R&D Investments and Productivity Growth

An empirical study of the German manufacturing sector over 45 years

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Abstract

Motivated by recent statistics that show significant growth in labor productivity, this paper seeks to analyze the relationship between domestic R&D, knowledge stock and productivity dynamics. Time series data of the German manufacturing industry is used to estimate a variable cost function with the stock of knowledge being dependent upon current and past R&D spending. The estimates indicate that 50% of the effects of R&D on the knowledge stock appear within four years. However, the rate of return on R&D are shown to be drastically declining; recent rates of return on R&D are estimated to have reached an all-time low spanning the last 45 years. Current yields of R&D are only one third compared to the sixties. In conclusion, though the productivity slowdown of the seventies seems to have been overcome, this is not attributed to R&D investments.

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O31: Economic Development, Technological Change, and Growth: Technological Change
L60: Industrial Organization: Industry Studies – Manufacturing
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Productivity, innovation, research and development, technology, productivity slowdown

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Introduction

In 2005, Germany spent about 55 bn EUR or 2.5% of the GDP on research and development (R&D). This makes Germany, by far, the most important location for research activities within the European Union. Only Sweden and Finland have a higher share of R&D relative to the GDP, with the absolute spending being much lower. Public sources in Germany contribute to about 35% of the R&D financing, which is modest by world-wide standards; significantly lower values are found only for Japan. With regards to private R&D spending, manufacturing is responsible for more than 90% and can, hence, be considered as the main engine for innovations (data from *Stifterverband*).

Do these enormous efforts pay off? In actual fact, recent data seems to confirm the positive effect of research input on productivity dynamics. Real spending on R&D, which declined during the first half of the nineties, managed a turnaround in 1996 and has grown by 25% since. Simultaneously, labor productivity growth also increased to about 4.5% annually compared to 3% in the first half of the nineties.[1] However, this raw data is not evidence for the causality between R&D investments and productivity dynamics. First, there may be a time lag between R&D and its impact on technology improvement, implying that the effects of the recent R&D upsurge have not yet materialized. Secondly, the relationship between R&D and productivity maybe looser than earlier. That is, the rate of return of R&D is not necessarily constant, but maybe decreasing. Finally, labor productivity growth is not only dependant on technological advances, but also on some of the following: economies of scale, substitution of labor by other inputs, decreasing X-inefficiency.

Motivated by this background, this paper is estimating the rate of return of private R&D investments in the German manufacturing sector over the last 45 years. Increasing R&D efforts should – perhaps with some lag (*Griliches, 1979*) – enhance the input-output relationship and therefore productivity. Though there is a plentitude of empirical evidence to support this issue in other countries, it has not received much attention 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. The important role of public science infrastructure for patent output is confirmed by *Blind and Grupp (1999)*, who estimate knowledge production functions for two German states.

This paper focuses on the time trend of R&D returns and their contribution to productivity over a time interval of more than 40 years. Whereas a significant impact of R&D on productivity is confirmed by most studies, the results from the literature on the time trend of R&D yields are not that apparent. 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)* observed 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. *Flaig and Rottmann (2001)* presented contradicting results, where a significant drop in the scale-adjusted rate of technical progress was presented.

The paper is structured as follows: In the first step, Section 2 sets out the theoretical framework for the empirical estimations. Using long-run R&D data of the German manufacturing sector, a knowledge stock variable is created. By including this knowledge stock variable in a variable cost function, the effect of R&D on production costs can be derived. Section 3 provides 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.

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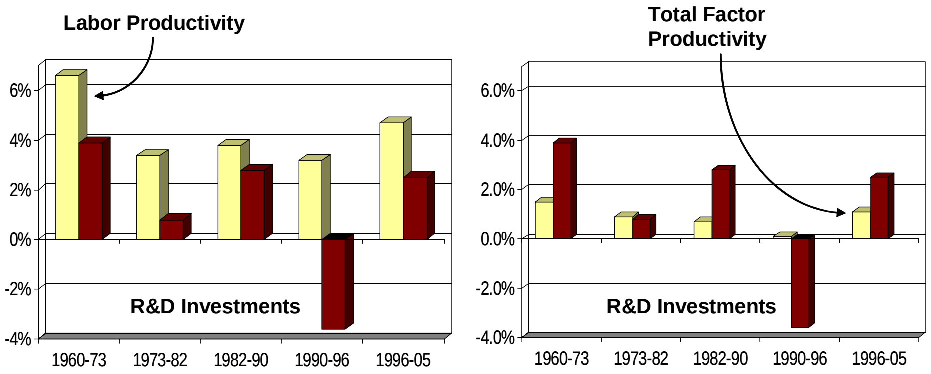
[1] Productivity growth in the manufacturing industry. Although on a lower level, a similar trend can be observed for the whole economy.

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

Before discussing the theoretical framework of the model, some facts on the long-run productivity development in the German manufacturing sector as well as the R&D investments are presented. Figure 1 shows that labor productivity growth, which is in the center of public interest, was cut in half after the first oil price shock in 1973/74. This phenomena is known as "productivity slowdown" (see e.g. *Bailey, 1981; Griliches, 1986*). However, Figure 1 also shows that there are clear signs for a reversal of this downwards trend. Starting with the implementation of deregulation measures at the beginnings of the eighties, a weak recovery of labor productivity growth could be observed, which lost some speed after the German unification. Since the mid of the nineties, however, the trend growth of labor productivity is at about 4.5%, 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, no reversal of this slowdown could be observed during the eighties. After the manufacturing industry suffered from a further slump of the TFP growth rate after the unification process, a strong recovery could be observed since the mid of the nineties. As for the real R&D investments, there seems to be a correlation to the productivity trend. Especially the productivity slowdown in the seventies and the latest recovery are accompanied by corresponding changes in R&D spending.

It is worth to be mentioned that the reversal in labor productivity growth is not limited to Germany, but can also be observed for other developed countries. For the US economy, which is the most important global benchmark, a strong rebound of labor productivity growth was found by *Nordhaus (2000)*. Especially new economy sectors are identified to contribute heavily to this positive development. Similar optimistic results and projections for the future are provided by *Jorgenson and Stiroh (2000)* and *Jorgenson, Ho and Stiroh (2002)*.

Figure 1: Labor Productivity, Total Factor Productivity and R&D Expenditures in German Manufacturing



Year-to-year change rates of hourly labor productivity, total factor productivity (TFP)[2] and real R&D expenditures, respectively.

To measure the impact of R&D efforts on these productivity figures, the basic framework as developed by *Griliches (1986)* is used. In this model, R&D expenditures create the stock of knowledge which enters the production function as an input. To determine 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.

In this paper, the knowledge variable is constructed similar to *Popp (2001)*, where the relationship between the knowledge stock K_t in period t and current as well as past R&D expenditures is not exogenous, but modeled by an endogenous lag structure. To be more specific, the construction of K_t is as follows:

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[2] 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.

$$K_t = \sum_{s=0}^{11} e^{-\beta_1 s}\left(1 - e^{-\beta_2 (s+1)}\right) \cdot RD_{t-s} \tag{1}$$

In equation (1), $e^{-\beta_1 s}$ describes the diffusion of knowledge over time, where s is representing the number of periods before the current period t. The decay of older knowledge is described by $1 - e^{-\beta_2 (s+1)}$. The product over both terms provides the total weight of R&D spending in period s for the knowledge capital stock in t. Both β-parameters and therefore the weights are endogenous. Due to data restrictions which are described in more details later, the maximum lag period is 11 years. Together with the current period, 12 years of R&D are allowed to influence the stock of knowledge at any period.

When searching for the impact of research and development on production costs, not only the relationship between K and R&D, but also the returns from the knowledge stock have to be considered. Actually, this paper relies on a variable cost function 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 the time trend representing technological change from sources other than private R&D, and K is the stock of knowledge capital. This 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 be 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 private (and domestic) R&D spending. Autonomous technological change may – for example – originate from quality increases of the variable inputs, from public research efforts, or from imported innovations. Its contribution on total factor productivity can be measured by the term

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

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

Of course, the effect of autonomous technological change can be disentangled by the factors of production:

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

η_t^i is the elasticity of input *i* with respect to the time index t, that is η_t^i informs about the percent change in the demand for factor *i* from one period to the next, all else equal. Negative signs indicate that autonomous technological change is input saving, positive signs indicate that t is input using.

Determining the role of autonomous technological change is done only for reasons of comparison. Actually, the main focus is on returns on R&D, which are measured by their long-run impact on production costs η_{RD}:

$$\eta_{RD,t} = \left[\sum_{s=0}^{11} e^{-rs} \left(\frac{\partial C_t}{\partial K_{t-s}} \frac{\partial K_{t-s}}{\partial RD_{t-s}} \right) \right] \frac{\overline{RD}}{C_t} . \tag{5}$$

η_{RD} measures the long-run percentage cost savings from a one-percent increase in research expenditures. A discount rate *r* of 0.10 was used for determining the present value of non-current cost savings.

Similar to the analysis of autonomous technological change, η_{RD} can also be broken down into the factor-specific elasticities of input demand on research and development:

$$\eta_{RD,t}^i = \left[\sum_{s=0}^{11} e^{-rs} \left(\frac{\partial^2 C_t}{\partial w_{i,t} \partial K_{t-s}} \frac{\partial K_{t-s}}{\partial RD_{t-s}} \right) \right] \frac{\overline{RD}}{\partial C_t / \partial w_{i,t}} \qquad i = 1,2,3,4 . \tag{6}$$

Again, a discount rate of 0.10 was used. η_{RD}^{i} indicate the long-run effects of R&D on the demand for the single inputs. Negative signs indicate that R&D is input saving, positive signs indicate that R&D is input using.

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

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

The nominator in (7) is the shadow value of a change in the stock of knowledge from K_{t-1} to K_t, i.e. the maximum amount firms would be willing to pay for the increase in the knowledge stock. Actually, $U_{K,t}$ estimates the relative change in production costs from the period-to-period change of the K-variable, which is dependent on a) the level of current and past R&D spending, and b) on the returns on R&D. Positive signs of U_K are indicating cost savings.

To implement the outlined model for empirical estimation, a functional form has to be assumed 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 translog form is used to allow for a more complex relation between the inputs and variable costs:

$$\begin{aligned} \ln C_t(w_t, y_t, t, K_t) &= a_0 + \sum_{i=1}^{4} a_i \ln w_{it} + b_1 \ln y_t \\ &+ \frac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4} a_{ij} \ln w_{it} \ln w_{jt} + \sum_{i=1}^{4} c_i \ln w_{it} \ln y_t \\ &+ b_{11}\frac{1}{2}\ln y_t \ln y_t + d_1 t + \sum_{i=1}^{4} e_i \ln w_{it} t + \\ &+ f_1 \ln K_t + \sum_{i=1}^{4} g_i \ln w_{it} \ln K_t \\ &+ h_0 D^{unific} \end{aligned} \qquad (8)$$

Four variable inputs, represented by labor, capital, energy and material, as well as the knowledge stock variable as a quasifix input are used to describe the production technology. To control for a possible endogeneity of the output variable y, the original values of y are substituted by instruments – see the data description for more details. A dummy variable D^{unific}, equal to one since 1991, was added to allow for a technology shift from the German reunification.

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

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

The cost share equations (9) are derived from the cost function (8) using Shephard's Lemma. The fourth cost share equation has to be deleted to avoid a singular variance-covariance matrix of the error terms.

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 restrictions:

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

Additive error terms, which are assumed to be normal distributed and contemporaneously correlated, are appended to the cost and the share equations. To determine the parameters of the cost function (8), equations (8) and (9) are estimated jointly by the iterative SURE estimator.

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 $\beta_1 = \upsilon/(1-\upsilon)$ and $\beta_2 = \lambda/(1-\lambda)$. By searching over the range $]0,1[$ 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 the German[3] manufacturing industry, which is responsible for more than 90% of all private R&D spending in Germany. Industry data were taken from national accounts (*Statistisches Bundesamt, Series 18*), providing annual information from 1960 to 2005. The output variable y is measured as production value in constant prices. Lagged values of y and the GDP, as well as a trend variable and a reunification dummy (equal to one for 1991 to 2005, zero before 1991) are used as instruments for y. This reduces the number of observations from 46 to 45. Wages are calculated as total expenses on labor[4] divided by the annual number of working hours both from employees and the self-employed less the working hours of the R&D staff. 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 determined 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 German manufacturing are available back to the year 1950 *(Stifterverband*). To calculate real values, current values are deflated by the price of labor.

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[3] Until 1990 only West Germany, from 1991 Western and Eastern Germany.

[4] 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.

This specific deflator was chosen because of the dominance of labor expenses for R&D spending: Even by conservative assumptions, labor accounts for at least 60% of all research expenses.[5] 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*).

Table 1 briefly describes the data used for estimation.

Table 1: Description of the data set

		1960	2005	yoy change rate*	standard deviation**
input prices (indices, 1980=100)	labor	15.0	288.0	0.068	0.038
	capital	27.1	201.1	0.047	0.057
	energy	25.6	152.0	0.045	0.097
	material	60.7	129.8	0.018	0.044
input quantities (costs, bn € of 1980 prices)	labor	231.5	113.9	-0.015	0.027
	capital	16.7	47.3	0.024	0.038
	energy	16.7	17.8	0.002	0.042
	material	157.2	727.0	0.036	0.044
cost shares	labor	0.246	0.215	-0.003	0.028
	capital	0.033	0.070	0.020	0.077
	energy	0.031	0.020	-0.008	0.063
	material	0.690	0.695	0.000	0.015
output (bn € of 1980 prices)	production	286.7	1028.7	0.030	0.041
R&D*** (bn € of 1980 prices)	firm R&D spending	0.93	12.45	0.052	0.098

* Arithmetic mean of year-to-year change rates.
** Standard deviation of year-to-year change rates.
*** First year is 1950; yoy change rates and standard deviation for 1950 to 2005.

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[5] This figure is calculated on the assumption of average wages and work time for research personal. Due to the typically 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 generated by the iterative SURE (seemingly unrelated regression equations) method, which simultaneous estimates the parameters of the cost function (8) and of the three factor share equations (9). This iterative method was repeated for all possible combinations of υ and λ (raster search). The final model was selected according to the value of the likelihood function of the SURE model, i.e. that combination of υ and λ was chosen which maximizes the likelihood function. As for the number of parameters and degree of freedoms, 24 free parameters have to be determined from 180 observations.[6] As can be seen form Table A-1 in the appendix, where the estimation results are provided, the wide majority of the parameter estimates are statistically significant from zero. All regularity conditions not implemented by restrictions were checked by ex-post tests, showing that the cost function is non-decreasing in output and non-decreasing in the input prices. Furthermore, all own-price elasticities of the inputs turned out to be negative and at least one cross-price elasticity turned out to be positive for each single input (Table A-2 in the appendix). This result is in line with the requirements of a well-behaved cost function.

In a next step, likelihood-ratio tests on simplified model structures were run to check for the statistical relevance of the flexible functional form and the relevance of R&D for production costs. 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 obviously not appropriate to depict all relevant economic information about the employed technology. Most important for the purpose of this study, the hypotheses that autonomous as well as R&D induced technical change are irrelevant can be rejected, too.

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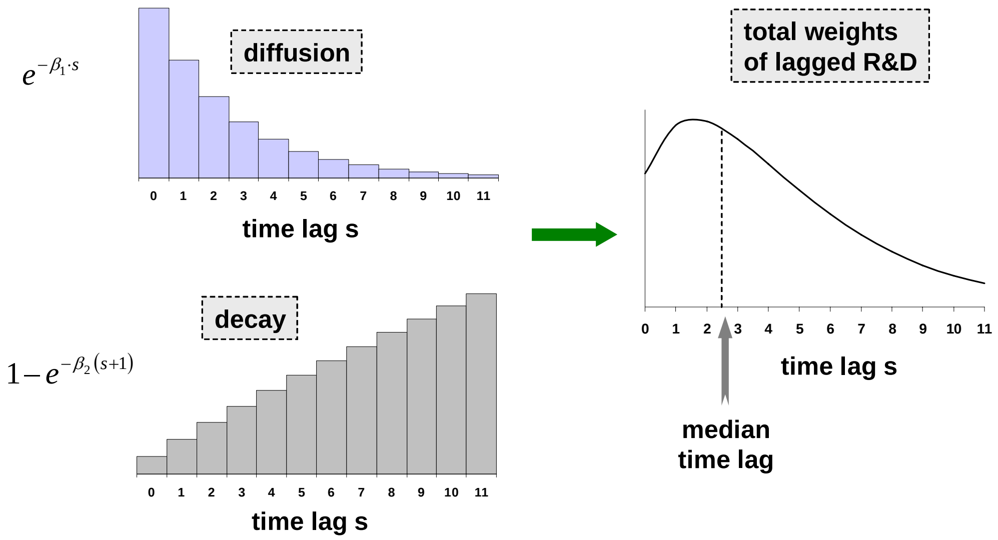
[6] 45 observations times 4 equations.

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

Hypothesis	λ_{LR}	degrees of freedom	$\chi^2_{0.01}$	Conclusion
a) homothetic technology $(c_i = 0 \quad i = 1,2,3)$	33.2	3	11.3	reject
b) homogenous in output $(c_i = 0 \;\; i = 1,2,3; b_{11} = 0)$	112.6	4	13.3	reject
c) no autonomous technical change $(d_1 = 0; e_i = 0 \;\; i = 1,2,3)$	91.4	4	13.3	reject
d) no impact from R&D $(f_1 = 0; g_i = 0 \;\; i = 1,2,3)$	44.1	4	13.3	reject
e) neither autonomous nor endogenous technological change	177.0	8	20.1	reject
e) constant returns from R&D $(g_i = 0 \;\; i = 1,2,3)$	24.4	3	11.3	reject

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

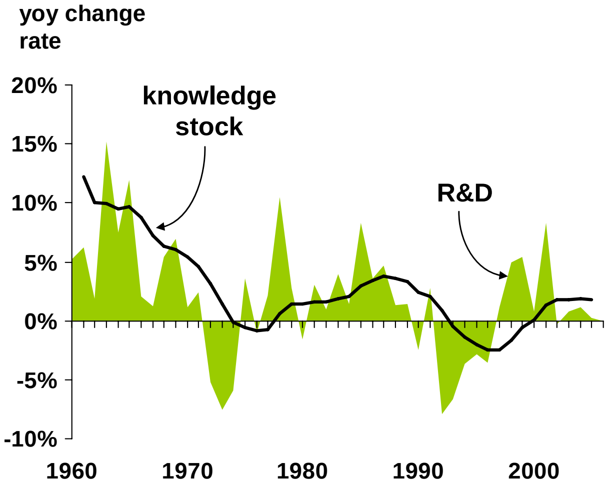
Figure 2: Impact of R&D on the knowledge stock over time



Diffusion and decay are calculated as $e^{-\beta_1 s}$ and $1-e^{-\beta_2(s+1)}$, respectively. Multiplying both values generates the total weights (see equation (1)).

In Figure 2, the estimated rates of decay and diffusion over time as well as the total effect of R&D for the stock of knowledge are presented. As can clearly be seen, the rates of decay and diffusion are not constant. Actually, the results are not surprising, but confirm our expectations about the effects of R&D over time: As more in the past the R&D investments are, as lower are the rates of diffusion. In contrast, rates of decay increase over time. Combining both results into total weights of R&D (right-hand side of the figure) produces an inverted U-shaped curve, with the maximum effect of R&D appearing 2 years after the research project. 50% of the total effect of R&D appear within the first 4 periods, i.e. the year of the R&D effort and the three consecutive years. This results are roughly in line with the estimates of *Popp (2001)*, who found the median impact at two years after patent grant.

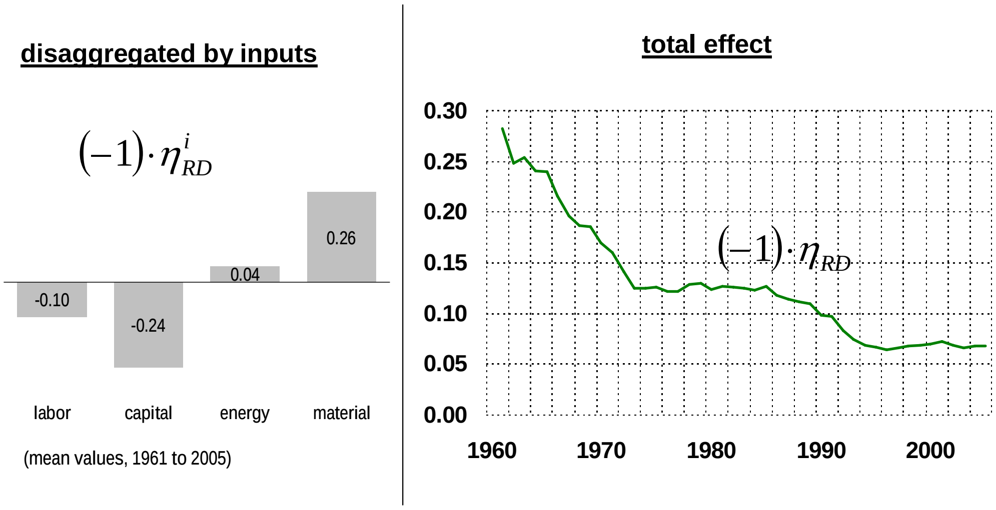
Figure 3: R&D spending and the knowledge stock of the German manufacturing sector



The knowledge stock is modeled to depend on the level of domestic R&D investments.

From the estimates of the diffusion and decay processes and together with the information about R&D spending, the level of the knowledge stock can be calculated. Figure 3 graphically describes the development of both variables in year-to-year change rates. Because the knowledge stock is dependent on the current plus eleven lagged values of R&D, the curve is much smoother than raw R&D spending. In general, Figure 3 does not leave much room for an optimistic interpretation: Because the trend of R&D spending was downwards during the last 50 years, the growth rate of the knowledge stock also got lower and lower. During the mid of the seventies and – more pronounced – during the nineties, the change rate of the knowledge stock was even slightly negative. However, it should not be forgotten that the level of the knowledge stock does not tell the full story of the effect of R&D. What we see in Figure 3 is the relation between R&D and the knowledge stock variable, not the effect of R&D on the cost function and therefore on productivity. For that we need to know the rates of return of the knowledge stock.

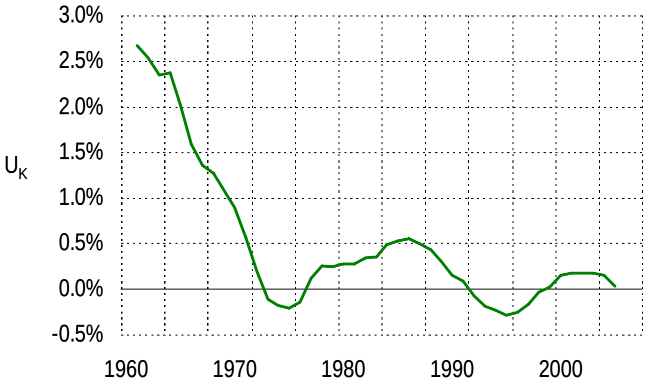
Figure 4: Long-run rate of returns on research and development



The right-hand side figure shows the elasticity of manufacturing production costs with respect to R&D spending. The left-hand side figure is breaking up this total effect into the single inputs. Positive values indicate productivity increases of R&D spending.

Using equation (5), the rates of returns η_{RD} are determined in a second step. The elasticity η_{RD} is the change in the present value of the production cost change from a one-time increase of R&D by 1%. The results of the calculations are presented in the right-hand side of Figure 4. As expected, the impact of research and development is cost-decreasing and therefore productivity-enhancing. More important than the absolute level of η_{RD} is the time trend of the returns, however: According to the estimation results, the productivity enhancing effect of additional spending for R&D is dramatically decreasing. Interestingly, this dissipation of the returns of R&D started already in the sixties and therefore well before the productivity slowdown could be observed. Actually, η_{RD} declined over the sixties and the early seventies from about -0.20 to -0.08. Being relatively constant at this level for more than a decade, a second decline can be observed from the mid of the eighties to the early nineties. Since that time, η_{RD} remained more or less unchanged until 2005, with the absolute level being extremely low, however. This trend is in line with the findings from *Hall (1993)* for the US, who analyzed the time interval from 1964 to 1990.

Figure 5: Total contribution of R&D on production costs

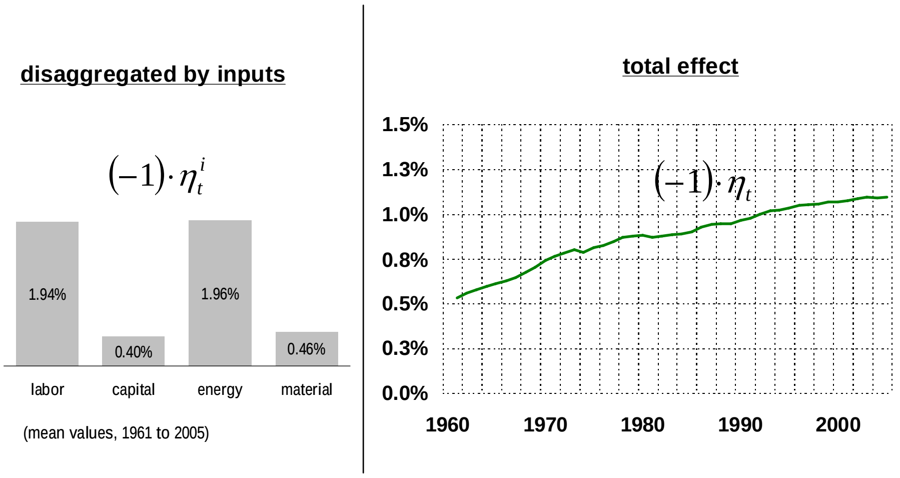


The graph shows the impact of the change of the knowledge stock on production costs. Past and current R&D spending as well as the returns on R&D determine the knowledge stock. Positive values indicate cost reductions.

The left-hand side of Figure 4 shows the effect of R&D on the single inputs. As the most interesting result, R&D is labor using. That is, there is positive effect of research and development on employment. The demand for capital is also stimulated by R&D investments. In contrast, the use of energy as well as of material input is reduced.

To derive the total contribution of R&D on productivity, the flow of returns from the knowledge stock has to be combined with the level of the knowledge stock, which in turn depends on the R&D spending. Given the parameter estimates and the observed values of R&D, year-to-year productivity change rates are calculated on the basis of equation (7). The results are shown in Figure 5. Because not only the returns on R&D declined, but also the trend growth rates of R&D (figure 3), the contribution of research activities to cost decreases and therefore productivity increases has become lower and lower. U_K declined from about 2% during the sixties to zero in the mid of the seventies. The following upsurge of R&D increased the implied yearly productivity gain to 0.5% at the end of the eighties. However, the recovery was short-living: Driven by the second drop of R&D returns and lower R&D spending, the first half of the nineties experienced again a decline of U_K to zero. The very recent increase in R&D spending could not change much at the generally pessimistic outcome.

Figure 6: The effect of autonomous technological change on productivity



The right-hand side figure shows the %-change of manufacturing production costs with respect to time. The left-hand side figure is breaking up this total effect into the single inputs. Positive values indicate productivity increases of autonomous technological change.

Interestingly, the results on autonomous technical change are significantly different from the results on the returns on R&D. As defined in equation (3), autonomous technical change η_t is the relative change of production costs from one year to the next. That is, this kind of technological advance is not explained by firm R&D investments, but is modeled as a function of time. Economically, η_t is depicting the ability to acquire technological knowledge from outside the own research laboratories, for example from non-domestic firms, from public research, or from factor quality. The results, as shown on the right-hand side in Figure 6, show a steady increase of autonomous technological change. Actually, the progress rate is estimated to accelerate from about –0.6% per year in the early sixties to -1.2% per year in the recent years. As can clearly be seen from a comparison of Figure 6 with Figure 5, η_t has clearly overtaken η_{RD} in its role as productivity engine since the early seventies.

The left-hand side of Figure 6 shows the effect of *t* on the single inputs. As in contrast to R&D, autonomous technological change decreases the demand for all inputs, that is all of the single factor productivities are increasing. According to the results, the effect on labor and energy are much stronger compared to the effect on capital and material. On the average, energy and labor input is estimated to decrease by about 2% per year, all else equal. This is five times the effect of autonomous technological change on capital and material.

Conclusion

This study estimates the impact of research and development on production costs, using time-series data of German manufacturing. R&D was found to be a statistically significant determinant of productivity, with the rate of return on R&D being unstable, however. The results show that current rates of return on R&D are much lower than during the sixties. Using the long-term elasticity of production costs with respect to R&D as indicator for the rate of return, the returns declined from about -0.25 during the sixties to just -0.07 recently. That is, current yields of R&D spending are only one third compared to 40 years ago. The recent upturn of the R&D investments could not compensate for this decline, implying that the absolute contribution of R&D to productivity growth is low. In contrast, autonomous technological change – e.g. imported technology improvements – is steadily gaining weight. Although autonomous technological change is now the main driver of TFP growth, it could not fully compensate for the downturn of R&D stimulated productivity effects.

In contrast to popular belief, domestic R&D spending is increasing, not decreasing the demand for labor. Capital input is also benefiting from R&D efforts. R&D decreases the demand for energy and material, however. Autonomous technological change reduces the demand for all inputs, with savings of labor and energy being the highest.

Obviously, the pessimistic results on declining returns of R&D have implications for research policy. Most important, the government should be careful in stimulating higher research expenditures. Actually, recent rates of return on R&D are estimated to have reached an all-time low spanning the last 45 years. This raises doubts about the objective of the German ministry of research to increase domestic R&D to 3% of the GDP. Interestingly, firms are also not convinced from attractive yields of their R&D investments: In spite of the recent upsurge, private spending on R&D is hesitant relative to the sixties and the eighties, perhaps mirroring the estimated decline of R&D returns.

Instead of increasing the level of R&D, economic policy should focus on an increase of the returns on R&D. For example, Germany is stated to suffer from a weak link between public and private research (*Beise and Stahl, 1999*). As *Audretsch and Lehmann (2005, 2006)* show, however, firms with a location close to universities can strongly benefit from spillovers. According to these authors, especially high-tech startups have an advantage from geographic proximity to natural science faculties. Therefore, a refocus of public research spending towards natural science – and not social science – and the creation of business parks close to the faculties of engineering and natural science can be a first step to reach this goal. Private spending on research and development will follow suit once the returns of R&D manage a turnaround.

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Appendix

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

Parameter	Estimate	t-statistic
a_0	1.0730	0.46
a_1	0.9590	6.65***
a_2	0.5503	8.16***
a_3	0.1326	6.90***
a_4	-0.6418	-3.85***
b_1	-0.5092	-0.75
a_{11}	0.0678	4.09***
a_{12}	0.0152	2.92***
a_{13}	0.0018	0.80
a_{14}	-0.0849	-6.12***
a_{22}	0.0561	15.59***
a_{23}	-0.0068	-5.86***
a_{24}	-0.0646	-14.07***
a_{33}	0.0201	26.65***
a_{34}	-0.0151	-6.11***
a_{44}	0.1646	12.60***
c_1	-0.1098	-4.85***
c_2	-0.0781	-7.00***
c_3	-0.0142	-4.87***
c_4	0.2022	7.42***
b_{11}	0.2143	2.20**
d_1	-0.0103	-6.82***
e_1	-0.0028	-5.78***
e_2	0.0004	1.78*
e_3	-0.0003	-4.18***
e_4	0.0027	5.32***
f_1	-0.0931	-1.62*
g_1	0.0720	4.63***
g_2	0.0282	3.91***
g_3	0.0024	1.20
g_4	-0.1027	-5.64***
h_1	0.1178	18.00***
Number of observations		180
R^2		0.99

*, ** and *** represent a significance level of 90%, 95% and 99%, respectively (two-sided).
All calculations were run by GAUSS.

Table A 2: Own and Cross Price Elasticities of Input Demand

Price elasticity of ... with respect to a price increase of...	labor	capital	energy	material
Labor	-0.48			
Capital	0.50	-0.05		
Energy	0.34	-0.22	-0.10	
Material	0.13	-0.03	0.00	-0.10

Arithmetic means for observation period (45 years).