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Working Paper 2006-14
http://www.bus.lsu.edu/economics/papers/pap06_14.pdf

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Revised in March 2006

Abstract

This paper investigates the significance of Research and Development (R&D) spillovers through intra- and international trade in intermediate goods for productivity growth in a panel of OECD industries during 1973-1994. In the model, four different sources of R&D are identified: R&D conducted in the particular industry itself, R&D conducted in the same industries in other countries, R&D conducted in other domestic industries, and R&D conducted in other foreign industries. I find that among R&D sources the most important contributions to productivity growth come from the domestic R&D efforts. Here, own R&D is important for both domestic innovation and for the productivity catch-up process. Evidence that international R&D spillovers also have significant effects on productivity growth is found to be less robust. My analysis also shows that human capital affects productivity directly as a factor of production.

JEL Classification: O40, F1, F2, and F3
Keywords: Productivity Growth, R&D Intensity, R&D Spillovers, and Human Capital

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1 Introduction

Many economists believe that differences in technological knowledge are the main source of productivity differences across countries and industries (see Romer (1990), Parente and Prescott (1994), and Howitt (2000)). From this perspective, the key question is how to close these gaps. The recent theoretical models in growth theory and international trade (see Grossman and Helpman (1991a)) argue that devoting more resources to the R&D sector and increased economic integration, such as free flows of goods and services, tends to increase technological knowledge, and this in turn will close the productivity gaps. Trade in goods may transmit technology in both direct and indirect ways. Firms may directly learn about new technologies and imitate them; indirectly, they may employ new intermediate goods, which are embodied in more advanced technologies in the production of final goods.

This paper presents an empirical model in which trade in intermediate goods is a conduit for R&D spillovers across industries and countries. In particular, the model relates productivity growth to R&D intensities through trade in goods. In the model, four different types of R&D are identified: R&D conducted in the particular industry itself, R&D conducted in the same industries in other countries, R&D conducted in other domestic industries, and R&D conducted in other foreign industries. I examine the significance of each of these sources for productivity growth in a panel of twelve industries in ten OECD countries between 1973 and 1994. The model is further extended by incorporating productivity catch-up and human capital variables to see their effects on both productivity growth and the significance of the R&D sources.

I find that among R&D sources the most important contributions to productivity growth come from the domestic R&D efforts. Here own R&D is important for both domestic innovation and for the productivity catch-up process. Although international R&D spillovers have positive effects on productivity growth, these effects are not robust. My analysis also shows that human capital affects productivity directly as factor of production.

This paper is related to two literatures: inter-industry and international R&D spillovers.

The studies in inter-industry spillovers literature typically address the rates of return on own R&D investments and R&D investments in other domestic sectors using firm or industry level data for a particular country.[1] The model presented in this paper, however, considers not only domestic spillovers, but also international R&D spillovers. The consideration of international R&D spillovers can provide better picture of the impacts of R&D investment and spillovers on productivity growth.

The study of international R&D spillovers through trade started with a seminal work by Coe and Helpman (1995), and has been further explored by Coe et al. (1997), Keller (1998) and (2000), Lichtenberg and de la Potterie (1998), and Xu and Wang (1999) (see Keller (2004) for a review of this literature). Most of these works have concentrated on the R&D spillovers using country-level aggregate data. Keller (2000) considers R&D spillovers at the industry level with his main focus on spillovers from the same industries in other countries. An exception is work by Keller (2002b), who also considers R&D spillovers from other domestic and foreign industries. He concludes that the most important contribution comes from own R&D, followed by R&D in other domestic industries and R&D in foreign industries of which the majority comes from other industries.

There are several differences in methodology and data between Keller (2002b) and the present work. First, Keller's model, like other models in international R&D spillovers studies, is based on a first generation endogenous growth model, which exhibits a scale effect.In contrast, the estimates of this paper are based on a model that is more consistent with the second generation endogenous models, which does not exhibit any scale effect, developed by Dinopoulos and Thompson (1998), Young (1998), and Howitt (1999).[2] Second, Keller uses the US domestic and import Input-Output (IO) data to measure the spillovers from domestic and foreign other industries, which implies that the production structures and technologies of other countries are the same with the US. In contrast, I control cross-

[1]See Griliches and Lichtenberg (1984), Scherer (1982), Terleckyj (1977), and Wolff and Nadiri (1993). In particular, see Nadiri (1993) Table 2 for summary of works in this literature.

[2]Savvides and Zachariadis (2005) also use a model similar to mine to address technology diffusion from the G5 countries to the developing countries.

country heterogeneity by using country specific IO data. Investigating the significance of country heterogeneity for the technology diffusion process is itself an interesting question to be explored. Third, this paper also considers the direct and indirect effects of human capital and own R&D on productivity along with a productivity catch-up variable. Inclusion of these variables, as will be shown below, considerably affects the size and significance of estimates.

The plan of this paper is as follows. Section 2 introduces the theoretical framework that underlies my analysis. Section 3 provides a review of the main features of the data. Important empirical issues along with the empirical findings and their interpretations are reported in Section 4. Section 5 offers some concluding remarks.

2 Theoretical Framework

Let industries be denoted by $i = 1, \ldots, I$ and countries by $c = 1, \ldots, C$. At any time t, in each industry i of country c, capital $K_{ic}(t)$, labor $L_{ic}(t)$, and technical efficiency $A_{ic}(t)$ are combined to produce output $Y_{ic}(t)$. The production function takes the form

$$Y_{ic}(t) = A_{ic}(t)F(K_{ic}(t), L_{ic}(t)). \tag{1}$$

In this production framework, I assumed that technical efficiency is Hicks-neutral and $F(\cdot,\cdot)$ satisfies the assumptions of constant returns to scale and diminishing marginal returns to each input factor. According to the first generation endogenous growth models,[3] the technical efficiency is given by

$$A(t) = N(t)^{\gamma}, \qquad \text{with} \qquad \dot{N}(t) = \eta R(t), \tag{2}$$

where $N(t)$ denotes the total number of intermediate goods, $R(t)$ is the total R&D effort spent to develop new products at time t, and $\gamma,\ \eta > 0$ are parameters. To simplify notation, above I suppressed the indices on A, N, and R. This specification generates a scale effect, i.e. productivity growth rate is proportional to L. Jones (1995), however, convincingly

[3] For details of this type of models, see Romer (1990), Barro and Sala-i-Martin (2004) Chapter 6 and 7, Grossman and Helpman (1991b) Chapters 3 and 4.

shows that there is little support, based on time-series behavior of these variables in the advanced countries, for such a scale effect.

As noted by Barro and Sala-i-Martin (2004) and Aghion and Howitt (1998), this scale effect will disappear if we consider the following specification for the R&D[4]

$$\frac{\dot{N}}{N} = \eta \frac{R(t)}{Y(t)}. \tag{3}$$

Note that (3) together with the specification for A in (2) imply that productivity growth is a linear function of R&D intensity:

$$\frac{\dot{A}}{A} = \beta^d \frac{R(t)}{Y(t)}, \tag{4}$$

where $\beta^d = \eta\gamma$.

In an environment where industries interact with each other in various ways, such as by selling goods and exchanging information domestically and internationally, the technical efficiency of an industry will not only be a function of its own R&D effort, but also of the R&D efforts of other domestic and foreign industries. To capture these additional effects, let R_{ic}^d denote the domestic R&D investment in industry i in country c, R_{ic}^{od} denote the total R&D spillovers from other domestic industries, R_{ic}^{sf} denote the total R&D spillovers from industry i in other countries, and R_{ic}^{of} denote the total R&D spillovers from other industries in other countries. The technical efficiency A_{ic} is then assumed to be of the following form

$$\frac{\dot{A}_{ic}}{A_{ic}} = \beta^d \frac{R_{ic}}{Y_{ic}} + \beta^{od} \frac{R^{od}}{Y_{ic}} + \beta^{sf} \frac{R_{ic}^{sf}}{Y_{ic}} + \beta^{of} \frac{R_{ic}^{of}}{Y_{ic}}, \tag{5}$$

where β^d, β^{od}, β^{sf}, and β^{of} are positive parameters.

An important question is how R&D investment of one industry affects another industry. In this paper, I assume that R&D spillovers occur across industries through trade in intermediate goods. Specifically, I assume that at any time the total amount of R&D that is transferred from industry j to industry i is industry j's $R\&D$ investment times the fraction

[4]Howitt (1999), for example, develops a Schumpeterian growth model with no scale effect and the model states that in the long-run productivity growth rate is an increasing function of R&D intensity, i.e. R/Y.

of output of industry j sold to the industry i:

$$\frac{\dot{A}_{ic}}{A_{ic}} = \beta^{d}_{ic}\frac{R_{ic}}{Y_{ic}} + \beta^{od}_{ic}\frac{1}{Y_{ic}}\sum_{j\neq i}\frac{M_{jic}}{Y_{jc}}R_{jc} + \beta^{sf}_{ic}\frac{1}{Y_{ic}}\frac{M^{f}_{iic}}{M^{f}_{ic}}\sum_{k\neq c}\frac{M_{ikc}}{Y_{ik}}R_{ik} + \beta^{of}_{ic}\frac{1}{Y_{ic}}\sum_{j\neq i}\frac{M^{f}_{jic}}{M^{f}_{jc}}R^{f}_{jc} \tag{6}$$

In the second term, M_{jic} is the total amount of goods sold by industry j to industry i in country c. Thus, the total amount of R&D that spillovers from sector j to sector i is $\sum_{j\neq i}(M_{jic}/Y_{jc})R_{jc}$. Construction of the third term is as follows. The total amount of R&D spillovers from sector i in other countries to country c is defined as $R^{f}_{ic} = \sum_{k\neq c}(M_{ikc}/Y_{ik})R_{ik}$, where M_{ikc} is the total amount of goods sold by industry i in country k to country c. M^{f}_{ic} is the total amount of goods sold by industry i in all other countries to country c, i.e. $M^{f}_{ic} = \sum_{k\neq c} M_{ikc}$ and M^{f}_{iic} is the total amount of imported goods of industry i sold to industry i in country c. Thus, the amount of R&D spillovers from the same industry in other countries to the industry i in country c, R^{sf}_{ic}, is R^{f}_{ic} multiplied by the fraction M^{f}_{iic}/M^{f}_{ic} of total amount of imported goods i sold to industry i. The fourth term is similarly constructed. Here R^{f}_{jc} denotes total amount of foreign R&D spillovers from industry j in other countries to country c, i.e. $R^{f}_{jc} = \sum_{k\neq c}(M_{jkc}/Y_{jk})R_{jk}$. This is brought by M^{f}_{jc} amount of goods and it is then distributed across all industries, and each industry i thus gets M^{f}_{jic}/M^{f}_{jc} share of R^{f}_{jc}.

This weighting scheme is used by Lichtenberg and de la Potterie (1998), Xu and Wang (1999), and Lichtenberg and de la Potterie (2001) in international technology diffusion studies and it has been used in previous empirical studies of inter-industry technology flows, see Terleckyj (1977), Scherer (1982), and Wolff and Nadiri (1993).[5] There is an alternative weighting scheme, which uses bilateral trade shares, proposed by Coe and Helpman (1995) and has been used in most of the empirical studies of international technology diffusion, see Coe and Helpman (1995), Coe et al. (1997), Keller (2001) and (2002b). I choose the first weighting scheme for two reasons. First, the bilateral trade shares weighting scheme reflects

[5]Long before the advent of endogenous growth theory, researchers estimated the relationship between productivity growth and R&D intensities. In fact, (5) is an extended version of the model that has been used in the inter-industry technology flow studies. The model presented in equation (5), however, considers not only domestic spillovers, but also international R&D spillovers.

the direction of R&D spillovers, but not their intensity. In other words, it incorporates only the composition of trade and not the level of trade.[6] In contrast, with the above weighting scheme, as I will show below, my model incorporates both of these effects and has a more correct theoretical and intuitive interpretation. Second, Lichtenberg and de la Potterie (1998) convincingly argue that the bilateral trade shares weighting scheme is theoretically subject to more "aggregation bias" than the first one.[7] But I will also report results based on the bilateral trade shares in section 4.4.

Note that equation (6) can further be rearranged as follows:

$$\frac{\dot{A}_{ic}}{A_{ic}} = \beta_{ic}^{d}\frac{R_{ic}}{Y_{ic}} + \beta_{ic}^{od}\sum_{j\neq i}\frac{M_{jic}}{Y_{ic}}\frac{R_{jc}}{Y_{jc}} + \beta_{ic}^{sf}\frac{M_{iic}^{f}}{M_{ic}^{f}}\sum_{k\neq c}\frac{M_{ikc}}{Y_{ic}}\frac{R_{ik}}{Y_{ik}} + \beta_{ic}^{of}\sum_{j\neq i}\frac{M_{jic}^{f}}{Y_{ic}}\frac{R_{jc}^{f}}{M_{jc}^{f}}, \tag{7}$$

where the terms M/Y within summations denote trade intensity. Intuitively, equation (7) says, for example, that the impact of R&D investment in industry j of country c on productivity growth in industry i of country c is proportional to trade intensity M_{jic}/Y_{ic} of industry i of country c with respect to industry j of country c multiplied by the R&D intensity R_{jc}/Y_{jc} of industry j in country c.

An advantage of this specification is that it incorporates both the level and the composition of trade. To see this, consider for example the second summation term on the right hand side of equation (7). Let $M_{ic} = \sum_{j\neq i} M_{jic}$ denote the total amount goods sold by other domestic industries to industry i and $m_{jic} = M_{jic}/M_{ic}$ denote the bilateral trade share. Then the summation of $\sum_{j\neq i}(M_{jic}/Y_{ic})(R_{jc}/Y_{jc})$ could be written as $(M_{ic}/Y_{ic})\sum_{j\neq i} m_{jic}(R_{jc}/Y_{jc})$. Here M_{ic} captures the the level of trade and m_{jic} picks up the composition of trade effect.

Implicit in (5), and hence in (6), is the assumption that all goods are endowed with the latest technology. However, diffusion of technology may take time. To capture this fact, I

[6] According to his weighting scheme, if two countries, for example, has the same trade composition, they will have the same foreign R&D effect.

[7] Aggregation bias refers to the implication that a merger between two countries or industries always increases the amount of R&D spillovers. For example, under the Coe-Helpman weighting scheme if two merging countries were the same size, the foreign R&D capital stocks would be doubled by merger. For details, see Lichtenberg and de la Potterie (1998)

introduce a lag structures in (5). With this modification, the discrete time presentation of (5) is given by

$$\triangle \ln A_{ic,t} = \beta^d \frac{R_{ic,t-1}}{Y_{ic,t-1}} + \frac{\sum_{\tau=1}^{\bar{\ell}} \beta_\ell^{od} R_{ic,t-\ell}^{od}}{Y_{ic,t-1}} + \frac{\sum_{\ell=1}^{\bar{\ell}} \beta_\ell^{sf} R_{ic,t-\ell}^{sf}}{Y_{ic,t-1}} + \frac{\sum_{\ell=1}^{\bar{\ell}} \beta_\ell^{of} R_{ic,t-\ell}^{of}}{Y_{ic,t-1}}, \qquad (8)$$

where $\triangle$ denotes the difference operator, i.e. $\triangle \ln A_{ic,t} = \ln A_{ic,t} - \ln A_{ic,t-1}$, $\bar{\ell}$ denotes the maximum length of lag, and β_ℓ^ν with $\nu = od,\ sf,\ of$ are parameters. Here $R_{\cdot,t-\ell}^\nu$ is defined as in (6) with R&D investments are lagged by ℓ periods. For my empirical implementation, I will set $\bar{\ell} = 3$. One may still believe that a three-year lag is not enough to capture the process of technology diffusion. In section 4.4, I will consider an alternative case where instead of using R&D investments, I use R&D stocks. The qualitative results, however, remain largely the same.

3 Data Description

3.1 Data Sources and Measurements

This section provides an overview of the data. The details about data sources and the construction of variables along with some statistics are reported in the appendix. I draw on a number of data sources to construct the industry level panel data set. The data on value added, investment, labor, compensation of labor, and price indices come from the Structural Analysis (STAN) database, OECD (1998d). OECD also compiles other databases that are, in terms of coverage, compatible with the STAN database. I use the OECD (1998a) Business Enterprise R&D (ANBERD) database for R&D investment data, the OECD (1998b) the Bilateral Trade Database (BTD) for international trade data, and the OECD (1995) and (2005) Input-Output (IO) database for the data on flows of domestic and imported goods across industries. The most attractive feature of these databases is that they are primarily based on member countries' annual National Accounts by activity tables. OECD compiles these tables in such a way that the final tables in all of these databases are one-to-one comparable in terms of industrial classification and coverage.

After cleaning and deleting missing values, I have constructed a panel data set on twelve manufacturing industries in ten countries between 1973 and 1994. The countries are Australia (AUS), Canada (CAN), Denmark (DNK), France (FRA), West Germany (GER),[8] Italy (ITA), Japan (JPN), the Netherlands (NLD), the United Kingdom (UK), and the United States (US). The twelve manufacturing industries are comprised of industries at two- to three-digit ISIC (International Standard Industrial Classification) level: food, beverage, and tobacco (ISIC 31), textile, apparel, and leather (ISIC 32), wood products and furniture (ISIC 33), paper products, and printing (ISIC 34), chemical products and drugs (ISIC 351+352), rubber and plastic products (ISIC 355+356), non-metallic mineral products (ISIC 36), basic metal industries (ISIC 37), metal products (ISIC 381), non-electrical equipment and machinery and professional goods (ISIC 382+385), electrical machinery (ISIC 383), and transport equipment (ISIC 384). The average share of the total value-added of these industries in the total gross domestic product across countries is about 22% between 1973 and 1994, and R&D expenditures of these industries comprise about 90% of the world's entire business enterprise R&D expenditures.

Technical efficiency (productivity) growth calculations at the industry level require real data on industry outputs and inputs of primary factors and intermediate goods. Price indices for intermediate goods are not available, so I calculated value-added productivity growth rates. With the data on real value-added, real physical capital stocks, and labor inputs, the Divisia-Tornquist technical efficiency (productivity) growth rates are measured as

$$\Delta \ln(A_{ic,t}) = \ln\left(\frac{Y_{ic,t}}{Y_{ic,t-1}}\right) - \bar{\alpha}_{ic,t} \ln\left(\frac{L_{ci,t}}{L_{ci,t-1}}\right) - (1-\bar{\alpha}_{ic,t}) \ln\left(\frac{K_{ci,t}}{K_{ci,t-1}}\right), \tag{9}$$

where $\bar{\alpha}_{ic,t} = 0.5(\alpha_{ic,t} + \alpha_{ic,t-1})$ and $\alpha_{ic,t}$ is the labor share of the value-added. This formulation is based on the assumptions that market are competitive and F exhibits constant returns to scale.

Two important points were considered in the measurement of productivity growth. First, the observed labor shares are quite noisy and sometimes exceed one. Following Harrigan

[8] The OECD continued to report statistics for West Germany until 1995.

(1997), I estimated a smoothed labor share series $\bar{\alpha}_{ic,t}$ from a regression

$$\alpha_{ic,t} = \delta_{ic} + \phi_i \ln\left(\frac{K_{ic,t}}{L_{ic,t}}\right) + \varepsilon_{ic,t}, \tag{10}$$

where the coefficient on the capital labor ratio is allowed to vary across industries. The smoothed labor shares are then used as labor cost shares in measuring productivity growth. Second, in measuring productivity growth, I also adjusted labor inputs by taking labor hours into account. This adjustment is important because according to the OECD (1998b) employment data, annual average working hours per employee vary substantially across countries; for example, in 1985 a French manufacturing worker on average worked 400 hours less than a Japanese manufacturing worker. In the robustness section, I will present results for the case when productivity growth is measured with unadjusted input factors.

3.2 Descriptive Statistics

Table 1 reports descriptive statistics on the key variables for the aggregate manufacturing sector across countries between 1973 and 1994. The second and third columns of Table 1 show that countries vary substantially in terms of their shares of total GDP (value-added) and total R&D in the sample.[9] For example, most of the production and R&D activities has been done in the United States, Japan, and Germany. The third column denotes R&D intensity, which is calculated by dividing total amount of R&D investment in twelve manufacturing industries to total amount of GDP generated by twelve manufacturing industries, of each country.

The import intensity for each country is calculated by dividing total imports of twelve manufacturing industries from the rest of the countries in the sample by the total value added of twelve manufacturing industries. Trade intensities across countries also show considerable variation. While Japan and the US are comparatively less open countries, Denmark and the Netherlands are the most open countries in the sample. The last column of Table 1 shows the growth rates of cross-section (across industries) standard deviations

[9] Here, total GDP of a given country does not refer to its whole-economy GDP. It refers to the sum of the value-added of its twelve manufacturing industries. Similarly, total R&D refers to the sum of the R&D investments of its twelve manufacturing industries.

Table 1: Descriptive Statistics Across Countries, 1973-1994 Averages, (%)

COUNTRY	Share of Total GDP in Sample	Share of Total R&D in Sample	R&D Intensity R_c/Y_c	Import Intensity M_c/Y_c	TFP Growth	Std(Ln(TFP)) Growth
Australia	1.5	0.5	1.9	67.3	1.5	-0.2
Canada	2.9	1.4	2.6	108.4	0.8	-2.8
Denmark	0.5	0.3	2.9	128.8	2.3	-4.8
France	8.0	6.9	5.3	65.4	2.6	-0.5
Germany	13.2	11.9	5.4	52.0	2.1	-1.6
Italy	7.0	2.6	2.0	49.4	3.7	-5.2
Japan	19.3	19.1	5.5	13.6	1.3	-3.6
Netherlands	1.6	1.4	5.2	180.4	3.2	-5.5
United Kingdom	7.0	6.4	5.4	81.2	2.0	-1.0
United States	39.0	49.5	7.9	31.0	2.1	-3.8

Notes: R_c, Y_c, and M_c denote the R&D investment, value-added, and total import (from other countries in the sample) of row country c.

of the logs of TFP within a given country. This column gives information about within country convergence. Convergence within a country can also be interpreted as a sign of cross-industry links. With this interpretation, this column reveals that there is relatively strong integration across domestic industries in Denmark, Italy, and the Netherlands.

Table 2 reports summary statistics for industries. It shows that the shares of total GDP and total R&D in the sample, and R&D intensities vary considerably by industry.[10] For example, while on average 13% of total GDP comes from food industry, the share of total R&D conducted in this industry is about 2%. Most of the R&D activities have taken place in Chemical, Machinery, Electrical, and Transport industries.

The fourth and fifth columns in Table 2 show that trade intensities in R&D intensive industries are considerably higher than those in other industries. Note that these are also industries where productivity growth is relatively high. The last column in Table 2 shows the growth rates of cross-section (across countries) standard deviations of the logs of TFP

[10]Here total GDP (R&D) of a given industry refers to the sum of the value-added (R&D investment) of that industries across all countries in the sample. I used whole-economic purchasing power parity exchange rates for conversions to international dollar.

Table 2: Descriptive Statistics for Industries, 1973-1994 Averages, (%)

INDUSTRY	Share of Total GDP in Sample	Share of Total R&D in Sample	R&D Intensity R_i/Y_i	Import Intensity M_i/Y_i	TFP Growth	Std(Ln(TFP)) Growth
Food	13.3	2.0	1.0	36.4	1.2	-4.1
Textile	6.8	0.6	0.5	69.2	2.4	1.3
Wood	4.2	0.3	0.4	33.2	1.3	-3.2
Paper	9.6	1.0	0.6	21.0	1.1	-1.8
Chemical	9.4	17.1	11.1	53.3	3.9	-5.8
Plastic	3.8	1.8	2.9	30.7	2.1	-0.1
Mineral	3.9	1.3	2.0	19.9	1.6	-0.2
Basic Metal	6.6	2.4	2.2	51.0	3.2	-3.9
Metal	7.6	1.5	1.2	20.1	1.8	-1.5
Machinery	13.4	19.1	8.7	56.0	2.2	-1.8
Electrical	10.1	23.3	14.2	46.0	3.5	-1.6
Transport	11.3	29.6	16.0	70.0	1.8	-2.1

Notes: R_i, Y_i, and M_i denote the R&D investment, value-added, and total import (from other countries in the sample) of row industry i.

within a given industry. In other words, it gives information on the convergence in a given industry across countries. It is important to see that there is rapid convergence in the R&D and/or trade intensive industries, which is consistent with the model proposed above. I will now turn to empirical implementation to see to what extent the above observations are robust.

4 Empirical Implementation

4.1 Econometric Framework and Issues

The starting point for the econometric framework is equation (8). I impose further conditions on this equation. First, I assume a 3-year lag structure, i.e. $\bar{\ell} = 3$. Second, the productivity growth is affected by some unobserved characteristics, which are likely to be correlated with the included explanatory variables. Some of these unobserved characteristics may be time invariant, such as institutional or geographic differences; or some of them may be time specific common macroeconomic shocks which affect productivity growth in all countries. With these modifications, the benchmark econometric specification will be

$$\begin{aligned}\triangle \ln A_{ic,t} \quad = \quad & \alpha_{ic} + \alpha_t + \beta^d \frac{R_{ic,t-1}}{Y_{ic,t-1}} + \frac{\sum_{\ell=1}^{3} \beta_\ell^{od} R_{ic,t-\ell}^{od}}{Y_{ic,t-1}} + \frac{\sum_{\ell=1}^{3} \beta_\ell^{sf} R_{ic,t-\ell}^{sf}}{Y_{ic,t-1}} \\ & + \frac{\sum_{\ell=1}^{3} \beta_\ell^{of} R_{ic,t-\ell}^{of}}{Y_{ic,t-1}} + \varepsilon_{ic,t}, \quad (11)\end{aligned}$$

where α_{ic} denotes the industry-country specific fixed effect, α_t denotes time dummy, and $\varepsilon_{ic,t}$ is the error term. In presenting results, following Kocherlakota and Yi (1997) and Savvides and Zachariadis (2005), I report the sum of the coefficients of lags to measure the effects of variables on economic growth, i.e. $\beta^\nu = \sum_{\ell=1}^{3} \beta_\ell^\nu$, for $\nu = od,\ sf,\ of$. In section 4.4, I extend this framework by including human capital and productivity catch-up effects.

Since specification (11) does not contain productivity levels and R&D capital stocks, which are sensitive to their initial benchmark estimates, the possible measurement errors are reduced considerably. I have also estimated productivity growth based on different initial physical capital stocks and the results remain mostly similar.

Although we included industry-country specific fixed effect and time dummy to reduce the correlation between the explanatory variables and error term, estimates obtained by using least-square procedure still may not be consistent. For example, when firms anticipate shocks, they will adjust their R&D and trade accordingly. To reduce such effects, I use smoothed trade intensities in my estimates.[11] Moreover, including lagged R&Ds in our specification will further mitigate the possible simultaneity problem. Of course, these are not entirely satisfactory solutions and the best is to use instrumental variable (IV) approach. Unfortunately, there are no good external instrumental variables to deal with this endogeneity issue. Following the literature, I will, therefore, rely on my specifications.

Estimation of equation (11) requires internationally comparable data on output, R&D investment, and import. Following much of the productivity and R&D spillovers literature, for example Dollar and Wolff (1993), Bernard and Jones (1996), Griffith et al. (2004), and

[11] For 1973-80 period, I used average of the trade intensities over this period; for 1981-87, I used the average of 1981-87; and for 1988-94, I used the average of 1988-94.

Keller (2002a) and (2002b), I use whole-economic purchasing power parity (PPP) exchange rates to convert these variables. As a robustness check, I also present results based on Sorensen and Schjerning (2003) industry specific PPP exchange rates.[12]

4.2 Basic Results

The regression results for equation (11) are reported in Table 3 in Columns (3.1) through (3.4). Column (3.1) shows regression results when the only regressor is own R&D intensity. The coefficient β^d is 0.357 with a standard error of 0.090. This is consistent with previous industry level estimates by Zachariadis (2003) and Griffith (2004). Column (3.2) shows regression results, when the second term in equation (11) is included. The estimated coefficient is 2.009 and it is highly statistically significant. This estimate is within the range of previous estimates in inter-industry technology flow studies (see Nadiri (1993) Table 2 for summary of works in this literature).[13] The coefficient β^d decreased to 0.286 and according to $\bar{R}^2$ and AIC,[14] this one is preferable to (3.1). In column (3.3), the spillovers from the same industry in other countries are included. Coefficient of this effect is positive and statistically significant at the 5% level. Column (3.4) presents results including the spillovers from other foreign industries. The coefficient on this term is positive and significant again at the 5% level.

The size of coefficients are quite different, as are their standard errors. To get a better understanding of the size of the effects reported in Column (3.4), Column (3.5) reports the

[12] I have not used Sorensen and Schjerning (2003) industry specific PPP exchange rates in my main analysis for the following reasons. First, those rates are not available for all industries in my sample. Second, these are expenditure-based, rather than production-based conversion factors, and are not fully appropriate to determine international comparability of productivity analysis (see Sorensen and Schjerning (2003)).

[13] This coefficient is relatively high compared with most of the previous estimates in that literature (average is around 1.0). There are, however, two reasons for my high estimate. First, I calculated TFP growth rates by using value-added, capital, and labor data, whereas calculations in inter-industry literature are based on output, capital, intermediate inputs, and labor data. As pointed out by Nadiri (1993), TFP growth rates based on value-added approach is about twice as high as the TFP growth rates based on the output approach. Second, I only consider twelve manufacturing industries, whereas those studies consider sectors at a more disaggregated levels together with other non-manufacturing sectors (typically 20-30 sectors). Presumably, with these modifications my point estimate would be around the average of the previous estimates.

[14] Akaike Information Criterion (AIC) is defined as $AIC = \ln(e'e/N) + 2K/N$, where $e'e$ is the sum of the residual squares, N is the number of observations, and K is the number of estimated parameters. Lower values for AIC are preferred.

Table 3: Regression Results for Benchmark Specification

	Coefficient	3.1	3.2	3.3	3.4	3.5
R&D Effects from						
Own Industry	β^d	0.357*	0.286*	0.178**	0.229*	0.190
		(0.090)	(0.093)	(0.100)	(0.099)	
Other Domestic Inds	β^{od}		2.009*	2.196*	1.973*	0.205
			(0.744)	(0.784)	(0.777)	
Same Foreign Inds	β^{sf}			1.967*	1.357*	0.195
				(0.492)	(0.543)	
Other Foreign Inds	β^{of}				5.348*	0.333
					(1.337)	
Adjusted R^2		0.178	0.183	0.187	0.195	
Akaike Infor. Crt.		-5.726	-5.730	-5.734	-5.744	

Notes: Dependent variable is $\triangle \ln A_{ic,t}$. There are 2640 observations between 1973 and 1994. All equations include industry-country specific constants and time dummies. $\beta^{\nu} = \sum_{\ell=1}^{3} \beta_{\ell}^{\nu}$, for $\nu = od,\ sf,\ of$. Numbers in parentheses are heteroskedastcity-consistent standard errors. Column (3.5) shows the standardized coefficients of the Column (3.4). * (**) means the corresponding coefficient is significant at the 5% (10%) level.

sum of standardized coefficients, which are obtained by multiplying the regression coefficient by the sample standard deviation of the explanatory variable and dividing by the sample standard deviation of the dependent variable. Thus, for example, a standardized coefficient of 0.190 means that a one-standard-deviation increase in the own industry R&D variable will increase the productivity growth by 0.190 standard deviations. Column (3.5) states that in terms of standardized coefficients the effects of the first three sources are largely the same.[15]

4.3 Extension of The Model

In the basic framework, differences in human capital across countries are ignored. The effect of human capital on productivity growth is emphasized in both theoretical and empirical growth literature, see Romer (1990), Grossman and Helpman (1991a), Engelbrecht (1997), and Griffith et al. (2004). Engelbrecht (1997), for example, extends the Coe and Helpman

[15]Sample means (standard deviations) of R/Y, R^{od}/Y, R^{sf}/Y, and R^{of}/Y are 0.038 (0.051), 0.007 (0.006), 0.003 (0.009), and 0.003 (0.004), respectively.

(1995) study of international R&D spillovers by including a human capital variable. He finds that human capital both directly and indirectly affects productivity.

Following Gammell (1996) and Griffith et al. (2004), I use country-level data on the fraction of the adult population that has attained higher education from Barro and Lee (2002) as a proxy for human capital (see Appendix). Note that education is measured at a country, not industry-country level. This is because there are no internationally comparable industry-country level human capital data. In any case, it may be appropriate to use country-level data on human capital to the extent that there is an externality within a country.

Human capital can affect productivity in two ways. First, it can directly affect productivity. Second, it can indirectly effect productivity by facilitating technology transfer. Intuitively, one might expect that given the same level of trade shares, countries which have higher human capital will benefit more from technology transmission through trade.

To consider these effects of human capital on productivity growth, I add human capital and interaction terms, where human capital is multiplied by R&D spillovers, into equation (11). Column (4.2) of Table 4 reports the results. Human capital term is positive and statistically significant. Note that only the interaction term $H * SF$ is significant and negative. Although with these coefficients the average marginal contribution of R&D spillovers from the same foreign industries is positive ($3.396 - 6.142 \times \overline{H} = 2.352$, where $\overline{H}$ is sample mean of H), having a significant negative coefficient for the interaction term is not plausible: it would imply that countries with more human capital will benefit less from the foreign R&D spillovers. Other interaction terms, however, are not statistically significant.

Several other authors have showed factor productivity convergence among OECD countries and/or industries, but main reasons for this convergence are diverse (see, for example Dowrick and Nguyen (1989), Benhabib and Spiegel (1994), Engelbrecht (1997), Griffith et al. (2004)), and Cameron et al. (2005). To control for the impact of other productivity catch-up factors, following Dowrick and Nguyen (1989), Engelbrecht (1997) and Coe et al. (1997), I therefore include a catch-up term CU, which is defined as $\ln(y_{im,t-1}/y_{ic,t-1})$, where

Table 4: Extended Model: Productivity Catch-up and Human Capital Effects are Included

	Benchmark Case (4.1)	Human Capital (4.2)	Catch-up Included (4.3)	No Spill. Interact. (4.4)	Preferred Results (4.5)	Beta Coeff. (4.6)
R&D Effects from						
Own Industry (RD)	0.229*	0.217*	0.167**	0.203*	0.202*	0.168
	(0.099)	(0.101)	(0.102)	(0.101)	(0.101)	
Other Domestic Inds. (OD)	1.973*	1.960*	1.498	1.450*	1.462**	0.152
	(0.777)	(1.107)	(1.101)	(0.537)	(0.774)	
Same Foreign Inds. (SF)	1.357*	3.996*	3.238*	0.794	0.835***	0.117
	(0.543)	(1.025)	(1.177)	(0.540)	(0.525)	
Other Foreign Inds. (OF)	5.348*	7.289*	7.123*	4.493*	4.496*	0.276
	(1.337)	(1.918)	(2.335)	(1.284)	(1.665)	
Human Capital (H)		0.238*	0.238*	0.133*	0.138*	0.252
		(0.077)	(0.077)	(0.051)	(0.050)	
Productivity Catch-up (CU)			0.011	0.015	0.020***	0.091
			(0.017)	(0.017)	(0.013)	
Interaction Effects						
H* OD		-1.126	-1.313			
		(3.312)	(3.283)			
H* SF		-6.142*	-5.096*			
		(2.186)	(2.235)			
H* OF		-5.118	-8.043			
		(5.751)	(6.047)			
H* CU			0.052	0.048		
			(0.102)	(0.098)		
RD* CU			0.626*	0.620*	0.619*	0.213
			(0.184)	(0.185)	(0.185)	
Adjusted R^2	0.195	0.203	0.214	0.209	0.210	
Akaike Infor. Crt.	-5.744	-5.750	-5.762	-5.760	-5.761	

Notes: Dependent variable is $\triangle \ln A_{ic,t}$. All equations include industry-country specific constants and time dummies. Numbers in parentheses are heteroskedastcity-consistent standard errors. Column (3.5) shows the standardized coefficients of the Column (4.5). * (**) [***] means the corresponding coefficient is significant at 5% (10%) [12%] level.

y_{ic} denotes the labor productivity and $y_{im,t-1} = \text{Max}\{y_{ic,t-1} : c \in C\}$ denotes the maximum labor productivity in industry i across all countries, into (11). A positive and significant coefficient for this term represents evidence of convergence across countries.

Column (4.3) shows the results when productivity catch up along with its interaction with human capital and own R&D effects are included. This and interaction terms are all positive; but only the R&D interacted term is statistically significant. Inclusion of these effects have considerably reduced the sizes and the significance of the direct own R&D and R&D effect from other domestic industries. The significance of $RD * CU$ reflects the Cohen and Levinthal (1989) and Griffith et al. (2004) findings that own R&D is important for both domestic innovation and for the productivity catch-up process, i.e. it has *two faces* in development process.

Results in Column (4.3) are to some extent different from the Engelbrecht (1997) findings for OECD countries. He finds that human capital has both direct and indirect effects on productivity growth. Column (4.3), however, states that the second effect is insignificant.[16] Insignificance of this interaction term, however, is consistent with the Benhabib and Spiegel (1994) results, where they also obtain insignificant effect when they restricted their sample to wealthiest countries in their sample.

In Column (4.4), interactions with R&D spillovers terms are excluded. The productivity catch-up (CU) and its interaction with human capital (H*PC) terms are still insignificant. While R&D effect from the same industry in other countries is now insignificant at conventional levels, the other R&D sources have positive and highly significants effect on productivity growth.

Column (4.5) is my preferred specification and it is the same with Column (4.4), except now the H*CU term is also excluded.[17] The results are mostly the same with that in

[16] Engelbrecht's (1997) findings in regard to the catch-up and human capital interacted with catch-up terms are puzzling. He obtains opposite signs for the catch-up and human capital interacted catch-up terms. Since his definition of catch-up term is the reciprocal of mine (i.e. $\ln(y_{ic,t-1}/y_{im,t-1})$), his human capital interaction term has wrong sign (see, Columns v and vi in Table 3 in his paper), implying that more human capital leads to a slower catch-up process.

[17] I also consider the case where I excluded only the CU term. However, the H*CU term still remains insignificant.

Column (4.4). Now, however, the productivity catch-up and the R&D spillovers from the same industry in other countries are significant at the 12% level.

Finally, Column (4.6) shows the standardized coefficients of Column (4.5). According to this column, the direct effect of own R&D now has a higher impact on productivity growth than that of R&D spillovers from other domestic and the same foreign industries. Indeed, given that own R&D also has second face, it is clear that the effect of own R&D is much higher than that in the benchmark specification. Comparing (4.5) and (4.6) with benchmark cases in Column (3.4) and (3.5) uncovers another striking result that has not been noticed by previous studies in inter-industry technology flow. Notice that the magnitude of the coefficient of R&D spillovers from other domestic industries is reduced substantially. As pointed out before, previous estimates of this coefficient have been relatively large (the average is around 1.0) and researchers have speculated that this most probably stems from the omission of foreign R&D effects (see, Xu and Wang (1999)). But my analysis reveals that the effects of foreign R&D spillovers are not significant on the magnitude of this coefficient. The important reason is the omission of productivity catch-up term in previous estimates.

4.4 Robustness

In this section I evaluate sensitivity of basic results to alternative approaches to measurements of various variables. Table 5 reports the regression results under different specifications and Table 6 shows the corresponding standardized coefficients.[18]

Recall from section 3.1 that in calculating productivity growth the labor data were adjusted. Column (5.2) of Table 5 reports results where productivity growth rate is calculated when this input factor is not adjusted. While R&D spillovers effects from the same industries in other countries is not significant, the productivity catch-up term became significant at the 10% level. The qualitative results about other coefficients remained by and large the

[18]Results in Table 5 based on regressions identical with that in Column (4.5) in Table 4, i.e. I exclude human capital interacted with R&D spillovers and productivity catch-up terms. Inclusion of these interaction terms yield qualitatively same results as in (4.3) and (4.4) in Table 4; except under the alternative weighting scheme the $H*OD$ term is negative and statistically significant, while interaction with foreign R&D spillovers terms are insignificant. Results are available upon request to the author.

Table 5: Robustness of Results Related to Measurement of Variables

	Extended Case (5.1)	Unadjusted TFP (5.2)	Industry PPP (5.3)	R&D Stock (5.4)	BTS Scheme (5.5)	US IO used (5.6)
R&D Effects from						
Own Inds. (RD)	0.202*	0.209*	0.220**	0.035*	0.317*	0.324*
	(0.101)	(0.106)	(0.113)	(0.014)	(0.096)	(0.096)
Other Dom Inds. (OD)	1.462**	1.369**	1.364*	0.182**	0.170*	0.173*
	(0.774)	(0.782)	(0.692)	(0.108)	(0.050)	(0.049)
Same Frgn Inds. (SF)	0.835***	0.596	0.908*	0.045	0.006	0.008**
	(0.525)	(0.537)	(0.461)	(0.090)	(0.004)	(0.005)
Other Frgn Inds. (OF)	4.496*	5.113*	4.757*	0.439*	0.005	0.003
	(1.665)	(1.549)	(1.487)	(0.171)	(0.003)	(0.003)
Human Capital (H)	0.138*	0.118*	0.118*	0.099*	0.164*	0.162*
	(0.050)	(0.050)	(0.050)	(0.050)	(0.051)	(0.050)
Catch-up (CU)	0.020*	0.027**	0.020	0.031*	0.030*	0.034*
	(0.013)	(0.014)	(0.014)	(0.013)	(0.012)	(0.012)
RD* CU	0.619*	0.529*	0.621*	0.567*	0.436*	0.409*
	(0.185)	(0.191)	(0.185)	(0.177)	(0.180)	(0.180)
Adjusted R^2	0.210	0.219	0.210	0.207	0.218	0.218
Akaike Infor. Crt.	-5.761	-5.737	-5.761	-5.759	-5.771	-5.771

Notes: Dependent variable is $\triangle \ln A_{ic,t}$. All equations include industry-country specific constants and time dummies. Numbers in parentheses are heteroskedasticity-consistent standard errors. * (**) [***] means the corresponding coefficient is significant at the 5% (10%) [12%] level.

same.

Column (5.3) reports results when industry-specific PPP exchange rates are used. As indicated above, industry-specific PPP exchange rates are not available for all industries.[19] Here results qualitatively are similar with that in Column (5.1); except now both of the foreign R&D spillovers terms are significant at the 5% level.

As discussed in section 2, the diffusion process may take longer than three periods. To

[19]Industry-specific exchange rates are available only for food, beverage, and tobacco industry, equipment and machinery industry, and total manufacturing industry. For fabricated metal products industries (i.e. metal sector (ISIC 381), electrical equipment sector (ISIC 383), and transport sectors (ISIC 384)) I used equipment and machinery industry conversion factors; for all other industries which do not have industry specific PPP, I used total manufacturing PPP.

Table 6: Standardized Coefficients of Table 5.

	Extended Case (6.1)	Unadjusted TFP (6.2)	Industry PPP (6.3)	R&D Stock (6.4)	BTS Used (6.5)	US IO used (6.6)
R&D Effects from						
Own Industry (RD)	0.168*	0.170*	0.168**	0.194*	0.263*	0.269*
Other Dom Inds. (OD)	0.152**	0.135**	0.143*	0.110*	0.264*	0.271*
Same Frgn Inds. (SF)	0.117***	0.080	0.123*	0.049	0.137	0.164**
Other Frgn Inds. (OF)	0.276*	0.303*	0.273*	0.169*	0.188	0.105
Human Capital (HK)	0.252*	0.212*	0.217*	0.181*	0.299*	0.295*
Productivity Catch-up (PC)	0.091***	0.118**	0.091	0.136*	0.134*	0.153*
RD*PC	0.213*	0.178*	0.214*	0.194*	0.151*	0.141*

Notes: Dependent variable is $\triangle \ln A_{ic,t}$. * (**) [***] means the corresponding coefficient is significant at the 5% (10%) [12%] level.

address this issue, I consider the following specification

$$\begin{aligned}\triangle \ln A_{ic,t} &= \alpha_{ic} + \alpha_t + \beta^d \frac{S_{ic,t-1}}{Y_{ic,t-1}} + \beta^{od} \frac{S^{od}_{ic,t-1}}{Y_{ic,t-1}} + \beta^f \frac{S^f_{ic,t-1}}{Y_{ic,t-1}} + \beta^{of} \frac{S^{of}_{ic,t-1}}{Y_{ic,t-1}} \\ &\quad + \beta^h H + \beta^c CU + \beta^{rc} \frac{S_{ic,t-1}}{Y_{ic,t-1}} * CU + \varepsilon_{ic,t},\end{aligned}$$

where S denote R&D stocks, which are calculated by using perpetual inventory method with 10% depreciation rate (see Griliches (1980) for R&D stocks constructions). Column (5.4) presents the results of this regression. This results qualitatively are very similar to that in (5.1); with the exceptions that while foreign R&D effects from the same industries is not significant even at the 15% level, productivity catch-up term is significant at the 5% level.

In constructing the R&D spillovers terms, I used trade to output ratios as a weighting scheme. As discussed in section 2, there is an alternative scheme, proposed by Coe and Helpman (1995), used in most of the international R&D spillovers literature. In this scheme, R&D spillovers are calculated by using bilateral trade shares (see Coe and Helpman (1995) and Keller (2002b)). Column (5.5) represents results, when I used this weighting scheme in estimating the extended model. Note that here foreign R&D spillovers are not statistically significant at conventional levels. Other terms are positive and usually highly significant.

Column (5.6) repeats Column (5.5) by using the U.S. IO tables, as Keller (2002b) does. Results are very similar with that in (5.5), except R&D spillovers from the same industries in other countries now have significant effect on productivity growth. How are these results comparable with Keller's findings? He estimates a nonlinear specification between TFP and R&D stocks[20] and he compares the relative size of the marginal contributions of R&D *stocks* to productivity *levels*, i.e. $\partial A_{ic}/\partial S_{ic}^{\nu}$, for $\nu = d,\ od,\ sf,\ of$. He finds that in terms of marginal productivity of each channel, about 50% of productivity increase comes from own R&D expenditures, 30% of it comes from R&D in other domestic industries, and finally 20% from R&D expenditures in foreign industries most of which comes from other foreign industries. Notice that coefficients in this paper represent the marginal contributions of R&D *intensities* to productivity *growth*. Thus, coefficients in Column (6.6) are not one-to-one comparable with his. But it is encouraging to see that under both approaches domestic sources play the most significant role. The effects of foreign R&D spillovers are different than the Keller's findings: while he finds that other foreign industries contribute more significantly to TFP level, this source does not have a significant effect to the TFP growth in my case (i.e. Column (5.6)).[21]

How important is to use common IO tables for all countries? Comparison of Column (5.5) with (5.6) gives a partial answer to this question. Although with U.S. IO tables the model fits data slightly better than the model with country-specific IO tables, some estimates and their significance are different under these two cases. These differences become more obvious when the standardized coefficients in columns (6.5) and (6.6) are compared. I have also experimented by using other countries IO tables instead of the U.S. and conclusion remain mostly the same: using common IO tables for all countries, the fit can be as good as the main results, but the point estimates and standardized coefficients (especially, of foreign

[20]Specifically, he estimates $\ln A_{ic} = \alpha_{ic} + \alpha_t + \beta \ln\left(S_{ic}^{d} + \beta^{od} S_{ic}^{od} + \beta^{sf} S_{ic}^{sf} + \beta^{of} S_{ic}^{of}\right)$, where S_{ic}^{ν}s denote R&D stocks for different sources, which are calculated by using bilateral trade shares, see Keller (2002b)

[21]His finding about the effect of spillovers from other foreign industries is not robust. When he uses technology flow matrix, which is based on patent data, this effect becomes insignificant at the 10% level and its contribution declines by 50%.

R&D effects) are significantly different across each specification.[22]

5 Concluding Remarks

In this paper, I have addressed the problem of R&D spillovers in a panel of OECD industries. I developed a simple and econometrically tractable model in which the technology flows among industries through trade in goods. This model incorporates four different types of R&D investments that might affect productivity growth. The first one is the effect of R&D conducted in an industry itself, the second is the effect of R&D conducted in the same industries in other countries, the third is the effect of R&D conducted in other domestic industries that supply inputs, and the fourth is the effect of R&D conducted in other foreign industries that supply inputs. I examine the significance of each of these sources for productivity growth in a panel of twelve industries in ten OECD countries between 1973 and 1994. The model is further extended by incorporating human capital and productivity catch-up effects.

My analysis shows that among these four different R&D effects the most important contributions are coming from domestic R&D efforts. Own R&D is found to be important for both domestic innovation and for the productivity catch-up process. Although international R&D spillovers have positive effects on productivity growth, these effects are not robust. My analysis also shows that human affects productivity directly as factor of production.

There are several directions that the present work can be extended. First, my human capital treatment was incomplete in two dimensions. I used country level education data instead of industry specific educational attainment and I did not take into account differences in skill composition of labor. Construction of industry level skill composition and education attainment data sets will be an important task in its own right. Once we have this data, the role of human capital can be addressed properly (see works by Harrigan (1999), Machin and Van Reneen (1998), and Griffith et al. (2004), where to some extent they incorporate

[22]The same conclusion holds even under first weighting scheme. Results are available upon request to the author.

these additional adjustments).[23]

Second, although bilateral trade data shows flows of goods at the industry level, these industries include many goods for which the technology content is relatively low. Consequently their role in transferring technologies will not be significant. For example, for a panel of OECD countries, Xu and Wang (1999) convincingly argue that trade in capital goods is more appropriate to assess the impact of international R&D spillovers. In the present context, the appropriate approach is to look at detailed technology content of each industry, and consider only trade in goods which have higher technology content. Third, some other channels could also be incorporated into this model. Lichtenberg and de la Potterie (2001), for example, investigate the significance of inward and outward foreign direct investment (FDI) along with trade as conduits for R&D spillovers. Keller (2001), on the other hand, considers the importance of trade, distance, and FDI in transmitting technologies. Incorporating these additional channels and investigating the significance of each will be an important step.

[23]To construct labor data adjusted for skill is more feasible than the first task. The United Nations has UNIDO database which shows wage bills of production and nonproduction workers in individual industries. Following Harrigan (1999) and Jorgenson and Fraumeni (1992), one can construct quality-adjusted labor input as translog index of two types of labor: production and nonproduction workers. Machin and Van Reneen (1998) have constructed industry-level education data from census surveys for seven OECD countries. However, this data set is not publicly available.

A Data Sources and Construction

The data in this chapter covers ten countries and twelve manufacturing sectors over the period of 1973-1995. The sample of countries, industries, and time coverage I used in my analysis was dictated by the availability of the data.

A.1 Data on Production, Capital Stocks, and Labor

Data on production, capital formation, and labor (number of employees) was taken from the STAN databases (1998d) and (2002). One of the important points in productivity analysis is the comparability of price deflators of sectors across countries. When the quality dimension has been taken into account in calculation of price deflators, the quality-adjusted (hedonic) deflators exhibit rapid deflation. From the STAN database manual it was not clear for which of these countries and to what extent deflators were used. My research suggests that the price deflators of the electrical equipment (ISIC 383) sectors of Japan, the UK, and the US might have been quality-adjusted. In Japan, for example,the price deflator declines about 300% between 1975 and 1990. In these cases, I have used the (simple) average of the price deflators of metal products (ISIC 381), non-electrical machinery and professional products (ISIC 382/5), and transport equipment (ISIC 384).

The STAN investment data was multiplied by a gross fixed capital formation price deflator of total manufacturing sector derived from the ISDB (1998c).[24] After constructing the real gross fixed capital formation for each sector in each country, I estimated capital stocks by using the perpetual inventory method,

$$K_{ic,t+1} = (1-\delta)K_{ic,t} + I_{ic,t}, \quad \forall i,\ c,\ t, \tag{12}$$

where K, I, and δ denote the capital stocks, investment, and depreciation rate, respectively; subscripts i, c, and t denote industry, country, and time. Benchmark capital stock series were calculated by

$$K_{ic,1970} = \frac{I_{ic,1970}}{g_{ic} + \delta}, \tag{13}$$

[24]For Japan, gross fixed capital formation price deflator was not available and I used aggregate gross fixed capital formation price deflator derived from annual National Accounts.

where g_{ic} is the average growth rate of investment series over 1970-1990. The depreciation rate was set to 8%, which is the average of the depreciation rates of equipment and machinery (11.68%) and non-residentially buildings (3.14%) (see Katz and Herman (1997)).

For the number of workers I used STAN (1998d) database.[25] The employee data includes all people engaged in production. The average annual hours per manufacturing worker were taken from Gronningen Industry Database and ISDB (1998c) database.

Data on the percentage of adult population that has attained higher education from Barro and Lee (2002) educational attainment database. Following Harrigan (1997) and Griffith et al. (2004), I have linearly interpolated the data.

A.2 Data on R&D Expenditures

Data on R&D expenditure comes from OECD ANBERD (1998a) database. The data covers both publicly and privately funded business enterprise R&D expenditures over the period of 1973-1997.[26] R&D expenditures also cover compensation for labor done in R&D sector, which is estimated to comprise (about) 50% of total R&D expenditure, Coe and Helpman (1995). One of the most important issues in constructing R&D intensity is finding an appropriate deflator for R&D expenditures. For each industry, following Coe and Helpman (1995), I assume that its R&D deflator is the simple average of the wage index and the industry output deflator. I used the aggregate manufacturing price deflator as a proxy to the wage index.[27] I have used whole-economy PPP to convert real R&D expenditures into internationally comparable levels.

[25] A few missing values were estimated from STAN (2002) employment trends.

[26] The data for Federal Germany R&D is available until 1993. The ANBERD database, however, contains total R&D expenditure conducted in unified Germany since 1991. Using the growth rate of R&D expenditures in unified Germany in 1993, I estimated R&D expenditure of Federal Germany for 1994.

[27] I have also experimented by using sectoral output deflator as R&D expenditure deflator, which is another common practice in R&D literature, see for example Machin and Van Reenen (1998) and Griffith et al. (2004). The estimated coefficients and their statistical significance remained by and large the same as the main results.

A.3 Data on Bilateral Trade

Data on bilateral trade comes from OECD BTD (1998b) database. The database covers the values of bilateral imports from all other OECD countries, and as well as some other partner countries in thousands of dollars at current prices over the period of 1970-1995.[28]

A.4 Data on Input-Output Tables

The data on domestic and imported goods flows come from the OECD (1995) and OECD (2005) IO databases. To my best knowledge, I am the first who use the second one. The most appealing feature of the IO database is that it covers both domestically produced and imported interindustrial flows of goods and services. There are two important issues with IO tables. First, the benchmark IO tables are usually (but not necessarily) constructed by five or seven years intervals. Therefore, the database does not contain yearly IO tables for countries. Moreover, the database is not covering all countries IO tables in a time-consistent manner. But for all countries except Italy, the database contain IO tables at least for three different years. In particular, it contains one set of IO tables for a year in late seventies (usually for 1977), and one set for a year in mid-eighties (usually for 1985), and one set for early nineties (usually for 1985). I used 1977 IO tables for 1973-1980, 1985 IO tables for 1981-1987, and 1990 IO tables for 1988-94 periods.[29] I also experimented by using these time varying IO tables, but qualitative results remain by and large the same. Second, the import IO tables show the distribution of total imports, i.e. the total imports from the rest of the world, not from the partner countries in our sample. Consequently, in the empirical implementation, I will assume import IO table coefficients for my sample will be the same as the import IO table coefficients in the IO database.

[28]For Federal Germany, data is available until 1991. I used United Germany trade flows in my analysis for the period between 1991-1994. From various sources I estimated the flow of trade for some industries for Federal Germany for the period of 1991-1994, but those flows were 5% to 10% less than the United Germany total flows. Consequently, their impact on my estimates was limited.

[29]For Italy, I had IO tables for two years: one for 1985 and another for 1992. I estimated missing years by using these two available table sets along with other IO tables for other countries.

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