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Do Trade Patterns and Technology Flows Affect Productivity Growth?

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This article presents a model suggesting that the pattern of a country's intermediate goods imports affects its level of productivity because a country that imports such goods primarily from technological leaders receives more technology than a country that imports primarily from follower countries. The importance of trade patterns in determining technology flows is quantified using industry-level data for machinery goods imports and productivity from eight member countries of the Organisation for Economic Co-operation and Development between 1970 and 1991. Three conclusions emerge from this work. First, the eight countries studied appear to benefit more from domestic research and development (R&D) than from R&D of the average foreign country. Second, conditional on technology diffusion from domestic R&D, a country's import composition matters only if it is strongly biased toward or away from technological leaders. Third, differences in technology inflows related to the pattern of imports explain about 20 percent of the total variation in productivity growth. The implications of these findings for developing countries are discussed.

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 raising rates of economic growth has long been recognized, but little is known about the specific policies that promote such diffusion, particularly at the international level.

A widely held view is that international trade leads to faster technological diffusion and higher rates of productivity growth (Helpman 1997). Whereas these changes are important for all countries, they have dramatic implications for developing countries as they seek to catch up with the technological leaders in the Organisation for Economic Co-operation and Development (OECD). International

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agencies such as the World Bank routinely recommend policies that foster international trade, in part because it is presumed to further international technology diffusion (World Bank 1991, 1998). To date, however, there is little sound evidence to support this view.[1]

The recent development of theories of endogenous technological change, in particular the work of Romer (1990) and Aghion and Howitt (1992), has stimulated new analyses of the relationship among trade, growth, and technological change in open economies (Grossman and Helpman 1991; Rivera-Batiz and Romer 1991). In that work the authors embed the recent theories in general equilibrium models to analyze how trade in both intermediate and final goods affects long-run growth. Technology is diffused in this framework by being embodied in intermediate inputs: if research and development (R&D) expenditures create new intermediate goods that are different (the horizontally differentiated inputs model) or better (the quality ladder model) from those already existing and if these goods are also exported to other economies, then the importing country's productivity will increase through the R&D efforts of its trade partner.

The framework suggested by these models is well suited to studying empirically how trade patterns determine technology flows that trigger productivity growth and what impact importing a new (or better) type of intermediate product might have. 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 the production of intermediate inputs. To the extent that the importing country succeeds in not paying in full for this increase in variety, it reaps an external benefit, or, spillover effect. Second, the import of specialized inputs might facilitate learning about the product, spurring imitation or innovation of a competing product.

In this article I use data on the G-7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) and Sweden to evaluate these mechanisms. The traded goods studied are machinery inputs for manufacturing industries, which are usually differentiated and imperfect substitutes. Machinery inputs are also often highly specialized, implying that the elasticity of substitution between inputs produced for two different industries is negligible.

In this setting I examine whether productivity growth in an importing country is increased by the R&D investments of its trade partners. It is clear that the pattern of trade in intermediate inputs is central to this technology diffusion hypothesis. Both the increasing variety and the reverse-engineering effects are tied to arm's length market transactions of goods.[2]

The first hypothesis concerns the composition of imports by a partner country. On average, countries that import largely from high-knowledge countries should, everything else equal, import more and better-differentiated input varie-

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

2. Of course, other mechanisms of international technology diffusion, such as foreign direct investment (FDI), do not depend on imports. On FDI, see Lichtenberg and van Pottelsberghe de la Potterie (1998a) and Wang and Xu (1996).

ties than countries importing largely from low-knowledge countries. As a result, productivity should be higher in such countries than in countries that import from low-knowledge countries.

The second hypothesis posits that for a given composition of imports, this effect is likely to be stronger the higher is a country's overall import share. There are many reasons why a higher import share (or more openness) might lead to higher growth rates, however, some of which have little to do with international technology diffusion (see, for example, Edwards 1993). Because the claim that import composition matters is shared by fewer other models than the claim that a high overall level of imports is beneficial, I focus on import composition in order to address the question of whether trade is an important determinant of international technology diffusion. For the same reason examining the effect of import composition is a more powerful test of the recent trade and growth models than is studying the overall effect of imports.[3]

A number of recent articles have attempted to assess the importance of imports in transmitting foreign technology to domestic industries and spurring total factor productivity (TFP) growth (Coe and Helpman 1995; Coe, Helpman, and Hoffmaister 1997; Evenson 1995; Keller 1997, 1998a, 1998b; Lichtenberg and van Pottelsberghe de la Potterie 1998b).[4] Coe and Helpman (1995), who initiated this research, find a significant positive correlation between TFP levels and a weighted sum of partner-country R&D stocks, in which bilateral import shares serve as weights.[5]

The interpretation of this finding is not clear, however. Using the same data, Keller (1998a) finds that the role played by the composition of imports is limited: alternatively weighted R&D stocks—in which import shares are created randomly—also lead to a positive correlation between foreign R&D and the importing country's R&D. Moreover, the average correlation is often larger than when foreign R&D is weighted using observed import shares.[6]

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

3. For further discussion of the implication of such model identification problems, see Evenett and Keller (1998).

4. Park (1995), Bernstein and Mohnen (1998), and Branstetter (1996) also estimate international R&D spillovers but do not include an explicit argument with respect to international trade. See also Eaton and Kortum (forthcoming).

5. Coe and Helpman (1995), as well as other authors, consider not only the effect of import composition but also the effect of technology inflows resulting from the level of imports, with the import composition given. Both might contribute to international technology diffusion. In this article, however, I focus primarily on the effect of import composition for model identification reasons.

6. Keller (1998a) and Coe, Helpman, and Hoffmaister (1997) also report regressions of TFP on unweighted R&D stocks, something that Coe and Helpman (1995) consider as well. The relationship of these regressions to the analysis in this article is discussed in section IV.

mediate goods trade. Second, most R&D is conducted in only a relatively small set of manufacturing industries (OECD 1991). Thus inferences that might be drawn from analysis of data at a more disaggregated level may not be possible based on country-level analysis. 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 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 such patterns.

In this article I analyze R&D, imports, and productivity at the two- and three-digit industry level. One is much more likely to observe trade flows embodying new technology at this level of aggregation than at the country level. I present estimation results for both TFP levels and TFP growth rates and address some of the open questions concerning common trends and simultaneity. (In appendix A I also report different sets of auxiliary regressions that analyze the robustness of the findings.) I also extend the Monte Carlo analysis of Keller (1998a), showing how such experiments are related to estimating an overall spillover effect from foreign R&D. This analysis allows me to determine whether some international R&D spillovers are related to trade patterns.

I. Theoretical Framework

The following gives a brief background of the recent theory that guides the empirical analysis performed here.[7] Long-run growth is endogenously determined by R&D investments, and technology is transmitted through trade in intermediate inputs. Assume that a country's output is produced according to

$$z = Al^{\alpha}d^{1-\alpha}, \ 0 < \alpha < 1 \tag{1}$$

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

$$d = \left(\int_0^{n^e} x(s)^{1-\alpha} ds \right)^{\frac{1}{1-\alpha}}. \tag{2}$$

The variable n^e denotes the range of intermediate inputs *employed* in a country; it can differ from n, the range of intermediate inputs *produced* in a country. The variable n increases when entrepreneurs devote resources to R&D (χ). If R&D capital does not depreciate, the range of intermediate inputs at time T will equal

$$n(T) = \int_{-\infty}^{T} \chi(t)dt \tag{3}$$

7. 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.

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 forgone consumption, or capital, denoted by k. Under certain conditions one can express the total intermediate input usage d in terms of capital k. Using equation 1, we can write the reduced-form expression for output as

$$z = A(n^{e})^{\alpha} l^{\alpha} k^{1-\alpha}. \tag{4}$$

If F is TFP, defined as $F \equiv z / l^{\alpha} k^{1-\alpha}$, using equation 4:

$$\log F = \log A + \alpha \log n^{e}. \tag{5}$$

Equation 5 shows that productivity is positively related to the amount of variety of the employed product.

Many countries, $v = (i,h,\ldots,V)$, will import foreign intermediates rather than use only domestic varieties, implying 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 the production of intermediate goods than would be possible without trade. Specialization raises productivity, because the constant elasticity of substitution specification in equation 2 implies that for a given quantity 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 a new product variety (by spending the fixed R&D cost, χ), whereas *all* countries can potentially employ the new product by importing it.

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

$$d_{ij} = \left(\int_0^{n_{ij}^{i}} x_{ij}^{i}(s)^{1-\alpha} ds + \gamma_{hj}^{i} \int_0^{n_{hj}^{i}} x_{hj}^{i}(s')^{1-\alpha} ds' + \ldots \right)^{\frac{1}{1-\alpha}}. \tag{6}$$

Here, $x_{ij}^{i}(s)$ denotes the quantity of an intermediate good of variety s used in sector j. The country that produces the intermediate good is given by the subscript; the superscript denotes the country that employs the intermediate good. Similarly, n_{ij}^{i} gives the range of domestically produced intermediate goods employed in country i's production of good j, and n_{hj}^{i} is the range of goods that country i imports from country h. The variable γ_{hj}^{i} determines the degree of substitutability between intermediates produced in country h and domestic intermediates produced in country i's industry j. If substitutability is perfect, then the γ's equal one.[8]

8. To capture the often highly specialized nature of machinery inputs for particular industries, I assume that only inputs of type j are productive in any country's sector j. Keller (1998b) also examines interindustry technology flows.

For simplicity, most theoretical work has concentrated on one-industry, two-country models (Rivera-Batiz and Romer 1991; Keller 1996).[9] As a result, empirical work using a multi-country, multi-industry setting has usually not estimated structural equations of such models of trade, technology diffusion, and growth. Instead, to go from the structural relationship of productivity and R&D in the one-sector closed-economy model (equation 5) to the multi-country, multi-industry context, researchers have related productivity to both domestic and foreign R&D, $\omega \neq v$:

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

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

However, the model of trade in intermediate inputs 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. Productivity in country v should depend on country v's bilateral import share from w, denoted by m_{w}^{v} (the import composition effect), as well as country v's overall import share, denoted by m_{v}. At the industry level this means that

$$F_{vj} = \Phi(S_{vj}, S_{wj}, m_{vj}, m_{wj}^{v}), \forall v, j. \tag{7}$$

One can think of the import shares in equation 7 as indicating the probability of receiving a new type of foreign intermediate. This is certainly the correct interpretation in the extreme case in which $m_{w}^{v} = 0$. In all other cases, however, there is not necessarily a link between the level of imports and the number of types of newly introduced intermediate goods in the local economy.[10] Grossman and Helpman (1991) suggest several reasons why it is likely that the number of new varieties adopted from a partner country is positively related to the import volume from that country. This assumption guides the empirical specifications in section III.

II. DATA

I examine data for eight OECD countries—Canada, France, Germany, Italy, Japan, Sweden, the United Kingdom, and the United States—in six sectors for the years 1970–91. (See appendixes B and C for data sources and the construction of the variables.) These sections include International Standard Industrial Classification (ISIC) 31 (food, beverages, and tobacco); ISIC 32 (textiles, apparel, and

9. Exceptions include Grossman and Helpman (1990), Feenstra (1996), and Aghion and Howitt (1998).

10. 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 available domestically. An interesting alternative, albeit one with problems of its own, has been considered by Klenow and Rodriguez-Clare (1996), who postulate that the number of different varieties of intermediate goods is related to the number of different trade partners a country has.

leather); ISIC 341 (paper and paper products); ISIC 342 (printing); ISIC 36 and 37 (mineral products and basic metal industries); and ISIC 381 (metal products). All sectors belong to ISIC class 3 (manufacturing). The reliability and comparability of the measurement of inputs and outputs is high in these sectors relative to nonmanufacturing sectors.

The data on imports of machinery come from the OECD *Trade by Commodities* statistics (OECD 1980). I have tried to identify machinery imports that have a high probability of being used exclusively in one of the six manufacturing industries. These commodity classes are (revision 2) Standard International Trade Classification (SITC) 727 (food-processing machines and parts); SITC 724 (textile and leather machinery and parts); SITC 725 (paper and pulp mill machinery, machinery for manufacturing of paper); SITC 726 (printing and bookbinding machinery and parts); SITC 736 and 737 (machine tools for working metals and metalworking machinery and parts); and (revision 1) SITC 7184 and 7185 (mining, metal-crushing, and glass-working machinery). The bilateral trade relations for these SITC classes are given in full in tables A-1 to A-6 in appendix A.

OECD (1991) data on R&D expenditures by sector are used to capture the ranges of intermediate inputs, n. These data cover all intramural business enterprise expenditures on R&D. Because none of these industries has a ratio of R&D expenditures to value added of more than 0.5 percent, it is reasonable to assume that insofar as their productivity benefits from R&D at all, it will be largely from R&D performed outside the industry. Because there are no internationally comparable data on R&D in the machinery industry products used in specific industries, I assume that R&D expenditures toward sector j's machinery inputs are equal to a certain constant share of the R&D performed in the country's nonelectrical machinery sector (ISIC 382), where all specialized new machinery inputs are likely to be invented.[11] R&D stocks are derived from the R&D expenditure series using the perpetual inventory method. Descriptive statistics on the cumulative R&D stocks are given in table A-7.

I construct the TFP index 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 variables l, the number of workers employed, and y, gross production, come from the STAN database. The growth of the TFP index, F, is the difference between output growth and input growth weighted by factor-cost shares, with the level of the F's normalized to 100 in 1970 for each of the 8×6 time series. Summary statistics for the TFP data are shown in table A-8.

11. This constant share is industry employment divided by total manufacturing employment over the years 1979–81. The employment data are from OECD (1994).

III. ESTIMATION RESULTS

Below I present and discuss TFP-level estimation results. Then, I report and discuss estimation results for TFP growth rate regressions.

TFP-Level Specification

Consider the following specification:

$$\log F_{vjt} = \mu_j d_j + \delta_v d_v + \sum_{c \in G7S} \beta_c (m_{cj}^v \log S_{cjt}) + \varepsilon_{vjt}, \forall v, j, t. \tag{8}$$

The subscript t indexes a period, c indexes any of the eight countries in our sample (denoted as $G7S$ in equation 8), d_j represents industry fixed effects, and d_v represents country fixed effects. In this specification the TFP level in any industry is related to R&D in 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.[12]

In equation 8 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—an unlikely outcome if a higher overall import share increases a country's chance of benefiting from foreign technology. Following Coe and Helpman (1995), I model the contribution of a country's openness to imports for a given import composition by including the overall import share, m_{vj}, in the specification:[13]

$$\log F_{vjt} = \mu_j d_j + \delta_v d_v + \sum_{c \in G7S} \beta_c (m_{vj} m_{cj}^v \log S_{cjt}) + \varepsilon_{vjt}. \tag{9}$$

I refer to a specification that does not include the overall import share, as in equation 8, as NIS; a specification that includes the overall import share is referred to as IS.[14]

12. This approach differs from that of Coe and Helpman (1995), who estimate one parameter for the effect of foreign R&D. In addition, here, the bilateral import shares enter linearly, not logarithmically.

13. For the own-R&D effect, m_{vj} is chosen such that $m_{vj} m_{vj}^v \log S_{vjt} = \log S_{vjt}, \forall v, j, t,$ that is, m_{vj} then equals one.

14. Lichtenberg and van Pottelsberghe de la Potterie (1998b) criticize Coe and Helpman's (1995) specification using the overall import share 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 de la Potterie (1998b) also point out that Coe and Helpman's weighting scheme suffers from a strong aggregation bias (country mergers or break-ups would strongly affect the estimated spillovers). I have not investigated this question in the present context, but Wang and Xu (1996) compare the weighting schemes proposed by Coe and Helpman (1995) and Lichtenberg and van Pottelsberghe de la Potterie (1998b), and propose a third scheme themselves.

Both specifications, equations 8 and 9, might be subject to simultaneity and omitted variable biases. These two problems would imply that the ordinary least squares (OLS) estimates are inconsistent, because the regressors and the error term are correlated. Since both productivity and R&D trend upward over time, part of the estimated correlation between the variables in equations 8 and 9 could be due to a common trend. In addition, the error could contain price or demand shocks that affect productivity and R&D jointly.[15]

To some extent, these problems can be reduced by imposing reasonable a priori restrictions on the dependent variable, TFP.[16] The importance of spurious correlation due to common trends can be assessed by comparing level regressions with results from growth regressions (presented in the next section), in which time-differencing eliminates common trends.[17]

Even with a growth specification, however, the possibility remains that exogenous shocks in the error term 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 serve as good instruments for cumulative R&D stocks for all countries, industries, and years in the sample.

If no good instruments are available, consistent parameters can still be estimated in the panel context by including a full set of fixed effects, provided the error can be decomposed into a permanent component that affects the regressor and a temporary component that does not. In this way, the part of the error that is correlated with the regressor will then be subsumed into the estimated fixed effect. Griliches and Hausman (1986) show that including a large number of fixed effects exacerbates errors-in-variables problems, however, which are also likely to be present in this context. The productivity-level specifications reported above together with the growth specifications reported below represent a compromise among these considerations. Additional auxiliary regressions are discussed in appendix E.

Results for the specifications given in equations 8 and 9 show that R&D stocks in all countries have a significant and positive influence on the TFP level of the receiving country (table 1). The magnitude of these effects, however, varies substantially. In the second specification, for example, results range from a low of 1.9 percent for Germany to a high of 27.6 percent for Sweden. The specifications account for one-third to one-half of the variation of the TFP indexes across countries, with the NIS specification yielding a higher R^2.

Do the results really say anything about the international diffusion of technology? To what extent, for example, do these results depend on correlating TFP

15. This section draws on Griliches (1979, 1995).

16. See appendix C for details.

17. For comparison purposes, in appendix E, I discuss TFP-level regressions that include time fixed effects.

Table 1. *Total Factor Productivity–Level Specifications*

Country	NIS[a]	IS[b]
Canada	0.101	0.201
	(0.027)	(0.043)
France	0.209	0.236
	(0.019)	(0.024)
Germany	0.071	0.019
	(0.009)	(0.009)
Italy	0.066	0.083
	(0.014)	(0.015)
Japan	0.068	0.127
	(0.014)	(0.020)
Sweden	0.206	0.276
	(0.022)	(0.025)
United Kingdom	0.188	0.150
	(0.022)	(0.027)
United States	0.111	0.080
	(0.007)	(0.011)
R^2	0.472	0.357

Note: All parameter values are statistically significant at the 5 percent level. Asymptotic standard errors are shown in parentheses. $n = 1{,}056$.

a. Specification does not include overall import share (see equation 8).

b. Specification does include overall import share (see equation 9).

with R&D, as opposed to physical capital? Perhaps technology is embodied in the physical capital stocks of the countries, and correlating TFP with foreign capital stocks would produce results similar to those found by correlating productivity with foreign R&D. To examine this question, I construct these physical capital stocks, denoted by K_{vjt}, and use them instead of the R&D stocks S_{vjt} in the specifications given by equations 8 and 9. The K_{vjt} variables are based on the estimated capital stocks in the nonelectrical machinery industries of the eight countries (ISIC 382); their construction is analogous to the R&D stocks S_{vjt}. In the NIS specification (equation 8) substituting K_{vjt} for S_{vjt} results in a drop in the R^2 from 0.472 to 0.169. In the IS specification (equation 9) 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 the economies' stocks of technology better than physical capital does.

The result that high stocks of weighted foreign R&D are associated with high domestic productivity is interesting, but as such it does not say much about the importance of the fact that the weighting variables are the observed bilateral import shares. If these shares are interpreted 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 if we had employed a different set of probability weights, corresponding to different import patterns.

To examine this issue, I conduct Monte Carlo experiments. I investigate two different questions.[18] First, conditional on the effect of domestic R&D on productivity, is there evidence indicating that the composition of intermediate imports matters for productivity growth across sectors? Second, is there support for the hypothesis that foreign and domestic R&D have different effects on productivity?

DOES PRODUCTIVITY PERFORMANCE REFLECT THE COMPOSITION OF INTERMEDIATE IMPORTS? In the following experiments I randomly switch the bilateral import shares of given importing countries. Let b denote a specific Monte Carlo replication, $b = 1,\dots,B$. The experiments are constrained such that only the composition of international demand is randomized. That is, the results are conditional on the domestic R&D effect: $\theta^v_{vj}(b) = 1$, $\forall v, j, b$. For all $w \neq v$ this means that

$$(10) \qquad \theta^v_{wj}(b) = m^v_{qj} \text{ with } \Pr = \frac{1}{7},\ q \in G7S \setminus v, \forall v, w, j.$$

The $\theta^v_{wj}(b)$ are constructed such that $\Sigma_w \theta^v_{wj}(b) = 1$, that is, any observed import share is assigned only once.[19] The two specifications are

$$(11) \qquad \log F_{vjt} = \mu_j d_j + \delta_v d_v + \sum_{c \in G7S} \beta_c [\theta^v_{cj}(b) \log S_{cjt}] + \varepsilon_{vjt}, \forall v, j, t, b$$

and

$$(12) \qquad \log F_{vjt} = \mu_j d_j + \delta_v d_v + \sum_{c \in G7S} \beta_c [m_{vj} \theta^v_{cj}(b) \log S_{cjt}] + \varepsilon_{vjt}, \forall v, j, t, b.$$

In 75 percent of the cases the average estimates of β_c are significantly different from zero and positive (table 2). In addition, these coefficients are sometimes smaller and sometimes larger than those obtained by employing observed import shares. Thus no clear pattern can be detected. Moreover, the regressions that

18. Another approach to gauge the importance of the m^v_{cj} might be to simply drop them from equations 8 and 9. In equation 8 only two of eight β_c parameters are then estimated to be significantly different from zero (that of Japan, at −2.02, and that of the United States, at 1.37). If the bilateral import shares in equation 9 are dropped, only the β_c parameters for Germany, Italy, and Sweden are significantly positive; the parameter 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 whether the import composition or only the fact that the m^v_{cj} are not equal to one also matters.

19. 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 $\sigma^v_{wj}(b)$ is equal to the value m^v_{wj}, for 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 × 6 = 48 independent sequences.

Table 2. *Total Factor Productivity–Level Regressions*

	NIS			IS		
Country	*Observed shares*[a]	*Import shares switched*[b]	*Shares switched*[c]	*Observed shares*[d]	*Import shares switched*[e]	*Shares switched*[f]
Canada	0.101**	0.159	0.191	0.201**	0.104	0.026
	(0.027)	(0.081)	(0.097)	(0.043)	(0.085)	(0.253)
France	0.209**	0.161**	0.132	0.236**	0.180**	0.028
	(0.019)	(0.063)	(0.068)	(0.024)	(0.081)	(0.156)
Germany	0.071**	0.118**	0.115**	0.019**	0.128**	0.107
	(0.009)	(0.042)	(0.052)	(0.009)	(0.049)	(0.132)
Italy	0.066**	0.087**	0.134	0.083**	0.083**	0.243
	(0.014)	(0.028)	(0.080)	(0.015)	(0.028)	(0.308)
Japan	0.068**	0.103**	0.123**	0.127**	0.097**	0.034
	(0.014)	(0.043)	(0.053)	(0.020)	(0.046)	(0.136)
Sweden	0.206**	0.172**	0.147**	0.276**	0.253**	0.200
	(0.022)	(0.053)	(0.072)	(0.025)	(0.042)	(0.244)
United Kingdom	0.188**	0.134**	0.134	0.150**	0.165	0.028
	(0.022)	(0.064)	(0.067)	(0.027)	(0.086)	(0.129)
United States	0.111**	0.082**	0.108**	0.080**	0.081	0.035
	(0.007)	(0.039)	(0.043)	(0.011)	(0.044)	(0.092)
R^2	0.472	0.490	0.522	0.357	0.379	0.260

**Significant at the 5 percent level

Note: Standard errors are shown in parentheses. n = 1,056. The NIS specification does not include overall import share; the IS specification does include overall import share.

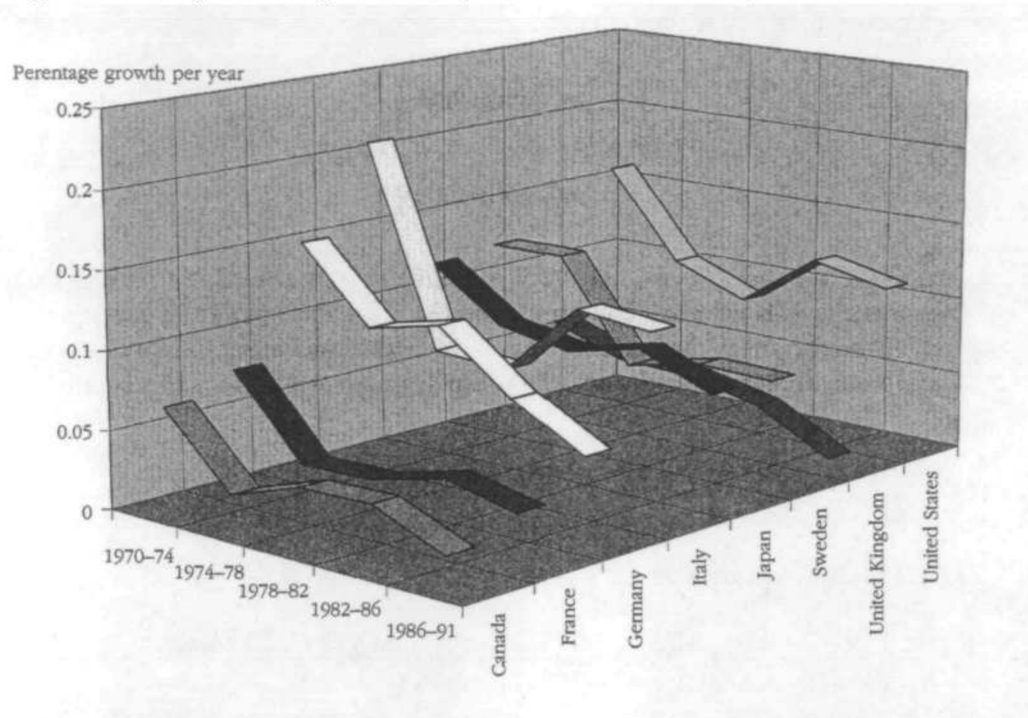
a. See equation 8.
b. See equation 11.
c. See equation 14.
d. See equation 9.
e. See equation 12.
f. See equation 15.

employ randomly switched import shares account for a slightly higher share of the variation in productivity 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 (1998a) that one cannot test the hypothesis of links between R&D, the trade pattern, and TFP simply by examining whether the parameter estimates are positive or the R^2 is high. Obviously, the regression results are to some degree invariant to the weights with which the R&D stocks are multiplied. This would be trivial if the R&D stocks of different countries were equal in size and moved together over time. However, as shown in table A-7, there are considerable differences in the cumulative R&D stocks of different countries. In addition, the R&D stocks of different countries do not grow at the same rates, nor do they rise and fall simultaneously (figure 1).[20] This reasoning, at least in its extreme form, thus cannot explain the finding

20. The average annual growth rates of the R&D stock estimates range from 3.64 percent for Canada to 11.88 percent for Italy. The standard deviations of these growth rates for different four-year subperiods across countries range from a low of 2.87 percent (1978–82) to a high of 5.15 percent (1970–74).

Figure 1. *Rate of Growth of Machinery R&D Across Countries, 1970–91*



that the parameter estimates are to some extent invariant to switching the import shares.

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

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 United States are estimated very imprecisely and are often not different from zero at standard significance levels (table 2). This result is consistent with the idea that the trade-related effect of R&D is identified primarily from countries with extreme trade patterns, such as that exhibited by the United States and Canada, which have very large import shares with each other (tables A-1 to A-6). This trade pattern differs substantially from a symmetric trade pattern, in which countries import equal shares from all partners. Technology flows from these countries do not significantly affect productivity once the import shares are randomized.

FOREIGN AND DOMESTIC INTERMEDIATE INPUTS: DOES IT MATTER HOW MUCH AND FROM WHERE? In these experiments I switch the observed bilateral shares randomly, including the weight on domestic R&D ($m^v_{vj} = 1, \forall v,j$). Any bilateral import share in replication b, $\sigma^v_{cj}(b)$ is thus equal to

$$\sigma^v_{cj}(b) = \begin{cases} m^v_{vj} \text{ with } \Pr = \frac{1}{8} \\ \vdots \\ m^v_{Vj} \text{ with } \Pr = \frac{1}{8} \end{cases}, \forall v, c, j. \tag{13}$$

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

$$\log F_{vjt} = \mu d_j + \delta d_v + \sum_{c \in G7S} \beta_c [\sigma^v_{cj}(b) \log S_{cjt}] + \varepsilon_{vjt}, \forall b, v, j, t \tag{14}$$

for the NIS specification and

$$\log F_{vjt} = \mu d_j + \delta d_v + \sum_{c \in G7S} \beta_c [m_{vj} \sigma^v_{cj}(b) \log S_{cjt}] + \varepsilon_{vjt}, \forall b, v, j, t \tag{15}$$

for the IS specification.

In 75 percent of the cases the Monte Carlo experiments result in coefficient estimates that are statistically indistinguishable from zero at the 5 percent level (table 2). For the model given by equation 14, half of the coefficient estimates are not significant; none of the β_c estimates for the model given by equation 15 is significant. The average R^2 in column three (0.522) is larger than that for the corresponding observed data regression. This finding is surprising, but could be spurious. Overall, the result that parameter estimates tend not to be significantly different from zero in the Monte Carlo experiment implies that if use of intermediate inputs, produced abroad or domestically, is determined randomly, the statistically significant relationship between R&D and productivity disappears.

To summarize, significant and quantitatively important productivity effects from R&D are found if the domestic source of technology diffusion is distinguished from foreign sources, while no robust relationship between R&D and productivity is found if domestic and foreign sources are treated symmetrically. It thus follows that the source of technology diffusion (domestic or foreign) matters. Moreover, because the domestic R&D weight, m^v_{vj}, is set to equal one, $\forall v,j$, whereas only the sum of foreign R&D weights equals one ($\sum_{w \neq v} m^v_{wj} = 1, \forall v,j$), the comparison of the observed share results and the randomized share results indicates that domestic R&D has a stronger impact on productivity than R&D from the average foreign country. This 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 given by equations 8 and 9. Overall, the results in the appendix suggest that the findings above are robust.

Estimation of TFP *Growth*

The TFP growth specifications corresponding to equations 8 and 9 are

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c \in G7\,S} \beta_c \left(m_{cj}^{v} \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall v, j, t \tag{16}$$

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

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c \in G7\,S} \beta_c \left(m_{vj} m_{cj}^{v} \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall v, j, t \tag{17}$$

where the value of the import share from v, m_{vj}, is set equal to one, $\forall v, j$. Dividing the period of observation into five subperiods of about four years each yields 240 observations (table 3).[21]

All slope coefficients are estimated to be positive. Moreover, in the IS model they are also significantly different from zero at the 5 percent level. The IS appears to be the preferred specification in this class of models. This result is consistent with the arguments given above as well as with the findings of Coe and Helpman (1995), even though the R^2 here is lower in the IS than in the NIS specification.

Only the results of the Monte Carlo experiments that were conditional on the effect of domestic R&D—those in which only the import shares were switched—are presented (table 3). The specifications are

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c \in G7\,S} \beta_c \left(\theta_{cj}^{v}(b) \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall b, v, j, t \tag{18}$$

and

$$\frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c \in G7\,S} \beta_c \left(m_{vj} \theta_{cj}^{v}(b) \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall b, v, j, t. \tag{19}$$

For each of these specifications I conduct 1,000 experiments. All Monte Carlo–based coefficients are estimated to be significantly greater than zero, confirming

21. The fact that the specifications given by equations 16 and 17 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 them here. See appendix E for more details.

Table 3. *Total Factor Productivity Growth Specifications*

	NIS		IS	
Country	*Observed shares*[a]	*Import shares switched*[b]	*Observed shares*[c]	*Import shares switched*[d]
Canada	0.351*	0.383**	0.415**	0.427**
	(0.178)	(0.122)	(0.158)	(0.022)
France	0.437**	0.431**	0.503**	0.512**
	(0.139)	(0.078)	(0.141)	(0.018)
Germany	0.198**	0.210**	0.235**	0.252**
	(0.067)	(0.027)	(0.060)	(0.009)
Italy	0.093*	0.126**	0.151**	0.157**
	(0.054)	(0.030)	(0.053)	(0.007)
Japan	0.068	0.077**	0.166**	0.169**
	(0.076)	(0.037)	(0.080)	(0.010)
Sweden	0.153**	0.155**	0.172**	0.189**
	(0.072)	(0.037)	(0.070)	(0.008)
United Kingdom	0.380**	0.358**	0.493**	0.508**
	(0.153)	(0.077)	(0.158)	(0.018)
United States	0.137**	0.108**	0.173**	0.173**
	(0.062)	(0.024)	(0.061)	(0.009)
R^2	0.127	0.134	0.105	0.109

*Significant at the 10 percent level

**Significant at the 5 percent level

Note: Standard errors are shown in parentheses. $n = 240$. The NIS specification does not include overall import share; the IS specification does include overall import share.

a. See equation 16.

b. See equation 18.

c. See equation 17.

d. See equation 19.

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 percent confidence interval for the coefficient of Canada in the IS specification is equal to $0.427 \pm (2 \times 0.022)$. That this interval also includes the estimate for the import-weighted R&D effect from Canada when employing observed data (0.415), implies that the Canadian trade-related R&D effect is not statistically 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 with the observed-share results are for Sweden in the IS specification and Japan in the NIS specification.

IV. Separating Trade-Related R&D Spillovers from Average R&D Spillovers

In this section I show how switching the import shares is related to an average spillover effect from foreign R&D. I also examine whether the pattern of international trade influences international technology diffusion.

Monte Carlo Experiments and Average Foreign R&D Spillovers

Consider the average of a particular off-diagonal R&D weight across the B simulations, $\sigma^v_w(\bar{b}) = 1/B\ \Sigma_b\sigma^v_w(b), \forall w \neq v$. Because the exchanging of the m^v_w is independent and identically distributed (i.i.d.) as $B \rightarrow \infty$, this average will be the same for all, $\sigma^v_w(\bar{b}) = \sigma(\bar{b}), \forall v,w$. With seven trade partners for any importing country, given that $7 \times \sigma(\bar{b}) = 1$, $\sigma(\bar{b}) = 1/7$.[22] Hence for any partner country's R&D variable across all B replications,

$$\text{(20)} \qquad \frac{1}{B}\sum_b\left(\sigma^v_w(b)\frac{\Delta S_{wj}}{S_{wj}}\right) = \frac{\Delta S_{wj}}{S_{wj}}\frac{\Sigma_b\,\sigma^v_w(b)}{B} = \sigma(\bar{b})\frac{\Delta S_{wj}}{S_{wj}}, \forall w \neq v.$$

Therefore, across all B replications the average regressors are the average annual growth rates, $\Delta S_{wj}/S_{wj}$, $w \neq v$, multiplied by $\sigma(\bar{b}) = 1/7$ for all partner countries and by $\Delta S_{vj}/S_{vj}$, the own-country R&D variable. Note, however, that the coefficients reported from the Monte Carlo experiments are averages across the OLS estimates from 1,000 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[23]

$$\text{(21)} \qquad \frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c\in G7S}\beta_c\left[m_{vj}\left(\sigma(\bar{b})\frac{\Delta S_{cjt}}{S_{cjt}}\right)\right] + \varepsilon_{vjt}.$$

Comparing this regression with the Monte Carlo–based results from table 3, it is clear that the Monte Carlo averages indeed estimate the average R&D spillover effect. The maximum relative difference between the estimated parameters is 2 percent (18.5 percent compared with 18.9 percent in the case of Sweden).[24]

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 that is related to international trade patterns. Consider the following regression:

$$\text{(22)} \quad \frac{\Delta F_{vjt}}{F_{vjt}} = \alpha_0 + \sum_{c\in G7S}\beta^I_c\left[m_{vj}\sigma(\bar{b})\frac{\Delta S_{cjt}}{S_{cjt}}\right] + \sum_{c\in G7S}\beta^{II}_c\left[m_{vj}\left(m^v_{cj} - \sigma(\bar{b})\right)\frac{\Delta S_{cjt}}{S_{cjt}}\right] + \varepsilon_{vjt}.$$

22. This argument applies to any way of creating random import shares as long as it is i.i.d. and imposes $\Sigma_w\,\sigma^v_{wj}(b) = 1, \forall b,v$. It encompasses the procedure in Keller (1998a) and also randomizations that create arbitrary random shares, as opposed to randomization through exchanging the observed import shares, as has been done here.

23. Even if m_{vj} does not enter the following equation, the regression is feasible because the weight for domestic R&D is set equal to one. Otherwise, the average spillover regression (without m_{vj}) would not be feasible, because the regressor $\sigma(\bar{b})\Delta S_w/S_w$ 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.

24. The estimated standard deviations in these two regressions are not comparable.

Table 4. *Total Factory Productivity Growth Estimations*

Country	*Average R&D spillover*[a]	*Import shares switched*[b]
Canada	0.426	0.427
	(0.156)	(0.022)
France	0.513	0.512
	(0.139)	(0.018)
Germany	0.252	0.252
	(0.062)	(0.009)
Italy	0.156	0.157
	(0.052)	(0.007)
Japan	0.167	0.169
	(0.080)	(0.010)
Sweden	0.185	0.189
	(0.069)	(0.008)
United Kingdom	0.508	0.508
	(0.157)	(0.018)
United States	0.173	0.173
	(0.061)	(0.009)
R^2	0.109	0.109

Note: All values significant at the 5 percent level. Standard errors are shown in parentheses. $n = 240$.
a. See equation 21.
b. See equation 19.

The eight regressors with parameters β^{I} measure the average R&D spillover effect, and the eight β^{II} coefficients estimate the marginal trade pattern–related effect, if any. If there is no separate effect of international R&D that works through the pattern of international trade, then the coefficients β^{II} will be equal to zero, and equation 22 will explain as much of the variation in productivity growth rates as the average R&D spillover specification (equation 21) (table 5). The specification allowing for an additional R&D spillover effect related to trade patterns explains more of the variation in TFP growth rates than the specification that captures only the average R&D spillover effect (the adjusted R^2 values are 9.6 percent compared with 7.8 percent). The marginal effect of the bilateral trade pattern thus explains about 20 percent of the productivity growth effect from international R&D spillovers.[25]

The β^{II} point estimates in table 5 can be interpreted to indicate that industries that purchase a large share of their imports from a particular country (that is, more than 1/7 of total imports) experience on average lower rates of productivity growth than those that import the same share from all trading partners. The

25. Table 5 shows the adjusted R^2 as the number of regressors in the two specifications differs. I have considered analogous regressions for the NIS growth specification, as well as for the TFP-level NIS and IS regressions to check the robustness of this finding. I estimate that bilateral trade patterns accounted for 7.8 percent of the total international R&D spillover effects in the TFP-level NIS specification and 26.5 percent of the total in the IS specification. 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 no significant marginal trade-related R&D spillover effect is estimated. Hence, while not perfectly robust, the pattern of bilateral trade is estimated to contribute significantly to understanding the total productivity effect from foreign R&D, accounting for about 20 percent of the effect in the preferred specification.

Table 5. *Total Factory Productivity Growth Estimations*

	Average spillover[a]	Average and trade spillover[b]	
Country	β_F	β^{I}	β^{II}
Canada	0.426**	0.389*	–13.61**
	(0.156)	(0.231)	(4.30)
France	0.513**	0.398**	4.11
	(0.139)	(0.181)	(3.39)
Germany	0.252**	0.126	–1.24
	(0.062)	(0.083)	(0.82)
Italy	0.156**	0.102*	–2.10
	(0.052)	(0.061)	(1.43)
Japan	0.167**	0.129	1.44
	(0.080)	(0.086)	(2.28)
Sweden	0.185**	0.165*	–1.22
	(0.069)	(0.090)	(2.19)
United Kingdom	0.508**	0.310	–5.12
	(0.157)	(0.189)	(6.19)
United States	0.173**	0.157**	–0.39
	(0.061)	(0.067)	(0.84)
Adjusted R^2	7.8	9.6	

* Significant at the 10 percent level.
** Significant at the 5 percent level.
Note: Standard errors are shown in parentheses. $n = 240$.

effect is estimated to be positive for France and Japan and negative for all other countries. It is significantly different from zero at the 5 percent level only for Canada, however.

V. Conclusions and Implications for Developing Countries

In this article I examine the evidence on the effect of technology diffusion on productivity growth through imports of new intermediate capital goods. I develop an empirical model in which domestic productivity is related to the number of varieties of imported differentiated inputs that are employed domestically. Based on the hypothesis that the number of varieties from partner countries is related to imports from those countries, I estimate the relation between domestic as well as import-weighted foreign R&D and domestic productivity.

Three conclusions emerge from the analysis. First, there is evidence that 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 toward or away from technological leaders. Third, differences in technology inflows related to the patterns of imports explain about 20 percent of the total variation in countries' productivity growth rates.

What are the implications of this analysis for developing countries? The results suggesting that domestic R&D has a larger influence on productivity than

R&D investments in the average country abroad must be qualified for developing countries, many of which spend only a fraction of their total spending on technology on formal R&D. It is likely that the contribution of foreign sources of technology is larger than that of domestic sources for many developing countries.

To confirm this conjecture requires high-quality industry-level measures of productivity and technological efforts in developing countries, 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 (2000). There, I estimate that in nine small OECD countries, the R&D of the G-5 countries (France, Germany, Japan, the United Kingdom, and the United States) taken together leads to productivity effects that are more than twice as large as those from own-country R&D investments.

Given the greater relative importance of foreign sources of technology for a typical developing country relative to the countries in this sample, one should expect differences in overall import share and import composition to have a stronger effect on differences in productivity growth in developing countries than I have estimated here. Intermediate input imports contribute to the international diffusion of technology and hence to the transfer of technology to developing countries. Everything else equal, a higher share of trade promotes that process.

The composition of imports matters. Productivity growth in a typical developing country might not depend too much on whether 50 percent of its imports come from the United States and 30 percent from Japan, or 30 percent from the United States and 50 percent from Japan. But productivity is likely to be much lower if the country were to significantly reduce the share of its imports from both the United States and Japan while increasing its share of imports from other developing countries that are not world technology leaders. The results obtained here suggest that relative import shares help explain productivity growth even in importing OECD countries. The impact on productivity of a change in import composition is likely to be an order of magnitude larger if developing-country trade patterns shift substantially between today's technological leaders and followers.

Appendix A. Data on Import Flows

The specialized machinery trade data come from OECD (1980). Import data for the first five industries are from mid-1980. For the sixth industry I was unable to obtain data for 1980 from SITC revision 2 and therefore use 1975 data from SITC revision 1. I use these tables to derive the variable m_{wj}^{v}, the bilateral import shares of country v with countries $w \neq v$ in sector j.

Table A-1. *Food-Processing Machinery Imports (SITC 727)*
(1980 U.S.$)

Exporting country	*Importing country* Canada	France	Germany	Italy	Japan	Sweden	United Kingdom	United States
Canada	0	938	113	7	2	26	915	4,141
France	1,398	0	7,682	7,231	1,050	837	4,631	3,960
Germany	8,513	30,099	0	18,442	11,268	11,446	30,004	36,143
Italy	4,292	22,397	10,812	0	2,403	1,461	7,634	9,431
Japan	290	38	1,832	1,709	0	156	728	8,114
Sweden	1,181	1,332	1,225	606	487	0	2,310	1,916
United Kingdom	3,655	6,274	4,638	3,226	1,679	1,800	0	8,551
United States	63,235	12,559	6,196	2,838	8,458	2,022	23,435	0

Table A-2. *Textiles and Leather Machinery Imports (SITC 724)*
(1980 U.S.$)

Exporting country	*Importing country* Canada	France	Germany	Italy	Japan	Sweden	United Kingdom	United States
Canada	0	801	660	1,232	207	38	2,140	21,275
France	4,151	0	38,542	49,901	3,465	1,353	28,705	34,619
Germany	22,409	187,433	0	259,344	55,555	31,400	116,170	262,163
Italy	23,122	78,772	68,873	0	15,124	6,155	67,436	68,070
Japan	11,110	28,372	39,932	22,546	0	1,966	40,419	139,266
Sweden	3,558	5,145	8,530	2,181	3,864	0	9,713	29,519
United Kingdom	9,953	40,817	47,110	42,585	8,856	6,632	0	53,270
United States	143,551	27,501	33,617	21,479	14,106	5,167	49,242	0

Table A-3. *Paper and Pulp Mill Machinery Imports (SITC 725)*
(1980 U.S.$)

Exporting country	*Importing country* Canada	France	Germany	Italy	Japan	Sweden	United Kingdom	United States
Canada	0	1,352	278	304	2,722	85	919	35,110
France	534	0	25,553	16,619	109	4,560	13,245	10,01
Germany	9,767	65,245	0	47,290	17,197	31,354	61,340	68,760
Italy	794	32,561	22,365	0	353	1,834	10,028	6,125
Japan	2,829	315	7,392	925	0	782	3,831	11,535
Sweden	5,245	6,911	18,014	4,779	1,572	0	7,263	21,098
United Kingdom	11,990	9,563	12,809	8,827	584	10,580	0	8,612
United States	88,992	8,093	19,794	4,411	11,152	7,982	18,720	0

Table A-4. *Printing and Bookbinding Machinery Imports (SITC 726)*
(1980 U.S.$)

Exporting country	Importing country: Canada	France	Germany	Italy	Japan	Sweden	United Kingdom	United States
Canada	0	441	272	543	153	309	2,663	8,537
France	944	0	13,589	13,497	169	6,140	31,642	8,090
Germany	18,467	133,716	0	105,198	77,149	41,834	141,982	143,425
Italy	2,320	26,061	21,148	0	10,622	2,711	20,418	51,072
Japan	6,224	4,786	5,332	3,420	0	2,227	21,027	60,713
Sweden	1,543	10,612	6,074	853	3,168	0	14,519	14,471
United Kingdom	19,206	25,519	19,636	19,271	5,219	9,126	0	49,020
United States	158,716	51,574	43,920	25,469	25,662	24,677	73,167	0

Table A-5. *Machine Tools and Metal-Working Machinery Imports (SITC 736 and 737)*
(1980 U.S.$)

Exporting country	Importing country: Canada	France	Germany	Italy	Japan	Sweden	United Kingdom	United States
Canada	0	826	1,904	295	1,636	295	8,508	117,564
France	9,137	0	110,469	50,354	4,034	11,574	48,758	46,705
Germany	41,546	318,019	0	223,334	87,011	129,441	288,330	345,307
Italy	11,821	138,858	154,121	0	6,504	23,166	77,445	63,596
Japan	30,259	44,462	122,266	8,507	0	28,770	122,686	617,156
Sweden	8,612	17,788	45,895	15,588	4,916	0	37,929	52,440
United Kingdom	41,064	58,034	83,115	44,457	6,081	25,671	0	169,590
United States	608,480	66,698	72,679	29,627	93,295	22,344	161,467	0

Table A-6. *Mining, Metal-Crushing, and Glass-Working Machinery Imports (SITC Revision 1, 7184 and 7185)*
(1975 U.S.$)

Exporting country	Importing country: Canada	France	Germany	Italy	Japan	Sweden	United Kingdom	United States
Canada	0	1,517	341	312	453	294	2,559	73,438
France	11,738	0	78,204	38,841	1,316	9,063	49,246	32,890
Germany	22,999	97,060	0	47,026	3,687	25,154	50,335	64,832
Italy	3,503	26,645	34,749	0	141	1,853	17,079	11,597
Japan	13,582	3,700	16,499	7,454	0	654	13,612	42,338
Sweden	12,421	10,708	22,294	9,466	1,739	0	19,019	10,239
United Kingdom	19,340	41,885	23,092	21,204	1,722	12,348	0	37,783
United States	644,606	75,425	46,474	22,419	37,028	18,733	104,457	0

Table A-7. *Summary Statistics on Machinery* R&D *Stocks*
(1985 U.S.$)

Country and industry	*Mean*	*Standard deviation*
Country		
Canada	92.79	34.75
France	417.40	222.53
Germany	1,403.29	1,148.55
Italy	123.03	143.10
Japan	919.80	670.24
Sweden	170.59	98.33
United Kingdom	665.71	305.32
United States	3,379.03	2,720.96
Industry		
Food	1,087.13	1,535.52
Textiles	1,363.09	2,036.03
Paper products	337.83	554.24
Printing	576.61	1,079.07
Minerals and basic metals	1,145.53	1,679.58
Metal products	960.72	1,457.14

Table A-8. *Summary Statistics on Annual Total Factor Productivity Growth, 1970–91*

Country and industry	*Mean*	*Standard deviation*
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
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

Appendix B. Data on Research and Development

The raw data on R&D expenditures come from OECD (1991). R&D surveys were not conducted annually in all countries included in the sample over the entire sample period, however. In the United Kingdom, for instance, surveys were conducted only every third year until well into the 1980s. In Germany R&D data are collected only every second year. This lack of annual data made it necessary to interpolate about 25 percent of all the R&D expenditure data.

The construction of the technology stock variable, n, is based on data on total business enterprise intramural expenditures on R&D for ISIC sector 382 (nonelectronic machinery), in constant 1985 U.S. dollars, with OECD purchasing power parity rates used for conversion. The OECD code for this series is BERD (see table 9B of OECD 1991). I use the perpetual inventory method to construct technology stocks, assuming that

$$n_{vt} = (1-\bar{\delta})n_{vt-1} + \chi_{vt-1}, \forall v, t = 2,\ldots,22$$

and

$$n_{v1} = \frac{\chi_{v1}}{g_v^n + \bar{\delta} + 0.1}.$$

The rate of depreciation, $\bar{\delta}$ is set at 0.05; g^n is the average annual growth rate of n over the period 1970–89 (the year endpoints for which data are available for all countries). Preliminary analysis using other values for the rate of depreciation, such as 0 or 0.1, shows that the rate of depreciation does not influence the estimation results significantly. The denominator in the calculation of n_1 is increased by 0.1 in order to obtain positive estimates of n_1 throughout.

Appendix C. Data on Labor, Physical Capital, and Gross Production

The OECD (1994) STAN database is the basic source for labor, physical capital, and gross production. It provides internationally comparable data on industrial activity by sector, including data on labor input, labor compensation, investment, production, and gross production for up to 49 three-digit ISIC industries (revision 2). STAN data are OECD estimates based on data submitted by OECD member countries. The OECD has tried to ensure international comparability (see OECD 1994).

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

$$k_{vt} = (1-\hat{\delta}_v)k_{vt-1} + inv_{vt-1}, \forall v, t = 2,\ldots,22$$

and

$$k_{v1} = \frac{inv_{v1}}{g_v^{inv} + \hat{\delta}_v}, \forall v$$

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 1970–91; and $\hat{\delta}$ is the rate of depreciation of capital. I use the following country-specific depreciation rates, taken from Jorgenson and Landau (1993): Canada, 8.51 percent; France, 17.39 percent; Germany, 17.4 percent; Italy, 11.9 percent; Japan, 6.6 percent; Sweden, 7.7 percent; the United Kingdom, 8.19 percent; and the United States, 13.31 percent. These figures, which are used throughout, are estimates for machinery in manufacturing in 1980.

According to equation 1, α_{vjt} is the share of the labor cost in production. Following the approach suggested by Hall (1990), the values of α_{vjt} are not calculated as the ratio of total labor compensation to value added (the revenue-based factor shares), both of which are included in the STAN database. Rather, using the framework of the integrated capital taxation model of King and Fullerton (see Jorgenson 1993, Fullerton and Karayannis 1993, and data provided in Jorgenson and Landau 1993), I construct cost-based factor shares that are robust in the presence of imperfect competition. The effective marginal corporate tax rate, τ, is given by the wedge between the before-tax (p_k) and after-tax rate of return (ρ)

(C-1) $$\tau = \frac{p_k - \rho}{p_k}.$$

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

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

(C-2) $$\rho = \iota + \pi$$

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. 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 me, using equations (C-1) and (C-2) to infer p_k, the user cost of capital. I use Jorgenson's values on manufacturing (the 1980 values are used for 1970–82 in my sample, the 1985 values are used for 1983–86, and 1990 values are used for 1987–91). This clearly introduces an error. In addition, Jorgenson's values are derived from a "fixed-p" approach, as opposed to the "fixed-r" approach employed here. Moreover, the results depend on the real interest rate chosen. Finally, τ varies by asset type, and ρ is a function of the type of financing used (equity versus debt primarily). These shortcomings in the construction of the cost-based factor shares are unavoidable given the lack of more detailed data.

Fullerton and Karayannis (1993) present a sensitivity analysis in several dimensions. I have experimented myself with different values for ι and found that the basic results presented above do not depend on a particular choice for ι. 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 that is robust to deviations from perfect competition.

To obtain robust wage shares, α, I deflate the current price of labor costs, wl, available in the STAN database (again using sectoral output deflators):

$$\alpha = \frac{wl}{wl + p_k k}.$$

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

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

This index 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 figure 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.

Appendix D. Relationship of Monte Carlo Experiments and Average R&D Spillover Regression

Consider, for simplicity, the model above with only one regressor (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

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

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

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

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

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

The right side of the expression can be rewritten to obtain

$$\text{(D-1)} \qquad \beta_1(\bar{b}) \simeq \frac{\Sigma_v\,\sigma(\bar{b})\frac{\Delta S_w}{S_w}\frac{\Delta F_v}{F_v}}{\Sigma_v\left(\frac{\Delta S_w}{S_w}\right)^2\left[\sigma(\bar{b})\right]^2} + \frac{\Sigma_v\,\frac{\Delta S_w}{S_w}\frac{\Delta F_v}{F_v}\,\Sigma_{b=1}^B\,\eta_w^v(b)}{B\,\Sigma_v\left(\frac{\Delta S_w}{S_w}\right)^2\left[\sigma(\bar{b})\right]^2}.$$

Because $\Sigma_{b=1}^B\,\eta_w^v(b) = 0$, however, the second term in expression D-1 will drop out, so that $\beta_1(\bar{b})$ is approximately equal to the OLS estimate of projecting $\Delta F_v/F_v$ on $\sigma(\bar{b})\Delta S_w/S_w$. Clearly, how good the approximation above is depends on how large $\left[\Delta S_w/S_w\right]^2\left(\left[\eta_w^v(b)\right]^2 + 2\eta_w^v(b)\sigma(\bar{b})\right)$ 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 $\lambda_w = \Delta S_w/S_w$, the case presented in table 4.

Appendix E. Sensitivity Analysis

The sensitivity of the results can be examined by considering a number of alternative specifications for both the productivity level and the growth regressions. As noted above, in principle, including a fixed effect for each industry allows consistent parameters to be estimated 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 equations 8 and 9:

$$\log F_{vjt} = \delta_{vj} d_{vj} + \sum_{c \in G7\,S} \beta_c (m_{cj}^{v} \log S_{cjt}) + \varepsilon_{vjt}, \forall v, j, t$$

and

$$\log F_{vjt} = \delta_{vj} d_{vj} + \sum_{c \in G7\,S} \beta_c (m_{vj} m_{cj}^{v} \log S_{cjt}) + \varepsilon_{vjt}, \forall v, j, t$$

where d_{vj} is dummy variable that equals 1 for the country-industry combination vj and zero otherwise. Including a separate fixed effect for every industry raises the number of fixed effects from 14 to 48 (6 × 8). The inclusion of more fixed effects raises the R^2 for both specifications, from 0.472 to 0.755 for the NIS and from 0.357 to 0.746 for the IS. In both specifications all of the estimated parameters β_c remain significantly different from zero at the 1 percent level, with the values ranging from 4.1 percent (for the United States in the NIS) to 61.5 percent (for France in the IS).

Inclusion of a trend (denoted *year*) yields

$$\text{(E-1)} \qquad \log F_{vjt} = \alpha year_t + \delta_{vj} d_{vj} + \sum_{c \in G7\,S} \beta_c (m_{cj}^{v} \log S_{cjt}) + \varepsilon_{vjt}, \forall v, j, t$$

and

$$\text{(E-2)} \qquad \log F_{vjt} = \alpha year_t + \delta_{vj} d_{vj} + \sum_{c \in G7\,S} \beta_c (m_{vj} m_{cj}^{v} \log S_{cjt}) + \varepsilon_{vjt}, \forall v, j, t$$

The trend increases the R^2 slightly (from 0.755 to 0.757 in the NIS and from 0.746 to 0.753 in the IS). It also lowers the estimated parameters β_c in both specifications—just as one would expect if there are common trends in levels. The new estimates range from a low of 2.4 percent (for the United States in the NIS) to a high of 44.1 percent (for France in the NIS). On average, the estimates fall by about 15–20 percent. However, 13 of 16 estimates from the specifications given by equations E-1 and E-2 remain significantly positive at the 5 percent level; the highest p-value is 21.1 percent.

In the growth specifications a major concern is whether all industries share a common growth rate. To test this, I run equations 16 and 17 including industry fixed effects to get:

$$\text{(E-3)} \qquad \frac{\Delta F_{vjt}}{F_{vjt}} = \delta_j d_j + \sum_{c \in G7S} \beta_c \left(m_{cj}^{v} \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall v, j, t$$

and

$$\text{(E-4)} \qquad \frac{\Delta F_{vjt}}{F_{vjt}} = \delta_j d_j + \sum_{c \in G7S} \beta_c \left(m_{vj} m_{cj}^{v} \frac{\Delta S_{cjt}}{S_{cjt}} \right) + \varepsilon_{vjt}, \forall v, j, t.$$

For specification E-3, one out of six industry fixed effects is estimated to be significantly different from zero at the 5 percent level. For specification E-4, none of the industry fixed effects is significant. The estimated parameters β_c are affected only slightly.

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

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

and

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

In specification E-5, 4 out of 14 fixed effects differ significantly from zero. In specification E-6, 3 out of 14 fixed effects are significant. These results suggest that the evidence that growth rates differ 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 30 percent of these values are estimated to be significantly different from zero.

Including more fixed effects does reduce the number of R&D parameters β_c that are estimated to differ significantly from zero. In the growth specification with overall import share, for example, when country-by-industry fixed effects are included, only the R&D stocks of Canada, Germany, the United Kingdom, and the United States are estimated to have a significantly positive effect on productivity (at the 10 percent level). This is to be expected in a cross-industry, cross-country TFP growth regression that does not exploit any between-industry variation. Overall, this analysis suggests that the results presented in the text are fairly robust.

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