NBER WORKING PAPER SERIES

GEOGRAPHIC LOCALIZATION OF INTERNATIONAL TECHNOLOGY DIFFUSION

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Working Paper 7509
http://www.nber.org/papers/w7509

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2000

I thank Don Andrews, Steve Bronars, Peter Debaere, Rob Feenstra, Don Fullerton, Sam Kortum, Preston McAfee, Carol Shiue, Tony Venables, and seminar participants at IGIER/Bocconi, the NBER, Rutgers, Texas A&M, Tilburg, and the University of Texas for helpful comments. This work has been supported by the National Science Foundation under grant number SES-9818902. Anne Golla and Paula Hernandez-Verme have provided excellent research assistance. The views expressed herein are those of the author and not necessarily those of the National Bureau of Economic Research.

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NBER Working Paper No. 7509
January 2000
JEL No. F1, F2, O3 O4

ABSTRACT

Convergence in per capita income across countries turns on whether technological knowledge spillover are global or local. This paper estimates the amount of spillover from R&D expenditures in major industrialized countries on a geographic basis. A new data set is used which encompasses most of the world's innovative activity at the industry-level between the years 1970 and 1995. First, I find that technological knowledge is to a substantial degree local, not global, as the benefits from foreign spillover are declining with distance: on average, a 10% higher distance to a major technology-producing country such as the U.S. is associated with a 0.15% lower level of productivity. Second, technological knowledge has become more global over the sample period. As a determinant of productivity, foreign R&D has significantly gained in importance relative to domestic R&D, and the extent to which knowledge spillover decline with distance has fallen by 20%. The finding of a falling but still high degree of localization has important implications for macroeconomics and growth, trade, and regional economics.

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International convergence in per capita income turns on whether the scope of technological knowledge spillover is global or local. Global spillover favor convergence, while a geographically limited scope of knowledge diffusion can lead to regional clusters of countries with persistently different levels of output per capita. Thus, whether the industrialized countries of the North and West will remain the rich permanently, or whether less developed countries will catch up hinges on whether knowledge spillover are global or local.

According to a widely held view, technological knowledge is truly global, because increasing economic interdependence as well as new means of telecommunications and the internet ensure that people in all countries have access to the same pool of technological knowledge. Even differences in the technology that is actually employed (as documented in Harrigan 1997, e.g.) are consistent with a global pool of technology if the rate of complementary human and physical capital investments or the incentive to adopt new technology varies across countries.[1] Alternatively, technological knowledge could be to some extent local. Helsinki, for instance, is located about 1,500 miles away from Bonn, around 6,900 miles from Washington, D.C., and 7,800 miles from Tokyo, while the distance from Canberra to Bonn, Washington, and Tokyo is 16,500, 16,000, and 8,000 miles, respectively. If knowledge spillover are local, then productivity in Finland should, *ceteris paribus*, be lower than in Australia, because the former is closer than the latter to Germany, the U.S., and Japan, the three countries that account for more than 75% of the world's spending on research and development (R&D).

I will investigate whether knowledge spillover are global or local by examining whether the distance between countries affects the magnitude of productivity gains from each others' R&D spending. Geographic distance should not matter for international technology diffusion if there is a global pool of technological knowledge or a country's technology level depends only on idiosyncratic non-spatial

[1]These points are emphasized by Mankiw (1995) and Prescott (1998), respectively.

factors. If knowledge spillover are to some extent local, however, this matters beyond its implications for international convergence for the following questions.

First, it determines the long-run effectiveness of macroeconomic policies that aim at raising a country's rate of technical change. With perfect international technology diffusion, one country's R&D subsidies would have the same effect on domestic growth as everywhere else in the world. A change in the rate of technical progress at the national level would have then no impact on a country's position in the long-run world ranking either. Moreover, if spillover are global, the public good nature of such policies would raise the question of how to insure that national policies will be at the efficient level, given the incentive of all countries to free-ride on the efforts of other countries.

Second, technology differences affect the comparative advantage and trade of countries (e.g., Trefler 1995). If technology diffusion is influenced by geographic factors, then also production functions and comparative advantage will vary systematically according to location, thereby influencing the trade patterns of the countries. This work on the geographic scope of technology diffusion will thus provide important information for future work on dynamic models of trade and comparative advantage such as proposed by Grossman and Helpman (1991).

Third, it matters for regional and urban economics, where a major concern for a long time has been to explain the agglomeration and the dispersion of economic activity across locations. By explicitly modeling transport costs, recent work on economic geography such as Krugman and Venables (1995) and Fujita et al. (1999) has explained these phenomena through the interaction of pecuniary externalities and increasing returns to scale. When geographic factors affect the diffusion of knowledge, localized technological externalities are an alternative explanation of economic agglomeration and dispersion.[2] Both explanations rely on geographic factors that relate the costs of transporting

[2]See the path-dependence results by Feenstra (1996) and Grossman and Helpman (1991, Ch. 8).

goods or transmitting knowledge to distance.[3] Estimating the spatial patterns of technology diffusion helps to assess the importance of geographic factors in explaining agglomeration and dispersion. It will also be useful for future research that identifies the exact nature of spatial externalities.

My approach follows a substantial amount of work showing that the link between R&D expenditures in one industry and productivity in another is best viewed as a process of technology diffusion (Scherer 1984, Griliches 1995). The theoretical framework underlying my estimates–presented in Appendix A–illustrates this mechanism between countries. I relate R&D spending in France, Germany, Japan, the U.K. and the U.S. (which I will refer to as the G-5 countries) to the productivity levels in nine *other* OECD countries. The first question is whether the magnitude of the productivity effects from G-5 country R&D depends on the bilateral geographic distance between technology sender and recipient country. A second question is whether these effects, if they exist, have become stronger or weaker over time.

Influential recent work in the area includes Jaffe et al. (1993) and Jaffe and Trajtenberg (1998). These authors have studied technology diffusion by comparing the location of patent citations with that of the cited patents, showing that U.S. patents are significantly more often cited by other U.S. patents than by foreign patents. These papers succeed in isolating the flow of technological knowledge by focusing on patent citations, but do not assess the economic impact of technology diffusion in terms of output or productivity.[4] Also Eaton and Kortum (1999, 1996) use data on patenting to estimate their country-level models of technology diffusion and productivity growth. Their diffusion parameter estimates confirm that technology diffusion is geographically localized in the sense that there is more within- than between-country diffusion. However, what identifies the diffusion parameters is that there is more patenting within- than across countries. In contrast, my

[3]The two mechanisms need not be exclusive. See, e.g., the theoretical framework in Appendix A.

[4]See also Bottazzi and Peri (1999) who examine patenting in European regions.

estimates on geography effects in technology diffusion are based directly on the distance between countries, not indirectly through a mechanism such as patenting which is known to be correlated with distance.

Other authors have studied productivity effects from both domestic and foreign R&D in a production function framework, typically estimating that the effect from domestic R&D is stronger than that from foreign R&D (Coe and Helpman 1995, Keller 1999a). This is consistent with the geographic localization of technology diffusion. However, the main focus in these papers is to evaluate the importance of a particular mechanism–international trade–as a conduit of technology diffusion. Here, I take a broader empirical approach, asking whether knowledge spillover are global or local without testing a particular model. Moreover, by exploiting cross-sectional variation in the relative distance of countries to their partner countries rather than distinguishing only between domestic and foreign R&D, my estimates are the first on international technology diffusion that are based on a relatively rich geographic structure.[5]

More generally, other recent work including Ciccone and Hall (1996) and Hanson (1998) has pointed to important geographic localization effects. The former find that productivity is positively correlated with the density of economic activity in the United States, while the latter obtains an estimate of the geographic scope of backward and forward trade linkages by estimating a spatial labor demand function for the United States. Neither paper is concerned with the geographic scope of knowledge spillover. In contrast, I will analyze knowledge spillover on a geographic basis by exploiting the variation of productivity effects from foreign R&D as the relative location of technology sender and recipient countries varies.

[5] Branstetter (1998) studies international technology diffusion between the U.S. and Japan with firm-level data; see also the related work by Bernstein and Mohnen (1998) and Nadiri and Kim (1996). Adams and Jaffe (1996) study geographic effects for domestic technology diffusion, estimating the effects of knowledge spillover among plants of the same firm in the U.S. chemicals industry between 1974-88. They find that the productivity-enhancing effects of parent firm R&D are significantly smaller for plants that are relatively far away than for plants that are relatively nearby.

In the next section, I provide an overview of the empirical setting by discussing the variation of R&D, bilateral distance, and productivity in my sample. Based on a model of trade, transportation costs, and growth which is described in Appendix A, section 2 presents the estimation equation and discusses major estimation issues. All estimation results can be found in section 3. The first set of results concerns the existence of localization effects, while the second documents whether technological knowledge has become more or less global over time. The concluding section 4 contains a summary and further discussion of the results. Appendix B provides some additional discussion of estimation issues, while a description of the sources and the construction of the productivity and R&D data can be found in Appendix C and D, respectively.

1 Empirical setting

This section takes an extended look at the data that I will employ below. Although much is already known about these countries and industries, the context provided by this overview will throw some important new light on how productivity, distance, and R&D expenditures in the sample vary.

1.1 Major country and industry characteristics in terms of GDP and R&D

I use data on manufacturing industries in fourteen OECD countries for the years 1970-1995. The input, output, and price data come from the *STAN* database, OECD (1998a). The source for R&D expenditure data is OECD (1998b). Manufacturing industries in the fourteen countries of my sample have accounted for about 18% of world GDP and approximately 76% of world GDP in manufacturing in 1980, and capture thus an important part of the world economy during this period. Moreover, R&D expenditures by these countries constitute at least 90% of the world's total innovative activity and almost all private R&D in the manufacturing sector for these years.

The included countries are Australia, Canada, Denmark, Finland, France, West Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, the United Kingdom, and the United States. The analysis encompasses almost all of manufacturing, subdivided into twelve industries at the two- to three-digit ISIC level.[6] These are food, beverages and tobacco (ISIC 31), textiles, apparel, and leather (ISIC 32), wood products and furniture (ISIC 33), paper 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 and instruments (ISIC 382+385), electrical machinery (ISIC 383), and transportation equipment (ISIC 384). Table 1 provides summary statistics on the relative size of the countries and industries in terms of GDP. While the size of the countries varies substantially in terms of GDP, it does so even more in terms of R&D expenditures. Table 2 reports summary statistics. The G-5 countries (France, Germany, Japan, the U.K. and the U.S.) conduct 93% of the total R&D in the sample, while their share of manufacturing GDP is only 74%. In the light of their dominant position, I will treat the G-5 countries as the only sources of foreign technology. Moreover, because the effects from foreign R&D might be very different in the G-5 and the non-G-5 countries, I will focus on the productivity effects of G-5 R&D in the other nine countries.

Also the cross-industry variation is higher for R&D than for GDP. Most of the R&D is done in chemicals, machinery, electronics, and transportation, accounting for a total of 87% of all R&D. An increase in R&D activity in these four industries amounts to a major change in national technological trends, which might, through inter-industry spillover, stimulate R&D and raise productivity in other industries as well. In that case, the relationship between R&D and productivity in the low-R&D industries would be jointly caused by changes in R&D investments of the high-R&D industries. This would lead to inconsistent estimates in my empirical analysis. Below, I will provide thus two sets

[6] Two industries have been dropped from the sample: ISIC 353+354, Petroleum and Refineries, because of relatively bad data, and ISIC 39, Other Manufacturing, because it includes rather different products across countries.

of results: for all twelve industries, and for the eight low-R&D industries. If the estimation results for both samples are similar, the estimation bias due to such simultaneity is likely to be limited.[7] R&D expenditures are transformed to stocks with the perpetual inventory method (see Appendix D). Table 3 shows that the average annual growth rates of R&D stocks vary substantially by country, from a high of 9.8% for Italy to a low of 4.8% for Finland. Among the G-5 countries, R&D growth has been highest in Germany (9.9%) and lowest in the U.K. (3.0%), with the U.S. in between (5.3%).

1.2 The relative location of the countries

The distance data in this paper is miles between the capital cities of the countries, as the crow flies (from Haveman 1998). Table 4 presents the distance data from the G-5 countries to the nine other OECD countries. Broadly speaking, three types of countries can be distinguished: (1) European countries, which are relatively close to the U.K., France, and Germany, about 6,000 miles away from the U.S., and around 9,000 miles away from Japan; (2) Canada, which is close to the U.S., 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. This means that I seek to estimate whether international technology diffusion is geographically localized from a relatively small and non-contiguous set of countries.

1.3 Multi-lateral total factor productivity indices

I will compare industry-level total factor productivity (TFP) for the nine non-G-5 countries in my sample. Recent work with similar comparisons for other purposes includes Bernard and Jones (1996), Harrigan (1997) and Griffith et al. (1999). TFP calculations require real, internationally comparable data on outputs, inputs, and intermediate goods. At the industry level, data exists only for labor

[7] Other possible reasons for simultaneity exist as well. In section 2 and Appendix B I discuss how these are addressed.

and physical capital, not for intermediate inputs. Therefore, the TFP calculations in this paper should be viewed as approximations to the true TFP measures. I employ the multi-lateral TFP index proposed by Caves, Christensen, and Diewert (1982). It is defined as

$$\ln F_{cit} = \left(\ln Z_{cit} - \overline{\ln Z_{it}}\right) - \bar{\sigma}_{cit}\left(\ln L_{cit} - \overline{\ln L_{it}}\right) - (1 - \bar{\sigma}_{cit})\left(\ln K_{cit} - \overline{\ln K_{it}}\right), \forall c, i, t, \tag{1}$$

where $c = 1, ..., C$; $i = 1, ..., I$; $t = 1, ..., T$; c indexes country, i indexes industry, and t is the subscript for time. The variable Z is gross output, L is labor inputs, and K denotes capital inputs. Further, $\overline{\ln Z_{it}}$ is average output, given by $\overline{\ln Z_{it}} = \frac{1}{C}\sum_c \ln Z_{cit}$; correspondingly, $\overline{\ln L_{it}} = \frac{1}{C}\sum_c \ln L_{cit}$ and $\overline{\ln K_{it}} = \frac{1}{C}\sum_c \ln K_{cit}$. The variable $\bar{\sigma}_{cit}$ is an average of labor cost shares, $\bar{\sigma}_{cit} = \frac{1}{2}(\alpha_{cit} + \bar{\alpha}_{it})$, where $\alpha_{cit}, \forall c, i, t$, is the cost share of labor, and $\bar{\alpha}_{it}$ is its country average, $\bar{\alpha}_{it} = \frac{1}{C}\sum_c \alpha_{cit}$. Following Hall (1990), I use cost-based factor shares, since these are, in contrast to revenue-based factor shares, correct even in absence of constant returns to scale.[8] This TFP index is superlative in the sense that it is exact for the flexible translog functional form. It is also transitive, so that the choice of the base country does not matter.

1.3.1 Input-utilization adjustments

Figure 1 shows the average indices for Australia, Italy, and Sweden.[9] Because these indices are relative to the country average for a given year, they do not increase as productivity increases over time in all countries. The upward trend in the two series for Italy, for instance, means that Italian TFP was rising relative to the mean of the nine OECD countries over this period. There are two series for each country, one adjusted and one unadjusted, because the OECD has not taken account of differences in labor and capital utilization. I have adjusted the data in the following way: the

[8] The cost shares incorporate country-specific information on the user cost of capital based on the international comparison project of Jorgenson and Landau (1993a); see Appendix C.

[9] These are unweighted industry averages. Size-weighted averages behave very similar.

number of employees in the STAN data base is multiplied by the average annual hours worked in each country's manufacturing sector, from OECD (1999). The actual usage of capital inputs has been estimated by generating capital stock series which adjust for cyclical factors; see Appendix C for details.

Figure 1 indicates that these adjustments are important. The productivity of Swedish industries is substantially underestimated if the relatively low number of annual working hours is not taken into account: on average between 1970 and 1995, the unadjusted value of relative TFP is -0.16, whereas the adjusted value is -0.03. The opposite is the case for Australia, where manufacturing employees work relatively long hours, and thus the adjusted TFP index is considerably below the unadjusted TFP index. These differences in input usage vary also over time, making it impossible to capture them by time-invariant fixed effects. For instance, in Italy input usage was above the mean until 1981 so that the adjusted TFP index is above the unadjusted index, while from 1981 on Italian input usage was slightly below the sample average. The adjusted data is preferred to the unadjusted data for the purpose of comparing productivity across countries, and I will hence use it in my benchmark specifications. However, I will also present basic specifications using unadjusted data to examine the robustness of my findings.

1.3.2 Average productivity by country over time

Figure 2 shows the country averages of the productivity indices for the nine sample countries plus the U.S., which has been the productivity leader throughout the period of 1970-95 according to my estimates.[10] First, the figure clearly indicates that the constructed indices are noisy measures of the true productivity in these countries. For instance, average productivity in Spain in the year of

[10]This as well as the following analysis is based on the input utilization-adjusted TFP data. Without these adjustments, U.S. productivity tends to be relatively *higher*, due to the relatively high number of annual hours worked in the U.S. compared with the most advanced European countries.

1985 was substantially higher than in both 1984 and 1986 according to Figure 2. A data problem is the most plausible explanation for that. Second, while the productivity advantage of the United States as the leader has fallen over the twenty-six years, there is no strong tendency of productivity convergence among the nine countries. In Figure 3, I compare the productivity rank average of countries in 1970 and 1995. High-performing countries are close to lower left corner (Netherlands and Canada) while low-performing countries are close to the upper right corner (Denmark, Spain, and Finland). Countries above the 45 degree line have fallen behind in the productivity ranking between 1970 and 1995, while those below the 45-degree line have gained. As indicated by the vertical distance to the 45-degree line, the largest absolute change in productivity has occurred in Italy, which gained more than three ranks on average. Also Norway's relative productivity increased substantially. Australia lost the highest number of ranks, with 2.58, while Canada is a close second (-2.5 ranks). Australia is also the most-remotely located country in the sample. Thus the drop in Australia's ranking is consistent with the idea that it has fallen back due to technology that is geographically localized in the vicinity of the G-5 countries. At the same time, less-remotely located Denmark has also fallen back over this period, suggesting that there are also other major factors explaining productivity performance.

1.3.3 The industry dimension: with-in country productivity convergence

This paper analyzes productivity dynamics at the industry level, which is important because the country average of the productivity levels masks a considerable amount of heterogeneity at the industry level. In fact, in 1970, a country is often productivity leader (rank 1) in one industry and at the same time productivity laggard (rank 9) in another industry. The average of the countries' TFP rank ranges in 1970 is seven (out of a maximum spread of eight). Over time, this spread has fallen, and by 1995, the average of the TFP rank range is down to five. This trend is confirmed by

Figure 4. The downward-sloping series is the average of the with-in country TFP standard deviation over time. Clearly, there is a trend towards *with-in country convergence* of productivity over these twenty-six years: on average, high productivity countries were able to improve productivity in their relatively low-performing industries, while low productivity countries lost ground even in their relatively high-performing industries. Correspondingly, there is *cross-country divergence* of productivity, as indicated by the upward-sloping series which is the standard deviation of the TFP country averages over time. This is an important finding. In general, it suggests that country-specific components in accounting for productivity differences have become more important over the sample period. Put differently, an increasing share of what leads to relatively good productivity performance appears to be associated with country- rather than with industry-characteristics. This is consistent with several possibilities. One is that strong domestic inter-industry spillover lead to uniform productivity levels across industries while there is no international technology diffusion at all. This might be called the complete localization scenario. It is also consistent with an increasing importance of foreign technology sources, where countries benefit from it to a varying degree, depending on their relative location. I will now turn to an empirical specification to examine this further.

2 Empirical model and estimation issues

There are various reasons why international technology diffusion might be related to geographic distance. My empirical analysis does not support or reject a particular theory. For concreteness, though, I have laid out in Appendix A a two-country model of growth and trade with transport costs that gives rise to the type of effect that will be considered in the following. The model implies that domestic total factor productivity F, defined as output divided by factor-share weighted capital- and labor inputs, is given, at a given point in time, by

$$\ln F = \ln \tilde{A} + \ln \left(N^{1-\alpha} + N_*^{1-\alpha} \xi_*(D) \right), \tag{2}$$

where the parameter α, $0 < \alpha < 1$, is the cost share of labor, and $\tilde{A}$ is a country-specific constant. The term N (N_*) is the existing range of domestic (foreign) intermediate products, which is proportional to cumulative R&D and an index of the countries' level of technological knowledge, and $\xi_*(D)$ is decreasing in the bilateral geographic distance (denoted D) between the domestic and the foreign economy. I will focus on estimating versions of equation (2), which contains the key prediction of interest: equation (2) says that domestic productivity is positively related to cumulative domestic as well as distance-deflated foreign R&D.

In section 3 below, I will use industry-level data for major OECD countries to estimate this relationship. The specification is as follows:

$$\ln F_{cit} = \alpha_{ci} + \alpha_t + \beta \ln \left[S_{cit} + \gamma \left(\sum_{g \epsilon G5} S_{git} \, e^{-\delta D_{cg}} \right) \right] + \varepsilon_{cit}, \forall c, i, t. \tag{3}$$

Here, S denotes cumulative R&D spending, g is an index for the group of G-5 countries (France, Germany, Japan, the U.K. and the U.S.), and D_{cg} is the bilateral geographic distance between country c and country g. The $\alpha_{ci}, \alpha_t, \beta, \gamma$, and δ are parameters to be estimated, and ε_{cit} is an error term whose properties I discuss below. The parameters α_{ci} captures differences in A across industries, while the term $e^{-\delta D_{cg}}$ captures the distance term $\xi_*(D)$ in equation (2) above. The parameter β is related to the elasticity of productivity with respect to own R&D, while γ determines the strength of the productivity effect from foreign R&D.

The parameter δ is of central interest in this paper, as it captures the degree of localization of R&D. This parameter, which I will refer to as the distance parameter, is identified from variation of the productivity effects of G-5 R&D in other countries conditional on bilateral distance. Denote $S_{git}\, e^{-\delta D_{cg}}$ as effective foreign R&D from country g. Positive estimates of δ mean that variation in productivity levels can be better explained by assuming that effective R&D from countries located relatively far away is smaller than that of other countries located relatively more closely. If foreign R&D raises domestic productivity (γ positive), then positive estimates of δ suggest that the benefits from foreign technology creation are decreasing with distance. This is the sense in which I will investigate whether international technology diffusion is geographically localized. In contrast, estimating $\delta = 0$ would mean that distance does not matter, and $\delta < 0$ would be consistent with the strength of technology diffusion being inversely related to distance.

While the existence of localization effects is the first major issue I will investigate, the second issue is whether the degree of localization of knowledge spillover has changed over time during my sample period. A priori, the fall in communication costs and other factors might suggest that technological knowledge has become more global during these years. To investigate whether this is the case, I will therefore allow the distance parameter to vary from the subperiod of 1970-82 to that from 1983-95 in the second set of estimations.

Two major estimation issues need to be confronted.[11] First, there is relatively little variation in bilateral distance in my sample. This will make it relatively difficult to obtain precise estimates of the parameter δ. Moreover, three of the G-5 and seven out of the nine other OECD countries are located in Europe. This could cause problems if the relations to European versus to non-European countries are very different in nature. To partly address the concern that international technology diffusion across different bilateral relations might be heterogeneous, I will present also distance parameters that vary by G-5 country. In addition, I will report results for the subsample of European countries. To the extent that these specifications lead to similar results, the relatively limited and particular

[11] The following issues are further discussed in Appendix B.

set of bilateral relations cannot be critical for my results.

The second concern in estimating equation (3) is that the error term is not orthogonal to the regressors, because any correlation would lead to inconsistent estimates. The disturbances capture idiosyncratic factors that affect measured productivity. Some could be industry-specific, such as receiving strong inter-industry spillover, and others might be common to all industries in a given country, such as shocks affecting the national business cycle. Using instrumental-variable estimation would be one solution to this. However, good instruments for R&D expenditures are here not available. Instead, I try to minimize the effects of simultaneity through my choice of specification. First, in constructing the TFP indices I have imposed a substantial amount of structure that should reduce simultaneity problems (see Appendix C). Second, real R&D is computed using an economy-wide deflator, whereas industry-specific deflators are used in the construction of the productivity indices. Third, my output measure is gross production and not value added, which reduces the likelihood of obtaining spurious regression results (see Basu and Fernald 1995).

Fourth, I focus on the productivity effects of G-5 R&D in *other* industrialized countries. This relationship is not as likely subject to common shocks as the relation of R&D and productivity in the same country. Further, by including domestic R&D expenditures in the equation I control for an important determinant of productivity that could induce simultaneity. Fifth, the estimation equations include time fixed effects (α_t) which control for shocks that affect the entire sample in a given year. Lastly, the country-by-industry fixed effects α_{ci} control for time-invariant factors that generate a spurious correlation between the error terms and the regressors. These capture differences in the average productivity levels which might be due to various factors other than the geographic localization of technological knowledge, but which are omitted in my analysis. I now turn to the estimation results.

3 Estimation Results

I first present estimation results for equation (3). The estimation method is non-linear least squares. The dependent variable is the log relative productivity level as defined by equation (1). The regressors are fixed effects for each year and for each country-by-industry combination, the domestic R&D stock, and the R&D stocks of the G-5 countries interacted with the bilateral geographic distance as described above. For the following estimations and simulations, I normalize distance so that $D = 1$ is equal to 235 miles, the smallest bilateral distance in my sample (between the Netherlands and Germany). This choice of units does not affect the size of the estimated elasticities.

3.1 Basic results

The results for equation (3) are shown in Table 5, column 1. Heteroskedasticity-consistent bootstrapped standard errors are shown in parentheses.[12] The productivity effect from domestic R&D, β, is estimated with $\beta = 0.054$. The corresponding elasticity is equal to $\varepsilon = \beta\Lambda^d$, where Λ^d is between zero and one and increasing in domestic R&D.[13] The average elasticity is equal to 0.018, with a standard deviation of 0.017.[14] The parameter γ measures the average productivity effect from distance-weighted G-5 country R&D relative to domestic R&D; it is positively estimated at 1.219.

The parameter estimate of δ is equal to 0.495. This estimate suggests that effective R&D from

[12] Also standard errors based on standard first-order asymptotics have been computed, but I found the bootstrapped standard errors to be more reliable. The non-linearity in δ seems to make the truncation of the distribution of parameters at the second-order less reasonable. Moreover, except for the parameter γ, the standard errors based on first-order asymptotics tend to be considerably smaller (often about 30%), so I report the more conservative bootstrapped standard errors. They are generated through block-wise resampling from the empirical error distribution, allowing for 108 different blocks, which corresponds to a potentially different variance for each country-by-industry pair. See Andrews (1999) for references and further results. I have also considered the possibility of spatial correlation among the disturbances. However, the covariance of fitted residuals among European countries, e.g., is not significantly different from the covariance of errors between European and non-European countries. This suggests that spatial correlation effects are not very strong.

[13] This elasticity varies by country, by industry, and over time; its definition is $\Lambda^d_{cit} = S_{cit} / \left[S_{cit} + \gamma \left(\sum_{g \epsilon G5} S_{git}\, e^{-\delta D_{cg}} \right) \right], \forall c, i, t.$

[14] Industry-level estimates of this elasticity have often been higher that that, but this difference is probably largely due to the fact that in contrast to many earlier studies, I use TFP relative to the sample mean as the dependent variable (see Griliches 1995 for a broader survey).

G-5 countries is falling with geographic distance. The finding is consistent with the localization hypothesis: productivity in countries that are far away from the G-5 countries is lower than in those located more closely, because technology diffusion and its productivity effects are geographically localized. How important are these effects? Figure 5 shows the total effective R&D from the technology sender point of view, for each G-5 country. While U.S. R&D is more than six times that of Germany, due to its relatively close location to a number of countries in my sample, effective German R&D is estimated to be slightly larger than effective U.S. R&D (34% versus 33%, respectively). For the U.K. and France I obtain shares of 18% and 15%, respectively, while Japan's share is not even 1% of the total effective R&D. Given G-5 country R&D, the effective G-5 R&D stocks are thus inversely related to the average distance to the sample countries: from the last row in Table 4, on average, Japan is almost three times the distance of Germany away from the sample countries.

Figure 6 shows the totals for the nine technology receiving countries. Total effective foreign R&D for the Netherlands is estimated to be highest (33%), followed by Canada (32%) and Denmark (12%). Among the European countries, effective foreign R&D is lowest in Finland (2%), while I estimate the lowest effective foreign R&D for Australia (close to 0%). The results suggest that the combined effect from three relatively small but near-by G-5 countries leads to a higher stock for the Netherlands than for Canada, even though the latter is close to the major R&D conducting country in the world, the United States. Another point to note is that even the difference between effective foreign R&D in the Netherlands or Denmark, which are located at the core of Europe, and Finland, which is on Europe's periphery, is substantial.

Figure 7 presents the full bilateral breakdown for all 9×5 effective foreign R&D stocks. The largest individual effect is that of the U.S. in Canada, followed by the German, U.K., and French effects in the Netherlands. At the other extreme, only Japanese R&D benefits Australia to a significant amount, and even here, the effective Japanese R&D is much smaller than Australia's own R&D stock.

Essentially, the estimates suggest that Australia does not benefit from foreign R&D at all, which might be too strong a result; I return to this point in section 4 below. Figure 8 is also based on these estimates. The different levels and sources of foreign technology for the Netherlands, Australia, and Canada are captured by the size and shape of the pentagons in the graph.

The elasticity of productivity in country c with respect to R&D in G-5 country g is closely related to the size of the effective foreign R&D stock from that country; it is given by $\varepsilon^f_{cg} = \beta\Lambda^f_{cg}$, where Λ^f_{cg} is between zero and one and increasing in effective R&D from country g.[15] The elasticity estimates range from close to $\beta = 0.054$ for U.S. R&D in Canada to almost zero for, e.g., the productivity elasticity of German R&D in Australia. The average is 0.007, varying strongly across bilateral pairs, with a standard deviation of 0.011. I have computed the elasticity of productivity with respect to distance $(\partial \ln F / \partial \ln D)$ to illustrate the influence of distance according to these estimates. This elasticity, denoted ε^D_{cg}, is related to the elasticity with respect to foreign R&D in the following way: $\varepsilon^D_{cg} = \varepsilon^f_{cg} \times (-\delta) \times D_{cg}$. The average (standard deviation) of the distance elasticity is equal to -0.015 (0.02). The estimates therefore suggest that doubling the distance to a G-5 country is on average associated with 1.5% lower productivity.

In column two of Table 5 I report the results from estimating equation (3) with only the relatively low-R&D industries. Any remaining simultaneity problem should be substantially reduced by focusing on these industries. The sample size is now one third lower. Relative to the full sample, I estimate a lower maximum domestic R&D elasticity[16] and a stronger effect from foreign R&D, while the distance parameter δ is again estimated to be positive. I also estimate equation (3) with Australia and Canada dropped from the sample, which reduces the sample size by 22%. Australia

[15] Its definition is given by $\Lambda^f_{citg} = \gamma S_{git} e^{-\delta D_{cg}} / \left[S_{cit} + \gamma \left(\sum_g S_{git}\, e^{-\delta D_{cg}} \right) \right]$, $\forall c, i, t, g$.

[16] Because the industry elasticity ε_i is related to the return to R&D, ρ_i, by $\varepsilon_i = \rho_i \times \frac{S_i}{F_i}$, $\forall i$, if arbitrage equalizes the return to R&D across industries ($\rho_i = \rho$, $\forall i$), then ε_i varies with S_i. This could explain the drop of the maximum elasticity ε from 0.054 to 0.039 for the low-R&D industries in column two.

might be a special case due to its extremely remote location relative to all G-5 countries, and Canada might be special because of its location adjacent to the U.S. which does the majority of all R&D in the world. Without Australia and Canada, the distance parameter is primarily identified from the relative strength of R&D originating in European G-5 countries versus the strength of U.S. and Japanese R&D in seven European countries. From the estimates, it is clear that the magnitude of the domestic R&D effect β is sensitive to the exclusion of Australia and Canada. The localization parameter δ is still estimated to be positive and not very different from that in the full sample.[17]

The last four columns in Table 5 provide some sensitivity analysis. In columns four and five I present results based on TFP indices that are only partially or not at all adjusted for input utilization. The main difference is that β is estimated to be 40% larger. This suggests that one picks up a substantial amount of spurious correlation when cyclical effects that affect both input utilization and R&D are not controlled for. Because both the foreign R&D elasticity as well as the distance elasticity are proportional to β, also these elasticities would be overestimated without adjusting for input utilization. Assuming a R&D depreciation rate of 0% instead of 10% leads to a higher domestic R&D effect estimate (see column 6 of Table 5).[18] Finally, in column 7 of Table 5 I present results for correlating productivity in period t with R&D in period $t-1$. In that case, the R&D stocks are pre-determined. If these results would vary substantially from my earlier estimates, it would mean that simultaneity might continue to play an important role. The regression results suggest that this is not the case.

While my estimates for δ are all consistent with the localization hypothesis, the estimates of β and γ are not fully robust across all specifications: β depends on whether Australia and Canada are

[17]Since the R&D and distance elasticities are proportional to β, they are somewhat lower for the specifications in column 2 and 3 of Table 5 compared to the benchmark specification of column 1. In column 2 (3, respectively), I obtain the following average elasticities: $\varepsilon = 0.007$ (0.005), $\varepsilon^f = 0.006$ (0.005), and $\varepsilon^D = -0.011$ (-0.008).

[18]A R&D depreciation rate of 0% is sometimes assumed to be the 'true' social rate of knowledge depreciation. *Ceteris paribus*, a lower rate of R&D depreciation implies faster growth of the R&D stocks, which, for a given return to R&D, implies a higher R&D elasticity. Thus, the higher estimate of β is consistent with that.

in the sample, and γ appears to be at times only weakly identified. One reason for this might be that specification (3) does not include G-5 country-specific parameters, which might be overly restrictive. I therefore estimate in the following section a specification which allows the distance parameter to vary by G-5 country.

3.2 Distance effects varying by G-5 country

Consider the following generalization of equation (3):

$$\ln F_{cit} = \alpha_{ci} + \alpha_t + \beta \ln \left[S_{cit} + \gamma \left(\sum_{g \epsilon G5} S_{git} \, e^{-\delta_g D_{cg}} \right) \right] + \eta_{cit}, \forall c, i, t. \tag{4}$$

The distance parameter is now allowed to vary by G-5 country, $\delta_g, \forall g$. The results for this specification are summarized in Table 6. While the estimate of β is similar to the corresponding regression in Table 5, γ is now higher than before. The distance parameters δ_g are all larger than zero, consistent with the localization hypothesis. Even though the δ_g vary substantially, the increase in explained variation in productivity levels due to this is very small, and a likelihood ratio test cannot reject the null hypothesis that $\delta_g = \delta$, $\forall g$. However, according to the Akaike Information Criterion (AIC) and other standard model selection criteria, the less restricted model (4) of Table 6 is preferred to that with a common distance parameter.[19] As will become clear below, it is also the more robust model. I will therefore consider specification (4) further.

The higher estimate of γ suggests a higher elasticity with respect to foreign R&D, which I find to be the case; in contrast, the average distance elasticity ε^D falls by a third.[20] The estimates of δ_g range between circa 0.2 for Germany to 0.85 for France. The standard errors suggest that all

[19] Akaike's Information Criterion is defined as: $AIC = \ln\left(\frac{e'e}{n}\right) + \frac{2K}{n}$, where $e'e$ is the residual sum of squares, n is the number of observations, and K is the number of estimated parameters. A lower value of AIC indicates a preferred model. The AIC penalizes the loss of degrees of freedom more heavily than the adjusted R^2, see Greene (1993, 244f.).

[20] The mean of the foreign R&D elasticity ε^f rises from 0.007 to 0.008. The average distance elasticity ε^D varies strongly across bilateral pairs, ranging between zero and -8.4%, with a standard deviation of 0.017,

distance parameters are quite precisely estimated, but some of them are more fragile than they appear: Japan's coefficient, e.g., is solely identified from the differential effect of Japanese R&D in Australia (where it is positive) and in the other eight countries (where it is essentially equal to zero). This suggests that the estimate of δ_J depends considerably on whether Australia is included in the sample or not. The results reported below confirm that. Moreover, the distance parameter for Germany, δ_G, is not always the smallest of the G-5 countries, as it is here.

Column 2 in Table 6 reports the results of estimating (4) with the low-R&D industries only. In contrast to the common-δ specification of Table 5, now the estimates of γ and δ_g remain fairly similar. Column 3 of Table 6 shows the results for the case when Australian and Canadian industries are dropped from the sample. As in the common-δ specification of Table 5, this leads to a substantially lower estimate of β. The relative foreign R&D effect γ is estimated not too different from the estimate for the full sample, but some uncertainty about the magnitude of γ remains. The distance parameters for the European G-5 countries are not very well identified, despite the relatively small standard errors. This is because the bilateral distance to all seven European countries is rather similar (especially for centrally located Germany). The estimate of δ_J drops, which is primarily due to the exclusion of Australia from the sample. Japan, which is the most-closely located G-5 country for Australia, generates relatively stronger R&D effects in Australia than elsewhere, but once only European countries are left in the sample, there is not sufficient variation to identify a differential productivity effect across countries.[21] The specification with lagged R&D in column 4 gives results similar to the benchmark specification in column 1.

In unreported results, I have also estimated the specification (4) with partially adjusted and unadjusted TFP, as well as for a R&D depreciation rate of 0%. The results are qualitatively similar.

[21] Also note that in contrast to the specifications in columns 1 and 2, here Akaike's Criterion favors the more constrained model of Table 5.

As a further specification check, I have allowed the parameter γ to vary by G-5 country (as in $\gamma_g S_g \, e^{-\delta D_{cg}}$), with either a common δ or with the δ's varying by G-5 country. While the distance parameters remain larger than zero, there is no evidence that γ varies significantly by G-5 country. I have also employed a different functional form for the distance effects, estimating $\tilde{\delta}_g$ in the modified effective foreign R&D expression $S_g \tilde{\delta}_g^{D_{cg}}$. For $0 < \tilde{\delta}_g < 1$, this is decreasing in distance D, whereas for values of $\tilde{\delta}_g > 1$ it is increasing in distance. Consistent with the localization hypothesis, I estimate $\tilde{\delta}_g$ between zero and one and usually close to the corresponding e^{δ_g}.

3.3 Localization effects over time

In this section I report results that indicate whether the technology localization effect has become stronger or weaker over time. The following specification will be used:

$$\ln F_{cit} = \alpha_{ci} + \alpha_t + \beta \ln \left[S_{cit} + \gamma \left(\sum_{g \epsilon G5} S_{git} \, e^{-\delta_g (1+\psi T_t) D_{cg}} \right) \right] + \phi_{cit}, \forall c, i, t, \tag{5}$$

where T_t is equal to zero for the years 1970-82 and equal to one for 1983-95. A positive value of ψ indicates that technology created in the G-5 countries has a geographically *more* localized productivity effect over time. In the benchmark specification–see column 1 in Table 7–, I estimate $\psi = -0.505$, which suggests that the degree of localization has *fallen* since the 1970s. This is consistent with the notion that technological knowledge has become more global over these twenty-six years. Compared to the analogous specification in Table 6, the inclusion of the time dummy leads to a higher estimate of β and δ_G and a lower estimate of δ_{US}, with otherwise similar results. The AIC model selection criterion indicates that the specification with time effect is marginally preferred to that without time effect. The estimate of ψ suggests that on average, the G-5 distance coefficients have fallen by about 50%. This means that effective foreign R&D, $S_g e^{-\delta_g D_{cg}}$, has generally been higher in the later subperiod, and has led to an increase in the average foreign R&D elasticity ε^f relative to the domestic elasticity, ε.[22] Thus the relative importance of foreign sources of technology has been substantially increasing according to these estimates.

There is a lot of heterogeneity across bilateral relations in how the relative importance of specific G-5 country technology sources has changed over time. For instance, Canada's only major source of technology among the G-5 countries remains the United States. In other countries, the estimates suggest large shifts in the relative importance of individual G-5 countries as foreign sources of technology. Figure 9 shows for instance that the U.S. has overtaken Germany as the major source of foreign technology in Finland. The decline in the distance parameters means that the distribution of foreign technology sources approaches that of the shares of the G-5 countries in total G-5 R&D. Once the distance parameters are all equal to zero, geographic distance has ceased to play a role in international technology diffusion, and all countries draw from a common global pool of technology which is replenished according to the R&D shares given in Table 2.

However, today geographic distance seems to be a major determinant of international technology diffusion. In Finland, for example, Germany had still 29% of the total effective foreign R&D during 1983-95 even though Germany accounted only for circa 9% of G-5 country R&D during that period. In contrast, Japanese R&D as foreign technology source in Finland was still negligible during 1983-95 according to my estimates, even though Japan accounted for 13% of all G-5 R&D. The situation in many other countries is similar. Figure 10 shows the standard deviation across the G-5 country shares in total effective foreign R&D for each of the nine countries. Except for Spain, the standard deviation has declined in every country. For the European countries, this is primarily associated with the declining importance of being close to Germany, which is accompanied by a decrease in the relative importance of German R&D and an increase for that of the United States. However, if

[22] The former rises from 0.009 to 0.011, while the latter falls from 0.013 to 0.006.

geography loses further in importance, the distribution of foreign technology sources will become less equal again for the European countries, because if the distance parameters approach zero in the long-run, the distribution of R&D shares will be less equal than it is right now.[23] Thus, for some countries, the slowly declining importance of geographic factors in technology diffusion is non-monotonically related to the degree of dispersion in their G-5 technology sources.

In the following I examine the robustness of these findings. The distance effect estimates for the sample of low-R&D industries in column 2 of Table 7 are similar and confirm an estimate of the parameter ψ that is less than zero, consistent with less localization over time. The results in columns 3 and 4 of Table 7 are based on the sample of European countries, and that with lagged R&D, respectively. Also here the estimate of ψ confirms qualitatively the earlier results. Overall, distance coefficients are estimated to fall (in absolute value) between circa 30% and 60% on average, depending on the specification. One needs to be cautious though to not overinterpret the individual parameter estimates of δ_g in Table 7, because some appear to be fragile in the light of the earlier estimates. In particular, some distance coefficients in column 1 of Table 6 do not lie in the interval of the estimates from the two subperiods in column 1 of Table 7, suggesting that some part of the variation in productivity levels identifies ψ, γ, and the δ_g only jointly. Therefore, to analyze the robustness of the less-localization result further, I have also estimated a specification where both γ and the distance parameters δ_g may change over time. The results are very similar.[24] In unreported results, I have obtained the result that the degree of localization has fallen over time also using unadjusted and partially adjusted TFP data, for choosing alternative R&D depreciation rates such

[23] The long-run standard deviation is about 0.233, calculated from the G-5 country shares in Table 2. Note that the G-5 country shares in the global pool of technology change over time as well. From Table 3, e.g., U.S. R&D growth over this period has been slower than in France, Germany, and Japan. This suggests that the long-run U.S. share in G-5 technology might be below 61%, its value in 1980.

[24] The effective foreign R&D term is then $\gamma(1+\lambda T_t)\left(\sum_{g \epsilon G5} S_{git}\, e^{-\delta_g(1+\psi T_t)D_{cg}}\right)$. If there is only a stronger effect from G-5 R&D over time but no change in the degree of localization, one expects that $\lambda > 0$ but $\psi = 0$. For the full sample (corresponding to column 1 in Table 7), I estimate $\lambda = 0.079$ and $\psi = -0.561$, suggesting that the less-localization result is robust to allowing for a differential effect of foreign R&D over time independent of distance.

as 0%, and for the alternative specification where effective foreign R&D is given by $S_g \tilde{\delta}_g^{D_{cg}}$. I will now turn to some concluding discussion of these findings.

4 Summary and discussion

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 paper provides, first, evidence suggesting that the international diffusion of technology is geographically localized in the sense that the productivity effects of R&D are declining with the geographic distance between sender and recipient countries. The average elasticity estimates of productivity with respect to distance varies across specifications from -1% to -2.4%. Using these averages to evaluate a particular bilateral effect, this suggests that Italy's productivity is 0.5 to 1.2 percent lower than Denmark's because of less technological diffusion from the U.K., due to a fifty percent higher bilateral distance to Italy compared to Denmark. This is a substantial effect and points to an important role for geographic factors in determining the availability of technological knowledge across different countries.

Second, the degree of localization of technology diffusion has significantly declined over the sample period. Again, estimates vary somewhat depending on specification. In the benchmark specification of Table 7, the average elasticity of productivity with respect to distance falls from -2.4% during the period of 1970-82 to -2.0% during 1983-95. This is a 20% smaller distance effect over a relatively short period of time, and suggests that the importance of geographic factors is declining rapidly today. While my estimates point thus in some ways to the demise of the importance of geographic distance, in other ways I probably overestimate its importance. For instance, although it is plausible that U.S. R&D is Canada's major foreign source of technology, my estimate of the U.S. share (exceeding 99%) appears to be too high, because surely, Japan, Germany, France and the U.K. together contribute more than 1% to Canada's stock of foreign technology. Other evidence, including from case studies, contradicts these findings.

Comparable results on the geography of technological diffusion from other work are scant at this point. Hanson (1998) estimates the geographic scope of demand linkages by correlating county-level wages with distance-weighted incomes in other U.S. counties. His results also imply a very high degree of localization, in that case for goods trade.[25] Nevertheless, the finding of strong geography effects for technology diffusion is even more striking, because a priori, if anything can be moved costlessly around the globe, it would be technological knowledge. Generally, the more knowledge-intensive the products are, the less plausible is it to assume that the volume of transactions between different locations has much to do with distance-related transport costs. Sending a software program by email from Austin, Texas to Dallas costs essentially the same as sending it to Sydney. So why are there strong location effects for technology diffusion?

One reason might be that my results will prove to be not robust in other samples, with different data, or with different specifications. As data on a larger set of countries, especially outside Europe, becomes available, it will be possible to re-examine the questions my work has tried to address. Moreover, it might be possible in the future to compute productivity indices that consistently account for differences in human capital across countries and industries. In terms of specification, I have focused here on international *within*-industry effects, while technology diffusion *between* industries–that is, across technology space–might be important as well. Further, the temporal dimension of technology diffusion has been collapsed into one point in time in my analysis that focuses on contemporaneous effects. While I have already presented results for a number of different specifications, these are certainly possibilities the reader should keep in mind.

[25] For instance, a typical simulation based on Hanson's estimates implies that a 10% reduction in the total personal income of the residents of Illinois reduces wages in counties circa 200 miles away by approximately 1% and leaves wages in counties 500 miles or more away essentially unchanged.

Second, my empirical analysis abstracts from the heterogeneity of technological knowledge. From previous analyses of the value of patents we know that most innovations are worth very little while a few are worth millions of dollars. If the innovations that are diffusing internationally are those which are relatively valuable,[26] then the value-adjusted stock of Japanese technology in Canada, e.g., might be substantially higher than I have estimated above. A third reason of why there might be comparably strong geography effects in technology diffusion as there are for goods trade could be that in fact the localization of neither is primarily caused by physical, distance-related transaction costs. As an alternative, Rauch (1999), e.g., presents a network/information cost-theory of trade that might also have some relevance for the diffusion of technology. Future work will have to further clarify what geographic distance means in economic terms. By providing estimates of its importance for international technology diffusion, this paper makes some progress towards this goal. Other research should also examine whether geographic effects are present in the diffusion of technology *among* the G-5 countries, as well as in the diffusion of technology to less developed countries.

From this analysis of technological knowledge spillover to nine OECD countries which are next to the world's technology frontier, a picture emerges where national technological developments in these countries have often ceased to play the most important role for their productivity. Effective German R&D is often several times higher than domestic R&D for the European countries, for instance, according to my estimates. There has been a trend towards the globalization of technology over the sample period. At the same time, geographic factors leading to clusters of countries that have access to a regional pool of technology are important today, and are likely to remain important for some time to come.

[26] See, e.g., Eaton and Kortum (1999) who relate the probability of international technology diffusion to the value of patents.

Table 1

Relative Country and Industry Size in terms of GDP

Country	Symbol	Total Manufacturing (1980) Million $ US 1990	Relative Size in Sample (Percent)	Relative Size incl. G-5 (Percent)
Australia	AUS	54745	8.3	2.1
Canada	CAN	72945	11.1	2.9
Denmark	DEN	20827	3.2	0.8
Finland	FIN	20878	3.2	0.8
Italy	ITA	270236	41.0	10.6
Netherlands	NL	39096	5.9	1.5
Norway	NOR	17792	2.7	0.7
Spain	SPA	130753	19.8	5.1
Sweden	SWE	31886	4.8	1.2
Sum of 9 Countries		659158		25.7
For reference:				
France	FRA	298530		11.7
Germany	GER	350658		13.7
Japan	JAP	332562		13.0
United Kingdom	UK	212000		8.3
United States	USA	778406		30.4

Industry	ISIC	Sum over 9 Countries Million $ US 1990	Relative Size in Sample (Percent)
Food	31	96019	15.0
Textiles	32	77154	12.1
Wood	33	37767	5.9
Paper	34	60232	9.4
Chemicals	351/2	48945	7.7
Rubber	355/6	22361	3.5
Non-met. Miner.	36	43257	6.8
Basic Metals	37	35949	5.6
Metal Products	381	54648	8.6
Machinery, Instr.	382/5	71180	11.1
El. Machinery	383	37358	5.8
Transportation	384	53819	8.4

Table 2

Relative Country and Industry Size in terms of R&D

Country	Symbol	Total Manufacturing (1980) Million $ US 1990	Relative Size in Sample (Percent)	Relative Size incl. G-5 (Percent)
Australia	AUS	10232	9.1	0.7
Canada	CAN	13777	12.3	0.9
Denmark	DEN	3296	2.9	0.2
Finland	FIN	3053	2.7	0.2
Italy	ITA	32436	28.9	2.1
Netherlands	NL	24708	22.0	1.6
Norway	NOR	2955	2.6	0.2
Spain	SPA	6398	5.7	0.4
Sweden	SWE	15569	13.8	1.0
Sum of 9 Countries		112424		7.2
For reference:			**Relative Size in G-5 (Percent)**	
France	FRA	98883	6.8	6.3
Germany	GER	130143	9.0	8.3
Japan	JAP	187597	12.9	12.0
United Kingdom	UK	143304	9.9	9.2
United States	USA	892037	61.4	57.0

Industry	ISIC	Sum over 9 Countries Million $ US 1990	Relative Size in Sample (Percent)
Food	31	30338	1.9
Textiles	32	17276	1.1
Wood	33	5642	0.4
Paper	34	17397	1.1
Chemicals	351/2	232369	14.9
Rubber	355/6	36695	2.3
Non-met. Miner.	36	21231	1.4
Basic Metals	37	45663	2.9
Metal Products	381	22566	1.4
Machinery, Instr.	382/5	243046	15.5
El. Machinery	383	382195	24.4
Transportation	384	509971	32.6

Table 3

Average Annual R&D Expenditure Growth, 1970-95
(percent)

By country	
AUS	6.53
CAN	9.29
DEN	7.06
FIN	4.84
ITA	9.75
NL	8.69
NOR	7.29
SP	7.50
SWE	5.30
Average	7.36
Std. Dev.	1.68
G-5 countries	
FRA	6.20
GER	9.90
JAP	8.40
UK	3.00
US	5.30

By industry	
Food	7.38
Textiles	6.64
Wood Products	8.57
Paper	5.45
Chemicals	8.03
Plastics	7.09
Non-met. Min. Prod.	5.10
Basic Metals	7.14
Metal Products	7.95
Non-elect. Machinery	9.40
Elect. Machinery	7.89
Transportation	7.67
Std. Dev.	1.21

Table 4

Geographic Distance from Nine 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
Average	6949	3422	9039	3284	3446	5228

Table 5

Specification with common distance parameter*

	Equation (3)	Low-R&D industries	European countries	Labor utilization-adjusted TFP	Unad-justed TFP	R&D de-preciation rate = 0%	Lagged R&D
β	0.054	0.039	0.028	0.076	0.077	0.068	0.051
	(0.007)	(0.010)	(0.013)	(0.017)	(0.015)	(0.017)	(0.009)
γ	1.219	3.498	1.339	1.281	1.054	1.124	1.054
	(0.060)	(0.073)	(0.068)	(0.060)	(0.060)	(0.060)	(0.061)
δ	0.495	0.357	0.384	0.581	0.441	0.452	0.336
	(0.098)	(0.027)	(0.163)	(0.054)	(0.045)	(0.054)	(0.034)
n	2808	1872	2184	2808	2808	2808	2700
R^2	0.779	0.809	0.791	0.727	0.732	0.789	0.794
AIC	-4.218	-4.317	-4.119	-3.889	-3.928	-4.219	-4.254

*Dependent variable is the multilateral TFP index as defined in equation (1). Standard errors in parentheses; β measures the effect of domestic R&D, γ the relative effect from G-5 R&D, and δ determines the distance effect ($\delta > 0$ is consistent with localization); n = number of observations, AIC = Akaike's Information Criterion, as defined in the text.

Table 6

Specification with varying distance parameters*

	Equation (4)	Low R&D industries	European countries	Lagged R&D
β	0.050	0.034	0.023	0.049
	(0.014)	(0.011)	(0.010)	(0.009)
γ	4.086	3.905	3.400	4.089
	(0.060)	(0.073)	(0.068)	(0.061)
δ_{US}	0.326	0.331	0.204	0.326
	(0.020)	(0.008)	(0.093)	(0.078)
δ_{UK}	0.665	0.560	0.303	0.592
	(0.086)	(0.087)	(0.007)	(0.124)
δ_J	0.358	0.376	0.071	0.277
	(0.079)	(0.077)	(0.017)	(0.087)
δ_G	0.214	0.156	0.500	0.229
	(0.078)	(0.066)	(0.031)	(0.050)
δ_F	0.860	0.852	0.508	0.852
	(0.040)	(0.030)	(0.021)	(0.018)
n	2808	1872	2184	2700
R^2	0.781	0.811	0.791	0.796
AIC	-4.223	-4.323	-4.117	-4.261

*Dependent variable is the multilateral TFP index as defined in equation (1). Standard errors in parentheses; β measures the effect of domestic R&D, γ the relative effect from G-5 R&D, and the δ_g determine the distance effects ($\delta_g > 0$ is consistent with localization); n = number of observations, AIC = Akaike's Information Criterion, as defined in the text.

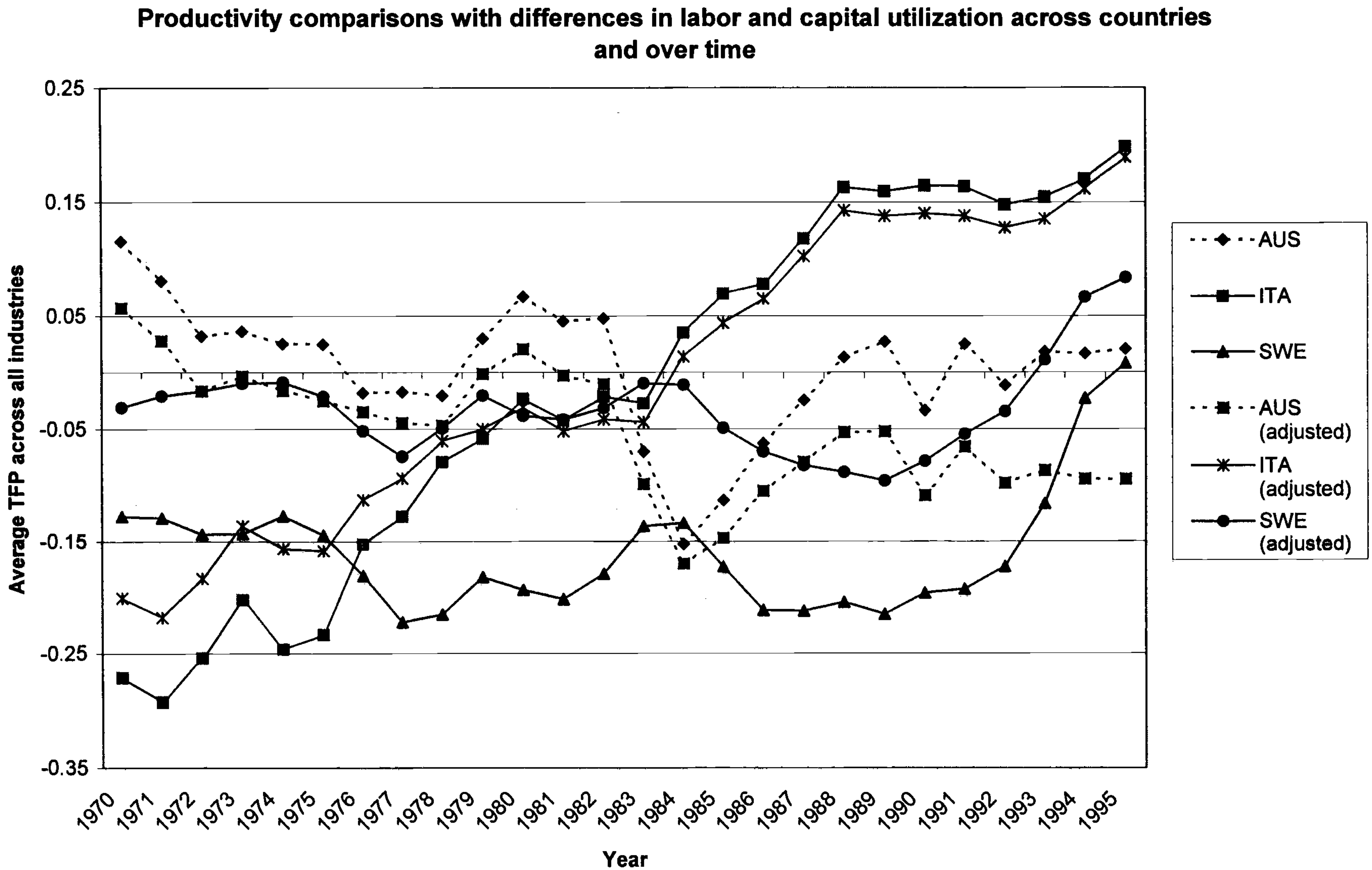
Table 7

Localization over time*

	Equation (5)	Low-R&D industries	European countries	Lagged R&D
β	0.060	0.053	0.025	0.051
	(0.009)	(0.009)	(0.012)	(0.005)
γ	4.089	3.895	3.402	4.091
	(0.060)	(0.073)	(0.068)	(0.061)
δ_{US}	0.195	0.193	0.398	0.245
	(0.018)	(0.032)	(0.075)	(0.028)
δ_{UK}	0.554	0.524	0.275	0.484
	(0.137)	(0.081)	(0.042)	(0.090)
δ_J	0.475	0.418	0.113	0.673
	(0.108)	(0.070)	(0.049)	(0.093)
δ_G	0.526	0.500	0.476	0.494
	(0.087)	(0.054)	(0.015)	(0.064)
δ_F	0.836	0.817	0.524	0.838
	(0.068)	(0.046)	(0.014)	(0.026)
ψ	−0.505	−0.467	−0.297	−0.611
	(0.049)	(0.058)	(0.020)	(0.063)
n	2808	1872	2184	2700
R^2	0.786	0.815	0.791	0.801
AIC	-4.247	-4.341	-4.118	-4.287

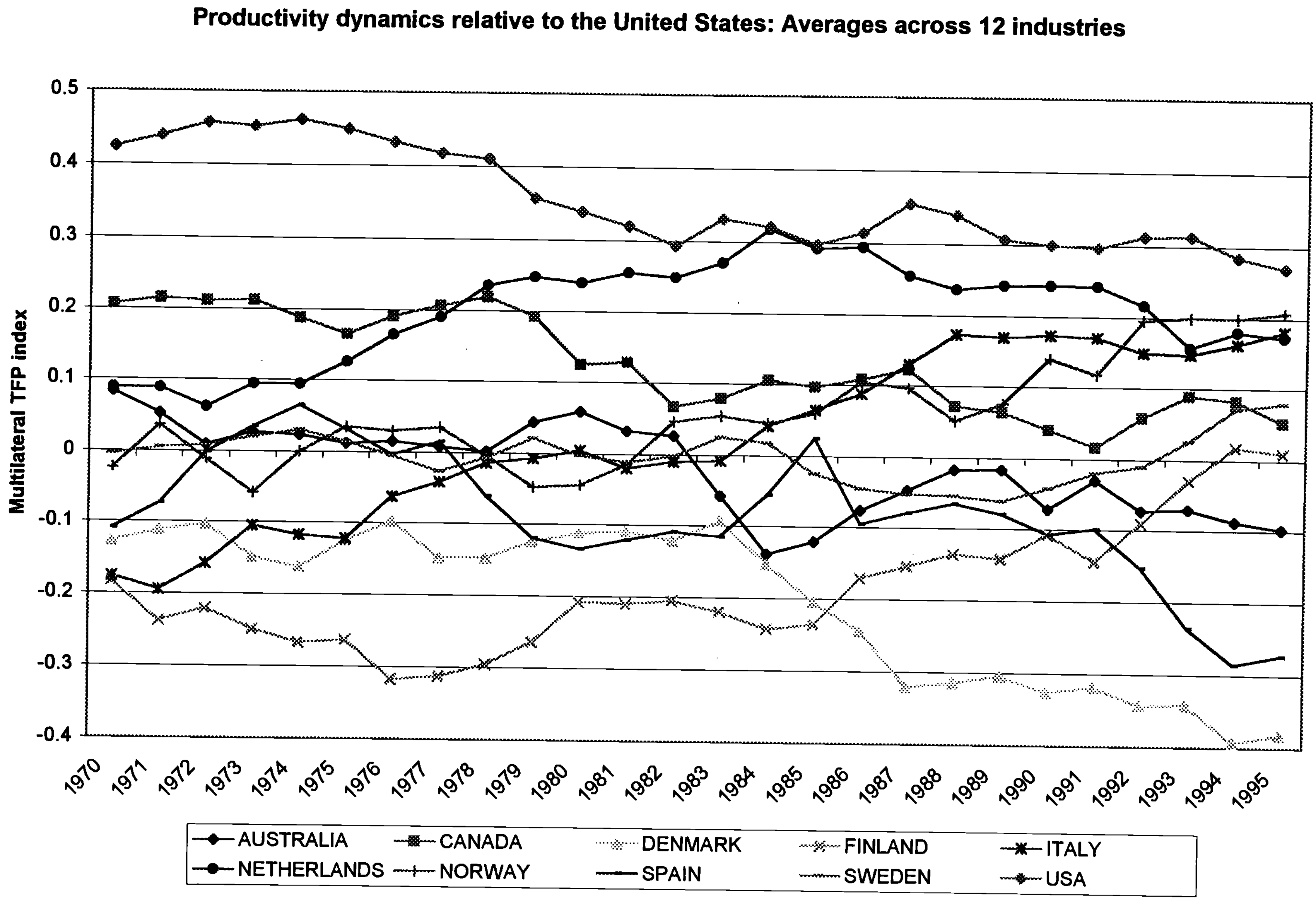
*Dependent variable is the multilateral TFP index as defined in equation (1). Standard errors in parentheses; β measures the effect of domestic R&D, γ the relative effect from G-5 R&D, and the δ_g determine the distance effects ($\delta_g > 0$ is consistent with localization). The parameter ψ governs the relative strength of localization between the years 1970/82 and 1983/85 ($\psi < 0$ is consistent with less localization over time); n = number of observations, AIC = Akaike's Information Criterion, as defined in the text.

Figure 1



Productivity comparisons with differences in labor and capital utilization across countries and over time
0.25
0.15
0.05
-0.05
-0.15
-0.25
-0.35
Average TFP across all industries
1970
1971
1972
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
Year
AUS
ITA
SWE
AUS (adjusted)
ITA (adjusted)
SWE (adjusted)

Figure 2



Productivity dynamics relative to the United States: Averages across 12 industries
Multilateral TFP index
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
1970
1971
1972
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
AUSTRALIA
CANADA
DENMARK
FINLAND
ITALY
NETHERLANDS
NORWAY
SPAIN
SWEDEN
USA

Figure 3

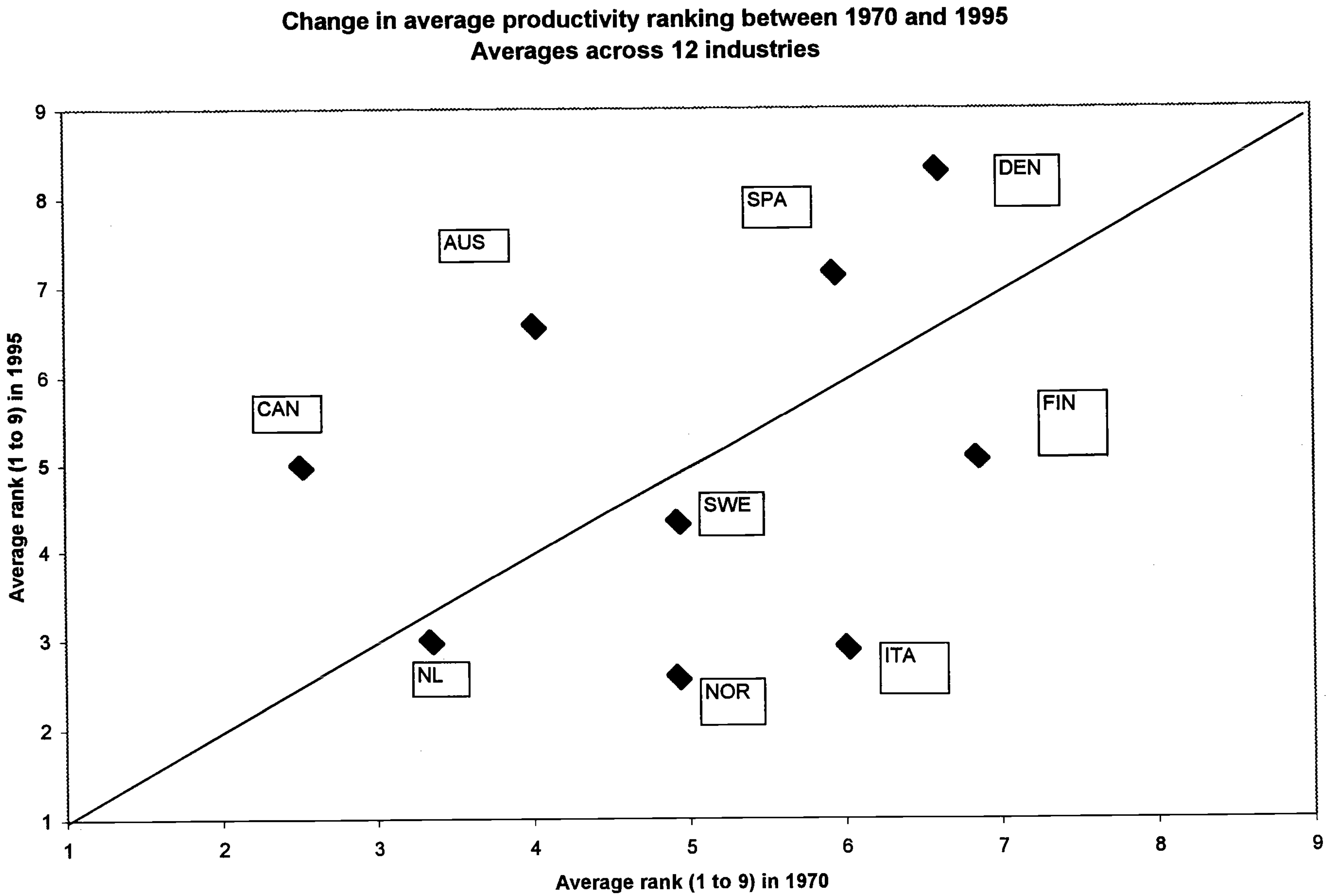
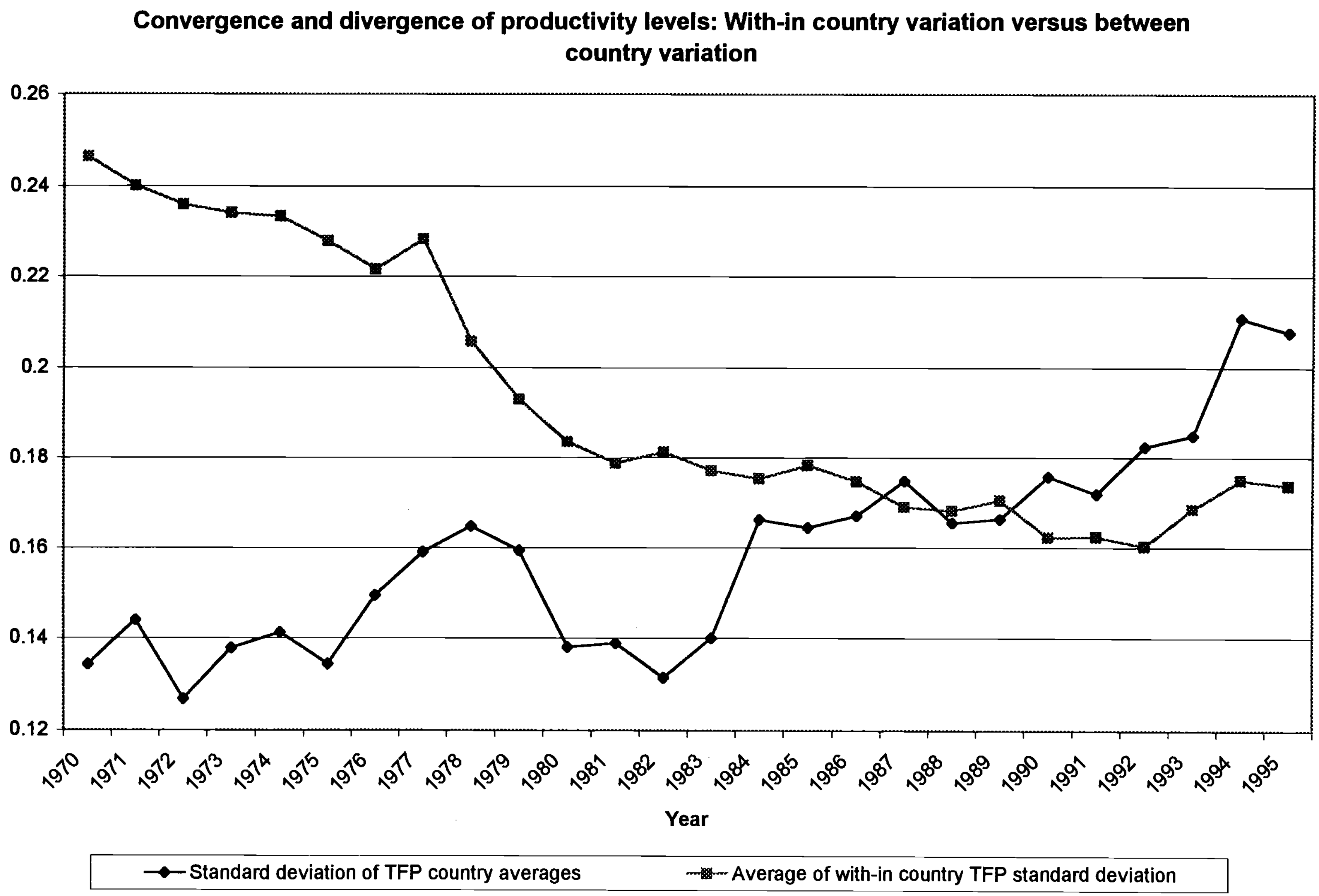

Change in average productivity ranking between 1970 and 1995
Averages across 12 industries
Average rank (1 to 9) in 1995
Average rank (1 to 9) in 1970
1
2
3
4
5
6
7
8
9
DEN
SPA
AUS
CAN
FIN
SWE
NL
NOR
ITA

Figure 4



Convergence and divergence of productivity levels: With-in country variation versus between country variation
0.26
0.24
0.22
0.2
0.18
0.16
0.14
0.12
1970
1971
1972
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
Year
Standard deviation of TFP country averages
Average of with-in country TFP standard deviation

Figure 5

Effective foreign R&D of the technology sender countries

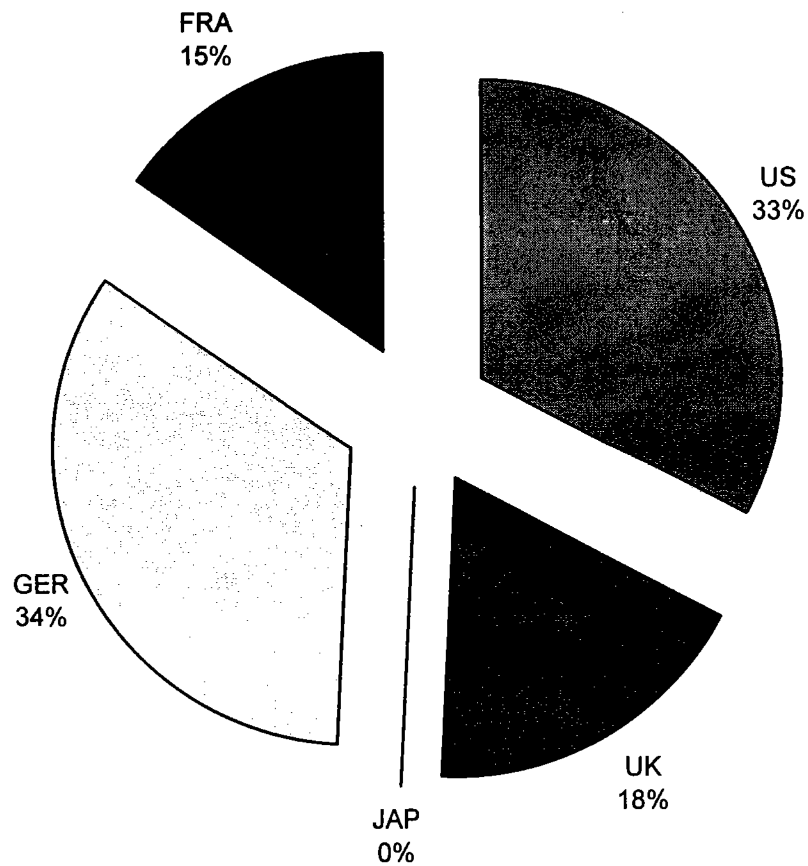


Figure 6

Distribution of total effective foreign R&D by technology receiving countries

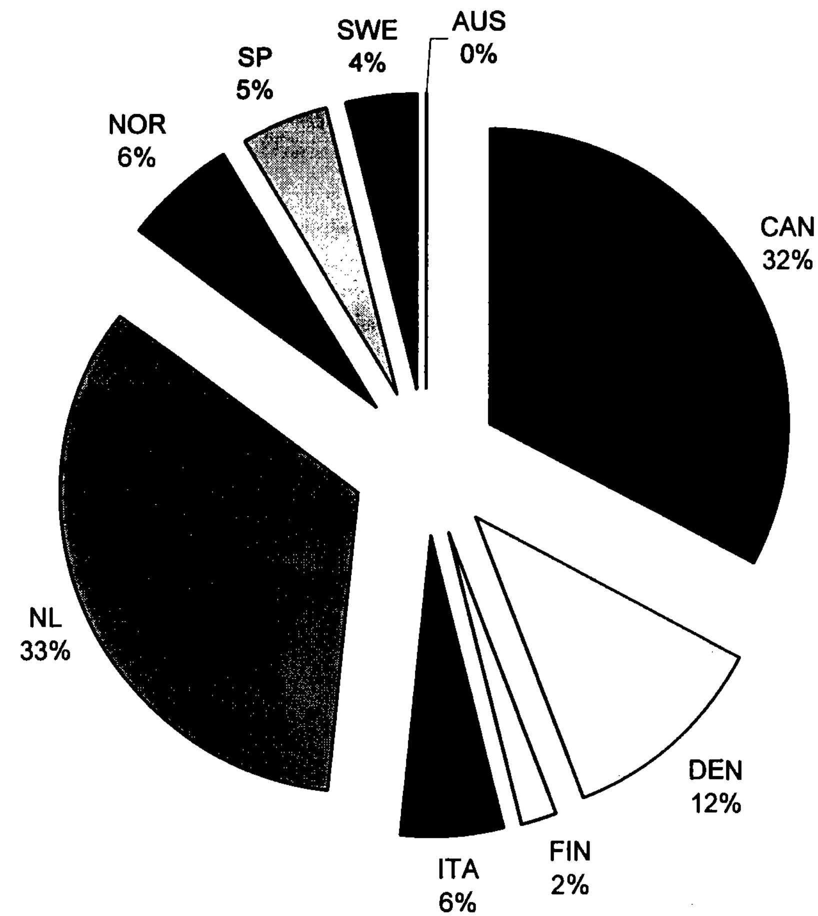
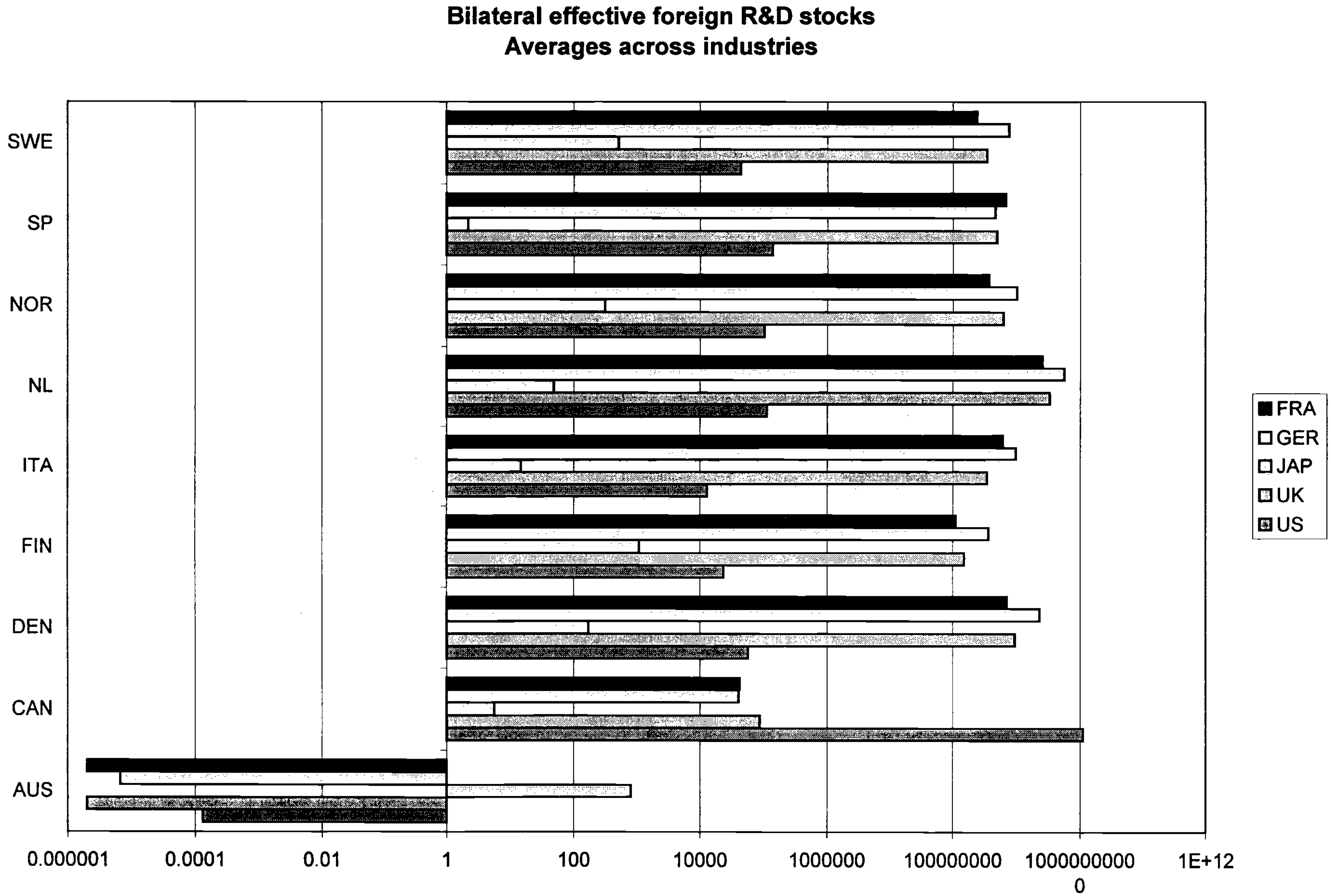


Figure 7



Bilateral effective foreign R&D stocks
Averages across industries
SWE
SP
NOR
NL
ITA
FIN
DEN
CAN
AUS
0.000001
0.0001
0.01
1
100
10000
1000000
100000000
1000000000
0
1E+12
FRA
GER
JAP
UK
US

Figure 8

Effective G-5 country R&D in the Netherlands, Canada, and Australia

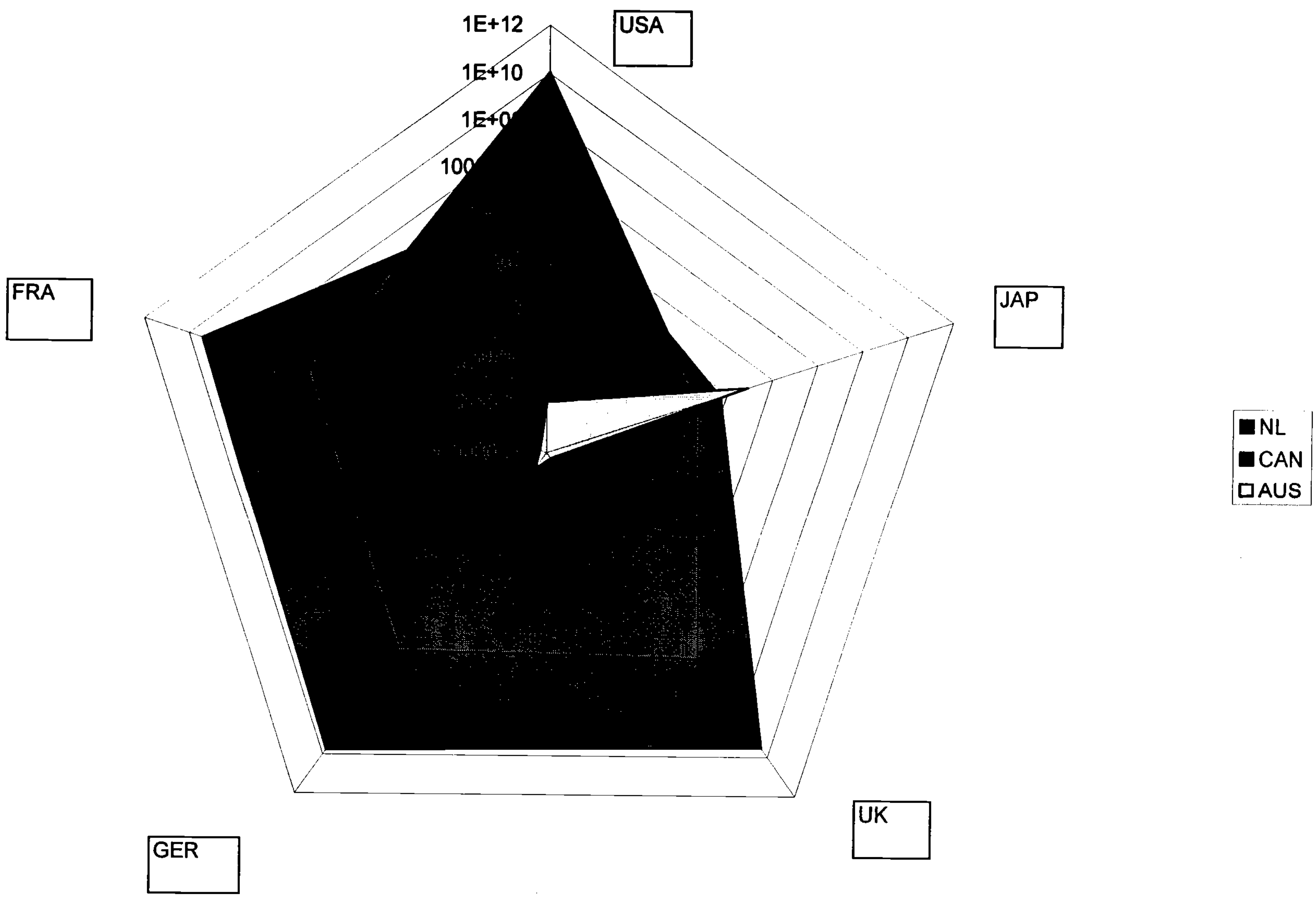
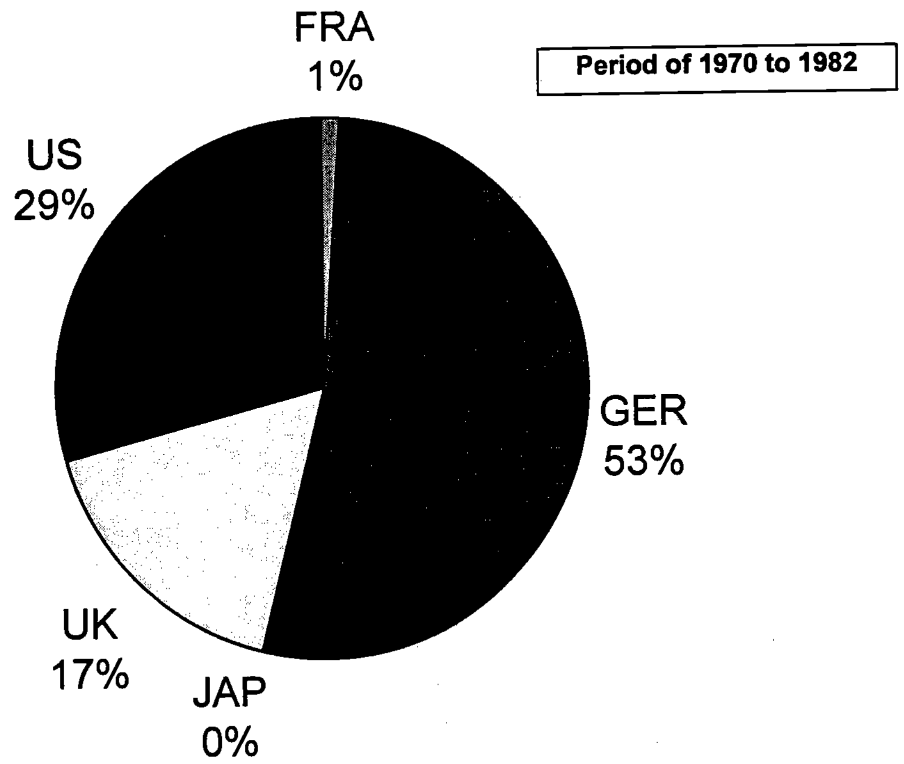


Figure 9

Distribution of Finland's effective foreign Research and Development over time



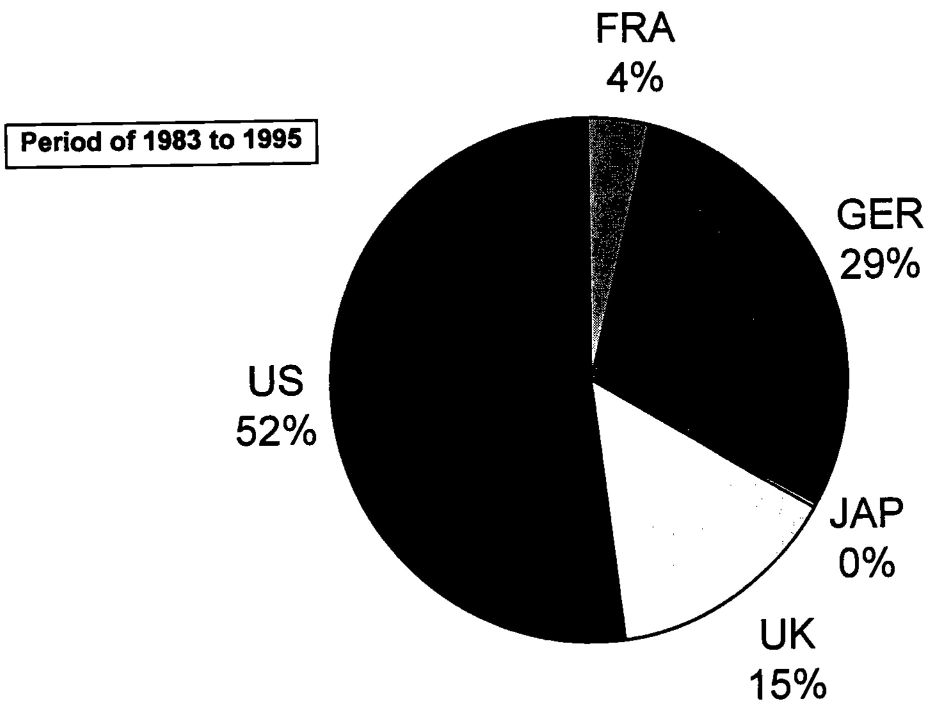
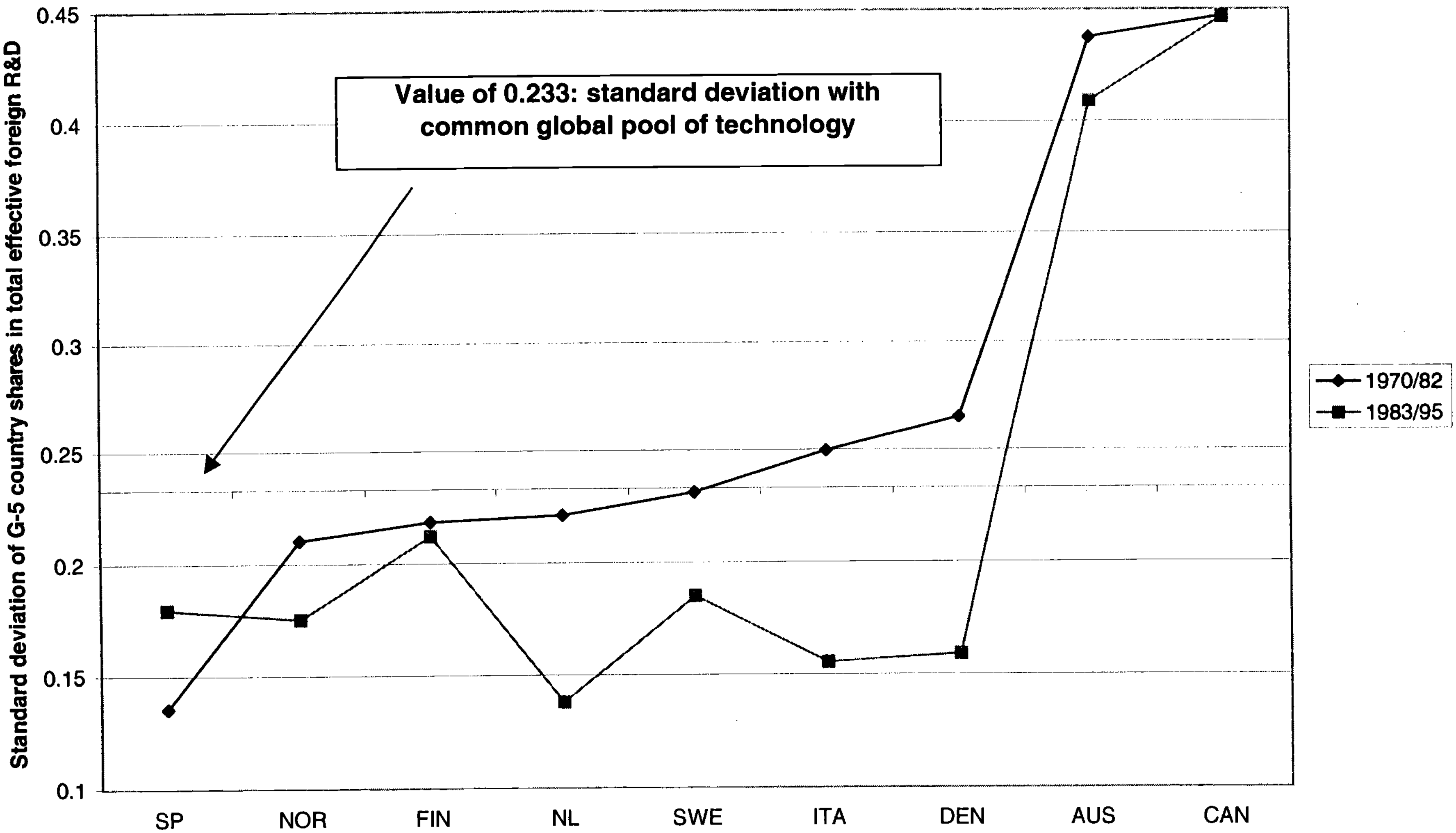


Figure 10

Changes in the variance of G-5 technology sources for nine OECD countries over time



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A Theoretical framework

According to the following model, technology diffusion is related to international trade, which itself is geographically localized. Consider two symmetric countries, home and foreign, that are located at distance D from each other. In the home country, output is produced according to the familiar CES-specification due to Dixit and Stiglitz (1977)

$$Z = AK^{1-\alpha}\left(\int^{N} d(i)^{\vartheta} di + \int^{N_*} m(i_*)^{\vartheta} di_*\right)^{\frac{\alpha}{\vartheta}}, 0 < \alpha, \vartheta < 1, \tag{6}$$

where $A > 0$ is a constant and K is capital. The $d(i)$ are $m(i_*)$ are domestic and foreign intermediate inputs of variety i and i_*, respectively. At a given point in time, there is a range N (N_*) of domestic (foreign) distinct input varieties. As in Romer (1990), these ranges are an index of the level of technology in each country; they are increased through R&D spending. Assuming for simplicity that $\alpha = \vartheta$, each of the atomistic final output producers is demanding domestic and foreign intermediate goods according to

$$\tilde{p} = \alpha AK^{1-\alpha}d^{\alpha-1} \qquad \tilde{p}_* = \alpha AK^{1-\alpha}m^{\alpha-1}, \tag{7}$$

where $\tilde{p}$ and $\tilde{p}_*$ is the price for any of the symmetric domestic and foreign intermediates, respectively. Each intermediate is produced by a monopolist using labor. Due to international transport costs as in Samuelson (1954), however, delivering x units of a foreign intermediate to the home country requires sending off xe^D units, which requires xe^D of labor. Let w and w_* be the home and foreign wage, respectively. One can show that optimal pricing of the monopolists implies $\tilde{p} = w/\alpha$ and $\tilde{p}_* = w_* e^D/\alpha$; further, the equilibrium quantities d and m are related by

$$m = d e^{\frac{-D}{1-\alpha}}. \tag{8}$$

Thus, when $D > 0$, the equilibrium usage of foreign intermediates is below that of domestic intermediates. Assuming that the two countries have exogenous endowments of labor of L and L_* which have no alternative usage, and using the fact that the countries are symmetric and hence $m = m_*$, it is possible to show that

$$d = L\left[N\left(1+e^{-\frac{D\alpha}{1-\alpha}}\right)\right]^{-1} \qquad m = L_*\left[N_* e^{D}(1+e^{\frac{1}{1-\alpha}})\right]^{-1}. \tag{9}$$

Let $\xi_d(D) = \left(1+e^{-\frac{D\alpha}{1-\alpha}}\right)$, $\xi_m(D) = e^D(1+e^{\frac{1}{1-\alpha}})$, and $\xi_*(D) = (\xi_m/\xi_d)^\alpha$; together with symmetry, this allows to write (6) as

$$Z = \tilde{A}K^{1-\alpha}L^\alpha\left[N^{1-\alpha} + N_*^{1-\alpha}\xi_*(D)\right], \tag{10}$$

where $\tilde{A} = A\xi_d^{-\alpha}$. Because $\partial\xi_*/\partial D < 0$, equation (10) predicts that home output is falling, all else equal, in the distance to the foreign economy.[27] If total factor productivity is defined as $F = \frac{Z}{K^{1-\alpha}L^\alpha}$, equation (10) leads to

$$\ln F = \ln\tilde{A} + \ln\left(N^{1-\alpha} + N_*^{1-\alpha}\xi_*(D)\right),$$

which is shown in the text above. A complete description of this model requires to specify preferences and the process determining N and N_*. For the purposes of this paper, this is not necessary, but the interested reader might consult Romer (1990) as well as Aghion and Howitt (1992).[28]

This is a simple framework. Economic geography, through its effect on trade and technology diffusion, is the only factor determining the spatial correlation of productivity, even though there may be other factors affecting the spatial pattern of productivity levels. There are also factors that may influence international technology diffusion beyond geographic distance, such as a common lan-

[27] Here, output is falling in D because imported inputs are employed at a lower equilibrium level due to the resource costs of distance-related shipping. At the extensive margin, greater distance might also lead to a range of imported inputs below N_* if international trade involves fixed costs; see Romer (1994).

[28] Multi-country models have been considered, e.g., in Eaton and Kortum (1999), Howitt (1998), and Keller (1999b).

guage. Moreover, even though this model is highly stylized, the broad conclusion that an economy's productivity is related to its geographic location is not unique to this trade-and-growth model: it is also consistent with some recent models in the economic geography literature, e.g. Krugman and Venables (1995). The analysis above is thus distinguished by a focus on geographic factors affecting knowledge spillover, and it allows to see how these factors alone help to explain variation in productivity levels across countries and over time.

B Estimation issues

B.1 Country as the unit of analysis

I consider technological knowledge diffusion among countries. In my sample, the latter are very different from each other–strong heterogeneity–, and for an analysis at the industry-level, the current data availability implies a relatively small sample.[29] There are at least two important reasons, however, of why an analysis of technology diffusion between countries appears to be the appropriate first step in this research agenda: first, whether technology diffuses between two economies or not is likely due to a significant degree to factors that typically operate at the country-level, such as institutions, language, history, and culture.[30] Second, economic policies, especially towards R&D and technological capacity, are typically adopted at the national level. These two reasons make the country level the natural unit of analysis for the purposes of this paper.

[29] Choosing economic regions (for instance, U.S. states or European regions) as the unit of analysis might therefore seem to be an attractive alternative, but the quality of the data, especially on regional productivity figures, would be considerably lower. Moreover, not only countries, but also regions within countries differ substantially in their technology-creating capacity as measured by R&D expenditures (for the states of the U.S., see NSF 1999), and technology absorption by other regions might be limited by the lack of adaptive R&D (e.g. Cohen and Levinthal 1989).

[30] This also points to the economic significance of national borders, the reasons of which are not very well understood to date (see Helliwell 1998 for a recent synthesis).

B.2 Simultaneity

There are numerous reasons of why the regressor function might not be orthogonal to the residual in the estimation equation. One possibility, strong inter-industry spillover, has already been mentioned above. Also price shocks could cause the dependent and independent variables to be jointly determined, if there is correlation between the R&D deflator and the output deflator. While instrumental-variable estimation is a way of addressing simultaneity problems, a standard choice of instruments for quantity series, namely factor prices, is not available for a broad sample as is used in this paper. Patenting activity is another measure of technological activity which is known to be correlated with R&D. However, patenting might be simultaneously determined with productivity as well. In the absence of good instruments, I rely on my choice of specification to deal with possible simultaneity problems.[31]

A powerful element in my approach are the country-by-industry ($C \times I = 9 \times 12$) fixed effects α_{ci}. As mentioned above, the α_{ci} capture differences in the average productivity levels which might be due to specific omitted variables. Moreover, the fixed effects also eliminate distance-related productivity differences between industries that are not caused by technology diffusion being geographically localized. For instance, the composition of products within the two- to three-digit industries of my sample might vary by country, and this could be correlated with the countries' location. Then, an alternative to the localization of technology-hypothesis to explain a distance parameter estimate of $\delta > 0$ is a technology matching hypothesis. According to that, the degree to which G-5 technology is suited to the needs of the nine other countries is inversely related to geographic distance. Since Australia is further away from the G-5 countries than Finland, e.g., this would mean that productivity in Australia is lower than in Finland. For my purposes, this correlation would be spurious because

[31] See also Griliches and Mairesse (1998) who give an overview of a number of approaches whose main common goal it is to identify production function parameters by avoiding simultaneity problems.

it does not mean that productivity effects from foreign R&D decline with distance. Therefore, the country-by-industry fixed effects are very important to obtain consistent estimates.[32]

C 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 economic activity at the industry level for OECD countries.[33] In constructing the multi-lateral TFP variable I have used data on labor and physical capital inputs. The number of workers engaged in country c and industry i at time t are taken from the STAN database. This includes employees as well as the self-employed, owner proprietors and unpaid family workers. These figures are adjusted by multiplying them by the average annual hours per manufacturing worker in country c and time t to arrive at the labor input measure, denoted L. The data on annual hours worked is from OECD (1999); a relatively small number of missing values has been interpolated. Physical capital stock data is not available in the STAN database, but gross fixed capital formation in current prices is. I first convert the industry investment flows into constant 1990 prices using country- and industry-specific deflators that are derived from the STAN database.[34] The capital

[32]The price one pays for that is to give up exploiting any between-industry variation in the analysis.

[33]The STAN figures are not those submitted by the OECD member countries, but they are based on estimates by the OECD, which tries to ensure greater international comparability. See OECD (1998a) for the details on adjustments of national data.

[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 movements, and the remaining 50% to price changes of total manufacturing in a given country.

stocks are then estimated using the perpetual inventory method, with

$$\begin{aligned}
\tilde{K}_{ct} &= (1-\delta_c^k)\,\tilde{K}_{ct-1} + inv_{ct-1}, \text{ for } t = 2, ..., 26,\ c = 1, ..., 9. \\
&\text{and} \\
\tilde{K}_{c1} &= \frac{inv_{i1}}{(g_i+\delta_c^k)}\ , c = 1, ..., 9,
\end{aligned} \tag{11}$$

where industry subscripts have been suppressed. The variable *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_c^k is the rate of depreciation for capital in country c. As far as possible, I use country-specific depreciation rates, taken from Jorgenson and Landau (1993b), Table A-3: Canada 8.51%, Italy 11.90%, and Sweden 7.70%. These numbers are estimates for machinery & manufacturing in the year 1980. For the remaining six countries, the average of the eight countries' depreciation rates that are listed in Jorgenson and Landau (1993b) has been used.

Capital is adjusted for differences in capacity utilization by first estimating a smooth output series $\widehat{\ln Z_{cit}}$ (from the regression $\ln Z_{cit} = \partial_{ci} + \zeta_t + \varphi_{cit}$). Adjusted capital is then[35]

$$K_{cit} = \tilde{K}_{cit} * (1 + (\widehat{\ln Z}_{cit} - \ln Z_{cit})), \forall c, i, t.$$

Let the parameter α be the share of the labor in total production costs. Following the approach suggested by Hall (1990), the α'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, Fullerton and Karayannis 1993) and data provided

[35] I impose a maximum absolute value on the adjustment term $\Theta_{cit} = (\widehat{\ln Z}_{cit} - \ln Z_{cit})$, mainly to avoid negative capital stock estimates: when $(\widehat{\ln Z}_{cit} - \ln Z_{cit}) > 0.8$, I set $\Theta_{cit} = 0.8$, and when $(\widehat{\ln Z}_{cit} - \ln Z_{cit}) < -0.8$, I set $\Theta_{cit} = -0.8$.

in Jorgenson and Landau (1993b). The effective marginal corporate tax rate ω is given by the wedge between before-tax (p) and after-tax rate of return ($\bar{\rho}$), relative to the former

$$\omega = \frac{p - \bar{\rho}}{p}. \tag{12}$$

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 $\bar{\rho} = r + \pi$, 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 (12), to infer the user cost of capital, p. From Jorgenson's Table 1-1 on ω, 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, ω varies by asset type, and third, $\bar{\rho}$ 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 do not depend on a particular value. 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, α is given by

$$\alpha = \frac{w\,L}{w\,L + p\,K}, \tag{13}$$

where wL are the constant price labor costs. Labor and capital inputs together with the factor shares allow to construct an index of relative total inputs $\ln I_{cit} - \overline{lnI}_{cit}$,

$$\ln I_{cit} - \overline{lnI}_{cit} = \frac{1}{2} * [\alpha_{cit} + \overline{\alpha}_{it}][\ln L_{cit} - \overline{\ln L_{it}}] + \frac{1}{2} * [(1-\alpha_{cit}) + (1-\overline{\alpha}_{it})][\ln K_{cit} - \overline{\ln K_{it}}], \tag{14}$$

for all c, i, and t, where $\overline{\ln L_{it}} = \frac{1}{C}\sum_c \ln L_{cit}$, $\overline{\ln K_{it}} = \frac{1}{C}\sum_c \ln K_{cit}$, and $\bar{\alpha}_{it} = \frac{1}{C}\sum_c \alpha_{cit}$. The relative TFP index is obtained by subtracting relative total input from relative output, see equation (1) in the text.

D Data on R&D Expenditures

The R&D expenditure data comes from OECD (1998b). I have been able to obtain consistent data for all twelve industries and the period of 1970-95 for fourteen countries. Even in these countries, however, 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 cubic spline interpolation techniques. The OECD (1998b) publication covers the years 1973-97; estimates for 1970-72 are based on data in hardcopy versions of the OECD's *Basic Science and Technology Statistics*. Expenditures qualify as R&D according to the OECD's

Frascati Manual definition.

The construction of the R&D stocks is based on data on total business enterprise intramural expenditure on R&D (denoted E_{cit});[36] the OECD code for this series is BERD. The estimates are available in constant 1990 $ U.S., using the OECD purchasing power parity rates for conversion. I use the perpetual inventory method to construct stocks, assuming that

$$\begin{aligned} S_t &= (1-\bar{\delta})\, S_{t-1} + E_{t-1}, \text{ for } t = 2, ..., 26 \\ &\text{and} \\ S_1 &= \frac{E_1}{(g^{RD}+\bar{\delta})}\ , \end{aligned} \tag{15}$$

where the industry and country subscripts have been suppressed. The rate of depreciation of the knowledge stock, $\bar{\delta}$, is set at 0.1, and g^{RD} is the average annual growth rate of S over the period of 1970-1995. A higher (lower) choice of $\bar{\delta}$ reduces (increases) the rate of growth of the knowledge stock over the period of observation. For some results presented in the text, I set $\bar{\delta}$ equal to zero, assuming a zero rate of depreciation for R&D capital.

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