Abstract

This paper investigates the productivity effects of interindustry R&D spillovers from publicly financed business R&D using data of West-German manufacturing industries. We test whether such productivity effects exist and whether they differ from productivity effects of spillovers from privately financed R&D. Our results suggest that it is important to distinguish between the productivity effects of spillovers from privately and publicly financed business R&D. In particular, estimation results of cointegrating regressions provide evidence of positive productivity effects of spillovers from privately financed R&D but fail to confirm a statistically significant effect of publicly financed R&D.

Keywords: R&D expenditures, Technological spillovers, Productivity
JEL Classification: H20,H23,O30,O38

Spillovers from Publicly Financed Business R&D: Some Empirical Evidence from Germany *

Werner Bönte
Universität Hamburg
Department of Economics
Von-Melle-Park 5
D-20146 Hamburg, Germany
e-mail: boente@econ.uni-hamburg.de

April 7, 2003

*The author is indebted to the Science Statistics — an affiliate of the Stifterverband für die Deutsche Wissenschaft — for the provision of data bases. The original version of this paper was presented at the EARIE-conference 2001, Dublin and seminars at the University of Hamburg. The author gratefully aknowledge helpful comments from conference and seminar participants. Any remaining errors are my responsibility.

I Introduction

Economic theory emphasizes the importance of an economy's R&D sector and of knowledge spillovers for long-run economic growth (see Aghion and Howitt (1992), Grossman and Helpman (1991) and Romer (1986, 1990)). These models show that market failures in the market of new goods and ideas may lead to suboptimal investments in business R&D and in turn to suboptimal economic growth. Knowledge spillovers, for example, drive a wedge between private and social rates of return to R&D. The results reported by Jones and Williams (1998) suggest that the level of optimal investment in R&D is much higher than the level of actual investment in R&D. Thus, public support to business R&D could, in principle, eliminate or reduce market failures.

Public R&D subsidies and R&D contracts are an important instrument of governments' technology policy in industrial economies. These are often aimed at particular R&D projects, firms or industries. Such *targeted* forms of public support to business R&D allow governments to decide what R&D projects should be publicly funded.[1] However, Klette et al. (2000: p. 472) state that "*...compared to the size of the programs and the emphasis put on technology policy by politicians, the effort to evaluate in quantitative terms the economic benefits and costs of R&D subsidies has been rather modest.*"[2]

If R&D spillovers were the main justification for public support to business R&D those R&D investments should be publicly financed for which the gap between the private and the social rate of return is large ("the spillover gap").[3] In the case of *targeted* public support, a successful policy means that the support is directed towards those industries, firms or R&D projects which generate knowledge spillovers and increase productivity of the recipient firms. Therefore, one indicator for the evaluation of the success of *targeted* public support to business R&D are the (ex post) measured productivity effects of spillovers from *publicly* financed business R&D.

In empirical literature such spillovers have not been explicitly taken into account until recently.[4] Mamuneas (1999) and Mamuneas and Nadiri (1996) provided empirical evidence for the existence of spillovers from publicly financed R&D performed in U.S. manufacturing industries.[5] In contrast to

[1] In contrast, *untargeted* public support to business R&D, like R&D tax credits or R&D personnel subsidies, are designed to increase all firms' R&D efforts in general. See Aghion and Howitt (1998; chapter 14) for a discussion on the pros and cons of targeted and untargeted R&D subsidies.

[2] Klette at al. (2000) discuss the conceptual problems of such evaluations.

[3] See Jaffe (1998).

[4] See Griliches (1992) for a survey.

[5] Their measure of publicly financed R&D also includes the R&D performed by goverment agents and nonprofit institutions.

previous empirical studies they do not exclusively focus on the direct productivity effects of R&D subsidies and public R&D contracts but they also study the *inter*industry spillovers from publicly financed (business) R&D.[6] From an ex post point of view, their results suggest that the U.S. technology policy has been quite successful in increasing the efficiency of U.S. manufacturing industries via interindustry R&D spillovers from publicly financed R&D.

In this paper we will show that productivity effects of spillovers from publicly financed business R&D may differ from those of privately financed R&D. The productivity effects of spillovers are determined by a "pure productivity effect" and by a "composition effect". The latter is determined by the distribution of publicly and privately financed business R&D across industries and by the composition of the industries' spillover sources. Both effects may be different for publicly and privately financed business R&D. We will investigate these effects empirically for 26 German manufacturing industries.

This paper contributes to the existing empirical literature in three ways: First, to our best knowledge this is the first study which investigates the productivity effects of spillovers from publicly financed business R&D in 2-digit West German manufacturing industries. So far, empirical studies on productivity effects of R&D spillovers in German industry have not examined privately and publicly financed business R&D separately.[7] Second, we estimate the relationship between R&D and productivity using cointegrated panel data. Until now only a few studies on productivity effects of R&D exist which make use of nonstationary panel data analysis.[8] Third, we present an alternative measure of technological association between industries. In contrast to the existing literature we do not use direct I-O linkages between industries to compute weighted R&D stocks from other industries but use the similarity in I-O transaction profiles in order to construct spillover measures.

The remainder of this paper is organized as follows. In the next section we lay out a simple conceptual framework for discussing the (possibly) different productivity effects of interindustry R&D spillovers from privately and publicly financed business R&D. In the third section the econometric specification is explained and in the fourth section data trends are discussed. Estimation results of the standard and nonstationary panel data analysis are presented in section 5. The paper ends with a summary and some concluding remarks.

[6] Direct productivity effects of publicly financed R&D have been examined, for example, by Griliches (1986), Lichtenberg and Siegel (1991) or Mansfield (1980).

[7] See, for example, Bönte (1997) and Harhoff (2000).

[8] See, for example, Frantzen (1998), Kao et al. (1999) and Los and Verspagen (2000).

II Conceptual Framework

One may ask whether in practice publicly financed R&D exhibits the same productivity effects as privately financed R&D. Particularly, two relevant questions are whether knowledge spillovers from privately and publicly financed R&D are identical and what the conditions are under which the differentiation between productivity effects of interindustry spillovers from privately and publicly financed R&D matters? In what follows this question will be addressed in more detail.

Assume that an industry i uses at least some part of the technological knowledge that has been produced by the innovative activities of other industries. These *inter*industry spillover effects are captured by a spillover variable S which enters the production function of industry i:

$$Y_i = f(X_i, S_i) \tag{1}$$

where Y_i is the output of industry i, X_i are industry i's own inputs (e.g. labor, physical capital and the industry's "own" stock of knowledge) and S_i denotes an industry's stock of externally available technological knowledge.

The variable S is assumed to be a function of the other industries knowledge stocks ($W_j, \;\; j \neq i$):

$$S_i = g(W_1, W_2, ..., W_{N-1}), \tag{2}$$

where the knowledge stocks are the result of the industries' R&D efforts in previous periods. If the development of an industry's knowledge stock is related to the source of finance of its R&D activities — here privately and publicly financed R&D — the knowledge production function of industry j can be written as:

$$W_j = h(K_{Pj}, K_{Gj}), \tag{3}$$

where the knowledge stocks that have been produced by privately and publicly financed R&D are approximated by the industries' privately and publicly financed R&D capital stocks (K_{Pj}, K_{Gj}). Think of K_{Pj} and K_{Gj} as the outcome (knowledge) of two different R&D projects.[9]

[9] We do not assume, however, that W_j is necessarily identical with the effective stock of knowledge that is used by industry j. If, for example, the results of a publicly financed R&D project conducted in industry j are irrelevant for the same industry, its effective knowledge stock will be left unchanged. In contrast, other industries may benefit from the results of that project which will increase their effective knowledge stocks. We are interested in the latter (interindustry) effect of publicly financed R&D and do not consider intraindustry effects.

The (different) effects of publicly and privately financed R&D will be discussed now. The effect of a change of privately and publicly financed R&D capital stocks on an industry's stock of knowledge can be expressed as:

$$dW_j = \frac{\partial W_j}{\partial K_{Gj}} dK_{Gj} + \frac{\partial W_j}{\partial K_{Pj}} dK_{Pj}, \tag{4}$$

and the effect on the externally available knowledge stock of industry i is:

$$dS_i = \sum_{j \neq i} \left(\frac{\partial S_i}{\partial W_j} \frac{\partial W_j}{\partial K_{Gj}} \right) dK_{Gj} + \sum_{j \neq i} \left(\frac{\partial S_i}{\partial W_j} \frac{\partial W_j}{\partial K_{Pj}} \right) dK_{Pj} \tag{5}$$

where the partial derivative $\partial S_i / \partial W_j$ is the change of industry i's externally available knowledge stock due to a change in the stock of knowledge of the jth industry. For the sake of simplicity it is assumed that the marginal effects of privately and publicly financed R&D on an industry's knowledge stock are the same for all industries ($\partial W_j / \partial K_{Gj} = \partial W / \partial K_G$; $\partial W_j / \partial K_{Pj} = \partial W / \partial K_P$). Then, we can rewrite equation (5) as follows:

$$dS_i = \frac{\partial W}{\partial K_G} \sum_{j \neq i} \omega_{ij} dK_{Gj} + \frac{\partial W}{\partial K_P} \sum_{j \neq i} \omega_{ij} dK_{Pj} \tag{6}$$

where ω_{ij} is $\partial S_i / \partial W_j$. The marginal productivities of publicly and privately financed R&D with respect to the production of (industry relevant) technological knowledge may differ ($\partial W / \partial K_G \neq \partial W / \partial K_P$).

Why should one expect to find such differences? The productivity of publicly financed R&D may be higher, for example, if publicly financed projects concentrate more on generic R&D while privately financed R&D concentrates on appropriable R&D. In that case, it may be easier for firms in other industries to make use of that knowledge which then expands their technological opportunities. On the other hand, the productivity may be lower if a large part of the knowledge that has been produced by publicly financed R&D is defence related.[10] Moreover, one might argue that x-inefficiency is a more severe problem in publicly financed R&D projects thereby reducing the relative productivity of publicly financed R&D.

To see the effects of a change in privately and publicly financed R&D on the productivity of a spillover receiving industry i, we write the total differential of equation (1) and substitute equation (6) into this expression. Thus, we get:

[10] Of course, it is possible that even this technological knowledge is diffused to the economy as a whole.

$$
\begin{aligned}
dTFP_i &= dY_i - \frac{\partial Y_i}{\partial X_i} dX_i = \frac{\partial Y_i}{\partial S_i} dS_i \\
&= \Theta \sum_{j \neq i} \omega_{ij} dK_{Gj} + \Psi \sum_{j \neq i} \omega_{ij} dK_{Pj} \\
&= \Theta dS_{Gi} + \Psi dS_{Pi}
\end{aligned} \tag{7}
$$

where the left side of the equation is the change in productivity of industry i ($dTFP$)[11] which is determined by the marginal productivity and the change of the externally available stock of knowledge. Note, that the „own" R&D capital stock of industry i does not appear on the right side of equation (7) since it is already included in X. If knowledge spillovers from an externally available knowledge stock exist and increase industry i's output the partial derivative $\partial Y_i / \partial S_i$ will be positive. The parameter Θ reflects the marginal productivity of publicly financed R&D ($\partial Y_i / \partial S_i \cdot \partial W / \partial K_G$) and the parameter Ψ reflects the one of privately financed R&D ($\partial Y_i / \partial S_i \cdot \partial W / \partial K_P$).

Equation (7) points out that the productivity effects of interindustry R&D spillovers from publicly and privately financed R&D may differ at least for two reasons. First, an increase in S_{Gi} will provoke a higher (lower) increase in productivity of the spillover receiving industry compared with an identical increase in S_{Pi} if the marginal productivity of publicly financed R&D capital stocks with respect to the production of (industry relevant) knowledge is higher (lower): $\Theta \lesseqgtr \Psi$. We call this the *pure productivity effect*. Second, they will differ if both are equally productive ($\Theta = \Psi$) but the changes in S_{Gi} and S_{Pi} are different. The last statement is trivial. Nevertheless, it deserves our interest because it highlights one important feature of public support to business R&D, namely the effectiveness of public support. In industrial economies the bulk of public support to business R&D is often targeted to a few industries. Now assume that industries are not equally capable of receiving spillovers from other industries ($\omega_{i1} \neq \omega_{i2} \neq .... \neq \omega_{iN}$). The value of ω_{ij} may be zero or very low for some industries (j). Suppose that, first, a government increases the public support to R&D solely in these industries and second, privately financed R&D increases in all industries. In that case, an identical increase in the overall privately and publicly financed R&D capital stocks ($dK_P = dK_G$) will lead to lower productivity effects of publicly financed R&D. Thus, the composition of the industries' externally available knowledge stocks matters. Therefore, we call this the *composition effect*.

[11] This is the change of ouput which cannot be explained by a change of an industry's own inputs.

III Econometric Specification

The previous theoretical considerations have shown that productivity effects of interindustry R&D spillovers from publicly financed R&D are determined by two effects: the pure productivity effect and the composition effect. The former will be quantified by using econometric estimation techniques and the latter by using a priori information. In what follows we describe the methodology used here.

First, the composition effect is quantified. In line with the majority of empirical studies on R&D spillovers it is assumed that the externally available knowledge stocks are simply the weighted sum of the other manufacturing industries' knowledge stocks:[12]

$$S_{Gi} = \sum_{j \neq i} \omega_{ij} K_{Gj}, \quad S_{Pi} = \sum_{j \neq i} \omega_{ij} K_{Pj}, \tag{8}$$

where ω_{ij} is assumed to be constant over time and $0 \leq \omega_{ij} \leq 1$. This parameter can be interpreted as the effective fraction of knowledge in industry j borrowed by industry i.[13] A value of one and $\omega_{ij} = \omega_{ji}$ means that the whole knowledge stock of each industry j is freely available to industry i and vice versa which implies that technological knowledge is a *pure public good*. In contrast, a value of zero rules out the existence of interindustry R&D spillovers. However, both are extreme cases. To avoid such strong assumptions, we make use of a priori information in order to calculate estimates of ω_{ij}.

In the empirical literature several approaches to the measurement of ω_{ij} exist. Most authors make use either of Input-Output or of patent data to construct measures of ω_{ij}. It is often argued, however, that the use of I-O data will be inadequate if one is interested in the quantification of knowledge spillovers. The latter are not necessarily related to purchases of inputs. The flow of knowledge between two industries may be important though the direct link between industries is small. The I-O measure fails to identify such effects.[14] Thus, measures of technological proximity based on patent data seem to be more useful to measure knowledge spillovers. However, the use of patent data has several shortcomings, too. The main objection to the use of patent data is their poor performance as an indicator of innovative output.

[12] Alternatively, Bernstein and Nadiri (1988) use R&D capital stocks of different industries as separate variables. However, with a growing number of spillover sources (industries) this approach is not really feasible. See Griliches (1992) for a discussion.

[13] See Griliches (1995), p. 65.

[14] See Branstetter (2000) and Griliches (1992) for a detailed discussion.

Not all the innovative output is patented by the industries and the number of patents may not tell much about their economic value.[15] Moreover, industries may have very different propensities to patent. The aerospace industry, for example, seems to have an extremely low propensity to patent compared with other industries. Thus, the number of patents is not a reliable indicator of this industry's innovative output.[16] Unfortunately, this is the industry in our sample to which government allocates the lion share of public support to business R&D.

Another data set which can be used to construct proximity measures is the firms' or industry's distribution of R&D expenditures across product areas.[17] By looking at the German industries' distribution of applied R&D expenditures across product areas we have found for higher-technology industries that these distributions overlap to a very limited extent. These industries spent on average less than 10% of their applied R&D expenditures in other than the industries' own product area. As a result, a proximity measure based on the similarity of such R&D profiles would indicate a low degree of proximity between industries. We think that such a measure is appropriate for firm level studies because there is more variation in the firms R&D profiles but is not very useful for the investigation of German industry level data.

Therefore, we present an alternative measure of proximity here which is based on the industries' input profiles. In contrast to previous studies using I-O data it is not the direct link between two industries that is at the center of interest but the degree of similarity of the input profiles. The correlation between input profiles of two industries is viewed as a measure of their *technological association*.[18] We assume that industries which employ the same types of intermediate inputs have similar production technologies. Of course, the intermediate inputs profile does not fully describe an industry's production technology. However, the combination of intermediate inputs is a relevant part of an industry's production technology. If, for instance, two industries, e.g. plastic products and rubber products industry, make use of an intermediate input purchased from a third industry, e.g. chemical industry, both industries turn this input into outputs and they have an incentive to reduce the costs of this input. Thus, both industries may benefit from each other's process innovations. Moreover, suppliers themselves may be a channel of knowledge spillovers because knowledge may flow from firms of

[15] See Griliches (1990).

[16] See Verspagen and Loo (1999).

[17] See, for example, Goto and Suzuki (1989) and Harhoff (2000).

[18] We have borrowed this idea from empirical studies on the identification of industrial clusters. See Lublinski (2001) for a survey of this literature.

one industry to firms of other industries via common suppliers.[19] Therefore, we argue that a high degree of similarity between input profiles may ease knowledge spillovers between industries.

The proximity measure is computed as follows. The value of intermediate inputs of the industries is disaggregated into the values of demands for the goods of N industries. Let a_i be a vector of the N shares of the value of individual intermediate inputs in the value of total intermediate inputs of industry i. The technological association between two industries can be approximated by the centered correlation coefficient (p_{ij}) between the vectors a_i and a_j of each pair of industries:

$$\omega_{ij} = p_{ij} = \frac{a_i\, a_j'}{\sqrt{(a_i a_i')(a_j a_j')}} \tag{9}$$

In contrast to traditional I-O weights this measure is symmetric ($p_{ij} = p_{ji}$), which implies that the effective fraction of knowledge in industry j borrowed by industry i is equal to the fraction of knowledge in industry i borrowed by industry j.[20] One may ask whether this assumption is realistic. According to the arguments presented above symmetry arises because similar production technologies allow the industries to benefit from each others' process innovations. Let us come back to our example of rubber and plastic products. It is likely that firms of the rubber products industry benefit as much from firms of the plastic products industry as vice versa since firms may imitate each other's process innovations. We take these industries to demonstrate the difference between the traditional I-O measure and the proximity measure used in this study. The former indicates low knowledge flows between the rubber and the plastic product industries ($\omega_{ij}, \omega_{ji} < 0.01$), whereas the latter suggests a remarkable potential for knowledge spillovers ($\omega_{ij} = 0.53$).

Though German statistical office provides data that allow us to calculate vectors containing 56 value shares of intermediate inputs we restrict the vector to the shares of 32 manufacturing industries. This is done to avoid that technologically dissimilar industries exhibit a high degree of technological association due to similarities in non-manufacturing purchases.[21]

The next step is the specification of the relationship between an industry's

[19] The latter are interested in a broad diffusion of process innovations among their customers.

[20] Such symmetric weights have also been assumed, for example, by Jaffe (1986) and Harhoff (2000).

[21] If, for example, two industries exhibit similar shares of services from the financial sector this does not coincide with our understanding of technological association.

level of productivity and interindustry R&D spillovers. First, we investigate whether there is any empirical evidence of interindustry R&D spillovers irrespective the source of finance. To do so, we use the following estimation equation and include the spillover variable S, which is simply the weighted sum of the manufacturing industries' *total* R&D stocks ($S_{it} = S_{Git} + S_{Pit}$):

$$\ln TFP_{it} = \mu_0 + \gamma \ln S_{it-3} + u_{it}, \qquad (10)$$

where parameter γ is the the elasticity of the industry's TFP with respect to the externally available knowledge stock and u_{it} is a disturbance term. The R&D capital stocks are lagged 3 years to allow for lags due to the diffusion of technological knowledge. Mansfield (1985) found that detailed information concerning new products and processes is known to the rivals within about a year. It is likely that knowledge transfer between different industries needs even more time. In addition, there will be a lag between knowledge transfer and commercial application.

To investigate the different productivity effects of publicly and privately financed R&D spillovers the two variables are included separately:[22]

$$\ln TFP_{it} = \mu_0 + \alpha \ln S_{Git-3} + \beta \ln S_{Pit-3} + u_{it}, \qquad (11)$$

where the parameters α and β represent the elasticities of the industry's TFP w.r.t. the publicly and privately financed R&D capital stocks S_{Git} and S_{Pit} and u_{it} is a disturbance term. If publicly (privately) financed R&D exhibits positive R&D spillovers one would expect to observe a positive and statistically significant estimate of the parameter α (β).

IV Data

The data used in this study consist of gross output, intermediate inputs, labor, physical and R&D capital for 26 (two digit) West-German manufacturing industries over the years 1979 to 1993.[23] R&D expenditure data at the industry level (three digit Wirtschaftszweige (WZ) level) are based on the surveys of the *Science Statistics*, an affiliate of the Stifterverband für die Deutsche Wissenschaft (a private non-profit organization), that are conducted every two (odd) years.[24] The R&D data contain industry-specific

[22] All variables are normalized to one for the year 1987.

[23] Because of data problems six industries had to be excluded from the sample. For these industries there are either no consistent price indices or data are not available (mineral oil refining, shipbuilding, aircraft, tobacco, beverages, leather and leather goods).

[24] R&D data collected by the *Science Statistics* form the basis for the national statistics on business R&D activities in Germany as well as for statistics of international institutions

information on total, privately and publicly financed R&D expenditures of the firms. In the questionnaire of the *Science Statistics* firms are asked for the sources of finance of their R&D expenditures. This measure of publicly financed R&D contains direct (project oriented) R&D subsidies as well as public R&D contracts and reveals (targeted) public support to business R&D from the performer's point of view.[25] The observation period begins in 1979 and ends in 1993 because of limited comparability with R&D data of the preceding and the following years.[26]

Data on gross output, intermediate inputs, employment and investment in physical capital are obtained from the yearly disaggregated (two digit SYPRO level) national income accounts (Statistisches Bundesamt, Fachserie 18). Industry-specific data on the average yearly hours worked are taken from the Statistics of the Institut für Arbeitsmarkt- und Berufsforschung (IAB). Compatibility with the R&D data is ensured since the industrial classification of the R&D data can be transferred to the industry classification of the national income accounts. For more detailed information on the data sources and the construction of the variables refer to appendix A.

insert table [1] about here

Table 1 presents the growth rates of the externally available R&D capital stocks.[27] Weighted as well as unweighted measures are reported to give first insights into the effects of different weighting schemes. As can be seen from table 1 a very different picture of the development of externally available R&D capital stocks emerges from the different weighting schemes. The unweighted R&D capital stocks exhibit similar growth rates across industries and therefore the variation between industries is relatively small.[28] However, the growth rate of the unweighted publicly financed R&D capital stocks is

(e.g. OECD statistics).

[25] In the questionaire firms are explicitely instructed not to include *in*direct R&D subsidies, like R&D personnel subsidies.

[26] In the year 1979 additional small and medium-sized firms — identified in the Federal R&D Incentive Programme — entered the survey which lead to a remarkable increase of measured R&D expenditures. The data of total R&D expenditures from 1991 onwards refer to unified Germany. Especially for this study the *Science Statistics* has kindly carried out an analysis of the data to estimate the total R&D expenditures of West-German manufacturing industries for the years 1991 and 1993.

[27] Because of data problems six industries had to be excluded from the sample but they are included in the computation of R&D capital stocks. (mineral oil refining, shipbuilding, aircraft, tobacco, beverages, leather and leather goods).

[28] This is not surprising since the only difference between the industries' spillover measures is each industry's own R&D capital stock which is excluded from the aggregate R&D capital stock.

0.3% on average and much lower compared to the growth rate of unweighted privately financed R&D (3.1%) which is due to the differences in the development of publicly and privately financed R&D expenditures. The growth rates of the weighted R&D capital stocks are, in contrast, not that similar. This is especially true for the publicly financed R&D capital stocks where the growth rates range from -1.55% to 0.79. The privately financed R&D capital stocks do also show more variation compared to the unweighted R&D capital stocks but here all growth rates are still positive. Taken together, weighting does strongly affect the measured growth rates of the spillover measures.

Since the unweighted spillover measure implies that all industries are equally capable of receiving R&D spillovers from all other industries (complete diffusion) differences between this measure and the weighted spillover measure give a hint on the relevance of the composition effect. In our sample the remarkable differences between the weighted and unweighted spillover measure of publicly financed R&D are due to the highly skewed distribution of the public support to business R&D. During the observation period the aerospace industry had the largest share (approximately 46%) in the publicly financed R&D capital stock of all manufacturing industries.[29] However, according to the measure of technological proximity used here, the knowledge of this industry spills over to a small group of high- and medium-high-technology industries whereas industries which have a very small technological association with the aerospace industry are not equally capable of gaining from R&D efforts of that industry.[30] Thus, the unweighted spillover measure is dominated by the development of R&D efforts in the aerospace industry while the weighted measure is not or to a lesser extent. Moreover, the development of the industries' publicly financed R&D capital stocks is very different. The publicly financed R&D capital stock of the aerospace industry, for example, has increased by approximately 25% during the observation period while the stocks of electrical engineering (36) and mechanical engineering (32) industries have decreased by roughly 18% and 20%.[31] Thus, the *composition effect* described in the previous section reduces the potential growth effects of publicly financed R&D drastically.

[29] The highest shares thereafter are those of electrical engineering (26%), chemical industry (7%) and mechanical engineering (7%).

[30] In most of the medium-low and low-technology industries the degree of technological association with the aerospace industry is below 0.05. But even for higher-technology industries it does not exceed a value of 0.3. This is far below a value of one which is implicitely assumed for unweighted R&D stocks.

[31] Of course, one can always obtain non-negative growth rates if the choosen deprecition rate of the R&D capital stocks is sufficiently small. See appendix A for the construction of the variables.

V Estimation

A Standard Panel Data Analysis

In this section the productivity effects of R&D spillovers from publicly financed R&D are investigated by using standard panel data analysis where the disturbance term u_{it} is specified as the sum of an unobservable industry-specific effect (μ_i) and a remainder disturbance (ν_{it}): $u_{it} = \mu_i + \nu_{it}$ and ν_{it} is i.i.d $(0, \sigma^2)$. The industry-specific effects are treated as fixed and control for time invariant effects, e.g. omitted variables and misspecifications.[32]

Each industry's own R&D capital stock K is included into the regressions to reduce the potential omitted variables problem. One reason for the inclusion are potential intraindustry R&D spillovers.[33] If they exist the level of total factor productivity will depend on the level of the industry's own knowledge stock. A statistically significant coefficient can be interpreted as empirical evidence of excess returns to the industries' own R&D.[34] One might expect that the impact of interindustry R&D spillovers may be higher for higher-technology industries than for less sophisticated industries because firms in higher-technology industries may have better opportunities to make use of knowledge flows from external sources.[35] Harhoff (2000), for example, reports that productivity effects from R&D spillovers differ between German firms in high-technology industries and those in other industries. Los and Verspagen (2000) have found that R&D spillovers have a positive impact on productivity of U.S. manufacturing firms and that the magnitude of this effect depends on a firm's (industry's) level of technology.

Therefore, we investigate whether differences between groups of industries with different levels of technology exist. The assignment to a level of technology is based on a revised version of the OECD's classification (high-, medium- and low-technology) where the medium-technology group is further disaggregated into two sub-categories: medium-high- and medium-low-technology (see table 1).[36] Since the level of aggregation in our data does not allow us to distinguish between high-technology and medium-high technology industries these categories are merged. We call this group of industries the higher-technology industries. Analogous, the medium-low and low-

[32] See Baltagi (1995).

[33] See Griliches (1995).

[34] For the computation of TFP index it was assumed that R&D exhibits the same rate of return as physical capital stocks.

[35] Cohen and Levinthal (1989) have argued that firms have to built up an absorptive capacity in order assimilate and exploit externally available knowledge.

[36] R&D intensity — the ratio of R&D expenditures to output — is the main criterion for classification. See Hatzichronoglou (1997) for further details.

technology-industries are merged. This group of industries is called the lower-technology-industries. We allow for differences between these two groups of industries by estimating a dummy variable model.[37]

The estimation results for equation (10) are presented in columns (1) and (2) of table 2. In column (1) the estimated coefficient of the spillover variable (S) is 0.303 and its conventional t-statistic is significantly large. The value of the estimated coefficient of the industries' *own* R&D capital stocks (K) as well as its t-statistic are much lower but still significant according to the conventional t-values. Next, we investigate whether differences between the two groups of industries exist. The results suggest that the impact of own R&D is significantly higher in higher-technology industry whereas the impact of interindustry R&D spillovers is significantly higher in lower-technology industries (see column (2)). The estimated coefficient of the spillover variable is even negative for the group of higher technology-industries. We turn now to the estimation results for equation (11) which are reported in columns (3) and (4) of table 2. The value of the estimated coefficient of privately financed R&D capital (S_P) is 0.276 and its t-value is 9.15. The value of the estimated coefficient of publicly financed R&D capital (S_G) is similar (0.24) but its t-value is much lower (2.64). Again, we allow for differences between the two groups of industries (see column 4). The results indicate that the impact of interindustry spillovers from privately financed R&D is significantly higher in lower-technology industries compared with higher-technology industries where the estimated coefficient negative. R&D spillovers from publicly financed business R&D do not seem to have any impact on productivity for both groups of industries.

insert table [2] about here

The results concerning the impact of R&D spillovers on productivity of higher-technology industries contradict our expectations. One explanation for this result may be the fact that the "computer" industry (50) is a clear outlier with respect to productivity growth. During the observation period this industry has experienced a much stronger productivity growth than other higher-technology industries. At the same time, the development of the spillover variables was very similar in higher-technology industries. This may lead to a negative correlation between productivity and interindustry R&D spillovers for the group of higher-technology industries. Therefore, we

[37] The spillover variables are interacted with a dummy variable that takes on the value of one for the group of lower-technology industries (medium-low and low-technology) and zero for the group of higher-technology industries (high-technology and medium-high-technology).

have excluded this industry from our sample and have reestimated equations (10) and (11) with a sample of 25 industries in order to check the robustness of results.

As can be seen from table 3, results change when the "computer" industry (50) is excluded. First, the value of the estimated coefficient of own R&D is no longer statistically significant irrespective whether we allow for differences between higher-technology industries and other industries or not. Second, the estimated coefficient of the spillover variable is now positive for higher-technology industries. But it is still statistically insignificant and there is still some empirical evidence for a difference between higher-technology industries and other industries with respect to the productivity effects of R&D spillovers (see column (3)). Third, the estimate of the coefficient of the spillover variable S_G as well as its t-value are much lower compared with the results presented above (see column (3)). However, the estimated coefficient of S_G is still statistically significant at the 5% level.

In order to check the robustness of our results, we have also investigated whether the exclusion of other higher-technology industries has a similar effect on estimation results but we have found that the results are hardly affected. Moreover, we have included the capacity utilization rate of the manufacturing sector to control for common business cycle effects because the revenue based measure of total factor productivity as well as the R&D variables may be affected by demand shocks, for instance. Again, results do not change.[38]

insert table [3] about here

B Nonstationary Panel Data Analysis

The validity of the standard panel data analysis rests on the assumption that the individual time series are stationary. However, since most of the data used in this study exhibit a clear trend we can not rule out the possibility that the data are nonstationary and that the results presented above are entirely spurious.[39] Since the results of a nonstationary panel data analysis may be very different from those of the standard panel data approach, we will present the results of such an analysis in this section.[40] The results are

[38]Industry-specific capacity utilization rates have also been used but estimation results are not affected. The capacity utilization rates are obtained from the Ifo Institute for economic research.

[39]Recently, this problem has gained a growing interest in the literature on panel data analysis. See Banerjee (1999) for an overview.

[40]This has been shown, for example, by Kao et al. (1999) who applied a nonstationary panel data analysis to Coe and Helpman's (1995) international R&D spillovers regression.

computed using NPT 1.3 for GAUSS (Chiang and Kao (2002)).

First, we present the results of panel unit root tests. We have used a test proposed by Im et al. (1997) which is based on the average of the (industries') augmented Dickey-Fuller (ADF) statistics. The results are reported in table 4. The null hypothesis that the productivity measure and the R&D capital stocks have a unit root can not be rejected at the 5% level of sigificance.[41] Thus, we assume for the further analysis that all variables have a unit root.

insert table [4] about here

Cointegration tests for panel data proposed by Pedroni (1995) and Kao (1999) are conducted to investigate whether the estimated equations are cointegrated or not.[42] Results of the tests are reported in table 5 where the upper half of the table presents the results of the full sample and the lower half those of the sample without the "computer" industry. As can be seen from the upper half of the table, the null hypothesis of no cointegration is rejected by Pedroni's tests but is failed to reject by Kao's augmented Dickey-Fuller type at least for columns (1) and (3). If the (outlier) "computer" industry is excluded from the sample all tests reject the null hypothesis at a 5% level of significance (see lower half of the table). These results suggest that the estimation equations are indeed cointegrated at least for the sample without the computer industry.

insert table [5] about here

Since the usual t-statistics based on standard OLS estimates are not valid if panel data are nonstationary, we make use of the DOLS and the FMOLS estimator which provide asymptotically unbiased estimates (see Kao and Chiang (2000)).[43] The equations (10) and (11) have been estimated by using these estimators. We present the estimation results for the sample without the "computer" industry in table 6 because cointegration can not be rejected for this sample.

insert table [6] about here

[41] It is fair to say that a low power of panel unit root tests may be a problem in panels with short time dimension. However, our results are in line with the findings of Coe and Helpman (1995) and Frantzen (1998), for example, who have also found that time series of TFP and R&D capital stocks are nonstationary.

[42] See Chiang and Kao (2002) and Pedroni (1995).

[43] See appendix B for a more detailed description of these estimators.

The DOLS and the FMOLS estimator yield similar results in most cases. The results provide clear empirical evidence for positive productivity effects of interindustry R&D spillovers. The value of the estimated coefficients of the spillover variable S are 0.24 and 0.29 and statistically significant at the 1% level (see columns (1a) and (1b)). There is also clear empirical evidence for a positive impact of R&D spillovers from privately financed business R&D whereas R&D spillovers from publicly financed R&D do not have a statistically significant effect on productivity. The estimated coefficients of S_P range from 0.213 to 0.319 and they are statistically significant at the 1% level (see columns (3a) and (3b)) which confirms the result of the standard panel data analysis. In contrast, the estimated coefficients of the variable S_G are now statistically insignificant at the 5% level. The estimation of the dummy variable model does not change this result. Again, the coefficient of S_G is statistically insignificant and results suggest that no difference between higher- and lower-technology industries exists. The results are less clear-cut for productivity effects of R&D spillovers from privately financed R&D. The FMOLS estimate suggest that a difference between higher-technology and lower-technology industries does not exist while the DOLS estimate indicates that the estimated coefficient of the variable S_p of the lower-technology group is higher than that of the group of higher-technology industries (see column 4a and 4b). One reason for this result may be the fact that our technology classification is very crude due to data restrictions.[44] Therefore, we think that the results reported in columns (3a) and (3b) are more reliable.

We have also applied the DOLS and FMOLS estimator to the full sample (including "computer" industry) and the results are very similar. In particular, the estimated coefficient of the publicly financed R&D capital stock is statistically insignificant. To save space these results are not presented here but they are available from the author upon request.

All in all, the results provide strong empirical evidence for positive productivity effects of interindustry R&D spillovers. However, the positive effects of interindustry R&D spillovers seem to have their origins in privately rather than in publicly financed R&D, since the estimation results do not reject the hypothesis that *no* linkage between total factor productivity and R&D spillovers from publicly financed R&D capital exists.

[44] Our technology-classification is based on the two-digit (SYPRO) classification. Firm level studies, like the studies of Harhoff (2000) and Los/Verspagen (2000), can make use of more detailed classifications, e.g. four digit classification.

VI Conclusion

In this paper the productivity effects of interindustry R&D spillovers from publicly financed business R&D have been investigated for West-German manufacturing industries. These productivity effects are determined by the marginal product of the publicly financed knowledge stock (pure productivity effect) and the knowledge diffusion across industries. The latter depends on the composition of the industries' spillover pools and the distribution of public support to business R&D across industries (composition effect).

Empirical results suggest that in German industry the potential growth effects of public support to business R&D are drastically reduced by the composition effect. According to our measure of technological association, a large part of knowledge which has been generated by public support to business R&D does not diffuse across industries. Moreover, results show remarkable variations in the compostion effect between industries. While the externally available knowledge stock that has been publicly financed grows in almost all higher-technology industries most of the lower-technology industries have experienced a decrease.

The second, more relevant question is whether the marginal product of R&D spillovers from publicly financed business R&D is positive at all. The estimation results of a standard panel data analysis provide empirical evidence of positive and statistically significant productivity effects of spillovers from publicly financed business R&D. The results change, however, when estimation methods of cointegrating regressions in panel data are applied to the sample. They still confirm a positive impact of interindustry R&D spillovers from privately financed R&D but fail to confirm a statistically significant effect of publicly financed R&D.

Reading the estimation results literally, they imply that the German technology policy has been rather unsuccessful in increasing the efficiency of West-German manufacturing industries via interindustry R&D spillovers. However, measurement problems should keep us from drawing definitive conclusions. It is implicitly assumed in this study — as in previous empirical studies — that R&D projects are exclusively financed either by firms or by the government. This differentiation may, however, be somewhat artificial since most of the publicly supported R&D projects performed in the industry may not be exclusively financed by the one or the other. In addition, the primary aim of publicly financed R&D may not be an increase in efficiency of private production but better health care or an increase in the level of national security.

Nevertheless, our results suggest that it is important to distinguish between productivity effects of R&D spillovers from privately and publicly financed business R&D. It would be desirable to distinguish various types of public R&D, such as health or defense related R&D. Unfortunately, our data do not provide information about these types of R&D and therefore this is left for future research. Another direction for future research are international comparative studies which could provide valuable insights since countries differ remarkably with respect to the governments' technology policy.

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A Data

The publicly and privately financed R&D capital stocks (K_G, K_P) of industry i in period t are constructed by the perpetual inventory method:

$$K_{Xit} = \sum_{\tau=0}^{\infty} I_{Xit-\tau}(1-\sigma_K)^{\tau} = I_{Xit} + (1-\sigma_K)K_{Xit-1}, \tag{12}$$

where I_{Xit} represents the publicly (privately) financed real R&D expenditures (X=G,P). The constant depreciation rate of R&D capital σ_K is assumed to be 15 per cent which is in line with the majority of empirical studies using this approach.

Computation of R&D stocks requires rather long series of real R&D expenditures for each industry. To estimate an industry's total R&D capital stock of the year 1979 R&D expenditures of the years 1971 to 1978 are used.[45] The benchmark for K in the year 1970 is computed by the ratio of R&D expenditure in year 1971 divided by the sum of the depreciation rate and the (pre-sample) growth rate of R&D.[46] We assume that the latter is equal to the growth rate of physical investment in the preceding decade. Real R&D expenditures equal nominal R&D expenditures divided by a R&D deflator. We construct an R&D deflator for each industry as a Thörnqvist index of price indices of intermediate inputs, wages and investment for the years 1979 to 1993 which we link with a price index of wages of the years 1971-1979.

Since the survey is conducted every two years there are missing observations in the years between the surveys. For those years only data of planned total R&D expenditures exist.[47]To estimate the privately and publicly R&D expenditures of these years we proceed as follows: Firstly, we calculate the arithmetic mean for the two adjacent years. Secondly, privately and publicly financed R&D expenditures of those years are estimated by multiplying the total R&D expenditures by the estimated ratio.

Official statistics do not contain real gross output and real intermediate inputs series at the industry level. Therefore, we have constructed industry-specific price indices to convert nominal output and nominal intermediate inputs in real output and real intermediate inputs. The output (intermediate inputs) price index for each industry has been obtained as follows: First we used a disaggregated output (input) table for 1990 to obtain weights for the respective bundle of goods (intermediate inputs) in each of the 26 industries.[48] Then the price index for each industry's gross output (intermediate inputs) were calculated as the weighted sum of official producer (intermediate input) price indices.[49]

Indices of labor input have been constructed for each industry using data on hours worked and compensation per hour. Individual labor inputs are classified by the employment status: blue-collar workers, white-collar workers and self employed persons. Physical capital input is measured as an index of two physical capital inputs: equipment and structures.[50]

[45]Because consistent data of privately and publicly financed R&D expenditures are not available for these years we assume that the share of privately financed R&D in total R&D is equal to the share of the year 1979.

[46]See Hall and Mairesse (1995), p. 270.

[47]Responding firms estimate their R&D expenditures or the growth rate for the year following the survey.

[48]These tables are taken from Fachserie 18, Reihe 2, Statistisches Bundesamt.

[49]Producer (output) price indices (domestic and foreign sales) were obtained from Fachserie 17, Reihe 2 and 8 (Statistisches Bundesamt). The Federal Statistical Office kindly provided the disaggregated intermediate input price indices.

[50]See Jorgenson et al. (1987) for a detailed description of the methodology.

Among others, Schankerman (1981) points out that double-counting of R&D inputs may produce biased estimation results.[51] To avoid this problem we have corrected the inputs and their revenue shares for R&D by using the industry-specific information on the composition of internal R&D expenditures (personnel expenditures, investment, other current expenditures). Intermediate inputs of each industry have been corrected for R&D inputs by subtracting internal R&D expenditures related to “other current R&D expenditures” (material) from total expenditures on intermediate inputs. In this study the labor input used in production comprises the inputs of blue-collar workers, white-collar workers and self employed persons. For the R&D correction of the labor input we have assumed that mainly white-collar workers are engaged in R&D.[52] The hours worked in R&D — calculated by dividing the R&D expenditures related to R&D personnel by the industry-specific white-collar hourly wage — were subtracted from the yearly total hours worked by white-collar workers. Through this correction the revenue share of white collar workers is reduced by the amount of R&D expenditures spent on R&D personnel. The correction of physical capital input and its revenue share is more difficult. We have assumed that investment related to R&D is mainly investment in equipment. Corrected capital stocks of equipment have been constructed for each industry by subtracting R&D related investment from investment in equipment and apply the perpetual inventory formula to the R&D corrected real investment in equipment.[53]

The index of total factor productivity used in this study is defined as the ratio of real gross output to a Thörnqvist index of total input (V_{it}). Annual growth rates of aggregate input in the *ith* industry are defined as follows:

$$\ln\left(\frac{V_{it}}{V_{it-1}}\right) = \sum \overline{w}_{li} \ln\left(\frac{X_{lit}}{X_{lit-1}}\right) . \qquad (13)$$

where X is the quantity of input l. In contrast to other empirical studies, R&D capital is explicitly included in the calculation of an industry's total factor productivity ($l = Z, L, C, K$). Total input growth is the weighted sum of individual input growth rates where the weights ($\overline{w}$) are the average revenue shares of inputs ($\overline{w}_{li} = 0.5\,[\,w_{lit} - w_{lit-1}]$). The input index is computed

[51] Without correction R&D inputs would be double counted since they are already included in intermediate inputs, labor and physical capital.

[52] This is supported by the data of the *Science Statistics*. According to these data, approximately 70% of the R&D personnel in German manufacturing industries are scientists, engineers or technicians. See Science Statistics (1996), table 16.

[53] Capital stocks of structures have also been computed by using the perpetual inventory method. Depreciation rates of equipment and structures at the industry level were computed from disaggregated national income accounts. The initial capital stocks are the net capital stocks of the year 1970 taken from the disaggregated national income account.

from these growth rates and normalized to one in the year 1987.[54] Assuming constant returns to scale, perfect competition and profit maximization an industry's property compensation can be computed as the difference between the value of output and the sum of (R&D corrected) expenditures on intermediate inputs and labor. Since each industry has three assets (structures, equipment and R&D capital) this residual is equal to the sum of the values of their capital services. Following Jorgenson et al. (1987) user costs of capital are calculated assuming an identical ex post rate of return for all assets.[55]

B FMOLS and DOLS Estimator

The standard time-invariant panel model is:

$$y_{it} = \alpha_i + x_{it}'\beta + u_{it,} \quad i = 1, ..., N, \; t = 1, ..., T, \tag{14}$$

where α_i are the "fixed effects" and $u_{it,}$ are the stationary disturbance terms. In contrast to standard panel data analysis, it is now assumed that all explanatory variables (x) are integrated of order one I (1) for all i:

$$x_{it} = x_{it-1} + \varepsilon_{it}.$$

Given this specification, the equation (14) states that y_{it} is cointegrated with x_{it} where β is the cointegrating vector. It is assumed that the explained and explanatory variables are independent across cross-sectional units.[56] The FM estimator of β, β_{FM} is:

$$\widehat{\beta}_{FM} = \left[\sum_{i=1} \sum_{t=1} (x_{it} - \overline{x}_i)(x_{it} - \overline{x}_i)' \right]^{-1} \left[\sum_{i=1} \left(\sum_{t=1} (x_{it} - \overline{x}_i)\widehat{y}_{it}^{+} - T\widehat{\Delta}_{\varepsilon u}^{+} \right) \right], \tag{15}$$

where $\widehat{\Delta}_{\varepsilon u}^{+}$ corrects for serial correlation and $\widehat{y}_{it}^{+}$ corrects for endogeneity. The

DOLS estimator of β (β_{DOLS}) can be obtained from the estimation of the following equation:

$$y_{it} = \alpha_i + x_{it}'\beta + \sum_{j=-q_1}^{q_2} c_{ij}\Delta x_{it+j} + \upsilon_{it.} \tag{16}$$

[54] The TFP index is also normalized to one in the year 1987.

[55] For a detailed description of the construction of the TFP index see Bönte (2002).

[56] For a detailed discussion of the assumptions see Kao and Chiang (2000).

where the lagged and lead values of the first difference of the explanatory variables are included.

Table 1: Average Annual Growth Rates of the Spillover Variables (1980 -1993 for 26 West-German Manufacturing Industries))

Industries$^{a)b)}$	(1)	(2)	(3)	(4)
HIGH-TECHNOLOGY AND MEDIUM-HIGH-TECHNOLOGY	S_G	S_{Gu}	S_P	S_{Pu}
Electrical Engineering, (36)	0.79	0.58	2.81	2.92
Precision and Optical Instruments (37)	-0.05	0.28	2.80	3.13
Mechanical Engineering (32)	0.28	0.34	3.24	3.27
Office Machinery and Data Process. Equip. (50)	0.15	0.30	2.85	2.94
Chemical Industry (24/40)	0.53	0.63	2.75	3.60
Manuf. of Road vehicles (33)	0.12	0.40	2.58	2.70
MEDIUM-LOW- AND LOW-TECHNOLOGY				
Manurfacture of Tools (38)	-0.34	0.15	2.50	3.07
Iron and Steel Industry (27)	0.60	0.38	2.88	3.14
Manufacture of Structural Metal Products (31)	0.02	0.23	2.63	3.08
Non-Ferrous Metal Industry (28)	0.12	0.28	2.35	3.12
Manufacture of Ceramic Goods (51)	-1.00	0.27	2.12	3.10
Drawing Plants, Cold Rolling Mills etc. (30)	0.05	0.24	2.51	3.08
Manufacture and Processing of Glass (52)	-0.82	0.27	2.25	3.08
Manufacture of Rubber Products (59)	-1.33	0.28	2.24	3.09
Manufacture of Plastic Products (58)	-1.55	0.27	1.96	3.10
Foundries (30)	-0.15	0.27	2.39	3.10
Stone and clay (25)	-0.75	0.27	2.24	3.11
Manufacture of Music Instr., Toys (39)	-0.35	0.27	2.35	3.10
Manufacture of Wood Products (54)	0.05	0.27	2.74	3.10
Textile Industry (63)	-1.55	0.28	2.00	3.14
Processing of Paper and Board (56)	-1.13	0.28	2.11	3.10
Manufacture of Pulp, Paper and Board (55)	-1.25	0.27	2.06	3.10
Wood Working (53)	-1.08	0.27	2.11	3.10
Food Industries (68)	-0.80	0.27	2.28	3.08
Printing and Duplicating (57)	-1.4	0.27	2.03	3.10
Clothing Industry (64)	0.02	0.27	1.80	3.1

Notes: Technology Classification is based on a revised OECD Classification, see Hatzichronoglu (1997). Numbers in parentheses are industry classification (SYPRO). S_G and S_{Gu} denote the weighted and unweighted sum of the publicly financed R&D capital stocks of other manufacturing industries. S_P and S_{Pu} denote the weighted and unweighted sum of the privately financed R&D capital stocks of other manufacturing industries.

Table 2: Interindustry R&D Spillovers and Total Factor Productivity (Pooled data 1982-1993 for 26 West-German Manufacturing Industries)

Dependent Variable: ln(Total Factor Productivity)

	(1)	(2)	(3)	(4)
$\ln K$	0.056	0.519	0.050	0.522
	(3.03)	(10.27)	(2.71)	(10.26)
$\ln S$	0.303	-0.221	—	—
	(9.26)	(-2.92)		
$\ln S_P$			0.276	-0.221
			(9.15)	(-1.90)
$\ln S_G$			*0.240*	*0.060*
			(2.64)	*(0.17)*
$D_{ML} \ln K$		-0.520		-0.527
		(-9.73)		(-9.83)
$D_{ML} \ln S$		0.552		
		(6.70)		
$D_{ML} \ln S_P$				0.547
				(4.54)
$D_{ML} \ln S_G$				*0.265*
				(0.72)
R^2	0.359	0.512	0.373	0.529

Notes: The conventional t-statistics are reported in parantheses. Number of observations: 312. All regressions include unreported industry-specific dummies. K is the industry's own R&D capital stock lagged one year. S is the weighted sum of the total R&D capital stocks of other manufacturing industries, lagged 3 years. S_G is the weighted sum of the publicly financed R&D capital stocks of other manufacturing industries, lagged 3 years. S_P is the weighted sum of the privately financed R&D capital stocks of other manufacturing industries, lagged 3 years. D_{ML} is the dummy variable of medium-low and low-technology industries.

Table 3: Interindustry R&D Spillovers and Total Factor Productivity (Pooled data 1982-1993 for 25 West-German Manufacturing Industries; without "computer" industry)

Dependent Variable: ln(Total Factor Productivity)

	(1)	(2)	(3)	(4)
$\ln K$	-0.0001	0.048	-0.002	0.051
	(-0.005)	(0.63)	(-0.14)	(0.68)
$\ln S$	0.284	0.11		
	(10.81)	(1.43)		
$\ln S_P$			0.260	0.074
			(10.65)	(0.64)
$\ln S_G$			*0.134*	*0.128*
			(1.80)	*(0.39)*
$D_{ML} \ln K$		-0.048		-0.056
		(-0.63)		(-0.73)
$D_{ML} \ln S$		0.210		
		(2.48)		
$D_{ML} \ln S_P$				0.251
				(2.12)
$D_{ML} \ln S_G$				*0.197*
				(0.59)
R^2	0.341	0.366	0.346	0.395

Notes: The conventional t-statistics are reported in parantheses. Number of observations: 300. All regressions include unreported industry-specific dummies. K is the industry's own R&D capital stock lagged one year. S is the weighted sum of the total R&D capital stocks of other manufacturing industries, lagged 3 years. S_G is the weighted sum of the publicly financed R&D capital stocks of other manufacturing industries, lagged 3 years. S_P is the weighted sum of the privately financed R&D capital stocks of other manufacturing industries, lagged 3 years. D_{ML} is the dummy variable of medium-low and low-technology industries.

Table 4: Results of Panel Unit Root Tests (based on Im et al. (1997), t-bar test)

		t-bar statistic*)	critical probability
productivity	$\ln TFP$	0.611	0.27
own R&D	$\ln K$	0.079	0.47
total spillover	$\ln S$	-1.267	0.10
privately financed	$\ln S_P$	-0.655	0.26
publicly financed	$\ln S_G$	1.511	0.07

Notes: *) This is the standardized t-bar statistic (see Im et al. 1997). One lagged first difference and a time trend included. Tests are computed by using GAUSS library NPT 1.3 developed by Chiang and Kao (2002).

Table 5: Results of Panel Cointegration Tests

Panel Cointegration Tests (26 industries)[a)]	(1)	(2)	(3)	(4)
Pedroni (1995) PC_1	-13.007	-15.694	-13.129	-15.999
	(0.000)	(0.000)	(0.000)	(0.000)
Pedroni (1995) PC_2	-12.454	-15.026	-12.570	-15.3186
	(0.000)	(0.000)	(0.000)	(0.000)
Kao-ADF (1999)	-0.821	-2.028	-0.871	-2.211
	(0.206)	(0.021)	(0.192)	(0.013)
Panel Cointegration Tests (25 industries)[b)]	(1)	(2)	(3)	(4)
Pedroni (1995) PC_1	-15.297	-15.819	-15.269	-16.189
	(0.000)	(0.000)	(0.000)	(0.000)
Pedroni (1995) PC_2	-14.646	-15.146	14.619	-15.499
	(0.000)	(0.000)	(0.000)	(0.000)
Kao-ADF (1999)	-2.001	-2.299	-1.994	-2.526
	(0.023)	(0.011)	(0.023)	(0.006)

Notes: Critical probabilities are reported in parentheses. a) Columns contain the results of cointegration tests based on the residuals of the regressions that are reported in columns with the same numbers in table 2. b) Columns contain the results of cointegration tests based on the residuals of the regressions that are reported in columns with the same numbers in table 3. Tests are computed by using GAUSS library NPT 1.3 developed by Chiang and Kao (2002).

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Table 6: Panel DOLS and FMOLS Estimation (25 West-German Manufacturing Industries, without "computer" industry)

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
$\ln K$	0.007	-0.012	0.058	0.148	0.004	-0.012	0.017	0.138
	(0.33)	(-0.40)	(0.54)	(1.01)	(0.17)	(-0.40)	(0.17)	(0.98)
$\ln S$	0.242**	0.292**	0.066	-0.068				
	(6.32)	(5.55)	(0.58)	(-0.43)				
$\ln S_P$					0.213**	0.319**	0.047	-0.381*
					(6.08	(6.61)	(0.32)	(-1.89)
$\ln S_G$					*0.132*	*0.086*	*0.170*	*0.733*
					(1.27)	*(0.60)*	*(0.47)*	*(1.48)*
$D_{ML} \ln K$			-0.046	-0.159			-0.010	-0.146
			(-0.42)	(-1.06)			(-0.10)	(-1.02)
$D_{ML} \ln S$			0.230*	0.412**				
			(1.89)	(2.47)				
$D_{ML} \ln S_P$							0.234	0.613**
							(1.55)	(2.95)
$D_{ML} \ln S_G$							*0.151*	*-0.081*
							(0.40)	*(-0.16)*
R^2	0.335	0.278	0.361	0.322	0.337	0.286	0.386	0.371

Notes: The t-statistics are reported in parantheses. Number of observations: 300. S_G is the weighted sum of the publicly financed R&D capital stocks of other manufacturing industries, lagged 3 years. S_P is the weighted sum of the privately financed R&D capital stocks of other manufacturing industries, lagged 3 years. * denotes significant at the 5 % level; ** denotes significant at the 1 % level. a) Estimation results using the FMOLS estimator. b) Estimation results using the DOLS estimator. The DOLS estimates are based on regressions that include one lead and two lags. Estimators are computed by using GAUSS library NPT 1.3 developed by Chiang and Kao (2002).