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KNOWLEDGE SPILLOVERS AT THE WORLD'S TECHNOLOGY FRONTIER

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ABSTRACT

Knowledge Spillovers at the World's Technology Frontier*

Convergence in *per capita* income turns on whether technological knowledge spillovers are global or local. Global spillovers favour convergence, while a geographically limited scope of knowledge diffusion can lead to regional clusters of countries with persistently different levels of income *per capita*. This Paper estimates the importance of geographic distance for technology diffusion, how this has changed over time, and whether international trade, foreign direct investment and communication flows serve as important channels of diffusion. The analysis is based on examining the productivity effects of R&D expenditures in the world's seven major industrialized countries between 1970 and 1995. First, I find that the scope of technology diffusion is severely limited by distance: the geographic half-life of technology, the distance at which half of the technology has disappeared, is estimated to be only 1,200 kilometres. Second, technological knowledge has become much more global from the early 1970s to the 1990s. Third, I estimate that trade patterns account for the majority of all differences in bilateral technology diffusion, whereas foreign direct investment and language skills differences contribute *circa* 15% each. Lastly, these three channels together account for almost the entire localization effect that would otherwise be attributed to geographic distance.

JEL Classification: E00, F10, F20, O30
Keywords: agglomeration, communication, convergence, divergence, economic geography, FDI, growth, international trade, knowledge spillovers, language skills, R&D, technology diffusion, total factor productivity

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NON-TECHNICAL SUMMARY

Convergence in *per capita* income depends on the degree of international technology diffusion. Strong diffusion of technological knowledge favours convergence, while the absence of it can lead to divergence if the domestic rate of technological change varies across countries. A case in point is the faster implementation of recent advances in information technology in the United States compared to other countries. This has been cited as a major reason why the United States' lead in *per capita* income over Japan has increased from 10% in 1990 to 20% by 1999. The scope of technology diffusion also matters for income convergence among the world's advanced ('North') and less developed countries ('South'). For instance, the issue is widely discussed in the context of the 'digital divide' scenario – the widespread fear that the internet might not lead to convergence, but instead to a further polarization of *per capita* income in the world. This Paper examines the scope of international technology diffusion by using data from the world's seven major industrialized countries – collectively referred to as the world's technology frontier – at the level of two-digit manufacturing industries during the years 1970 to 1995.

International technology diffusion is analysed on a geographic basis. It is well known, for instance, that foreign direct investment (FDI) patterns are affected by spatial factors, and it is a stylized fact that the volume of bilateral trade declines with distance. Because trade and FDI patterns might determine a country's access to embodied foreign technology in the form of advanced intermediate goods, these mechanisms are both plausible channels of technological diffusion. Disembodied technology diffusion in the form of direct communication could be another major way of how technological knowledge moves between countries, and while distance affects the likelihood of face-to-face interactions, it matters much less for communication *via* telephone or email. Rather, language and other cultural-historic factors play a relatively larger role for communication flows than for trade or FDI. At this time, however, relatively little is known on how geographic and other factors impact technology diffusion among countries.

The empirical analysis first addresses the question of whether geographic distance affects the degree of diffusion. In particular, do remotely located countries have a smaller stock of technological knowledge at their disposal than more centrally located countries? Second, we study whether this relationship has changed over time. The analysis has major implications for economic policies towards growth and innovation, because if technological knowledge diffuses fully as well as quickly, such policies cannot raise a country's relative welfare. Third, it is examined whether trade, FDI and communication matter as specific channels of technology diffusion. Going beyond the analysis of distance is important, because economic policy might be powerful in affecting trade, FDI or communication patterns, whereas it cannot, at least literally, affect a country's geographic location relative to other countries.

The findings are as follows: first, geographic distance has a strongly limiting effect on technology diffusion among these technology frontier countries. I find that the distance after which half of the technological knowledge that originates from the technology sending country has disappeared – the half-life of technology in terms of distance – is between only 800 and 1,900 kilometres. Second, the degree of localization of technology diffusion has declined substantially, by at least two thirds, over the sample period. While these estimates might to some extent overstate both the magnitude of the degree of localization at the beginning of the sample period, as well as the speed at which technology has become more global since the 1970s, the qualitative findings are very robust.

Another question that is addressed is what explains the level and the changes in the localization effect that are estimated. The channels of trade, FDI and direct communication, proxied by data on language skills, are considered as alternatives to distance above. It appears that a substantial portion of the distance effect in technology diffusion, and maybe all of it, can be accounted for by differences in trade, FDI, and communication links across countries. Out of the three channels, I estimate that trade is most important, with about two-thirds of the total diffusion effect, while differences in FDI and language skills account for about one-sixth each.

While it is possible to account for a substantial part of the distance effect in terms of trade, FDI and communication links, much less can be said at this point on what has caused the decline in the degree of localization of technology over the sample period. For instance, have transport costs for goods declined dramatically over the period 1970–95, so that there is now much more embodied technology diffusion through goods trade than existed earlier? FDI might also be in part what is behind the decrease in localization of technology, because the rate of growth of multinational activity has been relatively high over the last two decades. And of course the recent development of new communication technologies and the internet are strong *prima facie* reasons of why technology might have become less localized. A definitive answer in this regard, however, must await the greater availability of relevant data. This will allow to better address the important question of what are the main causes, and implications, of the recent decline in the localization of technological knowledge.

Knowledge spillovers–the external benefits from the creation of technological knowledge that accrue to parties other than the inventor–have a major impact on the extent of income convergence across countries. Strong spillovers favor convergence, while weak spillovers can lead to divergence if the domestic rate of technological change varies across countries. A case in point is the faster implementation of recent advances in information technology in the United States (U.S.) compared to other countries, which might be a major reason of why the U.S.'s lead in per capita income over Japan has increased from 10% in 1990 to 20% by 1999. The scope of knowledge spillovers also matters for income convergence among the world's advanced and less developed countries (the "North" and the "South", respectively). For instance, the issue is widely discussed in the context of the "digital divide" scenario–the widespread fear that the internet might not lead to convergence, but instead to a further polarization of per capita income in the world.

This paper studies empirically knowledge spillovers among the seven major industrialized countries–the world's technology frontier–on a geographic basis.[1] In particular, does the strength of knowledge spillovers vary with geographic distance? If so, then remotely located countries may have a smaller stock of technological knowledge at their disposal than more centrally located countries. I also examine whether knowledge has become more global over time by examining whether geographic distance influences knowledge spillovers in the same way during the 1970s and the 1990s. This has major implications for national economic policies towards growth and innovation, because such policies are only effective in raising a country's relative welfare as long as technological knowledge does not spill over fully as well as quickly. This paper also provides new evidence on the extent to which three widely cited channels for knowledge spillovers–trade, foreign direct investment (FDI), and communication flows–are important. From a policy perspective, understanding the influence of channels other than distance is important, because economic policy might be powerful in affecting trade, FDI, or commu-

[1] These countries–Canada, France, Germany, Italy, Japan, the United Kingdom (U.K.), and the U.S.–account for more than 90% of the world's R&D spending and are also by most other measures among the technologically most-advanced in the world.

nication patterns, whereas it cannot, at least literally, affect a country's geographic location relative to other countries.

The present study provides also an assessment of recent theories of growth in which knowledge spillovers are crucial to explain sustained increases in income and growth performances that differ across countries. Knowledge spillovers are central in Romer (1986, 1990), Lucas (1988), and Aghion and Howitt (1992), and their scope is critical for the long-run distribution of incomes in the multi-country models of Grossman and Helpman (1991), Lucas (1993), and Howitt (2000). Knowledge spillovers are also important for recent models of regional and urban economics that explain patterns of agglomeration and de-agglomeration (Krugman 1991, Fujita, Krugman and Venables 1999), because the pecuniary trade externalities that these authors emphasize often go hand-in-hand with knowledge spillovers.

This work is based on data for two- and three-digit manufacturing industries in Canada, France, Germany, Italy, Japan, the United Kingdom (U.K.), and the U.S.–the so-called G-7 countries– during the years of 1970 to 1995. It builds on a substantial amount of work showing that the link between the research and development (R&D) spending in one industry and productivity in another can be used to estimate knowledge spillovers (Griliches 1979, 1995, Scherer 1984).

The paper contributes to the existing empirical literature as follows. One set of papers estimates the relative magnitude of knowledge spillovers within- and across countries (Jaffe, Trajtenberg, and Henderson 1993, Irwin and Klenow 1994, and Eaton and Kortum 1999). I contribute to this in two ways: first, beyond the distinction of national versus international spillovers, I exploit cross-sectional variation in the relative distance of countries to their partner countries. Second, this paper provides estimates on the extent to which knowledge spillovers have become more global over time. Another literature is trying to assess the importance of trade as a mechanism of international knowledge spillovers (Coe and Helpman 1995, Keller 1998). In this regard, my contribution lies in considering not only the trade, but also simultaneously the FDI and communication channels for knowledge spillovers, as well as unidentified distance-related externalities.[2] The paper is complementary to recent estimates of localized externalities at the subnational level (Ciccone and Hall 1996, Ellison and Glaeser 1997, Hanson 2000, and Henderson 2001).[3] My analysis also contributes to explaining differences in production technologies across countries, which has been emphasized as an important factor for the specialization of production across countries as well as international trade (Harrigan 1997 and Trefler 1995, respectively).

To anticipate the results, I find that the scope of knowledge spillovers is severely limited by distance: the geographic half-life of knowledge spillovers, the distance at which half of them have disappeared, is estimated to be only 1,200 kilometers. However, between the early 1970s and the 1990s, knowledge spillovers have become much more global. The results also suggest that trade, FDI, as well as direct communication are among the channels through which knowledge spillovers operate, with trade being the most important. Lastly, I estimate that these three channels together account for almost the entire localization effect that would otherwise be attributed to geographic distance.

The remainder of the paper is as follows. The next section provides an overview of the data. Important econometric issues raised by the estimations are addressed in Section Two. All estimation results and the discussion of their economic significance can be found in Section Three. Section Four concludes with a general assessment of the results and notes a number of issues that will have to be addressed in the future.

1 Empirical setting

This section examines the data in some detail, providing a context that shows how R&D expenditures, productivity, geography, as well as trade, FDI, and communication links in the sample vary.

[2] This differs also from Keller (2000), who studies knowledge spillover flows to nine smaller countries.
[3] See also Redding and Venables (2001), who estimate geography effects with international data.

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

I use data on manufacturing industries in Canada, France, Germany, Italy, Japan, the U.K., and the U.S. for the years 1970-1995. All countries are members of the Organization for Economic Co-operation and Development (OECD), and the OECD STAN database is the primary source for the data on inputs, outputs, and prices (OECD 1999a). Manufacturing industries in these seven countries account for about 16% of world GDP and approximately two thirds of world GDP in manufacturing in 1980. Moreover, these countries perform the majority of R&D expenditures in the world (source: OECD 1998): ninety-four percent of all business enterprise R&D that is recorded in OECD statistics are conducted in the G-7 countries.[4]

The analysis encompasses almost all of manufacturing, subdivided into twelve industries at the two- to three-digit International Standard Industrial Classification (ISIC) level.[5] 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. The size of the countries varies substantially in terms of GDP. Canada's share of G-7 manufacturing is 3.15%, while the U.S. contributes 33.62%. By industry, food manufacturing is largest in the G-7 countries, but also transportation equipment as well as non-electrical machinery & instruments are industries that have a share of more than 10% in manufacturing. In terms of R&D, country size varies even more, see the middle columns in Table 1. The U.S. conducts about forty times as much R&D as Canada, and about four times as much as Germany. Japan spends about half

[4]The remainder of 6% is R&D in the Netherlands, Sweden, South Korea, and other countries. After the R&D expenditures in non-OECD countries are taken into account, it is plausible to assume that the G-7 countries conduct at least 90% of all business enterprise R&D in the world.

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

as much on R&D as does the United States. Also in the industry dimension, R&D expenditures are more concentrated than GDP is. Most of the R&D is done in chemicals, machinery, electronics, and transportation, accounting for a total of almost 90% of all R&D in manufacturing.

The R&D expenditure flows are transformed into stocks by using the perpetual inventory method.[6] Table 1, on the right, shows that the average annual growth rates of R&D stocks vary substantially by country, from a high of 11.82% for Germany to a low of 5.72% for the United Kingdom. Average R&D stock growth for the U.S. has been 7.36% per year.

1.2 Geographic features of the sample

The geographic distance between countries is measured as the smallest arc tan distance between the capital cities of the countries, as the crow flies (source: Haveman 1998). Table 2.1 allows to distinguish several groups of countries: the European G-7 countries, which are about 6,000 kilometers from the U.S. and Canada and 9,500 kilometers from Japan, while the latter is about 10,500 kilometers from Canada and the United States. In consequence, the countries' average distance to their six partner countries varies substantially: for the four European countries, it is around 4,000 kilometers, for the U.S. and Canada, it is about 6,000 kilometer, and for the relatively isolated Japan, it is close to 10,000 kilometers.

1.3 Bilateral trade and foreign direct investment patterns and data on language skills

The data on bilateral language skills, FDI, and trade is shown in Tables 2.2 to 2.4. The source for the bilateral import shares in Table 2.2 is the NBER's *Bilateral World Trade Database*, see Feenstra, Lipsey, and Bowen (1997). The FDI data come primarily from the OECD's *Activities of Foreign Affiliates,* OECD (1999c). Table 2.3 shows the share of employment of the outward FDI country in

[6] Details on the data sources and construction are described in an appendix that is available upon request.

the total manufacturing employment of the host country. For instance, line 2 in Table 2.3 indicates that German-owned multinationals account for 2.40% of manufacturing employment in France, while the share of U.S.-owned multinationals in France is, with 4.72%, about twice as large.

A number of considerations suggest to use caution in interpreting the results based on these numbers. First, mainly due to availability reasons, the data I use is at the aggregate, not at the industry level. While this implies losing the industry detail, it also means that these variables are employed on par with distance, which does not have an industry dimension either. Second, each set of bilateral relations is only for one year that is relatively late in or after the sample period.[7] This could mean that simultaneity afflicts the estimation results, because, e.g., changes in productivity influence the patterns of trade just as trade leads to embodied technology diffusion. However, the bilateral patterns are slow-changing over time, and the fact that the values are for total manufacturing (in the case of trade and FDI) or the country as a whole (in the case of language skills, see below) suggests that simultaneity is unlikely to be a major problem.[8]

The data on language skills in Table 2.4 shows the share of the population in the spillover recipient country that speaks the official language of the sender country. For instance, line 3 in Table 2.4 states that 41% of the population in Germany speaks English, while only 11% speaks French.[9] Both due to estimation of some of the data and for conceptual reasons, the inferences that can be made based on the language skills results below are those associated with the highest level of uncertainty. Conceptually, language knowledge in the population might be a poor indicator for the strength of communication links fostering knowledge spillovers among firms in two- to three-digit manufacturing industries. Moreover, bilateral language knowledge, for instance, the share of people in Italy that is

[7] For FDI and import patterns, this is the year 1991, while for language skill data, it is 1996/1998.

[8] I have confirmed this by using trade data for years other than 1991, which leads to similar results.

[9] In the case of Canada as a source for spillovers, I simplify by taking English as the sole official language. The data for the European countries comes from EU (1999) and the data for Canada comes from StatCan (2000). The EU (1999) survey asked the following question: "Which languages can you speak well enough to take part in a conversation, apart from your mother tongue?". To arrive at the estimates for language knowledge in the U.S. and Japan, I have used information on foreign nationals in these countries, in particular for Japan from JG (2000). I have confirmed that the results are not sensitive to employing other plausible values for these data series.

able to speak German, might be of limited relevance for understanding disembodied bilateral diffusion from Germany to Italy if communication is typically conducted in a third-country language, such as English. However, the analysis in West, Edge, and Stokes (2000) suggests that language knowledge in the population is correlated with business-relevant language skills. In addition, the evidence on changes in language skills over time in EU (1999) and other evidence suggest that the degree of coordination on one or a small number of languages is still limited. Overall, this suggests that this data on language skills will be useful in studying the importance of communication flows for bilateral knowledge spillovers.

1.4 Multi-lateral total factor productivity indices

I will compare industry-level total factor productivity (TFP) for the seven countries in the sample. Other recent work that has examined TFP indices for other purposes includes Harrigan (1997) and Griffith, Redding, and Van Reenen (2000). TFP calculations require real, internationally comparable data on outputs, inputs, and intermediate goods. The OECD STAN database contains estimates of value added, labor, and capital inputs, which I have used to construct TFP indices. The intermediate inputs data on which the value added series are based is not fully internationally comparable, which is one important reason of why the TFP indices in this paper should be viewed as approximations to the true TFP measures. I use the multi-lateral TFP index proposed by Caves, Christensen, and Diewert (1982a), which is defined as

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

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 value-added, L is labor inputs, and K denotes capital inputs. Further, $\overline{\ln Z_{it}}$ is 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, $\bar{\alpha}_{it} = \frac{1}{C}\sum_c \alpha_{cit}$. 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. In equation (1), the reference point is the geometric average of the seven countries.

The TFP index in equation (1) assumes that production is characterized by constant returns to scale. Building on the work by Caves, Christensen, and Diewert (1982b) and Hall (1990), I have also used cost-based instead of revenue-based factor shares to construct alternative TFP indices that are appropriate in the presence of scale economies. This allows me to see whether the estimation results are robust to deviations from the assumption of constant returns. Two other important characteristics of the TFP data are: First, industry-specific purchasing power parity- (PPP) exchange rate estimates are used to convert the industry outputs into a common currency, because there is evidence that PPP exchange rates vary substantially by industry (source: Pilat 1996). Second, I have adjusted the OECD STAN data on labor inputs to take account for differences in annual hours worked across countries, from OECD (1999b). This is important because annual hours worked in U.S. manufacturing, for example, were almost 40% higher than in certain European countries in some years over the sample period. I have also corrected the physical capital inputs series to account for cyclical determinants of factor demand. Figure 1 shows the adjusted and non-adjusted average productivity levels for the U.S. (on top), Germany (middle), and Japan (bottom), relative to the G-7 mean for each year. Without adjusting for differences in input usage, U.S. productivity would be increasingly over- and German productivity increasingly under-estimated, while productivity in Japan would be over-estimated throughout. Clearly, these differences would not be appropriately controlled for by using time-invariant country fixed-effects.

1.4.1 Industry-level productivity and average productivity over time

There is a substantial amount of within-country heterogeneity across industries. For instance, a country is frequently among the top performers in one industry while ranking near the bottom in another industry. This suggests that studying productivity at the industry level might have important advantages compared to an analysis at a more aggregate level. There are also differences of how variation in with-in country productivity levels has changed over time. For instance, in the U.S., the dispersion of productivity levels has fallen, whereas in Canada, the opposite has occurred. For the G-7 countries as a whole, a picture of slightly converging within-country productivity levels emerges, as indicated by the dashed line in Figure 2.

On average across industries, the U.S. has been the productivity leader throughout most of the sample period according to these estimates, even though the U.S.'s productivity advantage has generally been shrinking over time.[10] The solid line in Figure 2, which is more substantially downward-sloping, shows the standard deviation of the seven country averages of productivity over time. Clearly, the period of 1970-95 has been one of productivity convergence among the G-7 countries, albeit with a noticeable reversal towards divergence since the year 1991. These findings are consistent with a relatively high extent of knowledge spillovers among the countries at the world's technology frontier. However, if the trend towards productivity divergence after 1991 will be sustained, this could mean that the number of countries at the world's technology frontier will be smaller in the future than it is today.[11]

[10] Canada started out in second place in 1970, but has lost ground since, especially to Italy and France. Relative productivity in Germany was rising until about 1980 but fell subsequently, and by 1995 German productivity is approximately equal to the mean in the sample. In Japan and the U.K., productivity was below the sample average throughout the sample period according to my estimates.

[11] One reason for this trend towards divergence is that the U.S. is increasing its productivity lead over the other countries. It might be in part due to measurement issues, in particular the differential treatment of information technology (IT) price indices (IT includes computers). IT equipment prices have fallen much more rapidly in the U.S. than in other countries according to official numbers. This is largely due to the usage of hedonic price indices in the U.S., whereas other sample countries continue to use non-hedonic price deflators; see Scarpetta, Bassanini, Pilat, and Schreyer (2000). The extent to which this affects the estimation results below is limited, however, which is likely due to the fixed effects that are included in the specification; see Section Two below.

To investigate this further I will now turn to the formal econometric analysis.

2 Estimation equation and econometric issues

Geographic factors might affect the magnitude of knowledge spillovers for various reasons. For instance, according to many trade-and-growth models, technology moves across country borders when intermediate goods embodying new knowledge are traded (Grossman and Helpman 1991, Rivera-Batiz and Romer 1991). It is plausible to assume that it is easier to ship such intermediate goods to nearby locations than to more remote locations, so that the scope for knowledge spillovers is related to geographic distance.[12] The equilibrium in these models typically relates productivity in an importing country both to domestic R&D and to foreign R&D, conditional on bilateral distance. A specification that captures this is

$$\ln F_{cit} = \alpha_{ci} + \alpha_t + \beta \ln \left[S_{cit} + \sum_{g \neq c} \gamma S_{git} \, e^{-\delta D_{cg}} \right] + \varepsilon_{cit}, \forall c, i, t, \tag{2}$$

where $c = 1, ..., C$ indexes country, $i = 1, ..., I$ is an index for industry, and $t = 1, ..., T$ is the subscript for time. The variable F_{cit} is the TFP level, S_{cit} is country c's R&D stock, and D_{cg} is the geographic distance between countries c and g. The $\alpha_{ci}, \alpha_t, \beta, \gamma$, and δ are parameters to be estimated, and ε_{cit} is an error term with properties that I discuss below. The α's are fixed effects that control for unobserved heterogeneity, the parameter β measures the effect of R&D on productivity, while γ captures the relative effect from foreign R&D.[13]

The role of geographic distance is captured by the parameter δ, which I will refer to as the distance parameter. It is identified from variation of the productivity effects of R&D in other countries

[12] This can be formalized by assuming that commodity trade entails transport costs that are increasing with geographic distance (as in Samuelson 1954).

[13] The parameter β captures both 'true' knowledge spillovers as well as measurement spillovers. The latter do not constitute an externality, as they might be due only to price indices that do not perfectly adjust for product quality, for example (see Griliches 1995 for a discussion). The estimates should therefore be treated as an upper bound for the magnitude of true external effects.

conditional on bilateral distance, and thus reveals whether there is a geographic dimension to international knowledge spillovers. Denote the term $S_g e^{-\delta D_{cg}}$ as country c's effective 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 more closely. For positive values of γ (foreign R&D raises productivity), estimating $\delta > 0$ suggests that the benefits from foreign knowledge creation are decreasing with geographic distance. In contrast, $\delta < 0$ would mean that distant countries benefit more from a given country's R&D than near-by countries.

I will also present results based on a distance class specification that does not incorporate the exponential functional form. It is given by

$$\ln F_{cit} = \alpha_{ci} + \alpha_t + \beta \ln \left[S_{cit} + \sum_{g \neq c} \gamma \left(1 + \eta I_{cg}\right) S_{git} \right] + \varepsilon_{cit}, \forall c, i, t, \tag{3}$$

where $I_{cg} = 0$ if countries c and g are between $2,000$ and $7,500$ kilometers apart; $I_{cg} = 1$ for distances below $2,000$ kilometers, and $I_{cg} = -1$ for distances above $7,500$ kilometers. The distance parameter η identifies the higher (lower) effect of R&D among bilateral relationships of less than $2,000$ (more than $7,500$) kilometers, compared to the relative effect of foreign R&D of γ when I_{cg} is equal to 0. Positive estimates of η are consistent with fewer knowledge spillovers as bilateral distance increases. I will also augment the specifications (2) and (3) in simple ways to examine whether the distance parameters δ and η have changed over time. This would suggest a more or less localized pool of technological knowledge among the G-7 countries. Moreover, to analyze the specific channels of trade, FDI, and communication, I will modify equation (2) to include bilateral trade and FDI patterns as well as language skills data in ways that are analogous to the distance variable.

Major estimation issues that need to be addressed are as follows. First, the relatively narrow focus on the countries at the world's technology frontier implies that the number of bilateral relations is small, with only $C(C-1) = 42$, and half as many values for bilateral distance. Moreover, four countries are located in Europe and two in North America, so that the qualitatively distinct ranges that D_{cg} falls into is even more limited. This is part of what motivates the distance class analysis. In contrast to distance, there is no symmetry in the import, FDI, and language skill patterns, but generally, the relatively small sample of bilateral relations will likely affect the precision with which the parameters can be estimated.

Another concern is that the error term ε_{cit} is not orthogonal to the regressors, because this 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 spillovers, and others might be common to all industries in a given country, such as shocks affecting the national business cycle. Generally, this calls for instrumental-variable estimation; however, good instruments for the R&D variables are unavailable.[14] Instead, I will rely on specification choices in order to minimize the effects of simultaneity. First, a considerable amount of structure has been imposed in constructing the TFP indices.[15] Second, problems arising from the usage of common deflators should not be a major problem, because the R&D figures are based on economy-wide deflators while the TFP indices use industry-specific price data. Third, the estimation equations include time fixed effects which control for shocks that affect the entire sample in a given year. I will also provide separate estimates for the sample of low-R&D industries. Unlike transportation, chemicals, and machinery–the industries that account for most of the R&D (see Table 1)–, the R&D expenditures of the eight low-R&D industries are too small to significantly affect the economy-wide innovative activity. Therefore, simultaneity problems–if present in the full sample–will be much-reduced in this case, and the extent to which these estimates are similar to those obtained with the full sample will shed light on whether simultaneity is likely to be a problem.

[14] 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.

[15] Details are provided in an appendix that is available upon request.

Lastly, country-by-industry fixed effects control for time-invariant factors that generate a spurious correlation between the regressors and the error term. These fixed effects capture differences in productivity levels which are due to factors other than R&D conditional on geographic, trade, FDI, or language patterns. As an example, the composition of products within the two- to three-digit industries of the sample might vary by country, and this could be correlated with distance. Then an alternative to the geographically-limited-scope-of-knowledge-spillovers hypothesis is a technology matching explanation: if the degree to which one country's technology is suited to the needs of other countries is inversely related to geographic distance, productivity in Japan, e.g.,–which is on average further away from its G-7 partners than the other countries–could be relatively low just because Japan's G-7 partners generate technology that is a relatively poor match and thus unproductive in Japan. Clearly, such differences in productivity would not exist *because* of a geographically limited scope of knowledge spillovers. Analogous arguments can be made with respect to trade, FDI, and communication links. Thus, the country-by-industry fixed effects are important to avoid obtaining inconsistent estimates and spurious results in the analysis that follows.[16]

3 Estimation results

3.1 Knowledge spillovers and geographic distance

The first set of results addresses the question whether international knowledge spillovers are geographically localized or not (see Table 3). The dependent variable is the relative productivity level as defined in 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 partner countries interacted with

[16] Another concern is that the TFP variable might be stationary while the R&D stocks could be trending over time. The theory of panel unit root and cointegration analysis that then would apply in the non-linear setting of this paper is not fully developed to date. In that case, I would therefore rely primarily (and imperfectly) on the time fixed effects α_t to address this issue. For an investigation of these time-series issues in the estimation of spillovers in linear regression models, see Edmond (2000).

bilateral distance as described above. The estimation method is non-linear least squares.[17]

In the first result column, I estimate the exponential specification of equation (2) above. The productivity effect from R&D, β, is estimated with $\beta = 0.039$.[18] This number is in the range of values suggested by comparable studies.[19] The parameter γ, which measures the relative potency of distance-adjusted foreign R&D, is estimated to be $\gamma = 1.111$, and the parameter δ, which determines the extent to which foreign R&D is effective in determining productivity, is estimated at 0.147. This estimate suggests that effective R&D (the term $\gamma S_{git}\, e^{-\delta D_{cg}}$) is falling with distance. In specification (3.2), I allow for different R&D sender effects for the U.S., Japan, and Germany (the G-3-, or, the three major R&D countries, with parameter γ_2) on the one, and Canada, France, Italy, and the U.K. (with parameter γ_1) on the other hand. The G-3 technology sending effect appears to be somewhat larger than that of the non-G-3 countries, but to constrain all γ's to equal one, as in specification (3.3), is actually marginally preferred according to Akaike's Information Criterion.[20]

The distance parameter δ is estimated to be positive throughout. This finding is consistent with the idea that technological knowledge is localized, because it implies that the R&D of countries that are far away from a given country contributes less to its productivity than the R&D from near-by countries. In specification (3.4), I estimate the distance class specification (3) to see whether this result is robust. The parameter η is estimated to be positive, which confirms that the productivity effects from foreign R&D are localized for the G-7 countries. Recall that the distance class breakpoints are $2,000$ and $7,500$ kilometers. This means that η is identified from the difference in R&D effects of

[17] I have normalized the distance measure D_{cg} so that $D_{cg} = 1$ is equal to 341 kilometers, the shortest bilateral distance in the sample (between Paris and London). This affects the size of the parameters, but not the size of the other statistics discussed below.

[18] I rely mainly on bootstrapped standard errors for inference. They seem to be preferred, and in any case, they are often much larger than conventional asymptotic standard errors. The bootstrapped errors are heteroskedasticity-consistent (through block-wise resampling for each country-by-industry combination) and relatively robust to serial correlation (by resampling two consecutive errors at a time); see Andrews (1999) for references and further results. To be conservative, I report asymptotic standard errors when they are clearly larger, which is sometimes the case especially for the parameter γ. I have also examined whether spatial correlation remains in the residuals, without finding much evidence for it.

[19] For studies at this level of aggregation, Griliches (1995) reports typically estimates that are somewhat higher; however, many of the earlier studies do not consider productivity *relative* to the sample mean, as I do here.

[20] Akaike's Information Criterion (AIC) is defined as $\ln(\frac{e'e}{n}) + 2k/n$, where $e'e$ is the residual sum of squares, n is the number of observations, and k is the number of estimated parameters. The table also reports the R^2.

the European G-7 countries in Europe and the U.S.-Canada effect (less than $2,000$ kilometers), versus knowledge spillovers between North America and Europe (between $2,000$ and $7,500$ kilometers), versus spillovers to and from Japan. Together with the estimate of γ, the estimate of $\eta = 1.01$ suggests that the value of a foreign G-7 dollar of R&D per domestic dollar is on average seventy-four percent (i.e., $\gamma(1+\eta) = 0.74$) below $2,000$ kilometers, it is roughly 37% (i.e., $\gamma = 0.368$) across the Atlantic, while to and from Japan, the average value of a dollar of foreign R&D is essentially zero (i.e., $\gamma(1-\eta) \approx 0$).

For the exponential functional form in columns (3.1) to (3.3), an interesting statistic to compute is the half-life distance of knowledge spillovers, that is, the distance at which half of the R&D sent out from a technology-producing country has disappeared. This value D^* is calculated from $\frac{1}{2}S = S\,e^{-\delta D^*}$, leading with $\delta = 0.147$ from (3.1) to $D^* = 4.72$, or about 1,600 kilometers. Another measure of the strength of international knowledge spillovers in a given bilateral relation is the value of one foreign dollar of R&D per one dollar of domestic R&D, equal to $\gamma \exp(-\delta D_{cg})$. This is shown for all bilateral relations in Table 4a. For instance, according to the estimates in (3.2), the average value of a dollar of U.S. R&D in Canada is 78% of the value of a domestic dollar of Canadian R&D, and a dollar of German R&D in Italy has 64% of the domestic-R&D effect. Clearly, the distance effects implied by these estimates are quite strong, suggesting in particular few spillovers to and from Japan. To compare the results of the exponential and the distance class specifications, I have computed the average relative foreign R&D value within North America and Europe, respectively, and the average relative foreign R&D value for bilateral relationships involving Japan. For the former, one obtains 67% in the exponential specification, compared to 74% in the distance class specification, while the average for relationships involving Japan is estimated to equal zero in both the exponential and distance class specifications. Thus, the two specifications give broadly similar results. I now turn to analyzing the robustness of these findings.

3.2 Sensitivity analysis

The results of this analysis are reported in Table 5. I use the exponential functional form for the results presented in columns one to three, while the distance class specification is employed for the remaining columns four and five. In the first specification only the eight low-R&D industries are included. I estimate β at 0.025–significantly larger than zero at a 12% level–, down from 0.055 in the full sample.[21] The second column presents estimates when TFP indices are based on gross output instead of value added, which is an alternative approximation to true productivity. The distance parameter is estimated somewhat higher and the relative foreign R&D parameter is lower than before.

Using all-manufacturing PPP exchange rates instead of industry-specific exchange rates leads also to a stronger distance effect ($\delta = 0.273$ in specification 5.3). The distance effect estimated with TFP indices based on the assumption of increasing returns with a scale elasticity of 1.05 in (5.4) are similar to the distance effect in the benchmark result of (3.4). Finally, when factor input data is not adjusted for differences in input utilization, the R&D effect β is considerably higher than in the corresponding specification with adjusted TFP data (compare (5.5) with (3.4)). 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. Also here, though, one estimates a relatively large difference in the strength of technology diffusion across distance ($\eta = 0.716$).

In unreported analysis, I have used other combinations of data samples and specifications from Table 3, as well as a number of other specifications, such as lagged R&D. There is evidence that some of the variation in productivity levels is explained only by the variables jointly.[22] Overall though, I estimate a robust and significant geographic localization effect for international knowledge spillovers. In the exponential specification, the parameter β is about 0.03 to 0.07, varying in a reasonable way

[21] Because the industry R&D elasticity ε_i is related to the return to R&D, ρ_i by $\varepsilon_i = \rho_i \frac{S_i}{F_i}, \forall i$, 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 coefficient β (which is positively related to ε_i) when the sample contains the relatively low-R&D industries only.

[22] In the exponential specification, the bootstrap analysis reveals that the parameters β and δ are positively correlated, for instance.

across different samples and data constructions. The relative foreign R&D effects of the G-3 countries might be somewhat larger than for the other four countries, but this adds relatively little in terms of regression fit. In the distance class specification, the parameter β is of similar magnitude, if somewhat less precisely estimated, and the estimates of η lead to the same qualitative finding on the localization of international knowledge spillovers. Quantitatively, the magnitude of the distance effect varies across specifications. For the exponential functional form, the estimates of δ range from 0.123 to 0.300, which corresponds to half-life distances of about 800 to $1,900$ kilometers. In the distance class specification, η varies from about 0.7 to 1.0, which corresponds to a 70% to 100% premium (discount, respectively) for spillovers among countries that are below $2,000$ (above $7,500$, respectively) kilometers apart, relative to spillovers between North America and Europe.

3.3 Knowledge spillovers over time

In this section I turn to changes in the magnitude of spillovers over time. The exponential specification is extended to

$$\ln F_{cit} = \alpha_{ci} + \alpha_t + \beta \ln \left[S_{cit} + \sum_{g \neq c} \gamma \left(1 + \gamma^{ti} I_t\right) S_{git}\, e^{-\delta\left(1+\delta^{ti} I_t\right) D_{cg}} \right] + \varepsilon_{cit}, \forall c, i, t. \tag{4}$$

Here, I_t is an indicator variable that is equal to one for the years 1983 to 1995 and zero otherwise, and there are two additional parameters, γ^{ti} and δ^{ti}. The former picks up any change in the overall effect from foreign R&D, whereas the latter indicates whether the degree of localization of knowledge spillovers has changed. Values of $\delta^{ti} < 0$ are consistent with technological knowledge becoming more global over time. See Table 6 for the results.

In specification (6.1), the parameter γ^{ti} is constrained to zero. Relative to specification (3.1), the estimate of β is now somewhat higher. More importantly, the distance estimate increases from 0.147 to 0.490, while δ^{ti} is estimated to equal $\delta^{ti} = -1.188$. These estimates suggest a distance parameter of

0.490 for the subperiod 1970-82, and of $0.490 \times (1 + (-1.188)) = -0.092$ for the subperiod of 1983-95. With a standard error for δ^{ti} of 0.222, the distance effect in the second subperiod could be equal to zero, suggesting that geographic distance plays no role anymore by the end of the sample period. The next column in Table 6 indicates that the finding of less localization is independent of the change in the value of foreign R&D: γ^{ti} is estimated to equal 0.072, not significantly different from zero, and the estimate of δ^{ti} remains by and large unchanged.

In the distance class specification, I estimate the parameter η^{ti} in the expression $\eta \times (1 + \eta^{ti} I_t)$, analogously to δ^{ti}. The point estimate of η^{ti} in specification (6.3) is equal to -0.778, which suggests that the strength of technology diffusion during the 1990s varied substantially less across classes than it had during the early 1970s. In specification (6.4), the results for the exponential specification for the sample of the eight relatively low R&D-intensive industries is shown. Relative to the value of $\delta = 0.138$ for the entire sample period (see 5.1), also δ here is higher for the years 1970-82, and lower for the years 1983-95. In fact, one cannot reject the hypothesis that there is no distance effect during the later subperiod, which confirms the patterns obtained for the entire sample.

Overall, these results suggest that international knowledge spillovers have become much less localized over the sample period. In Figure 3, I show the total value of foreign G-7 country R&D received by Japan, France, and Canada over time (based on 6.3). The figure highlights that the total value of foreign R&D received by these countries has been converging sharply over time according to these estimates: while Japan received essentially zero in the early 1970s and France a total of about four dollars per dollar of domestic R&D, by the 1990s the value of the spillovers received by France was only about 30% higher than the corresponding value that benefited Japan.

Can this finding explain the dynamics of the productivity distribution across G-7 countries that emerges from Figure 2? As noted earlier, *ceteris paribus* one expects productivity convergence as knowledge becomes more global in the world. The overall downward trend in the variation of average productivity between 1970-95 is broadly consistent with that. The period of productivity divergence between 1990-95 is probably not being picked up by these over-time estimates yet as the subperiod mid-points are the years 1976 and 1989. In general, however, one must use caution here, because the link between the less-localization finding and convergence of productivity in Figure 2 is not a tight one. The estimated decrease of localization is only an average effect after a substantial amount of unobserved heterogeneity is controlled for, and as long as knowledge spillovers are not complete, immediate, as well as universal, less localization need not go hand in hand with convergence of productivity.

The next section analyzes a number of specific spillover mechanisms.

3.4 Beyond distance: trade, foreign direct investment, and communication as channels for knowledge spillovers

Table 7 shows the results of examining these three mechanisms. I restrict myself to the exponential specification and the TFP variable defined in (1) to keep the number of regression results relatively low. The bilateral imports variable M_{cg}, as well as the FDI variable V_{cg} and the language variable B_{cg} are introduced analogously to distance. For instance,

$$\ln F_{cit} = \alpha_{ci} + \alpha_t + \beta \ln \left[S_{cit} + \sum_{g \neq c} S_{git}\, e^{\tau M_{cg}} \right] + \varepsilon_{cit}, \forall c, i, t, \tag{5}$$

is the imports specification, where τ is the parameter corresponding to the import share variable. A positive value of τ is consistent with bilateral imports raising the extent of knowledge spillovers.

Specification (7.1) shows the basic geographic-distance result for comparison (see (3.3) in Table 3), while the second specification in Table 7 is equation (5).[23] The estimate of β changes relatively little, while the value of τ is positive, equal to $\tau = 0.403$.[24] In specification (7.3), I use the FDI

[23] To facilitate the non-linear estimation, I have scaled the trade, FDI, and language shares as follows: M_{cg} is multiplied by 10^2, V_{cg} by 10^3 and B_{cg} by 10.

[24] An estimate of τ larger than zero means that the relative effect from foreign R&D exceeds that from domestic R&D in all bilateral relationships as long as γ is constrained to equal one. This is not very plausible, so I have also experimented with estimating γ and τ jointly. As expected, γ then tends to be lower than one. However, freeing up the parameter γ makes the specification less robust. Because the emphasis here is on estimating the parameter τ (as well as ψ and λ

variable analogously and estimate the corresponding parameter at $\psi = 0.377$. Also the language skills variable enters with a positive coefficient (specification 7.4). There is a major effect here on the size of the R&D coefficient as well: β is estimated at 0.103, versus $\beta = 0.055$ in the distance specification. These results suggest that each candidate channel might indeed be associated with international knowledge spillovers. Notice that to the extent that the differences in empirical fit between the first four regressions in Table 7 are significant, that of the distance specification is lowest, followed by the FDI and the language skills specification, while the bilateral imports specification has the best fit.

It is important to consider more than one spillover channel at a time to learn about their relative strength, even though this makes the results less robust due to collinearity among the spillover channels. The following results are obtained: When distance is introduced together with the import shares in the exponential expression–as in $\exp(-\delta D_{cg} + \tau M_{cg})$–, this reduces the estimate of τ by about two thirds, from 0.403 in (7.2) to $\tau = 0.130$ in (7.5). Thus, differences in import patterns account no better for a substantial amount of variation in bilateral knowledge spillovers than differences in distance. In equation (7.6), I include the FDI variable together with distance. This results in a much larger estimate of β and a higher value of δ, while the FDI parameter ψ stays about the same relative to the FDI-only specification (7.3).

Specification (7.7) introduces distance together with the language skills variable. The coefficient on the language variable remains positive, while the estimate of the distance parameter turns negative, albeit not significantly different from zero.[25] Equation (7.8) introduces import and FDI patterns together with the language skills variable. All three variables enter with a positive coefficient. Finally,

below, plus comparing them), I give a high priority to robustness and have therefore kept the parameter γ constrained to one. If one sets a lower value for γ or estimates the parameter, this does not lead to qualitatively different findings in the comparison of τ, ψ, and λ; instead, it primarily affects the fixed effects estimates.

[25] One explanation for this is that the language variable picks up a relatively strong effect from U.S. R&D in Canada, plus an effect from U.S. R&D in Europe that is stronger than one would think on the basis of distance. Also, the language variable appears to identify stronger spillover inflows in Japan from English-language countries than from central European countries, all of which are roughly the same distance away from Japan.

when I add the distance variable to this, the point estimate of δ is negative, while the other three point estimates remain positive (specification 7.9). The fit of the regression is marginally improved through the inclusion of distance, but in contrast to the trade, FDI, and language parameters, δ is not significantly different from zero.[26]

I now turn to the absolute magnitude of inward knowledge spillovers, as well as the breakdown of the total effect by spillover channel (based on the estimates of specification 7.8). Let Γ_c be the sum of the three effects for a given spillover recipient country, $\Gamma_c \equiv \sum_g (\tau M_{cg} + \psi V_{cg} + \lambda B_{cg}), \forall c$.[27] Also, denote by s_c the share of the total effect by recipient country, $s_c \equiv \Gamma_c / \Gamma$, where $\Gamma \equiv \sum_c \Gamma_c$. First, the estimation results suggest that Canada benefits by far the most from foreign G-7 technological knowledge, with a share of $s_{CAN} = 0.256$. This is primarily the result of Canada's links to the U.S., from which Canada imports a relatively high share, whose subsidiaries have a strong presence in Canada, and the fact that in both countries, the English language is used. Canada is followed by the U.K., and the U.S., with $s_{UK} = 0.154$ and $s_{US} = 0.151$, respectively. France, Italy, and Germany are next ($s_{FRA} = 0.137$, $s_{ITA} = 0.128$, and $s_{GER} = 0.108$), whereas Japan benefits least from foreign G-7 technology according to these estimates ($s_{JP} = 0.066$).

For the analysis of the relative strength of the spillover mechanisms, let s_c^τ be the share of the total effect for country c due to the contribution of imports, $s_c^\tau \equiv \left(\sum_g \tau M_{cg}\right) / \Gamma_c$, and let s_c^ψ and s_c^λ be the shares due to FDI and language skills, defined analogously. Also, let s^τ, s^ψ, and s^λ be the average shares for a given spillover channel across countries (for instance, $s^\tau \equiv \left(\sum_c s_c^\tau\right) / C$). I estimate that the effect due to imports is highest on average, with $s^\tau = 0.691$, while the FDI and language effects are equal to $s^\psi = 0.148$ and $s^\lambda = 0.161$, respectively. This points to a relatively strong effect

[26] There might be important interactions between these channels for spillovers, for instance, the effect from language skills could be higher, the greater is the bilateral geographic distance. In principle, one could test for this by including an interaction variable, $D_{cg} \times B_{cg}$, and estimate an additional coefficient in the exponential term. In practice though, a comprehensive analysis of interaction terms appears to stretch the possibilities of the data to some extent, so I do not include it here. Note, however, that the non-linear specification picks up some interaction effects already as it is.

[27] This analysis of inward knowledge spillovers focuses on the term in the exponential part of $\sum_g S_g e^{\tau M_{cg} + \psi V_{cg} + \lambda B_{cg}}$. I do this for ease of interpretation, but it should be kept in mind that differences in effective R&D from abroad are also due to differences in S_g as well as the interaction of S_g with the exponential term.

due to embodied knowledge spillovers related to imports. At the same time, the other two channels are far from being negligible. Figure 4 shows, for instance, that the absolute effect from inward FDI in Canada exceeds that from imports in Japan. Moreover, the larger inward share of foreign-owned subsidiaries in Canada versus the U.K. explains more than forty percent of the difference in total inward technology diffusion between these two countries. Another indication of the importance of FDI for inward knowledge spillovers comes from comparing the European countries: here, the U.K. attracts the largest share of FDI, and 36.2% of the U.K. advantage over Germany in terms of total inward knowledge spillovers is due to the U.K.'s higher level of inward FDI.

Language skills have the highest contribution to inward spillovers in the U.K. and the lowest in Japan: 43.4% of the higher level of inward spillovers in the U.K. versus Japan can be attributed to the higher share of the population in the U.K. that speaks the languages of the G-7 knowledge source countries. Among the European countries, 76.8% of the higher level of spillover inflows in the U.K. relative to Italy are due to differences in language skills. And if language skills in Germany would be the same as the (generally lower) language skills in Italy, Germany would benefit about 6% less from G-7 knowledge spillovers than it actually does.

Table 4b, which is also based on the results in (7.8), allows to compare the strength of bilateral knowledge spillovers across different country pairs by showing the share of a sender country in a given spillover recipient's country total knowledge spillover inflows (the sum of trade, FDI, and language channels; this is denoted as the TFL-based measure). For instance, 69% of the spillover flows to Canada originate from U.S. R&D, while the share of the U.K. in Canada is much lower, equal to 13%. The estimates also suggest that the U.S. is the major source of all spillover inflows to Japan, with 63%. Germany accounts for more than a third of the inflows into Italy and France, but for less than 20% of the flows to the United Kingdom. Table 4c illustrates how these estimates differ from estimates simply based upon bilateral distance.[28] For instance, the value of -34.12 in the second column of Table 4c

[28]I have computed the distance-based shares underlying Table 4c from the *inverse* of the bilateral distances reported

indicates that the importance of French R&D in the United Kingdom would be far overestimated by using the distance-based instead of the TFL-based measure of knowledge spillovers. Put differently, France appears to be much less important for the U.K. than one would assume based on France's close relative location.

It is not the case, however, that the importance of near-by countries is always estimated to be higher with the distance-based measure. In particular, as a source of spillovers for Canada, the U.S. is even more important according to the TFL-based measure than one would assume based on its relatively close location to the U.S. (with a positive entry of 5.44, last column of Table 4c). The TFL-based measure also gives a more plausible picture of the importance of Canada as a source of U.S. knowledge spillover inflows than the distance-based measure, because the value of -27.94 suggests that Canada's location adjacent to the U.S. overestimates Canada's importance for the United States. The last row in Table 4c gives the average difference in sender country importance according to the TFL-based and the distance-based measure. The value of 23.76 for the U.S. confirms the notion that the U.S.'s importance as a source of spillovers for other G-7 countries would be underestimated if a simple distance-based criterion would be used to predict the magnitude of bilateral knowledge spillovers.

4 Summary and discussion

This analysis of knowledge spillovers among the seven major industrialized countries has produced a number of interesting results. First, geographic distance appears to have a strongly limiting effect on the scope of knowledge spillovers. While the estimates vary somewhat depending on specification, typically they imply a spillover half-life in terms of distance of 800 to 1,900 kilometers. Second, the degree of localization for knowledge spillovers has substantially declined over the sample period. Again, estimates vary somewhat, but it appears that the extent of localization has fallen by at least two thirds

in Table 2.1–giving a measure of closeness–, before forming the share of a bilateral relation in the closeness total for a given country.

from the 1970s to the 1990s. Third, I have presented a number of findings on the importance of trade, FDI, and language skills for international knowledge spillovers, to which I turn below.

How does the finding on the geographic localization of knowledge spillovers compare with other work? Irwin and Klenow (1994), in particular, estimate learning-by-doing spillovers in the semiconductor industry during the years 1974-92. These authors cannot reject the hypothesis that national and international knowledge spillovers are equal, or, put differently, that there is no localization of knowledge spillovers. However, this difference in terms of results can at least in part be explained by differences in what the two studies identify empirically.[29] One reason for why my results might be overstating the degree to which knowledge spillovers are geographically localized is the fact that my analysis abstracts from the value of knowledge being heterogeneous. It is well-known from analyses of the value of patents that their distribution is very skewed. Because the knowledge that spills over first is likely more valuable than the knowledge that spills over later, my analysis underestimates the value of small stocks of knowledge spillovers relative to larger stocks. In particular, taking account of heterogeneity might therefore raise knowledge spillovers to and from Japan. Caution is also needed to interpret the results on how the scope of knowledge spillovers has changed over time. While there are several mechanisms which seem to be plausible *a priori*, the dramatic magnitude that I estimate, often eliminating the localization effect completely over only twenty-five years, suggests that it might be overstated.

As data on a larger set of countries, especially outside Europe, becomes available, it will be possible to re-examine the questions I have addressed. Moreover, it might be possible in the future to compute

[29] Irwin and Klenow's firm-level data allows the authors to distinguish the own-firm effect from that coming from other domestic firms. At the same time, there is almost no variation in the bilateral distance to foreign sources of spillovers in their study, because semiconductor producers were located predominantly in either the U.S. or Japan. In contrast, my industry-level analysis cannot distinguish own-firm effects from other-domestic firm effects, but there is considerable variation in the distance to foreign knowledge spillover sources. Because Irwin and Klenow estimate that firms benefit much more from own learning than from outside-firm learning (domestically or internationally), their results are not inconsistent with what I have presented above. Another important difference is that Irwin and Klenow measure spillovers as the learning effects from cumulative production on market share, whereas I study the effects of R&D investments on relative productivity. It would be interesting to integrate an analysis of learning-by-doing spillovers with that of R&D spillovers in future work.

productivity indices that consistently account for differences in human capital across countries and industries. In terms of specification, I have focused on international *within*-industry effects, while knowledge spillovers *between* industries–that is, across technology space–is likely to be important as well. Further, the temporal dimension of knowledge spillovers has been collapsed into one point in time in my analysis that focuses on contemporaneous effects.

For the time being, then, what explains the level and the change in the localization effect that are estimated? I have considered the channels of trade, FDI, and direct communication, proxied by data on language skills, as alternatives to distance above. Recall that the interpretation of these findings requires caution for the reasons discussed in section 1.3. From this analysis, it appears that a substantial portion of the influence of distance on the scope of knowledge spillovers, and may be all of it, can be accounted for by differences in trade, FDI, and communication links across countries. Out of the three channels, I estimate that trade is most important, with about two-thirds of the total effect, while differences in FDI and communication flows account for about one-sixth each.[30] To the extent that this finding is confirmed by future research, it provides important information for areas where economic policy might be effective in attracting international knowledge spillovers. The results on language skills are of particular interest because they seem to capture differences in the diffusion of knowledge in a relatively direct way. Future work along these lines might consider other indicators of direct communication such as telephone call volume or email traffic, possibly at a disaggregated level and with a broader set of countries.

While it is possible to account for a substantial part of the distance effect in terms of trade, FDI, and communication links, much less can be said at this point on what has caused the decline in the degree of localization of knowledge spillovers over the sample period. Have transport costs for goods declined dramatically over the period of 1970-95? Direct evidence on this is scarce. Research in

[30] Given the strong negative correlation of trade with distance, trade is more likely to pick up any remaining spurious regional effect that the econometric specification does not control for than the other two mechanisms. This suggests that the share of two-thirds is likely to be an upper bound for the relative importance of trade for knowledge spillovers.

international trade using so-called gravity equations has frequently shown that the volume of trade falls sharply with geographic distance, but whether this effect has become substantially weaker during the sample period is not settled yet.[31] Thus, it cannot be ruled out that the finding of less localization for knowledge spillovers is related to the higher level of economic integration through trade that has been observed in recent years. As for foreign direct investment, the rate of growth in multinational activity over the last two decades has been even higher than the rate of growth of world trade, which means that FDI might also be in part what is behind the decline in the localization of knowledge spillovers. And of course the recent development of new communication technologies and the internet are strong *prima facie* reasons of why knowledge might have become less localized. A definitive answer in this regard, however, must await the greater availability of relevant data, because to date, relatively little is available on the extent to which FDI activity, communication flows, and other channels for knowledge spillovers have changed over time. This should allow to go further than this paper can towards addressing the important question of what are the main causes, and implications, of the recent decline in the degree to which international knowledge spillovers are localized.

[31] The estimate of the elasticity of trade with respect to distance is typically *not* substantially smaller for more recent periods, but this appears to be due primarily to changes in the composition of goods trade that go unnoticed at the relatively high levels of aggregation that are frequently analyzed.

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Table 1: Summary Statistics

Country	Symbol	Relative size in terms of GDP in sample* (%)	Relative size in terms of R&D in sample** (%)	R&D Stock Growth*** (%)
Canada	CAN	3.15	1.44	9.15
France	FRA	12.89	7.03	8.01
Germany	GER	15.15	11.78	11.82
Italy	ITA	11.67	3.31	11.30
Japan	JP	14.36	23.53	9.83
United Kingdom	UK	9.16	5.71	5.72
United States	US	33.62	47.19	7.36
		100.00	100.00	

Industry	ISIC	Relative size in terms of output in sample**** (%)	Relative size in terms of R&D in sample***** (%)	R&D Stock Growth*** All countries (%)
Food	31	14.66	1.90	9.17
Textiles	32	8.62	0.56	7.59
Wood	33	4.73	0.36	13.77
Paper	34	9.79	1.03	7.29
Chemicals	351/2	8.21	19.75	9.00
Rubber	355/6	3.39	1.70	7.69
Non-met. Miner.	36	4.75	1.04	8.02
Basic Metals	37	7.13	2.63	7.83
Metal Products	381	8.19	1.52	10.41
Machinery, Instr.	382/5	12.79	17.22	9.78
El. Machinery	383	7.00	24.63	9.33
Transportation	384	10.73	27.67	8.41
		100.00	100.00	

*Shares computed from value of total manufacturing production in 1980
**Shares computed from total manufacturing R&D in 1990
***Average annual growth of R&D stocks; R&D depreciation rate = 0.1
****Shares computed from value added in 1980; simple average across countries
*****Computed from R&D expenditures in 1990; simple average across countries

Table 2.1 Bilateral distance between capital cities (kilometers)

	CAN	FRA	GER	ITA	JP	UK	US
CAN		5652	5857	6735	10327	5367	734
FRA			400	1108	9723	341	6169
GER				1066	9357	511	6406
ITA					9867	1434	7222
JP						9570	10910
UK							5904
US							

Table 2.2 Bilateral trade shares*

		Exporter						
		CAN	FRA	GER	ITA	JP	UK	US
Importer	CAN		1.91	2.53	1.16	6.85	2.98	69.45
	FRA	0.68		21.82	11.00	3.48	8.64	8.64
	GER	0.68	11.09		9.79	5.90	7.49	6.75
	ITA	0.62	14.62	22.37		2.38	6.52	5.69
	JP	3.13	2.14	4.70	1.82		2.00	22.86
	UK	1.53	9.75	16.02	5.63	5.56		11.87
	US	20.05	2.76	5.13	2.40	18.92	3.98	

Table 2.3 Bilateral foreign direct investment shares**

		Outward FDI country						
		CAN	FRA	GER	ITA	JP	UK	US
FDI host country	CAN		1.86	2.49	0.49	1.93	5.94	16.27
	FRA	0.00		2.40	0.00	0.20	1.63	4.72
	GER	0.09	0.45		0.17	0.21	0.31	3.09
	ITA	0.12	2.20	1.20		0.23	0.73	2.90
	JP	0.00	0.01	0.07	0.00		0.05	0.68
	UK	1.05	1.09	0.72	0.00	1.10		7.26
	US	1.63	1.09	1.35	0.13	1.69	2.94	

Table 2.4 Patterns of bilateral language knowledge***

		Spillover source country						
		CAN	FRA	GER	ITA	JP	UK	US
Spillover Recipient	CAN		31.00	2.00	2.00	0.20	84.00	84.00
	FRA	32.00		9.00	6.00	0.07	32.00	32.00
	GER	41.00	11.00		2.00	0.06	41.00	41.00
	ITA	27.00	19.00	3.00		0.03	27.00	27.00
	JP	0.11	0.01	0.01	0.00		0.11	0.11
	UK	100.00	14.00	5.00	1.00	0.20		100.00
	US	100.00	1.11	2.10	1.03	0.22	100.00	

*Share of total manufacturing imports; in percent; Year 1991; source: Feenstra et al. (1997).
**Share of foreign-owned subsidiary employment in total employment; in percent
Year 1991; source OECD (1999c) and own estimates
***Share of population in recipient country that speaks the official language of the sender country; in percent;
Year 1996/98; source: EU (1999), StatCan (2000), estimates based on JG (2000), and own estimates

Table 3: Knowledge spillovers and geographic distance*				
	Exponential distance eq. (2) (3.1)	Exponential distance w/ γ_1, γ_2 (3.2)	Exponential distance $\bar{\gamma} = 1$ (3.3)	Distance classes eq. (3) (3.4)
β	0.039	0.046	0.055	0.048§
	(0.010)	(0.010)	(0.014)	(0.016)
γ	1.111			0.368
	(0.186)			(0.095)
γ_1		0.992		
		(0.068)		
γ_2		1.197		
		(0.067)		
δ	0.147	0.199	0.123§	
	(0.045)	(0.028)	(0.030)	
η				1.010
				(0.139)
n	2184	2184	2184	2184
R^2 (%)	85.07	85.08	85.06	85.03
AIC	-4.645	-4.648	-4.649	-4.644

*Dependent variable: multilateral TFP index, as defined in the text. Standard errors are in parentheses; β measures the effect of domestic R&D, γ the relative effect from foreign R&D (γ_1 for CAN, FRA, ITA, and for the UK, and γ_2 for US, JP, and GER), and δ as well as η determine the distance effect ($\delta > 0$ and $\eta > 0$ are consistent with distance-limited knowledge spillovers); n = number of observations, AIC = Akaike's Information Criterion, as defined in the text; § coefficient is only significantly different from zero at a 5% level.

Table 4a: Bilateral knowledge spillovers based on geographic distance *

		Spillover Sender CAN	FRA	GER	ITA	JP	UK	US	Recipient Average
Spillover	CAN		3.66	3.93	1.95	0.29	4.33	78.13	15.38
Recipient	FRA	3.66		94.94	51.96	0.41	81.30	3.28	39.26
	GER	3.25	78.55		53.25	0.51	73.62	2.85	35.34
	ITA	1.95	51.96	64.36		0.38	42.96	1.77	27.23
	JP	0.24	0.34	0.51	0.31		0.37	0.21	0.33
	UK	4.33	81.30	88.98	42.96	0.45		3.82	36.97
	US	64.64	2.71	2.85	1.47	0.21	3.16		12.51
	Sender Av.	13.01	36.42	42.60	25.32	0.37	34.29	15.01	23.86

Table 4b: Relative importance of foreign spillover sources by recipient country, all channels **

		Spillover Sender CAN	FRA	GER	ITA	JP	UK	US	Sum
Spillover	CAN		5.21	4.27	1.41	6.57	13.49	69.06	100.00
Recipient	FRA	4.95		33.51	14.89	4.84	18.12	23.68	100.00
	GER	7.96	20.91		16.68	10.13	19.58	24.74	100.00
	ITA	4.77	26.92	33.46		3.72	14.05	17.08	100.00
	JP	8.30	5.70	12.70	4.82		5.48	63.00	100.00
	UK	14.70	14.41	19.92	6.51	8.10		36.37	100.00
	US	37.56	5.12	8.41	3.12	24.81	20.99		100.00
	Sender Av.	13.04	13.04	18.71	7.91	9.69	15.28	38.99	

Table 4c: Difference in importance of foreign spillover sources by trade, FDI, and language vs. distance ***

		Spillover Sender CAN	FRA	GER	ITA	JP	UK	US	Sum
Spillover	CAN		-3.05	-3.70	-5.53	2.05	4.79	5.44	0.00
Recipient	FRA	2.34		-3.35	1.58	3.32	-25.18	21.29	0.00
	GER	5.03	-21.98		0.57	8.29	-13.98	22.06	0.00
	ITA	-0.30	-3.92	1.40		0.26	-9.78	12.35	0.00
	JP	-7.73	-11.33	-5.00	-11.96		-11.82	47.83	0.00
	UK	11.62	-34.12	-12.41	-5.02	6.37		33.57	0.00
	US	-27.94	-2.68	0.90	-3.53	20.41	12.85		0.00
	Sender Av.	-2.83	-12.84	-3.69	-3.98	6.78	-7.19	23.76	

* Value of $ 1 of foreign R&D relative to $ 1 of domestic R&D; in percent; based on specification (3.2)
** Share of knowledge sender country in total knowledge inflows of recipient country; in percent; based on (7.8)
*** Positive entries indicate that a sender country is more important for the recipient country according to its trade, FDI, and language links than according to its bilateral distance; vice versa for negative entries; in percentage points; based on (7.8)

Table 5: Sensitivity analysis*

	Low R&D industries (5.1)	Output-based TFP (5.2)	All-manufact. PPP exch. rates (5.3)	TFP based on IRS (5.4)	Unadjusted TFP (5.5)
β	$0.025^{\otimes}$	0.045	0.045	$0.044^{\S}$	$0.067^{\S}$
	(0.016)	(0.011)	(0.011)	(0.017)	(0.018)
γ		0.737		0.618	0.437
		(0.067)		(0.155)	(0.066)
δ	0.138	0.300	0.273		
	(0.079)	(0.100)	(0.021)		
η				1.077	0.716
				(0.086)	(0.067)
n	1456	2184	2184	2184	2184
R^2 (%)	85.37	83.43	83.09	85.48	80.97
AIC	-4.676	-4.565	-4.668	-4.608	-4.431

*Dependent variable: multilateral TFP index, as defined in the text. Standard errors are in parentheses; β measures the effect of domestic R&D, γ the relative effect from foreign R&D, and δ as well as η determine the distance effects ($\delta > 0$ and $\eta > 0$ means greater geographic distance is associated with fewer spillovers); n = number of observations, AIC = Akaike's Information Criterion, as defined in the text; $^{\otimes}$coefficient is significantly larger than zero at a 12% level; § coefficient is significantly different from zero only at a 5% level.

Table 6: The localization of knowledge spillovers over time*

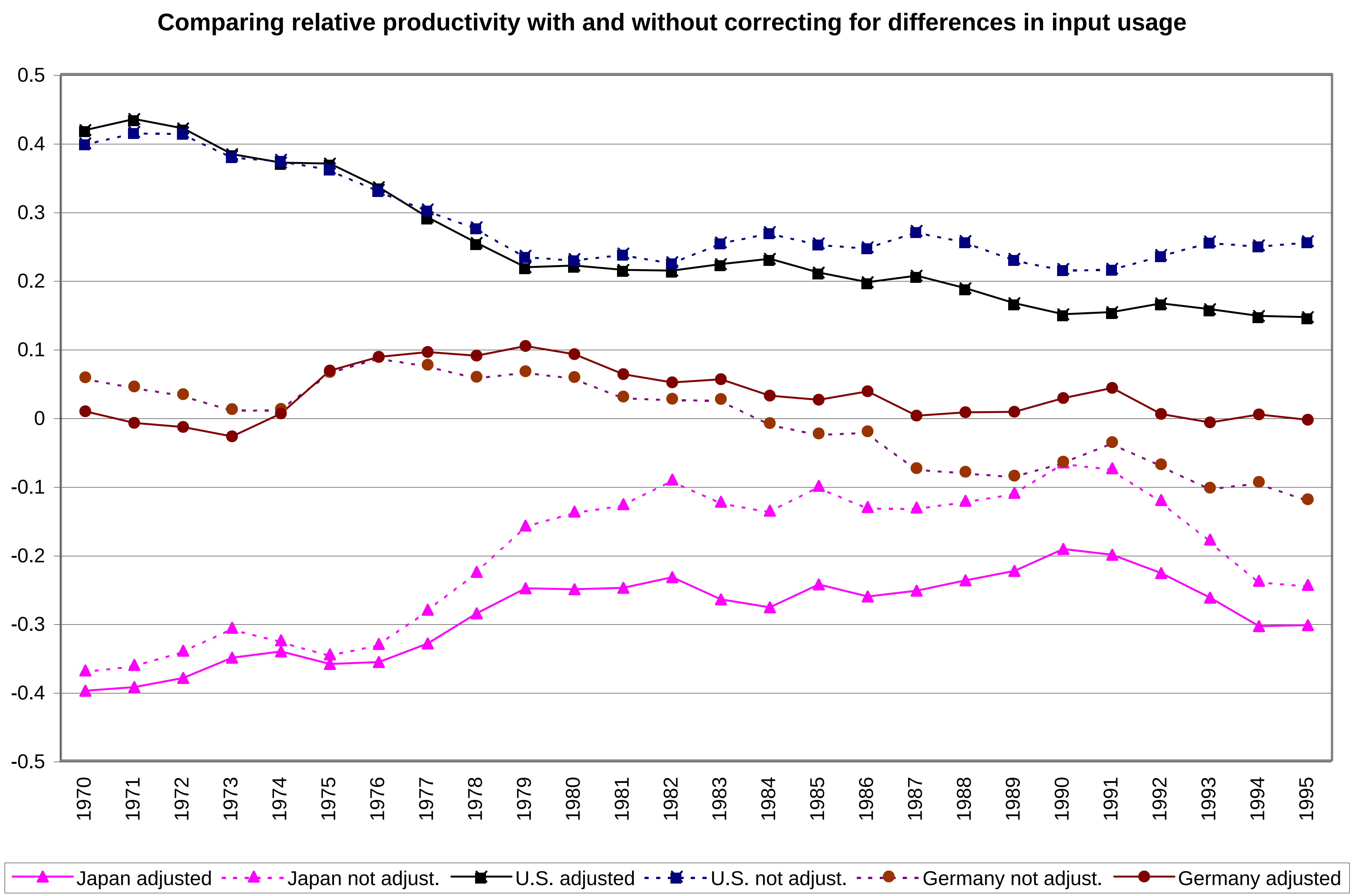
	Exponential w/ Δ in distance effect (6.1)	Exponential w/ Δ in distance and foreign effects (6.2)	Distance class w/ Δ in distance effect (6.3)	Exponential w/ Δ in distance effect Low R&D Industries (6.4)
β	0.052	0.057	0.067	0.066
	(0.010)	(0.010)	(0.012)	(0.013)
γ	1.127	1.104	0.498	
	(0.044)	(0.123)	(0.040)	
δ	0.490	0.466		0.472
	(0.091)	(0.073)		(0.069)
η			1.012	
			(0.124)	
γ^{ti}		0.072[¢]		
		(0.071)		
δ^{ti}	-1.188	-1.193		-1.174
	(0.222)	(0.305)		(0.304)
η^{ti}			-0.778	
			(0.079)	
n	2184	2184	2184	1456
R^2 (%)	86.65	86.70	85.35	86.75
AIC	-4.752	-4.755	-4.666	-4.773

*Dependent variable: multilateral TFP index as defined in the text. Standard errors are in parentheses; β measures the effect of domestic R&D, γ the relative effect from foreign R&D, and δ as well as η determine the distance effects ($\delta > 0$ and $\eta > 0$ says that greater distance is associated with a lower productivity effect). The parameters γ^{ti}, δ^{ti}, and η^{ti} estimate changes in the overall foreign (γ^{ti}) and distance effects; n = number of observations, AIC = Akaike's Information Criterion, as defined in the text; [¢] not significantly different from zero at standard levels.

Table 7: Trade, FDI, and language skills as channels for knowledge spillovers*									
	(7.1)	(7.2)	(7.3)	(7.4)	(7.5)	(7.6)	(7.7)	(7.8)	(7.9)
β	0.055	0.057	0.053	0.103	0.081	0.125	0.087	0.082	0.068
	(0.014)	(0.011)	(0.018)	(0.018)	(0.010)	(0.012)	(0.014)	(0.011)	(0.028)
δ	0.123				0.191	0.232	$-0.180^{¢}$		$-0.124^{¢}$
	(0.030)				(0.111)	(0.082)	(0.073)		(0.159)
τ		0.403			0.130			0.578	0.765
		(0.031)			(0.006)			(0.064)	(0.230)
ψ			0.377			0.370		0.081	0.073
			(0.027)			(0.046)		(0.017)	(0.014)
λ				0.390			0.662	$0.574^{\oplus}$	$0.975^{\oplus}$
				(0.029)			(0.100)	(0.183)	(0.555)
AIC	-4.649	-4.668	-4.661	-4.664	-4.678	-4.689	-4.685	-4.694	-4.697

*Dependent variable: multilateral TFP index, as defined in the text. Standard errors are in parentheses; β measures the effect of domestic R&D, δ the distance effect ($\delta > 0$ is consistent with localized spillovers), τ is the parameter on the import shares, ψ is the parameter on the FDI shares, and λ is the language parameter. If trade, FDI, or language facilitate knowledge spillovers, then τ, ψ, or λ, respectively, are expected to be greater than zero; 2184 observations, AIC = Akaike's Information Criterion, as defined in the text; $^{\oplus}$ coefficient is only significant at the 10% level, $^{¢}$ coefficient is not significantly different from zero at standard levels.

Figure 1



Comparing relative productivity with and without correcting for differences in input usage
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
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
Japan adjusted
Japan not adjust.
U.S. adjusted
U.S. not adjust.
Germany not adjust.
Germany adjusted

Figure 2

Productivity convergence or divergence: analysis within and between countries

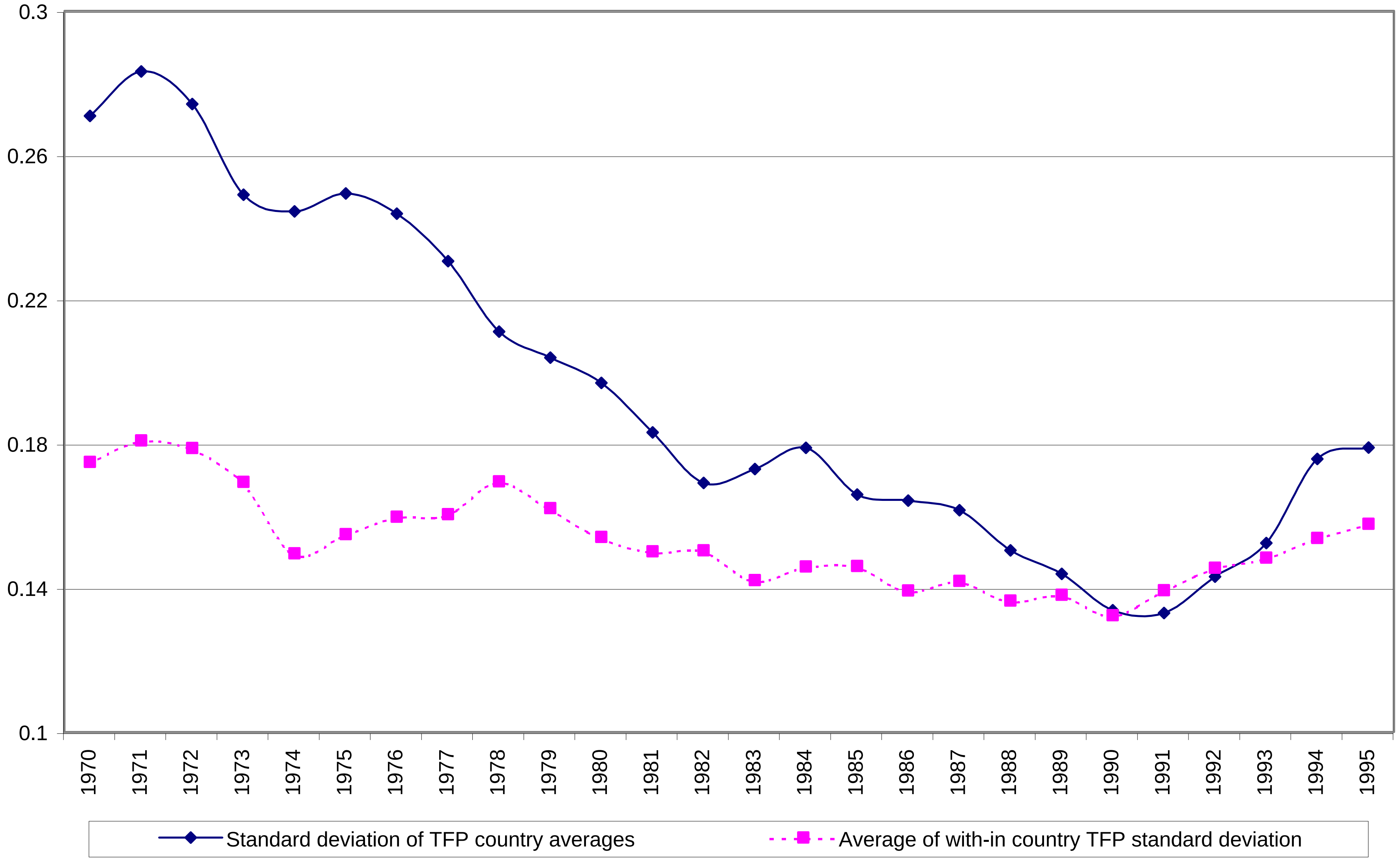


Figure 3

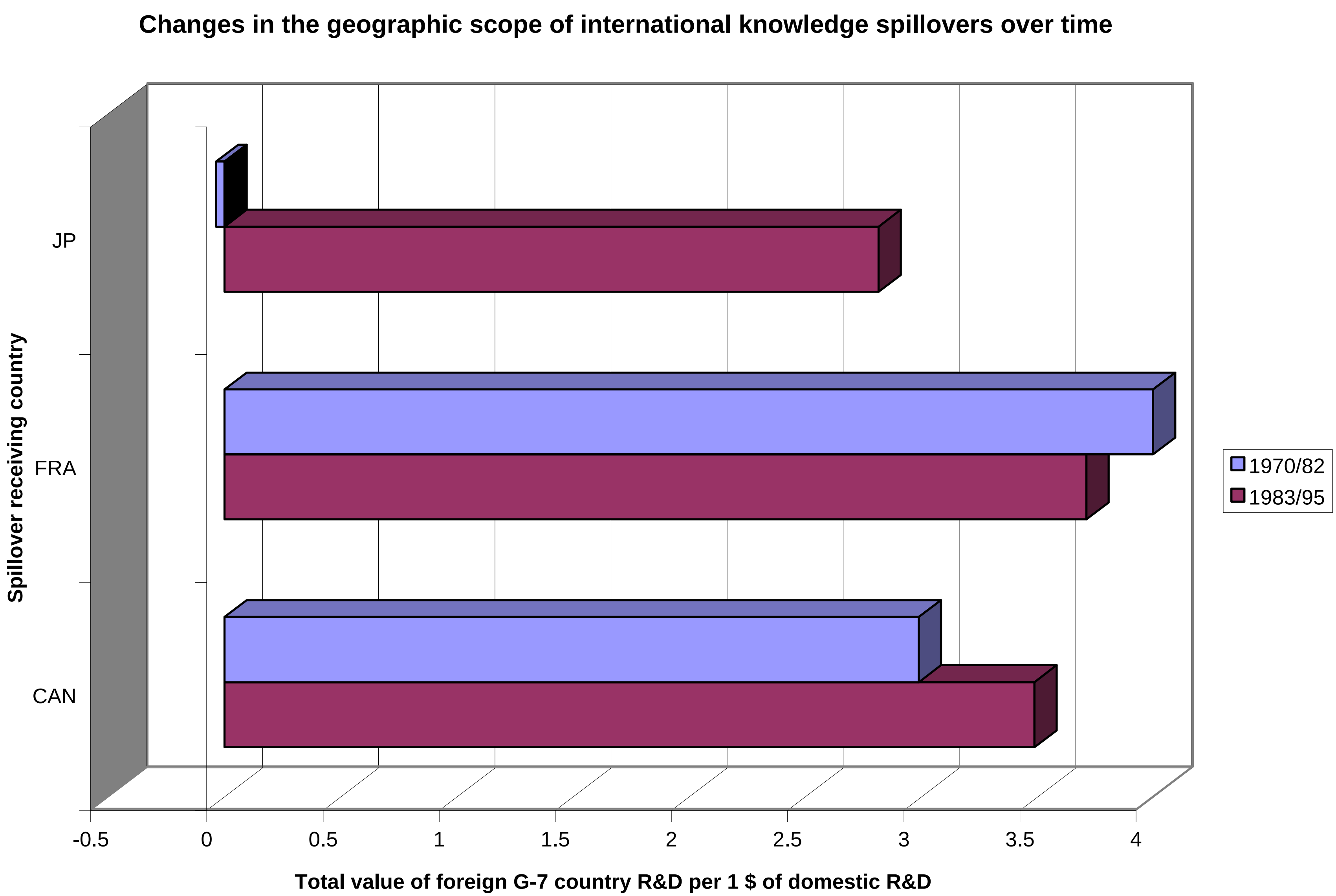
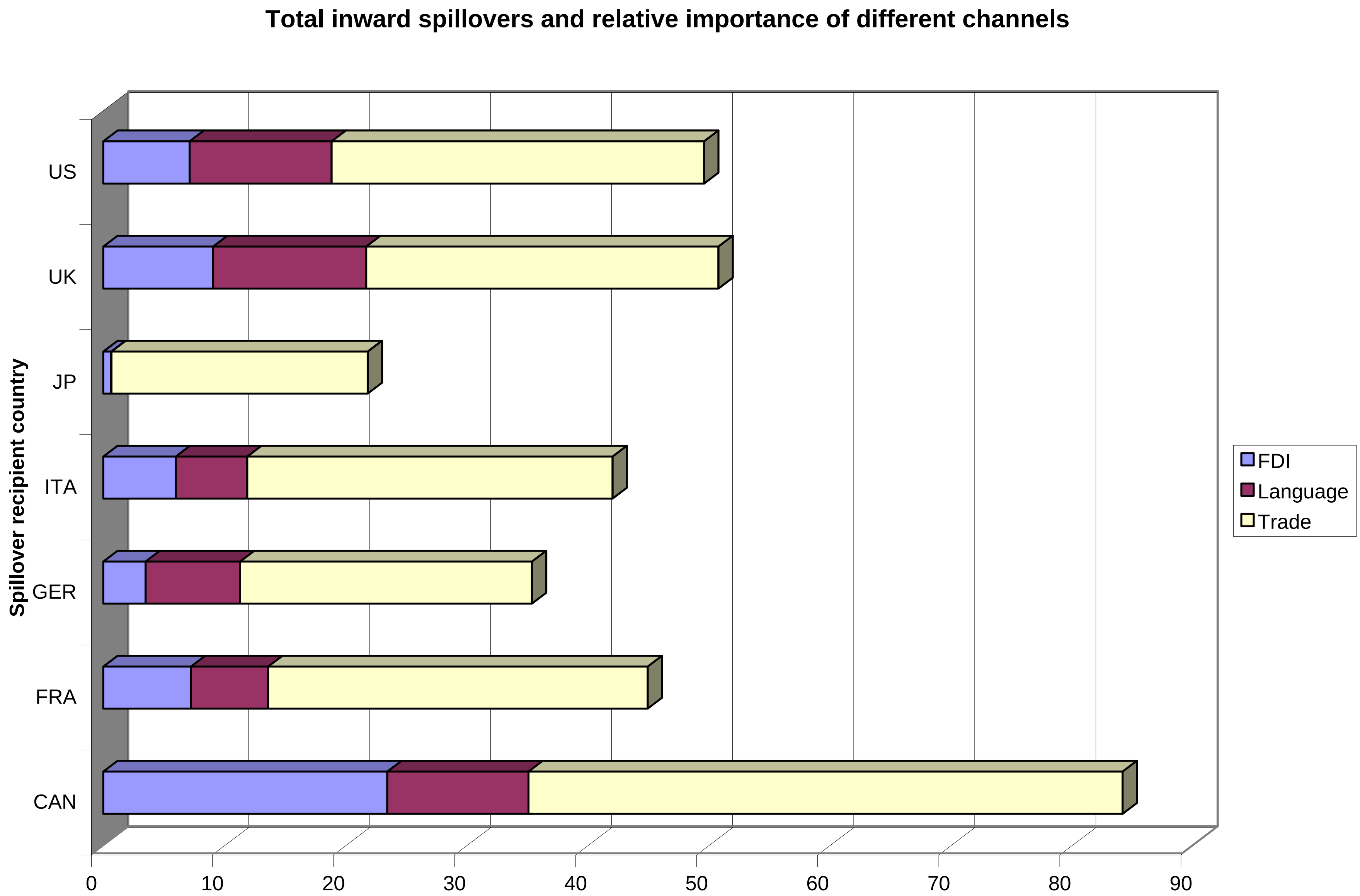

Changes in the geographic scope of international knowledge spillovers over time
Spillover receiving country
JP
FRA
CAN
-0.5
0
0.5
1
1.5
2
2.5
3
3.5
4
Total value of foreign G-7 country R&D per 1 $ of domestic R&D
1970/82
1983/95

Figure 4


Total inward spillovers and relative importance of different channels
Spillover recipient country
US
UK
JP
ITA
GER
FRA
CAN
0
10
20
30
40
50
60
70
80
90
FDI
Language
Trade