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SPILLOVERS AMONG RANDOMLY
MATCHED TRADE PARTNERS

Wolfgang Keller

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ABSTRACT

In this paper, I analyze recent findings by Coe and Helpman (1995) on trade-related international R&D spillovers. A Monte Carlo based robustness test is proposed which compares the elasticity of domestic productivity with respect to foreign R&D estimated by Coe and Helpman with an elasticity which is based on counterfactual international trade patterns. I show that also these randomly created trade patterns give rise to positive international R&D spillover estimates, which are larger and explain more of the variation in productivity across countries than if “true” bilateral trade patterns are employed. The finding casts doubt on the claim that patterns of international trade are important in driving R&D spillovers.

Wolfgang Keller
Department of Economics
University of Wisconsin
1180 Observatory Drive
Madison, WI 53706
and NBER
wkeller@ssc.wisc.edu

1. Introduction

The recent development of theories of endogenous technological change, in particular by Romer (1990) and Aghion and Howitt (1992), has triggered new work on the relation of trade, growth, and technological change in open economies. Most important in this area is the monograph by Grossman and Helpman (1991). These authors embed the new theories in multi-sector, multi-country 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 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 exported to other economies, then the importing countries are implicitly utilizing the technology from abroad. If, in addition, the importing country pays less than the intermediate good's full marginal product, then international trade in these intermediate goods triggers productivity increases in the importing country.

Even before the advent of the models of endogenous technological change, a vast literature had developed which related domestic R&D expenditures to

total factor productivity (TFP) growth.¹ The particular contribution of the new models of trade and growth therefore lies in the testable hypotheses one can derive with regard to trade and openness. In an influential paper, Coe and Helpman (1995) (henceforth CH) have recently derived and tested two implications of these models. The first regards the composition of imports: *ceteris paribus*, if one country imports primarily from other countries which have accumulated high levels of technological knowledge, then it should exhibit higher productivity levels than if it would import primarily from countries with comparatively low levels of technological knowledge (import composition effect). The second effect is related to the overall import share of a country: for a given composition of imports, a country should benefit more from foreign R&D creating innovative intermediate goods, the higher is the country's overall import share (overall import share effect).

At the center of the analysis by CH is what the authors call the "foreign stock of knowledge" of a given country. This variable is constructed as a weighted sum of the cumulative R&D expenditures of the country's trading partners, where the weights are given by the bilateral import shares.² According to CH, their analysis

¹See Nadiri (1993) for a survey.

²This is analogous to the domestic R&D-TFP literature: as initially proposed by Griliches (1979), authors have frequently tried to capture the degree to which productivity in one industry depends on R&D in others by computing weighted sums of outside R&D, where the weights are, for instance, input-output coefficients.

"underlines the importance of the interaction between international trade and foreign R&D" (p.860).

They conclude their analysis by stating that

"not only does a country's total factor productivity depend on its own R&D capital stock, but, as suggested by the theory, it also depends on the R&D capital stocks of its trade partners." (p.875).

Hence, CH argue that their analysis supports the view that international R&D spillovers are trade-related. This is the claim being investigated in the present paper. In doing so, I will focus largely on the import composition effect, as it relates more closely to the recent models of growth and intermediate inputs trade than the overall imports effect, which is likely to be a feature of a larger class of models.³ The analysis below relies on an approach which I call counterfactual estimation.⁴ It consists of Monte Carlo experiments in which the CH regressions are repeated with foreign knowledge stock variables which are computed on the basis of simulated and counterfactual patterns of international trade. These Monte Carlo experiments can be viewed as estimating international R&D spillovers among

³While this paper does not address identification issues, they are currently discussed in detail in other work in the international trade literature; see, e.g., Evenett and Keller (1997).

⁴Similar in spirit to the counterfactual estimation approach is Ben-David (1996) who shows that income convergence among countries which trade heavily with each other is faster than among randomly formed groups of countries.

randomly matched trade partners. The inference of whether international R&D spillovers are trade-related or not is then drawn by comparing the estimation results based on 'true' trade patterns with those based on counterfactual trade patterns.

The remainder of the paper is as follows. In section 2, the empirical implementation as well as the results of CH's estimation are given. The central section 3 describes how the counterfactual trade patterns are created in the Monte Carlo experiments, and presents the international spillover effects estimated from those trade patterns. Section 4 concludes.

2. Empirical Implementation and Results in Coe and Helpman (1995)

The empirical analysis in CH builds on recent work on R&D-driven endogenous technological change and trade in differentiated intermediate inputs. In those models,⁵ it is possible to derive an expression for output in country i , denoted y_i ,

⁵I am referring here specifically to the model of expanding horizontal product varieties. For the so-called quality ladder model, CH show that its implications with respect to the relation of foreign R&D and domestic TFP are essentially the same as those shown below. For more on the derivation of the estimating equation, see CH and Keller (1997); the theory is laid out in detail in Grossman and Helpman (1991).

as

$$y_i = A_i k_i^\alpha n_i^\alpha l_i^{1-\alpha}, \quad \forall i, \quad 0 < \alpha < 1, \quad (2.1)$$

where A_i is a country-specific constant, k_i are capital services, l_i labor services, and n_i is the range of differentiated intermediate goods employed in country i . Note that equation (2.1) exhibits constant returns in capital and labor alone, which implies that if an index of TFP is defined as

$$\log F_i = \log y_i - \alpha \log k_i - (1 - \alpha) \log l_i, \quad (2.2)$$

that it will be positively related to the range of intermediate goods employed

$$\log F_i = \log A_i + \alpha \log n_i, \quad \forall i. \quad (2.3)$$

With international trade, both domestic as well as foreign intermediate goods can be employed in country i . Because the tradability of domestic and foreign intermediates differs though, CH separate the domestic from the foreign range of intermediate goods (n_i^d and n_i^f , respectively)

$$\log F_i = \log A_i + \beta_1 \log n_i^d + \beta_2 \log n_i^f. \quad (2.4)$$

The expanding product varieties in countries i and $h \neq i$ are the result of R&D investments. With an appropriate choice of units, the range n_i^d , $\forall i$, is identical to the cumulative stock of R&D expenditures, S_i^d . The unobserved range of foreign intermediates which is employed in i , n_i^f , is captured by the foreign knowledge stock variable proposed in CH. It is constructed as follows

$$n_{it}^f = S_{it}^f = \sum_{h \neq i} (m_{hit} S_{ht}^d), \forall i, t. \quad (2.5)$$

Here, m_{hit} is the bilateral import share of country i from country h at time t . Hence, the construction of the variable S_i^f weights the cumulative R&D expenditures of country i 's trading partners by their bilateral import share. In this way the specification captures the notion that the domestic economy will reap, *ceteris paribus*, more international spillovers if it trades relatively more with countries which have invested heavily in R&D, and hence have large domestic knowledge stocks, S^d .

With these considerations, CH's first specification is given by

$$\log F_{it} = \beta_{0i} + \beta_1 \log S_{it}^d + \beta_2 \log S_{it}^f + \varepsilon_{it}, \forall i, t, \quad (2.6)$$

where ε_i is a mean-zero error term, and $\beta_{0i} = \log A_i$ are country-specific intercepts. A second specification allows the effect from domestic R&D to be different in the G-7 group countries relative to the smaller member countries of the OECD:

$$\log F_{it} = \beta_{0i} + \beta_G (G7_i \times \log S_{it}^d) + \beta_1 \log S_{it}^d + \beta_2 \log S_{it}^f + \varepsilon_{it}, \forall i, t, \quad (2.7)$$

where $G7_i$ is equal to one for any G-7 country, otherwise zero.

In order to capture the overall import share effect of trade-related R&D spillovers, CH propose a third specification, with

$$\log F_{it} = \beta_{0i} + \beta_G (G7_i \times \log S_{it}^d) + \beta_1 \log S_{it}^d + \beta_2 (m_{it} \times \log S_{it}^f) + \varepsilon_{it}, \forall i, t. \quad (2.8)$$

Here, m_{it} is country i 's overall import share. There are 21 OECD countries plus Israel in the CH sample, for the years 1971-90, making a total of 440 observations. Main data sources are the OECD's *Analytical Data Base* as well as its *Main Science and Technology Indicators*. The bilateral import shares are calculated from the IMF's *Direction of Trade* statistics; its values are shown for the year 1980 in Table 1.⁶ For instance, 32.89% of the US imports came from Canada, as opposed to only 1.46% of Germany's. In consequence, the level of the Canadian

⁶For a detailed description of the data employed, see CH.

cumulative R&D expenditures should be much more relevant for US productivity than it should be for Germany's.

The results of the three regression specifications in equations (2.6), (2.7), and (2.8) are given in Table 2, column *BIS* (for bilateral import shares).⁷ The foreign knowledge stock variable enters in all regressions with a positive coefficient which is large relative to the standard error of the parameter estimate.⁸ Note, first, that the specification (iii) performs best according to the R^2 criterion, which is consistent with the notion that, for a given import composition, international R&D spillovers are higher, the higher is a country's overall import share. Second, with regards to the composition of imports, the question is whether the regressions provide evidence in favor of the hypothesis that international R&D spillovers are related to the trade patterns of differentiated goods.

⁷These results are obtained using the data provided by David Coe. CH report somewhat lower R^2 for these regressions, but the point estimates are identical up to two decimals.

⁸In the table, conventional standard errors are given, which would be wrong if the regressions were estimating cointegrating relationships. But see the discussion on super-consistency in CH.

3. Counterfactual Estimation: Simulating Bilateral Import Shares

In evaluating the hypothesis that international R&D spillovers are trade-related, the foreign knowledge stock variable S^f constructed by CH is of central interest. A country's R&D benefit from abroad is taken to be a weighted average of these foreign countries' R&D efforts, where the weights are given by the bilateral import shares, m_{hit} (see equation 2.5). In the following, I will compare the estimation results of CH with those obtained from employing foreign knowledge stock variables which are based on random bilateral import shares. That is, rather than constructing the foreign knowledge stock variable S^f using the observed bilateral import shares, alternative foreign knowledge stock variables are computed on the basis of randomly created bilateral import shares (denoted RIS , for random import shares). Then, the CH regressions (i)-(iii) are repeated with the alternative foreign knowledge stocks. Finally, I compare the estimation results obtained by employing observed import patterns with those based on randomly created import patterns. Because each set of random bilateral import shares can be thought of as a counterfactual world of international import relations, I call this approach counterfactual estimation.

The random import shares are constructed as follows: for each Monte Carlo replication $b, b = 1, \dots, B$, I obtain one matrix $\Gamma(b)$ consisting of 484 (22×22) random elements $\gamma_{hi}(b)$ which are drawn from a uniform distribution with support $[0, 1]$ using the (pseudo) random number generator of the GAUSS package.⁹ The diagonal elements of $\Gamma(b)$ are then set to zero. In the next step the sum of each column is calculated, $\gamma_{\bullet i}(b) = \sum_{h \neq i} \gamma_{hi}(b)$. Finally, shares $\sigma_{hi}(b)$ are formed by

$$\sigma_{hi}(b) = \frac{\gamma_{hi}(b)}{\gamma_{\bullet i}(b)}, \quad \forall h, i, b, \quad (3.1)$$

with $\sum_h \sigma_{hi}(b) = 1, \forall i, b$. These 484 values $\sigma_{hi}(b)$ form the matrix $\Omega(b)$ of dimension 22×22 . Then, the foreign knowledge stock for this particular replication, $S^f(b)$, is computed from the values of the observed cumulative R&D stocks S^d and the matrix $\Omega(b)$ analogous to equation (2.5) above:

$$S_{it}^f(b) = \sum_{h \neq i} \sigma_{hi}(b) S_{ht}^d, \quad \forall i, t, b. \quad (3.2)$$

Lastly, I run three regression specifications in analogy to equations (2.6), (2.7), and (2.8) above, the only difference being that the foreign knowledge stock based on

⁹This function uses a seed value which is updated during the process; the initial seed value is 26875.

actual import patterns is replaced by the foreign knowledge stock variable based on simulated import patterns. For each specification, $B = 1000$ replications are conducted.¹⁰ The column *RIS* in Table 2 presents the mean and standard deviation (in parentheses) of the parameter estimates from the simulations, denoted $\beta_v^m(\bar{b})$, and $\beta_v^s(\bar{b})$, respectively, for $v = G, 1, 2$.

The estimates of key interest are the averages of the Monte Carlo coefficients on the simulated foreign knowledge stocks, $\beta_2^m(\bar{b})$, as those reveal how large an international R&D spillover is estimated based on counterfactual import patterns. Note that across all three specifications (i)-(iii), the Monte Carlo average is larger than the corresponding coefficient based on the 'true' foreign knowledge stock (that is, $\beta_2^m(\bar{b}) > \beta_2$). Furthermore, the part of the variation in TFP levels which is accounted for by the simulated foreign knowledge stocks is on average larger than if the 'true' foreign knowledge stock is employed: the R^2 in specification (i) is 0.630 for the observed and on average 0.702 for the simulated foreign knowledge stocks. Similar results hold for specifications (ii) and (iii).¹¹

¹⁰CH use bilateral import shares which are varying from year to year between 1971 to 1991; therefore, also the matrix $\Omega(b)$ varies by year in the Monte Carlo results presented below. The results are not qualitatively different, however, if a time-invariant import share matrix is employed in the simulations.

¹¹Both the result that $\beta_2^m(\bar{b}) > \beta_2$ and the fact that the average R^2 is larger in the Monte Carlo replications does not depend on the fact that, in all three specifications (i)-(iii), the coefficient on own-country R&D is estimated to be less (i.e., $\beta_1^m(\bar{b}) < \beta_1$) than in the Monte Carlo simulations.

It is therefore clear that the finding of international R&D spillovers in the context of CH's approach is not limited to employing the observed patterns of international trade: positive and large productivity effects are also estimated if the underlying variable $S^f(b)$ is unrelated to the patterns of international trade. Moreover, the counterfactual international trade patterns generate an even better empirical fit as measured by the R^2 criterion. These results imply that it is, on the basis of the CH results, not possible to argue that the import composition of a country matters for productivity in the way predicted by the recent trade and growth theories.

This is seen most clearly by comparing a specific simulated import share matrix $\Omega(b)$ with the actual import share matrix. The former is given in Table 3, while the latter was given for the year 1980 in Table 1. The simulated shares in Table 3 give, in the specification (iii),

$$\log F_{it} = \beta_{0i} + \beta_G (G7_i \times \log S_{it}^d) + \beta_1 \log S_{it}^d + \beta_2 (m_{it} \times \log S_{it}^f(b)) + \varepsilon_{it}, \forall i, t,$$

a value of $\beta_2(b)$ of 0.321 (s.e. 0.029), and a R^2 of 0.747. This is to be compared to $\beta_2 = 0.289$ (s.e. 0.041), and a R^2 of 0.706 in Table 1, *BIS*.¹² Observe that the

¹²For concreteness, the matrix $\Omega(b)$ has been fixed for all years in this simulation, whereas the CH results are derived employing time-varying bilateral import shares. Note, however, that

simulated pattern of international trade in Table 3 differ considerably from the 'true' pattern given in Table 1. Canada, for instance, has been importing most of its goods from the US; this share was 82.18% in the year 1980. Ireland, however, has been importing primarily from the United Kingdom (56.96% in 1980), whereas only 9.82% of Ireland's imports came from the US. The theory predicts that Canada benefits more from US technology embodied in intermediate inputs than does Ireland, and, all else equal, that the productivity level in Canada is higher than in Ireland. If the correlation of partner country's cumulative R&D stock and TFP level holds on average in the sample, one expects a positive coefficient β_2 and a high R^2 . However, in the simulated world of trade patterns given in Table 3, Canada imports only 2.15% from the US, whereas Ireland imports 6.41% from the US, and one estimates nevertheless a higher coefficient $\beta_2(b)$ (of 0.321, versus 0.289) at the same time where a larger share of variation in TFP levels is accounted for ($R^2(b) = 0.747$, versus 0.706).

Rather than considering alternative international trade patterns in the construction of the foreign knowledge stock, one can also ask what the estimated international R&D spillovers are if the foreign knowledge variable is simply com-

the actual bilateral import shares did not change dramatically over the period of 1971-91 in the countries under consideration.

puted as the unweighed sum of foreign countries R&D stocks, denoted \bar{S}^f ,

$$\bar{S}_{it}^f = \sum_{h \neq i} S_{ht}^d, \forall i, t. \quad (3.3)$$

Hence, international trade patterns are completely absent from the construction of the \bar{S}^f variable. The results of substituting the unweighed stock of foreign R&D (\bar{S}^f) for the import-share weighted stock of foreign R&D (S^f) in the three specifications (i)-(iii) leads to the results shown in Table 2, column *SS* (for simple sum). For all three specifications, the point estimate on the foreign knowledge stock \bar{S}^f is higher than if import shares are used to construct the S^f variable. In addition, the R^2 in the *SS* regressions are higher than those from the *BIS* (and also the *RIS*) specifications. Hence, the results employing unweighed sums of foreign R&D in these regressions confirm what the Monte Carlo results already indicated: the composition of imports of a country plays no particular role in estimating a positive and significant from foreign R&D on domestic productivity levels. Moreover, the variation in the sum of unweighed foreign R&D stocks accounts for more of the variation of TFP levels in this sample than if import-weighted R&D sums are employed.¹³

¹³It is not accidental that the *RIS* estimates are very similar to the *SS* ones reported in Table 2: the relation between the average Monte Carlo estimate and the *SS* specification is derived

4. Conclusion

In this paper, I have re-examined the evidence presented in CH on the question of whether international R&D spillovers are related to international trade along the lines of recent models of trade and growth. The results of CH are compared to results from regressions based on counterfactual patterns of international trade. It is shown that, on the basis of CH's results, it is not possible to argue that the actual pattern of international trade is important in their estimation of international R&D spillovers, because counterfactual trade patterns give rise to similarly large (or even larger) estimated international R&D spillovers. We also find positive international spillover effects in specifications which do not incorporate any particular pattern of international trade.

It is important to note, however, that these results do not imply that the pattern of international trade plays no role in the diffusion of embodied technology. Considering the complicated nature of the problem, the quality and degree of aggregation of the data, and the uncertainty with respect to the data generation process underlying the R&D and TFP series, the results in this paper might in fact seem rather unsurprising. However, it is clear from this analysis that the

in Keller (1997).

extent to which R&D spillovers are related to the pattern of international trade must be estimated in a model which allows simultaneously for trade-unrelated international technology diffusion.¹⁴

References

- [1] Aghion, P., and P. Howitt (1992), "A Model of Growth through Creative Destruction", *Econometrica* 60: 323-351.
- [2] Ben-David, D. (1996), "Trade and Convergence among Countries", *Journal of International Economics* 40: 279-298.
- [3] Coe, D., and E. Helpman (1995), "International R&D Spillovers", *European Economic Review* 39: 859-887.
- [4] Evenett, S., and W. Keller (1997), "On Theories Explaining the Success of the Gravity Equation", mimeographed, University of Wisconsin, Madison, March.

¹⁴Several of the issues mentioned in the last paragraph have been addressed in Keller (1997).

- [5] Griliches, Z. (1979), "Issues in Assessing the Contribution of Research and Development to Productivity Growth", *Bell Journal of Economics* 10: 92-116.
- [6] Grossman, G., and E. Helpman (1991), *Innovation and Growth in the Global Economy*, Cambridge, MA: MIT Press.
- [7] International Monetary Fund (1986), *Direction of Trade Statistics*, Yearbook 1986, IMF, Washington, D.C.
- [8] Keller, W. (1997), "Trade Patterns, Technology Flows, and Productivity Growth", mimeographed, University of Wisconsin, Madison, April.
- [9] Nadiri, M.I. (1993), "Innovations and Technological Spillovers", NBER Working Paper No. 4423, Cambridge, MA.
- [10] Romer, P. (1990), "Endogenous Technological Change", *Journal of Political Economy* 98: S71-S102.

Table 1

Bilateral Import Shares in 1980

In percent

from / to	U.S.	Japan	Germany	France	Italy	U.K.	Canada	Aus'tia	Austria	Belgium	Denmark	Finland	Greece	Ireland	Israel	Nether.	N.Z.	Norway	Portugal	Spain	Sweden	Switz.
U.S.	0	51.43	10.36	11.9	11.08	15.9	82.18	30.36	4.37	9.44	7.7	9.36	7.08	9.82	28.7	11.79	19.51	9.55	16.07	25.14	9.4	7.85
Japan	25.82	0	4.19	3.07	2.07	4.51	4.76	23.81	3.11	2.46	2.73	5.23	17.25	2.87	2.22	2.54	19.89	4.07	4.47	4.72	3.66	3.82
Germany	9.6	5.24	0	24.21	26.47	14.93	2.46	8.42	52.69	24.25	22.17	20.37	21.63	7.7	14.66	29.81	5.12	15.81	17.09	15.77	21.56	32.04
France	4.35	2.73	14.74	0	22.12	10.15	1.31	2.45	5.1	17.82	5.22	4.92	9.62	5.83	5	8.98	1.47	4.13	10.81	15.9	5.56	14.27
Italy	3.67	1.97	10.93	14.07	0	6.07	1.04	3.51	11.73	4.43	3.49	3.68	13.19	2.7	5.84	4.24	1.93	2.64	7.63	9.49	3.61	11.17
U.K.	8.04	4.11	9.2	8.08	7.06	0	3.36	12.98	3.55	9.96	14.61	13.86	7.09	56.96	12.47	10.95	16.18	16.72	12.87	9.03	15.24	9.65
Canada	32.89	9.95	1.46	1.16	1.63	3.72	0	3.81	0.6	0.91	0.6	1.18	1.15	1.51	1.48	1.01	3.35	2.74	1.33	1.52	1.19	0.65
Aus'tia	2.18	14.69	0.52	0.65	0.92	1.27	0.87	0	0.21	0.38	0.22	0.18	0.26	0.1	0.74	0.32	25.65	0.8	0.32	0.71	0.32	0.16
Austria	0.32	0.36	3.96	0.72	3.02	0.81	0.16	0.35	0	0.47	1.3	1.92	1.63	0.36	0.63	0.78	0.25	1.41	0.85	0.74	1.81	4.18
Belgium	1.57	0.79	9.87	12.5	5.68	6.28	0.42	1.05	2.68	0	4.14	2.7	3.05	2.23	7.5	18.05	0.58	3.86	4.55	3.06	4.22	4.78
Denmark	0.6	0.67	2.31	0.96	1.4	2.91	0.2	0.5	0.88	0.57	0	3.86	0.93	0.79	0.52	1.17	0.51	7.03	0.84	1	7.87	0.97
Finland	0.38	0.25	1.19	0.79	0.6	2.09	0.11	0.9	0.6	0.37	4.58	0	1.54	1.12	0.98	1.04	0.15	4.25	0.68	0.82	8.78	0.66
Greece	0.25	0.08	1.11	0.51	0.78	0.35	0.04	0.13	0.27	0.19	0.24	0.18	0	0.1	0.39	0.53	0.03	0.09	0.17	0.24	0.28	0.13
Ireland	0.34	0.17	0.61	0.84	0.42	4.67	0.17	0.38	0.24	0.46	0.37	0.32	0.56	0	0.22	0.69	0.15	0.29	0.27	0.69	0.4	0.29
Israel	0.77	0.48	0.45	0.34	0.49	0.62	0.09	0.32	0.31	0.41	0.19	0.41	0.57	0.31	0	0.36	0.13	0.24	0.88	0.24	0.25	0.4
Nether.	1.6	0.8	15.77	8.1	6.67	8.97	0.45	1.55	3.48	20.16	8.51	4.1	6.01	3.16	3.52	0	1.57	3.85	4.22	4.14	4.78	4.71
N.Z.	0.62	1.75	0.11	0.19	0.19	1.09	0.25	4.74	0.07	0.19	0.12	0.11	0.72	0.18	0.02	0.06	0	0.07	0.11	0.17	0.06	0.04
Norway	2.14	0.39	3.12	1.4	0.45	3.8	0.14	0.32	0.44	1.03	4.96	3.4	1.38	0.47	0.37	1.87	0.2	0	0.71	0.54	6.68	0.44
Portugal	0.24	0.12	0.48	0.57	0.48	0.88	0.09	0.12	0.34	0.27	0.55	0.77	0.25	0.34	0.3	0.37	0.1	0.67	0	0.92	0.88	0.34
Spain	1.05	0.82	1.81	4.32	2.53	2.09	0.32	0.47	0.54	1.06	0.89	1.43	1.4	0.95	0.74	1.2	0.58	0.85	8.1	0	1.02	1.1
Sweden	1.34	0.98	2.91	2.29	1.98	3.88	0.71	2.45	2.34	1.79	15.39	19.46	2.69	1.8	1.37	2.48	1.7	19.08	3.35	2.15	0	2.35
Switz.	2.24	2.24	4.89	3.36	3.95	5	0.89	1.38	6.46	3.36	2.04	2.55	2.01	0.69	12.32	1.75	0.94	1.86	4.89	3.01	2.41	0
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Source: IMF (1986)

TABLE 2

TFP estimation results; pooled data with 440 observations

	<i>BIS</i>	(i) <i>RIS</i>	<i>SS</i>	<i>BIS</i>	(ii) <i>RIS</i>	<i>SS</i>	<i>BIS</i>	(iii) <i>RIS</i>	<i>SS</i>
$\log S^d$	0.097 (0.009)	0.029 (0.002)	0.026 (0.011)	0.090 (0.008)	0.035 (0.002)	0.032 (0.010)	0.078 (0.008)	0.048 (0.001)	0.047 (0.008)
$G7 \times \log S^d$				0.135 (0.016)	0.097 (0.002)	0.095 (0.016)	0.157 (0.015)	0.159 (0.001)	0.159 (0.014)
$\log S^f$	0.092 (0.016)	0.156 (0.003)	0.161 (0.013)	0.060 (0.015)	0.125 (0.003)	0.129 (0.014)			
$m \times \log S^f$							0.289 (0.041)	0.329 (0.005)	0.335 (0.030)
R^2	0.630	0.702	0.705	0.683	0.728	0.729	0.706	0.747	0.748

In percent

from / to	U.S.	Japan	Germany	France	Italy	U.K.	Canada	Aus'tia	Austria	Belgium	Denmark	Finland	Greece	Ireland	Israel	Nether.	N.Z.	Norway	Portugal	Spain	Sweden	Switz.
U.S.	0	8.99	6.77	7.91	4.05	6.99	2.15	8.6	4.53	6.44	1.7	6.25	9.14	6.41	1.12	2.01	7.57	0.89	0.22	8.24	2.98	7.65
Japan	9.97	0	3.76	3.39	0.6	4.36	7.39	0	4.78	1.29	6.65	0.91	6.86	4.29	9.92	4.99	6.55	11.5	5.21	6.07	4.78	5.86
Germany	9.91	3.55	0	0.72	5.76	6.02	3.66	9.91	6.85	2.27	6.88	3.41	1.34	4.48	9.01	9.42	7.54	3.68	8.26	5.05	1.73	8.26
France	0.1	2.68	3.3	0	3.28	4.66	3.35	1.01	8.22	4.71	3.54	2.33	3.31	5.79	1.01	0.7	3.9	2.56	10.57	3.31	1.27	7.76
Italy	1.7	3.99	8.14	4.57	0	4.33	8.33	2.23	6.59	3.78	4.58	2.66	8.07	6.25	0.77	0.81	7.7	1.39	1.09	5.95	5.37	3.62
U.K.	4.28	5.36	5.17	7.51	6.2	0	2.17	0.52	1.99	1.1	2.18	4.84	2.9	3.55	1.13	4.78	0.89	2.94	0.57	6.09	8.64	5.26
Canada	8.39	10.37	8.54	0.03	4.01	4.85	0	8.53	7.09	4.15	7.83	0.71	3.36	1.89	9.76	3.99	4.42	0.38	1.96	6	3.49	0.79
Aus'tia	5.27	0.67	8.49	2.74	9.39	2.06	9.28	0	7.59	7.95	2.11	5.6	7	1.17	3.2	8.32	1.74	4.95	2.69	0.74	7.64	2.03
Austria	8.3	2.78	8.64	3.12	4.4	2.27	9.04	8.22	0	7.9	7.57	7.27	1.94	4.25	3.27	6.88	3.68	4.26	5.68	3.58	7.57	5.26
Belgium	10.32	9.31	5.3	4.18	1.05	1.05	3.06	3.34	6.73	0	3.06	8.34	0.01	7.09	2.48	5.81	2.75	2.41	10.03	7.12	7.28	8.01
Denmark	2.28	4.77	4.24	9.09	1.53	1.61	6.28	6.06	7.73	3.33	0	9	1.41	7.43	2.68	6.03	0.58	3	1.76	4.41	1.83	2.84
Finland	0.85	3.57	0.42	8.42	0.72	6.52	6.58	2.96	5.36	6.88	7.14	0	2.85	7.11	10.5	8.26	2.99	5.98	3.51	0.42	7.85	6.73
Greece	3.13	1.2	0.66	4.3	8.22	1.73	3.56	1.47	0.75	4.51	8.81	6.35	0	6.63	6.94	3.45	7.92	10.24	3.37	5.24	5.43	2.85
Ireland	2.23	10.11	5.11	6.45	8.6	6.74	5.16	0.17	6.33	5.03	3.88	5.74	9.25	0	6.8	0.02	6.91	0.75	3.18	5.32	2.59	5.61
Israel	8.51	2.87	1.48	7.94	3.78	7.11	0.49	4.84	0.11	2.6	1.56	8.53	5.4	6.23	0	8.81	4.34	5.4	0.87	4.38	3.34	1.94
Nether.	4.29	5	0.52	3.81	6.57	7.16	7.55	4.18	4.63	6.6	4.7	5.84	9.82	4.79	7.44	0	6.69	10.66	2.63	5.71	8.92	3.92
N.Z.	4.34	2.04	9.03	2.1	4.44	5.68	2.87	8.12	3.86	2	4.18	7.57	8.46	7.08	1.08	3.94	0	5.91	10.41	4.77	1.91	7.66
Norway	3.78	0.96	0.57	0.17	5.74	3.99	3.79	3.02	2.44	5.45	2.72	0.34	4.4	6.29	1.7	2.26	7.18	0	6.72	5.95	8.44	8.23
Portugal	3.23	2.8	4.29	2.84	0.28	5.93	6.39	7.62	4.48	4.47	6.9	5.1	4.54	3.88	1.47	0.61	5.23	5.1	0	0.73	3.35	1.86
Spain	3.46	5.52	6.71	7.03	6.44	4.18	6.53	9.28	0.53	7.53	0.66	2.13	1.23	4.19	5.83	8.66	1.31	1.99	9.09	0	0.86	2.74
Sweden	0.18	9.1	2.36	9.25	9.43	5.75	1.55	6.91	3.15	6.06	5.01	1.46	3.91	1.06	7.94	2.39	5.69	6.29	7.66	3.62	0	1.13
Switz.	5.48	4.36	6.49	4.43	5.5	6.99	0.81	2.97	6.25	5.96	8.34	5.61	4.79	0.14	5.95	7.88	4.43	9.71	4.5	7.29	4.72	0
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100