Innovative Slowdown, Productivity Reversal?

Estimating the Impact of R&D on Technological Change

Günter Lang*
University of Augsburg, Germany
February 2002

Abstract

Motivated by the observed reversal in labor productivity growth since the beginnings of the nineties, this paper is analyzing the relationship between R&D expenditures and productivity. Time series data of the German manufacturing industry is used to estimate a variable cost function, with the stock of knowledge being modeled as a quasifix input. The estimates show that the extracted yield is non-constant over the observation period. Current rates of return on own R&D are measured to be significantly lower than during the sixties, and no signs of a significant reversal are detected. The long-term elasticity of production costs with respect to R&D reduced from –0.04 to just -0.02, the elasticity of labor demand from –0.40 to -0.15. Since the growth rates of real R&D were also declining, the contribution of R&D to productivity growth is currently stagnating at the lowest level since 1960.

JEL classification:

D24: Production, Capital and Total Factor Productivity, Capacity.
O31: Innovation and Invention: Processes and Incentives

Keywords:

Technology, innovation, research and development, productivity

* PD Dr. Günter Lang, University of Augsburg, Department of Economics, D-86135 Augsburg, Germany, e-mail guenter.lang@wiwi.uni-augsburg.de.

Introduction

In 1999, Germany spent 47 bn € on research and development (R&D), which accounts for one third of the EU-wide figure. When calculating the ratio between R&D expenditures and GNP, only for Sweden a higher share is found, thus confirming the lead position of Germany within the European Union. Public sources contributed to about 35% of the financing, which is modest even by worldwide standards: Significantly lower values are found only for Japan. On the private side, manufacturing is responsible for more than 90% of R&D spending and can therefore be expected as the motor of innovations (data from *Stifterverband*).

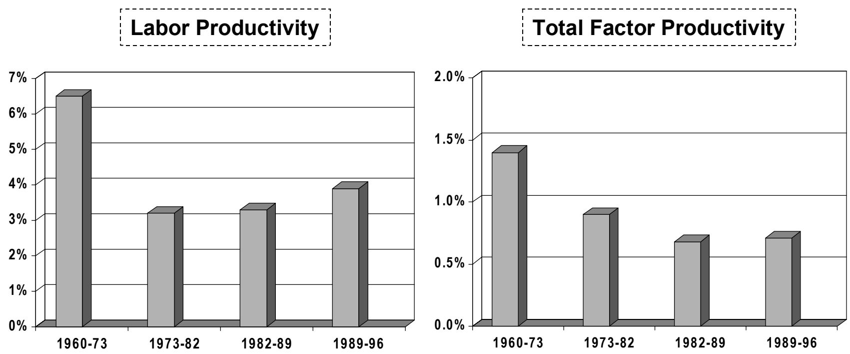
Motivated by the important role of manufacturing, the current paper is estimating the relationship between private R&D expenditures and productivity growth in this sector. Increasing R&D efforts should – perhaps with some lag (*Griliches, 1979*) – enhance the input-output relationship and therefore productivity. As in contrast to many other highly-developed countries, this important issue has not found wide interest in Germany (see e.g. *Hall and Mairesse, 1995*, for France, *Wakelin, 2001*, for UK, *Goto and Suzuki, 1989*, for Japan, or *Hall, 1993*, for the US). As an important exception, *Harhoff (1998)* is analyzing the relationship between R&D expenditures and productivity on the firm level, finding a strong positive role of R&D on labor productivity.

A specific focus of this paper is on the time trend of R&D returns and their contribution to productivity. Actually, technological change is considered the main source of productivity growth and to be the key variable for sustainable macroeconomic growth (*Solow, 1957*). This raises the question whether the observed productivity slowdown during the seventies (see e.g. *Bailey, 1981; Griliches, 1986*) is the result of slowing growth in R&D expenditures, of lower yields from the stock of knowledge capital built up by R&D, or whether the slowdown is not related to innovative activities. As is well known, productivity growth may also be driven by organizational issues as the degree of specialization between firms, increasing economies of scale, or reduced X-inefficiencies from optimized firm-internal structures and enhanced incentives for the employees. Any stagnation of these engines would also result in a productivity slowdown.

The answer from the literature on disentangling productivity change seems not to be clear. For example, *Hall (1993)* sees strong evidence in favor of declining rates of returns on R&D. In contrast, *Scherer (1993)* is pronouncing a singular negative effect of the oil-price shock for productivity growth, estimating even increasing yields of research expenditures since the eighties. For Germany, *Harhoff (1998)* is observing a slight increase in the rate of returns on R&D during the eighties. *Flaig and Steiner (1993*) emphasize the role of economies of scale, measuring no tendency for a slowdown of the innovative dynamics. This result is not supported by a recent paper from *Flaig and Rottmann (2001)*, however, where a significant drop in the scale-adjusted rate of technical progress is presented.

Facing the latest figures from productivity change, the contribution of R&D for the observed turnaround is of special interest. Actually, as Figure 1 shows, there are clear signs for a halt of the productivity slowdown or even for a reversal. Take labor, for example, where the year-to-year growth rate has halved immediately after the first oil price shock in 1973/74. Starting with the implementation of deregulation measures at the beginnings of the eighties, a weak recovery of labor productivity growth could be observed, which gained some speed after the German unification. During the last years, labor productivity was running at about 4%, which compares to just 3% after the first oil price shock. Similarly, the annual change in total factor productivity was declining from about 1.4% to 0.8% in the mid-seventies. As in contrast to labor productivity, this growth rate was further declining during the eighties, before a small recovery can be observed after the unification process. However, even from this more pessimistic measure a stop in the process of productivity slowdown can be concluded. Support for this interpretation can be found from the latest US data, where *Nordhaus (2000)* measures a strong rebound in labor productivity, with new economy sectors heavily contributing to this positive development. Naturally the question arises, whether this reversal is due to higher yields from R&D, increasing R&D expenditures, or whether the sources are not related to innovative activities.

Figure 1: Time Trends of Labor Productivity and Total Factor Productivity in German Manufacturing



Mean values of year-to-year changes in hour productivity and total factor productivity (TFP)[1], respectively.

The structure of the paper is as follows. Section 2 sets out the theoretical framework used to estimate the relationship between R&D and technological change. Section 3 is providing information on the data, before the results are presented in section 4. The last section tries to connect the empirical evidence with economic policy making.

[1] The year-to-year growth rate of total factor productivity is measured by the Tornquist discrete continuous Divisia index, which is given by

$g_t^{TFP} = \ln\left(\frac{y_t}{y_{t-1}}\right) - \sum_{i=1}^{4}\left[\frac{s_{i,t-1}+s_{i,t}}{2}\ln\left(\frac{x_{i,t}}{x_{i,t-1}}\right)\right]$. The variables y, x and s are representing output quantity, input quantities and cost share of input , respectively.

The cost function framework and the construction of the stock of knowledge

Following *Griliches (1986)*, R&D expenditures are used to create a stock of knowledge, which is assumed to be an input like labor or capital. When creating the stock of knowledge, one has to consider two opposed effects from the variable "time" (*Griliches, 1979*): First, the innovative effect from research and development may be appearing not immediately after investing in research and development. It takes some time to generate new knowledge, and – additionally – the knowledge has to spread throughout the economy before its effect can be measured. This process is known as diffusion. Second, older knowledge is becoming obsolete because of new inventions. The substitution of old knowledge by new innovations is known as decay.

As in *Popp (2001)*, this relationship between the stock of knowledge K_t and current as well as past R&D expenditures is modeled by an endogenous lag structure. To be more specific, the K_t values are calculated as in the following relationship:

$$K_t = \sum_{s=0}^{12} e^{-\beta_1 s}\left(1 - e^{-\beta_2 (s+1)}\right) \cdot RD_{t-s} \tag{1}$$

In equation (1), β_1 is capturing the decay of knowledge over time, while s is representing the number of periods before the current period t. Because of the second world war, no data before 1948 on R&D is available, which restricts the maximum lag period to 12. Together with the current period, 13 years of R&D are assumed to influence the stock of knowledge at any period. The rate of diffusion is given by the parameter β_2. Both β-parameters and therefore the weights are endogenous.

When searching for the impact of research and development on productivity, not only the relationship between K and R&D, but also the yield from the stock of knowledge has to be estimated. To solve this problem, a traditional cost function has been supplemented by the knowledge stock variable K_t, which in turn is a function of past and current R&D. The restricted variable cost function can therefore be written as

$$C = C(y, w, t, K(RD)), \tag{2}$$

where C is the cost of production except R&D expenses, y denotes output quantity, w is a vector of input prices for variable inputs, t is a time trend representing technological change from sources other than internal R&D, and K is the stock of knowledge capital. The restricted cost function implicitly assumes that firms are adjusting the levels of their variable inputs to their cost-minimizing values given the quasifix value of K. Principally, it would also possible to estimate the decision process on research on development and therefore on the stock of knowledge (see e.g. *Morrison*, 1992, for an adjustment process on physical capital). However, with the main focus on the relationship between R&D and productivity, this paper is following the majority of empirical studies and only estimates demand equations for variable inputs.

Putting together, the variable cost functions allows for two types of technological change: autonomous technological change, captured by t, and self-induced technological change as a result from own R&D expenditures. Autonomous technological change may originate from quality increases of the variable inputs or from public research. Its contribution on total factor productivity can be measured by the elasticity

$$\eta_t = \frac{\partial C}{\partial t}\frac{1}{C} = \frac{\partial \ln C}{\partial t}. \tag{3}$$

η_t describes the relative change in production costs caused by the movement from one period to the next one.

If one is interested in the contribution of autonomous technological change on factor-specific productivities, the following measures can be used:

$$\eta_t^i = \frac{\partial C}{\partial w_i}\frac{\partial w_i}{t}\frac{1}{x_i} \qquad i = 1,2,3,4. \tag{4}$$

η_t^i is the elasticity of input *i* with respect to the time index t.

The long-run impact of research and development on production costs is calculated by

$$\eta_{RD,t} = \left[\sum_{s=0}^{12} \frac{\partial C_t}{\partial K_{t-s}} \frac{\partial K_{t-s}}{\partial RD_{t-s}} \right] \frac{\overline{RD}}{C_t} . \tag{5}$$

η_{RD} can be interpreted as rate of return on R&D, since it measures the (long-run) percentage cost savings from a one-percent increase in research expenditures.

To make the results comparable to studies explaining the growth rate of labor productivity, the long-run elasticity of labor demand on research and development is derived as follows:

$$\varepsilon^{l}_{RD,t} = \left[\sum_{s=0}^{12} \frac{\partial^2 C_t}{\partial w_{l,t} \partial K_{t-s}} \frac{\partial K_{t-s}}{\partial RD_{t-s}} \right] \frac{\overline{RD}}{\partial C_t / \partial w_{l,t}} . \tag{6}$$

The index *l* is identifying labor input. ε^{l}_{RD} are therefore long-run savings of labor caused by increased research expenditures, expressed as elasticity value.

Finally, to identify the total contribution of the research expenditures on productivity, the following calculation schedule is used:

$$U_{K,t} = \frac{C(w_{t-1}, y_{t-1}, t-1, K_{t-1}) - C(w_{t-1}, y_{t-1}, t-1, K_t)}{C_{t-1}(w_{t-1}, y_{t-1}, t-1, K_{t-1})} . \tag{7}$$

The nominator in (7) is the shadow value of a change in the stock of knowledge from K_{t-1} to K_t, given that the set of the other relevant variables take the values from the period $(t-1)$. $U_{K,t}$ estimates the relative change in production costs from the period-to-period change of the K-variable, with positive values indicating a cost advantage. Aside from the levels of w, y and t, the result from (7) is dependent on the yield from the knowledge stock, and – second – on past and current investments into research and development.

To implement the outlined model for empirical estimation, a functional form has to be provided for the variable cost function (2). As in contrast to many other studies on the impact of R&D, not a Cobb-Douglas functional form, but a more flexible form is used to allow for complex relationships between the inputs and the output level. To be more specific, the following translog cost function is employed:

$$
\begin{aligned}
\ln C_t(w_t, y_t, t, K_t) &= a_0 + \sum_{i=1}^{4} a_i \ln w_{it} + b_1 \ln y_t \\
&+ \frac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4} a_{ij} \ln w_{it} \ln w_{jt} + \sum_{i=1}^{4} c_i \ln w_{it} \ln y_t \\
&+ \frac{1}{2} b_2 \ln y_t \ln y_t + d_0 t + \frac{1}{2} d_1 t^2 + d_2 \ln y_t t + \sum_{i=1}^{4} e_i \ln w_{it} t + \\
&+ f_0 \ln K_t + f_1 \ln K_t t_t + \sum_{i=1}^{4} g_i \ln w_{it} \ln K_t
\end{aligned} \tag{8}
$$

Four variable inputs, represented by labor, capital, energy and material, are used to describe the production process.

To better exploit the information from the data set, equation (8) is estimated together with the following cost share functions:

$$
s_{it} = \frac{\partial \ln C_t}{\partial \ln w_{it}} = \frac{x_{it} w_{it}}{C_t} = a_i + \sum_{j=1}^{4} a_{ij} \ln w_{jt} + c_i \ln y_t + e_i t + g_i \ln K_i \qquad i = 1,2,3 \tag{9}
$$

The relationship between absolute costs and cost shares is generated by applying Shephard's Lemma on the variable cost function. This powerful procedure increases the number of observations to the 4-fold, without increasing the number of parameters to be estimated. Both autonomous technological change, captured by t, as well as the level of knowledge K are allowed to influence absolute costs C as well as the cost structure, represented by the share equations.

In order to characterize a well-behaved technology, the cost function has to meet certain regularity conditions: C must be increasing in the input prices and in the output quantity, linear homogenous in the input prices, and concave with regard to the input prices (*Chambers, 1988, Chapter 2*). Linear homogeneity in input prices and the symmetry of the cost function are ensured by imposing the following (usual) restrictions:

$$
a_{ij} = a_{ji} \quad \sum_{j=1}^{4} a_{ij} = 0 \quad \sum_{i=1}^{4} a_i = 1 \quad \sum_{i=1}^{4} c_i = 0 \quad \sum_{i=1}^{4} e_i = 0 \quad \sum_{i=1}^{4} g_i = 0 \tag{10}
$$

As is well known from empirical studies, concavity in input prices is often violated, resulting in positive own-price elasticities of the input quantities. To deal with this problem, one can either use the Cholesky-factorization introduced by *Lau (1978)*, or alternatively the eigenvalue procedure *(Talpaz et al., 1989*). The last-mentioned is using the fact that all eigenvalues of a negative-semidefinite matrix are non-positive. Therefore, by adding the non-linear inequality

$$\max\left[eig\left(H_{ww}\left(C\left(w,y,t,K\right)\right)\right)\right] < 0\,, \tag{11}$$

concavity for a certain set of exogenous variables can be ensured. In equation (11), $H_{ww}\left(C\left(w,y,t,K\right)\right)$ is denoting the Hesse matrix of the cost function with respect to input prices. For empirical realization, arithmetic means of the exogenous variables were used, guaranteeing local concavity of the cost function. Global concavity was not implemented, because the necessary parameter restrictions would rule out any complementary relationships between the inputs. The main advantage of a flexible functional form, i.e. the ability to represent a wide range of technologies, would otherwise be deleted *(Diewert and Wales, 1987*).

Additive error terms, which are assumed to be normal distributed and contemporaneously correlated, are appended to the cost and the revenue equations. To determine the parameters of the cost function (8), the cost equation and three share functions are estimated jointly by maximum likelihood (for the likelihood function see *Greene, 2000, Chapter 15*.). The fourth cost share equation has to be deleted, because the sum of the error terms from 3 share functions are equal to the error term of the fourth input share. Otherwise the variance-covariance matrix of the error terms would be singular.

The rates of decay β_1 and of diffusion β_2 are not estimated directly, but by a raster search. Following *Popp (2001),* both parameters are found by searching for that combination of β_1 and β_2 which maximizes the value of the maximum likelihood function. To carry out this raster search, β_1 is defined as $\beta_1 = \upsilon/\left(1-\upsilon\right)$ and $\beta_2 = \lambda/\left(1-\lambda\right)$. By searching over the range $\left]0,1\right[$ for both υ and λ, the time structure between R&D and impact on the production technology is endogenized.

Description of the Data

The model described above is estimated for West German manufacturing, which is responsible for more than 90% of private research and development expenditures in Germany. Industry data were taken merely from national accounts (*Statistisches Bundesamt*), providing annual information from 1960 to 1996. As output measure the production value in constant prices is used. Wages are calculated as total expenses on labor[2] divided by the annual number of working hours both from employees and the self-employed. The price of capital is constructed as user cost of capital $p_K = \left(r + \delta - \dot{p}_I / p_I\right) p_i$, where r is the interest rate, δ is the rate of depreciation, and $\dot{p}_I / p_I$ is the change in the price of investment goods. Nominal expenses for capital can be found by multiplying p_K with the quantity of capital employed, which is measured by the net capital stock in constant prices.

Energy demand is part of a broadly defined material variable and not explicitly shown at the national accounts. The costs of energy use are found by multiplying the physical demand for energy, which is disaggregated into electricity, oil and coal demand (*Statistisches Bundesamt, Series 4*), with current wholesale prices. Expenses on material are corrected by the nominal energy costs as defined above. An implicit price deflator for material is calculated on the basis of nominal expenses and the value of the intermediate input in constant prices.

Nominal R&D expenses for West German manufacturing are available back to the year 1948 *(Stifterverband*). To calculate real values, current values are deflated by the price of labor. This specific deflator was chosen because of the dominance of labor expenses for R&D spending: Even with conservative assumptions, labor accounts for at

---

[2] Total expenses on labor are defined as the sum of actually paid wages plus hypothetical wages for the labor input from the self-employed, valued by the wage-rate of the employees.

least 60% of all research expenses.[3] When additionally considering the above-average depreciation rates of real capital used in the research laboratories, the employed deflator seems to be more realistic than alternative measures like the price index for investment goods (see e.g. *Harhoff, 1998*) or the implicit price deflator of the value-added variable *(Hall and Mairesse, 1995*). As will be discussed later, some results of the study are not invariant against the choice of the R&D deflator. In order to correct for double counting, the variable input factor labor is downward corrected by R&D efforts.

Information about absolute values of the variables and some statistical data are given in *Table 1*. All input price indices are scaled to take the value 100 in 1980.

Table 1: Description of the data set

		1960	1996	mean change*	standard devia-tion**
input prices	labor	15.0	227.7	0.079	0.033
	capital	27.5	154.9	0.051	0.071
	energy	31.2	113.0	0.040	0.089
	material	60.7	126.5	0.022	0.047
cost shares	labor	0.246	0.260	0.002	0.027
	capital	0.033	0.062	0.020	0.071
	energy	0.031	0.015	-0.018	0.059
	material	0.690	0.663	-0.001	0.012
output	bn € (1980-prices)	286.7	828.9	0.031	0.043
R&D***	bn € (1980-prices)	0.24	9.06	0.050	0.107

* Arithmetic mean of year-to-year change rates.
** Standard deviation of year-to-year change rates.
*** First year is 1948.

[3] This figure is calculated on the assumption of average wages and work time for research personal. Because of the high qualification of the research staff, the actual wage rate and therefore the actual labor cost share within the R&D cost block is probably underestimated.

Empirical results

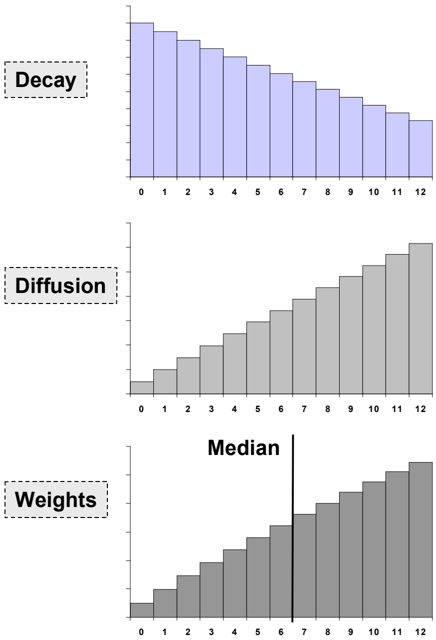
Parameter estimates were obtained by maximum likelihood estimation of the cost function (8) and three factor share equations (9). Considering the imposed restrictions, 30 free parameters have to be determined from 148 observations. The final result of this numerical optimization is presented in the appendix of this paper (Table A 1). All regularity conditions not implemented by restrictions were checked by ex-post tests, which show that the cost function is non-decreasing in output and non-decreasing in the input prices. The wide majority of the parameter estimates are found to be statistically significant. Furthermore, likelihood-ratio tests on simplified model structures were run to check for the statistical relevance of the flexible functional form and the contribution of R&D. Their results are presented in Table 2. As a main conclusion from these statistical tests, the use of a flexible functional form is strongly supported. Simplified functional relationships are therefore not suitable to depict all relevant economic information about the employed technology. Furthermore, the assumption that autonomous as well as R&D induced technical change are irrelevant can be rejected, too.

Table 2: Likelihood-ratio-tests on simplified model structures

Hypothesis	λ_{LR}	degrees of freedom	$\chi^2_{0.01}$	Conclusion
a) homothetic technology ($c_i = 0 \quad i = 1,2,3$)	81.8	3	11.3	reject
b) homogenous in output ($c_i = 0 \;\; i = 1,2,3;\, b_2 = 0;\, d_2 = 0$)	194.3	5	15.1	reject
c) no autonomous technical change ($d_0 = 0;\, d_1 = 0;\, d_2 = 0;\, e_i = 0 \;\; i = 1,2,3;\, f_1 = 0$)	292.2	7	18.5	reject
d) no impact from R&D ($f_0 = 0;\, f_1 = 0;\, g_i = 0 \;\; i = 1,2,3$)	78.4	5	15.1	reject
e) constant returns from R&D ($f_1 = 0;\, g_i = 0 \;\; i = 1,2,3$)	77.0	4	13.3	reject

λ_{LR} as value of the likelihood-ratio statistics; χ^2 gives the critical values.

Figure 2: Impact of R&D over Time

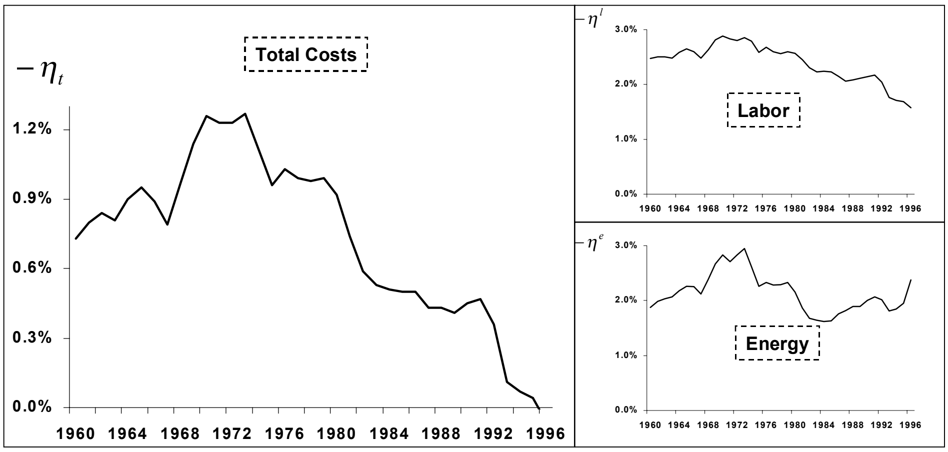


Decay and diffusion calculated as $e^{-\beta_1 s}$ and $1-e^{-\beta_2(s+1)}$, respectively. Multiplying both values produces the weights (see equation (1)).

In Figure 2, the estimated rates of decay and diffusion as well as the weights of lagged R&D for the stock of knowledge are presented. The estimates indicate sizeable lags between R&D expenditures and their impact on K, with the median being measured at six years. This result seems to be in contrast to *Popp (2001*), who found the median impact at two years after patent grant. However, considering lags between R&D efforts and the patent process, the difference between *Popp's* two year estimate and the present calculations is not surprising.

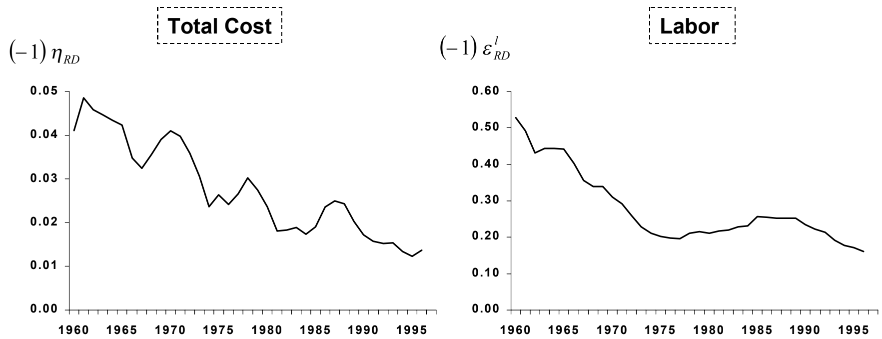
Because of the focus of this study on productivity, the most important property from the estimated parameters is the ability to quantify the relationship between t, R&D and production costs. Figure 3 shows the estimates for autonomous technical change, defined as elasticity of production costs with respect to the trend variable t. Economically, this measure is depicting the ability to acquire technological knowledge created outside the own research laboratories. As can be seen, the contribution of autonomous technological change on total factor productivity is exhibiting a slight increase during the sixties, followed by a dramatic decline lasting until recently. Taking absolute values, the progress rate slumped from more than 1% per year to an interval ranging from 0% to 0.3%. There are no signs for a reversal of this negative trend. Figure 3 also shows two partial demand elasticities with respect to autonomous technological change, illustrating that the disaggregation of η_t is not uniformly transported into the single inputs. Labor, for example, is mirroring this time path at a higher level. In contrast, the time structure of energy demand is much more complex, recently exhibiting an upwards trend of autonomous technological change.

Figure 3: The effect of autonomous technological change on productivity



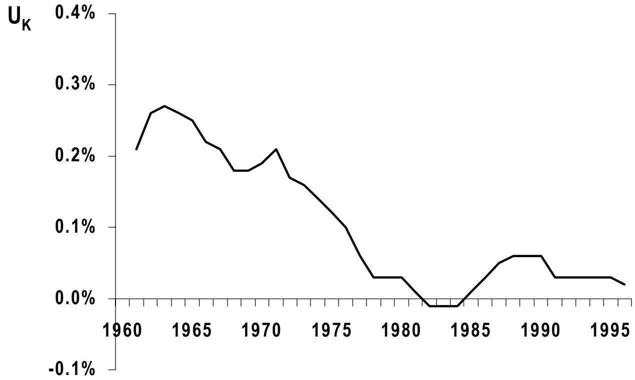
Aside from autonomous progress, internal research and development investments are the second source of innovative improvements. To see the full yields of R&D, the long run elasticities of total costs (η_{RD}) and labor demand (ε^l_{RD}) with respect to the research input are calculated. Both measures, which can be interpreted as return on the created stock of knowledge, are presented in Figure 4. As expected, the impact of research and development is productivity-increasing. What seems more important, however, is the time trend of the yields: The productivity enhancing effect of additional spending for research and development is clearly decreasing. Interestingly, this dissipation of the yields from R&D started in the sixties and therefore well before a productivity slowdown could be observed. For example, the long-run elasticity of labor demand with respect to R&D was shrinking from about –0.50 at the beginnings of the sixties to about –0.20 in 1975. After a small recovery, which lasted from 1980 to 1990, this decline has continued until recently (see *Harhoff, 1998*, for a similar time structure during 1979 until 1989). Even more persistent appears the slump in η_{RD}, which represents the long-run elasticity of total costs on R&D: The estimations show a decline from about –0.04 to values in the range between –0.02 and –0.01. With some optimistic interpretation, that downwards trend has slowed since 1980, and we may conclude that the yields are now stagnating at low levels. These tendencies as well as the absolute values are in line with the findings from *Hall (1993)* for the US, who analyzed the time interval from 1964 to 1990.

Figure 4: Long-run Rate of Returns on Research and Development



To derive the total contribution of R&D on productivity, the flow of yields from the knowledge stock has to be combined with the level of the knowledge stock, which depends on the historical development of research expenses. Given the parameter estimates and the observed values of R&D, year-to-year impact rates can be calculated on the basis of equation (7). The results of these calculations are presented in Figure 5. As clearly can be seen, the declining rate of return was not offset by increasing growth rates of K. On the contrary, firms decided to reduce the growth of (real) R&D expenditures, which transmitted – with some lag – into declining growth rates of the knowledge stock (see Table A 2 in the appendix). Starting in the early sixties, U_K steadily declined over two decades and reached the zero-line in 1982. Since then a very small recovery can be observed. Compared with the former results on η_t, the contribution from internal R&D on productivity growth is somewhat below the level from autonomous technological change.

Figure 5: Impact of the Change in the Knowledge Stock on Production Costs



Arithmetic means of year-to-year change rates.

Putting the results from Figure 3 and Figure 5 together, the conclusion is that the aggregate contribution of innovative activities – both from internal R&D as well as from autonomous sources – is declining. The observed reversal in raw productivity measures, as presented in the introduction to this paper, is therefore the result from successful internal optimization, not from a rebound of innovative power. Within the estimated model, the main force of internal optimization is the exploiting of economies of scale, which are estimated at about 0.94[4]. Enhanced management abilities, especially more appropriate specialization structures between the firms, may also be "hidden" in the industry-wide data, however.

How robust are the estimates against variations in the data or in the model setup? To find an empirical answer on this question, a bundle of alternative specifications have been run. It turned out that the findings on autonomous technological change, especially the strong downwards trend, is very robust. More sensitive, however, are the results about the rates of decay and diffusion as well as the results on the rate of return of R&D. For example, the described decline of the yields from R&D disappears if one substitutes the labor price deflator by the output price index (which exhibits significantly lower growth rates). What remains, however, is the downward trend of the total effect of R&D on productivity, as depicted in Figure 5. The main conclusion from before, that the contribution from innovations is declining, is therefore confirmed.

---

[4] Defined as elasticity of the cost function with respect to the output variable (*Chambers, 1988, 68 ff.*). Values less than one indicate increasing economies of scale.

Finally, it seems to be worthwhile that technological change does not only affect the costs of production, but also the cost structures of the firms. The parameters e_i and g_i, presented in Table 3, contain this information. Because of their predominantly high significance levels, the hypothesis of a Hick's neutral technological change has to be rejected. Both autonomous as well as R&D induced technological change appear as labor saving, whereas the use of capital as well as the use of material is supported. Opposite signs are found for the energy variable, with a positive relationship between research expenditures and the energy share, which is in contrast to the negative sign of the *t*-variable.

Table 3: Impact of technical change on the cost structure

	Labor share	Capital share	Energy share	Material share
Autonomous technical change	-0.0044***	0.0003**	-0.0003***	0.0045***
Research and Development	-0.0469***	0.0211***	0.0058***	0.0200***

Value of the partial derivative of the relevant cost share equation with respect to t and to $\ln K$, respectively.

Conclusion

This study has estimated the impact of research and development expenditures on productivity dynamic, using time-series data of West German manufacturing. R&D was found to be a significant determinant of productivity, with the extracted yield being non-constant over time. As the most interesting result, current rates of return on own R&D are estimated to be significantly lower than during the sixties. The long-term elasticity of production costs with respect to R&D declined from about –0.04 to just -0.01 or –0.02, the elasticity of labor demand from about –0.40 to about –0.15. Since the growth rates of real R&D were also decreasing, even reached zero during the last decade, the contribution of R&D to productivity growth is stagnating at very low levels. Similarly, autonomous technological change from outside the manufacturing sector is estimated to be declining since 1975. During the last years, its contribution to TFP growth is at modest 0%-0.2% annually. The observed reversal from the productivity slowdown, which started at the beginnings of the nineties, is therefore caused by forces outside the innovative system, e.g. by an enhanced exploitation of economies of scale.

Obviously, these pessimistic results, especially those on declining yields on research expenditures, have important policy implications. First of all, because of the low yields the government should be careful in stimulating higher research expenditures. Any expansion of the patent right or the grant of research subsidies may result in a misallocation of resources. As a second conclusion, it should be considered to redirect public resources into those areas which are important for the observed productivity reversal. Namely low transaction costs are the key towards optimized vertical firm structures. Higher investments into public infrastructure will probably support this organizational challenge. And third, the engine producing yields from R&D inputs is possibly neither exogenous nor a black box. Possible measures to improve the input-output relationship, e.g. by an enhanced knowledge transfer between the public and the private research staff, should be strengthened.

References

Bailey, M. N. (1981), The Productivity Growth Slowdown by Industry, Brookings Papers on Economic Activity 2, pp. 423 – 454.

Chambers, R. (1988), Applied Production Analysis: A Dual Approach, Cambridge(US): Cambridge University Press.

Diewert, W., Wales, T.J. (1987), Flexible Functional Forms and Global Curvature Conditions, Econometrica 55, pp. 43 – 68.

Flaig, G., Rottmann, H. (2001), Input Demand and the Short- and Long-Run Employment Thresholds: An Empirical Analysis for the German Manufacturing Sector, German Economic Review 2, Issue 4, pp. 367 – 384.

Flaig, G., Steiner, V. (1993), Searching for the "Productivity Slowdown": Some Surprising Findings from West German Manufacturing, Review of Economics and Statistics 75, pp. 57 – 65.

Goto, A, Suzuki, K. (1989), R & D Capital, Rate of Return on R & D Investment and Spillover of R & D in Japanese Manufacturing Industries, The Review of Economics and Statistics, Vol. 71, Number 4, pp. 555 – 564.

*Greene, W. (2000),*Econometric Analysis, 4th edition, London: Prentice Hall.

Griliches, Z. (1979), Issues in Assessing the Contribution of Research and Development to Productivity Growth, Bell Journal of Economics, pp. 92 – 116.

Griliches, Z (1986), Productivity, R & D and Basic Research at the Firm Level in the 1970s, American Economic Review 76, pp. 141 – 154.

Hall, B.H. (1993), Industrial Research during the 1980s: Did the Rate of Return Fall?, Brookings Papers on Economic Activity 2 (Microeconomics), pp. 289 – 343.

Hall, B.H., Mairesse, J. (1995), Exploring the Relationship between R&D and Productivity in French Manufacturing Firms, Journal of Economics 65, pp. 263 – 293.

Harhoff, D. (1998), R&D and Productivity in German Manufacturing Firms, Economics of Innovation and New Technology 6, pp. 29 – 49.

Lau, L. (1978), Testing and Imposing Monotonicity, Convexity and Quasi-Convexity Constraints, in: *Fuss, M., McFadden, D. (eds.),* Production Economics: A Dual Approach to Theory and Applications, Amsterdam: North-Holland, pp. 409 – 453.

Morrison, C.J. (1992), Unraveling the Productivity Growth Slowdown in the U.S., Canada and Japan: The Effects of Subequilibrium, Scale Economies and Markups, Review of Economics and Statistics 74, pp. 381-393.

Nordhaus, W.D. (2000), Productivity Growth and the New Economy, Cowles Foundation discussion papers no. 1284, Yale University.

Popp, D. C. (2001), The Effect of New Technology on Energy Consumption, Resource an Energy Economics 30, pp. 215 – 239.

Scherer, F.M. (1993), Lagging Productivity Growth: Measurement, Technology and Shock Effects, Empirica 20, pp. 5-24.

Solow, R. M. (1957), Technical Progress and the Aggregate Production Function, Review of Economics and Statistics 39, pp. 312 – 320.

Statistisches Bundesamt, Series 4, Series 17, Series 18.

Stifterverband, Statistiken über Forschung und Entwicklung.

Talpaz, H., Alexander, W. P., Shumway, C.R. (1989), Estimation of Systems of Equations Subjects to Curvature Constrains, Journal of Statistical Computation and Simulation 32, pp. 201 – 214.

Wakelin, K. (2001), Productivity Growth and R&D Expenditure in UK Manufacturing Firms, Research Policy 30, pp. 1079 – 1090.

Appendix

Table A 1: Parameter estimates for the translog cost function (8)

Parameter	Estimate	t-statistic
a_0	14.3045	2.09 **
a_1	0.7253	7.45 ***
a_2	0.3283	10.60 ***
a_3	0.0720	3.07 ***
a_4	-0.1256	-1.27
b_1	-4.5938	-2.20 **
a_{11}	0.1558	14.05 ***
a_{12}	-0.0096	-2.38 **
a_{13}	-0.0086	-3.40 ***
a_{14}	-0.1377	-11.30 ***
a_{22}	0.0518	23.82 ***
a_{23}	-0.0014	-1.23
a_{24}	-0.0408	-9.95 ***
a_{33}	0.0227	33.39 ***
a_{34}	-0.0127	-4.07 ***
a_{44}	0.1912	12.54 ***
c_1	-0.0335	-2.21 **
c_2	-0.0460	-9.82 ***
c_3	-0.0074	-2.03 **
c_4	0.0869	5.84 ***
b_2	0.8446	2.67 ***
d_0	0.1207	2.22 **
d_1	0.0010	4.33 ***
d_2	-0.0217	-2.68 ***
e_1	-0.0044	-13.55 ***
e_2	0.0003	2.24 **
e_3	-0.0003	-5.20 ***
e_4	0.0045	12.40 ***
f_0	-0.0624	-2.07 **
f_1	0.0019	1.33
g_1	-0.0469	-5.74 ***
g_2	0.0211	8.41 ***
g_3	0.0058	2.85 ***
g_4	0.0200	2.30 ***
Number of observations		148

Standard errors for Maximum Likelihood from the inverse of the Hesse matrix.
*, ** and *** represent a significance level of 90%, 95% and 99%, respectively (two-sided).
All calculations were run by GAUSS.

Table A 2: R&D Expenses and the Stock of Knowledge

	1948-60	1961-73	1974-81	1982-89	1990-96
Real R&D	0.116	0.042	0.017	0.032	-0.034
Stock of Knowledge		0.074	0.008	0.0268	-0.002

Arithmetic means of year-to-year change rates (calculated as difference in logs).

Table A 3: Own and Cross Price Elasticities of Input Demand

Price elasticity of ... with regard to price increase of...	labor	capital	energy	material
labor	-0.15			
capital	0.09	-0.01		
energy	-0.10	0.00	-0.02	
material	0.05	-0.01	0.01	-0.05

Arithmetic means for observation period (37 years).