Trade Patterns, Technology Flows, and Productivity Growth*

Wolfgang Keller†
Department of Economics
University of Wisconsin-Madison

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Abstract

This paper presents a model of international trade in differentiated intermediate goods. Because intermediates are invented through costly R&D investments, employing foreign intermediates implies sharing the return to R&D with the inventor country. I first derive a relation of how domestic productivity is related to foreign R&D investments. In the subsequent empirical analysis, industry level data for eight OECD countries between 1970-91 is used to estimate that relation. The robustness of interpreting empirical findings is emphasized, to which effect I employ Monte-Carlo techniques, and the part of international R&D spillovers that is related to trade is quantified. I find evidence, first, that domestic and foreign R&D affect productivity differently, in contrast to assuming symmetric effects. Second, the productivity effects resulting from R&D vary substantially by which country conducts the R&D. Third, I find that the composition of a country's import partners does not significantly affect the estimated effect from foreign R&D, indicating a large component in the benefit from foreign R&D which is not related to trade. Lastly, I estimate that international trade contributes about 20% to the total productivity effect from foreign R&D.

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†1180 Observatory Drive, Madison, Wi 53706; email: wkeller@facstaff.wisc.edu.

1. Introduction

The recent development of theories of endogenous technological change, in particular by Romer (1990) and Aghion and Howitt (1992), have triggered new work on the relations of trade, growth, and technological change in open economies (Grossman and Helpman 1991, Rivera-Batiz and Romer 1991a). In these papers, the authors embed the recent theories in multi-sector 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 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 impact of receiving a new input in the importing country might take various forms. First of all, there is the direct effect of employing a larger range of intermediate inputs in final output production: For a given amount of primary resources, output is increasing in the range of differentiated inputs (Ethier 1982). To the extent that the importing country succeeds in not paying in full for this increase-in-variety, it is reaping an external, 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 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 Ethier-Romer model. In addition, they are often highly specialized for a particular industry, implying that the elasticity of substitution between machinery produced for two different industries is negligible.[1]

In this setting, I ask whether productivity growth in a particular industry of an importing country is increased 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 spillovers hypothesis. Both the 'increasing variety' as well as the 'reverse-engineering' effects discussed above are tied to arm's length market transactions of goods. This is in contrast to many other possibilities by which technological knowledge can diffuse and which do not rely on arm's length transactions per se.[2]

One 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 a higher TFP level in the former importing countries. Second, for a given composition of imports, this effect is likely to be stronger, the greater the overall import share of a country is. A number of papers have recently attempted to assess the importance of imports in transmitting foreign R&D into domestic industries, spurring total factor productivity (TFP), including Coe and Helpman (1995), Coe et al. (1995), Evenson (1995), Keller (1996a, 1996b), as well as Lichtenberg and van Pottelsberghe (1996).[3] In Coe and Helpman (1995), the authors find a significantly positive correlation between TFP levels and a trade-weighted sum of partner country R&D stocks, where bi-

[1] See Keller (1996a) for an analysis focusing on inter-industry relations.

[2] See Griliches (1979) and Nadiri (1993) for more discussion, and the latter paper for a recent survey.

[3] The papers by Park (1995), Bernstein and Mohnen (1994), and Branstetter (1996) are also estimating international R&D spillovers, but do not contain an explicit argument with respect to international trade.

lateral import shares serve as weights. The interpretation of this finding is not clear, though, because Keller (1996b), using the same data, finds that the composition of countries' imports plays no particular role in obtaining this correlation: Alternatively weighted R&D stocks–where import shares are created randomly–also lead invariably 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.

While making the point that the Coe and Helpman (1995) results do not depend on the observed patterns of imports between countries, it does not imply that R&D spillovers are unrelated to international trade. For instance, these papers use aggregate import data to compute the trade share weights for a given importing country. Overall import relations between countries, however, might be a very poor measure of intermediate inputs trade relations. Another interpretation of the findings by Keller (1996b) is that the characteristics of the data and the data generating process call for a different, and perhaps more general, econometric specification in the first place. Moreover, even if trade is not all what is driving international R&D spillovers, it is necessary to quantify the effect of trade in order to assess its relative importance.

In this paper, therefore, I plan to address several of these issues. First of all, I conduct an analysis of R&D, imports, and TFP 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 a country-level. Secondly, I present estimation results for both TFP level as well as TFP growth rate specifications, addressing some of the open questions concerning characteristics and time series properties of the data. Thirdly, I extend the Monte-Carlo analysis conducted by Keller (1996b), showing how these type of experiments are related to estimating a general spillovers effect from foreign R&D. With this, it is, fourthly, possible to determine whether there exists a trade-related part of internationally R&D spillovers; I find that this is the case, and it is estimated to be about 20% of the total benefit derived from foreign R&D.

The remainder of the paper is as follows. In the next section, I describe the model which motivates the empirical analysis below. Section 3 contains a discussion of the characteristics and construction of the data. In the following section 4, the basic empirical results are presented, and contrasted with those from the corresponding Monte-Carlo experiments. The following section discusses how general international R&D spillovers estimates are related to the Monte-Carlo experiments, and how they can be empirically separated from trade-related effects. Section 6, finally, concludes.

2. The Model

This section will give a theoretical background for the empirical analysis presented below. I emphasize the empirical implementation of these models; for more on this type of models, see, e.g., Grossman and Helpman (1991) and Rivera-Batiz and Romer (1991a, 1991b).

Assume that the final good $j,\ j = 1,...,J$, in country v, $v = i,h,...,V$, at time t is produced according to

$$y_{vjt} = A_{vj}\, {l_{vjt}}^{\alpha_{vj}} {d_{vjt}}^{1-\alpha_{vj}}, \text{ with } 0 < \alpha_{vjt} < 1, \forall v, j, t, \tag{2.1}$$

where A_{vj} is a constant, l_{vjt} are labor services used in sectoral final output production, and d_{vjt} is a composite input consisting of horizontally differentiated intermediate products x of variety s. For a specific country i, d_{ijt} is defined as

$$d_{ijt}=\left(\gamma^i_{ijt}\int_0^{n^i_{ijt}}x^i_{ijt}(s)^{1-\alpha_{it}}\,ds+\gamma^i_{hjt}\int_0^{n^i_{hjt}}x^i_{hjt}(s')^{1-\alpha_{hj}}\,ds'+...+\right)^{\frac{1}{1-\alpha_{ijt}}}. \tag{2.2}$$

Here, $x^i_{ijt}(s)$ denotes the quantity of an intermediate of variety s used in sector j, where the country in which the intermediate is produced is given by the subscript, and the superscript denotes the country where the intermediate is employed. Similarly, n^i_{ijt} gives the range of domestically produced intermediate goods utilized in country i's good j production, and the n^i_{wjt}, $w\neq i$, give the ranges of imported goods. We think of the x's as differentiated capital goods. Assume that all varieties are different, and that $\gamma^i_{ijt}=1,\forall i,j,t$; the γ^i_{wjt} are functions to be defined below. Note that only inputs of type j are productive in the sector j of any country, corresponding to the often highly specialized nature of machinery inputs for particular industries.

Concentrating on inputs utilized in country i's sector j at time t, let p_i and p_w denote the rental prices which are asked by the producers of intermediate input variety x_i, respectively x_w. It follows from (2.1) and (2.2) that the first order conditions for choosing x_i and x_w are

$$p_i=(1-\alpha_i)\,x_i{}^{-\alpha_i}L^{\alpha_i} \tag{2.3}$$

and

$$p_w=(1-\alpha_w)\,\gamma_w x_w{}^{-\alpha_w}L^{\alpha_i},\forall w\neq i. \tag{2.4}$$

Intermediate goods producers are monopolists who choose the profit maximizing quantity x, given the inverse demands in (2.3) and (2.4). The production technology for all intermediates produced in one country is the same. In any country, one unit of any intermediate in sector j is produced linearly by using one unit of the local good j. This leads to a constant-markup formula for the price of intermediates from country v (where I have dropped the index of any particular variety because they are produced, and enter (2.1), symmetrically)

$$p_v=\frac{r_v}{1-\alpha_v},\forall v, \tag{2.5}$$

where r_v is the interest rate prevailing in country v. Assume, for simplicity, that the functions γ_w are given by $\gamma_w=x_w^{\alpha_w-\alpha_i}\frac{(1-\alpha_i)^2 r_w}{(1-\alpha_w)^2 r_i},\forall w\neq i$; then, using (2.5) and (2.3), (2.4), it can be shown that all intermediates, whether domestically produced (x_i) or imported (x_w), are employed at the same level, x_i.

In equilibrium, there will be trade in intermediate goods in this model. Define capital k_i as foregone consumption. This will be equal to the resources needed to produce the quantity $n_i x_i$ of the domestic varieties, plus the resources to obtain the foreign intermediates, $\sum_w n_w x_w, w\neq i$. A unit of domestic intermediates, selling at price p_i, buys p_i/p_w units of an intermediate of country $w\neq i$. Hence, if trade is balanced, $\sum_w \frac{p_w}{p_i}n_w x_w$ units of domestic intermediates must be exported in order to obtain the quantity $\sum_w n_w x_w$ of foreign intermediates. It follows that capital k_i is given by

$$k_i=n_i x_i+\sum_{w\neq i}\frac{p_w}{p_i}n_w x_w=(n_i+\sum_{w\neq i}\frac{p_w}{p_i}n_w)\,x_i. \tag{2.6}$$

In a situation where the interest rates are equalized internationally at rate r,[4] we have, from (2.6) and (2.5), that

$$x_i = \frac{k_i}{\left[n_i + \sum_{w \neq i} \mu_w n_w\right]}, \tag{2.7}$$

and $\mu_w \equiv \left(\frac{1-\alpha_i}{1-\alpha_w}\right)$.

Define a standard measure of total factor productivity (TFP)

$$\log F_{vjt} = \log y_{vjt} - \alpha_{vj} \log l_{vjt} - (1-\alpha_{vj}) \log k_{vjt}, \forall v, j, t.$$

The output term $\log y_{vjt}$ is given by $\log A_{ij} + \alpha_{ij} \log l_{ijt} + (1-\alpha_{ij}) \log d_{ijt}$, with

$$\begin{aligned} \log d_{ijt} &= \frac{1}{1-\alpha_{ij}} \log \left[n_{ijt} x_{ijt}^{1-\alpha_{ij}} + \sum_w \gamma_w n_{wjt} x_{wjt}^{1-\alpha_{wj}} \right] \\ &= \frac{1}{1-\alpha_{ij}} \log \left[\frac{k_{ijt}^{1-\alpha_{ij}}}{\left[n_{ijt} + \sum_{w \neq i} \mu_{hj} n_{wjt}\right]^{1-\alpha_{ij}}} \left(n_{ijt} + \sum_w n_{wjt} \mu_{wj}^2 \right) \right]. \end{aligned}$$

On substitution, one has for the TFP index

$$\log F_{ijt} = \log A_{jt} + \log \left[\frac{n_{ijt} + \sum_w \mu_{wj}^2 n_{wjt}}{\left[n_{ijt} + \sum_{w \neq i} \mu_{wj} n_{wjt}\right]^{1-\alpha_{ij}}} \right]. \tag{2.8}$$

Equation (2.8) shows that the log-level of TFP is a function of the ranges of intermediate goods which are employed in the importing country; n_{ijt} gives the domestic range, and the n_{wjt} are the foreign ranges.

As a benchmark case, consider a model where countries are perfectly symmetric. Then, one has that $\mu_w = 1, \forall w \neq i$. Further, given the CES structure and symmetry across intermediates, any sector of any country will demand all intermediate inputs which are available worldwide, so that n_{ijt} and n_{wjt}, the ranges of intermediates employed in country i, are now equal to the ranges produced in countries i and w. Under these circumstances,

$$\log F_{ijt} = \log A_{jt} + \alpha_{ij} \log \left[n_{ijt} + \sum_{w \neq i} n_{wjt} \right] = \log A_{jt} + \alpha_{ij} \log n_{gjt}, \tag{2.9}$$

where n_{gjt} is the range of intermediates which is produced for the sector j globally.

The ranges of intermediate varieties are increased through devoting resources to R&D (Romer 1990). Although these ranges are not observed, under certain assumptions on depreciation and obsolescence, the ranges are equal to the respective cumulative R&D spending, S_v, which itself is observable. In the symmetric model with V countries, the variable n_g in equation (2.9) will be equal to $V \times S_v$.

For the case where countries are asymmetric in size and with respect to R&D spending, and, consequently, intermediates are neither traded symmetrically nor to the same degree, it is critical to know the relation between countries' cumulative R&D spending S_v, and the ranges employed in country i,

[4] In the symmetric version of this model which can be shown to have a stable balanced growth path, r will be equalized in equilibrium.

n_v^i. The relation of TFP and the ranges of intermediates employed can in general be written as (industry subscript suppressed)

$$F_i = \Psi\left(A_i; n_i^i; n_w^i\right) = \Phi\left(A_i; S_i, m_i^i, m_i; S_w, m_w^i\right), \forall i, w \neq i, \tag{2.10}$$

where m_i is country i's overall import share, m_i^i is the weight the country's own R&D receives, and m_w^i is country i's import share from country $w \neq i$. One can think of the import shares in (2.10) as being related to the likelihood of receiving a new type of foreign intermediate. This is certainly so in the extreme case when $m_w^i = 0$.[5] 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. Especially if one also considers indirect effects, in particular the possibility that importing leads to local learning through reverse engineering and the subsequent invention of new inputs, it is clear that the volume of imports can be a very bad measure of the increase in varieties which are available domestically.[6] Despite these considerations, however, it is likely that the number of new varieties employed from a partner country is positively, although presumably not linearly, related to the import volume from that country.[7]

3. Data

This study employs data for eight OECD countries in six economic 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 group plus Sweden.[8]

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 machin-

[5] Of course, even with $m_v^i = 0$, a country can obtain foreign knowledge which is not embodied in goods.

[6] An alternative view is implemented 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. Also note that in the fully symmetric model, the level of the intermediate x_i does not enter in determining the productivity effect, see (2.9). In that model, as the number of countries rises, the value of bilateral imports actually falls with the equilibrium level x_i. A paper which considers some asymmetries between intermediates from different countries is Rivera-Batiz and Romer (1991b).

[7] In Grossman and Helpman (1991), Ch.6.5, the authors discuss several reasons of why this should be the case.

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

ery, 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.

Data from the OECD (1991) on R&D expenditures by sector is utilized to capture the ranges of intermediate inputs, n_v. This data covers all intramural business enterprise expenditure on R&D. Because none of these industries has a ratio of R&D expenditures to GDP 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 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.[9] R&D stocks are derived from the R&D expenditure series using the perpetual inventory method,[10] 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 cost 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 parameter α above then is the share of labor in total production cost. 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* 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 $8x6$ time series. In Table A-8 of the appendix, I show summary statistics for the TFP data.

4. Estimation Results

In this section, I will present estimation results for different specifications of the function $\Phi(.)$ above. The following section discusses TFP level estimation results, whereas below, I present estimation results for TFP growth rate regressions.

4.1. TFP Level Specification

Consider, as a specification of the function $\Phi(A_{ij}; S^d_{ijt}; m^i_{ij}; S^d_{wjt}; m^i_{wj})$ above, the following

$$\log F_{ijt} = \alpha_0 + \mu d_j + \delta d_v + \sum_v \beta_v \left(m^i_{vj} \log S^d_{vjt} \right) + \varepsilon_{ijt}, \tag{4.1}$$

where d_j and d_v are industry-, and country- fixed effects, respectively. In this specification, the TFP level in any industry is a function of cumulative R&D in all eight countries, with a domestic weight (m^i_{ij})

[9] This constant share is the share of an industry in employment in total manufacturing employment, over the years 1979-81.

[10] Hence, there is no variation in the proportional change of the R&D stock of industry j, and industry $j+1$ between time t and $t+1$, for any given country i. Any differential effect on TFP in sectors j and $j+1$ of an importing country is therefore due to differences in the patterns of bilateral trade, the main focus of the paper.

set to one, and the weights of the partner countries given by the bilateral import shares ($\sum_w m^i_{wj} = 1, \forall i$); the country-elasticities β_v are constrained to be the same across importing countries.[11]

According to (4.1), the import composition matters for the TFP level of a country, with the import-share interacted R&D stocks capturing the technology inflows into that country. However, (4.1) implies that two countries with the same import composition, but different overall import shares, should benefit to the same degree from foreign R&D–which is unlikely. Following Coe and Helpman (1995), we can model this through an interaction of the overall import share, m_{ij}, with the R&D variable[12]

$$\log F_{ijt} = \alpha_0 + \mu d_j + \delta d_v + \sum_v \beta_v \left(m_{ij}\, m^i_{vj} \log S^d_{vjt} \right) + \varepsilon_{ijt}. \tag{4.2}$$

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. Results for the specifications (4.1) and (4.2) are given in Table 1, with standard errors in parentheses; a $^{**}(^{*})$ denotes significantly different from zero at a 5(10)% level.

From Table 1, we see that all countries' R&D stocks are estimated to have a significant and positive influence on the TFP level of the importing 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 TFP levels across countries, with the higher R^2 for the NIS specification. The result that high stocks of scaled foreign R&D are associated with high domestic levels of TFP is interesting, but does not say much about the importance of the fact that the scaling 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.

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

4.1.1. Domestic and International Inputs: does it matter how much from where?

In the Monte-Carlo experiments which follow, I will exchange trade partners randomly. Let b denote a specific Monte-Carlo replication, $b = 1, \ldots, B$. For a given importing country, say i, I exchange the observed bilateral shares randomly. This means that any bilateral import share in replication b, $\sigma^i_{vj}(b)$,

[11]The specification differs from Coe and Helpman's (1995) in that I allow the R&D elasticity to vary by country, whereas Coe and Helpman estimate one parameter for the whole set of partner countries, which changes across observations. In addition, here, the import shares enter linearly, not in logs. The specification can be thought of being derived from a reduced form expression for TFP of the form $F_{ijt} = A_{ij} \Pi_v \left(S^d_{vjt} \right)^{\beta_v m^i_{vjt}} e^{\varepsilon_{ijt}}$.

[12]For the own R&D effect, m_{ij} is chosen such that $m_{ij}\, m^i_{ij} \log S^d_{ijt} = \log S^d_{ijt}$, i.e., m_{ij} then equals one.

is equal to[13]

$$\sigma^i_{vj}(b) = \begin{cases} m^i_{ij} \text{ with } \Pr = \frac{1}{8} \\ \vdots \\ m^i_{Vj} \text{ with } \Pr = \frac{1}{8} \end{cases}, \forall v, j. \quad (4.3)$$

Because $m^i_{ij} = 1$ and $\sum_w m^i_{wj} = 1$, it holds that $\sum_v \sigma^i_{vj}(b) = 2$. Note that in setting up this experiment, I ignore the distinction between the domestic weights m^i_{ij}, and bilateral import shares m^i_{wj}, $w \neq i$. Hence, the experiment allows to see whether, conditional on the ex-ante chosen value for $m^i_i = 1$ and the specification of Φ, 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

$$\log F_{ijt} = \alpha_0 + \mu d_j + \delta d_v + \sum_v \beta_v \left(\sigma^i_{vj}(b) \log S^d_{vjt}\right) + \varepsilon_{ijt}, \forall b, \quad (4.4)$$

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

$$\log F_{ijt} = \alpha_0 + \mu d_j + \delta d_v + \sum_v \beta_v \left(m_{ij}\, \sigma^i_{vj}(b) \log S^d_{vjt}\right) + \varepsilon_{ijt}, \forall b. \quad (4.5)$$

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

One sees that the Monte-Carlo experiments result in coefficient estimates which are in 75% of the cases statistically indistinguishable from zero. In particular, for the model (4.4), this is true for half of the coefficient estimates, and for the model (4.5), it is true for all countries' estimates. 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 and domestically) is determined randomly, the effect of R&D on the importing sector's TFP is not statistically different from zero. Therefore, it helps to know which intermediates come from the domestic, as opposed to foreign economies if one wants to predict an importing sector's TFP level.[14]

The next experiment control for the domestic R&D effect and asks whether the composition of imports matters for domestic TFP levels.

4.1.2. Does the TFP performance reflect the composition of intermediate imports?

I now constrain the Monte-Carlo experiments such that only the composition of the international demand is randomized. That is, the results are conditional on the domestic R&D effect: $\theta^v_{vj}(b) = 1, \forall v, b$.

[13] For a given industry and importing country, I draw eight numbers from a uniform distribution with support $[0,1]$. These are matched with the eight (that is, including 'imports' from own) observed 'import' shares to form a 8×2 matrix. This matrix is then sorted in ascending order on the random number column. In this way, the probability that any trade share $\sigma^i_{vj}(b)$ is equal to the value m^i_{vj}, all v, is equal to 1/8. A new sequence of trade relations (the eight 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.

[14] Obviously, this depends on how large a weight the domestic R&D variable receives (here, its weight is equal to one).

For all $w \neq i$, we have

$$\theta^i_{wj}(b) = m^i_{qj} \text{ with } \Pr = \frac{1}{7},\ q \in V \setminus i, \forall w, j. \quad (4.6)$$

The $\theta^i_{wj}(b)$ are constructed such that $\sum_w \theta^i_{wj}(b) = 1$, that is, any observed trade share is assigned only once. The two specifications, for a given country i, are

$$\log F_{ijt} = \alpha_0 + \mu d_j + \delta d_v + \sum_v \beta_v \left(\theta^i_{vj}(b) \log S^d_{vjt}\right) + \varepsilon_{ijt}, \forall b, \quad (4.7)$$

and

$$\log F_{ijt} = \alpha_0 + \mu d_j + \delta d_v + \sum_v \beta_v \left(m_{ij}\, \theta^i_{vj}(b) \log S^d_{vjt}\right) + \varepsilon_{ijt}, \forall b. \quad (4.8)$$

The results of these two experiments, for $B = 1000$, are shown in result columns three and six of Table 2. The parameter estimates now 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 comparable part of the variation in TFP levels as the observed-data regressions.

The fact that it is not necessary to impose the observed import shares to estimate significant international R&D spillovers confirms the result of Keller (1996b) that one cannot test the hypothesis of the R&D-trade-TFP link simply by examining whether the parameter estimates are positive, or how high the R^2 of these regressions is. Obviously, the regression results are invariant to some degree to whatever weights the R&D stocks are interacted with. 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.[15] Therefore, this explanation, at least in its extreme form, cannot be the reason for the finding of fairly invariant parameter estimates.

Another interpretation of the results in Table 2 is that what the regressions pick up is mainly a strong general effect from foreign R&D; that is, although imports are in part related to international technology flows, this effect is overshadowed by the general R&D spillover effect. This is discussed further in section 5 below. A third interpretation is that much of the estimated correlation is spurious, perhaps the consequence of interpolation in the data, or due to the time-series properties of the data generation process. It is the latter point which I intend to address first, by presenting results from a TFP-R&D growth specification. This is appropriate if the benchmark capital stocks for physical capital (underlying the TFP variable) as well as for the R&D capital stocks have been estimated with an error, as is very likely; further, the growth specification is also preferred in the case of unobserved, time-invariant heterogeneity among the industries.[16]

[15]The average annual rate of growth of the R&D stock estimates ranges from 3.64% for the 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).

[16]The data generation process underlying the variables, especially whether they are integrated of order one or less, also influences the choice of specification. However, the unit root and cointegration tests I have conducted fail to settle this issue in the present context.

4.2. TFP Growth Estimation

The TFP growth specifications corresponding to (4.1) and (4.2) above are, for an importing country i,

$$\frac{\Delta F_{ijt}}{F_{ijt}} = \alpha_0 + \sum_v \beta_v \left(m^i_{vj} \frac{\Delta S^d_{vjt}}{S^d_{vjt}} \right) + \varepsilon_{ijt}, \tag{4.9}$$

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 including the overall import share is now given by

$$\frac{\Delta F_{ijt}}{F_{ijt}} = \alpha_0 + \sum_v \beta_v \left(m_{ij}\, m^i_{vj} \frac{\Delta S^d_{vjt}}{S^d_{vjt}} \right) + \varepsilon_{ijt}, \tag{4.10}$$

where, again, the value of the import share from i, m_{ij}, is set equal to one, $\forall i, j$. 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.

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 is in line with the arguments given above, as well as with findings in Coe and Helpman (1995).

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, only the results conditional on the effect from domestic R&D are shown in Table 3. The specifications are, for an importing country i,

$$\frac{\Delta F_{ijt}}{F_{ijt}} = \alpha_0 + \sum_v \beta_v \left(\theta^i_{vj}(b) \frac{\Delta S^d_{vjt}}{S^d_{vjt}} \right) + \varepsilon_{ijt}, \forall b, \tag{4.11}$$

and

$$\frac{\Delta F_{ijt}}{F_{ijt}} = \alpha_0 + \sum_v \beta_v \left(m_{ij}\, \theta^i_{vj}(b) \frac{\Delta S^d_{vjt}}{S^d_{vjt}} \right) + \varepsilon_{ijt}, \forall b. \tag{4.12}$$

For each of these two experiments, I conduct $B = 1000$ replications. Again, all Monte-Carlo based coefficients are estimated to be significantly above zero, confirming the earlier results from TFP level regressions. Moreover, now, 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. In the following section, I will show how the latter is related to a general spillover effect from foreign R&D, and determine whether there is a marginal contribution of international trade.

5. Separating Trade-related from General R&D Spillovers

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

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

$$\frac{1}{B}\sum_b \left(\sigma_w^i(b)\frac{\Delta S_{wj}^d}{S_{wj}^d}\right) = \frac{\Delta S_{wj}^d}{S_{wj}^d}\frac{\sum_b \sigma_w^i(b)}{B} = \sigma(\bar{b})\frac{\Delta S_{wj}^d}{S_{wj}^d}.$$

Therefore, across all B replications, the average regressors are just the average annual growth rates, $\frac{\Delta S_{wj}^d}{S_{wj}^d}, w \neq i$, multiplied by $\sigma(\bar{b}) = 1/7$ for all partner countries, and simply $\frac{\Delta S_{ij}^d}{S_{ij}^d}$ as the own-country R&D variable. Note, however, that the coefficients reported from the Monte-Carlo experiments are averages across the OLS estimates from 1000 replications, not OLS estimates from employing the average regressors. Nevertheless, as I show in the appendix, 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 general R&D spillover effects. In Table 4, I present the following general R&D spillover regression

$$\frac{\Delta F_{ijt}}{F_{ijt}} = \alpha_0 + \sum_v \beta_v \left[m_{ij}\left(\sigma(\bar{b})\frac{\Delta S_{vjt}^d}{S_{vjt}^d}\right)\right] + \varepsilon_{ijt}. \tag{5.1}$$

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 general R&D spillover effect; the maximum relative difference between the estimated parameters in columns four and five is 2% (18.5% versus 18.9% in the case of Sweden).[17]

5.2. Estimating the Trade Component of International R&D Spillovers

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

$$\frac{\Delta F_{ijt}}{F_{ijt}} = \alpha_0 + \sum_v \beta_v^I \left[m_{ij}\,\sigma(\bar{b})\frac{\Delta S_{vjt}^d}{S_{vjt}^d}\right] + \sum_v \beta_v^{II}\left[m_{ij}\left(m_{vj}^i - \sigma(\bar{b})\right)\frac{\Delta S_{vjt}^d}{S_{vjt}^d}\right] + \varepsilon_{ijt}, \tag{5.2}$$

Regressors with parameters β^I measure the general R&D spillover effect, and the β^{II} coefficients estimate the marginal trade-related effect, if any. In particular, if there is no separate effect of international R&D which works through 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 TFP growth rates as the general R&D spillover specification (5.1). The result of this comparison is seen in Table 5. The specification allowing for

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

an additional trade-related R&D spillovers effect explains more of the variation in TFP growth rates, with an adjusted R^2 of 9.6%, versus 7.8% in the specification which captures solely the general R&D spillovers effect. Therefore, the marginal effect of trade contributes a little less than 20% to the overall spillovers effect.[18]

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 (that is, more than $1/7$ per cent) from Canada have experienced on average a lower rate of TFP 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 relation of trade patterns, technology flows, and productivity growth. Along the lines of recent theory on R&D-driven growth and trade, a model has been developed where domestic TFP 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 TFP.

I find, first, that there is a lot of variation in the estimated TFP effects from different countries' R&D investments. Secondly, the findings suggest that domestic and foreign R&D investments are not perfect substitutes in their effect on TFP. This implies that theoretical models of the type discussed above need to incorporate factors which imply asymmetric effects of domestic and foreign intermediate inputs embodying technology in order to be consistent with the data. Third, I find that, conditional on the effect of domestic R&D on TFP, the composition of a country's imports does not significantly affect the degree to which it benefits from foreign R&D. While there are several possible reasons for that, including the possibility that the econometric specification is too limited to allow finding anything else, I argue that it is primarily due to the presence of a strong general spillover effect from foreign R&D investments. This effect is unrelated to international trade, driven perhaps by mechanisms such as foreign direct investment, the relative importance of which still needs to be established. For international trade, the analysis in this paper has allowed to quantify its contribution to the total effect derived from foreign R&D investments, which is about 20%.

[18] 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 trade to the overall R&D spillover 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 growth specification *NIS*, however, no significant marginal trade-related R&D spillover effect is estimated. Hence, while not perfectly robust, generally, the trade mechanism is estimated to contribute significantly to the overall benefit from foreign R&D, and it is in the order of 20% in the preferred specification presented in Table 5.

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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 I have used data from 1975 for SITC Revision 1. These tables are used to calculate the variable m^i_{wj}, the bilateral import shares of country i with countries $w \neq i$ in sector j.

B. Data on R&D

The raw data on R&D expenditures comes from OECD (1991). It is more patchy than the OECD data on output, investment, and employment, which is discussed below. This is not so much a problem of the sectoral breakdown, because the national statistical offices do collect their R&D data along the lines of the two- or three-digit ISIC classification. But 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 (rd) for ISIC sector 382 (non-electronical machinery), in constant 1985 US \$, 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

$$\begin{aligned} n_{it} &= (1-\delta)\, n_{it-1} + rd_{it-1}, \text{ for } t = 2,...,22 \\ &\text{and} \\ n_{i1} &= \frac{rd_{i1}}{(g^n_i + \delta + 0.1)} \; . \end{aligned} \tag{B.1}$$

The rate of depreciation δ 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.

C. Labor, Physical Capital, and Gross Production

For these variables, the OECD (1994) *STAN* database is the basic source. It provides internationally comparable data on industrial activity by sectors, primarily for OECD countries. 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 there are not the submissions of the member countries to the OECD, but the OECD estimates based on them, which try to ensure greater international comparability. See OECD (1994) for the details on adjustments of national data.

In constructing the TFP variable F, I consider only inputs of labor and physical capital (in particular, there is no data on quality-adjusted labor input 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, because 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 again estimated using the perpetual inventory method, with–suppressing the industry subscripts–

$$\begin{aligned} k_{it} &= (1-\delta_i)\,k_{it-1} + inv_{t-1}, \text{ for } t = 2,\ldots,22,\ i = 1,\ldots,8 \\ &\text{and} \\ k_{i1} &= \frac{inv_{i1}}{(g_i^{inv}+\delta_i)},\ i = 1,\ldots,8, \end{aligned} \tag{C.1}$$

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 δ is the rate of depreciation. I use country-specific depreciation rates, taken from Jorgenson and Landau (1993), Table A-3

Canada: 8.51%	Japan: 6.6%
France: 17.39%	Sweden: 7.7%
Germany: 17.4%	United Kingdom: 8.19%
Italy: 11.9%	United States: 13.31%

These numbers, which are used throughout, are estimates for machinery in manufacturing in the year 1980.

According to equation (2.1), α_{ijt} will be the share of the labor cost in production. Following the approach by Hall (1990), the α_{ijt}'s are not calculated as the ratio of total labor compensation to value added (the revenue-based factor shares), both of which is included in the *STAN* database, but cost-based factor shares are constructed which are robust in the presence of imperfect competition. For this I use 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). 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

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

For us, the variable of interest is p_k, the user cost of capital. It will be 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 will be

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

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. Our approach then is 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, on the one hand, 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 myself experimented with different values for ι, and found that the basic results presented above do not depend on a particular choice for ι. On the other hand, this approach has the advantage of using all data on the user cost of capital compiled in Jorgenson and Landau (1993) to arrive at a TFP 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

$$\alpha = \frac{wl}{wl + p_k k}. \tag{C.4}$$

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

$$\begin{aligned} \ln\left(\frac{I_{ijt}}{I_{ijt-1}}\right) &= \frac{1}{2} * \left[\alpha_{ijt} + \alpha_{ijt-1}\right] \ln\left(\frac{l_{ijt}}{l_{ijt-1}}\right) \\ &+ \frac{1}{2} * \left[(1-\alpha_{ijt}) + (1-\alpha_{ijt-1})\right] \ln\left(\frac{k_{ijt}}{k_{ijt-1}}\right). \end{aligned} \tag{C.5}$$

This gives a series of growth of total factor input. Calculating log differences of year-to-year gross production, and taking the difference between this and total input growth, I have constructed a TFP growth series. A value of 100 in 1970 is chosen for each of the $8x6$ time series, for all industries j and countries i.

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

Consider, for simplicity, the model above with only one regressor (with industry and time subscripts are suppressed): $\frac{\Delta F_i}{F_i} = \alpha_0 + \beta_1 \theta_v^i(b) \frac{\Delta S_i^d}{S_i^d} + \varepsilon_i$. Let $\theta_v^i(b) = \sigma(\overline{b}) + \eta_v^i(b), \forall b$, where $\eta_v^i(b)$ 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

$$\beta_1(b) = \frac{\sum_i \left(\theta_v^i(b) \frac{\Delta S_i^d}{S_i^d} \frac{\Delta F_i}{F_i}\right)}{\sum_i \left(\theta_v^i(b) \frac{\Delta S_i^d}{S_i^d}\right)^2} = \frac{\sum_i \left(\sigma(\overline{b}) \frac{\Delta S_i^d}{S_i^d} \frac{\Delta F_i}{F_i} + \eta_v^i(b) \frac{\Delta S_i^d}{S_i^d} \frac{\Delta F_i}{F_i}\right)}{\sum_i \left(\left[\sigma(\overline{b}) + \eta_v^i(b)\right] \frac{\Delta S_i^d}{S_i^d}\right)^2}, \forall b.$$

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

$$\begin{aligned}
\beta_1(\bar{b}) &\simeq \frac{\sum_{b=1}^{B}\sum_i\left(\sigma(\bar{b})\frac{\Delta S_i^d}{S_i^d}\frac{\Delta F_i}{F_i} + \eta_v^i(b)\frac{\Delta S_i^d}{S_i^d}\frac{\Delta F_i}{F_i}\right)}{B\sum_i\left(\frac{\Delta S_i^d}{S_i^d}\right)^2\left[\sigma(\bar{b})\right]^2} \\
&= \frac{\sum_i \sigma(\bar{b})\frac{\Delta S_i^d}{S_i^d}\frac{\Delta F_i}{F_i}}{\sum_i\left(\frac{\Delta S_i^d}{S_i^d}\right)^2\left[\sigma(\bar{b})\right]^2} + \frac{\sum_i \frac{\Delta S_i^d}{S_i^d}\frac{\Delta F_i}{F_i}\sum_{b=1}^{B}\eta_v^i(b)}{B\sum_i\left(\frac{\Delta S_i^d}{S_i^d}\right)^2\left[\sigma(\bar{b})\right]^2}.
\end{aligned} \tag{D.1}$$

Because $\sum_{b=1}^{B}\eta_v^i(b) = 0$, 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 $\frac{\Delta F_i}{F_i}$ on $\sigma(\bar{b})\frac{\Delta S_i^d}{S_i^d}$. Clearly, how good the approximation above is depends on how large $\left[\frac{\Delta S_i^d}{S_i^d}\right]^2\left(\left[\eta_v^i(b)\right]^2 + 2\eta_v^i(b)\sigma(\bar{b})\right)$ is, or, more generally, $\lambda_i^2\left(\left[\eta_v^i(b)\right]^2 + 2\eta_v^i(b)\sigma(\bar{b})\right)$. In particular, if $\lambda_i = \log S_i^d$, then the average Monte-Carlo estimate will differ more from the general spillover regression than if $\lambda_i = \frac{\Delta S_i^d}{S_i^d}$, as presented in Table 4.

TABLE 1

TFP Level Specification; 1056 observations

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

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	General 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

	General Spillover	General and Trade-Spillover	
	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)
$\bar{R}^2$	7.8	9.6	