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The Evolution of the World's Technology Frontier, 1973-2002

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Abstract

While economists generally agree that technology differences must figure prominently in any successful account of the cross-country income variation, much less is known on where such technology differences come from. In this paper, they are explained in terms of domestic technical change and international technology diffusion. We are studying the recent importance of factor accumulation, R&D investments, and technological spillovers for cross-country output differences in the major industrialized countries. The empirical analysis encompasses seventeen countries in four continents over three decades, at a level disaggregated enough to identify innovations in important high-tech sectors. Technology diffusion is related to trade, foreign direct investment, and other mechanisms. Preliminary results show that technology spillovers are crucial in accounting for cross-country output differences. Imports are shown to be a channel of technology diffusion, with important differences across industries and countries. Technology diffusion through inward foreign direct investment appears to be of major importance, and a more powerful conduit of technology diffusion than trade.

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I. Introduction

There is general agreement now among economists that productivity differences must figure prominently in any successful account of the cross-country income variation--differences in labor and capital are just not big enough to explain these income differences.[3] At the same time, productivity differences, where they come from and how they evolve over time are not well understood at this point.[4] In this paper, productivity differences are explained in terms of domestic technical change and international technology diffusion.

Research and development (R&D) spending is the major input in technical change. Technical change generates knowledge, which because of its partly non-rival nature has both private and social returns. Past innovative efforts benefit today's inventors, and today's invention in some country generates externalities, or spillovers, for producers in other countries. We seek to understand how R&D investments and technological spillovers have shaped cross-country output differences in the major industrialized countries. How important is domestic technical change relative to technology diffusion from abroad? Why are some countries more successful than others in transferring technology from abroad? These are the questions that this study wants to answer.

One advantage of analyzing technical change as the fundamental driver of income differences is that the key input of technical change, R&D, is easily observable. Thus, we have built a rich database to make progress on these issues. It is relatively comprehensive; our empirical analysis encompasses seventeen countries in four continents over three decades. The database is also detailed enough to identify innovations in important high-tech sectors.

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[3] Hall and Jones (1999) have made this point forcefully.
[4] At the same time, several authors have explored specific hypothesis, such as institutions (Acemoglu et al. 2001) and social infrastructure (Hall and Jones 1999).

Any theory of productivity differences, whether it is based on institutions, geography, or something else, must also incorporate the interdependence of countries, and how this affects income differences. This is particularly so because the level of economic integration today is unprecedented in the economic history of the world. In our framework, spillovers give rise to the diffusion of technology across countries. We link these spillovers to international trade and foreign direct investment.

Preliminary results show that productivity differences are to a major extent due to differences in R&D investments across industries and countries. Moreover, technology spillovers are important in accounting for cross-country income differences. Imports are shown to be a channel of technology diffusion, with important differences across industries and countries. Technology diffusion through inward foreign direct investment (FDI) appears to be of major importance, and a more powerful conduit of technology diffusion than imports in our analysis.

One contribution of our analysis is that it shows that international technology spillovers are heterogeneous across countries, both by source as well as recipient countries. We also address the question of whether trade matters for international technology diffusion. The evidence on this has been mixed so far (Coe and Helpman 1995, Keller 1998). In contrast to much of the large literature that has emerged to address this issue (including Caselli and Coleman 2001, Eaton and Kortum 2001, Xu and Wang 1999), we specify an alternative to trade-related technology diffusion, thereby putting the hypothesis to a real test. We find robust evidence for imports-related technology diffusion, but its importance relative to other diffusion mechanisms varies. We also show that international technology diffusion has accelerated over time, which confirms and extends Keller's (2002) result in a broader sample and different methods. We also address the question whether FDI leads to technology diffusion or not, a question of considerable policy importance since frequently subsidies are used to attract FDI. On this issue, Aitken and Harrison (1999) argue that FDI spillovers do not exist, while Keller and Yeaple (2005) find evidence to the contrary.[5] Our contribution in this respect is that we study FDI, trade, and other spillovers jointly, which enables us to provide a breakdown of the relative importance of different mechanisms.

The structure of the paper is as follows. In section II we describe the new dataset that is underlying our empirical analysis, before turning to estimation issues in section III. The empirical results are found in section IV, and section V provides a concluding discussion.

II. Data

We have assembled a new dataset with the following characteristics. First, with a sample period from 1973 to 2002, there are three decades of data. This period is long enough to cover both the productivity slowdown in the 1970s as well as the surge of innovations in the 1990s, which is useful for identifying the major factors. Second, we study technical change at the industry-level. This is important because technical trends tend to break in an uneven way across sectors; in the 1990s, it was primarily information and technology sectors. Thus, rather than analyzing manufacturing or the entire economy, where such changes tend to be muted, we examine disaggregated data for twenty-two manufacturing industries. This allows special emphasis on particularly technology-intensive sectors. Recent evidence has highlighted that international technology diffusion varies a lot across industries.[6] And third, our sample includes

[5] Lichtenberg and van Pottelsberghe (2001) find significant FDI spillover effects for outward, but not for inward FDI at a country level of aggregation.
[6] See Keller and Yeaple (2005), for example.

17 relatively advanced countries in four continents, which together account for the large majority of the world's R&D expenditures.[7]

Internationally comparable figures on employment, output, and sectoral prices come from Groningen Growth and Development Centre (GGDC) database (van Ark et al. 2005) for the years 1979-2002. We have combined this with data on employment, output and sectoral prices for 1973-78, from the OECD's STAN database (OECD 2005a). This is also the basis for the GGDC figures. Also from the OECD's STAN database comes data on investment. Data on sample countries' business R&D (ANBERD database, OECD 2005b), as well as on the bilateral trade among them (BTD database, OECD 2005c) are also from OECD. In contrast to international trade, there are no internationally comparable data on the industry-level activities of foreign-owned firms in these 17 countries. At the same time, we were able to assemble data on US-owned firms in the countries that attract most of the outward FDI of the United States (source: US Bureau of Economic Analysis 2005). This should enable us to do a first analysis of the relative importance of trade and FDI at the industry level, because the US is probably the most important source of foreign technology in all other sample countries.

The measure of output in this analysis is value added, since internationally comparable data on intermediate inputs is not available.[8] Labor inputs are measured by the number of workers. We have constructed capital stocks and R&D stocks for each industry in each country and year from the investment data using the perpetual inventory method as given in Appendix C. Since availability varies by individual data series, our sample is an unbalanced panel.

[7] The countries in sample are: Australia, Belgium, Canada, Denmark, Finland, France, United Kingdom, Germany, Ireland, Italy, Japan, South Korea, the Netherlands, Norway, Spain, Sweden and USA.
[8] Details on data sources, construction and estimation are provided in the Appendices A through C.

For each country, there are 660 possible observations with 22 industries and 30 years (1973-2002). As Table 1 indicates, the dataset is complete for many series. The major exceptions are (i) Belgium, for which R&D data becomes available only in 1987; (ii) Ireland, for which investment data starts only in 1992, and (iii) South Korea, where R&D data is only recorded from 1995 onwards. In addition, there are some missing values during the 1970s. By industry, there is a maximum of 510 observations for each industry. As the lower part of Table 1 shows, data availability by industry varies little. This means that such data availability differences will not have an important influence on the results.

Table 2 provides information on R&D intensities, defined as R&D expenditures over value added, in both the country and the industry dimension. Across countries, the R&D intensity varies by a factor of three to four, with values from 3.1% for the low R&D-intensity countries Ireland and Spain to values of 10.0% and 10.6% for the high R&D-intensity countries US and Netherlands, respectively.[9] As we have already noted above, the R&D intensity varies a great deal more across industries. In our sample, the R&D intensity for the wood products industry is the lowest, with 0.6% on average. The R&D intensities for the food, textiles, and paper industries are also relatively low, ranging between 0.7% and 1.1%. In contrast, the R&D intensity in the radio, television, and communications equipment industry is with 26.1% more than 40 times as high as for wood products. Also high are the R&D intensities of the aircraft (23.8%), computer (21.3%), and pharmaceuticals (18.0%) industries. Moreover, as the table indicates, there is a substantial amount of variation in R&D intensities for a given country or industry. For instance, Ireland's computer industry (industry #14) has an R&D intensity of only one tenth of the average across countries, while in another high-R&D intensity industry,

[9] South Korea's average R&D intensity is, with 6.1%, considerably higher than Ireland's or Spain's, but this is in part due to the fact that for South Korea the average is computed with data from 1995 onwards, a time by which South Korea's R&D spending had substantially grown.

communications equipment (industry #16), Ireland’s R&D intensity is quite close to the average across countries.

Tables 3-5 provide summary statistics on employment, capital stocks, and R&D stocks by industry and by country. In particular, Table 5 indicates that the size of the US industry’s R&D is by far the largest of all 17 countries: the median US industry’s size in terms of R&D is 39.6% of the sample. Next in size is Japan (median of 27.4%), followed by Germany (7.5%), France (6.5%), and the UK (4.9%). Also the remaining G-7 countries, Canada and Italy, are among the more important producers of technology (R&D shares 2.5% and 2.3%, respectively).

It is well-known that international trade varies substantially across countries and industries. Table 6 gives a glimpse of that by showing the share of the US in total imports by partner country and industry. In Canada almost three quarters of all imports come from the US. In contrast, most European countries import only around 10-15% of their goods from the US (except the UK where the US share is 21.6%). By industry, the US share of total imports has been highest for aircraft, followed by computers. For imports, we study their importance as diffusion mechanism from Canada, France, Germany, the UK, Japan, and the US (referred to as the G6 countries)

However, when it comes to evaluating the joint impact of imports and FDI in technology diffusion, in the absence of FDI data at the industry level for all sample countries, we will study imports and FDI as diffusion mechanisms looking at the US as the sole source. Given the relative importance of the US in terms of R&D, with a median size of about 40%, and average size of 47% in the sample (see Table 5), this should give us a good first cut at this question of the relative importance of imports and FDI in technology diffusion. Table 7 shows that the aircraft and computer industries have the highest imports (from the US) to industry value added ratios.

Inward FDI (from the US) is also relatively high in the computer industry, but not in the aircraft industry (second column). Overall, the correlation between imports and FDI from the US by industry is positive and substantial (0.48). By country, our data does only identify the major eight host countries of US FDI (Table 7, right side). The relative importance of imports and inwards FDI from the US are by far greatest in Canada, with a share of US-owned foreign affiliate employment of 36.2%, and an imports share of 69.3%. As the correlation statistic of 0.988 at the bottom of the table indicates, countries that receive a lot of imports from the US also tend to receive a lot of FDI from the US. This is consistent with factors that facilitate trade, such as the short geographic distance between the US and Canada, appear also to benefit FDI between these countries. Moreover, this effect is not solely due to Canada, since even if Canada is excluded, the correlation of FDI and imports is still 0.725.

We now turn to estimation issues in this setting.

III. Estimation

Technology in this paper is the residual contribution to output that is not due to measured inputs (Solow 1957, Hall and Jones 1999). Consider the Cobb-Douglas production function for industry i at time t in country c:

(1) $$Y_{cit} = A_{cit} K_{cit}^{\beta_k} L_{cit}^{\beta_l},$$

where $i = 1,\dots, 22$; c = 1,…, 17; and t = 1973,…, 2002. Here, Y is output, K is capital, L is labor, and $ß_k$ and $ß_l$ are the elasticities of capital and labor, respectively.[10] The term A in equation (1) is an index of technology, or productivity. It follows that

[10] These may vary by industry, which we will discuss below.

(1') $\ln A_{cit} = \ln Y_{cit} - \beta_k \ln K_{cit} - \beta_l \ln L_{cit}$

Assuming values for $ß_k$ and $ß_l$ —a choice roughly in line with national income statistics is $ß_k$ =1/3 and $ß_l$ =2/3 —, the technology term *A* can be computed from (1') with data on inputs and outputs. In this paper, regression analysis is used to estimate $ß_k$ and $ß_l$, and relate technology to R&D spending. From equation (1),

(1") $y_{cit} = \beta_k k_{cit} + \beta_l l_{cit} + u_{cit}$,

where for any variable *Z*, *z = lnZ*, and u_{cit} is equal to $\ln A_{cit} = a_{cit}$. Following Griliches (1979) and others, technology *a* is determined by domestic R&D expenditures, *R*, and other factors, **X**

(2) $a_{cit} = \beta_0 + \gamma r_{cit} + \mathrm{X}ß + \varepsilon_{cit}$,

where ε is a stochastic error term. One major element of **X** is foreign R&D, which has been shown to have an important effect on domestic technology recently.[11] In addition, we will examine international trade and FDI as mechanisms of international technology diffusion. Substituting (2) in (1") yields our main estimation equation

(3) $y_{cit} = \beta_0 + \beta_k k_{cit} + \beta_l l_{cit} + \gamma r_{cit} + \mathrm{X}ß + \varepsilon_{cit}$.

Equation (3) is an augmented production function. A number of generic issues exist in the estimation of the capital and labor coefficients, and moreover, in the multivariate regression context any bias in $ß_k$ and $ß_l$ generally leads to biases in γ and **ß** as well. A major econometric issue confronting production function estimation is the possibility that some of these inputs are unobserved. In that case, if the observed inputs are chosen as a function of the unobserved inputs, there is an endogeneity problem and OLS estimates of the coefficients of the observed inputs will be biased. Specifically, even in the case where capital and labor are the only inputs, if the error term is composed of two parts

[11] See the survey by Keller (2004).

(4) $\varepsilon_{cit} = \omega_{cit} + u_{cit}$,

where u_{cit} is noise (or measurement error in y_{cit}), while ω_{cit} (which could be a determinant of productivity or demand) is observed by agents who choose the inputs. This implies that OLS will generally not yield unbiased parameter estimates because $E[l_{cit}\ \varepsilon_{cit}] \neq 0$ or $E[k_{cit}\ \varepsilon_{cit}] \neq 0$, or both. The unobservable factor ω_{cit} does not have to be varying over time or across groups in order to have this effect.[12] Along these lines, $\omega_{cit} = \omega_{ci}$ may capture time-invariant productivity differences across industries, or $\omega_{cit} = \omega_t$ may be shocks that affect all industries in the sample.

We will employ several estimators in order to address this issue. First, we assume that the unobserved term ω_{cit} is given by country-, industry-, and time-effects that are fixed and can be estimated as parameters:

(4') $\varepsilon_{cit} = \eta_c + \mu_i + \tau_t + u_{cit}$,

If (4') holds, OLS will yield consistent and unbiased estimates (in fact, OLS will then be the best linear unbiased estimator). Second, we will employ the General Method of Moments (GMM) techniques developed by Arellano, Blundell, Bond, and others (Arellano and Bond 1991, Blundell and Bond 2000). Assume that

(4'') $\varepsilon_{cit} = \varsigma_{ci} + \tau_t + u_{cit}$,

where year fixed effects (τ_t) control for common macro effects; ς_{ci} is the unobservable industry component, and u_{cit} is a productivity show following an AR(1) process, $u_{cit} = \rho u_{cit-1} + \psi_{cit}$. The industry component ς_{ci} may be correlated with the factor inputs (l_{it}, k_{it}, and r_{it}) and elements of **X**, and ς_{ci} may also be correlated with the residual productivity shock u_{cit}. Assumptions over the

[12] A group here is a country-by-industry combination, denoted by the subscript *ci*.

initial conditions and over the serial correlation of u_{cit} yield moment conditions for combining equations in levels (of variables) with equations in differences (of variables) for a System GMM approach. In both equations, one essentially uses lagged values to construct instrumental variables for current variables.

Third, we adopt the approach developed by Olley and Pakes (1996). This involves assumptions on the structure of the model (on timing, invertability, dimensionality, etc.) such that ω_{cit} can be expressed as a function of investment i_{cit} and capital k_{cit}.

(4''') $\varepsilon_{cit} = \omega_{cit} + u_{cit} = g(i_{it}, k_{it}) + u_{cit}$,

where the function g(.) is unknown.[13] The idea is that conditional on capital, we can learn about ω_{cit} by observing i_{cit}, that is, $i_{cit} = f(\omega_{cit}, k_{cit}) = g^{-1}(\omega_{cit}, k_{cit})$. In essence, investment serves as a proxy for the unobserved ω_{cit}. Once a consistent estimate of ω_{cit} is obtained, the source of the potential endogeneity problem in equations (3, 4) is eliminated, and the production function parameters can be estimated. We will employ both a variant of Olley and Pakes' two-step procedure as well as the more recent one-step GMM procedure proposed by Wooldridge (2005).

We also compare these regression-based estimates of β_l and β_k with direct estimates from on the OECD STAN's data on labor's share in total compensation, as cost minimization together with CRS implies that β_l is equal to labor's share, and β_k is equal to one minus labor's share in total costs. This also allows to obtain an alternative estimate of the technology term *a*, which will be related to R&D and **X** (equation 2).

[13] See also Griliches and Mairesse (1998) and Ackerberg, Caves, and Frazer (2005) for a discussion of these assumptions.

IV. Empirical Results

1. The Contributions of Labor and Capital

Initially we focus our attention on the input parameters for capital and labor. Table 8 reports OLS estimates for β_k and β_l from

$$(5) \qquad y_{cit} = \beta_0 + \beta_k k_{cit} + \beta_l l_{cit} + \varepsilon_{cit} ,$$

which is a restricted version of equation (3) from above.[14] The columns in Table 8 correspond to results for different assumptions on the regression error ε_{cit}. When the equation only includes a constant, β_k is estimated around 0.43 and β_l at about 0.57, and the null hypothesis of constant returns to scale cannot be rejected (*p*-value of 0.27).[15] Including time- (8.2), country- (8.3), and industry fixed effects (8.4) improves the fit in terms of $\overline{R}^2$ of the equation, and it leads to relatively modest changes in the estimates (β_k falls to 0.375, while β_l rises to 0.626). Also with fixed effects, the model seems well-characterized with constant returns to scale (*p*-value of 0.98 in 8.4). When we allow for deterministic fixed effects for each country-by-industry combination (also called within-estimation), however, we estimate β_k to be much higher and β_l to be much lower (see 8.5).[16] This probably reflects well-known problems of the within-estimator in the presence of measurement error (Griliches and Hausman 1986).

Since OLS may suffer from endogeneity problems, in Table 9, we compare the least squares estimates with alternative estimators. First, consider the case where there is no unobserved heterogeneity (no fixed effects). Column (9.1) repeats the least squares estimates of (8.1) for convenience. Specification (9.2) employs the System GMM IV estimator (Blundell and

[14] We have computed physical capital stocks using the perpetual inventory method and depreciation rate of 5%. The R&D stocks are computed using a rate of depreciation of 15%. The labor measure is the total number of employees.
[15] Heteroskedasticity-consistent (Huber-White) standard errors are reported in all OLS regressions.
[16] This within-estimator involves estimating C x I = 17 x 22 = 374 group fixed effects. In contrast, (8.4) involves C + I = 17 + 22 = 39 fixed effects.

Bond 2000). Labor and capital are treated as endogenous and may be correlated with the error through a random group fixed effect ς_{ci}. Labor and capital are instrumented with their own appropriately lagged values, which accounts for the lower number of observations in the System GMM compared to the OLS estimation. We include three instruments, l_{t-2}, l_{t-3}, and k_{t-2}, and given two endogenous variables (l_t, k_t) there is one overidentifying restriction. At the bottom of (9.2), the *p*-value of 0.968 for the Sargan test of overidentification statistic says that one cannot reject the null hypothesis that the instruments, as a set, are exogenous.[17]

The last two rows in Table 9 test for serial correlation in the equation's first differences using LM tests. Generally, as the lag length increases, the quality of the instrument declines. In order to avoid a weak -instruments problem, the lag order should be low while at the same time the lagged value should not be itself endogenous as well. The AR(2) test in the last row of Table 9 indicates that because the evidence for second-order autocorrelation in the first-differenced residual is limited, variables at date (*t-2*) and earlier are marginally valid instruments.[18]

The next two columns present two different versions of the Olley-Pakes (1996) estimator. Specification (9.3) follows closely the Olley-Pakes (OP) original two-step procedure. In step one the unobservable ω_{cit} (see equation (4''')) is approximated by a third-order polynomial in investment and capital, which allows the identification of β_l. In the second step, the assumption that capital is uncorrelated with the innovation ω_{cit}, which follows a first-order Markov process, ensures the identification of β_k. In column (9.4), we show the results of implementing the Olley-

[17] Note that including more instruments and thereby yielding more overidentifying restrictions, it is possible to reject the null that the instruments as a set are exogenous. At the same time, it is well-known that this test has low power when the number of overidentifying restrictions is high due to an overfitting problem, which suggests keeping the number of instruments low.

[18] With a *p*-value of 8.8%, they are valid at a 5%, but not at a 10% level of significance. Interestingly, the evidence for first-order serial correlation is weaker than for second-order serial correlation (*p*-values of 28.2% versus 8.8%, respectively). The structure of this IV GMM framework implies that the opposite is the case. This is probably due to a misspecification problem. As we will show below, once domestic and foreign R&D are included, the evidence for first-order serial correlation is typically stronger than for second-order serial correlation.

Pakes estimator in the one-step GMM procedure recently proposed by Wooldridge (2005), which is denoted as OP/W.[19] The OP results yield a labor coefficient of 0.53 (see 9.3), similar to that for the one-step variant (9.4), where we estimate β_l to be 0.51. However, the capital coefficient using the OP method is estimated to be 0.63, considerably higher than 0.45, obtained with the OP/W estimator, and our OLS estimates of β_k.

For all three estimators, System GMM, OP, and OP/W, the introduction of fixed effects leads to a slightly higher labor coefficient, as it does for OLS (see Table 9). However, the capital coefficient using the OP method is now estimated to be not significantly different from zero anymore (p-value of about 0.14), and the point estimate is also quite different from the earlier one without fixed effects (0.23, before 0.63). In contrast, the OP/W one-step estimator is producing results that are more stable.[20]

It is instructive to compare the estimates of β_l with an average labor share in the data of 0.647, which with constant returns to scale yields 0.353 for β_k.[21] These values are close to System GMM estimates with fixed effects (9.6), as well as to the OLS estimates (9.5). Summarizing, we estimate the labor elasticity in the range of 0.56 to 0.68, and our preferred point estimate is towards the higher end of that range. Constant returns to scale seems quite plausible from our results, putting the capital share around 0.32.

2. The effects of domestic and foreign R&D

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[19] This assumes that ω_{cit} is a random walk (not only first-order Markov), and the identification for both β_l and β_k comes solely from moment conditions that correspond to Olley and Pakes' second stage.
[20] This may suggest that step-one identification in OP is weak in this context; Ackerberg, Caves, and Frazer (2005) discuss some of the issues involved.
[21] The average labor share in the data is computed as the average of labor compensation over value added (the median is, with 0.662, similar).

After having examined the quantitative contributions of capital and labor to value added, we now turn our attention to R&D spending. In Table 10, the OLS specification in column 2 introduces the industry's domestic R&D stock in addition to its capital and labor (shown again in column 1 for convenience). For this, we have estimated equation (3) by excluding the **X** control variables. Both capital and labor coefficients fall with the inclusion of R&D (β_l now estimated 0.437, and β_k 0.299). The coefficient on R&D is 0.271, which is at the higher end in the range of earlier results.[22] The R&D elasticity of 27% implies a rate of return of about 80%.[23] In the System GMM specification shown in column 3, R&D is treated as endogenous; its coefficient estimate is not very different than if it's treated as exogenous (0.246 in (3) versus 0.271 in (2)).[24] Using the one-step Olley-Pakes estimator leads to a somewhat lower R&D coefficient, at 0.179, and to a higher capital coefficient, as before (see Table 9). Overall, these results are consistent with earlier studies showing that domestic R&D is an important determinant of productivity.

The analysis of international R&D spillovers begins with those from the US, the country that has higher R&D spending than any other country in the world. The OLS results (using the full form of equation 3, where X represents foreign R&D) in the first column of Table 11 estimate positive and significant R&D elasticities for both domestic and US R&D.[25] With OLS, endogeneity is a major concern, so we move to the System GMM and Olley-Pakes techniques in

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[22] This may be due to two factors: first, relative to other R&D studies we use relatively broad industry aggregates. With manufacturing divided into 22 industries, our estimate may pick up some industry-level externalities. Second, we do not control yet for foreign technology spillovers; as will become clear from Table 11, they are important. See Griliches (1995) for more discussion.

[23] The average of value added here is 10251, the average R&D is 3402.7, and 0.271*10251/3402 = 0.817. Additional rates of return for foreign R&D will be reported below.

[24] We include l_{t-2}, l_{t-3}, k_{t-2}, and r_{t-2} as instruments, where r_{t-2} is the R&D stock lagged by two years.

[25] In these regressions, we avoid double-counting of the foreign R&D variables. Under domestic R&D variable, the data of each country enters for its domestic industries, whereas under foreign R&D the data for domestic industries are zero. In the first specification of Table 12, for example, under variable "domestic R&D", US R&D data enter for US industries, while under variable "US R&D" US R&D data enter for industries in all other countries except for the US. In general, foreign R&D variables are introduced as $I_c \cdot r_c$, where I_c is an indicator variable that is 0 if this observation is for country c, and 1 otherwise.

colunmns (2) and (3). US R&D is estimated with a foreign elasticity of between 23 and 35%, higher than the domestic R&D elasticity, which comes in between 15 and 18%. Does this mean that for the average country, US R&D has a stronger effect on its productivity than domestic R&D? Not necessarily, since this specification may be omitting important international R&D spillovers. In some countries, especially in Europe, the R&D from other major technology producers may well be more important than US R&D.

Some evidence for that can be seen by the drop for the US R&D effect, from 35% to 17%, when Japanese and German R&D are included in column 4. Adding also the next three largest countries in terms of R&D, France, the UK, and Canada, one sees that the international R&D spillovers are in fact relatively diffuse: for all six countries, we estimate significant spillover effects in the average sample country (columns 5-6). We will refer to these six countries, US, Japan, Germany, France, UK, and Canada, as the G6 countries. At the same time, international spillovers from these countries vary substantially: the preferred System GMM estimates (column 5) range from 4.2% for the UK to 15.2% for Japan. [26] This is in line with earlier results pointing to heterogeneous source country effects (Keller 2000). Moreover, in contrast to column 2 where only the US is considered a source of foreign technology, when R&D for all G6 countries is included, the elasticity of domestic R&D is estimated to be higher than that from any foreign source. This highlights the importance of domestic technology creation.

Another important question is how international R&D spillovers have changed over time—specifically, is there evidence for more technology diffusion in recent years? The results in columns 7 to 10 in Table 11 shed new light on that by dividing the 30 years of our sample into

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[26] In the IV GMM specification, we include l_{t-2}, l_{t-3}, k_{t-2}, and r_{t-2} as instruments, as before, while the foreign R&D variables are treated as exogenous. The Sargan overidentification test provides evidence that the instruments, as a set, are exogenous (*p*-value of 0.313). Moreover, there is some evidence for first-order serial correlation in the differenced residuals (p-value of LM test of 0.210), whereas there is none for second-order serial correlation (*p*-value of 0.989). The IV GMM technique thus seems to work well.

subperiods. First, we present the results for, roughly, the 1980s and 1990s. This is useful because our dataset is more complete for this period. We find that for all G6 countries with the exception of the UK, the foreign R&D elasticity has increased over time. The effect is substantial in some cases: for the US the R&D elasticity almost tripled, and for Japan it increased around six-fold.[27]

Overall, this suggests that even though the effect of R&D in the domestic economy has remained the same, international technology diffusion has become significantly stronger over the last three decades.[28]

3. Total factor productivity and labor productivity as dependent variables

By estimating a single elasticity each for capital and labor, our analysis so far has implicitly assumed that factor elasticities are identical across countries, years, and industries. We now relax that assumption by presenting results based on total factor productivity, computed using data on the cost share for labor together with imposing constant returns to scale (using equation 3). We will also present results for labor productivity in this section.

These results are in Table 12. When the dependent variable is TFP, the domestic R&D elasticity is estimated to be lower than with value added as dependent variable. This may in part be due to the fact that industries with large capital stocks tend to have high capital shares as well.[29] By assuming that the capital elasticity is constant, the value added regression does not account for that, and the high value added is attributed in part to R&D (which is positively correlated with capital). Furthermore, in the value added regressions, we did not impose CRS assumption, in which case R&D might be capturing any non-CRS effects.

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[27] We find similar results also when we divide the entire sample period of 1973 to 2002 into two subperiods with 15 years each.
[28] Our findings extend the results of Keller (2002) in this respect.
[29] The correlation of the cost share of physical capital with physical capital is 11%.

The size of the international R&D spillover coefficients for Germany and the UK is lower than in the value added regressions (the UK's is not significant anymore), but the coefficients for the US, Japan, France, and Canada are comparable (see Table 12, columns 3-4). The highest foreign spillover elasticities are estimated for R&D from Japan, the US, and Canada.[30] This is exactly what we found when factor elasticities were restricted across sectors, countries, and time; see the right-most column in Table 12 which reports the baseline IV System GMM estimates of Table 11, (5) with inputs on the right hand side for reference. One difference is that for the TFP specification we are unable to find suitable instruments, as the LM test for second-order serial correlation indicates (*p*-value of 3.7%).[31] In the value-added specification with inputs on the right hand side, this is not the case; it is one reason of why we prefer it to the TFP specification in this context.

Finally, we also report results with labor productivity as dependent variable, shown in column 5 of Table 12. Relative to the value-added results (column 6), the domestic R&D is estimated to be somewhat lower (12.0% versus 15.7%), but otherwise the estimates are quite similar. Overall, these results are broadly consistent with those based on value added as dependent variable, and they suggest that the restrictions imposed by common factor shares are not what is driving our results.

4. Spillover heterogeneity both by source and destination

[30] The strong result on Canada may be in part explained by the fact that the US contributes to Canadian R&D in a substantial way through R&D conducted in US-owned multinationals located in Canada. More generally, it is important to keep in mind that the OECD's R&D statistics are compiled on the basis of geography, not on the basis of ownership.

[31] We estimate the model with two period lagged R&D, r_{t-2}, as instrument for the endogenous r_t, so the equation is just identified. If we include further lags of R&D as additional instruments, the Sargan test rejects the overidentification restrictions, another sign that the instruments are not valid.

The average R&D spillovers from the major technology producing countries is only part of the full picture of international technology diffusion, since there is evidence that international R&D spillovers vary substantially across bilateral relations (Keller 2002). There are two dimensions that are of particular interest to us here. First, we consider the US as the technology source and ask how the strength of US technology spillovers varies across countries. Second, we examine the degree to which Canada, as the technology recipient country, benefits from foreign technology spillovers originating in different countries.

The average US spillover in our sample is around 23%, as we have shown in Table 11 (specification 3, using the Olley-Pakes/Wooldridge one-step GMM method). Allowing for heterogeneity across countries, using the following equation,

$$y_{cit} = \beta_0 + \beta_k k_{cit} + \beta_l l_{cit} + \gamma\, r_{cit} + \sum_{c' \in 16, c' \neq US} \beta_{c'}\, r_{USit} + \sum_{c'' \in G5, c'' \neq US} \beta_{c''}\, r_{c''it} + \varepsilon_{cit}$$

one finds that US R&D has effects ranging from a low of 18.6% in France to a high of more than twice that, 46.5%, in Ireland (Table 13a, column 2). Controlling for R&D spillovers from other G6 countries, the spillover effects from US R&D vary widely. They range from essentially zero to the maximum of 27.7% in Ireland (column 3). The strong effect in Ireland may in part reflect technology transmission related to US foreign direct investment (Dell Computers, etc.).[32] In Canada, we estimate an elasticity of 16.5% (second only to Ireland). In contrast, the average for the other nine countries in which US R&D has a positive effect is only 5.7%. Moreover, in five countries—Australia, France, Italy, Korea, and the Netherlands—, US R&D has no significant positive effect at all once we control for R&D spillovers from other G6 countries. Overall, the benefits for Canada from US technology creation are considerably above those that other countries are experiencing.

[32] At the same time, Ireland is a somewhat special case in this analysis, because Irish data becomes only available in the mid-1990s, at the height of the recent technology boom (see Table 1 on data availability).

If US R&D generates heterogeneous spillover effects, this may well be the case for other G6 country R&D as well. While generally estimating more spillover parameters makes both the model less parsimonious and yields less precise estimates, we can focus on a given country and ask whether it benefits from G6 R&D more or less than other countries in the sample. In the case of Canada, Table 13b summarizes the results of estimation of the following equation:

$$(6) \qquad y_{cit} = \beta_0 + \beta_k k_{cit} + \beta_l l_{cit} + \gamma\, r_{cit} + \gamma_{CAN} I(CAN)\, r_{cit} + \sum_{c' \in G6} \left(\beta_{c'} + \beta_{c',CAN} I(CAN)\right) r_{c'it} + \varepsilon_{cit}\,,$$

where *I(CAN)* is an indicator function that equals one if *c* = Canada, and zero otherwise. The set G6 includes the countries Canada, France, Germany, Japan, the UK, and the US. In equation (6), ($\gamma + \gamma_{CAN}$) measures the domestic R&D elasticity in Canada, while γ estimates the domestic R&D elasticity in the average sample country. Similarly, the spillover effect from US R&D in Canada is given by ($\beta_{US} + \beta_{US,CAN}$), whereas the average spillover effect from US R&D is just $ß_{US}$, and analogously for the spillovers from the other G6 countries.

If one abstracts from international R&D spillovers, Canada seems to benefit from domestic R&D somewhat less than the average country in the sample (column 1). This would be somewhat puzzling in the light of earlier results showing that Canadian R&D generates strong R&D spillovers in other countries. Indeed, the result is reversed once we control for G6 R&D spillovers: as column 2 in Table 13b shows, while in the average sample country the domestic R&D elasticity is about 14%, in Canada it is about 36%. Hence Canada's domestic technology creation appears to be highly productive.[33]

Turning to the foreign spillover effects, we see that Canada benefits from some foreign countries more, and from others less than the average country in the sample. Specifically,

[33] Again, we note that part of the R&D conducted in Canada occurs in affiliates of foreign-owned companies. It is not obvious that foreign R&D conducted in Canada has the same implications for economic welfare as Canadian-owned R&D.

Canada gains two to three times as much from US and German R&D than countries do on average. In contrast, Canada benefits from Japan and France are only about half or less of those going to the average country. Moreover, Canada does not benefit from R&D spillovers coming from the UK while other countries do. These results are obtained using either the System GMM or the one-step Olley-Pakes methods (columns 2 and 3, respectively).

While explaining these patterns is beyond the purpose of this paper, we think that doing so will be crucial to understanding what the major driving forces in international technology diffusion are.

5. Technology diffusion and imports

International trade has long been considered as a channel of technology diffusion. The most influential recent test, based on open economy versions of Romer's (1990) and Aghion and Howitt's (1992) endogenous growth models, asks whether a country's productivity is higher, all else equal, if it imports predominantly from high-R&D countries.[34] This would be consistent with technology being embodied in the imported goods, as well as with imports-related learning effects. Empirically authors tend to find that the composition of imports of countries has *not* a major effect on productivity along these lines.[35] In general, this could mean that imports are indeed not a major channel of technology diffusion. It could also merely imply that an ancillary assumption of the empirical approach is rejected. Specifically, a maintained assumption in the typical approach is that foreign R&D elasticities are the same in all countries.[36] This hypothesis

[34] Coe and Helpman (1995) were the first to test this prediction.
[35] See Keller (2004) for additional discussion.
[36] To see this, consider the foreign R&D stock defined as $S_c = \sum_{c' \in C} m_{cc'} S_{c'}$, where $S_{c'}$ is the R&D stock of country c', and $m_{cc'}$ is the share of imports coming from foreign country c' in the total imports of country c. For simplicity, suppose that there are only two foreign countries, 1 and 2, and that half of the countries import only from country 1,

is easily rejected in our sample; recall that the size of average R&D spillovers varies by a factor of three or more among countries such as Japan and the UK (Table 11). Moreover, spillover patterns may not be captured too well by linear import shares. As we have seen above, US R&D has no significant effect in about one third of the sample countries, although they import on average roughly the same from the US as the other countries in the sample.[37]

Therefore we opt for a more flexible approach, the results of which are presented in Table 14. For a given industry and year, we compute the share of country c's imports from the US ($m_{c,USit} = M_{c,USit} / \sum_{c'} M_{c,c'it}$), and interact that variable with US R&D to estimate

$$(7) \qquad y_{cit} = \beta_0 + \beta_k k_{cit} + \beta_l l_{cit} + \gamma\, r_{cit} + \sum_{c' \in G6} \beta_{c'}\, r_{c'it} + \chi_{US}\, m_{c,USit}\, r_{USit} + \varepsilon_{cit},$$

where χ_{US} is the new parameter of interest. If $\chi_{US} > 0$, industries that import relatively much from the US benefit from imports-related R&D spillovers, in addition to any other US R&D effect picked up by $ß_{US}$. Because the degree to which any industry imports from the US is endogenous and likely affected by how high US R&D spending in this industry is, we use the System GMM estimation technique that deals with this appropriately.[38] In specification (1) of Table 14, χ_{US} is not significantly different from zero at standard levels. Since we have primarily considered R&D spillovers from the G6 countries, we focus the analysis to imports from these six countries as well. Hence we define import shares as a fraction of total imports from these six countries, $m^{G6}_{c,c'it} = M_{c,c'it} / \sum_{c' \in G6} M_{c,c'it}$, and include both its interaction with US R&D as well as the import share itself:

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while the other half of countries imports only from country 2. If only a single foreign R&D parameter is estimated, as is typically done, this means that R&D spillovers from country 1 are assumed to be exactly as strong as R&D spillovers from country 2.

[37] Australia, France, Italy, Korea, and the Netherlands do not significantly benefit from US R&D once other G5 technology sources are controlled for (Table 13a, (3)). These five countries import on average 20% from the US, while the other eleven countries import on average 21% from the US (Table 6).

[38] The US imports-R&D interaction is instrumented by its value two years lagged. Diagnostic tests at the bottom of column 1 provide evidence that this IV strategy is valid. The foreign R&D variables are treated as exogenous.

(7') $$y_{cit} = \beta_0 + \beta_k k_{cit} + \beta_l l_{cit} + \gamma\, r_{cit} + \sum_{c' \in G6} \beta_{c'}\, r_{c'it} + \chi_{US}^{G6}\, m_{c,USit}^{G6}\, r_{USit} + \sum_{c',c'' \in G5; c' \neq c'' \neq US} \nu_{c''}^{G6} m_{c',c''}^{G6}\, r_{c''it} + \varepsilon_{cit}.$$

Specification (2) in Table 14 indicates that χ_{US}^{G6} is estimated at 0.221, while the direct US spillover effect falls essentially to zero ($ß_{US}$ = 0.004). This suggests that spillovers from the US are strongly related to imports. The value of 0.221 implies a US spillover elasticity of 5.7%, evaluated at the mean import share (of 25.6%). This is lower than the value of 8.7% that we found for the direct US R&D without allowing for imports-related spillovers. The difference is, however, that now the US spillovers that an industry receives are a function of its import share. That ranges from 0 to 98.97 percent in our sample, which means that the US R&D spillover elasticity ranges from 0 to 21.9%, a range that includes the earlier spillover estimate of 8.7% when we abstracted from imports-related spillovers.[39]

The result that US R&D spillovers are strongly related to imports from the US does not change as we extend equation (7') to include imports effects for Japan and Germany, as well as import effects for France, the UK, and Canada (specifications (3) and (4) in Table 14, respectively). As is the case for the US, spillovers from UK R&D appear to be also primarily related to imports from the UK; both the System GMM and the Olley-Pakes/Wooldridge GMM results, columns 4 and 5, find insignificant R&D but significant imports-R&D interactions effects for the UK. The opposite is true for Germany and Japan, where the direct R&D effect is positive, while there is no evidence for imports-related R&D spillovers. For the remaining two countries, Canada and France, we find both imports-related and other R&D spillover effects, with the evidence for spillovers associated with imports from Canada being stronger.

[39] There is a negative correlation between imports from the US and value added (ν_{US}^{G6} is equal to -2.102). This does not necessarily mean that a higher import share from the US is associated with lower productivity—this depends on the size of US R&D in this particular industry. The elasticity of productivity with respect to the import share at the average US R&D level is -0.21, while at the 75th percentile it is 0.12.

It is interesting to see what the relative economic importance of spillovers related to imports, versus not related to imports is. Canada's direct R&D elasticity estimate is 0.129 in the System GMM specification, and the imports-R&D interaction effect is 0.193. In this sample, on average about 4.9% of the G6 imports come from Canada, so that the average imports-related R&D elasticity is slightly less than 1 percent (0.193 times 0.049). At the 95th percentile, Canada's share in G6 imports is 27%, leading to an imports-related R&D elasticity of around 5 percent. What does this mean for the relative importance of imports-related R&D spillovers from Canada vis-à-vis its total spillover? Evaluated at the average import-share of 4.9%, the fraction of spillovers from Canada related to imports is about 7%.[40] For countries with higher import shares from Canada, such as the US, the value at the 95th percentile of imports may be more relevant, and it is about 0.29.

The case of France is different, mainly because the countries in the sample import more from France than from Canada; on average, France accounts for 13.9% of all imports from G6 countries in this sample. On average, imports-related R&D spillovers account for a fraction of 0.16 in the total spillovers from France, and this value goes to 0.33 and higher for countries that import a lot from France.[41] In sum, it appears that even for bilateral relations where imports are a conduit of international R&D spillovers, imports may typically account for 10 or perhaps 20% of the total spillover effect.

In the following section, we therefore also consider FDI as a diffusion mechanism.

6. Foreign direct investment and imports as diffusion mechanisms

In this section, we estimate the relative importance of FDI- and imports-related R&D spillovers at the industry level in a broad sample covering most of the world's R&D investments.

[40] This is calculated as (0.193*0.049)/(0.129+0.193*0.049), where 0.129 = $ß_{CAN}$ in Table 14, column 4.

[41] At the 95th percentile of $m^{G6}_{c,FRAit}$, about 37% of French spillovers are associated with imports from France.

This analysis focuses on the US as technology source, because the US is the only country for which we have been able to obtain a time series on bilateral FDI at the industry level. This information is available for the years 1983-2002 and eight FDI host countries (see Table 7 for details on the FDI data). The results of this section are summarized in Table 15.

In column 1 we show again the baseline results with international R&D spillovers from the G6 countries (from Table 11, (5)). When the sample is limited to the set of observations for which there is US FDI data (column 2), the domestic R&D, capital, and labor elasticities are quite similar to the larger sample. There are some differences in terms of the foreign spillover estimates, however, in that the effects from Japanese and Canadian R&D are much lower than in the larger sample. With a focus on the relative contribution of US imports and FDI to the international diffusion of technology, changes in the relative importance of these countries' R&D is of second-order importance. More important for present purposes, the relatively high US spillover estimate of 0.476 for the FDI sample (column 2) indicates that US R&D is here important.

We estimate

$$(8) \qquad y_{cit} = \beta_0 + \beta_k k_{cit} + \beta_l l_{cit} + \gamma\, r_{cit} + \sum_{c' \in G6} \beta_{c'}\, r_{c'it} + \nu_{US} n_{c,USit}\, r_{USit} + \phi_{US} e_{c,USit} r_{USit} + \varepsilon_{cit},$$

where the imports variable $n_{c,USit}$ as imports of country c from the US, relative to the importing industry's value added, Y: $n_{c,USit} = M_{c,USit} / Y_{cit}$. The FDI variable $e_{c,USit}$ is defined as the share of all workers that are employed in US-owned affiliates, $e_{c,USit} = L^{US}_{cit} / L_{cit}$. Since both imports as well as inward FDI from the US may be endogenous, we use the System GMM IV estimator.[42]

[42] For the estimations in column 3 and 4, in addition to l_{t-2}, l_{t-3}, k_{t-2}, and r_{t-2}, we use the one-period lagged FDI- and imports-R&D interactions as instruments, not the two-period lagged values. This avoids losing additional observations due to lagging, and the one-period lagged instruments are also stronger. Our diagnostic tests find these instruments to be valid, as there is no strong evidence for negative first-order serial correlation (*p*-value of 0.119), and the Sargan test has a *p*-value of 0.456.

The imports-R&D interaction is estimated with a negative, and the FDI-R&D interaction with a positive coefficient, but both point estimates are close to zero (column 3).

This changes as we include the imports and FDI variables also linearly (column 4). Now the coefficient on the imports-R&D interaction is estimated at 2.9% while the FDI-R&D estimate is equal to 8.9%. To understand what these estimates mean economically, we need information on the magnitude of the imports and FDI variables. For the US, the average imports to value added ratio is 0.48, while the average share of employment of US affiliates in foreign countries' employment is 0.20. Thus, the average imports-related US spillover is estimated at 1.4%, while the average FDI-related effect is 1.8%. This suggests that FDI-related spillovers are relatively more important than imports-related spillovers in this sample.

These estimates of FDI- and imports-related US R&D spillovers are plausible also in the light of the direct US R&D spillover estimate, which is now 44.7%, whereas without the FDI- and imports-related R&D interactions, the estimate was 47.6% (column 2 and 4 of Table 15). The difference between the estimates is about three percentage points, which is close to the sum of the average FDI- and imports-related R&D spillovers (1.4% + 1.8% = 3.2%). It is tempting to take this also as evidence that most international spillovers are related neither to imports nor to FDI,[43] but this may not be the case because the direct US R&D elasticity appears to be exceptionally large in the sample for which we have FDI data. Further analysis may have to await the availability of detailed FDI data for more countries.

We now turn to an analysis of rates of return to R&D in this sample.

7. Domestic and international rates of return to R&D investments

[43] The relative importance of FDI and imports together may be gauged as 0.032/(0.032+0.447) = 6.7%, where 0.032 is the combined effect from FDI- and imports related spillovers, and 0.447 is the non-FDI, non-imports elasticity.

The results in this paper are derived under the functional form of constant elasticity across country-industry. Hence, the domestic (denoted by subscript D) rate of returns to R&D for country c, ρ_c^D, is obtained using the following formula $\rho_c^D = \gamma \frac{Y_c}{R_c} \equiv \frac{\partial y_{cit}}{\partial r_{cit}} \frac{Y_c}{R_c}$, where the lower case letters are the log forms of the upper case ones. The results of this calculation based on the γ value of Specification (5) in Table 11 are given in Table 16.

As discussed in Griliches (1982), loosely speaking this is social excess rate of return to investment in R&D. It is a social rate of return because it is based in output in constant prices rather than profit calculations. It is excess because the conventional inputs to labor and capital already include most of the R&D expenditures once at "normal" factor prices.[44] These returns are very high for all countries, ranging from minimum of 10% for the U.S. to maximum of 70% from Spain. Even though one might hesitate to take these numbers literally, as they are derived under the assumption of constant elasticity of output with respect to R&D capital for all countries and industries, they provide a good indication of the relative strength of domestic R&D to productivity growth.

The rate of return siphoned to foreign countries (denoted by subscript F, is obtained by $\rho_c^F = \beta_c \frac{\sum_{c'\in 16, c'\neq c} Y_{c'}}{R_c} \equiv \frac{\sum_{c'\in 16, c'\neq c} \partial y_{c'it}}{\partial r_{cit}} \frac{\sum_{c'\in 16, c'\neq c} Y_{c'}}{R_c}$. However, in our calculation, instead of using own country's R&D, R_c, in the denominator, we have used the same 16 foreign countries' R&D, $R_{c'}$ (as is the case in value added). The results are presented in Table 17.

It is clear that the excess return from R&D expenditure occurs more in domestic economy than it siphons outside. For example, in the case of U.S., every single dollar spent on R&D expenditure generates 10 cents extra return in the U.S. and 9 cents to foreign countries. This is true for all countries; especially for the UK the rate of return of its R&D expenditure captured by

[44] See Schankerman (1981) for discussion why it cannot be said exactly excess return.

the domestic economy is four times higher than that by foreign countries. Among these G-6 countries, the country with highest rate of returns to R&D is Canada, in terms of both what it captures from its own R&D (27%), and what it benefits from others' R&D (12%).

Despite this fact that domestic return dominates foreign return, foreign spillover is also substantial. In case of U.S., the average annual spillover of 171 billion PPP dollars to other OECD countries is slightly bigger than the GDP of Sweden and slightly smaller than the GDP of Belgium. Japan has the highest share of spillover supplied to foreign country in its GDP at 3.5 percent, a rate slightly higher 2.8 percent for the U.S.

V. Summary and Discussion

This paper has described the evolution of the world's technology frontier during the years 1973 to 2002. We have shown that R&D investments are a central determinant of productivity differences across industries and countries. Moreover, international technology spillovers contribute heavily to cross-country differences as well, and they have become stronger over time. International technology spillovers are shown to vary according the particular circumstances in each country and in each industry. We find major imports-related effects for technology originating from the US and the UK, but much less diffusion through imports from Japan and Germany. Next, we need to know whether this difference is driven by technology or industry differences, or country characteristics. The impact of FDI on technology diffusion, exceeding that of imports in to our analysis, indicates that much may be learned from future research exploiting general patterns of FDI by countries other than the United States.

Identifying this heterogeneity, and getting a grasp on its sources will go a long way to understanding the empirical microfoundations of international technology diffusion. There are by now a number of attractive models of international technology diffusion—see Keller (2004)--, and once these microfoundations are added, we expect that it should be possible to explain income differences across countries much better than possible to date.

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Table 1: Data availability

Country	Name	Number of Observation: Value added	Labor	Capital	R&D
1	Australia (AUS)	636	660	600	660
2	Belgium (BEL)	636	660	660	352
3	Canada (CAN)	660	660	660	660
4	Denmark (DNK)	660	640	630	660
5	Finland (FIN)	656	660	660	660
6	France (FRA)	630	651	660	660
7	Great Britain (UK)	654	636	660	660
8	Germany (GER)	660	658	660	652
9	Ireland (IRL)	504	540	165	528
10	Italy (ITA)	654	660	660	654
11	Japan (JPN)	654	660	660	660
12	S. Korea (KOR)	660	660	660	176
13	Netherlands (NLD)	636	654	660	660
14	Norway (NOR)	654	660	660	641
15	Spain (SPN)	654	550	594	660
16	Sweden (SWE)	648	660	660	648
17	USA	630	660	660	636

Industry (International Standard Industrial Classification-ISIC 3)		Value added	Labor	Capital	R&D	Industry Description
1	15-16	504	505	491	468	1. FOOD PRODUCTS, BEVERAGES AND TOBACCO
2	17-19	504	505	491	468	2. TEXTILE, TEXT. PRODUCTS, LEATHER AND FOOTWEAR
3	20	498	499	491	468	3. WOOD AND PRODUCTS OF WOOD AND CORK
4	21-22	504	505	491	468	4. PULP, PAPER, PAP. PRODUCTS, PRINTING & PUBLISHING
5	23	504	499	480	468	5. COKE, REFINED PETROLEUM PRODUCTS & NUCLEAR FUEL
6	24ex2423	504	499	491	468	6. CHEMICALS EXCLUDING PHARMACEUTICALS
7	2423	480	494	491	468	7. PHARMACEUTICALS
8	25	498	499	491	468	8. RUBBER AND PLASTICS PRODUCTS
9	26	504	505	491	468	9. OTHER NON-METALLIC MINERAL PRODUCTS
10	271+2731	498	493	474	462	10. IRON AND STEEL
11	272+2732	492	492	474	468	11. NON-FERROUS METALS
12	28	504	499	485	468	12. FABRICATED METAL PRODUCTS
13	29	492	499	491	462	13. MACHINERY AND EQUIPMENT
14	30	492	499	485	468	14. OFFICE, ACCOUNTING AND COMPUTING MACHINERY
15	31	470	499	485	456	15. ELECTRICAL MACHINERY AND APPARATUS
16	32	486	499	485	462	16. RADIO, TV AND COMMUNICATION EQUIPMENT
17	33	498	493	485	468	17. MEDICAL, PRECISION AND OPTICAL INSTRUMENTS
18	34	498	499	474	462	18. MOTOR VEHICLES, TRAILERS AND SEMI-TRAILERS
19	351	492	499	474	462	19. BUILDING AND REPAIRING OF SHIPS AND BOATS
20	353	480	469	414	455	20. AIRCRAFT AND SPACECRAFT
21	352+359	504	486	444	468	21. RAILROAD EQUIPMENT
22	36-37	480	493	491	454	22. OTHER MANUFACTURING AND RECYCLING

Table 2: R&D Intensities by Country & Industry (R&D expenditures over value added; in %), 1973-2002

Country / Industry	AUS	BEL	CAN	DNK	FIN	FRA	UK	GER	IRL	ITA	JPN	KOR	NLD	NOR	SPN	SWE	USA	Average
1	1.0	1.2	0.5	1.4	1.7	0.8	1.2	0.6	0.9	0.2	2.2	1.2	1.9	1.3	0.3	1.8	1.3	1.1
2	0.4	1.9	0.8	0.4	1.0	0.7	0.5	1.0	1.7	0.0	1.5	1.0	0.7	1.2	0.2	1.1	0.5	0.9
3	0.4	0.8	0.4	0.4	0.9	0.3	0.1	0.9	1.2	0.1	1.8	0.3	0.3	0.9	0.1	0.4	0.6	0.6
4	0.6	1.2	0.8	0.2	1.3	0.3	0.5	0.3	0.2	0.1	0.8	0.7	0.2	1.1	0.2	1.8	1.1	0.7
5	1.2	3.2	10.9	1.6	4.4	4.1	9.4	2.2	0.5	1.6	3.1	1.8	6.0	3.8	1.0	2.4	8.2	3.8
6	4.5	10.4	2.2	5.6	6.4	7.6	6.3	11.3	0.9	3.3	13.1	5.3	9.3	9.6	1.8	5.6	8.1	6.5
7	4.2	25.5	13.4	26.4	25.0	22.6	36.2	20.1	5.9	10.2	17.0	3.8	24.1	7.6	6.3	36.3	21.5	18.0
8	1.0	3.5	0.8	1.6	3.4	3.9	0.9	2.3	2.2	1.4	5.3	2.7	1.7	2.4	1.2	3.0	3.4	2.4
9	1.1	2.3	0.5	1.4	2.1	2.0	1.3	1.5	1.6	0.2	4.3	1.6	0.6	1.5	0.4	1.8	2.4	1.6
10	3.3	2.4	0.7	2.7	2.0	2.9	1.6	1.8	2.2	1.0	3.6	1.2	13.7	4.7	0.8	4.0	1.4	2.9
11	1.8	4.2	3.8	0.1	11.1	4.9	2.0	2.1	1.2	0.9	5.5	1.7	7.6	4.7	0.7	3.5	2.2	3.4
12	0.7	2.1	0.8	0.9	2.0	0.7	0.8	1.4	2.0	0.3	1.8	1.1	0.8	1.7	0.4	2.4	1.4	1.3
13	3.2	5.7	1.8	4.7	5.4	3.4	3.9	4.8	2.2	1.1	6.6	5.7	3.8	6.7	1.5	8.6	4.1	4.3
14	13.7	9.7	34.2	18.6	17.9	14.4	16.4	13.4	2.1	21.0	24.8	11.5	72.3	30.5	5.7	15.6	40.0	21.3
15	3.6	6.1	3.6	4.5	9.5	5.4	8.9	6.5	3.8	2.3	15.5	9.2	47.2	6.6	1.9	11.1	7.2	9.0
16	19.7	38.7	37.4	16.2	23.0	34.9	23.7	38.9	24.6	17.2	14.9	21.6	11.3	39.3	9.5	42.0	31.2	26.1
17	11.6	13.5	3.1	12.9	14.3	17.4	6.0	5.6	2.3	1.9	15.6	6.8	5.6	13.0	2.8	13.3	13.6	9.4
18	5.3	2.3	1.0	4.9	2.7	11.0	7.6	10.8	5.1	8.8	33.1	15.1	7.9	6.0	2.6	16.2	14.7	9.1
19	3.8	1.7	0.0	4.4	2.2	1.1	2.6	2.3	2.9	2.1	2.0	2.4	1.0	2.1	3.0	3.2	2.3	2.3
20	1.4	12.8	20.3	0.1	2.5	64.0	30.7	55.6		22.0	22.5	32.3	15.4	4.2	23.6	31.3	42.6	23.8
21	4.2	15.5	1.8	8.5	9.2	4.7	5.9	7.2	0.9	3.1	7.1	4.6	1.8	2.1	3.0	6.9	11.3	5.8
22	0.7	1.9	0.8	4.5	1.0	0.8	1.3	0.2	0.5	0.2	1.6	2.2	0.5	0.9	0.4	0.8	1.5	1.2
Average	**4.0**	**7.6**	**6.3**	**5.5**	**6.8**	**9.5**	**7.6**	**8.7**	**3.1**	**4.5**	**9.3**	**6.1**	**10.6**	**6.9**	**3.1**	**9.7**	**10.0**	

Industry:
1 FOOD PRODUCTS, BEVERAGES AND TOBACCO
2 TEXTILES, TEXTILE PRODUCTS, LEATHER AND FOOTWEAR
3 WOOD AND PRODUCTS OF WOOD AND CORK
4 PULP, PAPER, PAPER PRODUCTS, PRINTING AND PUBLISHING
5 COKE, REFINED PETROLEUM PRODUCTS AND NUCLEAR FUEL
6 CHEMICALS EXCLUDING PHARMACEUTICALS
7 PHARMACEUTICALS
8 RUBBER AND PLASTICS PRODUCTS
9 OTHER NON-METALLIC MINERAL PRODUCTS
10 IRON AND STEEL
11 NON-FERROUS METALS
12 FABRICATED METAL PRODUCTS
13 MACHINERY AND EQUIPMENT
14 OFFICE, ACCOUNTING AND COMPUTING MACHINERY
15 ELECTRICAL MACHINERY AND APPARATUS
16 RADIO, TELEVISION AND COMMUNICATION EQUIPMENT
17 MEDICAL, PRECISION AND OPTICAL INSTRUMENTS
18 MOTOR VEHICLES, TRAILERS AND SEMI-TRAILERS
19 BUILDING AND REPAIRING OF SHIPS AND BOATS
20 AIRCRAFT AND SPACECRAFT
21 RAILROAD EQUIPMEN
22 OTHER MANUFACTURING AND RECYCLING

Table 3: Employment by Country & Industry (Total number of workers engaged; in 1000), 1973-2002

Country Industry	AUS	BEL	CAN	DNK	FIN	FRA	UK	GER	IRL	ITA	JPN	KOR	NLD	NOR	SPN	SWE	USA	Average
1	180	106	259	92	56	617	610	1008	57	474	1512	290	171	55	412	75	1769	456
2	114	105	178	34	50	511	608	629	30	1196	1872	1034	58	15	422	29	1975	521
3	48	15	114	14	40	116	93	210	5	229	433	64	27	23	106	48	776	139
4	127	60	253	57	86	346	505	650	21	293	1046	188	149	51	172	118	2209	372
5	6	8	17	1	4	41	34	44	1	29	47	31	8	2	11	3	165	27
6	31	57	77	14	17	186	258	526	14	186	343	112	76	9	101	25	795	166
7	24	15	17	10	3	72	82	115	4	87	152	49	12	7	42	14	262	57
8	46	24	80	20	16	205	243	367	9	174	408	168	30	8	98	26	839	162
9	54	45	56	25	20	195	214	369	13	316	607	160	37	12	184	26	605	173
10	45	52	57	3	15	113	196	377	1	152	443	115	10	6	71	40	544	132
11	35	13	50	6	3	48	71	125	1	39	154	21	3	13	23	11	331	56
12	113	69	137	47	33	464	514	863	13	625	1138	199	107	20	246	87	1496	363
13	62	51	117	73	62	416	564	1361	14	560	1410	288	85	28	166	109	1936	429
14	9	1	15	2	3	65	54	91	12	25	249	34	8	2	12	7	304	52
15	39	38	56	19	18	305	234	614	11	246	771	139	15	12	87	34	905	209
16	26	26	40	12	18	219	207	235	8	119	998	318	84	7	36	37	686	181
17	15	7	46	14	6	129	163	371	12	108	301	57	16	5	33	21	945	132
18	75	60	132	8	8	341	326	789	5	260	300	200	27	5	176	69	891	216
19	14	2	19	14	16	41	93	59	1	41	155	85	29	35	42	14	197	50
20	14	6	36	1	3	86	168	69		35	29	5	11	3	11	13	696	74
21	18	4	11	1	4	27	23	51	5	37	48	15	5	3	19	6	100	22
22	74	41	109	34	22	233	214	350	11	310	1025	174	140	14	185	61	1054	238
Average	**53**	**37**	**85**	**23**	**23**	**217**	**249**	**422**	**12**	**252**	**611**	**170**	**50**	**15**	**121**	**40**	**886**	

Industry:
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3 WOOD AND PRODUCTS OF WOOD AND CORK
4 PULP, PAPER, PAPER PRODUCTS, PRINTING AND PUBLISHING
5 COKE, REFINED PETROLEUM PRODUCTS AND NUCLEAR FUEL
6 CHEMICALS EXCLUDING PHARMACEUTICALS
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9 OTHER NON-METALLIC MINERAL PRODUCTS
10 IRON AND STEEL
11 NON-FERROUS METALS
12 FABRICATED METAL PRODUCTS
13 MACHINERY AND EQUIPMENT
14 OFFICE, ACCOUNTING AND COMPUTING MACHINERY
15 ELECTRICAL MACHINERY AND APPARATUS
16 RADIO, TELEVISION AND COMMUNICATION EQUIPMENT
17 MEDICAL, PRECISION AND OPTICAL INSTRUMENTS
18 MOTOR VEHICLES, TRAILERS AND SEMI-TRAILERS
19 BUILDING AND REPAIRING OF SHIPS AND BOATS
20 AIRCRAFT AND SPACECRAFT
21 RAILROAD EQUIPMEN
22 OTHER MANUFACTURING AND RECYCLING

Table 4: Capital Stock by Country & Industry (in millions US $ PPP 1995; depreciation rate 5%), 1973-2002

Country Industry	AUS	BEL	CAN	DNK	FIN	FRA	UK	GER	IRL	ITA	JPN	KOR	NLD	NOR	SPN	SWE	USA	Average
1	16594	12985	25896	7187	6021	86839	71686	90587	1866	51045	185117	17602	20110	8994	281099	13162	208600	65023
2	2968	7472	8518	1905	3742	49331	149243	55343	191	81862	296768	30862	4453	2521	48541	11032	67496	48367
3	4320	1493	15695	6026	3407	32114	5833	29192	127	24598	36093	3999	2218	1915	60364	8156	197478	25472
4	5446	4655	56782	6748	19295	42461	47327	64735	671	22516	181316	7971	10049	6136	12015	31031	301844	48294
5	2088	4321	9109	393	2027	119765	16579	157046		154219	76206	7119	11264	1335	467503	1294	82224	69531
6	4523	11830	30143	2140	2954	21799	28479	56146	1687	27394	132325	15961	16743	2736	9157	3800	182623	32379
7	27520	908	1724	1341	495	4139	6722	12792	888	67543	20557	1823	1400	276	4128	2129	29922	10842
8	4354	3916	5817	1717	885	15423	20566	23375	296	26622	101676	9879	4722	1038	69146	1988	43792	19718
9	4846	5293	11828	5057	3230	35631	97304	50441	283	38025	123337	9318	5976	2367	290051	4808	73137	44761
10	13097	15110	59115	337	1938	55118	299485	27978		35365	152557	21770	5080	1710	4707	5254	106343	50310
11	12189	1692	16181	10161	485	16744	3908	14811		6139	41326	2959	5924	2054	1091	871	42579	11195
12	4404	3041	10619	2861	1355	119318	31115	45543	185	64298	67331	8919	7958	1804	4329	3856	82341	27016
13	14653	2657	3795	4082	3139	21204	100915	100058	258	59904	88925	7744	5447	1345	7657	6071	84170	30119
14	347	26	379	46	33	1719	1700	3007	2629	1335	19015	2971	336	26	130	230	15988	2936
15	3151	5326	4742	719	1496	17969	13936	27430	385	14357	36627	7669	675	1626	2575	1234	24039	9645
16	410	3572	3522	467	891	5568	10144	22359	4018	7495	76619	38584	6057	272	1153	2350	110343	17284
17	548	388	1091	537	257	13657	5342	21036	470	4379	14495	871	1481	460	214	547	46015	6576
18	4584	52465	14760	201	478	50853	28172	86869		35869	128157	13409	3384	437	12202	8768	150550	36947
19	709	71	477	1612	3167	368	7046	2235		6513	37655	6441	1389	3243	597	5318	18415	5954
20		21865	2160		9134	12517	10799	3322		2433	30404	453	435	131	271	973	45681	10041
21		74	1983	13	782	1473	842	3833		3273	10154	121172	232	127	379	317	3415	9871
22	286	21026	3271	677	1331	18245	36243	65811	253	24192	12880	1843	3677	1062	5542	685	46877	14347
Average	**6352**	**8190**	**13073**	**2582**	**3025**	**33739**	**45154**	**43816**	**947**	**34517**	**84979**	**15425**	**5410**	**1892**	**58311**	**5176**	**89267**	

Industry:
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17 MEDICAL, PRECISION AND OPTICAL INSTRUMENTS
18 MOTOR VEHICLES, TRAILERS AND SEMI-TRAILERS
19 BUILDING AND REPAIRING OF SHIPS AND BOATS
20 AIRCRAFT AND SPACECRAFT
21 RAILROAD EQUIPMEN
22 OTHER MANUFACTURING AND RECYCLING

Table 5: R&D Capital Stock by Country & Industry, 1973-2002

Country Industry	AUS	BEL	CAN	DNK	FIN	FRA	UK	GER	IRL	ITA	JPN	KOR	NLD	NOR	SPN	SWE	USA	Average
1	409	240	476	198	167	1096	2087	954	158	226	5614	396	922	145	565	356	7444	1262
2	48	186	172	16	35	603	784	580	36	47	2166	231	61	16	90	47	1349	380
3	42	20	113	12	44	102	117	335	5	15	654	9	21	33	12	31	2191	221
4	158	158	765	20	350	285	570	359	15	35	2290	159	62	123	69	692	7285	788
5	29	125	657	3	46	2393	2930	707	1	2873	2456	339	1957	27	956	25	12509	1649
6	421	2404	1028	180	304	5138	4667	16772	77	1650	19293	2070	3169	279	484	473	37713	5654
7	395	1642	958	807	224	4933	7867	6262	182	2754	11124	570	1204	174	727	2056	34051	4466
8	134	193	140	59	86	1756	501	1659	32	662	5632	425	126	35	649	136	5297	1031
9	136	194	102	90	74	973	948	1148	28	104	4652	337	60	38	326	131	4111	791
10	347	281	185	11	78	851	763	1101	4	421	5941	528	202	95	128	295	2864	829
11	203	142	783	2	67	565	285	521	2	97	2769	123	85	232	37	80	3146	538
12	149	232	253	59	92	862	774	2122	33	442	2639	235	154	88	138	351	5695	842
13	447	636	474	536	532	2629	4528	14884	49	1324	15476	1282	618	285	406	1814	19443	3845
14	109	55	1092	47	51	1338	773	2393	154	475	21709	7246	2943	40	204	174	37251	4474
15	359	476	493	106	320	2170	4457	10418	61	1011	13536	660	3032	196	338	577	16067	3193
16	888	2984	6365	290	1201	10005	7222	17525	1150	4377	37832	58261	2144	497	992	4149	95387	14781
17	229	213	253	313	165	5004	1681	2743	68	305	5872	259	237	124	141	459	39287	3374
18	719	327	454	166	34	9379	4930	20788	23	4824	20511	6722	384	41	1002	2175	67340	8225
19	80	5	1	104	56	68	295	203	2	176	473	448	31	180	135	163	3237	333
20	40	164	3155	0	12	17188	13097	9333	4	2476	1454	413	230	10	540	903	148638	11627
21	53	77	107	20	37	254	127	364	4	245	514	54	9	12	84	94	2223	252
22	42	101	136	303	20	260	903	124	9	118	1741	135	131	17	54	31	2448	387
Average	**247**	**493**	**826**	**152**	**182**	**3084**	**2741**	**5059**	**95**	**1121**	**8379**	**3677**	**808**	**122**	**367**	**692**	**25226**	
% sample	0.5	0.9	1.5	0.3	0.3	5.8	5.1	9.5	0.2	2.1	15.7	6.9	1.5	0.2	0.7	1.3	47.4	
Median	**153**	**194**	**464**	**75**	**76**	**1217**	**925**	**1403**	**30**	**431**	**5133**	**405**	**216**	**91**	**265**	**323**	**7365**	
% sample	0.8	1.0	2.5	0.4	0.4	6.5	4.9	7.5	0.2	2.3	27.4	2.2	1.2	0.5	1.4	1.7	39.2	

Note: The industry names are as given in the above tables.

Table 6: US Share in Total Imports (average over the sample period; in %), 1973-2002

Country Industry	AUS	BEL	CAN	DNK	FIN	FRA	UK	GER	IRL	ITA	JPN	KOR	NLD	NOR	SPN	SWE	Average
1	25.5	3.5	65.5	7.5	6.5	5.8	8.2	6.2	9.7	3.6	45.4	53.0	10.8	7.9	18.1	7.9	17.8
2	16.3	3.0	55.3	2.0	2.5	3.4	11.4	2.6	4.4	7.1	15.0	16.2	2.1	2.2	10.6	3.4	9.8
3	36.1	7.3	89.8	5.1	8.0	4.7	13.3	9.5	7.5	24.1	40.4	47.7	4.3	2.2	21.1	6.4	20.5
4	32.5	4.3	88.4	4.1	6.4	7.2	15.6	9.6	6.6	13.5	50.8	47.1	8.4	3.9	11.7	6.6	19.8
5	66.2	2.3	81.0	1.2	3.9	6.8	7.7	3.1	1.2	16.7	45.7	36.3	5.8	7.2	19.6	2.6	19.2
6	39.2	11.2	81.1	4.7	7.5	11.5	19.1	11.3	15.5	6.9	49.8	29.8	13.7	7.1	11.8	8.9	20.6
7	22.9	14.6	60.4	4.8	5.8	19.9	19.9	15.9	12.2	16.1	34.3	21.0	11.4	5.7	18.4	8.1	18.2
8	25.2	5.2	78.7	2.9	4.3	5.2	19.4	6.0	8.0	4.9	42.3	29.0	5.2	3.6	5.4	4.1	15.6
9	15.5	3.6	72.3	1.6	4.2	3.6	17.7	5.6	6.7	4.2	31.5	22.3	2.8	2.7	4.2	4.4	12.7
10	8.5	1.4	59.6	0.4	0.5	0.8	8.7	1.0	1.8	2.1	11.8	4.9	0.9	1.6	2.3	1.0	6.7
11	23.7	11.9	75.6	1.8	3.8	9.3	21.0	7.5	8.5	8.5	30.3	14.7	4.7	2.7	7.1	5.3	14.8
12	28.6	4.5	81.7	2.4	4.4	5.4	24.0	7.4	9.1	8.0	54.8	32.1	4.6	4.2	16.2	6.4	18.4
13	34.9	8.9	77.8	6.9	7.1	11.1	27.8	14.4	15.2	10.3	48.2	26.8	11.0	10.9	10.2	9.7	20.7
14	51.5	17.3	80.7	19.8	30.3	34.6	33.3	30.4	49.5	16.8	73.2	48.5	25.2	30.1	23.2	28.9	37.1
15	27.9	5.9	82.1	5.3	6.0	12.3	27.9	15.6	18.5	9.1	60.4	24.6	12.0	8.2	9.1	8.1	20.8
16	21.3	7.5	67.9	8.9	14.8	19.3	27.2	16.4	25.6	11.3	63.7	45.4	13.4	13.4	12.7	14.8	24.0
17	41.9	15.4	76.1	16.0	18.1	28.7	38.0	28.5	38.3	20.1	63.9	31.6	27.1	20.7	19.0	21.8	31.6
18	14.3	2.8	87.7	1.0	3.1	2.3	19.2	3.9	0.7	1.0	27.4	19.5	1.6	4.3	3.4	3.7	12.3
19	23.0	10.6	72.7	3.0	6.5	9.5	24.8	13.7	4.9	12.7	38.5	4.6	14.8	2.7	19.5	5.0	16.7
20	75.7	51.3	79.8	72.1	60.3	61.7	54.5	31.7	74.0	52.5	88.7	83.5	58.3	73.6	62.8	64.3	65.3
21	16.8	2.3	61.8	1.9	2.9	2.4	13.1	5.7	7.4	3.6	42.5	13.1	8.0	6.4	7.5	5.7	12.6
22	25.9	15.3	70.7	4.9	6.7	10.2	22.8	11.1	15.4	9.9	38.0	29.2	7.1	4.9	8.2	9.1	18.1
Average	**30.6**	**9.6**	**74.8**	**8.1**	**9.7**	**12.5**	**21.6**	**11.7**	**15.5**	**12.0**	**45.3**	**30.9**	**11.5**	**10.3**	**14.6**	**10.7**	

Industry:
1 FOOD PRODUCTS, BEVERAGES AND TOBACCO
2 TEXTILES, TEXTILE PRODUCTS, LEATHER AND FOOTWEAR
3 WOOD AND PRODUCTS OF WOOD AND CORK
4 PULP, PAPER, PAPER PRODUCTS, PRINTING AND PUBLISHING
5 COKE, REFINED PETROLEUM PRODUCTS AND NUCLEAR FUEL
6 CHEMICALS EXCLUDING PHARMACEUTICALS
7 PHARMACEUTICALS
8 RUBBER AND PLASTICS PRODUCTS
9 OTHER NON-METALLIC MINERAL PRODUCTS
10 IRON AND STEEL
11 NON-FERROUS METALS
12 FABRICATED METAL PRODUCTS
13 MACHINERY AND EQUIPMENT
14 OFFICE, ACCOUNTING AND COMPUTING MACHINERY
15 ELECTRICAL MACHINERY AND APPARATUS
16 RADIO, TELEVISION AND COMMUNICATION EQUIPMENT
17 MEDICAL, PRECISION AND OPTICAL INSTRUMENTS
18 MOTOR VEHICLES, TRAILERS AND SEMI-TRAILERS
19 BUILDING AND REPAIRING OF SHIPS AND BOATS
20 AIRCRAFT AND SPACECRAFT
21 RAILROAD EQUIPMEN
22 OTHER MANUFACTURING AND RECYCLING

Table 7: Share of OECD countries' imports and FDI from the US
(median imports to value added, and foreign-employed to total employment; in %)

Industry		Imports/value added	Share FDI	Country	Imports/value added	Share FDI
1	Food	3.4	7.5	**Australia**	16.1	6.5
2	Textiles	4.0	2.1	**Canada**	69.3	36.2
3	Wood	9.2	1.9	**France**	3.2	4.5
4	Paper	4.5	3.3	**UK**	8.6	7.6
5	Petroleum			**Germany**	3.1	2.7
6	Chemicals	13.7	17.6	**Italy**	4.0	4.5
7	Drugs	12.5	17.9	**Japan**	3.0	0.4
8	Rubber, Plas.	5.4	4.9	**Netherlands**	11.8	7.3
9	Stone, Glass	2.2	3.2			
10	Iron, Steel	3.0	2.4			
11	Oth. Metals	25.6	2.8			
12	Metal Prod.	2.9	3.3			
13	Mach. & Eq.	17.2	13.4			
14	Computers	88.8	57.7			
15	El. Mach.	14.7	15.8			
16	Communic Eq	31.3	4.5			
17	Instruments	33.4	15.3			
18	Cars	6.9	16.5			
19	Ships	3.7	4.8			
20	Aircraft	94.9	2.8			
21	Railroad	20.3	7.8			
22	Other Man.	3.6	24.0			
Median		**9.2**	**4.9**		**6.3**	**5.5**
Corr(Imp, FDI)		**0.480**			**0.988**	

Table 8: OLS Results

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Labor	0.567	0.611	0.583	0.626	0.308
	(0.010)	(0.010)	(0.011)	(0.018)	(0.028)
Capital	0.427	0.391	0.396	0.375	0.75
	(0.010)	(0.009)	(0.010)	(0.013)	(0.014)
Time FE	no	yes	yes	yes	yes
Country FE	no	no	yes	yes	no
Industry FE	no	no	no	yes	no
Country x industry FE	no	no	no	no	yes
N	10,289	10,289	10,289	10,289	10,289
$\bar{R}^2$	0.875	0.891	0.902	0.917	0.965

Standard errors are in parentheses

Table 9: Instrumental Variables and Olley-Pakes Results

	(1) OLS	(2) IV System GMM	(3) OP	(4) OP/W GMM	(5) OLS	(6) IV System GMM	(7) OP	(8) OP/W GMM
Labor	0.567	0.6	0.528	0.511	0.626	0.676	0.548	0.557
	(0.010)	(0.006)	(0.046)	(0.010)	(0.018)	(0.012)	(0.054)	(0.018)
Capital	0.427	0.394	0.628	0.447	0.375	0.342	0.234	0.513
	(0.010)	(0.004)	(0.087)	(0.110)	(0.013)	(0.005)	(0.164)	(0.105)
Time FE	no	no	no	no	yes	yes	yes	yes
Country FE	no	no	no	no	yes	yes	yes	yes
Industry FE	no	no	no	no	yes	yes	yes	yes
N	10289	9309	9925	9954	10289	9309	9925	9954
$\bar{R}^2$	0.875				0.917			
Sargan Overid Prob>chi2		0.968				0.425		
AR(1) test Prob>z		0.282				0.371		
AR(2) test Prob>z		0.088				0.081		

Standard errors in parentheses

Table 10. Domestic R&D and Productivity

	(1) OLS	(2) OLS	(3) IV System GMM	(4) OP/W GMM
Labor	0.626	0.437	0.469	0.431
	(0.018)	(0.017)	(0.012)	(0.009)
Capital	0.375	0.299	0.291	0.446
	(0.013)	(0.009)	(0.006)	(0.048)
Domestic R&D		0.271	0.246	0.179
		(0.009)	(0.006)	(0.005)
Fixed effects #	yes	yes	yes	yes
N	10,289	9,444	8,487	9,099
AR(1) test Prob>z			0.948	
AR(2) test Prob> z			0.297	

Standard errors in parentheses
Country-, industry-, and fixed effects are included

Table 11: International R&D Spillovers

	(1) OLS	(2) IV System GMM	(3) OP/W GMM	(4) IV System GMM	(5) IV System GMM	(6) OP/W GMM	(7) IV System GMM 1980-1991	(8) IV System GMM 1992-2002
Labor	0.562	0.59	0.497	0.683	0.693	0.582	0.737	0.798
	(0.014)	(0.011)	(0.009)	(0.011)	(0.010)	(0.009)	(0.012)	(0.014)
Capital	0.232	0.224	0.404	0.161	0.147	0.244	0.114	0.128
	(0.008)	(0.005)	(0.045)	(0.005)	(0.005)	(0.041)	(0.005)	(0.008)
Domestic R&D	0.202	0.184	0.154	0.159	0.157	0.139	0.142	0.141
	(0.007)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)	(0.007)
US R&D	0.351	0.348	0.228	0.165	0.087	0.071	0.034	0.098
	(0.013)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.011)	(0.012)
JPN R&D				0.24	0.152	0.151	0.024	0.153
				(0.007)	(0.008)	(0.007)	(0.011)	(0.013)
GER R&D				0.131	0.095	0.078	0.079	0.086
				(0.007)	(0.007)	(0.006)	(0.010)	(0.012)
FRA R&D					0.108	0.074	0.115	0.171
					(0.008)	(0.006)	(0.010)	(0.012)
UK R&D					0.042	0.047	0.075	0.072
					(0.007)	(0.006)	(0.010)	(0.012)
CAN R&D					0.137	0.091	0.095	0.127
					(0.007)	(0.006)	(0.009)	(0.011)
N	9195	8364	8893	8239	8239	8767	3648	3709
Sargan Overid Prob>chi2		0.248		0.459	0.313		0.553	0.415
AR(1) test Prob>z		0.347		0.249	0.21		0.078	0.937
AR(2) test Prob>z		0.778		0.984	0.989		0.727	0.522

Standard errors in parentheses; all regressions include country-, industry- and time fixed effects

Table 12: Total Factor Productivity and Labor Productivity as Dependent Variable

	(1) OLS	(2) IV System GMM	(3) IV System GMM	(4) OP/W GMM	(5) IV System GMM	(6) IV System GMM
Labor						0.693
						(0.010)
Capital						0.147
						(0.005)
Capital/Labor					0.160	
					(0.005)	
Domestic R&D	0.187	0.160	0.050	0.122	0.120	0.157
	(0.010)	(0.006)	(0.006)	(0.006)	(0.004)	(0.005)
US R&D			0.126	0.104	0.096	0.087
			(0.013)	(0.011)	(0.008)	(0.008)
JPN R&D			0.151	0.198	0.151	0.152
			(0.012)	(0.010)	(0.008)	(0.008)
GER R&D			0.032	0.039	0.104	0.095
			(0.010)	(0.009)	(0.007)	(0.007)
FRA R&D			0.084	0.062	0.112	0.108
			(0.012)	(0.010)	(0.007)	(0.008)
UK R&D			-0.004	0.019	0.045	0.042
			(0.012)	(0.010)	(0.007)	(0.007)
CAN R&D			0.119	0.099	0.134	0.137
			(0.011)	(0.009)	(0.007)	(0.007)
N	9444	8844	8554	8785	8464	8239
Sargan Overid Prob>Chi2		n/a*	n/a*		n/a*	0.313
AR(1) test Prob>z		0.000	0.000		0.293	0.210
AR(2) test Prob>z		0.113	0.037		0.989	0.989

Standard errors in parentheses; all regressions include country- , industry- and time fixed effects
* equation is exactly idenfied

Table 13a: US R&D Spillovers

		(1) OP/W	(2) OP/W	(3) OP/W
Domestic R&D		0.154	0.165	0.148
		(0.004)	(0.005)	(0.004)
US R&D		0.228		
		(0.007)		
	in AUS		0.195	-0.016
			(0.013)	(0.013)
	in BEL		0.260	0.033
			(0.015)	(0.014)
	in CAN		0.255	0.165
			(0.011)	(0.012)
	in DNK		0.260	0.044
			(0.013)	(0.012)
	in FIN		0.235	0.045
			(0.012)	(0.011)
	in FRA		0.186	0.018
			(0.011)	(0.014)
	in UK		0.245	0.097
			(0.011)	(0.013)
	in GER		0.188	0.047
			(0.011)	(0.013)
	in IRL		0.465	0.277
			(0.022)	(0.021)
	in ITA		0.192	-0.016
			(0.011)	(0.011)
	in JPN		0.195	0.117
			(0.011)	(0.012)
	in KOR		0.232	0.006
			(0.021)	(0.019)
	in NLD		0.228	0.009
			(0.011)	(0.011)
	in NOR		0.266	0.054
			(0.012)	(0.012)
	in SPN		0.248	0.043
			(0.013)	(0.012)
	in SWE		0.244	0.032
			(0.011)	(0.011)
JPN R&D				0.163
				(0.008)
GER R&D				0.069
				(0.007)
FRA R&D				0.043
				(0.010)
UK R&D				0.068
				(0.009)
CAN R&D				0.133

			(0.007)
N	8893	8893	8767

Standard errors in parentheses; all regressions include fixed effects, as well as labor and capital (coefficients suppressed)

Table 13b: Spillovers in Canada

		(1) IV GMM	(2) IV GMM	(3) OP/W GMM
Domestic R&D		0.249	0.141	0.134
		(0.006)	(0.006)	(0.004)
	in CAN	0.222	0.359	0.244
Foreign R&D				
US			0.049	0.050
			(0.008)	(0.007)
	in CAN		0.150	0.104
JPN			0.100	0.120
			(0.008)	(0.007)
	in CAN		0.039	0.059
GER			0.062	0.060
			(0.007)	(0.006)
	in CAN		0.197	0.196
FRA			0.088	0.067
			(0.007)	(0.006)
	in CAN		0.034#	0.023
UK			0.038	0.046
			(0.007)	(0.006)
	in CAN		-0.039#	-0.001#
CAN			0.285	0.177
			(0.010)	(0.009)
N		8487	8239	8767
Overid [p-val]		0.123	0.318	
AR(1) [p-val]		0.946	0.246	
AR(2) [p-val]		0.297	0.954	

#: Not significantly different from zero at 5% level
Standard errors in parentheses; all specifications include fixed effects (country, industry, year), as well as labor and capital

Table 14: International Technology Diffusion through Imports

	(1) IV GMM	(2) IV GMM	(3) IV GMM	(4) IV GMM	(5) OP/W GMM
Domestic R&D	0.158	0.156	0.159	0.159	0.141
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Foreign R&D					
US	0.090	0.004	0.029	0.029	0.015
	(0.009)	(0.010)	(0.013)	(0.016)	(0.011)
JPN	0.153	0.166	0.169	0.150	0.158
	(0.008)	(0.008)	(0.009)	(0.010)	(0.008)
GER	0.093	0.080	0.104	0.100	0.086
	(0.007)	(0.007)	(0.011)	(0.012)	(0.008)
FRA	0.107	0.089	0.084	0.071	0.058
	(0.007)	(0.007)	(0.008)	(0.011)	(0.008)
UK	0.043	0.042	0.042	0.005	0.018
	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)
CAN	0.136	0.156	0.153	0.129	0.095
	(0.007)	(0.007)	(0.007)	(0.008)	(0.006)
US share in total imports*US R&D	0.010				
	(0.007)				
US share in G6 imports*US R&D		0.221	0.170	0.249	0.156
		(0.016)	(0.023)	(0.027)	(0.019)
JPN's share in G6 imports*JPN R&D			-0.025	0.044	-0.020
			(0.029)	(0.031)	(0.022)
GER's share in G6 imports*GER R&D			-0.085	-0.037	-0.025
			(0.027)	(0.027)	(0.017)
FRA's share in G6 imports*FRA R&D				0.100	0.049
				(0.056)	(0.029)
UK's share in G6 imports*UK R&D				0.255	0.221
				(0.049)	(0.029)
CAN's share in G6 imports*CAN R&D				0.193	0.057
				(0.033)	(0.020)
US share in G6 imports		-2.102	-1.547	-1.553	-1.131
		(0.170)	(0.224)	(0.425)	(0.212)
JPN's share in G6 imports			0.249	0.341	0.608
			(0.263)	(0.489)	(0.247)
GER's share in G6 imports			0.837	1.145	0.557
			(0.222)	(0.510)	(0.236)
UK's share in G6 imports				-1.172	-1.169
				(0.500)	(0.265)
CND's share in G6 imports				-0.541	0.106
				(0.475)	(0.240)
N	8145	8145	8145	8145	8719
Overid [p-val]	0.354	0.384	0.377	0.286	
AR(1) [p-val]	0.197	0.139	0.13	0.054	
AR(2) [p-val]	0.99	0.981	0.861	0.707	

Standard errors in parentheses; the import share from FRA is excluded from (5) and (6) to avoid collinearity
All regressions include labor and capital, as well as country-, year-, and industry fixed effects (not reported)

Table 15: Imports and FDI in international technology diffusion

	(1) IV GMM	(2) IV GMM	(3) IV GMM	(4) IV GMM	(5) OP/W GMM
Labor	0.693	0.696	0.707	0.686	0.668
	(0.010)	(0.017)	(0.018)	(0.018)	(0.017
Capital	0.147	0.155	0.134	0.133	-0.430
	(0.005)	(0.010)	(0.011)	(0.010)	(0.330)
Domestic R&D	0.157	0.123	0.114	0.121	0.098
	(0.005)	(0.010)	(0.010)	(0.01)	(0.009)
US R&D	0.087	0.476	0.551	0.447	0.316
	(0.008)	(0.031)	(0.032)	(0.038)	(0.034)
US(Imp*R&D)			-0.008	0.029	-0.005
			(0.001)	(0.008)	(0.008)
US(FDI*R&D)			0.019	0.089	0.086
			(0.004)	(0.028)	(0.021)
US Imp				-0.388	-0.017
				(0.077)	(0.087)
US FDI				-0.639	-0.598
				(0.246)	(0.183)
Other Foreign R&D					
JPN	0.152	0.041	0.018	-0.031	0.050
	(0.008)	(0.015)	(0.016)	(0.017)	(0.018)
GER	0.095	0.063	0.068	0.042	0.058
	(0.007)	(0.011)	(0.011)	(0.012)	(0.011)
FRA	0.108	0.085	0.085	0.066	0.080
	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
UK	0.042	-0.001	0.006	-0.005	0.023
	(0.007)	(0.011)	(0.011)	(0.011)	(0.010)
CAN	0.137	0.005	-0.021	0.016	0.001
	(0.007)	(0.010)	(0.010)	(0.014)	(0.011)
N	8239	1919	1755	1755	1755
Overid [p-val]	0.313	0.794	0.456	0.449	
AR(1) [p-val]	0.21	0.196	0.119	0.123	
AR(2) [p-val]	0.989	0.67	0.239	0.262	

Standard errors in parentheses; all regressions include country-, industry-, and year fixed effects

Table 16. Domestic R&D returns and spillovers, 1973-2002

	Rates of returns to R&D capital	Share of R&D spillover in GDP	Rate of returns to R&D expenditure
Australia	1.32	2.25	0.39
Belgium	0.55	3.33	0.16
Canada	0.92	3.00	0.27
Denmark	0.79	2.45	0.23
Finland	0.78	3.60	0.23
France	0.51	3.36	0.15
Great Britain	0.56	3.49	0.17
Germany	0.51	3.94	0.15
Ireland	1.87	8.31	0.55
Italy	1.44	3.63	0.42
Japan	0.47	3.77	0.14
Korea	0.26	5.84	0.08
Netherlands	0.42	2.77	0.12
Norway	0.74	2.39	0.22
Spain	2.37	3.75	0.70
Sweden	0.39	3.63	0.11
USA	0.35	3.23	0.10
Average	**0.46**	**3.48**	**0.14**

Note: These calculations are based on coefficient of domestic R&D in Table 11, Specification 5. First column is obtained directly using the formula, by multiplying the common coefficient (the elasticity) by country specific ratio of real value added to R&D capital. The second column is obtained by dividing total spillovers of R&D capital by respective country's GDP. The total spillover, in turn, was obtained by multiplying the rates of return by the amount of domestic R&D capital. To obtain the rate of R&D expenditure (last column), we adjust the rate of return to R&D capital (Column 1) by 0.3, the average ratio of R&D expenditure to R&D capital. All data are average of 30 years (1973 – 2002) that the estimation was based on.

Table 17. R&D spillovers and its rate of returns, 1973-2002

	R&D benefits spilled to foreign countries		Rates of returns to R&D expenditures		
	In millions	Share in source country's GDP	In domestic economy	In foreign countries	Total
Source countries					
USA	171,032	2.8	0.10	0.09	0.19
Japan	81,488	3.5	0.14	0.13	0.27
Germany	30,572	2.1	0.15	0.08	0.23
France	21,284	2.1	0.15	0.09	0.24
UK	7,318	0.8	0.16	0.04	0.20
Canada	7,161	1.3	0.27	0.12	0.39

Note: These calculations are based on the coefficients of country specific R&D in Table 11, Specification 5. To calculate Column 1, we multiplied the country specific foreign rate of returns to R&D capital by respective country's R&D capital. The second column is the share of spillovers that the countries siphon to all 16 foreign countries (column 1) in their own GDP. The third column is the rate of returns to R&D expenditure incurred in these countries but benefit taken by foreign countries. Column 4 is taken from Table 16, which measures the domestic rates of return to R&D. the last column sums both domestic and foreign returns.

Appendix A: Data Note

The paper uses several databases of OECD which have been supplemented from other different sources as required. The main data we have used from OECD are: Analytical Business Expenditure in Research and Development (ANBERD) database, Structural Analysis (STAN) database, Commodity, Trade and Production (COMTAP) database, and Bilateral Trade (BTD) database. We have also used data from Groningen Growth and Development Centre (GGDC). Data on employment of US foreign affiliates in foreign countries are taken from US Bureau of Economic Analysis. Besides, we have used data directly from the website of national statistical agencies in Canada, Japan, the UK and the US to complement some of the missing cells. The industries for the study are based on International Standard Industrial Classification (ISIC) Rev. 3 code. We have used data from both old system Revision 2 (ISIC Rev. 2), and ISIC Rev. 3. Since ISIC Rev. 2 has data on only 22 manufacturing industries and ISIC Rev. 3 has data on 31 industries, including 22 that are in ISIC 2, the study takes the 22 industries which are common to both systems as sample (the ISIC rev. 3 code and industry names are provided in Table 1). The data for the study covers 30 years, from 1973 to 2002. In what follows, we will provide a detail data description and related concordance that we have used.

ANBERD: These data are available in two series: ANBERD 2 and ANBERD 3, the former based on ISIC Rev. 2, and the latter based on ISIC Rev. 3 industry code. Although these two data series covers different number of countries and industries, they are complement to each other. ANBERD 2 data start from 1973 and covers till about 1995-97, and ANBERD 3 data start from 1987 and go at least till 2002 for most of the countries (except for Ireland in which case they stop at 2001). Regarding country coverage, ANBERD 2 has data only for 15 countries in the sample (missing are Belgium and Korea) whereas the ANBERD 3 covers all 17 countries.

We have combined both data series; if there were overlap between two datasets, we have taken them from ANBERD 3. For 13 countries (Australia, Canada, Denmark, Finland, France, Great Britain, Ireland, Japan, Netherlands, Norway, Spain, Sweden and USA) we have taken data from ANBERD 2 from 1973 to 1986 and from ANBERD 3 from 1987 onward. For the remaining four countries, we have proceeded as follows. For Italy, the data from 1973 to 1990 are from ANBERD 2, and for the rest of the years, they are from ANBERD 3. For Belgium, the R&D data start from 1987, and that for Korea from 1995. Regarding Germany, the ANBERD 2 data covers West Germany from 1973 to 1995 and united Germany from 1991 to 1995, and ANBERD 3 covers united Germany from 1995 and onward. So to create a complete series for Germany, we took data for West Germany from 1973 to 1990 and for united Germany from 1991 to 1994 (both from ANBERD 2) and from united Germany from 1995 to 2002 (from ANBERD 3).

For all countries the ANBERD 2 database and for most countries the ANBERD 3 database are in national currency. The only difference is that for Belgium, Finland, France, Germany, Ireland, Italy, Netherlands and Spain the ANBERD 3 data are in Euro, whereas the ANBERD 2 data for these countries are in national currency. Hence, to bring data in common currency, we converted the ANBERD 2 data for these countries into Euro using irrevocable exchange rate.[45]

When combined, the data are available from 1973 to 2002 for all countries and industries with the following missing values. The data for 6 countries (Australia, France, Germany, Japan, Spain and Sweden) are available for all industries throughout the sample period. For Canada, Italy and US, the data are missing only for one industry each. For another three countries (Finland, UK and Netherlands), data for two industries are missing for some years. For remaining five countries, data were missing for more than three industries, in most cases though not throughout the sample period but for some years.

Since the ANBERD (both series) data are in current price, we use the industry value added deflator based on GGDC and STAN databases (more on these two databases later) to convert them into 1995 prices. Finally, using we converted them into 1995 purchasing power parity (PPP) US dollar.

COMTAP and BTD: Trade data come from three OECD databases: (1) COMTAP for years 1970-1979, (2) BTD 2 for years 1980-1989 and (3) BTD 3 for years 1990-2003. Trade data are complete for all 17 countries except for

[45] The national currency per EURO rate is as below: Belgium = 40.3399; Finland = 5.94573; France = 6.55957; Germany = 1.95583; Ireland = 0.787564; Italy = 1936.27; Netherlands = 2.20371, and Spain = 166.386.

Korea, which starts only from 1994. Both COMTAP and BTD 2 are based on ISIC Rev. 2, whereas BTD 3 is based on ISIC Rev. 3. For Germany, the import data are taken for West Germany from 1970 to 1989 and for united Germany from 1991 and onward. We converted all three COMTAP, BTD 2 and BTD 3 databases into 22 sample industries.

The trade data, which are in US dollar, are converted into 1995 purchasing power parity (PPP) dollar. Since the PPP to US $ exchange rate is not readily available, we used two other available series from STAN database to obtain it as follows:

$$\frac{\text{PPP in U.S. dollar}}{\text{U.S. dollar}} = \frac{\text{National currency } / \text{U.S. dollar}}{\text{National currency} / \text{PPP in U.S. dollar}}$$

Multiplying the U.S. dollar trade data by the rate on the left hand side in year 1995, we obtained trade data in PPP at 1995 rate.

STAN: We have used value added, gross fixed capital formation (investment), employment (persons engaged and hours worked) and labor compensation data from STAN database. We have used mainly STAN 3 database which are based on ISIC Rev. 3 industry code and start coverage from 1970 till more recent years. However, it appears that for early years for some countries, data that are available on STAN 2 database are not available in STAN 3. In such cases, we used the STAN 2 database to cover the missing values in STAN 3. Furthermore, we realize that some of the entries which are empty in both STAN 2 and STAN 3 databases were available in old STAN data CD. In such cases, we have used data from old CD to refill the empty cells. Thus our data construction was based on the premise that use as much as they are available in STAN 3, if possible recover the missing cells from STAN 2, and if still missing recover them from old CD.

In STAN 3, value added and investment data are available in nominal terms, and in real terms, i.e. as volumes. The former are in national currencies. The volumes are expressed as index numbers with national reference year equal to 100. Since, for the study, we need both value added and investment in value not as index, we performed the following two steps. First, we converted the index into value. Second, since different countries index values were based on different reference year, we re-based the reference year for all countries in 1995. The first step was performed the follows:

$$\text{(A1)} \qquad p_r y_t = \frac{I_t \times p_r q_r}{100}, \qquad\qquad t = 1973 \text{ to } 2002,$$

where $p_r q_t$ is the constant price value added in reference year price, *r*; $p_t y_t$ is the value added in current price, and $p_r q_r$ is the current price value added in the reference year, and *I* stands for index data in the database (in case of investment, the similar equation was used with value added data replaced by investment data). Since both I_t and $p_r y_r$ are available in the data, we were able to compute the expression on the left-hand side. The calculation in (A1) is based on the fact that $I_t = (p_r q_t / p_r q_r) \times 100$.[46]

In the data, the reference years are not the same for all sample countries. For both value added and investment indices, the reference year is 2000 (2000 = 100) for six countries, 1995 for nine countries and 1997 for Canada.[47] In the second step, for those countries whose reference years are different from 1995, we converted their value at constant price given by equation (A1) into 1995 by using the following mechanism:

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[46] However, the volume indices were not available for some industries in some countries and year. So in an attempt to use the same indices across all countries, we have moved up to more aggregate indices to compute constant price investment. This amounts to assuming that the price change for more disaggregate level of industries was the same as the price change in more aggregate industry level. In sum, we used the index of ISIC 24 for ISIC 24x2423 and ISIC 2423 for all countries and of ISIC 2423 for Norway; the index of ISIC 27-28 for industries ISIC 271 and ISIC 273. Furthermore, we used the index of ISIC 30-33 for industries ISIC 30, ISIC 31, ISIC 32, and ISIC 33. And finally, we used the index of ISIC 34-35 for industry ISIC 34 and for industries ISIC 351, ISIC 353 and ISIC 352+359.

[47] A note on West Germany (GEW) and United Germany (GER)) is needed here. For GEW, data run from 1970 to 1991, whereas for GER they run from 1991 to 2002. We have taken data for a period of 1970-1990 from GEW and

(A2) $$\mathrm{p}_{1995}\mathrm{q}_{\mathrm{t}} = \frac{p_{1995}q_{1995}}{\mathrm{p}_{\mathrm{r}}q_{1995}} \times \mathrm{p}_{\mathrm{r}}q_t, \qquad t = 1973 \text{ to } 2002,$$

where $\mathrm{p}_{1995}\mathrm{q}_{\mathrm{t}}$ is value added in 1995 price; $p_{1995}q_{1995}$ is current price value added in 1995; $\mathrm{p}_{\mathrm{r}}q_{1995}$ is value added in 1995 in reference year price, and $\mathrm{p}_{\mathrm{r}}q_t$ is the value from equation (A1). Note that for countries whose reference year was 1995 Equation (A2) holds as an identity. We repeated (A2) for investment series as well.

STAN 2 current price value added and investment data were in the same currency as in STAN 3 except for Belgium, Finland, France, Germany, Ireland, Italy, Netherlands and Spain, which in national currency, not in Euro. We converted STAN 2 data for these countries into EURO first. Regarding constant price data, unlike STAN 3, the STAN 2 database does not have investment data in constant price and those in value added are also in actual value, not in index. But they are based on 1990 prices. We converted the constant price value added from 1990 price to 1995 prices using the following formula:

(A3) $$\mathrm{p}_{1995}\mathrm{q}_{\mathrm{t}} = \frac{p_{1995}q_{1995}}{\mathrm{p}_{1990}q_{1995}} \times \mathrm{p}_{1990}q_t$$

Similarly, the constant value added data from old CD, which are basically STAN 2 data, are also in value but in 1985 prices. To convert these data into 1995 price, we need to do the following:

(A3') $$\mathrm{p}_{1995}\mathrm{q}_{\mathrm{t}} = \frac{p_{1995}q_{1995}}{\mathrm{p}_{1985}q_{1995}} \times \mathrm{p}_{1985}q_t\,.$$

However, since we have neither current value added, $p_{1995}q_{1995}$, nor constant value added, $\mathrm{p}_{1985}q_{1995}$, data for 1995 in this source, we converted the data in old CD into 1995 prices using the following procedure:

(A4) $$\mathrm{p}_{1995}\mathrm{q}_{\mathrm{t}} = \left(\frac{p_{1995}q_{1990}}{\mathrm{p}_{1985}q_{1990}}\right)_M \times \mathrm{p}_{1985}q_t\,,$$

where the expression inside the parenthesis is for total manufacturing, denoted by subscript *M*. The expression inside the bracket has no industry dimension but has only country dimension as we have estimated it for each country. The numerator in this expression is taken from STAN 3 and the denominator from data in CD. We used this ratio of constant value added in year 1990, one based on price in 1995 and the other in year 1990, for all industries.

By doing so, we have data on value added and investment (both at constant and current prices) employment, and compensation.

GGDC: We have taken data for value added (both in current price and in constant price) and employment (both persons engaged in employment and hours worked) from GGDC. This dataset is comparable with the OECD STAN database but provides a dataset without gaps by complementing STAN with information from industry and services statistics and additional (historical) national accounts data for individual countries. The GGDC database have total of 57 industries, with 27 in manufacturing. We concorded the 27 industries into our sample of 22 industries. The industries in GGDC could be easily concorded, except for two industries in which case we have to decompose these two GGDC industries into two each. In GGDC, the ISIC 24 is not split into ISIC 24x2423 and 2423. Similarly, industry ISIC 27 is not disaggregated into ISIC 271 and ISIC 272.

To split GGDC 24 and 27 into two industries each, we used the value added at current price data from STAN database where data on ISIC 24x2423, ISIC 2423, ISIC 271 and ISIC 272 are reported separately. We computed the annual share of value added of 24x2423 and 2423 in ISIC 24 and used that share to decompose GGDC ISIC 24 into two categories. We did the same for ISIC 271 and 272, using the value added shares of these two industries in ISIC 27. This refilling mechanism was possible only for 13 countries. Among the remaining four countries, for the Netherlands the STAN database has data on 24x2423 and 2423, whereas those for ISIC 271 and

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for a period of 1991-2002 from GER to make a complete (1970-2002) series for Germany. However, in volume index, it needed some work to make them based on the same reference year, as the index for GEW is based on 1991 = 100 and the volume index for GER is based on 1995 = 100. We choose to base them both in year 1995 = 100. For this purpose, we took the benefit of the fact that for both GEW and GER, there are indices for year 1991. So based on the index of GER in 1991 basing it on 1995 = 100 and combine them with GER series.

ISIC 272 are available only from 1995 to 1999. Hence, to split data throughout the sample period for ISIC 27, we used the average share of these two industries in that period. For Ireland, we had no information to split ISIC 27. For Norway it was just the opposite, we could split ISIC 27 but not ISIC 24. For Australia, STAN did not have information on either of two industries. Hence, to split ISIC 27 for Ireland, ISIC 24 for Norway, and both ISIC 24 and ISIC 27 for Australia, we used the 50/50 rule. Even though this type of breakdown is not very realistic, we don't expect these cells to bias our results as they represent only 0.1 percent of the data cells for the study.

We combined the data on value added (both at current and constant price) and employment from STAN and GGDC, taking data from STAN for years 1973 to 1978 and from GGDC for years 1979 and onward. The reason for taking data from GGDC whenever they were available rather than from STAN was that the data on the former were complete, whereas on the latter there were several missing cells. Then using the combined value added data in current price and constant price, we calculated value added deflator, d_t, which was used to deflate the investment and R&D data.

(A5) $d_t = p_t q_t / p_{1995} q_t$, *t = 1973 to 2002,*

where $p_t q_t$ is the current price value added given in the data. Then, we converted these national currency value added and investment data into 1995 PPP. Furthermore, the PPP converted series of constant price value added was used to compute labor employment per person engaged.

Employment of US Foreign Affiliates in Foreign Countries

These data are taken from US Bureau of economic analysis. They are available for all sample industries except for the ISIC 35 which was not decomposed into three industries that we are interested in. Hence, we divided the entry in ISIC 35 into three industries by one-third. The drawback, however, of these series is that they are available only for seven countries: from 1983 for Canada and Japan and from 1989 for Australia, France, Germany, Italy, Netherlands and UK. We have used this data as a separate variable in our estimation, with other countries as missing values.

Appendix B: Supplementing and Estimating Missing Data

The variables that are used for the study are trade, US employment in foreign affiliates, value added, employment, R&D, labor compensation, and physical investment. The data on trade are almost complete except for few years for Korea, so we have not estimated the missing values for this variable either. Even though the data on employment in US affiliates are missing, we did not estimate them, as there is no reasonable way to do so. The value added and employment data after 1979, when we had them from GGDC, are complete. However, there are some missing values prior to 1979 for these variables. Among the three remaining variables, even though there are some data missing for R&D and labor compensation, the frequency of missing cells is more frequent in investment data. Below, we describe how we estimated some of the missing cells in investment data. We have also estimated few missing cells in value added, employment, R&D expenditure and labor compensation using similar techniques.

As mentioned above, the investment data are available in both current and constant prices. For the study, the preference would be to use constant price investment data, as they are based on more appropriate deflators. However, if we rely in constant price investment there will be a lot of missing cells. In terms of availability, the constant price investment data are a subset of current price investment in a sense that almost all data that are available in former series are also available in the latter but not vice versa. For example, even though the investment data in current price are available, they are completely missing in constant price for three countries (Australia, UK, and Korea). Similarly, even though the data in current price for Finland, France, Japan, Denmark and Sweden are available from 1973, the constant indices for these countries start only in 1975, 1978, 1980, 1993 (for the last two countries) respectively. Finally, there is a gap of four years in data availability for Ireland, as the current price data start in 1991 and those in constant price in 1995. Besides, even for other countries and years, when we compare data availability by industry, the data gap in current price and constant price are substantial. Hence, in this study, we have used the current price investment data by deflating them by value added deflators.

For the missing value, when possible, first we used national statistical agencies' to refill the data if possible. This was done only for UK, Canada, the US and Japan. For UK, all of 2001 and 2002 data were obtained from Table 6 "gross fixed capital formation" of Input-output Supply and Use Tables from National Statistics UK. Data for Canada for most of 2001 and 2002 were taken from Statistics Canada. Similarly most of the data for 2001 and 2002 for the US were supplemented using Bureau of Economic Analysis "historical-cost investment in private fixed assets by industry" from the website. For Japan, the STAN database has investment data only in current price that too only in STAN 2 which extends only till 1993; STAN 3 does not have data on Japan. We supplemented these data by acquiring a file from Department of National Accounts, Economic and Social Research Institute in Japan, which has data from 1980 onward in constant price. Hence our investment series for Japan will be a mixed of two series: till 1979 we use the investment in current price by deflating with value added deflator, and from 1980 to 2002 we use data series which were already in constant price (using investment deflator).

Before describing estimation methods of the missing values, a closer look at the industry level current price investment data shows that even though the data for industries ISIC 15-16, 17-18, 21-22, 25, 26 and 36 were more or less complete, there were missing values for other industries. With sample period of 30 years (1973-2002), 22 industries and 17 countries (30 x 22 x 17), we have total of 11,220 cells of information. Out of them, 1,930 (about 17 percent) cells of data were missing. To estimate part of missing cells we used three different approaches. The first approach is based on the assumption that the investment share of 3- or 4-digit level industry in 2-digit level industry remained the same as it was in the preceding three years. This method is used to estimate data mostly for industries at 3- and 4-digit level and for more recent years. Since there are two 4-digit industries (ISIC 24x2423 and ISIC 2423) and three 3-digit industries (ISIC 351, ISIC 353, ISIC 352+359), we have used this method mostly for these five industries. The method, called Method 1, is given by the following equation:

(B1) $\mathrm{i}_t\left(3/4\right) \equiv \omega \mathrm{i}_t\left(2\right)$,

where $\mathrm{i}_t\left(2\right)$ is the investment at 2-digit industry; $\mathrm{i}_t\left(3/4\right)$ is the investment at 3 or 4 digit industries within that 2-digit industry in time period *t;* $\omega = \left(\sum_k \frac{i_{t-k}\left(3/4\right)}{i_{t-k}\left(2\right)}\right)\Big/3$, (k *= 1, 2, 3),* is the average share of investment at 3- or 4-digit industry within its 2-digit industry investment in the preceding three years. Since the data at 3- and 4-digit industries were missing only for the most recent years, this method is mostly used to fill data for years 1999 through 2000. But in few cases, we have used this method to regain data even earlier period. For a couple of countries we used this method to decompose data for individual industries ISIC 30, 31, 32 and 33, when data on ISIC 30-33 was given, and for ISIC 271, 272 when data for ISIC 27 was given and for ISIC 351 and 352+359 when data for ISIC 35 was given.

The second estimation method —Method 2— is used for those industries which have data available for at least three-fifths and less than four-fifths of sample period (between 18 and 23 years). We used the change in current price value added to estimate investment as given below:

(B2) $i_{t+1} = i_t \exp\left[\ln\left(y_{t+1}/y_t\right)\right]$,

where i_t is investment in current price, and *y* is value added in current price. In most cases the data were available for early periods and we used (B2) to estimate data for later period. In few cases, the data were available for later periods and were missing for earlier period. In this case, we used $i_{t-1} = i_t \exp\left[\ln\left(y_{t-1}/y_t\right)\right]$ to estimate the missing values. In very few cases, the data were missing in both ends with data available only for the middle period. In that case, we used (B2) to estimate data only for the later period and left the earlier period empty.

For those industries which have data for at least 24 years, we used the growth rate of investment—Method 3—to estimate investment in the current year as follows:

(B3) $i_{t+1} = i_t\left[1+\ln\left(i_t/i_{t-1}\right)\right]$

Equation (B3) is good to estimate data for later period given that the earlier period data were available. To refill data for earlier period, we used $i_{t-1} = i_t\left[1+\ln\left(i_t/i_{t+1}\right)\right]$.

For investment, 140 cells were filled up using method 1; about 466 cells were filled up using Method 2, and about 126 cells were filled up using Method 3. Hence, altogether 732 of the 1,930 missing cells were filled up. The remaining 1,198 were left empty either because the data for industries were empty throughout or were available for less than 18 years, the cut off number of years for data refinement. Among them, nine industries (distributed in different countries) had no entry at all (contributing 270 empty cells). The other empty cells were distributed in different industries and countries, more in Belgium, Ireland, Denmark and few in France, Spain and Sweden.

Then we used value added deflators to convert adjusted current price investment into constant price, and further converted them into 1995 PPP dollar.

In very few cases, we have augmented the value added and deflator prior to 1979 using Method (3). In case of current value added, we filled 143 cells and in case of deflator, we filled 274 cells. In case of R&D, we filled 270 cells using this method.

We have also augmented data for labor compensation using the following mechanism:

(B4) $$w_{t+1} = w_t \exp\left[\ln\left(e_{t+1}/e_t\right)\right]$$

where *w* is the labor compensation, and *e* is the labor employment. For most of the empty cells we have used equation (B4). However, for a few cells, especially if they occur at the beginning of the period (year 1973) where we don't have the employment growth rate for this year, we used the following process

(B4') $$w_{t-1} = w_t\left[1+\ln\left(w_t/w_{t+1}\right)\right]$$

The labor compensation data for Canada for year 2002 were missing from the database and were supplemented using data from Statistics Canada.

For those industries whose labor compensation to value added shares were greater than 0.85 and less 0.2 have been replaced by median value of compensation to value added, median across all countries and all years for the given industry.

Appendix C: Method to Construct Capital Stock

Using two sets of constant price physical investment and the combination of two as another set, we computed three sets physical capital stock. We also computed capital stock of R&D expenditure. For that purpose, we used the following perpetual inventory method to construct the stock of R&D and of physical capital for country c, industry I year t:

(C1) $$\kappa_{cit} = \iota_{cit-1} + \left(1-\delta\right)\kappa_{cit-1},$$

where κ represents both physical and R&D capital and ι represents both physical and R&D investment, and δ is the depreciation rate. Based on the common practice, we use 5% depreciation rate for physical capital and 15% for R&D. The beginning of period capital stock (both physical and R&D) was given as follows:

(C2) $$\kappa_1 = \iota_0 + \left(1-\delta\right)\iota_{t-1} + \left(1-\delta\right)^2 \iota_{t-2} + ...$$

$$= \sum_{s=0}^{\infty} \iota_{-s}\left(1-\delta\right).^s = \iota_0 \sum_{s=0}^{\infty}\left[\frac{1-\delta}{1+g}\right]^s = \frac{\iota_1}{g+\delta}$$

where *g* is the average annual growth rate of constant price investment andR&D expenditure throughout the study period.