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# "PRODUCTIVITY, R&D SPILLOVERS AND TRADE"

By
Jan Fagerberg
(University of Oslo, ESST & NUPI)

and

Bart Verspagen
(ECIS, Eindhoven University of Technology &
MERIT, Maastricht University)

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**ECIS - Eindhoven Center for Innovation Studies**
**Eindhoven University of Technology - Faculty of Technology Management**
**PO Box 513**
**5600 MB Eindhoven**
**The Netherlands**

**email:** bart.verspagen@merit.unimaas.nl

## 1. Introduction

That innovation and diffusion of technology drives long run productivity growth is by now commonly accepted. The crucial question is how. For instance, what is the role of own R&D in the firm, industry or country, as opposed to R&D done elsewhere? Is the former a precondition for rapid productivity growth, or is it possible to prosper by exclusively relying on imported technology? These are questions of high theoretical and practical importance. But the answers are not so clear yet. In fact, as we will show in the next section, the existing evidence points in very different directions. Can this conflicting evidence be reconciled to give a consistent picture? This is the question we address in this paper. We do this in two steps. First, we consider the different theoretical approaches, the empirical relationships they entail, and the related evidence. Then we present a comprehensive data set, consisting of 1974 – 1992 annual data for 14 countries and 22 manufacturing industries, which we use to discriminate between some of the most popular arguments in this area, and to explore the reasons behind some of the conflicting evidence presented in the existing empirical literature. We discuss the findings and implications in the concluding section.

## 2. Theory and evidence

There are basically three streams of thought in this area worth mentioning (see Fagerberg, 1994, for an overview). The first is the old neoclassical theory, which focuses solely on the public good aspects of technology. Second, there is a less 'orthodox', and more empirically based, tradition, often called the 'technology-gap' theory of economic growth (Fagerberg, 1987), characterised by a more comprehensive analysis of the different aspects of technology, and the interaction between technology and other variables that take part in the growth process. Third, and more recent, there is the so-called new growth theory, which, to some extent, combines insights from the two other streams.

Of these three approaches, the first is clearly the least relevant. If technology is a completely public good, freely available to anyone, it cannot be used as an explanatory factor behind differences in productivity growth (although it may have an impact on worldwide growth). Hence, for technology to explain growth differences, diffusion of technology must require efforts and/or capabilities that cannot be taken for granted. It is such a perspective that forms the basis for the ‘technology gap theory’ of economic growth. The starting point was the observation that for countries lagging behind the world best-practice technology level, innovations do not arise so much from original research, as from imitation of technologically more advanced countries. This inspired Gerschenkron (1962) to introduce the term ‘advantage of backwardness’, i.e., the possibility that countries lagging behind the technology frontier can grow relatively rapidly by using a backlog of knowledge created elsewhere. However, he also pointed out that exploiting this backlog is not an easy process, but requires a lot of investments, infrastructures and institution building. Abramovitz (1979), arguing along the same line, used the concept ‘absorptive capacity’ to denote the domestic capability to assimilate foreign spillovers. Thus, instead of technology as a free public good, a picture emerges in which imitation of more advanced foreign technology is a costly activity, that requires investment in indigenous capabilities, capital equipment, infrastructure, etc. Without a sufficient level of such investments, a country is unlikely to benefit from backwardness, and risk of falling behind relative to the technology leaders, rather than catching up (Verspagen 1991).

New growth theory combines a traditional neoclassical framework with a richer description of technology that allows for proprietary aspects as well as spillovers. However, these theoretical advances have not yet produced many new insights on diffusion. Typically, very stylised assumptions are adopted: either spillovers are completely global in scope, or completely national, at the level of the country or industry (see, e.g., Grossman and Helpman, 1991). If spillovers are global, we are more or less back to the traditional neoclassical model, at least as far as diffusion is concerned. With national spillovers, market size matters, and hence we should expect higher returns to R&D in larger economies. Apart from this, there are relatively few testable predictions that have been derived from this framework, and it is seems fair to say that the advent of new growth theory has not - or at least not until very recently - led to much new applied work on diffusion.[1]

Apart from descriptive analyses, empirical work based on these perspectives usually consists of cross-country regressions with the growth rate of labour productivity as the dependent variable, and the level of initial labour productivity, used as an indicator of initial backwardness, and variables reflecting absorptive capacity (and other relevant factors) as independent variables. The latter include investment in fixed capital and human capital, R&D expenditures, openness to international trade, etc. Studies of this type (see Fagerberg 1994 for an overview) have generally arrived at positive signs for many of the latter, while the level of initial GDP per capita usually turns up negatively. This may be seen as a confirmation of the potential advantages of international technology diffusion for countries behind the technology frontier.

It may be argued, however, that the gap in productivity relative to the frontier is a very wide measure of the potential for diffusion, open to rival interpretations,[2] and that more precise measures would be desirable. New technology may diffuse in many different ways: embodied in goods or services that make use of new technology, through foreign direct investments by multinational firms or by imitative activities by domestic firms, drawing on a multitude of sources, as well as (necessary) complementary assets/capabilities. Ideally, one would have wished to take all of these into account, but this has generally not been possible due to lack of relevant data. For instance, data on technology flows by multinationals are almost non-existent.[3]

One option that has been followed with some success is to weight R&D in other countries with imports to arrive at a measure of imported R&D. For instance, one study based on this methodology (Coe and Helpman 1995) reports that the impact of imported R&D on productivity is positive and significant, and comparable to that of

[1] Arguably, the recent contributions by Coe and Helpman (1995), Coe, Helpman and Hoffmaister (1997) and Eaton and Kortum (1997) may be exceptions to this rule. We discuss these below.
[2] For instance, following the traditional neoclassical perspective, the negative impact of a relatively high initial productivity level may be explained by decreasing returns to capital-labour substitution.
[3] One possibility is to use patents applied for or granted by foreigners as a measure of foreign technology flows. See Eaton and Kortum (1997).

domestic R&D.[4] They also found that the returns to domestic R&D are higher in large countries, consistent with some of the predictions from new growth theories. This implies that for most small and medium-sized countries, foreign R&D is a more important source of productivity growth than domestic R&D (since domestic R&D is likely small compared to total foreign R&D). However, others, using essentially the same type of indicator of imported R&D, fail to reproduce these results (Verspagen, 1994, Gittleman and Wolff, 1995). In fact, the latter do not find any significant impacts of imported R&D on productivity. This calls for some caution in interpreting the existing evidence.

The reasons for this state of affairs are not clear. One possible explanation could be weaknesses in methodology. For instance, in these studies, R&D in other countries is weighted by the shares of these countries in the total imports of the country in question. Hence, it matters for the estimate of imported R&D whether a country imports fruit from, say, high-R&D US or low-R&D Spain. Furthermore, since these studies focus on the country as a whole, there is no distinction between direct R&D in the industry, and R&D done in other industries in the same country. However, a much more elaborate study by Papaconstantinou et al. (1995), using a detailed sector breakdown, did not find any significant impact of imported R&D either.

This may indicate that what causes these different results is not so much how variables are measured, but rather what kind of statistical/econometric framework is adopted. The problem here is the conventional one in empirical studies of technology: that time series are short, and that one is left with either doing a cross-section, or pooling time-series and cross-sectional data (i.e., a panel). The exercises that do not find any significant impact of imported R&D are all cross-sectional in nature, while the one that finds such effects uses a panel. Verspagen (1997b), who has presented an elaborate test, using sector-level data for a number of OECD countries, and different weighting schemes reflecting different assumptions on how technology flows are embodied confirms that this is the case. He found that the impact of foreign R&D is much more significant when a panel is used than in a traditional cross-sectional test. Commenting on this finding, he suggested that one possible reason is that the former,

[4] Lichtenberg and van Pottelberghe (1996) apply a similar model, but use FDI flows between countries

in contrast to the latter, usually contain country dummies, that are likely to pick up differences in time- and sector-invariant factors such as, for instance, absorptive capacity across countries. Hence, following this interpretation, the positive impact of imported R&D found in some studies (panel data) is strongly conditional on differences in absorptive capacity and other factors. Thus, achieving high productivity growth through imports of, say, high-tech machinery, may not be as easy as some existing studies, taken at face value, might lead us to believe.

Another weakness of the studies discussed above is that these only contain one measure of technology diffusion, R&D embodied in goods and services, or FDI, and disregard other types of technology flows, that may be equally or more relevant. This may easily lead to biased estimates. At the other extreme, initial GDP per capita (or productivity) used in earlier studies as an indicator for potential spillovers, certainly has a much broader and less specific interpretation. Hence, in order to test the degree to which the models using specific measures of embodied R&D spillovers underestimate total knowledge spillovers, it seems natural to include both initial productivity levels and the ‘imported R&D’ variables into a single regression framework. This is what will be done in the remainder of this paper. In order to distinguish the two approaches we are trying to combine, we will refer to the initial productivity variable as incorporating 'disembodied' spillovers, and the imported R&D variable as an 'embodied' spillover variable.

## 3. Exploring the impact of innovation and diffusion on productivity growth

In order to perform the joint test of the impact of embodied and disembodied knowledge flows on productivity, we will use data from the OECD STAN, ANBERD and BITRA databases (with two exceptions noted below). Our dependent variable is growth of labour productivity. The explanatory variables are growth of capital intensity, growth in the own R&D stock, growth of embodied R&D spillovers (domestic and foreign) and disembodied spillovers (proxied with the level of labour productivity lagged one year). The data set consists of annual data for 14 countries and 22 manufacturing industries between 1974 and 1992.

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to weight R&D.

A general problem with empirical analyses on pooled data time-series cross-sectional is to distinguish between information relating to the time-series and cross-sectional dimensions of data. Failure to do so may lead to biased interpretations of, for example, how changes over time take place (see the previous section). Depending on the purpose of the analysis, various methods may be used to reduce this problem. If, as in this case, the time series dimension is what we want to focus at, what such methods do is to sort out – fully or in part – the share of the total variance that refers to the cross-sectional dimension.

One commonly used method in panels is to introduce dummies for the cross-sectional units, e.g., one dummy per country and sector. This is equivalent to estimating the equation on a data set for which country and sector means of the variables have been subtracted. However, if the data are given in levels, some of the cross-sectional information may still influence the results. This is so because large sectors and countries will still have larger values (deviations from means), and hence be more influential in the regression than small sectors and countries. To eliminate this possibility, we decided to estimate the model in first differences (of logs), which is equivalent to estimate the model in growth rates (only the initial level of labour productivity is not specified as a first difference, by nature of the variable). This obviously wipes out a lot of the cross-sectional variance that might otherwise have distorted the result, but it does not imply that country and sector dummies may not be relevant. For instance, time-and sector- invariant factors such as differences in absorptive capacity may still be reflected in the country dummies, as may differences in sectoral trends in sector dummies.

With respect to the definition of variables, labour productivity is defined as value added in constant prices in US dollars (taken from STAN, which applies sectoral producer price indices), divided by labour input (the number of persons employed as data on hours worked were not available). The latter also applies to the other explanatory variables (i.e., divided by labour input). The capital stock is constructed by applying a perpetual inventory method to the time series for investment (converted into constant prices, in investment PPP to the US dollar, the latter taken from the Penn

World Tables), using an exogenous deprecation rate of 15% per year.[5] The same approach is used to construct so-called knowledge stocks, using investments in R&D instead of investment in physical capital. In this case, a specific deflator is not available, and the PPP for GDP (again from the Penn World Tables) is used to convert to a common currency.

We use several R&D stocks, the first of which is so-called own R&D, defined as sectoral R&D expenditures. For the domestic indirect knowledge stock, *IRD*, this is done as follows:

$$IRD_{ik} = \sum_j \omega_{jk} RD_{ij} (1 - m_{ij}),$$

where $m$ denotes the share of imports on the domestic market, $\omega_{jk}$ is the share of inventions made in sector $j$ spilling over to sector $k$ (see below), $RD_{ij}$ denotes R&D expenditures in country $i$ and sector $j$. For the indirect international knowledge stock, IRF, the definition is:

$$IRF_{ik} = \sum_h \sum_j \omega_{jk} RD_{hj} s_{ihj} m_{ij},$$

where $s_{ihj}$ is the share of country $h$ in imports of goods $j$ into country $i$. Thus, indirect R&D is both weighted by both imports and sectoral technology flows.

The weights for the sectoral technology flows are based on information contained in patents from the European patent Office (EPO), and are taken from Verspagen (1997a).[6] We follow earlier contributions such as Verspagen (1997a) and Van Meijl (1995) in setting the diagonal of the spillover matrix to zero ($\omega_{jj} = 0$) when calculating domestic spillovers. The reason for doing so is that if the diagonals are relatively important, 'own' (direct) R&D and (domestic) spillovers will be correlated due to double counting, leading to multicollinearity. Setting $\omega_{jj} = 0$ avoids double counting by internalising intra-sectoral spillovers into the elasticity of 'direct' (own) R&D. For foreign spillovers, there is no double counting, so there is no direct danger for

[5] The initial capital stock (at time $t$) is calculated as investment at $t$+1 times 5, consistent with an initial growth rate of the stock of 5%. In the estimations, the two first observations for the knowledge and capital stocks were omitted, in order to avoid problems related to the initialization of these stocks.
[6] Verspagen (1997) discusses several possible weighting schemes. We employ only one of these schemes here (Verspagen's EPO1 measure), although we carried out all regressions with three different schemes. For the estimates here, the differences between the schemes turn out to be relatively minor.

multicollinearity (nor is it possible to ‘internalise' spillovers similarly to the domestic case). Thus, the diagonal is not set to zero for foreign R&D spillovers.

Our basic regressions are documented in Table 1. The first two columns report estimates using OLS on the complete panel, i.e., cross-country, cross-sector and time series dimensions are taken into account. In these regressions, no attempt has been made to take into account country- or sector specific factors by including dummy variables. In this set-up, all variables have the expected sign, and are highly significant. The first column documents a specification without disembodied spillovers (initial productivity), whereas the second column includes this variable. Including initial productivity increases the explanatory power of the regression, without changing the estimates of the other variables much (apart form the constant term). Initial productivity itself is also highly significant. These results confirm that both imported R&D and disembodied spillovers are important, and that these are complementary rather than alternative sources of growth.

Column 3 introduces country- and sector-dummies into the model, to take into account differences between sectors in terms of underlying technological opportunities, sectoral productivity levels, and differences between national systems of innovation with respect to absorptive capacity and other factors.. The dummies are specified as intercepts, and are set up in such a way that the benchmark case is the sector ‘other manufacturing’ in the United States. $F$-tests for the inclusion of dummies point out that both types are highly significant. In terms of explanatory power, they add 2%-points to the $R^2$.

In terms of the coefficients obtained for our explanatory variables, the main effect of the inclusion of dummies is to increase the (absolute) value of the disembodied knowledge spillovers variable (initial productivity). Our interpretation of this result is as follows. Part of the effect picked up by the dummy variables will be related to the capability to assimilate spillovers. Thus, the model with dummies, to a certain extent, takes this factor into account, which means that any distortion due to mis-specification will be less than in the model without dummies. We see this as a confirmation of the

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Estimations with alternative schemes are therefore not documented explicitly, but are available from hypothesis, central to the technology gap theory, that the potential for technology diffusion across countries is only partly realised due to differences in absorptive capacities across countries. Interestingly, the estimated effects of embodied R&D spillovers (whether ‘imported’ from abroad or stemming from domestic industry) are less influenced by the inclusion of dummies than the disembodied knowledge flows (as captured by the initial productivity level). This might indicate that it is more challenging in terms of capabilities to exploit the latter than the former.

With regard to the sector dummies, a number of sectors which are usually considered as ‘low-tech’ have relatively large estimates for the dummy variables. This includes textiles, wood, paper & printing, and non-metallic minerals (glass etc.). These are sectors which spend relatively little on R&D. We interpret this result as showing that for these sectors, significant productivity gains may be realised without formal R&D.

In the country dimension, all dummy variables, except the one for Japan, turn out to be negative, which indicates a general tendency for the United States (the benchmark country) and Japan to grow relatively rapidly compared to the others. The G7 member countries (Canada, Japan, Italy, France, and UK, with the exception of Germany) show values close to, and not significantly different from, zero. Many of the countries in the European periphery (Denmark, Spain, Norway and Sweden) perform relatively bad, with strongly negative dummies (Finland is the main exception to this trend). This may indicate that these small, peripheral countries have less developed absorptive capacities than other countries. Also, there seems to be a ‘large country effect’ at work here, since most G7 countries grow fast compared to the others.

To compare these results with previous work we also report (column 4 and 5, table 1) two purely cross-sectional regressions (i.e., excluding the part of the total variance that relate to the time-series dimension). This is done by taking the means of all individual time series, yielding only 268 observations, and estimating the model on these. Column 4 does not include any dummies, whereas column 5 includes both country- and sector dummies as before. In both cases own R&D totally loses its significance, while disembodied catch up becomes much less important (compared to

the authors on request.

the corresponding models on time-series data , column 2 and 3, table 1). In contrast, the estimated impact of embodied R&D spillovers is actually higher than when estimated on the full data set, but less significant, i.e., estimated with less precision. In fact, when dummies are included, foreign indirect R&D loses its significance altogether.

This shows that the method of estimation matters for the results, as argued previously. The most likely reason for this is that when the time series information is left out the analysis, it becomes more difficult to distinguish between the various sources of productivity growth such as, for instance, the potential for diffusion compared to what is actually realised due differences in absorptive capacity and other factors. Moreover, multicollinearity problems multiply. Hence, we put more reliance in the estimates on the full data set, including the time-series dimension, and allowing for differences in sectoral and country specific trends (column 3).

As is evident from Table 1, the explanatory power of the regression is relatively limited. To some extent, this has to do with estimating in first differences (rather than levels), which is known to be associated with lower $R^2$s. In an attempt to increase the explanatory power of the model, and test various hypotheses that may be found in the literature, we experimented with a number of additional variables that might be deemed relevant, including so-called interaction effects. These results are documented in Table 2. We used the functional form specified in column 3 in Table 1 (i.e., OLS on complete panel with country and sector dummies), but we no longer document the dummies.

The first column of Table 2 introduces an interaction term between own R&D and initial labour productivity (relative to the sector mean).[7] This interaction term turns up as positive and highly significant. Other variables in the regression, including own R&D and initial labour productivity are not affected to any significant extent (compare column 3 in Table 1). Our interpretation of this result is that (direct) R&D is more productive in countries or sectors with high levels of productivity. In other

[7] I.e., we specified the interaction term as the product of the own R&D variable as used before and a new variable, which is defined as the natural log of initial labour productivity minus the mean for the sector of that variable.

words, in addition to the 'advantage' of backwardness implied by disembodied spillovers, there is also a disadvantage of backwardness in terms of a lower efficiency of R&D.[8]

The second column of Table 2 introduces a similar interaction term, but now between own R&D and the capital labour ratio (relative to the sector mean). This interaction term is also positive and significant, while the other variables are again relatively unaffected. Our interpretation of this result is that R&D and capital are strongly complementary: high capital intensity enhances the efficiency of R&D, and R&D enhances the efficiency of capital. The third column of Table 2 shows that when both interaction effects are introduced simultaneously, both of them loose in terms of significance (particularly the one with labour productivity).

In column 4, an interaction term between openness to imports and own R&D is introduced. Openness is defined as the share of imports in total sectoral consumption (i.e., production plus imports minus exports), again calculated by subtracting the sector mean. We include this variable in order to test the commonly found hypothesis that exposing a sector to foreign competition has a beneficial effect on productivity. Our results do not yield any support for this hypothesis, however, because neither the openness variable nor the related interaction term turns up significantly.

Column 5 tests for the effects of scale economies. We define scale as the number of employees (again, relative to the sector mean), but we obtained similar results to the ones documented here using output as an indicator of scale. Somewhat surprisingly, perhaps, the result point out that there are significant diseconomies of scale, i.e., R&D is more efficient in small sectors/countries. However, as pointed out previously, large countries tend to have higher trend growth rates, so we cannot rule out scale effects altogether. But they do not seem to reside in R&D.

The results using the interaction terms indicate that the efficiency of R&D is greatly influenced by a number of variables. Table 3 documents the extent of this impact in

[8] Obviously, there is also another possible interpretation: that countries with above average own R&D are less efficient in assimilating disembodied spillovers. This interpretation seems to make less sense than the one offered in the text.

terms of rates of return to R&D and fixed capital. The first part of the table documents the rates of return on fixed capital investment and R&D, which are calculated by dividing the elasticities of column 3 in Table 1 by the sample means for the capital / output and R&D / output ratio. It is shown that the rate of return on R&D is higher than the one for capital (0.23 vs. 0.15). This may be due to a risk premium on R&D, but may also reflect differences in private and social returns at the sector level, since the estimate reported here is likely to capture some of the effects of intra-sectoral R&D spillovers.

The second part of Table 3 compares the 'total' rate of return on R&D at various levels of productivity, capital intensity and scale, on the basis of the estimations with interaction terms in Table 2. This is done by multiplying a value for initial productivity, the capital labour ratio, and scale with the coefficient obtained on the interaction term, and then adding this to the coefficient obtained on own R&D. We used the sample means (zero by definition for the interaction terms), and the sample means plus/minus one standard deviation as values for the variables.

In the case of interaction between R&D and labour productivity, the estimated rates of return of R&D vary between 14% (low productivity) and 39% (high productivity). A similar finding results for interaction between R&D and capital intensity, with estimated returns on R&D between 10% (low capital intensity) and 37% (high capital intensity). These differences are rather large, and show that the returns to R&D are higher in technologically and economically more advanced sectors and countries. This points out that, in general, the disadvantages of backwardness related to the efficiency of R&D may be quite large. In the case of scale, for which our results were somewhat counter-intuitive, the estimated returns to R&D range between 7% (high scale) and 29% (low scale).

Finally, we carry out a decomposition of the growth rate of labour productivity, as predicted by our basic model, into the various components corresponding to the variables. These results are documented in Table 4. The first column of this table gives results based on Equation 2 in Table 1, i.e., the estimations without dummy variables. In this case, we are unable to distinguish between potential catch-up due to disembodied spillovers and the effect of absorptive capacity. The net effect of the two, called "net catch-up", is defined as the sum of the effect related to initial labour productivity and the constant term. Catch-up defined in this way accounts for about half of total growth of labour productivity of the average country/sector.[9] Investments in physical capital is responsible for about one fifth, as is investments in own R&D. Embodied R&D spillovers account for only 13%, with foreign spillovers taking the largest part (about two thirds). Thus, overall, embodied R&D spillovers seem to be of relatively modest importance compared to other sources of growth.

Using the estimations for the dummy variables in Equation 3 in Table 1, we are able to make a (rough) distinction between potential catch-up and the effect of differences across countries in terms of absorptive capacity. Much in the same way as before, "net catch up" is defined as the sum of the contribution of initial labour productivity, the constant term and the means of the sector- and country dummies. The contribution for disembodied spillovers ("net catch up") is somewhat larger than in the previous case, consistent with the finding of a higher absolute value of the coefficient for initial labour productivity when dummies are included. As argued previously, differences in absorptive capacity across countries are likely to be reflected in the estimated country dummies. Note that the choice of the US as the 'reference' country implies that we set this country as the 'standard' of absorptive capacity. The mean of the estimated country dummies is negative, indicating that on average absorptive capacity on average is below the US level. If we subtract this mean from "net catch up", we get a larger number, which reflect what the contribution might have been had absorptive capacity on average matched the level in the US ("potential catch up"). The results indicate that the potential for profiting from disembodied technology flows is substantial, about twice the level of what is actually realised. Hence, differences in absorptive capacity appear as a very important factor in productivity growth.[10]

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[9] The average growth rate of labour productivity is 2.6% per year.

[10] Finally, it must be noted that to the extent that other variables are influenced by absorptive capacity, our method may assign too much weight to absorptive capacity in relation to disembodied spillovers. The estimation results seem to warrant this, however, given the fact that the initial labour productivity coefficient is much more affected by the inclusion of country and sector dummies than the other variables.

## 4. Concluding remarks

This paper has examined the impact of various indicators of international technology diffusion on productivity growth. After a review of the available literature, we conclude that there are two main approaches in the field. One approach specifies international technology spillovers as a rather broad process, of which the potential is (negatively) related to the level of initial labour productivity. The other approach takes a more restrictive point of view, and tries to measure technology spillovers in a very specific way, namely by R&D embodied in (imported) goods. In order to contrast the two points of view, we refer to them as the 'disembodied spillover' view and the 'embodied spillover' view (respectively). The empirical analysis we undertake was aimed at investigating whether the 'embodied spillover' view may indeed be too restrictive, i.e., what are the results if we include both initial productivity and 'imported R&D' in a regression. Our conclusions are:

1) The conflicting evidence in the literature relates mainly to differences between cross-sectional and time-series tests. The former fail to reveal the full potential of technology diffusion for productivity growth, mainly due to the problems of taking into account differences in absorptive capacity across countries.
2) Both R&D-embodied and disembodied technology flows are important for productivity, and appear as complementary rather than alternative sources of productivity growth. Overall, the impact of embodied and diembodied technology flows seems to be much larger than that of direct (own) R&D, consistent with previous findings in the literature (Coe and Helpman 1995, Eaton and Kortum 1997). However, the disembodied flows are found to be of much greater quantitative importance than the embodied ones.
3) Differences across countries in absorptive capacity appear to be very important growth, particularly for the ability to exploit disembodied technology flows, as emphasized by among others Gittleman and Wolff (1995) and Eaton and Kortum (1997).
4) Previous analyses on panel data (Coe and Helpman 1995, Table 3, Verspagen 1997b, Table 2) have found relatively high elasticities of embodied R&D flows (whether imported or domestic) compared to those of direct R&D. Our study, focusing more on the time-series aspects, finds smaller elasticities of embodied

R&D flows than those reported previously, and definitely smaller than for direct R&D.

5) Investment in R&D and physical capital appear as complimentary, the one enhances the efficiency of the other. The productivity of R&D was also found to increase with labour productivity.
6) There are no signs of higher returns to R&D in larger economies, in contrast to some of the predictions of new growth theories.

In summary, the picture that emerges from this study is that there are several, complementary diffusion channels, of which embodied R&D spillovers are only one (and not a major one), that differences in absorptive capacity matter a lot, particularly for disembodied technology flows, and that own R&D is very important for productivity, both in its own right, and in interaction with other variables that take part in the growth process.

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**Table 1. Estimation results for models of productivity growth with indirect and direct R&D, with and without dummy variables (p-values between brackets)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Capital Labour ratio | 0.180 (0.000) | 0.182 (0.000) | 0.181 (0.000) | 0.167 (0.002) | 0.239 (0.000) |
| Own R&D | 0.083 (0.000) | 0.078 (0.000) | 0.082 (0.000) | -0.003 (0.899) | -0.006 (0.805) |
| Domestic indirect R&D | 0.025 (0.007) | 0.023 (0.012) | 0.019 (0.032) | 0.059 (0.024) | 0.073 (0.014) |
| Foreign indirect R&D | 0.030 (0.004) | 0.029 (0.006) | 0.025 (0.015) | 0.095 (0.029) | 0.081 (0.132) |
| Initial labour productivity | | -0.019 (0.000) | -0.045 (0.000) | -0.007 (0.045) | -0.020 (0.000) |
| Constant | 0.014 (0.000) | 0.206 (0.000) | 0.467 (0.000) | 0.084 (0.018) | 0.206 (0.000) |
| Country Dummies | | | | | |
| Australia | | | -0.021 (0.010) | | -0.011 (0.173) |
| Canada | | | -0.009 (0.227) | | -0.002 (0.826) |
| Germany | | | -0.019 (0.018) | | -0.004 (0.624) |
| Denmark | | | -0.036 (0.000) | | -0.019 (0.037) |
| Spain | | | -0.023 (0.092) | | -0.016 (0.155) |
| Finland | | | -0.011 (0.175) | | 0.009 (0.289) |
| France | | | -0.007 (0.372) | | -0.002 (0.842) |
| United Kingdom | | | -0.003 (0.700) | | 0.014 (0.067) |
| Italy | | | -0.005 (0.593) | | 0.011 (0.199) |
| Japan | | | 0.009 (0.251) | | 0.023 (0.007) |
| Netherlands | | | -0.011 (0.275) | | 0.018 (0.050) |
| Norway | | | -0.036 (0.000) | | -0.019 (0.029) |
| Sweden | | | -0.023 (0.014) | | -0.007 (0.463) |
| Sector Dummies | | | | | |
| Food etc. | | | -0.006 (0.641) | | -0.024 (0.041) |
| Textiles etc. | | | 0.052 (0.000) | | 0.034 (0.003) |
| Wood etc. | | | 0.059 (0.000) | | 0.042 (0.000) |
| Paper & printing | | | 0.076 (0.000) | | 0.032 (0.015) |
| Chemicals | | | 0.026 (0.033) | | 0.015 (0.141) |
| Pharmaceuticals | | | 0.010 (0.425) | | 0.003 (0.749) |
| Refined Oil | | | 0.021 (0.095) | | 0.014 (0.201) |
| Rubber & plastic | | | 0.003 (0.785) | | -0.002 (0.849) |
| Glass etc. | | | 0.037 (0.003) | | 0.025 (0.022) |
| Ferrous metals | | | 0.017 (0.155) | | 0.005 (0.640) |
| Nonferrous metals | | | 0.011 (0.381) | | 0.008 (0.426) |
| Metal products | | | -0.008 (0.523) | | -0.007 (0.472) |
| Computers & office machines | | | 0.005 (0.678) | | 0.005 (0.594) |
| Machinery | | | 0.025 (0.039) | | 0.018 (0.088) |
| Electronics | | | 0.031 (0.010) | | 0.023 (0.031) |
| Electrical machinery | | | 0.013 (0.272) | | 0.003 (0.735) |
| Transport equipment nec | | | 0.005 (0.688) | | 0.001 (0.902) |
| Ships and boats | | | 0.013 (0.280) | | 0.002 (0.878) |
| Automobiles | | | -0.005 (0.656) | | 0.002 (0.830) |
| Aerospace | | | 0.030 (0.013) | | 0.020 (0.051) |
| Instruments | | | 0.001 (0.875) | | -0.005 (0.655) |
| Adj. R2 | 0.05 | 0.06 | 0.08 | 0.09 | 0.36 |
| N | 3722 | 3722 | 3722 | 268 | 268 |
| F-tests for Null hypothesis: | | | | | |
| All dummies = 0 | | | 4.46 (0.000) | | 4.36 (0.000) |
| All country dummies = 0 | | | 4.37 (0.000) | | 6.03 (0.000) |
| All sector dummies = 0 | | | 4.98 (0.000) | | 3.49 (0.000) |

(1), (2), (3): OLS on panel, no dummies

(4), (5): OLS on time series means (BETWEEN)

**Table 2. Introducing additional variables and interaction effects into the basic regressions explaining productivity growth (OLS on complete panel, constant and country and sector dummies included, but not documented, p-values between brackets**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Capital Labour ratio | 0.172 (0.000) | 0.177 (0.000) | 0.173 (0.000) | 0.181 (0.000) | 0.186 (0.000) |
| Own R&D | 0.093 (0.000) | 0.083 (0.000) | 0.089 (0.000) | 0.081 (0.000) | 0.064 (0.000) |
| Domestic indirect R&D | 0.019 (0.033) | 0.019 (0.036) | 0.019 (0.036) | 0.019 (0.033) | 0.018 (0.042) |
| Foreign indirect R&D | 0.025 (0.016) | 0.025 (0.017) | 0.025 (0.017) | 0.025 (0.016) | 0.025 (0.017) |
| Initial labour productivity | -0.049 (0.000) | -0.046 (0.000) | -0.048 (0.000) | -0.045 (0.000) | -0.047 (0.000) |
| Additional Variables | | | | | |
| Openness | | | | -0.005 (0.598) | |
| Scale | | | | | -0.008 (0.017) |
| Interaction of own R&D with | | | | | |
| Initial labour productivity | 0.108 (0.008) | | 0.063 (0.162) | | |
| Capital Labour ratio | | 0.098 (0.002) | 0.077 (0.024) | | |
| Openness | | | | 0.042 (0.513) | |
| Scale | | | | | -0.027 (0.006) |
| N | 3722 | 3722 | 3722 | 3722 | 3722 |
| R2 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |

**Table 3. Rates of return (excluding spillover effect) of R&D and fixed, based on sample means and coefficients in Tables 1 and 2**

| | | | |
|---|---|---|---|
| Rate of return on: | | | |
| fixed capital | 0.146 | | |
| own R&D | 0.232 | | |
| Rates of return including interaction effects: | | | |
| | Efficiency of R&D at: | | |
| | Mean | Mean + 1 std | Mean – 1 std |
| Initial productivity | 0.263 | 0.388 | 0.137 |
| Capital labour ratio | 0.234 | 0.369 | 0.100 |
| Scale | 0.181 | 0.072 | 0.289 |

**Table 4. The sources of productivity growth, according to different specifications of the model, in percentual shares of the 'average' sector/country**

| Source | Equation 2, Table 1 | Equation 3, Table 1 |
|---|---|---|
| Capital labour ratio | 21 | 18 |
| Own R&D | 19 | 16 |
| Dom. R&D spillovers | 4 | 3 |
| For. R&D spillovers | 9 | 6 |
| net catch-up | 47[1] | 57[2] |
| of which: | | |
| potential catch-up[3] | | 100 |
| (lack of) absorptive capacity[4] | | -43 |

[1] Sum of contributions of initial labour productivity and constant.
[2] Sum of the two lines below.
[3] Sum of contributions of initial labour productivity, constant and sector dummies.
[4] Sum of contributions of country dummies.

WORKING PAPERS

Ecis

Other ECIS working papers (January 1999):

98.1 Per Botolf Maurseth & Bart Verspagen, Knowledge Spillovers in Europe and its Consequences for Systems of Innovation.

98.2 Jan Fagerberg & Bart Verspagen, Productivity, R&D Spillovers and Trade.

98.3 Leon A.G. Oerlemans, Marius T.H. Meeus & Frans W.M. Boekema, Learning, innovation and proximity.

99.1 Marius T.H. Meeus, Leon A.G. Oerlemans & Jules J.J. van Dijck, Regional systems of innovation from within.

99.2 Marcel P. Timmer, Climbing the Technology Ladder Too Fast? : An International Comparison of Productivity in South and East-Asian Manufacturing, 1963 – 1993.