Geographic Localization of International Technology Diffusion*

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Abstract

I analyze the international diffusion of technology by estimating the spatial distribution of productivity effects of G-5 country R&D spending in nine OECD countries. The sample encompasses most of the world's innovative activity and more than two thirds of the world's manufacturing activity at the industry-level during the years 1970-95. The main finding is robust evidence that the productivity effects of R&D are declining with the geographic distance between sender and recipient countries. On average, a 10% larger distance away from the G-5 countries is associated with a 1% lower productivity level due to the reduced benefits from G-5 R&D. Further results are: First, international sources of technology diffusion are jointly about twice as important for productivity in the smaller OECD countries as the country's own R&D investments. Second, the importance of international technology diffusion has been rising substantially over the sample period.

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1 Introduction

Helsinki is located around 1,500 miles away from Bonn, while it is around 6,900 miles to Washington, D.C., and 7,800 miles to Tokio. Canberra is located around 16,500 miles away from Bonn, there are about 16,000 miles to Washington, D.C., and about 8,000 miles to Tokio. Does it matter for productivity in Finland relative to Australia that Helsinki is closer to Germany, the U.S., and to Japan than Canberra, thereby gaining more from the technology that diffuses from these three countries?

According to many accounts in the business press, technological knowledge is truly global in today's integrated world markets.[1] Not only can any good or service be delivered anywhere, but with knowledge diffusing through the internet and new means of telecommunications, people in every country of the world have access to the same knowledge. This view is also shared by a number of economists, e.g. Mankiw (1995) and Prescott (1997). If there exists a world stock of technological knowledge that is common to all countries, geographic distance cannot matter for international technology diffusion. In this paper, I bring new evidence to bear on this issue by examining whether the geographic distance between industrialized countries affects the degree of international technology diffusion among them.

This is an important question for several reasons. First, it has major implications for understanding the dynamics of economic growth. There is a widely shared view that the ultimate source of long-run growth in output per capita is technological progress, which means an augmented knowledge base and the ability to produce more output with a given set of inputs.[2] With many countries, the long-run distribution of per-capita output is determined by whether the process of technical progress in different countries is independent from each other. If technology diffuses across countries, then

[1] Also see Cairncross (1997), e.g., who pronounces 'the death of distance'.

[2] E.g., Mankiw (1995, 9) writes that "...it is obvious that living standards rise over time largely because knowledge expands and production functions improve."

national rates of technical progress have no impact on a country's long-run position in the ranking of countries, while if technological knowledge stays within the countries' national boundaries, then national rates of technical progress, and consequently national policies towards R&D will determine a country's long-run per capita output ranking (Grossman and Helpman 1991, Ch. 7,8, Feenstra 1996).

Strong effects of technology diffusion across countries also tend to lead to long-run convergence of per capita output across countries. At the same time, it is clear that perfect technology diffusion throughout the world does not guarantee that the long-run per capita output levels converge, because there might be differences in the rates of human and physical capital investments of the countries as well as their ability and incentive to adopt new technology across countries. The latter effects are emphasized by Mankiw (1995) and Prescott (1997), respectively. However, if technology does not diffuse but advances at different national rates, per-capita output levels will have to diverge eventually (e.g. Evans 1996), which indicates that international technology diffusion favors convergence. Thus, the extent of international technology diffusion has major implications for the long-run distribution of per-capita output in the world.

Second, differences in technological knowledge across countries have also figured prominently in recent work on comparative advantage and international trade. Several authors have shown that differences in production functions across countries are a major determinant of the international specialization of production as well as the volume of trade (Trefler 1995, Harrigan 1997, Davis and Weinstein 1998). However, there is no empirical work yet on the dynamics of trade and comparative advantage which is based on a theory that explains how factor endowments and technology change over time.[3] The evidence on international technology diffusion in this paper provides more informa-

[3]Trefler (1995) estimates parameters from data for 1967 and 1983 (e.g. Tables 2, 4), but he makes no attempt to explain how his cross-sectional estimates evolve over time. Harrigan (1997) uses panel data for OECD countries, but the time dimension of the data is primarily used to control for unobserved heterogeneity, not to estimate parameters

tion on the spatial correlation of changes in production functions. Together with more work on how quickly technology diffuses across countries, this will provide a basis that allows to aim at estimating dynamic models of trade and comparative advantage.[4]

Third, starting with Krugman (1991), there has been a considerable amount of recent work on the location of economic activity in geographic space, or, more broadly, in the area of 'economic geography'.[5] In contrast to other fields of economics, here it is common to explicitly model geographic space by introducing costs for moving goods and at times also for factors. The interaction of increasing returns and transport costs gives rise to complex dynamics that could explain both the agglomeration and the dispersion of economic activity in industries, regions, and even the world, with immediate consequences for the economies' trade. However, empirical work is at a relatively early stage, and so far the most influential papers are actually not on economic geography, but on so called 'border effects' (see McCallum 1995, Engel and Rogers 1996): they demonstrate that even if one controls for geographic distance, national borders matter in a major way for key economic variables.[6] By providing new estimates on the spatial patterns of technology diffusion, this paper provides relevant information for this literature.[7]

In the remaining sections of the paper, I discuss how it relates more specifically to the existing work on the geographic scope of international technology diffusion (section 2), where also a number of caveats will be discussed. The following section presents the econometric framework that will be used. An overview of the data is presented in section 4, with more details on sources and data construction

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that explain production function changes over time.

[4] Also Helpman (1998) emphasizes the need for this.

[5] The textbook treatment of Fujita et al. (1998) contains some important references.

[6] McCallum (1995) shows that controlling for geographic distance, the trade among Canadian provinces is much higher than between Canadian provinces and the US, while Engel and Rogers (1996) demonstrate that, again controlling for geographic distance, deviations from Jevon's law of one price are much larger across the US-Canada border than within one of the countries. See also Helliwell (1998) for a broader account.

[7] For instance, 'economic geography' effects might be important for determining the geographic scope of technology diffusion while at the same time the pattern of changes in the production functions of different economies might trigger the agglomeration or dispersion of economic activity.

provided in the appendix. In section 5 I present the main results, and section 6 concludes.

2 Earlier Empirical Work on the Geographic Scope of Technology Diffusion

Below I analyze the international diffusion of technology by estimating the strength and spatial distribution of productivity effects of G-5 country R&D spending in nine smaller OECD countries as well as among the G-7 countries.[8] The main finding is strong evidence that the productivity effects of R&D are declining with the geographic distance between sender and recipient countries. Here I start out by discussing some of the earlier work on the geographic scope of technology diffusion.

Jaffe et al. (1993) and Jaffe and Trajtenberg (1998) study whether technology diffusion is geographically localized by comparing the location of patent citations with that of the cited patents. Their indicator of technology diffusion between two locations is thus that a patent in some location A cites another in location B. In Jaffe et al. (1993), the authors are interested primarily in the geographic localization of patent citations within the U.S., but it is also shown that US patents are significantly more often cited by other US patents than by foreign patents.[9] In Jaffe and Trajtenberg (1998), the authors estimate from G-5 country data that patents whose inventors reside in the same country are typically 30 to 80% more likely to cite each other than inventors from other countries.

Their analysis then comes close to estimating what Klette et al. (1999), going back to Griliches (1979) call pure 'knowledge spillovers', as opposed to 'rent spillovers' that arise because the inventor cannot fully appropriate the return to her innovation. To be able to isolate these effects is an advantage of the Jaffe et al., Jaffe and Trajtenberg framework. A disadvantage is, however, that

[8] The G-5 countries are France, Germany, Japan, the UK, and the US. The G-7 countries consist of the G-5 countries plus Canada and Italy.

[9] This is after controlling for factors that also induce a higher citation frequency among US patents relative to US-Foreign patents, but have nothing to do with localized technology diffusion, such as differences in industrial composition.

without relating technology diffusion to output or productivity measures, it is difficult to assess the economic impact of technology diffusion. Moreover, given that technology diffusion is identified with patent citations, if international patenting is geographically localized–which is the case–, then the same must hold for international technology diffusion.

Eaton and Kortum (1998, 1996) have developed country-level models of patenting, technology diffusion and productivity growth that also provide evidence on the geographic extent of technology diffusion. As in Jaffe et al. (1993), patenting in a foreign country gives the indication that technology has diffused to that country.[10] A major advantage of their approach is that it allows the estimation of a number of structural parameters for the G-5 countries. Eaton and Kortum's results show that technology diffusion is considerably faster within than between countries, which suggests the geographic localization of technology diffusion in this sense. However, what identifies the diffusion parameters primarily is data on within- and between-country patenting activity,[11] which is well-known to be geographically localized. Thus it will be interesting to see whether one also estimates geographic localization effects for technology diffusion without imposing the structure of international patenting on the analysis.

Other research has estimated productivity effects from both domestic and foreign R&D in a production function framework, including Coe and Helpman (1995), Branstetter (1998), and Keller (1999). These studies employ the Griliches (1979) R&D weighing methodology according to which the contribution of R&D from different external sources is captured by constructing a weighted R&D variable, where the weights capture a particular technology diffusion mechanism that is being evaluated.[12] Both Branstetter (1998) and Keller (1999) estimate that the effect from domestic R&D

[10]Eaton and Kortum's work is not based on patent citations, however. Rather, if a given patent is taken out in second country (the first being usually the country of the inventor), this indicates that the technology has diffused *to potential competitors* in the second country, and therefore the invention needs patent protection.

[11]Sam Kortum in a discussion of an earlier draft of the present paper, ES January 1999 meetings, New York City.

[12]In Coe and Helpman (1995), the foreign R&D variable is the bilateral import-share weighted sum of a country's trade partner's R&D; Branstetter's (1998) weights are increasing in the similarity of two firms' patent portfolios, and

is stronger than that from foreign R&D, which is consistent with the idea that technology diffusion is geographically localized.[13] Helliwell (1998, Ch. 6) has argued that Coe and Helpman's (1995) results lead to the same conclusion.

However, in terms of 'economic geography' that is being considered in these studies, none of these studies go beyond the mere distinction between domestic and foreign R&D. Moreover, it is not clear what structure these studies impose on the estimation by using specific R&D weights to compute the foreign R&D variables. In effect there are two hypothesis being evaluated: first, that the R&D weights identify a certain diffusion mechanism, and second, that this mechanism is empirically important.[14] It seems therefore preferable to use R&D variables that are not weighted for present purposes.

The closest paper to what I present below is Adams and Jaffe (1996). These authors estimate the relationship between firm-level R&D and plant-level productivity for the US chemicals industry between 1974-88. They find that the productivity-enhancing effects of parent firm R&D are diminished by geographic distance of the plant away from the parent's research lab. This result parallels the basic finding in this paper. At the same time, there are important differences. First, Adams and Jaffe's result is based on technology diffusion within the US, so their paper is silent on international technology diffusion. Second, it is also based on technology diffusion within firms (the parent plant plus one or more subsidiary plants). It is clear that if technology creation is costly, then firms have an incentive to prevent technology diffusion to other firms. However, if the technology is equally useful in all plants of the firm, one would expect that the parent distributes the technology fully to

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Keller (1999) employs weights based on input-output relations, import relations, and micro data on technology flows.

[13] According to Keller (1999), the ratio of the foreign to the domestic R&D effect is about one third in his industry-level analysis among eight highly industrialized countries. In Branstetter's (1998) analysis of technology diffusion between US and Japanese firms, the relative effect from foreign R&D is less than one third, and at times, surprisingly, even negative.

[14] The R&D weights amount to exclusion restrictions that were originally adopted in this literature to address degree-of-freedom problems. See Keller (1999, 1998) for more on this issue.

all subsidiaries.[15] At any rate, within firm and across firm technology diffusion might, or might not be related to geographic distance in the same way.

The more general point is that Adams and Jaffe (1996) develop their estimates from a carefully matched firm-level data set for a particular industry in a particular country, whereas I present below results from a sample that encompasses most of the world's innovative activity and more than two thirds of the world's manufacturing activity at the industry-level. The two studies at different levels of aggregation, with their respective strengths and weaknesses, complement each other. Lastly, Adams and Jaffe (1996) treat geographic distance as a binary variable in their estimation ('close' and 'far' plants according to some threshold), and then find that there are stronger productivity effects for the first than for the second set of plants. Adams and Jaffe mention that they do this because their data would probably not support the estimation of continuously declining effects with distance. In contrast, in the analysis below this can be done.

There are a number of caveats to this paper. First, the only inputs I consider in constructing the total factor productivity (TFP) indices are physical capital and labor services. To the extent that high productivity industries are also those where workers are particularly skilled, ignoring human capital as an input implies an upward bias for R&D effects if this is positively correlated with human capital, as one would expect. I have not been able to obtain comparable data on industry-level human capital inputs for these industries. However, Engelbrecht (1996) has re-done the country-level Coe and Helpman (1995) regressions when differences in education are controlled for. He estimates parameters that are only somewhat lower than those of Coe and Helpman (1995).

Second, in focusing on geographic distance, other important dimensions of international technol-

[15] This in fact is the assumption being made in theories of multinational enterprises: firm-specific knowledge is perfectly mobile and available to the same extent–because it is non-rival–in all subsidiaries of a multinational; e.g., see Markusen (1995). If this assumption is at least qualitatively valid, then Adams and Jaffe's findings of geographically localized effects of technology diffusion *within* a firm establishes an upper bound for *across* firm- and perhaps also across country- technology diffusion. Alternatively, if within firm technology diffusion were truely costless, then Adams and Jaffe's result must be to some extent spurious; see the discussion below.

ogy diffusion such as its temporal and cross-industry dimension are neglected in this paper. That is, productivity in a given industry and country, as well as at a given period, is related to R&D in the same industry and period of the country itself as well as to R&D in other countries. I do not think that there is a sufficiently long time series in this sample that would allow precise estimation of the time path of the R&D effect on productivity.[16] Adams and Jaffe (1996) as well as Keller (1999) contain some analysis of technology diffusion across technology fields or industries, respectively.

Third, the empirical findings are consistent with more than one theory. I interpret the productivity effects from foreign R&D as technology, or, knowledge diffusion, a technological externality in the sense of Pigou. However, the effects could also capture pecuniary externalities which, in the presence of increasing returns, have the same implications as technological externalities.[17] At present, the empirical approach does not distinguish between these theories. Further, taken as given that in this paper it is technological externalities that are being estimated, the empirical findings do not determine a particular mechanism that transmits the technology across countries. International trade and foreign direct investment are among the most plausible ways of how technology is diffusing across economies, but this paper stops short of modeling and identifying these mechanisms.

I now turn to the econometric modeling framework.

3 Econometric Model

I will estimate the magnitude of productivity effects of R&D in a multi-country, multi-industry context. Consider a model where productivity f_{ijt} in some industry j of country i at time t is related

[16] But see, e.g., Pakes and Griliches (1984) on estimating distributed lag structures with short panels.

[17] The combination of pecuniary externalities, deriving from backward- and forward-linkage effects, and increasing returns has been emphasized in many models of the recent literature on economic geography. Hanson (1998) has made an attempt to estimate those effects; see also the related paper by Ciccone and Hall (1996).

to R&D in the same industry, denoted s_{ijt}, as well as to R&D in other countries $h \neq i$, s_{hjt}.

$$\ln f_{ijt} = \alpha + \beta \ln s_{ijt} + \gamma \ln \left(\sum_{h \neq i} \theta_h s_{hjt} \right) + \varepsilon_{ijt}, \forall i, h, j, t, \tag{1}$$

where ε is an error term whose properties I discuss below, and α, β, γ and the θ_h are parameter to be estimated. Several complications arise in this setting.[18] First, insofar as R&D spillovers are estimated (i.e., benefits from outside R&D), it is important to note that data collection and preparation methods of the statistical agencies create spurious spillover effects in the estimation.[19]

Second, as mentioned above, the magnitude of the measured TFP effects depends to some degree on the extent to which the supplying industry can appropriate the improvements in the quality of its product. While I do not have a way of estimating how large these effects are, and whether they are invariant across sectors and countries, the presence of these effects generally suggests that the productivity effects estimated below should be viewed as an upper bound on the productivity effects from outside-industry R&D that would occur if the technology-creating firm could charge the full quality-adjusted price.

Apart from these issues, the major econometric concern is simultaneity and omitted variable problems associated with estimating (1). Either of these two issues would imply that least squares estimates are inconsistent. For instance, because productivity and R&D are both trending upwards over time, part of the estimated correlation is likely due to a common trend. In addition, the error could also contain price or demand shocks that affect productivity and R&D jointly.[20] Given my

[18] See Griliches (1995, 1979).

[19] One main reason for this is the unavailability of deflators which fully adjust for increases in the quality of a product, and even if they exist, these deflators are not continuously, but only discretely adjusted. Therefore, measured TFP in sector j is affected by productivity improvements in industry $k \neq j$ to the extent that it purchases from k and that these improvements have not been incorporated in the official input price indices of industry j.

[20] Specifically, both R&D and output (on which the productivity index is based) are deflated by a price index, implying that as long as these price indices are significantly correlated, in the presence of price shocks this alone will lead to spurious correlation (a 'double-deflation' problem).

interest in estimating the geographic scope of international technology diffusion, spatial correlation of the TFP and R&D variables is of great importance. Extending the specification (1) to include a geographic distance component, this leads to

$$\ln f_{ijt} = \alpha + \beta \ln s_{ijt} + \gamma \ln \left(\sum_{h \neq i} \theta_h \, s_{hjt} \, d_{ih}^{-\delta_h} \right) + \varepsilon_{ijt}, \quad \forall i, h, j, t, \tag{2}$$

where d_{ih} gives the distance in miles between locations i and h, and the δ_h are additional parameters to be estimated. If some of the shocks that generate a spurious positive correlation between R&D and TFP are itself spatially localized, that would tend to generate positive estimates of δ_h in addition to a positive estimate of γ.

The primary candidate to solve this problem is instrumental variable (IV) estimation. However, a standard choice for instrumenting quantity series, namely real factor prices, is not available in the R&D context. In fact, I have been unable to obtain data on other variables which would provide goods instruments for cumulative R&D stocks and that exists for all countries, industries, and years in this sample. The straight-forward IV approach is not feasible in the present context.

Nevertheless, the problems can be reduced by imposing reasonable a priori restrictions on the dependent variable, TFP.[21] The effect of trends as well as time-specific shocks that affect all industries in the same way (e.g. global demand shocks) can be eliminated by estimating a time fixed effect for every period. I have also constructed data on R&D employment as an alternative to R&D expenditure data. Employment data is in physical units ('real'), and thus not subject to the 'double-deflation' problem mentioned earlier that might afflict the R&D expenditure data. Further, even though no good instruments are available, consistent parameters can still be estimated in the panel

[21] See the appendix for some details. Several of my choices are designed to reduce the probability of spurious spillover findings.

context through the inclusion of a full set of fixed effects if ε_{ijt} obeys

$$\varepsilon_{ijt} = \nu_{ij} + u_t, \tag{3}$$

$u_t \sim N\left(0, \sigma_u^2\right)$, where ν_{ij} is a permanent component that affects the regressors, while u_t is a temporary component that does not.[22] Under these circumstances, the part of the error that is correlated with the regressor will then be subsumed into the fixed effects (which are not of primary interest). I assume that (3) holds, and now turn to discussing the data that will be used.[23]

4 Data Overview

In this paper I use data on manufacturing industries in fourteen OECD countries for the years 1970-1995 (for more details on the data sources and construction, see the appendix). The input, output, and price data comes from the OECD's *STAN Industrial Database*, OECD (1998a). The data sources for R&D is OECD (1998b), covering 1973-1995, and earlier versions of the OECD's *Basic Science and Technology Statistics* for 1970-72. The data set captures an important part of the world economy during this period: in 1980, it covers ca. 18% of world GDP and approximately 76% of the GDP in world manufacturing. The R&D expenditures in these industries amount to at least 90% of the world's total innovative activity and almost all private R&D in the manufacturing sector.

The data set includes all countries for which I have been able to estimate productivity estimates at the two- to three-digit industry level so far; the countries are Australia, Canada, Denmark,

[22] With respect to the estimated distance effects δ_h, note that the bilateral geographic distance is indeed time-invariant.

[23] Estimation in first-differences is another way of eliminating time-invariant unobserved heterogeneity, but it greatly increases errors in variables problems in these regressions. While this is also to some extent the case when a large number of fixed effects are included (see Griliches and Hausman 1986), estimation in levels with country-by-industry fixed effects appears to be the strongly preferred specification in the present case. A detailed and more general discussion of the identification problems involved in the above specification can be found in Manski (1993).

Finland, France, West Germany,[24] Italy, Japan, the Netherlands, Norway, Spain, Sweden, the United Kingdom, and the United States. The industry classification uses the United Nation's International Standard Industrial Classification (ISIC) system, covering almost all of manufacturing with twelve subdivisions.[25] These are food, beverages and tobacco (ISIC 31), textiles, apparel, and leather (ISIC 32), wood products and furniture (ISIC 33), paper, paper products and printing (ISIC 34), chemicals and drugs (ISIC 351+352), rubber and plastics (ISIC 355+356), non-metallic mineral products (ISIC 36), basic metals (ISIC 37), metal products (ISIC 381), non-electrical machinery, computers, and instruments (ISIC 382+385), electrical machinery (ISIC 383), and transportation equipment (ISIC 384).

Figure 1 presents the relative size of the economies in terms of total manufacturing value added in 1980. The U.S. has a share of 30% in the sample, followed by Japan and Germany, with 13% each. Figure 2 shows the relative size by industry. There are three industries that account for more than 10% of value added in the year 1980: food, beverages, and tobacco (ISIC 31), transportation equipment (ISIC 384), and electrical machinery (ISIC 383). The smallest sector in terms of value added is textiles (ISIC 32).

Total factor productivity (TFP) growth series for each industry are constructed from estimates on weighed factor inputs (physical capital and labor) and outputs (gross production). Following Hall (1990), the weights used to construct the input growth series are cost-based factor shares, since these are, contrary to revenue-based factor shares, correct even in absence of constant returns to scale. The cost shares incorporate important country-specific information on the user cost of capital based on the work of Jorgenson and Landau (1993). Finally, I have indexed the level of TFP for all industries to a common value (equal to one hundred) in the initial year of the sample.

[24]The R&D data after 1991 is for the unified Germany, while the STAN data is for the former West Germany throughout.

[25]I have dropped the classes ISIC 353+354, Petroleum and Refineries, because of bad data, and ISIC 39, Other Manufacturing, because it includes rather different products across countries.

Empirical results on international technology diffusion from two different samples will be presented below: first, I consider the relationship of R&D expenditures in the G-5 countries and productivity in the remaining nine smaller OECD countries between 1970 and 1995. Second, the relationship of R&D employment and productivity among the G-7 countries between 1979 and 1993 is analyzed. Tables 1 and 2 show summary statistics on TFP growth for these samples.

On average across twelve industries, productivity growth was highest in Italy among the nine smaller OECD countries (Table 1), with an annual rate of growth of 4.87% between 1970-82 and 3.97% between 1983-95. Productivity growth was only around 1.6% over the entire period in Spain, and in Denmark as well as in the Netherlands, productivity growth slowed down substantially in the later subperiod. By industry, the productivity growth rate ranged between a low of 1.42% in food manufacturing to 4.6% in electrical machinery.

Among the G-7 countries between 1979 and 1993, TFP growth was highest in Italy, with an average rate of 3.51% (Table 2). Productivity growth in Canada, Germany and Japan averaged only between 0 and 1% per year between 1979-93; the data displays a marked slowdown in the later years in this sample. In the US, productivity growth is estimated to have been 2% per year between 1979-93. Also among the G-7 countries between 1979-93, the TFP growth in the food industry was lowest of all twelve industries, with about -0.1% per year. Productivity growth among the G-7 countries was highest in the electrical machinery industry, with 4.07%; this industry was also the productivity growth leader in the other sample. The correlation of the productivity growth rates by industry across the two samples is 0.95,[26] which is consistent with the idea that technology is diffusing internationally.

The source of the R&D data is OECD (1998b). Based on the official submissions from its member countries, the OECD has created the *Analytical Business Enterprise R&D* (ANBERD) as well as

[26]This is only in part due to the fact that Canada's and Italy's industries are in both samples.

the *Analytical Researchers, Scientists and Engineers* (ANRSE) database. For the first sample, I use the R&D expenditure data, which covers all intramural business enterprise (i.e., private) R&D. The R&D expenditure data has been transformed to stock measures using the perpetual inventory method.

Figure 3 shows the distribution of R&D across the 14 countries in the year 1980: the US does 58% of all R&D in these countries, followed by Japan (12%), the UK (9%), Germany (8%), and France (6%).[27] The G-5 countries together conduct 93% of all R&D in the entire sample, while Norway, Spain, and Denmark engage in less than 0.5% of the fourteen countries' R&D. Comparing Figure 3 with Figure 1, the distribution of R&D in the sample is considerably more concentrated than the distribution of value added. For this reason, I will focus on the G-5 countries as foreign sources of technology in the analysis below.

Turning to the shares of R&D by industry, it is clear from Figure 4 that not only is R&D concentrated by country, but also by industry: most R&D is conducted in the transportation equipment industry (including air and space; 34%), followed by the electrical machinery industry (24%), the machinery, computers & instruments industry (16%), and chemicals (including drugs), with 15%. On the other end of the spectrum, the wood products and furniture industry conducts less than 0.5% of all R&D.

Given the relatively uniform distribution of value added across industries, the concentration of R&D in certain industries implies very different R&D intensities across industries. This can be seen from Figure 5; for instance, the transportation equipment industry has a R&D intensity more than fifty times higher than the wood industry. The four industries with relatively high R&D intensities are the same where also most of the R&D spending takes place, namely: (1) chemicals, (2) machinery, computers & instruments, (3) electrical machinery, and (4) transportation equipment. Below I will

[27] For the larger part of the sample period, though, Germany conducts more R&D than the U.K.

present some results from samples that are restricted to these four R&D intensive industries.

Table 3 provides summary statistics on R&D expenditures for the twelve industries and fourteen countries. The average growth rates by country were highest overall in Germany and Italy, with about 11.8% and 11.3% per year over both subperiods, and lowest in the U.K., with ca. 5.8% per year. The growth of R&D expenditures was slowing down from the first subperiod, 1970-82 to the second, 1983-95, from an average of 10.78% to 7.06%; in fact, in every single country, the growth rate of R&D expenditures fell over time.

By industry, R&D expenditure growth was strongest in the wood products and furniture industry, albeit at a very low level (recall Figure 4). The second-highest average rate of growth was for the machinery, computers & instruments industry, with 10.63%, where R&D growth was lowest on average in the textiles and non-metallic minerals (stone, clay, glass etc.) industries, with 7.78% and 7.84%, respectively. Also note that the R&D growth rates by country vary more than by industry (standard deviation by country is between 1.7% and 1.96%, whereas by industry it is 1.12%).

I use R&D employment data on the number of researchers, scientists, and engineers, from the OECD ANRSE database (OECD 1998b). Internationally comparable data on R&D employment by industry is only available for the G-7 countries for the period of 1979-93. Also the R&D employment figures have been converted into stocks using the perpetual inventory method, see the appendix for details. Table 4 shows summary statistics for the R&D employment data.

R&D employment growth was lowest in the UK, with 5.65% per year on average, and highest in Italy, with 13.73% per year. The average annual growth rate of R&D employment was 9.66%, with a standard deviation of 2.29%. By industry, R&D employment growth was lowest in the paper & printing industry, with 6.25% per year, and highest in the metal products industry, with 15.35%. The R&D intensive industries have annual R&D employment growth rates that are average or slightly above in the sample. As indicated by a standard variations given in Table 4, there is slightly more

variation by industry than by country in R&D employment growth for the G-7 countries between 1979-93.

The distance data I use in this paper is miles between capital cities of the countries, as the crow flies; it is taken from Haveman (1998). Table 5a presents the distance data from the G-5 countries to the nine smaller OECD countries, and Table 5b the distance among the G-7 countries. Among the smaller OECD countries, one can distinguish three types of countries: (1) European countries, which are close to the UK, France, and Germany, about 6,000 miles away from the US, and around 9,000 miles away from Japan; (2) Canada, which is close to the US, about 5,500 miles away from the European G-5 countries, and about 10,000 miles away from Japan; and Australia, which is around 16,500 miles away from all G-5 countries except for Japan, which is about 8,000 miles away. Figure 6 visualizes the G-5 distances of the Netherlands, Canada, and Australia, and underscores that the latter country is the most remote of the nine smaller countries in the sample. Among the G-7 countries, Japan is situated relatively remotely.

I now turn to the estimation results.

5 Estimation Results

5.1 G-5 R&D Expenditure Effects in Nine Smaller OECD Countries

5.1.1 Analysis with Twelve Manufacturing Industries

First, the relationship between G-5 country R&D expenditures and productivity in the nine smaller OECD countries between 1970 and 1995 is analyzed. Consider the following specification:

$$\ln f_{ijt} = \alpha_t + \mu_{ij} + \beta \ln s^e_{ijt} + \gamma (1 + \phi D_t) \ln \left(s^e_{Bjt}\, d_{iB}^{-\delta_B} + \theta_U\, s^e_{Ujt}\, d_{iU}^{-\delta_U} \right) + \varepsilon_{ijt}, \forall i, j, t, \qquad (4)$$

where f_{ijt} is the TFP index in country i's industry j at time t, α_t are time fixed effects (26 parameters), μ_{ij} are country-by-industry fixed effects (9×12) parameters, and the variable s^e_{ijt} are the R&D expenditures of the industry in country i itself. The variable s^e_B is UK R&D expenditures, s^e_U are US R&D expenditures, d_{iB} is country i's distance to the UK, d_{iU} is country i's distance to the US, and D_t is an indicator variable that is equal to 1 for the years 1983-95, and zero otherwise. The parameters of interest are β (effect from domestic R&D), γ, which gives the effect from US and UK R&D, the parameter θ_U which indicates the relative strength of US R&D, the parameter ϕ which captures whether the effect from US and UK R&D has been constant over the two subperiods, and δ_B, δ_U which indicate whether the effect from UK and US R&D depends on the distance between technology sender (the US and UK) and receiver (country i). I have estimated equation (4) using non-linear least squares; the results are given in Table 6, first column.

The own R&D elasticity is precisely estimated with $\beta = 6.9\%$, which is in the range of six to ten percent which has been estimated in similar regressions so far (Griliches 1995).[28] In the first subperiod (1970-82), the effect from foreign R&D, γ, is estimated to be already larger than the domestic effect, with 0.092 (s.e. of 0.009). With a parameter $\phi = 0.104$, the effect from US and UK R&D in the later subperiod (1983-95) is about ten percent larger, suggesting a relative increase in the importance of foreign sources of technology diffusion (here: the US and UK) for productivity increases. The potency of US R&D is estimated to be slightly below that of the UK ($\theta_U = 0.983$, while the effect for UK R&D is normalized to equal $\theta_B = 1$), but one cannot reject the hypothesis that θ_U is equal to one.

The parameters associated with the bilateral distance to the US and the UK, δ_U and δ_B, are both estimated to be significantly positive and larger than one, at 1.616 and 1.286, respectively. This

[28] The standard errors are given in brackets in the tables; a **(*) means that a parameter is significantly larger than zero at a 5% (10%) level in a one-sided test. The standard errors are from the inverse of the computed Hessian.

means that the variation in productivity levels can be explained better when the 'effective' US and UK R&D expenditures from the point of view of the nine smaller OECD countries are falling when their distance to the US and the UK is increasing.[29] Thus, these estimates reject the hypothesis that bilateral distance does not matter or even raises 'effective' foreign R&D, corresponding to estimates of δ that are equal to zero or negative, respectively. Moreover, the fact that we estimate $\delta_U > \delta_B$ suggests that the effectiveness of US R&D is declining more rapidly with geographic distance than the UK's does. I have calculated what the estimated parameters of equation (4) imply for log productivity in the smaller OECD countries as a function of distance away from the US and the UK, evaluated at the mean of the data. Figure 7 summarizes this analysis. At the rear upper corner of the diagram, when the distance to the UK and the US are both equal to zero, productivity is highest. The estimates imply that productivity in Australia is more than 40% lower than in Canada due to their different location relative to the US and the UK, all else equal. This is a very big effect, and it needs to be seen whether it is confirmed by other estimates.

While the exact impact of geographic distance on productivity varies by technology sending country, both because of differences in bilateral distances as well as because δ_h varies by country, a rough estimate can be obtained as follows. Suppose that the δ_h are estimated to be close enough so that they are not significantly different, at $\bar{\delta}$. Consider a technology receiving country i that is, hypothetically, at the same distance, $\bar{d}_i$, from all technology sending countries. The productivity effect from foreign R&D is then given by $\gamma \ln \left[\bar{d}_i^{-\bar{\delta}} \left(\sum_h \theta_h s_h\right)\right] = \gamma \ln \left(\sum_h \theta_h s_h\right) + \gamma \left(-\bar{\delta}\right) \ln \bar{d}_i$. Hence, as a first approximation, the elasticity of productivity with respect to (equi-) distance away from the technology sender is equal to $\eta = \gamma \times \left(-\bar{\delta}\right)$. For the results in column 1 of Table 6, η is between -11.79% and -14.4%. Hence, a 10% increase in distance is associated with a decline in productivity

[29] It might be useful to think of technology flows that are being 'deflated' by bilateral geographic distance in this context.

of more than 1% according to these estimates.

In equation (5), I have included R&D of all G-5 countries into the specification:

$$\ln f_{ijt} = \alpha_t + \mu_{ij} + \beta \ln s^e_{ijt} + \gamma\,(1 + \phi D_t) \ln \left(\sum_{h \epsilon G5} \theta_h \, s^e_{hjt} \, d_{ih}^{-\delta_h} \right) + \varepsilon_{ijt}, \qquad (5)$$

where the index h is for the G-5 countries, and θ_U, the potency of US R&D is normalized to one. Column 2 in Table 6 shows the results of this regression. Relative to column 1, the effect from own R&D, β, falls slightly to 5.7%, while the effect from foreign R&D rises, to $\gamma = 0.107$. The θ_h parameters, indicating the relative potency of R&D from a given G-5 country, are all fairly similar and close to one. In fact, one cannot reject the null hypothesis that the θ's of the G-5 countries, except for the UK which is larger ($\theta_B = 1.121$), are equal to each other. Also in specification (5), a positive value for ϕ is estimated, indicating that the effect of foreign R&D on productivity in the nine smaller OECD countries has increased over time.

The distance parameters δ_h are all estimated to be larger than one, although they vary substantially across countries. The highest degree of localization is found for US R&D, with a value $\delta_U = 2.267$. This could be due to strong productivity effects of US R&D in near-by Canada. I estimate the lowest degree of localization for British R&D, with an estimate of $\delta_B = 1.019$, which is consistent with relatively strong productivity effects of UK R&D in 17,000 thousand miles away Australia. The estimates for Japan, Germany, and France are equal to $\delta_J = 1.489$, $\delta_G = 1.237$, and $\delta_F = 1.486$, respectively.

Even though the estimated standard errors in specification (5) are small relative to the point estimates, it is reasonable to ask how sure one can be about the size of the distance parameters. Is there enough variation in the data to identify these parameters? In order to address this question, I have re-estimated the equation with two smaller samples: in the specification underlying column 3 of

Table 6, the observations for Australia are left out, and in that shown in column 4, those for Canada are dropped from the sample. Because Australia is the most remotely located country in the sample (see Table 5a), one would expect that if the effects from foreign R&D are falling with geographic distance, the estimated effects from G-5 R&D are higher when Australia is eliminated than in the full sample. This is what I find: in column 3, the effect from G-5 R&D rises from $\gamma = 10.7\%$ in the full sample to $\gamma = 12.8\%$. At the same time, the effect from domestic R&D falls, from a value of 5.7% to 4.2%.[30]

Further, relative to the full sample, I estimate a lower value of δ_J and higher values of δ_B, δ_G, and δ_F. The finding that Japanese R&D is now estimated to have a less localized effect and European R&D a more localized effect is consistent with the hypothesis that international technology diffusion is geographically localized, because Australia is relatively close to Japan while it is relatively far from the European G-5 countries. In addition, the potency of UK R&D, θ_B, is estimated to be lower when Australia is excluded, consistent with the idea that due to historical reasons, there is a relatively strong effect from UK R&D in Australia.

Excluding Canada from the sample also increases the estimate of γ relative to the benchmark specification (compare columns 2 and 4 in Table 6). Of all nine smaller OECD countries, Canada is located closest to the US and relatively far away from Japan (only Spain is further away from Japan; see Table 5a). Thus, if international technology diffusion is geographically localized and the δ estimates pick up this effect, one would expect that if the observations for Canada are dropped from the sample, US R&D is estimated to have a less, and Japanese R&D to have a more localized effect. This is what I find: the parameter δ_U drops sharply, from 2.267 down to 1.662, while δ_J rises from 1.489 to 1.609.

[30] At times I will be discussing how the point estimates vary upon excluding parts of the sample even though the parameters might not differ in a statistical sense.

This concludes the analysis of productivity effects of G-5 R&D expenditures with the full sample of industries. I now turn to results from the four most R&D-intensive industries in the sample.

5.1.2 Analysis with Four R&D-Intensive Industries

These industries are (1) chemicals, including drugs (ISIC 351+352), (2) machinery, computers, and instruments (ISIC 382+385), (3) electrical machinery (ISIC 383), and (4) transportation equipment (ISIC 384). The specification follows (5),

$$\ln f_{ijt} = \alpha_t + \mu_{ij} + \beta \ln s^e_{ijt} + \gamma (1 + \phi D_t) \ln \left(\sum_{h \epsilon G5} \theta_h \, s^e_{hjt} \, d_{ih}^{-\delta_h} \right) + \varepsilon_{ijt},$$

where I now estimate now $4 \times 9 = 36$ country-by-industry fixed effects, μ_{ij}. The number of observations is down to 936, and the results are shown in Table 7, column 1. The estimated θ_h's vary little by country. Therefore, I have constrained them to be the same. The benchmark specification is thus given by

$$\ln f_{ijt} = \alpha_t + \mu_{ij} + \beta \ln s^e_{ijt} + \gamma (1 + \phi D_t) \ln \left(\sum_{h \epsilon G5} s^e_{hjt} \, d_{ih}^{-\delta_h} \right) + \varepsilon_{ijt}. \tag{6}$$

Results from estimating (6) are in column 2 of Table 7. One sees that both the effect from domestic as well as that from foreign R&D is higher in the sample of R&D-intensive industries, compared to the full sample (as in Table 6): β goes up from 5.7% to 11%, and γ from 10.7% to 63.1%. That there is an increase is quite plausible, because if the marginal product of R&D spending across different industries is roughly equalized, then the R&D elasticities in high R&D-intensity industries should be higher than in the average R&D-intensity industry. However, it is interesting to note that the parameter for foreign R&D increases by 400%, while the domestic R&D elasticity only doubles. This could suggest that the *relative*, within-industry contribution of foreign sources of productivity

increases is higher for high R&D-intensity industries than for low R&D intensity industries.

Also in the smaller sample of R&D-intensive industries, I find that the productivity effect from G-5 R&D has increased from the earlier to the later subperiod: $\phi = 0.092$, which is about half as large as the same parameter in the full sample. The distance parameters δ's are all significant and larger than one, as before. In fact, the point estimates do generally not differ very much from those obtained in the full sample. One possible explanation for this is that it is primarily the R&D-intensive industries that determine the estimated δ's anyway. There are two exceptions to this: the US distance effect falls from $\delta_U = 2.267$ to $\delta_U = 1.943$ in the sample of R&D-intensive industries, and the UK parameter δ_B is now about 1.5, as are those of the remaining G-5 countries. In contrast, in the full sample, δ_B is estimated to be around 1, that is, substantially lower than the δ's of the other countries.

When the observations for Australia are eliminated (column 3 of Table 7), the effect from G-5 R&D, γ, is estimated to be 81.8%, up from 63.1% in the benchmark specification. This is consistent with overall stronger international technology diffusion once remotely located Australia is dropped from the sample. However, also the productivity effect from domestic R&D, β, goes up considerably, suggesting that the productivity effects from domestic R&D in Australia are below the sample average. The exclusion of Australia leads again to a lower estimate of δ_J (less localization) and higher δ's for the European countries, consistent with the idea that technology diffusion is localized and this effect is identified by the δ estimates. However, now the changes in the estimates are generally less pronounced, with only δ_J changing substantially.

The results in column 4 of Table 7 are based on the exclusion of Canada from the sample. This leads to a lower estimate of δ_U, 1.837 versus 1.943 in the benchmark specification, meaning that the productivity effects of US R&D are now estimated to be less localized. The distance parameter of Japanese R&D, δ_J, increases from 1.445 in the benchmark to 1.55 now, suggesting

that the productivity effect from Japanese R&D is now estimated to be more concentrated. Given the bilateral distances of the US and Japan to Canada, relative to the other eight smaller OECD countries in the sample, these results are reasonable, and they confirm the findings from the full sample that have been discussed above.[31] I now turn to results based on R&D employment data from the G-7 countries.

5.2 Productivity and R&D Employment in the G-7 Countries

5.2.1 Analysis with Twelve Manufacturing Industries

The R&D employment data set has annual observations from 1979-93 for twelve industries in Canada, France, Germany, Italy, Japan, the UK, and the US. Apart from the fact that the sample is smaller, there is the complication that foreign technology sender and technology receiving countries are one and the same. In order to reduce problems arising from simultaneity, I limit myself to analyzing what the productivity effects of R&D in the US, Japan, and Germany are in the complement set of countries.

The first specification considers the effects from German and Japanese R&D in Canada, France, Italy, Japan, and the U.S.:

$$\ln f_{ijt} = \alpha_t + \mu_{ij} + \beta \ln s_{ijt} + \gamma (1 + \phi D_t) \ln \left(s_{Gjt}\, d_{iG}^{-\delta_G} + \theta_J\, s_{Jjt}\, d_{iJ}^{-\delta_J} \right) + \varepsilon_{ijt}, \qquad (7)$$

where s_{ijt} is cumulative R&D employment of country i in industry j at time t, and D_t is an indicator variable that takes the value one if the observations is for 1986-93, and zero otherwise. I estimate equation (7) with non-linear least squares. The results are shown in Table 8.

[31] I have also tried several alternative specifications to check the sensitivity of these findings. First, the effect from foreign R&D enters additively in logs, not log-linearly: $\beta \ln \left(s_{ijt}^{e} + \eta \left(\sum \theta_h\, s_{hjt}^{e}\, d_{ih}^{-\delta_h} \right) \right)$. Also in this specification, the δ_h are estimated to be significantly larger than zero. Second, I have experimented with including fewer fixed effects, and although this reduces the precision of the parameter estimates, the δ_h remain larger than zero.

The estimated productivity effects are in general considerably smaller now.[32] As seen from column 1 in Table 8, the productivity effect from domestic R&D in Canada, France, Italy, the UK and the US is about $\beta = 0.01$, with a p-value of 4.8% in a one-sided test. The productivity effect from Japanese and German R&D is estimated to be larger, with an estimate of γ of 1.6%, also significantly larger than zero at standard levels. The distance parameters of Germany and Japan are estimated to be similar, with $\delta_G = 1.026$ and $\delta_J = 1.002$. The parameter ϕ turns out to be larger than two, which would mean that the productivity effect of German and Japanese R&D tripled from 1979-85 to 1986-93. Even though this is possible, based on a priori grounds as well as on the earlier estimates for the parameter ϕ, it is not very likely. Another problem with (7) is that it is misspecified to the extent that US R&D has important productivity effects in Canada, which seem to exist from the results given above.

Column 2 of Table 8 presents the results of relating productivity in Canada, France, Italy, Japan, and the UK to their own R&D employment as well as that in the US and Germany

$$\ln f_{ijt} = \alpha_t + \mu_{ij} + \beta \ln s_{ijt} + \gamma (1 + \phi D_t) \ln \left(s_{Gjt}\, d_{iG}^{-\delta_G} + \theta_U\, s_{Ujt}\, d_{iU}^{-\delta_U} \right) + \varepsilon_{ijt}. \tag{8}$$

The contribution from foreign R&D rises substantially, from $\gamma = 1.6\%$ to $\gamma = 5.1\%$, which could be due to the productivity effects from US R&D in Canada. Somewhat surprisingly, US R&D is estimated to be only one fourth as potent as German R&D, with a value of $\theta_U = 0.254$. However, 60% of the observations are for European countries, where German R&D might well have stronger productivity effects than US R&D. Also here, I estimate the distance parameters δ to be significantly

[32] In principle, this could be due to the different sample–that the analysis is on within G-7 country relations during the years 1979-93–, or due to replacing the R&D expenditure variables with R&D employment variables, or both. To examine this question, I have re-estimated the specifications in this section with R&D expenditure data, finding also with that data similarly smaller effects. Thus, the drop in the estimated effects appears to be related primarily to the specific set of countries and sample period. This also suggests that 'double-deflation' problems associated with the R&D expenditure data are not too great.

larger than zero, with $\delta_G = 0.935$ and $\delta_U = 1.096$. Further, the US effect is more localized than that of Germany, paralleling a finding from above. The parameter ϕ is now estimated to be 0.522, suggesting that the effect from US and German R&D in the remaining G-7 countries has increased by about 50% between 1979-85 and 1986-93.

The results of column 3 in Table 8 are for specification (8) when the observations for Canada are dropped from the sample. This should allow to get an idea of whether the δ's identify the degree of localization of international technology diffusion. As expected, the parameter δ_U falls, indicating that in the absence of near-by Canada, US R&D is estimated to have a somewhat more diffused productivity effect in other G-7 countries; further, δ_G rises upon excluding Canada from the sample, suggesting that the productivity effect from German R&D is estimated to be more localized. Even though δ_U is still estimated to be larger than δ_G, with 1.061 and 0.996, respectively, the two parameters are now rather close.

5.2.2 Productivity and R&D Employment in Four R&D-Intensive Industries

In Table 9, I report results from focusing on the four R&D intensive industries ((1) chemicals, (2) machinery, computers & instruments, (3) electrical machinery, and (4) transportation equipment). Parallel to the results presented in Table 8, the first specification considers productivity effects from German and Japanese R&D in the remaining G-7 countries.

$$\ln f_{ijt} = \alpha_t + \mu_{ij} + \beta \ln s_{ijt} + \gamma (1 + \phi D_t) \ln \left(s_{Gjt}\, d_{iG}^{-\delta_G} + \theta_J\, s_{Jjt}\, d_{iJ}^{-\delta_J} \right) + \varepsilon_{ijt}, \qquad (9)$$

with 4×5 country-by-industry fixed effects μ_{ij}. The domestic R&D elasticity is now $\beta = 0.059$, versus 0.01 for all industries, and the effect from foreign R&D is given by $\gamma = 0.103$, compared with 0.016 for all industries; hence, both estimates are about six times as high as for the full sample. There appears

to be little difference in the potency of Japanese and German R&D, with θ_J estimated to be 0.995, but the productivity effects from German R&D are estimated to be somewhat more localized than those from Japanese R&D, with $\delta_G = 1.116$ and $\delta_J = 1.048$. The parameter ϕ, indicating whether the productivity effects from foreign R&D have been increasing over time, is now 0.42, which is more plausible than the corresponding estimate of ca. 2 in Table 8.

In column 2, the productivity effects of German and US R&D in the remaining G-7 countries are estimated. The domestic and foreign R&D parameters are $\beta = 0.121$ and $\gamma = 0.079$; in contrast to the results from the full sample, the domestic effect exceeds the foreign effect here. US R&D is estimated to have almost the same potency as German R&D in the sample ($\theta_U = 0.93$), but the two distance parameters differ strongly: for the US, I estimate $\delta_U = 1.451$, whereas for Germany, the point estimate is equal to 0.687. Consequently, the effect from US R&D is much more geographically localized than the German effect. In the third column of Table 9, the observations for Canada are dropped from the sample, bringing the number of observations down to 240. This lowers the estimate for δ_U, from 1.451 to 1.266, and it raises the distance effect estimate of Germany, from 0.687 to 0.852; these results support the hypothesis that international technology diffusion is geographically localized and the degree of this effect being captured by the estimated δ's. The time profile parameter ϕ is about 0.6 for these specifications, suggesting that foreign sources of technology diffusion have become considerably more important in the late 1980s and early 1990s.[33]

6 Conclusions

I have analyzed the international diffusion of technology by estimating the spatial distribution of productivity effects of G-5 country R&D spending in other OECD countries. This sample includes

[33] I have also experimented with several alternative specifications for the R&D employment data set, but none of these changed qualitatively the major findings discussed above.

most of the world's innovative activity during the years 1970-95. There is evidence for geographic localization of international technology diffusion in the sense that the productivity effects of R&D are declining with the geographic distance between sender and recipient countries. On average, a 10% larger distance away from the G-5 countries is typically associated with a productivity level that is more than 1% lower due to the reduced benefits from G-5 R&D. This is a substantial effect, even if one takes into account that many technology receiving countries are not remotely located relative to *all* G-5 countries, but rather, they are far away from some and relatively close to other G-5 countries.

It is further estimated that international sources of technology diffusion are jointly about twice as important for productivity in the smaller OECD countries as the country's own R&D investments. Among the G-7 countries, the analysis suggests that domestic sources are about as important for productivity increases as foreign sources. The results suggest that the relative strength of foreign sources of technology–in terms of elasticities–is declining with country size; this in itself is consistent with geographic localization of technology diffusion, because within a country, distance is relatively small and technology diffuses quickly. I also estimate that the importance of international technology diffusion has been rising substantially over the sample period. It has increased by 10-20% for the smaller OECD countries between the mid-seventies and around 1990, whereas among the G-7 countries, technology diffusion from abroad has gone up by about 40% between the early 1980s and around 1990.

Future work should shift the focus also on the across-industry dimension as well as the temporal dimension of technology diffusion. With the accumulation of a core set of robust empirical regularities on international technology diffusion, one needs to think about what theory can explain this process, in order to estimate it.

Table 1

Average Annual TFP Growth in Nine Smaller OECD Countries

	1970 - 82	1983 - 95
Australia	0.0207	0.0286
Canada	0.0163	0.0238
Denmark	0.0325	0.0054
Finland	0.0269	0.0404
Italy	0.0487	0.0397
Netherlands	0.0428	0.0092
Norway	0.0278	0.0324
Spain	0.0183	0.0142
Sweden	0.0233	0.0282

Industry	ISIC	1970 - 95
Food	31	0.0142
Paper	34	0.0228
Plastics	355/6	0.0247
Basic Metals	37	0.0226
Chemicals	351/2	0.0302
Textiles	32	0.0244
Metal Products	381	0.0251
Wood Products	33	0.025
Stone etc.	36	0.0254
Transportation	384	0.0244
Machinery incl Computers	382/5	0.0339
Elect. Machinery	383	0.046

Table 2

Average Annual TFP Growth for the G-7 Sample

	1979-93
CAN	0.0095
FRA	0.0181
GER	0.0072
ITA	0.0351
JAP	0.0038
UK	0.0188
USA	0.02

Industry	ISIC	1979 - 93
Food	31	-0.0009
Textiles	32	0.0145
Wood Products	33	0.0149
Paper	34	0.0117
Chemicals	351/2	0.0144
Plastics	355/6	0.0121
Stone etc.	36	0.0154
Basic Metals	37	0.013
Metal Products	381	0.0147
Machinery incl Computers	382/5	0.0224
Elect. Machinery	383	0.0407
Transportation	384	0.0198

Table 3

Average Annual R&D Expenditure Growth

	1970 - 82	1983 - 95	Average
AUS	0.0752	0.0654	0.0703
CAN	0.1098	0.0726	0.0912
DEN	0.1095	0.0701	0.0898
FIN	0.1157	0.0866	0.1012
FRA	0.1002	0.0608	0.0805
GER	0.1503	0.0853	0.1178
ITA	0.1268	0.0988	0.1128
JAP	0.1153	0.0819	0.0986
NL	0.0911	0.0547	0.0729
NOR	0.1141	0.0657	0.0899
SP	0.1198	0.0936	0.1067
SWE	0.1094	0.0617	0.0856
UK	0.0767	0.0382	0.0575
USA	0.0947	0.0529	0.0738
Mean	0.1078	0.0706	
Std. Dev.	0.0196	0.017	

	1970 - 95
Textiles	0.0778
Stone etc.	0.0784
Paper	0.0792
Basic Metals	0.0868
Plastics	0.0877
Transportation	0.0919
Food	0.0941
Elect. Machinery	0.0957
Chemicals	0.0968
Metal Products	0.1025
Machinery incl Computers	0.1063
Wood Products	0.113
Mean	0.0925
Std Dev.	0.0112

Table 4

Average Annual R&D Employment Growth in G-7 countries From Estimated Stocks

	1979 - 93
UK	0.0565
US	0.0819
FRA	0.0931
GER	0.0956
JAP	0.1043
CAN	0.1076
ITA	0.1373
Mean	0.0966
Std. Dev.	0.0229

Industry	1979 - 93
Paper	0.0625
Basic Metals	0.0702
Stone etc.	0.0845
Plastics	0.0856
Food	0.0871
Textiles	0.0875
Chemicals	0.0933
Transportation	0.0995
Electrical Machinery	0.1032
Machinery, Computers, Instruments	0.1146
Wood Products	0.118
Metal Products	0.1535
Mean	0.0966
Std. Dev.	0.0241

Table 5a

Geographic Distance from Nine Smaller OECD Countries to the G-5 Countries
In Miles

	USA	UK	Japan	Germany	France	Average
Australia	15958	17004	7966	16557	16943	14886
Canada	734	5367	10327	5857	5652	5587
Denmark	6518	957	8700	660	1028	3572
Finland	6938	1824	7826	1532	1912	4007
Italy	7222	1434	9867	1066	1108	4139
Netherlands	6198	359	9300	235	428	3304
Norway	6238	1156	8414	1048	1343	3640
Spain	6096	1265	10775	1421	1055	4123
Sweden	6641	1433	8180	1182	1544	3796

Table 5b

Geographic Distance among the G-7 Countries
In Miles

	USA	UK	Japan	Italy	Germany	France	Canada
USA		5904	10910	7222	6406	6169	734
UK			9570	1434	511	341	5367
Japan				9867	9357	9723	10327
Italy					1066	1108	6735
Germany						400	5857
France							5652

Table 6

Effects from R&D Expenditure in Nine Smaller OECD Countries; 12 industries

	Equation (4)	Equation (5)	Equation (5) w/o Australia	Equation (5) w/o Canada
Own R&D: β	0.069**	0.057**	0.042**	0.052**
	(0.006)	(0.007)	(0.009)	(0.008)
Foreign R&D: γ	0.092**	0.107**	0.128**	0.136**
	(0.009)	(0.008)	(0.012)	(0.009)
US: θ_U	0.983**	1 (set)	1 (set)	1 (set)
	(0.060)			
UK: θ_B	1 (set)	1.121**	1.087**	1.099**
		(0.060)	(0.063)	(0.063)
JAP: θ_J		1.002**	1.052**	0.988**
		(0.060)	(0.063)	(0.063)
GER: θ_G		0.995**	0.931**	0.918**
		(0.060)	(0.063)	(0.063)
FRA: θ_F		0.999**	0.971**	1.012**
		(0.060)	(0.063)	(0.063)
Dist. to US: δ_U	1.616**	2.267**	2.056**	1.662**
	(0.052)	(0.060)	(0.063)	(0.063)
To UK: δ_B	1.286**	1.019**	1.121**	1.095**
	(0.049)	(0.050)	(0.056)	(0.052)
To JAP: δ_J		1.489**	1.108**	1.609**
		(0.060)	(0.052)	(0.063)
To GER: δ_G		1.237**	1.612**	1.827**
		(0.056)	(0.063)	(0.063)
To FRA: δ_F		1.486**	1.707**	1.384**
		(0.060)	(0.063)	(0.061)
Time profile: ϕ	0.104**	0.207**	0.155**	0.142**
	(0.028)	(0.026)	(0.025)	(0.021)
# of observations	2808	2808	2496	2496
R^2	0.7857	0.7911	0.7868	0.7965

Table 7

Effects from R&D Expenditure in Nine Smaller OECD Countries; 4 Industries

	Fully Parametrized	Benchmark Specification	Benchmark w/o Australia	Benchmark w/o Canada
Own R&D: β	0.109**	0.110**	0.179**	0.103**
	(0.022)	(0.022)	(0.026)	(0.024)
Foreign R&D: γ	0.632**	0.631**	0.818**	0.637**
	(0.031)	(0.031)	(0.037)	(0.033)
US: θ_U	1 (set)	1 (set)	1 (set)	1 (set)
UK: θ_B	1.020**	1	1	1
	(0.103)	(*rest'd*)	(*rest'd*)	(*rest'd*)
JAP: θ_J	1.007**	1	1	1
	(0.103)	(*rest'd*)	(*rest'd*)	(*rest'd*)
GER: θ_G	1.001**	1	1	1
	(0.103)	(*rest'd*)	(*rest'd*)	(*rest'd*)
FRA: θ_F	1.020**	1	1	1
	(0.103)	(*rest'd*)	(*rest'd*)	(*rest'd*)
Dist. to US: δ_U	1.943**	1.943**	2.030**	1.837**
	(0.050)	(0.050)	(0.062)	(0.106)
To UK: δ_B	1.498**	1.495**	1.530**	1.505**
	(0.080)	(0.079)	(0.083)	(0.079)
To JAP: δ_J	1.444**	1.445**	1.316**	1.550**
	(0.041)	(0.040)	(0.048)	(0.069)
To GER: δ_G	1.484**	1.482**	1.530**	1.827**
	(0.060)	(0.060)	(0.062)	(0.063)
To FRA: δ_F	1.406**	1.406**	1.408**	1.444**
	(0.064)	(0.064)	(0.057)	(0.070)
Time profile: ϕ	0.092**	0.092**	0.095**	0.088**
	(0.009)	(0.009)	(0.008)	(0.009)
# of observations	936	936	832	832
R^2	0.8315	0.8314	0.8328	0.8379

Table 8

Effects from R&D Employment in the G-7 Countries: 12 Industries

	Equation (7)	Equation (8)	Equation (8) w/o Canada
Own R&D: β	0.010**	0.012**	0.009
	(0.006)	(0.007)	(0.011)
Foreign R&D: γ	0.016**	0.051**	0.107**
	(0.007)	(0.013)	(0.021)
JAP: θ_J	0.989**		
	(0.096)		
US: θ_U		0.254**	0.281**
		(0.101)	(0.115)
Dist. to GER: δ_G	1.026**	0.935**	0.996**
	(0.104)	(0.094)	(0.095)
To JAP: δ_J	1.002**		
	(0.105)		
To US: δ_U		1.096**	1.061**
		(0.093)	(0.099)
Time profile: ϕ	2.087**	0.522**	0.313**
	(0.105)	(0.103)	(0.109)
# of observations	900	900	720
R^2	0.8052	0.7694	0.7886

Table 9

Productivity and R&D Employment in the G-7 Countries: Four Industries

	Equation (9)	Benchmark: US, GER as Technology Senders	Benchmark w/o Canada
Own R&D: β	0.059**	0.121**	0.135**
	(0.018)	(0.021)	(0.019)
Foreign R&D: γ	0.103**	0.079**	0.078**
	(0.044)	(0.029)	(0.030)
JAP: θ_J	0.995**		
	(0.182)		
US: θ_U		0.930**	0.973**
		(0.182)	(0.204)
Dist. to GER: δ_G	1.116**	0.687**	0.852**
	(0.162)	(0.160)	(0.185)
To JAP: δ_J	1.048**		
	(0.127)		
To US: δ_U		1.451**	1.266**
		(0.174)	(0.196)
Time profile: ϕ	0.420**	0.593**	0.669**
	(0.173)	(0.174)	(0.197)
# of observations	300	300	240
R^2	0.7768	0.7154	0.6983

Figure 1

Relative Size of Total Manufacturing in Fourteen OECD Countries: Value Added in 1980

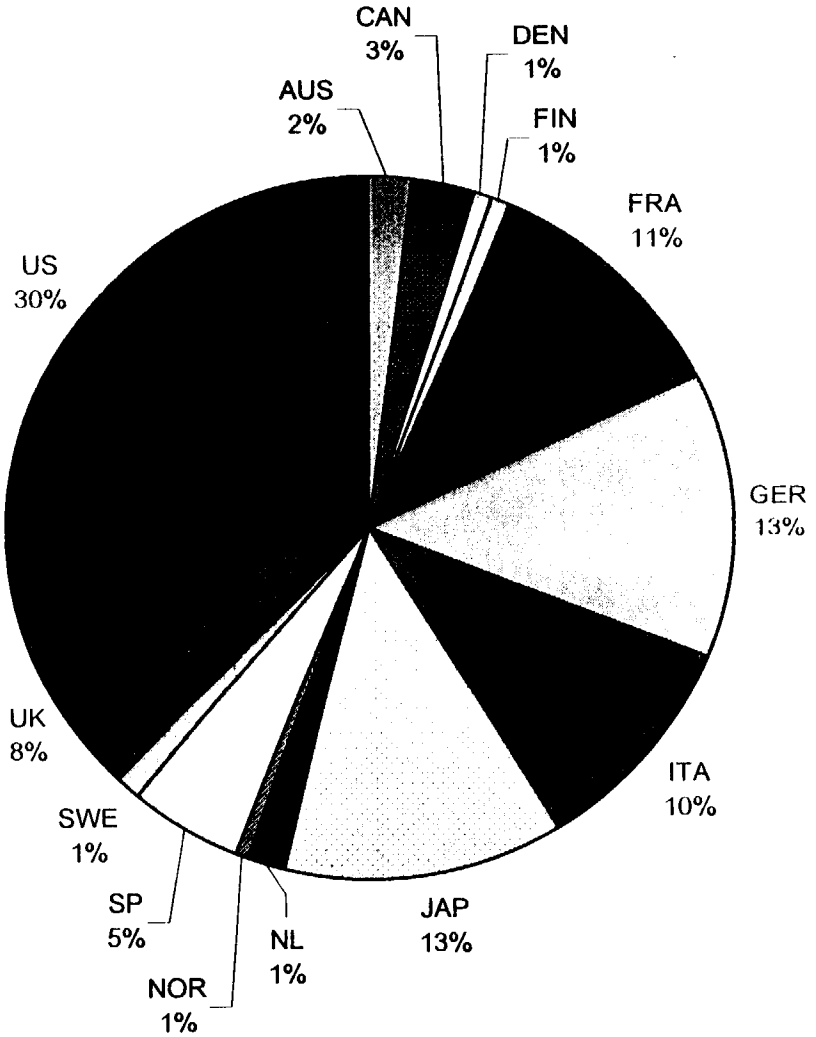


Figure 2

Relative Size of Industries, Average from Fourteen Countries: Value Added in 1980

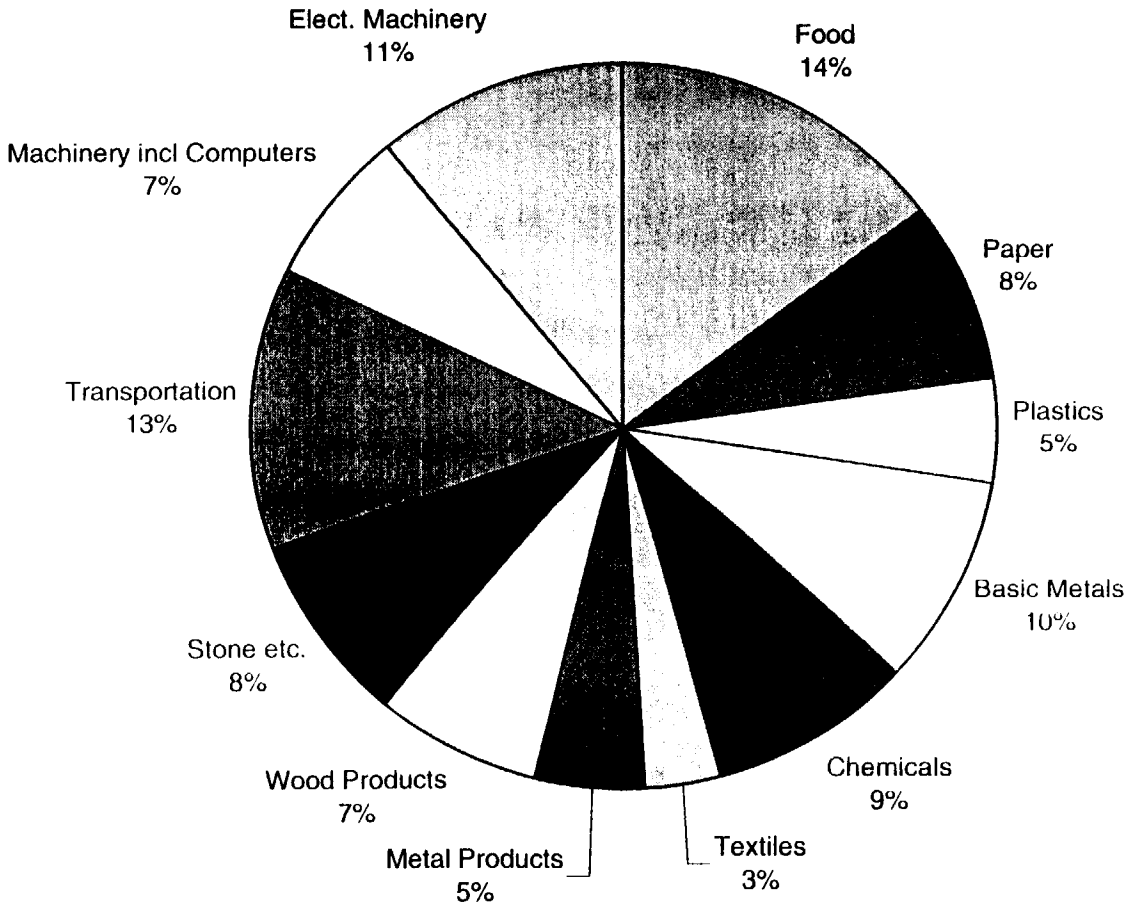


Figure 3

Relative Country Size in Terms of R&D Expenditures: Manufacturing in Fourteen Countries in 1980

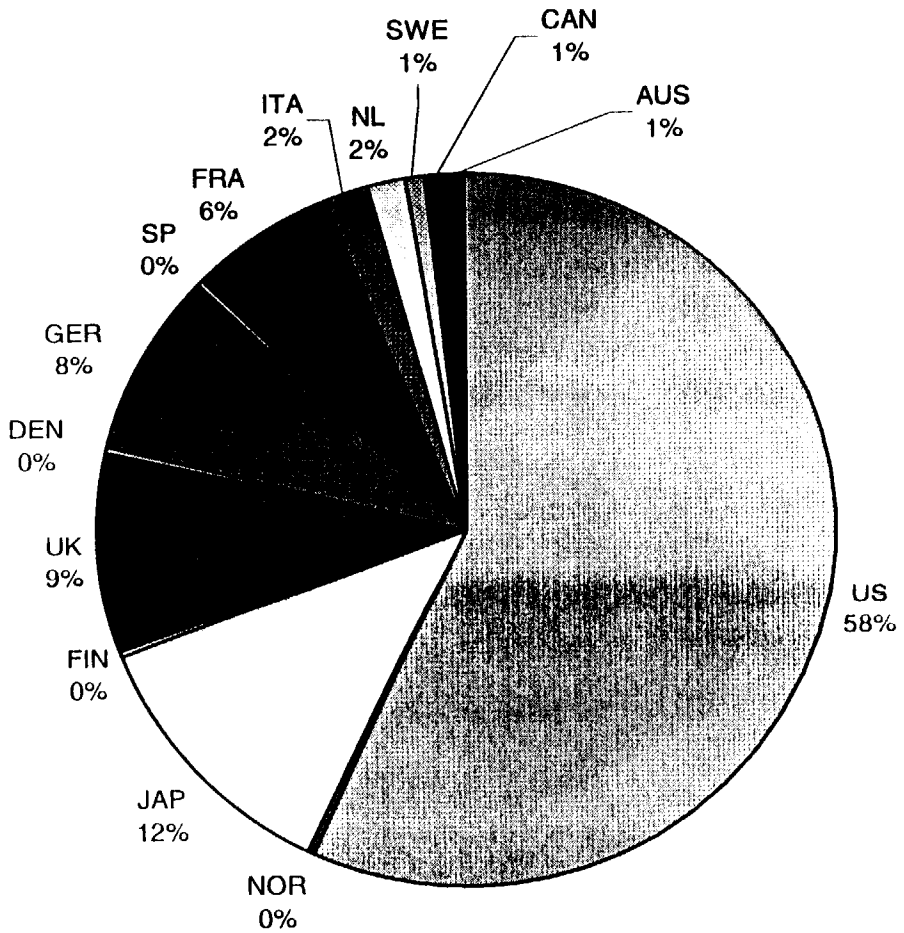


Figure 4

Relative Size of Industries in Terms of R&D Expenditures: Twelve Manufacturing Industries in 1980

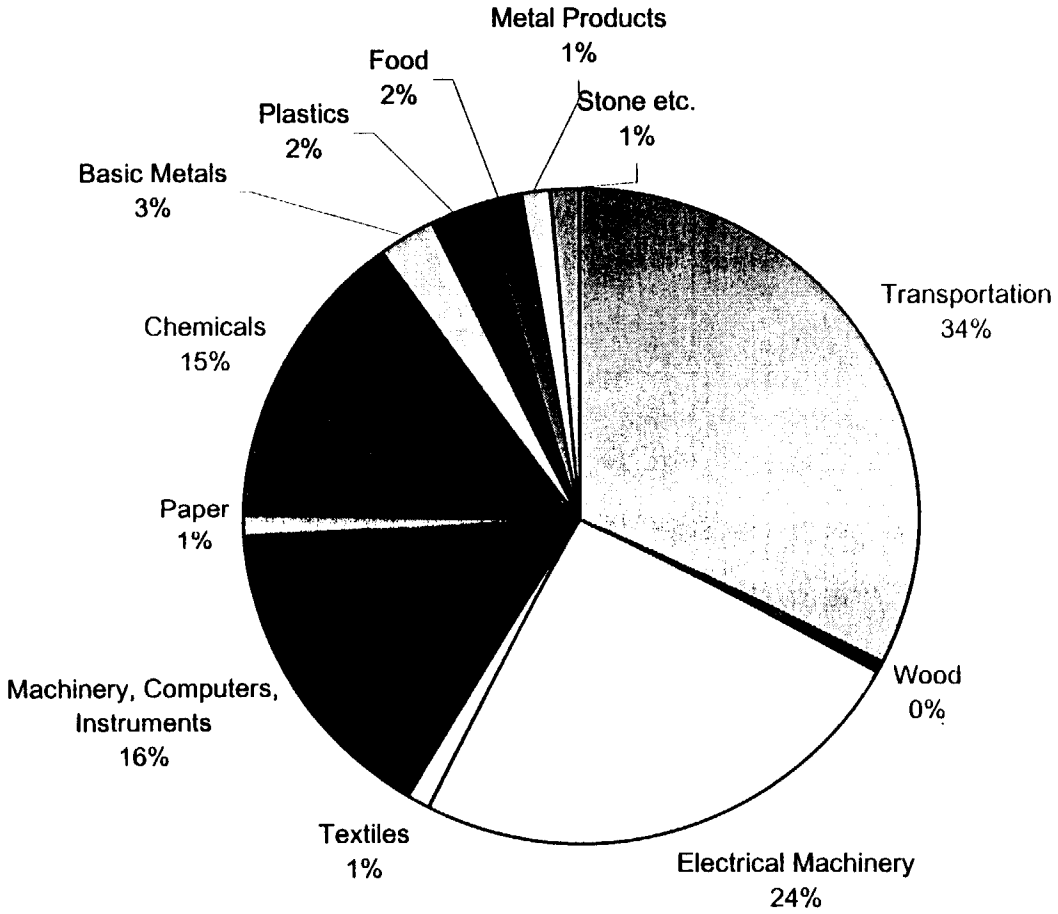


Figure 5

R&D Intensity by Industry: Average from Fourteen Countries, 1980

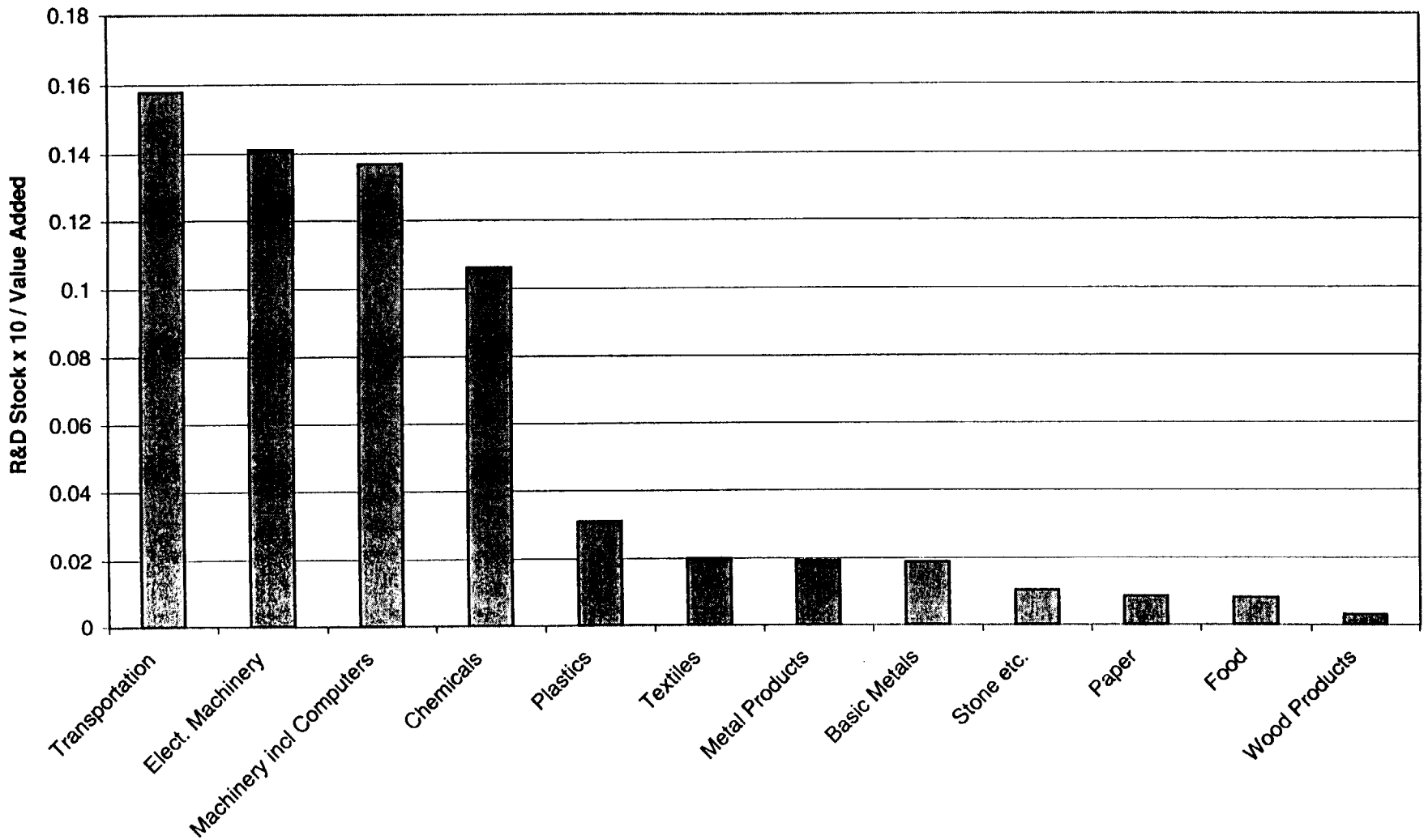


Figure 6

The Geographic Distance of Australia, Canada, and the Netherlands from the G-5 Countries

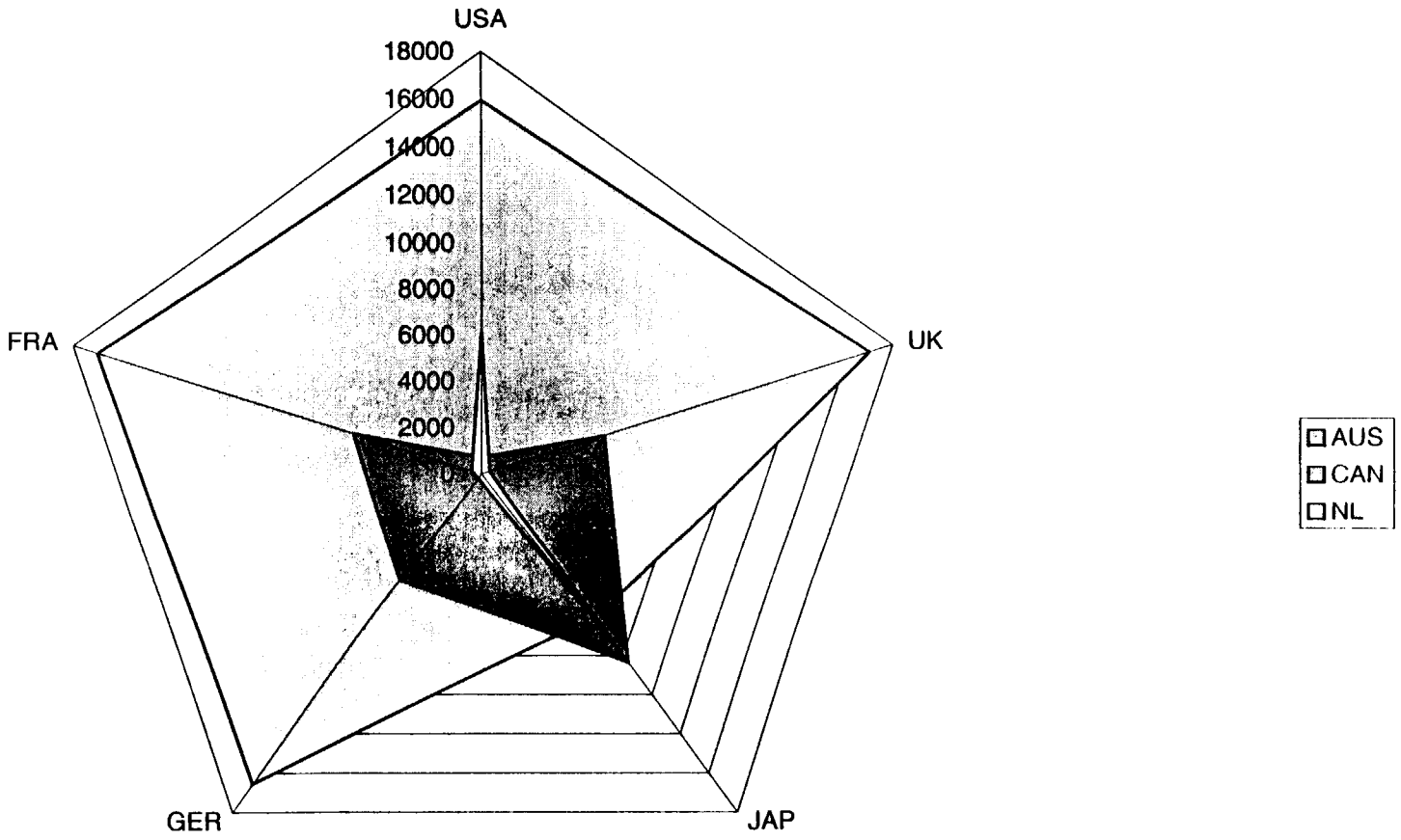
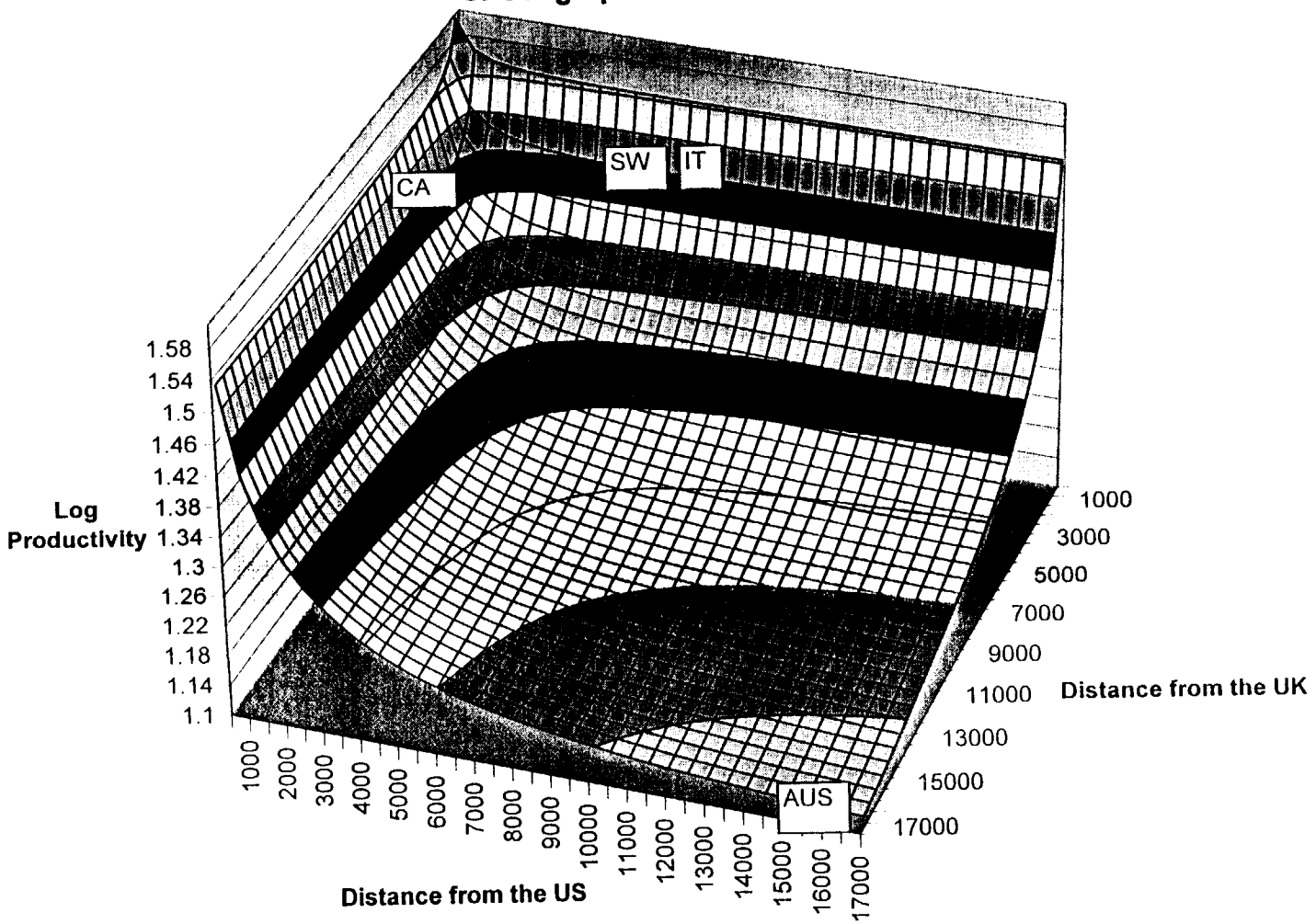


Figure 7

R&D from the UK and the US: Productivity Effects in Smaller OECD Countries as a Function of Geographic Distance



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A Data on labor inputs, physical capital, and gross production

Data on these variables comes from the OECD (1998a) STAN database. It provides internationally comparable data on industrial activity by sectors for OECD countries. The STAN figures are not those submitted by the OECD member countries, but based on estimates by the OECD, which tries to ensure greater international comparability. See OECD (1998a) for the details on adjustments of national data.

In constructing the TFP variable, I consider only inputs of labor and physical capital. Data on labor inputs l can be extracted directly from the STAN database–the number of workers engaged. This includes employees as well as the self-employed, owner proprietors and unpaid family workers. The physical capital stock data is not available in that data base, but gross fixed capital formation in current prices is. I first convert the sectoral investment flows into constant 1990 prices using country- and industry-specific deflators that are derived from the STAN database.[34] The capital stocks are then estimated using the perpetual inventory method, with–suppressing the industry subscripts–

$$\begin{aligned} k_{it} &= (1-\delta_i^k)\, k_{it-1} + inv_{it-1}, \text{ for } t = 2,...,26, \ i = 1,...,14 \\ &\text{and} \\ k_{i1} &= \frac{inv_{i1}}{(g_i+\delta_i^k)}, \ i = 1,...,14, \end{aligned} \tag{10}$$

where inv is gross fixed capital formation in constant prices (land, buildings, machinery and equipment), g is the average annual growth rate of inv over the period 1970-1995, and δ^k is the rate of depreciation for capital. As far as possible, I use country-specific depreciation rates, taken from Jorgenson and Landau (1993b), Table A-3: Canada 8.51%, France 17.39%, Germany 17.40%, Italy

[34] STAN contains data series on both value added in current and constant 1990 prices, which allows to deduce deflator series. However, I found that these series varied implausibly much from year to year. Therefore, the deflators to compute constant value investment and constant value production are smoothed; they are based on giving a weight of 50% to industry-specific price developments, and the remaining 50% to price changes of total manufacturing in a given country.

11.90%, Japan 6.60%, Sweden 7.70%, the United Kingdom 8.19%, and the United States with 13.31%. The numbers, which are used throughout, are estimates for machinery & manufacturing in the year 1980. For the remaining six countries, the average of the eight countries' depreciation rates above has been used.

Let the parameter $\tilde{\alpha}$ be the share of the labor in total production costs. Following the approach suggested by Hall (1990), the $\tilde{\alpha}$'s are not calculated as the ratio of total labor compensation to value added (the revenue-based factor shares), but as cost-based factor shares which are robust in the presence of imperfect competition. For this I use the framework of the integrated capital taxation model of King and Fullerton (see Jorgenson 1993 and Fullerton and Karayannis 1993) and data provided in Jorgenson and Landau (1993b). The effective marginal corporate tax rate ψ is given by the wedge between before-tax (p) and after-tax rate of return (ρ), relative to the former

$$\psi = \frac{p - \rho}{p}. \tag{11}$$

Here, the variable of interest is p, the user cost of capital. It will be a function of the statutory marginal tax rate on corporate income, available investment tax credits, the rates of depreciation, and other determinants.

In the case of equity financing, the after-tax rate of return will be $\rho = r + \pi$, where r is the real interest rate and π is the rate of inflation. Jorgenson (1993) tabulates the values for the marginal effective corporate tax rate in Table 1-1. According to the "fixed-r" strategy, one gives as an input a real interest rate r and deduces the tax rate. In this case, I use a value of $r = 0.1$, which, together with the actual values of π allows, using equation (11), to infer the user cost of capital, p. From Jorgenson's Table 1-1 on ψ, I use the values on "manufacturing" (the 1980 values given are used for 1970-1982 in the sample, the 1985 values for 1983-1986, and Jorgenson's 1990 values are used

for 1987-1991). This certainly introduces an error; in addition, the Jorgenson Table 1-1 is derived from a "fixed-p" approach, as opposed to the "fixed-r" approach employed here. Further, the results depend on, first, the chosen real interest rate, second, ψ varies by asset type, and third, ρ is a function of the way of financing (equity versus debt primarily). Hence, due to unavailability of more detailed data, there are several shortcomings in the construction of the cost-based factor shares. However, the chapter by Fullerton and Karayannis (1993) presents a sensitivity analysis in certain dimensions that can be used to estimate the sensitivity of the estimated cost-based factor shares. I have also experimented with different values for the real interest rate, and found that the basic results presented above do not depend on a particular value. In the end, the main advantage of using the cost-based factor share approach is that it uses all data on the user cost of capital compiled in Jorgenson and Landau (1993a) while at the same time producing factor shares that are robust in the absence of perfect competition.

Having obtained the series on the user cost of capital and capital stock data, $\tilde{\alpha}$ is given by

$$\tilde{\alpha} = \frac{w\,l}{w\,l + p\,k}, \tag{12}$$

where wl are the constant price labor costs. Labor and capital inputs together with the factor shares allow to construct a Thornqvist index of total inputs I_t

$$\begin{aligned} \ln\left(\frac{I_{ijt}}{I_{ijt-1}}\right) &= \frac{1}{2} * [\tilde{\alpha}_{ijt} + \tilde{\alpha}_{ijt-1}] \ln\left(\frac{l_{ijt}}{l_{ijt-1}}\right) \\ &+ \frac{1}{2} * [(1-\tilde{\alpha}_{ijt}) + (1-\tilde{\alpha}_{ijt-1})] \ln\left(\frac{k_{ijt}}{k_{ijt-1}}\right). \end{aligned} \tag{13}$$

This gives a series of growth of total factor input. The TFP growth series is obtained by subtracting total input from output growth. A value of 100 in 1970 is chosen for each of the 14×12 time series, for all industries j and countries i.

B Data on R&D

B.1 R&D Expenditure Data

The R&D expenditure data comes from OECD (1998b). I have only been able to obtain consistent data for all twelve industries and the period of 1970-95 for the fourteen countries mentioned above. Even in these countries, there is not necessarily a R&D survey in each year: in the United Kingdom, for instance, R&D surveys were held only every third year until well into the 1980s, and in Germany, R&D data is collected only bi-annually. I rely on the OECD estimates of missing R&D expenditure data; the OECD has developed these by fitting cubic spline interpolation techniques. In cross-checking these estimates with earlier estimates that I have prepared myself (see Keller 1999), I found the OECD estimates to be quite plausible. The OECD (1998b) publication covers the years 1973-97; estimates for 1970-72 are derived from hardcopy versions of the OECD's *Basic Science and Technology Statistics.*

The construction of the R&D stocks is based on data on total business enterprise intramural expenditure on R&D (denoted e_{ijt}).[35] The OECD's *Frascati Manual* offers more details on what qualifies as R&D. The estimates are available in constant 1990 US $, using the OECD purchasing power parity rates for conversion; the OECD code for this series is BERD. Also here, I use the perpetual inventory method to construct stocks, assuming that (industry and country subscripts are suppressed)

$$\begin{aligned} s_t^e &= (1-\tilde{\delta})\, s_{t-1}^e + rd_{t-1}^e, \text{ for } t = 2, ..., 26 \\ &\text{and} \\ s_1^e &= \frac{rd_1^e}{(g^{RD}+\delta)}, \end{aligned} \tag{14}$$

[35] The exception is Italy, where also extramural R&D expenditure is covered.

where rd^e denotes R&D expenditures. The rate of depreciation of the knowledge stock, $\tilde{\delta}$, is set at 0, and g^{RD} is the average annual growth rate of s^e over the period of 1970-1995. A higher (lower) choice of $\tilde{\delta}$ reduces (increases) the rate of growth of the knowledge stock over the period of observation. As mentioned in the text, I have experimented with other plausible values for the knowledge depreciation rate, ranging between 0.05 and 0.2, but this did not lead to qualitatively different results relative to what I report above.

B.2 R&D Employment Data

R&D employment data on researchers, scientists, and engineers is available also from OECD (1998b), but only for a shorter period (1979-93) and fewer countries (primarily the G-7 countries). The data gives full-time equivalents of R&D personnel as defined in the *Frascati Manual* of the OECD. In general, OECD countries use two different systems to classify personnel engaged in R&D: one by occupation (following the International Standard Classification of Occupation, ISCO), and one by level of formal qualification (according to the International Standard Classification of Education, ISCED). However, all G-7 countries provide data on business enterprise R&D personnel by occupation (ISCO), which seems to be more useful for present purposes anyway. In the ISCO classification, R&D personnel can be distinguished into three groups:

- The researchers, scientists and engineers engaged in the conception or creation of new knowledge, products, processes, methods and systems. Also included are managers and administrators engaged in the planning and management of the scientific and technical aspects of a researcher's work. They are usually of a rank equal to or above that of persons directly employed as researchers and will often be former or part-time researchers.

- The technicians and equivalent staff whose main tasks require technical knowledge and ex-

perience in one or more fields of the sciences. Technicians participate in R&D projects by performing scientific and technical tasks involving the application of concepts and operational methods, normally under the supervision of researchers.

- Other supporting staff, the skilled and unskilled craftsmen, secretarial and clerical staff participating in R&D projects or directly associated with such projects.

For more details on the R&D employment data as well as the adjustments performed by the OECD to ensure greater international comparability, see OECD (1998b). The perpetual inventory method has been employed analogous to the construction of the stocks based on R&D expenditure data, except that the knowledge depreciation rate here is assumed to be 0.1, and in the calculation of the initial stock for the year 1979, I have added 0.2 in the denominator to obtain positive initial stocks for all data series.