.

In the following section, we put forward a relatively new concept to measure technical change – the Data Envelopment Analysis. In principle, it measures efficiency and therefore the result of innovative activity. We will show that using DEA it is possible to assess also the evolutionary nature of technical change.

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[3] See Antonelli/De Liso (1997), Westermann (1996) or Kurdas (1994) for an overview and critique.
[4] See Dosi (1988).
[5] See David (1975) p. 62.
[6] Of course, this argument holds only if the additional utility an innovation creates equals the increase in price.

3. Assessing Localised Technological Change with Data Envelopment Analysis

The analytical approach we apply to measure localised technological change is non-parametric and known as the ***D****ata* ***E****nvelopment* ***A****nalysis* (**DEA**).[7] Applying this method, it is possible to obtain scores for relative efficiency for each firm of a sample. The choice of a non-parametric approach helps to take into account the above-assumed technological heterogeneity by explicitly allowing for parametrically different production functions.[8]

Principally DEA computes index numbers for total factor productivity where for each firm j ($j=1,...,n$) a productivity index h_j is given by:

$$h_j = \frac{u^T Y_j}{v^T X_j} \qquad \textbf{(Erreur! Argument de commutateur inconnu.)}$$

Y_j is a vector of outputs and X_j a vector of inputs of firm j. Vector u and vector v contain the aggregation weights u_r and v_i respectively. Here, h_j is an index for total factor productivity where the specific aggregation weights are determined endogenously and can differ from firm to firm. The basic principle of DEA is to determine the indices h_j in such a way that they can be interpreted as efficiency parameters. Thus, the most efficient firms of a sample are characterised by an h of 1, all less efficient firms by an h of less than 1.

This leads to a problem of linear fractional programming that can be modified to an orthodox linear program. This ordinary LP is easily solved using the simplex algorithm.[9] Performing this step and transforming the resulting primal to its dual problem one arrives at the envelopment form of DEA:

$$\begin{aligned} \min\ q_l - e\, e^T s_l^+ - e\, e^T s_l^- & \\ s.t.: & \\ Y\, l_l - s_l^- &= Y_l \\ q_l X_l - X\, l_l - s_l^+ &= 0 \\ l_l, s_l^+, s_l^- &\geq 0 \end{aligned} \qquad \textbf{(Erreur! Argument de commutateur inconnu.)}$$

Y_l and X_l are the vectors of outputs and inputs respectively of firm l, Y and X are the matrices of outputs and inputs of all firms of the sample. The parameter q_l to be minimised accounts for efficiency, the vector l_l provides information about reference sets, s^+ and s^- are the excess inputs and output slacks respectively, vector e^T contains only elements 1, and e is the positive so-called Non-Archimedean constant[10]. The interpretation and the purpose of these variables and parameters will be discussed in the following paragraphs.

The parameter q_l to be minimised in (2) states to which level the inputs of firm l must be reduced proportionally in order to become efficient relative to the most efficient companies

[7] It is based on the seminal work of Charnes/Cooper/Rhodes (1978) and Banker/Charnes/Cooper (1984).
[8] For a detailed description of the matching features of the DEA method and the concept of localised technological progress, see Westermann (1996), pp 114-115.
[9] See Charnes and Cooper (1962).
[10] See Charnes/Cooper (1984).

within the sample. Firms with no possible reduction are labelled efficient with q =1 and constitute the efficient or «accessable-practice» frontier of an industry. We interpret this efficiency frontier within the context of our study as the sectoral technological frontier. Therefore, q_l provides information about the vertical position of the production technique of firm *l*.

It should become clear that a simple proportional reduction of inputs does not necessarily lead to efficiency in the Pareto-Koopmanns sense. In order to correct for this the remaining excess inputs s^+ and output slacks s^- are taken into account in the objective function. In a final step the proportional reduction q_l and possible slacks are integrated into a single measure of efficiency i_l applying a method suggested by Ali and Lerme (1990).

In order to take into account the technological development of the different branches within our sample a „best technology frontier« (**BTF)** is constructed for each year and for each branch. BTF means that an increase in the technological performance of firm *l* in year *t* that shifts the efficiency frontier at one point is maintained even if firm *l*'s efficiency decreases in the following year *t+1*. This guarantees that the technological performance of a company within a certain sample is always evaluated against the best technologies implemented so far.[11]

In addition to this vertical or efficiency structure, the DEA methodology allows also to cluster firms that apply quite similar techniques. This enables us to detect horizontal structures by referring to the vector l_l which contains the weights of all firms which serve as reference for firm *l*. Consequently, l_l provides information about who are firm *l*'s reference firms and the following assumption holds: the higher the weight of firm *p* in l_l the closer is the technique of *l* to the one of *p*. Thus, the weights of the l-vector can be used to assign below best-practice firms to the closest best-practice firm on the frontier. Those clusters are labelled „technology fields«[12] and are themselves aggregated according to the production technique applied by the respective efficient firms. This is accomplished by constructing a „hierarchical phylogenetic tree«[13] (see Table 1) taking into account the factor intensities as distinct features of different production techniques.[14]

Table 1: Distinction between production technique categories

	1 - high use of factor		2 - low use of factor			
Labour	1			2		
Capital	11	12		21		22
Material	112	121	122	211	212	221

Source: Westermann (1996), p. 150.

4. A DEA-based Model to Determine the Innovativeness of a Firm

4.1 An Evolutionary Model

From the preceding section it becomes clear that the DEA measures the comparative result of a firm's innovative activities. In order to acknowledge the endogeneity and evolutionary

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[11] See Westermann (1996)

[12] For a theoretical foundation of this interpretation see Bernard/Cantner/Westermann (1996) or Westermann (1996).

[13] See Mani (1991).

[14] For theoretical reasons, categories 111 and 222 do not apply.

nature of these activities it is necessary to introduce variables that are capable to explain a firm's innovativeness with past innovative activities. This can be achieved by using the DEA score from previous periods as an explanatory variable. To account for horizontal technological diversity, the currently adopted technique or factor combination is included as an explanatory variable (see table 1). This information is derived from the l vector in equation (2). If this type of factor combination is interpreted as a technological trajectory, it should show an effect on the development of vertical technological diversity. The more general development of technical diversity is accounted for by including a time variable. Finally, we control for influence of branch. Different branches may have different patterns of technological development especially if the effects of different production technologies or trajectories are considered. Formally, we may write our model of a firm *i*'s innovativeness *i* at time *t* as

$$i_t^i = f(i_{t-1}^i, T_t^i, b^i, Y_t) \tag{3}$$

where T represents the production technique, b the branch and Y the year. Technique and branch are nominal variables and Y a quasi-nominal variable, so we construct a general linear ANCOVA model with T, Y and b as factors and i_{t-1} as a covariate. In addition, interaction terms are constructed for branch and technique as well as for branch and year. The former captures the branch specific effects of different factor combinations and the latter accounts for branch specific technological development. We expect the covariate to be positive, representing the beneficial influence of previously accumulated knowledge. The influence of the factors is a priori undetermined.

The major drawback of our model is that due to the lack of appropriate data we cannot directly compare the influence of the factors mentioned above and investments in R&D or the size of an R&D stock. However, evidence from an earlier study shows that the effect of R&D expenditures is inconclusive (see Westermann 1996). The effect also varies considerably across industries.

4.2 Some Empirical Results

We investigate the innovative behaviour with a sample of about 450 German manufacturing firms divided in 12 sectors: automobiles, construction, chemicals, iron, electronics/electrical, optics, beverages, plastics/rubber, machinery, paper, shipbuilding and textiles. Entries and exits are considered. Almost all firms are of the legal form «shareholder's company». The period under consideration is 1982 to 1993. The data is taken from annual reports. To compute the efficiency score *i* we define suitable variables for one output and three inputs. For the output variable we aggregate «total sales», «inventory changes» and «internally used firm services» and deflate this figure by a composed price index. On the input side, we distinguish between «labour», «capital» and «material». Capital is calculated applying the perpetual inventory method and is corrected for inflation and annual deviation in capacity use. Labour is approximated by multiplying the number of workers of a firm by a sector-specific index of effective working hours per year. Material consists of the profit&loss entry «raw material and supplies» and is deflated with a sector-specific input goods price index. All observations are finally pooled in one single database.

All factors and covariates under consideration as well as the model as a whole turn out to be highly significant (see table 2).[15] The overall fit of the model is satisfying. The partial r^2-values suggest that the efficiency of a firm in the preceding period contributes most to the explanation of total variation. Also, the effect of the interaction term between branch and year is remarkable.

Table 2: ANCOVA results - sources of variation

Source of variation	Sum of Squares	DF	Mean Square	F	Significance of F	Partial r^2
Constant	1.339	1	1.339	303.62	0.000	0.058
Covariate						
ι(t-1)	44.58	1	44.58	10105.73	0.000	0.672
Main Effects						
technique	0.092	5	0.018	4.156	0.001	0.004
branch	0.176	11	0.016	3.622	0.000	0.008
year	0.745	11	0.068	15.363	0.000	0.033
2-way interactions						
technique*branch	0.735	38	0.019	4.387	0.000	0.033
year*branch	2.561	121	0.021	4.797	0.000	0.105
Explained	90.006	187	0.481	109.11	0.000	
Residual	21.721	4924	0.004			
Adjusted Total	111.728	5111				
corrected r^2 = 0.798						

The strong positive influence of the covariate confirms the hypothesis that previously accumulated knowledge contributes a large part to the explanation of a firm's innovativeness. In fact, the dominance of this explanatory variable within the model suggests that a firm's innovativeness is predominantly characterised by the evolutionary component. To account for technology spillovers, we also included the ratio of material use to labour as well as the investment ratio into the model, but found no evidence for a significant influence. Similarly, the firm size is negligible for the explanation of efficiency. The significance of the technique factor and the technique*branch interaction might be interpreted as the presence of economy-wide and branch-specific lines of technological development or technological trajectories. Similarly, the significance of the year factor and the year*branch interaction indicates the presence of general and branch-specific technological development. By examining the estimated means for different factors, we may take a closer look on the properties of trajectories and general advance of technology.

Figure 1 shows the estimated means for each technique.[16] Firms that apply technique 212 – high use of capital and low use of labour and material – have the highest estimated efficiency. Also, combinations of high capital use with high use of either labour (112) or material (211) yield relatively high efficiency. Techniques involving a high use of labour (122) entail a low efficiency. However, in combination with high use of capital (112) and material (121), there is no exceptionally low estimation. Similarly, firms that apply a purely material intensive technique (221) are estimated to have a relatively low efficiency, while combinations with other factors do not show this effect. As a result, the capital-intensive trajectory seems to be the most promising with respect to technical efficiency. To shed

[15] We do not intend to conceal that Levene's test for equality of variances fails to confirm the null hypothesis of equal error variances across groups, even after a transformation of the data.
[16] The figure 1 and 2 and table 3 show estimated (not observed) means from within the linear model. Covariates are hold at their mean value.

some light on the effect of different techniques in different branches, examination of the interaction term will be useful. The estimated means for four important branches are given in table 3.

Figure 1: estimated mean of *i* by technique

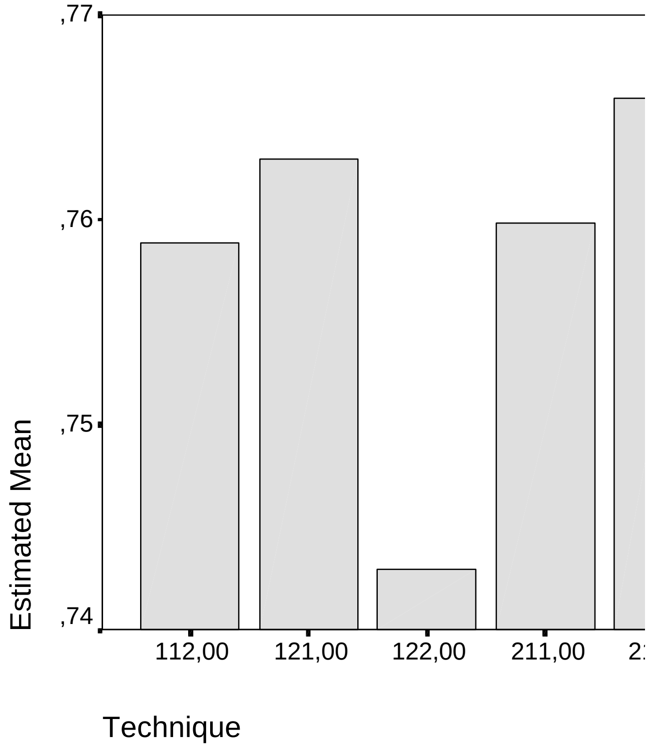


Table 3: estimated means of *i* by branch*technique[a]

branch / technique	automobiles	chemicals	machinery	electronics/ electrical
112		0.754	0.757	
		(0.012)	(0.067)	
121			0.721	
			(0.022)	
122	0.742	0.748	0.721	0.736
	(0.006)	(0.003)	(0.003)	(0.005)
211	0.775	0.750	0.697	0.779
	(0.013)	(0.009)	(0.009)	(0.048)
212	0,763	0.791	0.705	0.741
	(0.011)	(0.010)	(0.004)	(0.006)
221	0,776		0.861	0.742
	(0.039)		(0.019)	(0.006)

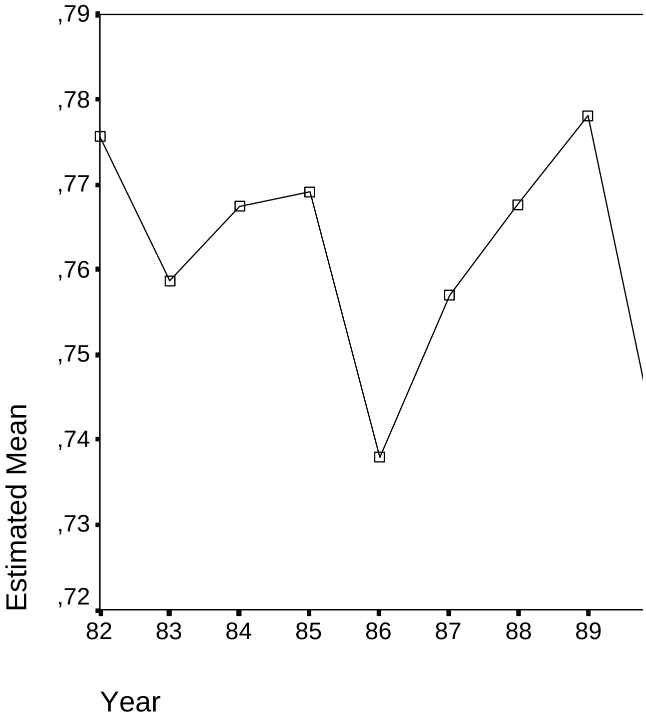
[a] standard errors in parentheses.

The results show that the effect of the application of a particular technique varies considerably across branches. While a purely capital-intensive technique will yield high efficiency in chemicals, the corresponding figure in automobiles and electronics/electrical is mediocre and relatively low in machinery. Purely material-intensive techniques that entailed a relatively low efficiency in the entire population of firms have a quite contrary effect in the four industries listed in table 3. Material intensity might be interpreted as low vertical integration, i.e. the firm in question buys relatively many pre-assembled inputs. In this context, the high efficiency of material intensive firms at least in the automobiles, machinery and electronics/electrical industries is not really surprising.

The examination of the estimated means by year will show how the vertical structure of efficiency evolved over time. As can be seen in figure 2, the general trend is downwards. This means that fewer firms produce near to the best-technology frontier as time progresses. Although there may be firms that produce on this frontier in a particular year, the frontier could be theoretically formed by technologies implemented in earlier years. This would mean that all firms in the entire industry experience deteriorating productivity. Usually, the frontier would consist of older and contemporary technologies. This still indicates rising vertical heterogeneity within sectors, where an enlarging gap emerges between technological leaders and followers. If we interpret this chronological pattern as determined by a technological paradigm, we conclude that technological knowledge does not significantly diffuse in the period 1982-1993.[17] If there is diffusion, laggard firms should be able to catch up with the best technologies implemented so far or at least should be able to hold their position. The finding that they are falling back suggests that new technologies are implemented by few leading firms and that these technologies are responsible for an increasing productivity advantage of the leaders. This interpretation is further backed by the analysis of the branch*jahr interaction. There, we find that in mature industries such as paper, shipbuilding, textiles, iron and plastics/rubber the phenomenon of deteriorating productivity of laggards does not exist. In these sectors, no new technologies are present that would enable certain firms to step ahead. For future developments, this implies large *potential* productivity growth in sectors currently experiencing the falling-behind of laggards due to the diffusion of technology currently implemented by entrepreneurs.

[17] The analysis of data in the 1993-1997 period, which is still in progress, indicates that this trend did not change in most sectors.

Figure 2: estimated mean of *i* by year.



5. Conclusions

Considering the difficulties constructing evolutionary models of innovative behaviour of firms using conventional measures of technological progress, we apply an alternative method, the DEA. We use the results from this method to show that a firm's innovativeness is to a high degree characterised by its evolutionary, cumulative nature. We show that technological trajectories of different factor combinations can be identified. There is also some evidence that effects of technological paradigms can be addressed.

For the individual firm and for economic policy, the consequence of the large impact of the evolutionary component in our model is that effects from technology spillovers may have been overstated. If experience and learning-by-doing or learning-by-using are the main determinants of further development of technologies, then attempts to diffuse knowledge may yield limited success. Instead, it would be necessary to provide incentives for the application and improvement of key technologies.

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