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HOW TRADE PATTERNS AND TECHNOLOGY FLOWS AFFECT PRODUCTIVITY GROWTH

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ABSTRACT

This paper examines the evidence on technology diffusion through trade in differentiated intermediate goods. Because intermediates are invented through costly research and development (R&D) investments, employing imported intermediates implies an implicit sharing of the technology that was created in other countries. The model predicts that the import patterns of countries matters for productivity, because a country that imports primarily from technological leaders receives more technology embodied in intermediate goods than another that imports primarily from follower countries. I try to quantify the importance of trade patterns in determining technology flows that affect productivity by using industry level data for machinery goods imports and productivity in eight OECD countries between 1970-91. First, there is evidence that these countries benefit more from domestic R&D than from R&D of the average foreign country. Second, conditional on technology diffusion from domestic R&D, the import composition of a country matters, but only if it is strongly biased towards or away from technological leaders. Third, I estimate that differences in technology inflows related to the countries' patterns of imports explain about 20% of the total variation in the countries' productivity growth. The implications of these findings for developing countries are discussed.

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1. Introduction

There is wide agreement among economists today that differences in physical and human capital accumulation alone do not explain the large variation in economic growth across countries. The important complementary role of technological diffusion in achieving higher rates of economic growth has long been recognized, but little is known about the specific policies which promote such diffusion, particularly at the international level.

A widely held view is that international trade leads to faster technological diffusion and to higher rates of productivity growth (e.g., Helpman 1997). While this would be important for all countries, it has dramatic implications for less developed countries as they seek to catch up with the technological leaders in the OECD. International agencies such as the World Bank routinely recommend policies that foster international trade, in part because it is presumed to benefit international technology diffusion (World Bank 1991, 1998). However, there is little sound evidence to support this view to date.[1]

The recent development of theories of endogenous technological change, in particular by Romer (1990) and Aghion and Howitt (1992), has triggered new analyses of the relation of trade, growth, and technological change in open economies (Grossman and Helpman 1991, Rivera-Batiz and Romer 1991). In this work, the authors embed the recent theories in general-equilibrium models to analyze the impact of both trade in intermediate as well as final goods on long-run growth. Technology diffuses in this framework through being embodied in intermediate inputs: If research and development (R&D) expenditures create

[1] See the review of the literature below, as well as Aghion and Howitt (1998) for a broader discussion.

new intermediate goods which are different (the 'horizontally differentiated inputs' model) or better (the 'quality ladder' model) from those already existing, and if these are also exported to other economies, then the importing country's productivity is increased through the R&D efforts of its trade partner.

The framework suggested by these models is well-suited to study empirically how trade patterns determine technology flows that trigger productivity growth, and the impact of importing a new (or better) type of intermediate product might take various forms. First, the possibility of employing a larger range of intermediate inputs in output production allows for a productivity-enhancing increase in the degree of specialization in intermediate inputs production. To the extent that the importing country succeeds in not paying in full for this increase-in-variety, it is reaping an external benefit, or, "spillover" effect. Secondly, the import of specialized inputs might facilitate learning about the product, spurring imitation or innovation of a competing product.

In this paper, I will use data on the G-7 group of countries[2] plus Sweden to evaluate these mechanisms. The traded goods here are machinery inputs for manufacturing industries; these inputs are usually differentiated and imperfect substitutes, as in the model mentioned above. In addition, they are often highly specialized for a particular industry, implying that the elasticity of substitution between inputs produced for two different industries is negligible.

In this setting, I ask whether productivity growth in an importing country is increased

[2]These are: Canada, France, Germany, Italy, Japan, the U.K., and the U.S.

by the R&D investments–leading to a larger variety of differentiated machinery–of its trade partners. It is clear that the pattern of trade in intermediate inputs is a central element of this technology diffusion hypothesis. Both the 'increasing variety' as well as the 'reverse-engineering' effects are tied to arm's length market transactions of goods.[3]

The first hypothesis concerns the composition of imports by partner country: Countries which import to a larger extent from high-knowledge countries should, all else equal, import on average more and better differentiated input varieties than countries importing largely from low-knowledge countries. Consequently, this should lead to relatively higher productivity levels in the former countries. Second, for a given composition of imports, this effect is likely to be stronger, the higher the overall import share of a country is.

However, there are many reasons why a higher import share (or, more 'openness') might lead to higher growth rates, some of which have little to do with international technology diffusion (see e.g. Edwards 1993). Because the prediction that the import composition matters is shared by fewer other models than that high overall imports are beneficial, focusing on the former is a more direct approach to address the question whether trade is an important determinant of international technology diffusion than an emphasis on the overall import share effect. For the same reason, examining the import composition effect is a more powerful test of the recent trade and growth models than studying overall import effects.[4]

A number of recent papers have attempted to assess the importance of imports in trans-

[3]Of course, there are other mechanisms of international technology diffusion that do not depend on imports, for instance, foreign direct investment (FDI) inflows; on FDI, see Lichtenberg and van Pottelsberghe (1998b) as well as Wang and Xu (1996), for instance.

[4]For further discussion of the implication of such 'model identification problems', see Evenett and Keller (1998).

mitting foreign technology into domestic industries and spurring total factor productivity (TFP) growth, including Coe and Helpman (1995), Coe et al. (1997), Evenson (1995), Keller (1997, 1998a, 1998b), as well as Lichtenberg and van Pottelsberghe (1998a).[5] In Coe and Helpman (1995), the paper that started this literature, the authors find a significantly positive correlation between TFP levels and a weighted sum of partner country R&D stocks, where bilateral import shares serve as weights.[6]

The interpretation of this finding is not clear, though, because Keller (1998b), using the same data, finds that the role played by the countries' composition of imports in obtaining this result is limited: Alternatively weighted R&D stocks–where import shares are created randomly–also lead to a positive correlation between foreign R&D and the importing country's R&D, and the average correlation is often larger than when foreign R&D is weighted using observed import shares.[7]

While making the point that the correlations of Coe and Helpman (1995) do not depend on the observed patterns of imports between countries, the results of Keller (1998b) do not imply that R&D spillovers are unrelated to international trade. First, these papers use aggregate import data to compute the trade share weights for a given importing country. Overall import relations between countries, however, are likely to be a very poor measure

[5]The papers by Park (1995), Bernstein and Mohnen (1998), and Branstetter (1996) are also estimating international R&D spillovers, but do not contain an explicit argument with respect to international trade. See also the paper by Eaton and Kortum (1998).

[6]Coe and Helpman (1995), as well as other authors, do not only consider the import composition effect, but also the technology inflow effect resulting from the level of imports, with the import composition given: both might contribute importantly to international technology diffusion. In this paper, however, I focus primarily on the import composition effect, for the model identification reasons mentioned above.

[7]Keller (1998b) and Coe et al. (1997) also report regressions of TFP on unweighted R&D stocks, something that also Coe and Helpman had considered (1995, p.864). The relation of these regressions to the analysis in this paper will be discussed in section 5 below.

of intermediate inputs trade relations. Second, most R&D is conducted in only a relatively small set of manufacturing industries (e.g., OECD 1991). This means that an analysis at the country level does not allow as strong inferences as might be possible at a more disaggregated level. Third, common trends and shocks that affect R&D and productivity simultaneously might lead to spurious regression results that cloud any 'real' international technology diffusion that is related to trade patterns. Finally, even if trade patterns are not the only determinants of international technology diffusion, it is necessary to quantify their contribution in order to assess the relative importance of trade patterns.

In this paper I conduct an analysis of R&D, imports, and productivity at a two- and three digit industry level. At this level of aggregation, one is much more likely to observe trade flows embodying new technology than at the country-level. Further, estimation results for both TFP level as well as TFP growth rate specifications are presented, addressing some of the open questions concerning common trends and simultaneity.[8] I also extend the Monte-Carlo analysis conducted by Keller (1998b), showing how such experiments are related to estimating an overall spillover effect from foreign R&D. This allows to determine whether there exists a part of international R&D spillovers that is related to trade patterns.

The main findings are the following: First, there is evidence that these countries benefit *more* from domestic R&D than from R&D of the average foreign country. Second, conditional on technology diffusion from domestic R&D, the import composition of a country matters, but only if it is *strongly biased* towards or away from technological leaders. Third,

[8]In the appendix I also report different sets of auxiliary regressions that analyze the robustness of the findings.

I estimate that differences in technology inflows related to the countries' patterns of imports explain about 20% of the total variation in the countries' rates of productivity growth. The implications of these findings for developing countries are discussed in the concluding section of this paper.

In the next section, I briefly describe the theoretical framework that motivates the empirical analysis. Section 3 contains a discussion of the characteristics and construction of the data. In section 4, the empirical results are presented, and contrasted with those of the corresponding Monte-Carlo experiments. The following section shows how the estimates of overall international R&D spillovers are related to the findings in the Monte-Carlo experiments; I also demonstrate how the marginal contribution of the import composition can be separately identified from the average spillover effect. Section 6, finally, concludes.

2. Theoretical Framework

The following gives a minimal background of the recent theory that guides the empirical analysis in this paper.[9] Long-run growth is endogenously determined by R&D investments, and technology is transmitted via trade in intermediate inputs. Assume that a country's output is produced according to

$$z = A l^{\alpha} d^{1-\alpha}, \; 0 < \alpha < 1 \tag{2.1}$$

[9]See Aghion and Howitt (1992), Grossman and Helpman (1991), Rivera-Batiz and Romer (1991), and Romer (1990); the books by Barro and Sala-i-Martin (1995) and Aghion and Howitt (1998) offer broader perspectives on the topic.

where A is a constant, l are labor services, and d is a composite input consisting of horizontally differentiated goods x of variety s :

$$d = \left(\int_0^{n^e} x(s)^{1-\alpha} \, ds \right)^{\frac{1}{1-\alpha}} . \tag{2.2}$$

The variable n^e denotes the range of intermediate inputs which are *employed* in this country; it can be distinct from n, the range of intermediate inputs *produced* in this country. The latter is increased by entrepreneurs devoting resources to R&D (χ). If R&D capital does not depreciate, the range of intermediates at time T will equal

$$n(T) = \int_{-\infty}^{T} \chi(t) \, dt, \tag{2.3}$$

that is, the cumulative resources devoted to R&D up to time T; I define $n(T) \equiv S(T)$.

The goods $x(s)$ are best thought of as differentiated capital goods; they are produced with foregone consumption, or capital, denoted k. Under certain conditions, one can express the total intermediate input usage d in terms of capital k, and write, using (2.1), a reduced-form expression for output as

$$z = A \; (n^e)^{\alpha} \, l^{\alpha} \; k^{1-\alpha}. \tag{2.4}$$

If F is total factor productivity (TFP), defined as $F \equiv \frac{z}{l^{\alpha} \, k^{1-\alpha}}$, equation (2.4) together with this definition leads to

$$\log F = \log A + \alpha \log n^e. \tag{2.5}$$

Equation (2.5) shows that productivity is positively related to the size of the employed product variety.

With many countries, $v = i, h, .., V$, foreign intermediates will be imported in exchange for domestic varieties. This implies that each country employs a larger range of intermediate goods than it produces itself. In this sense, the possibility of trade allows each country a greater degree of specialization in intermediate goods production than would be possible without trade. This increases productivity because the constant elasticity of substitution-specification in equation (2.2) implies that for a given amount of primary resources, output is increasing in the range of differentiated inputs (Ethier 1982). International trade leads to increases in productivity because *only one* country has to invent any new product variety (by spending the fixed R&D cost χ), whereas *potentially all* countries can employ the new product by importing it, thereby benefiting from the new foreign technology.

When there are many countries and industries, denoted $j = 1, ..., J$, the composite input d of country i's industry j, d_{ij}, is given by

$$d_{ij} = \left(\int_0^{n^i_{ij}} x^i_{ij}(s)^{1-\alpha}\, ds + \gamma^i_{hj} \int_0^{n^i_{hj}} x^i_{hj}(s')^{1-\alpha}\, ds' + ...+ \right)^{\frac{1}{1-\alpha}}. \tag{2.6}$$

Here, $x^i_{ij}(s)$ denotes the quantity of an intermediate of variety s used in sector j. The country in which the intermediate is produced is given by the subscript, whereas the superscript denotes the country in which the intermediate is employed. Similarly, n^i_{ij} gives the range of domestically produced intermediate goods utilized in country i's good j production, and n^i_{hj} is the range of goods that country i imports from country h. The variable γ^i_{hj} determines the degree of substitutability between intermediates of country h and domestic intermediates in country i's industry j. If the substitutability is perfect, then the γ's are equal to one.[10]

For simplicity, theoretical work so far has largely concentrated on one-industry, two-country models (e.g., Rivera-Batiz and Romer 1991, Keller 1996).[11] In consequence, empirical work using a multi-country, multi-industry setting has usually not estimated structural equations of such a model of trade, technology diffusion, and growth. Rather, to go from the structural relationship of productivity and R&D in the one-sector closed-economy model, equation (2.5), to the multi-country, multi-industry context, authors have related productivity not only to domestic, but also foreign R&D, $w \neq v$:

$$F_{vj} = \Psi(n_{vj}^{v}, n_{wj}^{v}) = \Phi\left(S_{vj}, S_{wj}, ..., ...\right), \forall v, j,$$

where $\Psi(.)$ and $\Phi(.)$ are unknown functions.

However, the model of intermediate inputs trade predicts that productivity in country v is related to R&D in country $w \neq v$ only to the extent that country v employs imported intermediates from country w. This should depend on country v's bilateral import share from w, denoted m_{w}^{v}, (the import composition effect) as well as country v's overall import

[10] I assume that only inputs of type j are productive in any country's j sector, corresponding to the often highly specialized nature of machinery inputs for particular industries. A study that also examines inter-industry technology flows is Keller (1998a).

[11] Exceptions to this include Grossman and Helpman (1990), Feenstra (1996), and Aghion and Howitt (1998, Ch. 12).

share, which is denoted by m_v. At the industry level, this means:

$$F_{vj} = \Phi\left(S_{vj}, S_{wj}, m_{vj}, m_{wj}^v\right), \forall v, j. \tag{2.7}$$

One can think of the import shares in (2.7) as indicating the probability of receiving a new type of foreign intermediate. This is certainly the right interpretation in the extreme case when $m_w^v = 0$. Other than that, there is no necessary link between the level of imports and the number of newly introduced intermediate goods types in the local economy.[12] However, Grossman and Helpman (1991, Ch. 6.5) discuss several reasons of why it is likely that the number of new varieties employed from a partner country is positively related to the import volume from that country. This is also the assumption that guides the empirical specifications in section 4 below.

3. Data

This paper employs data for eight OECD countries in six sectors according to the International Standard Industrial Classification (ISIC) as well as the Standard International Trade Classification (SITC), for the years 1970-1991. The included countries are Canada, France, Germany, Italy, Japan, Sweden, the United Kingdom, and the United States; hence, the G-7

[12]Especially if one also considers indirect effects, such as the possibility that importing leads to local learning through reverse engineering and the subsequent invention of new inputs, it becomes clear that the *volume* of imports is an imperfect measure of the increase in varieties which are available domestically. An interesting alternative, although not without problems of its own, has been considered by Klenow and Rodriguez (1996) who postulate that the number of different intermediate good varieties is related to the number of different trade partners a country has.

group plus Sweden.[13]

I use the following breakdown by sector (adjusted revision 2): (1) ISIC 31 Food, beverages, and tobacco; (2) ISIC 32 Textiles, apparel, and leather; (3) ISIC 341 Paper and paper products; (4) ISIC 342 Printing; (5) ISIC 36 & 37 Mineral products and basic metal industries; (6) ISIC 381 Metal products. All sectors belong to ISIC class 3, that is, manufacturing. In these sectors, the reliability and comparability of the measurement of inputs and outputs is high compared to non-manufacturing sectors.

The data on imports of machinery comes from the OECD *Trade by Commodities* statistics, OECD (1980). I have tried to identify machinery imports which will with high likelihood be utilized exclusively in one of the above manufacturing industries. These commodity classes are (Revision 2) SITC 727: Food-processing machines and parts, providing inputs to the ISIC 31 industry; SITC 724: Textile and leather machinery and parts (corresponding to ISIC 32); commodity class SITC 725: Paper & pulp mill machinery, machinery for manufacturing of paper (corresponding to ISIC 341); commodity class SITC 726: Printing & bookbinding machinery and parts (corresponding to ISIC 342); commodity classes 736 & 737: Machine tools for working metals, and metal working machinery and parts (corresponding to ISIC 381); and, by SITC classification, Revision 1, commodity classes 7184 & 7185: Mining machinery, metal crushing and glass-working machinery (corresponding to ISIC 36 & 37). The bilateral trade relations for these SITC classes are given in full in Tables A-1 to A-6 in the appendix.

[13]See the appendix for more details on data sources and the construction of the variables.

Data from the OECD (1991) on R&D expenditures by sector is utilized to capture the ranges of intermediate inputs, n. This data covers all intramural business enterprise expenditure on R&D. Because none of these industries has a ratio of R&D expenditures to value added of more than 0.5%, it is reasonable to assume that insofar as their productivity benefits from R&D at all, it will be to a large extent due to R&D performed outside the industry. However, there is no internationally comparable data on machinery industry R&D towards products which are used in specific industries. Therefore, I assume that R&D expenditures towards a sector j's machinery inputs is equal to a certain constant share of the R&D performed in the country's non-electrical machinery sector (ISIC 382), where all specialized new machinery inputs are likely to be invented.[14] R&D stocks are derived from the R&D expenditure series using the perpetual inventory method, and descriptive statistics on the cumulative R&D stocks are given in the appendix, Table A-7.

The TFP index is constructed using the *Structural Analysis Industrial (STAN) Database* of the OECD (1994). The share parameter α is, by profit maximization of the producers, equal to the ratio of total labor- to production costs. As emphasized by Hall (1990), using cost-based rather than revenue-based factor shares ensures robustness of the TFP index in the presence of imperfect competition, as in the model sketched above. Building on the integrated capital taxation model (see Jorgenson 1993 for an overview), I construct cost-based labor shares. The variable l is the number of workers engaged, directly from the *STAN* database. The measure of y is gross production, which also comes from the *STAN*

[14]This constant share is the share of an industry in employment in total manufacturing employment, over the years 1979-81; the employment data is from OECD (1994).

database. The growth of the TFP index F is the difference between output and factor-cost share weighted input growth, with the level of the F's normalized to 100 in 1970 for each of the 8×6 time series. In Table A-8 of the appendix, summary statistics for the TFP data are shown.

4. Estimation Results

I will now present estimation results for different specifications of the function $\Phi(.)$ in equation (2.7) above. The first section discusses TFP level estimation results, whereas below, I report estimation results for TFP growth rate regressions.

4.1. TFP Level Specification

Consider the following specification

$$\log F_{vjt} = \mu_j d_j + \delta_v d_v + \sum_{c \in G7S} \beta_c \left(m_{cj}^v \log S_{cjt} \right) + \varepsilon_{vjt}, \forall v, j, t. \tag{4.1}$$

Here, the t subscript indexes a period t, and c indexes any of the eight G-7 plus Sweden countries in our sample (denoted as the set $G7S$ in equation 4.1). Further, d_j and d_v are industry-, and country- fixed effects, respectively. In this specification, the TFP level in any industry is related to cumulative R&D of the same industry in all eight countries. The domestic weight, $m_{vj}^v, \forall v, j$, is set to one, and the weights of the partner countries are given by the bilateral import shares: $\sum_{w \neq v} m_{wj}^v = 1, \forall v, j$. The eight country-elasticities β_c are constrained to be the same across importing countries.[15]

In equation (4.1), the import shares pick up differences in import composition across countries, which according to the theory affect the degree to which the importing country benefits from foreign technology. The specification also implies that two countries with the same import composition but different overall import shares benefit to the same degree from foreign R&D–which is unlikely if a higher overall import share increases a country's chance to benefit from foreign technology. Following Coe and Helpman (1995), the contribution of a country's openness to imports for a given import composition can be modeled through including the overall import share, m_{vj}, into the specification[16]

$$\log F_{vjt} = \mu_j d_j + \delta_v d_v + \sum_{c \in G7S} \beta_c \left(m_{vj} \, m_{cj}^{v} \log S_{cjt} \right) + \varepsilon_{vjt}. \tag{4.2}$$

I will refer to a specification without the overall import share, as in (4.1), as NIS, whereas a specification with the overall import share is referred to as IS.[17]

Both specifications, equations (4.1) and (4.2), might be subject to simultaneity and omitted variable bias. Either of these two problems would imply that the ordinary least

[15]Estimating eight β_c parameters differs from Coe and Helpman (1995) who instead estimate one parameter for the effect from foreign R&D. In addition, here, the bilateral import shares enter linearly, not logarithmically.

[16]For the own R&D effect, m_{vj} is chosen such that $m_{vj} \, m_{vj}^{v} \log S_{cjt} = \log S_{cjt}, \forall v, j, t$, i.e., m_{vj} then equals one.

[17]Lichtenberg and van Pottelsberghe (1998a) criticize Coe and Helpman's (1995) specification with the overall import share, IS in my notation, because it implies an indexation bias. Their criticism does not apply here, because I have not indexed the R&D stocks. Lichtenberg and van Pottelsberghe (1998a) also point out that Coe and Helpman's weighing scheme suffers strongly from an aggregation bias (country mergers or break-ups would affect the estimated spillovers strongly). I have not investigated this question in the present context, but Wang and Xu (1996) contains a comparison of the weighing schemes proposed by Coe and Helpman (1995) and of Lichtenberg and van Pottelsberghe (1998), as well as a third which is proposed by Wang and Xu (1996) themselves.

squares (OLS) estimates are inconsistent, because the regressors and the error term are then correlated. One aspect of this is that because productivity and R&D are both trending upwards over time, part of the estimated correlation between the variables in (4.1, 4.2) could be due to a common trend. In addition, the error could also contain price or demand shocks that affect productivity and R&D jointly.[18]

To some extent, however, these problems can be reduced by imposing reasonable a priori restrictions on the dependent variable, TFP.[19] Further, the importance of spurious correlation due to common trends can be assessed by comparing level regressions with results from growth regressions which I present in the next section, because in the latter, the time-differencing eliminates common trends.[20]

Even with a growth specification, however, there is still the possibility that exogenous shocks in the error are correlated with changes in R&D activity. The solution to this problem is typically instrumental variable (IV) estimation. However, a standard choice for instrumenting quantity series, namely real factor prices, is not available in the R&D context. Moreover, it is hard to obtain data on other variables that would provide goods instruments for cumulative R&D stocks that exist for all countries, industries, and years in this sample.

If no good instruments are available, consistent parameters can still be estimated in the panel context through the inclusion of a full set of fixed effects, provided the error can be decomposed into a permanent component that affects the regressor and into another, tempo-

[18]In the following I draw on Griliches (1979, 1995).

[19]See the appendix for some details. Several of my choices are designed to reduce the probability of spurious spillover findings that have been alleged, e.g., by Basu and Fernald (1995) in a different context.

[20]In appendix E, I also discuss TFP level regressions that include time fixed effects, for comparison purposes.

rary, component that does not: the part of the error that is correlated with the regressor will then be subsumed into the estimated fixed effect. However, Griliches and Hausman (1986) show that this procedure of including a large number of fixed effects exacerbates errors in variables problems, which are also likely to be present in this context. The productivity level specifications above together with the growth specifications reported below represent a compromise among these considerations, and further auxiliary regressions are discussed in appendix E.

Results for the specifications (4.1) and (4.2) are given in Table 1, with standard errors in parentheses; a **(*) denotes that a parameter is significantly different from zero at a 5(10)% level. From Table 1, one sees that all countries' R&D stocks are estimated to have a significant and positive influence on the TFP level of the receiving country. The magnitude of these effects, however, varies substantially, with, e.g. for the second specification, a low for Germany with 1.9%, and a high for R&D from Sweden, with 27.6%. The specifications account for a third to one half of the variation of the TFP indices across countries, with the higher R^2 for the NIS specification.

One might ask whether the results really say anything about the international diffusion of technology: to what extent do these results depend on correlating TFP to R&D, as opposed to physical capital, for instance? Perhaps technology is embodied in the physical capital stocks of the countries, and correlating TFP to foreign capital stocks would produce similar results as correlating productivity to foreign R&D. To examine this, I have constructed these physical capital stocks, denoted by K_{vjt}, and used them instead of the R&D stocks S_{vjt} in the specifications (4.1) and (4.2).[21] In the NIS specification (4.1), the result of substituting K_{vjt} for S_{vjt} is a drop in the R^2 from 0.472 to 0.169, and for the IS specification (4.2), the R^2 also falls substantially, from 0.357 to 0.179. Thus, variation in R&D levels accounts for much more of the variation in TFP levels, suggesting that cumulative R&D captures better the economies' stocks of technology than physical capital does.

The result that high stocks of weighted foreign R&D are associated with high domestic levels of productivity is interesting, but as such it does not say much about the importance of the fact that the weighing variables are the observed bilateral import shares. Interpreting these shares as the probability that the importing country receives new intermediate inputs from a partner country, a natural question to ask is how the estimated parameters would look like if we had employed a different set of probability weights, corresponding to different import patterns. This is what the following Monte-Carlo experiments show.[22]

Here, I address two different questions: First, conditional on the effect from domestic R&D on productivity, is there evidence to assume that the composition of intermediate imports trade matters for productivity growth across sectors? Second, is there support for the hypothesis that there is a distinction between effects on productivity resulting from foreign as opposed to domestic R&D?

[21]The variables K_{vjt} are based on the estimated capital stocks in the non-electrical machinery industry of the countries (ISIC 382); their construction is analogous to the R&D stocks S_{vjt}, see section 3 above.

[22]Another approach to gauge the importance of the m^v_{cj} might be to simply drop them from specifications (4.1) and (4.2). In the specification corresponding to (4.1), only two out of eight parameters β_c are estimated to be significantly different from zero, that of Japan at -2.02, and that of the U.S., with 1.37. If the bilateral import shares in (4.2) are dropped, then only the parameters β_c for Germany, Italy, and Sweden are significantly positive, while that for France is significantly negative and those of the other countries are not significantly different from zero. Clearly, according to this test, the bilateral import shares matter. What is not clear so far, however, is that the import composition matters, too, or only the fact that the m^v_{cj} are not equal to one; see the analysis below.

4.1.1. Does the productivity performance reflect the composition of intermediate imports?

In the following experiments, I will exchange the bilateral import shares of a given importing country randomly. Let b denote a specific Monte-Carlo replication, $b = 1, ..., B$. The experiments are constrained such that only the composition of the international demand is randomized. That is, the results are conditional on the domestic R&D effect: $\theta_{vj}^{v}(b) = 1, \forall v, j, b$. For all $w \neq v$, this means

$$\theta_{wj}^{v}(b) = m_{qj}^{v} \text{ with } \Pr = \frac{1}{7}, \; q \in G7S \setminus v, \forall v, w, j. \tag{4.3}$$

The $\theta_{wj}^{v}(b)$ are constructed such that $\sum_{w} \theta_{wj}^{v}(b) = 1$, that is, any observed import share is assigned only once.[23] The two specifications are

$$\log F_{vjt} = \mu_j d_j + \delta_v d_v + \sum_{c \in G7S} \beta_c \left(\theta_{cj}^{v}(b) \log S_{cjt}\right) + \varepsilon_{vjt}, \forall v, j, t, b, \tag{4.4}$$

and

$$\log F_{vjt} = \mu_j d_j + \delta_v d_v + \sum_{c \in G7S} \beta_c \left(m_{vj}\, \theta_{cj}^{v}(b) \log S_{cjt}\right) + \varepsilon_{vjt}, \forall v, j, t, b. \tag{4.5}$$

[23] For a given industry and importing country, I draw seven numbers from a uniform distribution with support $[0, 1]$. These are matched with the seven observed import shares to form a 7×2 matrix. This matrix is then sorted in ascending order on the random number column. In this way, the probability that any import share $\sigma_{wj}^{v}(b)$ is equal to the value m_{wj}^{v}, all w, is equal to 1/7. A new sequence of trade relations (the seven numbers from the uniform distribution with support $[0, 1]$) is drawn for every importing country and every industry, making a total of $8 \times 6 = 48$ independent sequences.

The results of these two experiments, for $B = 1000$, are shown in result columns two and five of Table 2. Displayed are the averages $\beta_c(\bar{b})$ and the standard deviation of $\beta_c(\bar{b})$, in parentheses, for each of the eight R&D stocks. The average estimates of β_c are, in 75% of the cases, significantly different from zero and positive. In addition, these coefficients are sometimes smaller, and sometimes larger than those obtained employing observed import shares: no clear pattern can be detected. Moreover, the regressions which employ randomly exchanged import shares account for a slightly higher share of the variation in productivity levels than the observed-import share regressions.

The fact that it is not necessary to impose the observed import shares to estimate significant international R&D spillovers parallels the finding of Keller (1998b) that one cannot test the hypothesis of the R&D-trade pattern-TFP link by simply examining whether the parameter estimates are positive, or how high the R^2 of these regressions is. Obviously, the regression results are to some degree invariant to the weights with which the R&D stocks are multiplied. This would be trivially so if the R&D stocks of different countries are equal in size and move together over time. However, as shown in Table A-7 in the appendix, there are considerable differences in the cumulative R&D stocks of different countries. In addition, Figure 1 shows that the R&D stocks of different countries exhibit neither growth at approximately the same rates, nor do they rise and fall simultaneously.[24] Therefore, this explanation, at least in its extreme form, cannot be the reason for the finding that the

[24] The average annual rate of growth of the R&D stock estimates ranges from 3.64% for Canada to 11.88% for Italy; and the standard deviation of these growth rates for different four-year subperiods across countries ranges from a low of 2.87% (1978-82) to a high of 5.15% (1970-74).

parameter estimates are to some extent invariant to exchanging the import shares.

Another interpretation of these results is that even though the import composition of countries matters, conditional on the effect from own R&D, its impact is limited. It is important to realize that the effect of a country's import composition on its productivity is primarily identified from particularly low and particularly high import shares. Clearly, if all countries would import from their partners to the same extent, the exchanging of bilateral import shares would have no effect on the regression results at all.

This notion will be made more precise below. At this point, it is worth noting that the parameters for R&D from Canada and the US are estimated very imprecisely and often not different from zero at standard significance levels in Table 2, equations (4.4, 4.5). This is consistent with the idea that the trade-related effect from R&D is primarily identified from countries with 'extreme' trade patterns: according to Tables A-1 to A-6 in the appendix, the US is the only country in this sample that imports a relatively large share from Canada, and conversely, Canada imports between 70-80% from the US. Hence, the US and Canadian trade patterns differ substantially from a symmetric trade pattern in which countries import equal shares from all partners. It is notably technology flows from these countries that do not significantly affect productivity anymore once the import shares are randomized.

In the following section, I will include the weight on domestic R&D into the randomization experiment to ask whether it matters for productivity whether the technology is created abroad or domestically.

4.1.2. Foreign and Domestic Intermediate Inputs: does it matter how much from where?

In these experiments, I exchange the observed bilateral shares randomly, including the weight on domestic R&D, equal to $m_{vj}^v = 1, \forall v, j$. This means that any bilateral import share in replication b, $\sigma_{cj}^v(b)$, is equal to

$$\sigma_{cj}^v(b) = \begin{cases} m_{vj}^v \text{ with } \Pr = \frac{1}{8} \\ \vdots \\ m_{Vj}^v \text{ with } \Pr = \frac{1}{8} \end{cases}, \forall v, c, j. \tag{4.6}$$

Because $m_{vj}^v = 1$ and $\sum_{w \neq v} m_{wj}^v = 1, \forall v, j$, it holds that $\sum_c \sigma_{cj}^v(b) = 2, \forall v, j$. Hence, the experiment allows to understand whether, conditional on the ex-ante chosen value for $m_{vj}^v = 1, \forall v, j$, it is important to distinguish between embodied technology in intermediate inputs from domestic, on the one hand, versus from foreign producers, on the other. The equations are

$$\log F_{vjt} = \mu d_j + \delta d_v + \sum_{c \in G7S} \beta_c \left(\sigma_{cj}^v(b) \log S_{cjt} \right) + \varepsilon_{vjt}, \forall b, v, j, t, \tag{4.7}$$

for the specification without overall import share (NIS), and, for the IS specification:

$$\log F_{vjt} = \mu d_j + \delta d_v + \sum_{c \in G7S} \beta_c \left(m_{vj} \, \sigma_{cj}^v(b) \log S_{cjt} \right) + \varepsilon_{vjt}, \forall b, v, j, t. \tag{4.8}$$

The results are shown in Table 2, third and sixth result columns. In the table, I report the average slope estimate $\beta_c(b)$ from $B = 1000$ replications, as well as the standard deviation of $\beta_c(b)$ (in parentheses) and the average R^2.

The Monte-Carlo experiments result in coefficient estimates which are in 75% of the cases statistically indistinguishable from zero at a 5% level. For the model (4.7), half of the coefficient estimates are not significant, and none of the β_c estimates for the model (4.8) is significant. The average R^2 in column two, with 0.522, is larger than for the corresponding observed-data regression. This is somewhat surprising, but the finding could well be spurious. Overall, the result that parameter estimates tend to be not significantly different from zero in the Monte-Carlo experiment implies that if intermediate input usage, from abroad or domestically, is determined randomly, there is no statistically significant relation between R&D and productivity anymore.

To summarize, there are significant and quantitatively important productivity effects from R&D if the domestic source of technology diffusion is distinguished from foreign sources while one fails to estimate a robust relationship between R&D and productivity if domestic and foreign sources are treated symmetrically. It follows that the source of technology diffusion, whether domestic or foreign, matters. Moreover, because the domestic R&D weight m_{vj}^v is set to equal one, $\forall v, j$, whereas only the sum of foreign R&D weights equals one ($\sum_{w \neq v} m_{wj}^v = 1, \forall v, j$), the comparison of the observed-share results and the randomized-share results suggests that domestic R&D has a *stronger* impact on productivity than R&D from the average foreign country. This result suggests that international technology diffusion might be nationally, or, more generally, geographically localized for these countries.

In appendix E, I discuss some auxiliary regressions that include more fixed effects and a time trend in the basic specifications (4.1) and (4.2). Overall, the results in the appendix suggest that the findings above are fairly robust. I now turn to specifications based on productivity and R&D growth rates.

4.2. TFP Growth Estimation

The TFP growth specifications corresponding to (4.1) and (4.2) above are

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c \in G7S} \beta_c \left(m^v_{cj} \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall v, j, t, \tag{4.9}$$

where $\frac{\Delta x}{x}$ denotes the average annual growth rate of any variable x, and $m^v_{vj} = 1, \forall v, j$. The specification which includes the overall import share is given by

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c \in G7S} \beta_c \left(m_{vj}\, m^v_{cj} \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall v, j, t, \tag{4.10}$$

where the value of the import share from v, m_{vj}, is again set equal to one, $\forall v, j$. Dividing the period of observation into five subperiods of approximately four years each, these regressions have 240 observations. The results are shown in Table 3, result columns one and three.[25]

All slope coefficients are estimated to be positive, although only in the model which includes the overall import share, IS, all estimates are significantly different from zero at a 5% level. The latter appears to be the preferred specification in this class of models, which

[25]The fact that specifications (4.9) and (4.10) do not include industry- or country fixed-effects means that these industries are assumed to share a common growth rate. In reality, this assumption might be violated, and I have run some auxiliary regressions that include industry- and country fixed-effects into these growth regressions. In most cases, these fixed effects are not estimated to be different from zero at standard levels of significance, so I do not include these fixed effects here. See appendix E for more details.

is in line with the arguments given above as well as with the findings in Coe and Helpman (1995), even though the R^2 here is lower in the IS than in the NIS specification.

The results of the corresponding Monte-Carlo experiments are shown in result columns two and four of Table 3. Contrary to the TFP level regressions above, in Table 3, only the results conditional on the effect from domestic R&D–exchanging only the import shares–are presented. The specifications are

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c \in G7S} \beta_c \left(0^v_{cj}(b) \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall b, v, j, t, \tag{4.11}$$

and

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c \in G7S} \beta_c \left(m_{vj}\, 0^v_{cj}(b) \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall b, v, j, t, . \tag{4.12}$$

For each of these two experiments, I conduct 1000 experiments. All Monte-Carlo based coefficients are estimated to be significantly above zero, confirming the earlier results from productivity level regressions. Moreover, the mean estimates from the Monte-Carlo experiments are very similar to the coefficients in the corresponding observed-trade share regression. For instance, a 95% confidence interval for the coefficient of Canada in IS, (4.12), is given by $0.427 \pm 2 \times 0.022$. Given that this interval also includes the estimate for the import-weighted R&D effect from Canada when employing observed data (with 0.415), this implies that the Canadian trade-related R&D effect is statistically not different from a randomized Canadian R&D effect, as captured by the average Monte-Carlo estimate. The only parameters β_c that are significantly different in the randomized-share results, compared to the observed-share results, are for Sweden in the IS and for Japan in the NIS specification.

In the following section, I will show how the exchanging of the import shares is related to an 'average' spillover effect from foreign R&D. Further, it will be determined whether there is a marginal contribution from the pattern of international trade to international technology diffusion.

5. Separating Trade Pattern-Related from Average R&D Spillovers

5.1. Monte-Carlo Experiments and Average Foreign R&D Spillovers

Consider the average of a particular off-diagonal R&D weight across the B simulations, $\sigma_w^v(\bar{b}) = \frac{1}{B}\sum_b \sigma_w^v(b)$, $\forall w \neq v$. Because the exchanging of the m_w^v is independent and identically distributed (i.i.d.), as $B \to \infty$, this average will be the same for all, $\sigma_w^v(\bar{b}) = \sigma(\bar{b}), \forall v, w$. Further, with 7 trade partners for any importing country, given that $7\times\ \sigma(\bar{b}) = 1$, it is the case that $\sigma(\bar{b}) = 1/7$.[26] Hence, for any partner country's R&D variable across all B replications,

$$\frac{1}{B}\sum_b \left(\sigma_w^v(b)\frac{\Delta S_{wj}}{S_{wj}}\right) = \frac{\Delta S_{wj}}{S_{wj}}\frac{\sum_b \sigma_w^v(b)}{B} = \sigma(\bar{b})\frac{\Delta S_{wj}}{S_{wj}}, \forall w \neq v.$$

Therefore, across all B replications, the average regressors are the average annual growth rates, $\frac{\Delta S_{wj}}{S_{wj}}$, $w \neq v$, multiplied by $\sigma(\bar{b}) = 1/7$ for all partner countries, and $\frac{\Delta S_{vj}}{S_{vj}}$ as the own-country R&D variable. Note, however, that the coefficients reported from the Monte-

[26] This argument applies to any particular way of creating random import shares as long as it is i.i.d. and imposes $\sum_w \sigma_{wj}^v(b) = 1, \forall b, v$. It encompasses the procedure in Keller (1998b) and also randomizations that create arbitrary random shares, as opposed to randomization through exchanging the observed import shares, as in this paper.

Carlo experiments are averages across the OLS estimates from 1000 replications, not OLS estimates from employing the average regressors. Nevertheless, as I show in appendix D, the two will be very similar under certain circumstances, both because the regression equation is linear and because the trade weights enter the specification linearly. The Monte-Carlo based estimates can then be viewed as estimating average R&D spillover effects. In Table 4, I present the following average R&D spillover regression[27]

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c \in G7S} \beta_c \left[m_{vj} \left(\sigma(b) \frac{\Delta S_{cjt}}{S_{cjt}} \right) \right] + \varepsilon_{vjt}. \tag{5.1}$$

For convenience, I have reproduced the corresponding Monte-Carlo based results from Table 3. Comparing these two regressions, it is clear that the Monte-Carlo averages indeed estimate the 'average' R&D spillover effect; the maximum relative difference between the estimated parameters in columns four and five is two percent (18.5% versus 18.9% in the case of Sweden).[28]

5.2. Estimating the Contribution of Trade Patterns in Accounting for Productivity Growth across Countries

The previous section suggests a direct way of assessing whether there is a marginal international R&D spillover which is related to the patterns international trade. Consider the

[27]The following regression is feasible because the weight for own R&D is set to equal one. If this were not the case, the average spillover regression would not be feasible because the regressor $\sigma(\bar{b})\frac{\Delta S_w}{S_w}$ would not vary by importing country. See the discussion in Lichtenberg (1993) on estimating the impact of a general R&D spillover effect that is the same for all countries.

[28]The estimated standard deviations in these two regressions are not comparable.

following regression:

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c \epsilon G7S} \beta_c^I \left[m_{vj}\, \sigma(b) \frac{\Delta S_{cjt}}{S_{cjt}} \right] + \sum_{c \epsilon G7S} \beta_c^{II} \left[m_{vj} \left(m_{cj}^v - \sigma(b) \right) \frac{\Delta S_{cjt}}{S_{cjt}} \right] + \varepsilon_{vjt}, \quad (5.2)$$

The eight regressors with parameters β^I measure the average R&D spillover effect, and the eight β^{II} coefficients estimate the marginal trade patterns-related effect, if any. In particular, if there is no separate effect of international R&D which works through the patterns of international trade, then the coefficients β^{II} will be equal to zero, and the regression (5.2) will explain as much of the variation in productivity growth rates as the average R&D spillover specification (5.1). The result of this comparison is seen in Table 5. The specification allowing for an additional trade pattern-related R&D spillovers effect explains more of the variation in TFP growth rates than the specification which captures solely the average R&D spillovers effect, with an adjusted R^2 of 9.6% versus 7.8%, respectively. Therefore, the marginal effect of the bilateral trade patterns contributes about 20% to our ability to account for the productivity growth effects from international R&D spillovers.[29]

The β^{II} point estimates in Table 5 can be interpreted as follows: The negative coefficient for Canada, for instance, means that industries which had imported overproportionately

[29] In Table 5 the adjusted R^2 is shown, as the number of regressors in the two specifications differs. I have considered analogous regressions to (5.2) for the growth specification without the overall import share (NIS), as well as for the TFP level regressions NIS and IS to check the robustness of this finding. In the level NIS specification, I estimate a contribution of bilateral trade patterns to accounting for the total international R&D spillover effects of 7.8%; in the IS specification, it is 26.5%. In these cases, the restricted regression setting the β^{II} coefficients to zero is rejected at all standard levels of significance. In the NIS growth specification, however, no significant marginal trade-related R&D spillover effect is estimated. Hence, while not perfectly robust, generally, the pattern of bilateral trade is estimated to contribute significantly to understanding the total productivity effect from foreign R&D, and in the preferred specification, it is about 20%.

(that is, more than 1/7 per cent) from Canada have experienced on average a lower rate of productivity growth. The effect is estimated to be positive for France and Japan, and negative for all other countries; however, it is only in the case of Canada significantly different from zero at a 5% level.

6. Conclusion

In this paper, I have examined the evidence on technology diffusion and productivity growth through imports of new intermediate capital goods. Along the lines of recent theory on R&D-driven growth and trade, an empirical model has been developed where domestic productivity is related to the number of varieties of differentiated inputs from abroad which are employed domestically. Based on the hypothesis that these ranges of varieties from partner countries are related to imports from those countries, I estimate the relation between domestic as well as import-weighted foreign R&D and domestic productivity.

We have seen, first, that there is evidence that these countries benefit *more* from domestic R&D than from R&D of the average foreign country. Second, conditional on technology diffusion from domestic R&D, the import composition of a country matters, but only if it is strongly biased towards or away from technological leaders. Third, I estimate that differences in technology inflows related to the countries' patterns of imports explain about 20% of the total variation in the countries' productivity growth rates.

What are the implications of this analysis for developing countries (LDCs)? The results suggesting that domestic R&D has a larger influence on productivity than R&D investments in the average country abroad has to be qualified for LDCs, because many LDCs spend only a fraction of their total technological efforts on formal R&D. But even taking this fact into account, it is likely that the contribution of foreign sources of technology is larger than that of domestic sources for many LDCs.

To confirm this conjecture requires high-quality industry-level measures of productivity and technological efforts in LDCs, which are often difficult to obtain. The conjecture that the relative contribution of foreign sources of technology is higher, the smaller is the country's relative contribution to the world's pool of technological knowledge, seems to be confirmed, however, by results in Keller (1999): there, I estimate that in nine smaller OECD countries, the R&D of the G-5 countries (US, UK, Japan, Germany and France) taken together leads to productivity effects that are more than twice as large as those from own country R&D investments.

Given the relatively higher importance of foreign sources of technology for a typical LDC compared to the countries in this sample, one should expect that differences in overall import share and import composition have both a *stronger* effect on differences in productivity growth in LDCs than I have estimated in this paper. Intermediate input imports are contributing to the international diffusion of technology, and hence to the transfer of technology to LDCs. A higher share of trade benefits that process, all else equal.

Further, the composition of imports matters. Productivity growth in a typical LDC might not depend too much on whether it imports to 50% from the U.S. and to 30% from Japan, or to 30% from the U.S. and to 50% from Japan. But productivity is likely to be much lower in this LDC if it were to change its import patterns so as to import a much lower share from the U.S. and Japan taken together, and at the same time increase its share of imports from other LDCs that are not technology leaders in the world. From the results above we have seen that the relative import shares help to explain productivity growth in the importing country, even though the available technological knowledge in *any* of the countries is high relative to a typical LDC. Relative to this, the impact of a change in the import composition on productivity is likely to be an order of magnitude larger if LDC trade patterns shifted substantially between the group of countries that are technological leaders and those that are followers in the world today.

TABLE 1

TFP Level Specification; 1056 observations

Country	Model (4.1)	Model (4.2)
CAN	0.101** (0.027))	0.201** (0.043)
FRA	0.209** (0.019)	0.236** (0.024)
GER	0.071** (0.009)	0.019** (0.009)
IT	0.066** (0.014)	0.083** (0.015)
JAP	0.068** (0.014)	0.127** (0.020)
SWE	0.206** (0.022)	0.276** (0.025)
UK	0.188** (0.022)	0.150** (0.027)
USA	0.111** (0.007)	0.080** (0.011)
R^2	0.472	0.357

TABLE 2

Total Factor Productivity Levels Regressions; 1056 observations

	NIS Specifications			IS Specifications		
	Observed Shares Eq. (4.1)	Imp. Shares Exchanged Eq. (4.4)	Shares (8) Exchanged Eq. (4.7)	Observed Shares Eq. (4.2)	Imp. Shares Exchanged Eq. (4.5)	Shares (8) Exchanged Eq. (4.8)
CAN	0.101** (0.027))	0.159 (0.081)	0.191 (0.097)	0.201** (0.043)	0.104 (0.085)	0.026 (0.253)
FRA	0.209** (0.019)	0.161** (0.063)	0.132 (0.068)	0.236** (0.024)	0.180** (0.081)	0.028 (0.156)
GER	0.071** (0.009)	0.118** (0.042)	0.115** (0.052)	0.019** (0.009)	0.128** (0.049)	0.107 (0.132)
IT	0.066** (0.014)	0.087** (0.028)	0.134 (0.080)	0.083** (0.015)	0.083** (0.028)	0.243 (0.308)
JAP	0.068** (0.014)	0.103** (0.043)	0.123** (0.053)	0.127** (0.020)	0.097** (0.046)	0.034 (0.136)
SWE	0.206** (0.022)	0.172** (0.053)	0.147** (0.072)	0.276** (0.025)	0.253** (0.042)	0.200 (0.244)
UK	0.188** (0.022)	0.134** (0.064)	0.134 (0.067)	0.150** (0.027)	0.165 (0.086)	0.028 (0.129)
USA	0.111** (0.007)	0.082** (0.039)	0.108** (0.043)	0.080** (0.011)	0.081 (0.044)	0.035 (0.092)
R^2	0.472	0.490	0.522	0.357	0.379	0.260

TABLE 3

TFP Growth Specification; 240 observations

	NIS		IS	
Country	Observed Shares Eq. (4.9)	Imp. Shares Exchanged Eq. (4.11)	Observed Shares Eq. (4.10)	Imp. Shares Exchanged Eq. (4.12)
CAN	0.351* (0.178)	0.383** (0.122)	0.415** (0.158)	0.427** (0.022)
FRA	0.437** (0.139)	0.431** (0.078)	0.503** (0.141)	0.512** (0.018)
GER	0.198** (0.067)	0.210** (0.027)	0.235** (0.060)	0.252** (0.009)
IT	0.093* (0.054)	0.126** (0.030)	0.151** (0.053)	0.157** (0.007)
JAP	0.068 (0.076)	0.077** (0.037)	0.166** (0.080)	0.169** (0.010)
SWE	0.153** (0.072)	0.155** (0.037)	0.172** (0.070)	0.189** (0.008)
UK	0.380** (0.153)	0.358** (0.077)	0.493** (0.158)	0.508** (0.018)
USA	0.137** (0.062)	0.108** (0.024)	0.173** (0.061)	0.173** (0.009)
R^2	0.127	0.134	0.105	0.109

TABLE 4

TFP Growth Estimation; 240 observations

Country	Average R&D Spillover Eq. (5.1)	Imp. Shares Exchanged Eq. (4.12)
CAN	0.426** (0.156)	0.427** (0.022)
FRA	0.513** (0.139)	0.512** (0.018)
GER	0.252** (0.062)	0.252** (0.009)
IT	0.156** (0.052)	0.157** (0.007)
JAP	0.167** (0.080)	0.169** (0.010)
SWE	0.185** (0.069)	0.189** (0.008)
UK	0.508** (0.157)	0.508** (0.018)
USA	0.173** (0.061)	0.173** (0.009)
R^2	0.109	0.109

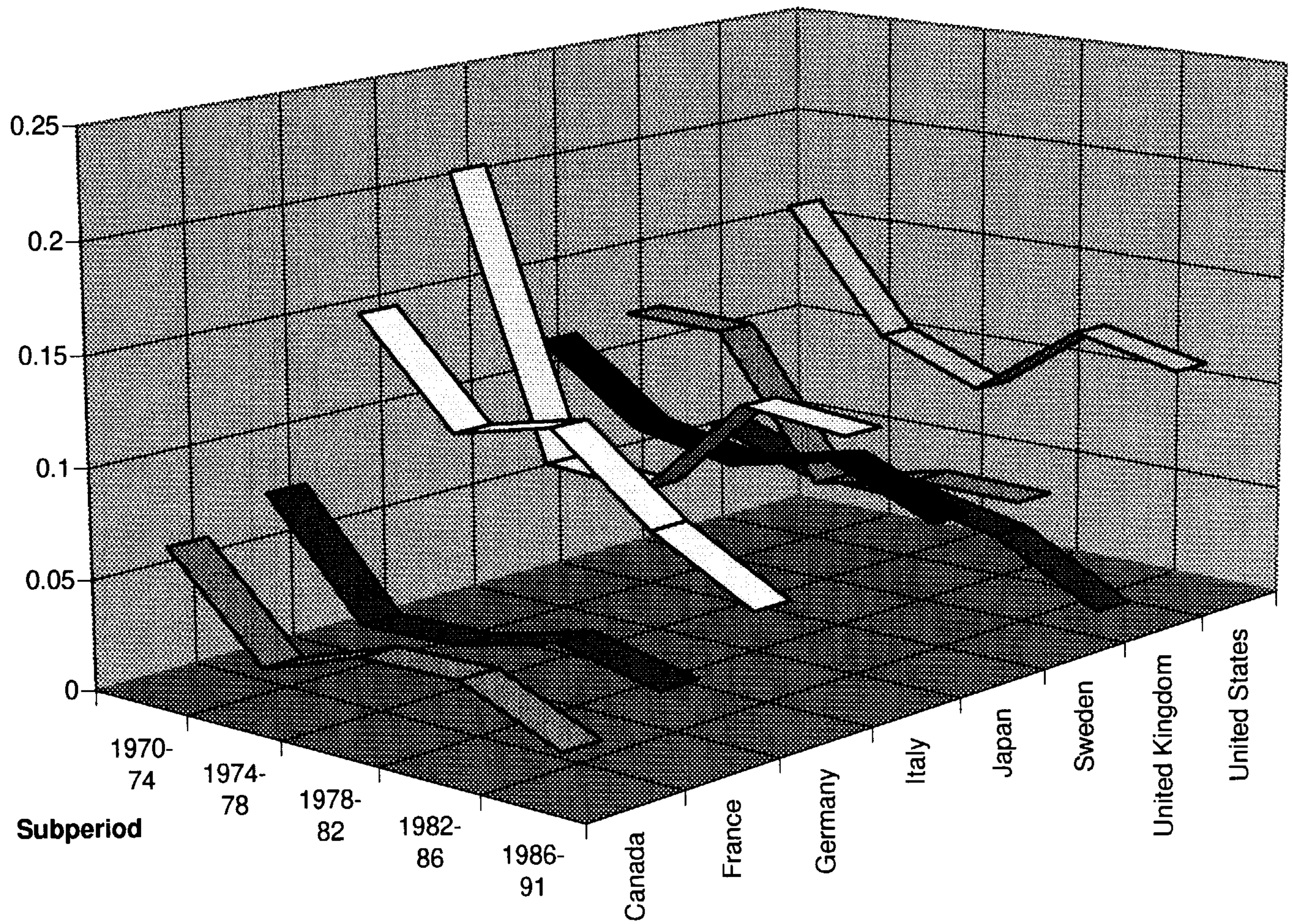
TABLE 5

TFP Growth Estimations; 240 Observations

	Average Spillover Eq. (5.1)	Average and Trade-Spillover Eq. (5.2)	
	β_v	β^I	β^{II}
CAN	0.426** (0.156)	0.389* (0.231)	−13.61** (4.30)
FRA	0.513** (0.139)	0.398** (0.181)	4.11 (3.39)
GER	0.252** (0.062)	0.126 (0.083)	−1.24 (0.82)
IT	0.156** (0.052)	0.102* (0.061)	−2.10 (1.43)
JAP	0.167** (0.080)	0.129 (0.086)	1.44 (2.28)
SWE	0.185** (0.069)	0.165* (0.090)	−1.22 (2.19)
UK	0.508** (0.157)	0.310 (0.189)	−5.12 (6.19)
USA	0.173** (0.061)	0.157** (0.067)	−0.39 (0.84)
Adjusted R^2	7.8	9.6	

Figure 1

Machinery R&D Growth Rates Across Countries



References

[1] Aghion, P., and P. Howitt (1998), *Endogenous Growth Theory*, Cambridge, MA: MIT Press.

[2] Aghion, P., and P. Howitt (1992), "A Model of Growth through Creative Destruction", *Econometrica* 60: 323-351.

[3] Barro, R., and X. Sala-i-Martin (1995), *Economic Growth*, New York: McGraw-Hill.

[4] Basu, S., and J. Fernald (1995), "Are Apparent Productivity Spillovers a Figment of Specification Error?", *Journal of Monetary Economics* 36: 165-88.

[5] Bernstein, J., and P. Mohnen (1994), "International R&D Spillovers between U.S. and Japanese R&D Intensive Sectors", *Journal of International Economics* 44: 315-38.

[6] Branstetter, L. (1996), "Are Knowledge Spillovers International or Intranational in Scope? Microeconometric Evidence from the U.S. and Japan", mimeo, Harvard University, August.

[7] Coe, D., and E. Helpman (1995), "International R&D Spillovers", *European Economic Review* 39: 859-887.

[8] Coe, D., E. Helpman, and A. Hoffmaister (1997), "North-South R&D Spillovers", *Economic Journal* 107: 134-149.

[9] Eaton, J., and S. Kortum (1998), "International Patenting and Technology Diffusion: Theory and Evidence", *International Economic Review*.

[10] Edwards, S. (1993), "Openness, Trade Liberalization, and Growth in Developing Countries", *Journal of Economic Literature* 31: 1358-93.

[11] Ethier, W. (1982), "National and International Returns to Scale in the Modern Theory of International Trade", *American Economic Review* 72: 389-405.

[12] Evenett, S., and W. Keller (1998), "On Theories Explaining the Success of the Gravity Equation", NBER Working Paper # 6529, Cambridge, MA, April.

[13] Evenson, R. (1995), "Industrial Productivity Growth Linkages Between OECD Countries: 1970-1990", mimeo, Yale University, New Haven, CT.

[14] Fullerton, D., and M.Karayannis (1993), "United States", Chapter 10 in D. Jorgenson and R. Landau (eds.), *Tax Reform and the Cost of Capital*, The Brookings Institution, Washington, D.C., pp.333-367.

[15] Griliches, Z. (1995), "R&D and Productivity: Econometric Results and Measurement Issues", in P. Stoneman (ed.), *Handbook of the Economics of Innovation and Technological Change*, Blackwell, Oxford, UK, pp.52-89.

[16] Griliches, Z. (1979), "Issues in Assessing the Contribution of Research and Development to Productivity Growth", *Bell Journal of Economics* 10: 92-116.

[17] Griliches, Z., and J. Hausman (1986), "Errors in Variables in Panel Data", *Journal of Econometrics* 31: 93-118.

[18] Grossman, G., and E. Helpman (1991), *Innovation and Growth in the Global Economy*, Cambridge, MA: MIT Press.

[19] Hall, R.E. (1990), "Invariance Properties of Solow's Productivity Residual", in P. Diamond (ed.), *Growth/Productivity/Employment*, MIT Press, Cambridge, MA., pp.71-112.

[20] Helpman, E. (1997), "R&D and Productivity: The International Connection", NBER Working Paper # 6101, Cambridge, MA, July.

[21] Jorgenson, D.W. (1993), "Introduction and Summary", Chapter 1 in D. Jorgenson and R. Landau (eds.), *Tax Reform and the Cost of Capital*, The Brookings Institution, Washington, D.C., pp.1-56.

[22] Jorgenson, D.W., and R.Landau (1993), "Appendix" in D. Jorgenson and R. Landau (eds.), *Tax Reform and the Cost of Capital*, The Brookings Institution, Washington, D.C., pp.369-406.

[23] Keller, W. (1999), "Geographic Localization in International Technology Diffusion", in progress, University of Texas, Austin, February.

[24] Keller, W. (1998a), "Trade and the Transmission of Technology", mimeo, University of Wisconsin, Madison, June.

[25] Keller, W. (1998b), "Are International R&D Spillovers Trade-related? Analyzing Spillovers Among Randomly Matched Trade Partners", *European Economic Review* 42: 1469-81.

[26] Keller, W. (1997), "How Trade Patterns and Technology Flows Affect Productivity Growth", Policy Research Working Paper No. 1831, The World Bank, Washington, D.C., September

[27] Keller, W. (1996), "Absorptive Capacity: On the Creation and Acquisition of Technology in Development", *Journal of Development Economics* 49: 199-227.

[28] Klenow, P., and A. Rodriguez-Clare' (1996), "Quantifying Variety Gains from Trade Liberalization", mimeo, University of Chicago Business School, Chicago, IL, October.

[29] Lichtenberg, F. (1993), "R&D Investment and International Productivity Differences", in H. Giersch (ed.), *Economic Growth in the World Economy*, Tuebingen, Germany: J. C. B. Mohr.

[30] Lichtenberg, F., and B. van Pottelsberghe de la Potterie (1998a), "International R&D Spillovers: A Comment", *European Economic Review* 42: 1483-1491.

[31] Lichtenberg, F., and B. van Pottelsberghe de la Potterie (1998b), "Does Foreign Direct Investment Transfer Technology Across Borders?", mimeo, Columbia University, New York City.

[32] Nadiri, M. I. (1993), "Innovations and Technological Spillovers", NBER Working Paper No. 4423, Cambridge, MA.

[33] OECD (1994), *STAN Database for Industrial Analysis*, OECD, Paris.

[34] OECD (1991), *Basic Science and Technology Statistics*, various years, OECD, Paris.

[35] OECD (1980), *Trade by Commodities.* Market Summaries, Statistics of Foreign Trade, Series C, Imports; years 1975 (Vol.2) and 1980, OECD, Paris.

[36] Park, W. (1995), "International R&D Spillovers and OECD Economic Growth", *Economic Inquiry* 33: 571-591.

[37] Rivera-Batiz, L., and P. Romer (1991a), "Economic Integration and Endogenous Growth", *Quarterly Journal of Economics* CVI: 531-555.

[38] Romer, P. (1990), "Endogenous Technological Change", *Journal of Political Economy* 98: S71-S102.

[39] Wang, J., and B. Xu (1996), "International R&D Spillovers: The Role of Capital Goods Trade and Foreign Direct Investment", mimeo, University of Florida, Gainesville, November.

[40] World Bank (1998), *Knowledge for Development.* World Development Report, 1998/99, The World Bank, Washington, D.C.

[41] World Bank (1991), *The Challenge of Development.* World Development Report, 1991, The World Bank, Washington, D.C.

A. Import Flows Data

The specialized machinery trade data comes from OECD (1980). See Table A-1 to A-6 for the absolute values of imports between the countries in US dollars of 1980 and 1975, respectively: The import data I use for the first five industries is from 1980, exactly in the middle of the period of observation; for the sixth industry, I have been unable to obtain data for 1980 according to SITC Revision 2, so data from 1975 for SITC Revision 1 is employed for this industry. From these tables, the variable m^v_{wj}, the bilateral import shares of country v with countries $w \neq v$ in sector j is derived.

B. Data on R&D

The raw data on R&D expenditures comes from OECD (1991). However, R&D surveys were not conducted annually in all countries included in the sample over the entire sample period. In the United Kingdom, for instance, they were held only every third year until well into the 1980s. In Germany, R&D data is collected only bi-annually. This required to estimate about 25% of the all the R&D expenditure data, which is done by interpolation.

The construction of the technology stock variable n is based on data on total business enterprise intramural expenditure on R&D for ISIC sector 382 (non-electronical machinery), in constant 1985 US dollars, and it uses the OECD purchasing power parity rates for conversion. The OECD code for this series is BERD, given in Table 9B of OECD (1991). I use the perpetual inventory method to construct technology stocks, assuming that

$$
\begin{aligned}
n_{vt} &= (1-\tilde{\delta})\, n_{vt-1} + \chi_{vt-1}, \ \forall v, t = 2, ..., 22 \\
&\text{and} \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (B.1) \\
n_{v1} &= \frac{\chi_{v1}}{(g_v^n + \tilde{\delta} + 0.1)} .
\end{aligned}
$$

The rate of depreciation $\tilde{\delta}$ is set at 0.05, and g^n is the average annual growth rate of n over the period of 1970-1989 (the year endpoints for which there is data available for all countries). Preliminary analysis using other values for the rate of depreciation such as 0, or 0.1, shows that this does not influence the estimation results considerably. The denominator in the calculation of n_1 is increased by 0.1 in order to obtain positive estimates of n_1 throughout. As described in the text, the industry-specific R&D expenditures are derived by splitting up the ISIC 382 stocks according to the employment share of a particular industry in total manufacturing employment over the period of 1979-81.

C. Labor, Physical Capital, and Gross Production

For these variables, the OECD (1991) *STAN* database is the basic source. It provides internationally comparable data on industrial activity by sectors. This includes data on labor input, on labor compensation, investment, production, and gross production for up to 49 3-digit ISIC industries (revision 2). The STAN figures are not the submissions of the member countries to the OECD, but rather he OECD estimates based on them. In particular, the OECD has tried to ensure greater international comparability; see OECD

(1994) for details.

In constructing the TFP variable F, I consider only inputs of labor and physical capital (there is no data on human capital by industry). Data on labor inputs l is taken directly from the *STAN* database (number of workers engaged). This includes employees as well as the self-employed, owner proprietors and unpaid family workers. The physical capital stock data is not available in that database, but gross fixed capital formation in current prices is. I first convert the investment flows into constant 1985 prices. The deflators used for that are output deflators, as investment goods deflators were unavailable to me. The output deflators are derived from figures on value-added both in current as well as constant 1985 prices, both included in the *STAN* data base. The capital stocks are then estimated using the perpetual inventory method, with–suppressing the industry subscripts–

$$\begin{aligned} k_{vt} &= (1-\hat{\delta}_v)\, k_{vt-1} + inv_{vt-1},\ \forall v, t = 2, ..., 22, \\ &\text{and} \\ k_{v1} &= \frac{inv_{v1}}{(g_v^{inv} + \hat{\delta}_v)},\ \forall v, \end{aligned} \tag{C.1}$$

where inv is gross fixed capital formation in constant prices (land, buildings, machinery and equipment), g^{inv} is the average annual growth rate of inv over the period 1970-1991, and $\hat{\delta}$ is the rate of depreciation of capital. I use country-specific depreciation rates, taken from Jorgenson and Landau (1993), Table A-3: Canada: 8.51%, France: 17.39%, Germany: 17.4%, Italy: 11.9%, Japan: 6.6%, Sweden: 7.7%, the United Kingdom: 8.19%, and the United States with 13.31%. These numbers, which are used throughout, are estimates for machinery in manufacturing in the year 1980.

According to equation (2.1), α_{vjt} is the share of the labor cost in production. Following the approach suggested by Hall (1990), the α_{vjt}'s are not calculated as the ratio of total labor compensation to value added (the reveme-based factor shares), both of which is included in the *STAN* database. Rather, I construct cost-based factor shares that are robust in the presence of imperfect competition. For this the framework of the integrated capital taxation model of King and Fullerton (see Jorgenson 1993 and Fullerton and Karayannis 1993) and data provided in Jorgenson and Landau (1993) are used. The effective marginal corporate tax rate τ is given by the wedge between before-tax (p_k) and after-tax rate of return (ρ), relative to the former

$$\tau = \frac{p_k - \rho}{p_k}. \tag{C.2}$$

Here, the variable of interest is p_k, the user cost of capital. It is a function of the statutory marginal tax rate on corporate income, available investment tax credits, the rates of depreciation, etc.

In the case of equity financing, the after-tax rate of return is

$$\rho = \iota + \pi, \tag{C.3}$$

where ι is the real interest rate, and π is the rate of inflation. Jorgenson (1993) tabulates the values for the marginal effective corporate tax rate, τ, in Table 1-1. Then I use the so-called "fixed-r" strategy ("fixed-ι" in my notation), where one gives as an input a real interest rate and deduces τ. In this case, I use a value of 0.1 for the real interest rate, which, together with the actual values of π allows, using equations (C.2) and (C.3) to infer p_k, the user cost of capital. From Jorgenson's Table 1-1 on τ, I use the values on "manufacturing" (the 1980 values given are used for 1970-1982 in my sample, the 1985 values for 1983-1986, and Jorgenson's 1990 values are used for 1987-1991). This certainly introduces an error; in addition, the Jorgenson Table 1-1 is derived from a "fixed-p" approach, as opposed to the "fixed-r" approach employed here. Further, the results depend on the chosen real interest rate. Also, τ varies by asset type, and ρ is a function of the way of financing (equity versus debt primarily). That is, there are several shortcomings in the construction of the cost-based factor shares due to unavailability of more detailed data. The chapter by Fullerton and Karayannis (1993) presents a sensitivity analysis in several dimensions. In addition, I have experimented myself with different values for r, and found that the basic results presented above do not depend on a particular choice for r. The main advantage of this approach is that it uses all data on the user cost of capital compiled in Jorgenson and Landau (1993) to arrive at a productivity index which is robust to deviations from perfect competition.

Having obtained the series on the user cost of capital p_k and k, all what is left to obtain robust wage shares α is to deflate the current price labor costs wl, available in the *STAN* data base (again using sectoral output deflators), and form

$$\alpha = \frac{w\,l}{w\,l + p_k\,k}. \tag{C.4}$$

Labor and capital inputs together with the factor shares allow to construct a Thornqvist index of total inputs I_t

$$\log\left(\frac{I_{vjt}}{I_{vjt-1}}\right) = \frac{1}{2} * [\alpha_{vjt} + \alpha_{vjt-1}] \log\left(\frac{l_{vjt}}{l_{vjt-1}}\right) + \frac{1}{2} * [(1-\alpha_{vjt}) + (1-\alpha_{vjt-1})] \log\left(\frac{k_{vjt}}{k_{vjt-1}}\right). \tag{C.5}$$

This gives a series of growth of total factor inputs. Calculating log differences of year-to-year gross real production, and taking the difference between this and total input growth results in the TFP growth series. A value of 100 in 1970 is chosen for each of the 8×6 time series, for all industries j and countries v.

D. Relation of Monte-Carlo Experiments and Average R&D Spillover Regression

Consider, for simplicity, the model above with only one regressor (with industry and time subscripts are suppressed):

$$\frac{\Delta F_v}{F_v} = \alpha_0 + \beta_1 \theta_w^v(b) \frac{\Delta S_w}{S_w} + \varepsilon_v.$$

Let

$$\theta_w^v(b) = \sigma(b) + \eta_w^v(b), \forall b,$$

where $\eta_w^v(b)$ is the deviation of the trade share from its expected value–partner country-by-partner country–of 1/7. Then the OLS estimate of $\beta_1(b)$ equals

$$\beta_1(b) = \frac{\sum_v \left(\theta_w^v(b)\frac{\Delta S_w}{S_w}\frac{\Delta F_v}{F_v}\right)}{\sum_v \left(\theta_w^v(b)\frac{\Delta S_w}{S_w}\right)^2} = \frac{\sum_v \left(\sigma(\bar{b})\frac{\Delta S_w}{S_w}\frac{\Delta F_v}{F_v} + \eta_w^v(b)\frac{\Delta S_w}{S_w}\frac{\Delta F_v}{F_v}\right)}{\sum_v \left(\left[\sigma(\bar{b}) + \eta_w^v(b)\right]\frac{\Delta S_w}{S_w}\right)^2}, \forall b.$$

If the denominator is approximated by $\sum_v \left(\frac{\Delta S_w}{S_w}\right)^2 \left[\sigma(\bar{b})\right]^2, \forall b, v$, this means that the average of the Monte-Carlo estimates, $\beta_1(\bar{b}) = \frac{1}{B}\sum_b \beta_1(b)$, equals

$$\beta_1(\bar{b}) \simeq \frac{\sum_{b=1}^{B}\sum_v \left(\sigma(\bar{b})\frac{\Delta S_w}{S_w}\frac{\Delta F_v}{F_v} + \eta_w^v(b)\frac{\Delta S_w}{S_w}\frac{\Delta F_v}{F_v}\right)}{B\sum_v \left(\frac{\Delta S_w}{S_w}\right)^2 \left[\sigma(\bar{b})\right]^2}.$$

The right hand side can be rewritten so as to obtain

$$\beta_1(\bar{b}) \simeq \frac{\sum_v \sigma(\bar{b})\frac{\Delta S_w}{S_w}\frac{\Delta F_v}{F_v}}{\sum_v \left(\frac{\Delta S_w}{S_w}\right)^2 \left[\sigma(\bar{b})\right]^2} + \frac{\sum_v \frac{\Delta S_w}{S_w}\frac{\Delta F_v}{F_v}\sum_{b=1}^{B}\eta_w^v(b)}{B\sum_v \left(\frac{\Delta S_w}{S_w}\right)^2 \left[\sigma(\bar{b})\right]^2}. \tag{D.1}$$

Because $\sum_{b=1}^{B}\eta_w^v(b) = 0$, however, the second term in (D.1) will drop out, so that $\beta_1(\bar{b})$ is approximately equal to the OLS estimate of projecting $\frac{\Delta F_v}{F_v}$ on $\sigma(\bar{b})\frac{\Delta S_w}{S_w}$. Clearly, how good the approximation above is depends on how large $\left[\frac{\Delta S_w}{S_w}\right]^2 \left(\left[\eta_w^v(b)\right]^2 + 2\eta_w^v(b)\sigma(\bar{b})\right)$ is, or, more generally, $\lambda_w^2 \left(\left[\eta_w^v(b)\right]^2 + 2\eta_w^v(b)\sigma(\bar{b})\right)$. In particular, if $\lambda_w = \log S_w$, then the average Monte-Carlo estimate will differ more from the average spillover regression than if $\lambda_w = \frac{\Delta S_w}{S_w}$, the case presented in Table 4.

E. Sensitivity Analysis

The following briefly discusses the sensitivity of the results by considering a number of alternative specifications for both the productivity level as well as the growth regressions. First, as noted above, including a fixed effect for each industry allows in principle to estimate consistent parameters with OLS if the error is of the form $\varepsilon_{vjt} = u_{vj} + \eta_t$, because the correlation between error and regressor due to u_{vj} will be subsumed into the fixed effects. Including a separate fixed effect for every industry leads to the following specifications, analogous to (4.1) and (4.2),

$$\log F_{vjt} = \delta_{vj} d_{vj} + \sum_{c \in G7S} \beta_c \left(m_{cj}^v \log S_{cjt} \right) + \varepsilon_{vjt}, \forall v, j, t, \tag{E.1}$$

and

$$\log F_{vjt} = \delta_{vj} d_{vj} + \sum_{c \in G7S} \beta_c \left(m_{vj}\, m_{cj}^v \log S_{cjt} \right) + \varepsilon_{vjt}, \forall v, j, t, \tag{E.2}$$

where d_{vj} is dummy variable that equals 1 for the country-industry combination vj, and zero otherwise. This raises the number of fixed effects from $6+8=14$ as in the text to $6 \times 8 = 48$ here. The inclusion of more fixed effects raises the R^2 for both specifications, from 0.472 to 0.755 for the NIS specification (without the overall import share), and from 0.357 to 0.746 for the IS specification. In both specifications, even though the estimated parameters β_c change from those reported in Table 1, all are significantly different from zero at a 1% level, ranging from 4.1% (U.S., NIS) to 61.5% (France, IS).

The further inclusion of a trend (denoted *year*), leading to

$$\log F_{vjt} = \alpha year_t + \delta_{vj} d_{vj} + \sum_{c \in G7S} \beta_c \left(m_{cj}^v \log S_{cjt} \right) + \varepsilon_{vjt}, \forall v, j, t, \tag{E.3}$$

and

$$\log F_{vjt} = \alpha year_t + \delta_{vj} d_{vj} + \sum_{c \in G7S} \beta_c \left(m_{vj}\, m_{cj}^v \log S_{cjt} \right) + \varepsilon_{vjt}, \forall v, j, t, \tag{E.4}$$

has the following effects. First, it increases the R^2 slightly (to 0.757 from 0.755 for NIS, and to 0.753 from 0.746 for IS). Second, it lowers the estimated parameters β_c in both specifications; this is what one expects if there are common trends in levels. Now, the estimates range from a low of 2.4% (U.S., NIS) to a high of 44.1% (France, NIS); on average, they fall by about 15-20%. However, out of sixteen estimates β_c from the specifications (E.3) and (E.4), thirteen parameters remain significantly positive at a 5% level, and the highest p-value of all sixteen estimates is 21.1%.

In the growth specifications, a major concern is whether all industries share a common growth rate. Thus, I run (4.9) and (4.10) with industry fixed effects included:

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \delta_j d_j + \sum_{c \in G7S} \beta_c \left(m_{cj}^v \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall v, j, t. \tag{E.5}$$

and

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \delta_j d_j + \sum_{c \in G7S} \beta_c \left(m_{vj}\, m_{cj}^v \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall v, j, t. \tag{E.6}$$

For specification (E.5), I estimate one out of six industry fixed effects significantly different from zero at a 5% level, and for specification (E.7), none of the industry fixed effects is significant. The estimated parameters β_c are affected very little.

Including country fixed-effects in addition to the industry fixed-effects leads to these specifications:

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \mu_v d_v + \delta_j d_j + \sum_{c \in G7S} \beta_c \left(m_{cj}^v \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall v, j, t, \tag{E.7}$$

and

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \mu_v d_v + \delta_j d_j + \sum_{c \in G7S} \beta_c \left(m_{vj}\, m_{cj}^v \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall v, j, t. \tag{E.8}$$

In specification (E.7), four out of fourteen fixed effects differ significantly from zero, whereas in (E.8), three out of fourteen fixed effects are significant. Based on these results, the evidence for different growth rates across industries is not very strong. Even when one includes country-by-industry fixed effects (that is, $6 \times 8 = 48$ fixed effects), only about thirty percent of these are estimated to be significantly different from zero.

However, including successively more fixed effects reduces the number of R&D parameters β_c that are estimated to differ significantly from zero. For instance, in the growth specification with overall import share, when country-by-industry fixed effects are included, only the R&D stocks of Canada, Germany, the U.K., and the U.S. are estimated to have a significantly positive effect on productivity (at the 10% level). This is to be expected in a cross-industry, cross-country TFP growth regression that does not exploit any between-industry variation, though. Overall, this analysis suggests that the results presented in the text are fairly robust.

TABLE A-1 Food-processing machinery imports (SITC 727) (1980 US $)

from/to	CAN	FRA	GER	IT	JAP	SWE	UK	USA
CAN	0	938	113	7	2	26	915	4141
FRA	1398	0	7682	7231	1050	837	4631	3960
GER	8513	30099	0	18442	11268	11446	30004	36143
IT	4292	22397	10812	0	2403	1461	7634	9431
JAP	290	38	1832	1709	0	156	728	8114
SWE	1181	1332	1225	606	487	0	2310	1916
UK	3655	6274	4638	3226	1679	1800	0	8551
USA	63235	12559	6196	2838	8458	2022	23435	0

TABLE A-2 Textiles and leather machinery imports (SITC 724) (1980 US $)

from/to	CAN	FRA	GER	IT	JAP	SWE	UK	USA
CAN	0	801	660	1232	207	38	2140	21275
FRA	4151	0	38542	49901	3465	1353	28705	34619
GER	22409	187433	0	259344	55555	31400	116170	262163
IT	23122	78772	68873	0	15124	6155	67436	68070
JAP	11110	28372	39932	22546	0	1966	40419	139266
SWE	3558	5145	8530	2181	3864	0	9713	29519
UK	9953	40817	47110	42585	8856	6632	0	53270
USA	143551	27501	33617	21479	14106	5167	49242	0

TABLE A-3 Paper & pulp mill machinery imports (SITC 725) (1980 US $)

from/to	CAN	FRA	GER	IT	JAP	SWE	UK	USA
CAN	0	1352	278	304	2722	85	919	35110
FRA	534	0	25553	16619	109	4560	13245	10501
GER	9767	65245	0	47290	17197	31354	61340	68760
IT	794	32561	22365	0	353	1834	10028	6125
JAP	2829	315	7392	925	0	782	3831	11535
SWE	5245	6911	18014	4779	1572	0	7263	21098
UK	11990	9563	12809	8827	584	10580	0	8612
USA	88992	8093	19794	4411	11152	7982	18720	0

TABLE A-4 Printing and bookbinding machinery imports (SITC 726) (1980 US $)

from/to	CAN	FRA	GER	IT	JAP	SWE	UK	USA
CAN	0	441	272	543	153	309	2663	8573
FRA	944	0	13589	13497	169	6140	31642	8090
GER	18467	133716	0	105198	77149	41834	141982	143425
IT	2320	26061	21148	0	10622	2711	20418	51072
JAP	6224	4786	5332	3420	0	2227	21027	60713
SWE	1543	10612	6074	853	3168	0	14519	14471
UK	19206	25519	19636	19271	5219	9126	0	49020
USA	158716	51574	43920	25469	25662	24677	73167	0

TABLE A-5 Machine tools, metal-working machinery imports (SITC 736 & 737) (1980 US $)

from/to	CAN	FRA	GER	IT	JAP	SWE	UK	USA
CAN	0	826	1904	295	1636	295	8508	117564
FRA	9137	0	110469	50354	4034	11574	48758	46705
GER	41546	318019	0	223334	87011	129441	288330	345307
IT	11821	138858	154121	0	6504	23166	77445	63596
JAP	30259	44462	122266	8507	0	28770	122686	617156
SWE	8612	17788	45895	15588	4916	0	37929	52440
UK	41064	58034	83115	44457	6081	25671	0	169590
USA	608480	66698	72679	29627	93295	22344	161467	0

TABLE A-6 Mining, metal crushing & glass working machinery imports (SITC Rev. 1, 7184 & 7185) (1975 US $)

from/to	CAN	FRA	GER	IT	JAP	SWE	UK	USA
CAN	0	1517	341	312	453	294	2559	73438
FRA	11738	0	78204	38841	1316	9063	49246	32890
GER	22999	97060	0	47026	3687	25154	50335	64832
IT	3503	26645	34749	0	141	1853	17079	22597
JAP	13582	3700	16499	7454	0	654	13612	42338
SWE	12421	10708	22294	9466	1739	0	19019	10239
UK	19340	41885	23092	21204	1722	12348	0	37783
USA	644606	75425	46474	22419	37028	18733	104457	0

Table A - 7 Summary Statistics on Machinery R&D Stocks

(1985 US $)

	Mean	Standard Deviation
By Country		
Canada	92.79	34.75
France	417.4	222.53
Germany	1403.29	1148.55
Italy	123.03	143.1
Japan	919.8	670.24
Sweden	170.59	98.33
United Kingdom	665.71	305.32
United States	3379.03	2720.96
By Industry		
Food	1087.13	1535.52
Textiles	1363.09	2036.03
Paper Products	337.83	554.24
Printing	576.61	1079.07
Minerals and Basic Metals	1145.53	1679.58
Metal Products	960.72	1457.14

Table A - 8 Summary Statistics on Total Factor Productivity Growth

(Annual growth over 1970 - 1991)

	Mean	Standard Deviation
By Country		
Canada	0.0119	0.0086
France	0.0256	0.0102
Germany	0.0278	0.0074
Italy	0.0207	0.0188
Japan	0.0137	0.0092
Sweden	0.0205	0.0198
United Kingdom	0.0203	0.0041
United States	0.0149	0.0088
By Industry		
Food	0.0091	0.0087
Textiles	0.0217	0.0108
Paper Products	0.0263	0.0101
Printing	0.0141	0.0096
Minerals and Basic Metals	0.0276	0.0156
Metal Products	0.0178	0.0098