ARE INTERNATIONAL R&D SPILLOVERS COSTLY FOR THE UNITED STATES?

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Abstract—Coe and Helpman, among others, report positive and equivalent R&D spillovers across groups of countries. However, the nature of their econometric tests does not address the heterogeneity of knowledge diffusion across countries. We empirically examine these issues in a sample of 10 OECD countries by extending both the time span and the coverage of R&D activities in the data set. We find that the elasticity of total factor productivity with respect to domestic and foreign R&D stocks is extremely heterogeneous across countries and that data cannot be pooled. Thus, panel estimates conceal important cross-country differences. The United States appears to be a net loser in international R&D spillovers. Our interpretation is that when competitors catch up technologically, they challenge U.S. market shares and investments worldwide. This has implications for U.S. productivity.

I. Related Literature

IN a seminal paper, Coe and Helpman (1995; henceforth CH) provide empirical evidence on trade-related international R&D spillovers by using panel data for 21 OECD countries and Israel over the period 1971–1990. Their main findings are that the domestic (S^d) and foreign (S^f) R&D capital stocks affect domestic total factor productivity (TFP) positively and that S^d has a bigger effect than S^f on large countries, whereas the opposite holds for smaller countries. The more open the smaller countries are, the more likely they are to benefit from S^f. According to Navaretti and Tarr (2000, p. 2), CH's work is the "most quoted reference" in the field.

The finding of significant R&D spillovers across countries is consistent with the growth literature. The endogenous-growth literature, in particular, posits endogenous innovations as key propagators of long-run economic growth.[1] Productivity transmissions of this kind are not only important for developed countries; they are also vital for promoting economic growth in developing countries. Indeed, Coe, Helpman, and Hoffmaister (1997) report significant R&D spillovers from 22 OECD countries to a group of 77 developing countries.

CH's findings have been subjected to rigorous scrutiny. Engelbrecht (1997) reexamines the sensitivity of CH's results by including measures of human capital and productivity catch-up and finds that R&D spillovers remain significant, although their magnitude is reduced. Keller (1998) focuses on the weights (actual import shares) used by CH to compute S^f and shows that the role of trade patterns may not be that important in determining the extent of R&D spillovers. However, Coe and Hoffmaister (1999) provide evidence which reconfirms the importance of trade patterns in knowledge diffusion. Lichtenberg and van Pottelsberghe (1998) show that CH's weighting scheme biases the measurement of S^f and that their indexation scheme also biases the estimates of spillover coefficients. Using their own proposed alternative weighting scheme, they still find significant spillovers, although of somewhat reduced magnitude.

CH used panel cointegration tests. At the time, unfortunately, the econometrics of panel cointegration was not fully developed. Kao, Chiang, and Chen (1999) reexamine R&D spillovers using CH's data and specifications but address the econometrics of panel cointegration tests in a more formal and complete manner. Interestingly, Kao et al. do not find evidence of international spillovers—the effect of S^f on TFP appears insignificant—when they use a dynamic OLS (DOLS) estimator shown to have better power properties. Recently, van Pottelsberghe and Lichtenberg (2001) extended CH's analysis by treating foreign direct investment (FDI) as a channel of technology diffusion. They use only 13 of CH's 22 sample countries and apply panel cointegration tests developed by Pedroni (1999). They find evidence of significant R&D spillovers. To sum up, the general picture emerging from this strand of literature supports the argument for positive and significant international R&D spillovers across countries.

II. Motivation

The multicountry panel studies reviewed above address an important issue of knowledge diffusion. However, a common feature of these econometric tests is that they do not capture the dynamic heterogeneity of knowledge spillovers across countries. For example, these panel tests imply that slope coefficients, error variances, and adjustment dynamics are identical across countries or groups of countries. A disquieting outcome is that technology diffusion appears to generate equivalent productivity gains across countries irrespective of whether the country is a technological leader (such as the United States) or follower (such as Canada).[2]

Time series studies that do not impose any cross-country restrictions and that analyze knowledge spillovers at

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[1] See, among others, Romer (1990), Aghion and Howitt (1998), and Grossman and Helpman (1991).

[2] Although the multicountry panel studies have examined the group-specific elasticity by incorporating group dummies in the regressions, our argument for heterogeneity goes much deeper (see section IV).

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country level are conspicuously lacking.[3] This paper aims to fill this gap. We examine the long-run relationship between TFP, S^d, and S^f by employing Johansen's (1991) multivariate VAR in a sample of 10 OECD countries (henceforth G10).[4] Although we attach more weight to the Johansen method, we nevertheless check the robustness of our results by employing the fully modified OLS (FMOLS) estimator of Phillips and Hansen (1990). The further contributions of this paper are as follows.

First, we extend the R&D data to 35 years (1965–1999) from the 20 years (1971–1990) analyzed by all of the studies reviewed above. Second, all studies reviewed above only analyze business-sector R&D. We analyze both business-sector and total R&D activity (that is, total R&D expenditure incurred within national boundaries). This is important because the non-business-sector R&D activity is not trivial; it also allows us to examine if the extent of knowledge spillovers is sensitive to data aggregation, a point emphasized by Griliches (1992).[5] Third, we examine whether or not global technology diffusion is beneficial to the United States. The United States has been the technological leader of the capitalist world since World War II, and technological and industrial rivalries exist between it, the European Union, and Japan.[6] In a world characterized by technological rivalry, knowledge diffusion can, in principle, be positive or negative.[7] In fact, bilateral spillover studies and studies based on micro data indicate that knowledge spillovers are not beneficial to the United States.[8] We address this issue by modeling two important aggregates of R&D activities (business-sector and total R&D data) at the country level. Fourth, we address some of the concerns surrounding the panel tests. Levine and Zervos (1996, p. 325) state that panel regressions mask important cross-country differences and suffer from "measurement, statistical, and conceptual problems." Pesaran and Smith (1995) point out the heterogeneity of coefficients across countries. We formally test whether data can be pooled across our sample countries and whether panel estimates correspond to country-specific estimates. Finally, we also evaluate the stability of spillover elasticities through the tests of the stability of cointegrating ranks and cointegrating parameters.

To preview our main results, R&D dynamics across G10 countries are found to be heterogeneous.[9] As a result, data cannot be pooled. We find a robust cointegrating relationship between TFP, S^d and S^f (or mS^f) involving total R&D data under the Johansen method; however, the evidence is not as robust for the business-sector R&D data.[10] This shows the importance of analyzing total R&D data. Tests reject the null that panel estimates correspond to country-specific estimates. Thus, panel tests conceal important cross-country differences, a concern echoed by many. We also find that it is not always valid to normalize the relationship on TFP; causality may run from TFP to S^d. For the United States, we find international R&D spillovers to be significantly negative for total R&D data, and the finding is robust to estimation methods and VAR lengths. Business-sector R&D data also show either insignificant or significantly negative spillovers for the United States. On balance, accumulation of R&D by G10 partners appears to hurt U.S. TFP. Tests also reveal that cointegrating ranks and the long-run parameters are stable over quite a long period.

The rest of the paper is organized as follows. Section III covers data issues; section IV discusses the issues of heterogeneity; section V discusses model specification and econometric methodology; section VI presents empirical results; and section VII summarizes and concludes.

III. Data

Our sample consists of 10 OECD countries: Canada, Denmark, France, Germany, Ireland, Italy, Japan, the Netherlands, the United Kingdom, and the United States. Data frequency is annual for a period of 35 years (1965–1999). The data series required for the core analysis of this paper are TFP, S^d, and S^f for the business-sector and total R&D activities. Details of their construction as well as other

[3] Our EconLit Bid search under "R&D Spillovers" scored 141 hits (returns). All empirical papers used panel estimators, and none was a time series study.

[4] Data constraints prevent modeling beyond G10 countries (see appendix for details).

[5] Although the share of non-business-sector (higher education; government and private nonprofit institutions) R&D has tended to decline over the years, it nevertheless accounted for 34.91% of overall R&D expenditure incurred by our sample countries during 1990–1998. A discussion-paper version of this paper (Luintel and Khan, 2003) reports data on the distribution of R&D activities across countries.

[6] The E.U.'s Galileo satellite program, the Eurofighter, and the Airbus are examples of technological rivalry between Europe and America.

[7] For example, if spillovers from the United States accrue to its product market rivals, this may cost the United States a productivity loss. Further, the accumulation of R&D by the European Union and Japan may gradually replace U.S. investments both at home and abroad and reduce U.S. productivity.

[8] See Park (1995), Mohnen (1999), Eaton and Kortum (1996), and Blonigen and Slaughter (2001), to name but a few. The latter, in particular, report that inward FDI and Japanese new plant (greenfield) investments do not contribute to U.S. skills, nor do the imported inputs appear to upgrade U.S. productivity levels.

[9] Although Nadiri and Kim (1996) also report heterogeneous R&D spillovers across G7 countries, this paper differs fundamentally from theirs and makes new contributions. First, we follow a country-by-country time series approach and address the important issue of nonstationarity, whereas they estimate pooled regressions. We show that it is invalid to pool the data set (see section IV). Second, their approach (the use of country dummies) only allows for country-specific parameters, whereas our approach addresses both the heterogeneity of parameters and adjustment dynamics. Third, they follow CH in constructing S^f, whereas we follow the more refined approach of Lichtenberg and van Pottelsberghe (1998). They only analyze total R&D, whereas we analyze both business-sector and total R&D activity. Fourth, their main focus is how spillover affects the cost and structure of production, whereas we focus directly on TFP, in CH's tradition. Nadiri and Kim report positive R&D spillovers across all G7 countries, but we find significantly negative spillovers for the United States (see section VI). In a world characterized by technological rivalry, this last is a unique and interesting finding.

[10] The product mS^f is the import-interacted S^f, where m is a time-varying import ratio.

relevant data and their sources are given in the appendix. Figure 1 plots TFP, S^d, and S^f.

France, Italy, Japan, and the Netherlands show more or less smooth increases in total factor productivity except for some reductions around 1974–1975. Canada's TFP shows a prolonged period of stagnation and/or decline from the early 1970s to the mid-1980s and then again in the early part of the 1990s. Danish productivity shows a prolonged slowdown during 1988–1994, although brief productivity drops are also evident in the aftermath of the first and second oil shocks. Germany shows quite a sizable downturn in TFP after 1990, which may be attributed to reunification. Irish productivity appears quite stagnant during the first half of the 1980s but recovers thereafter. U.K. productivity shows three episodes of decline: mid-1970s, early 1980s, and late 1980s extending well into the 1990s. U.S. TFP appears stagnant for quite a long period from the mid-1960s to the early 1980s, but shows improvements after 1984. Griliches (1994) argues that the decline in U.S. productivity may have started as early as the mid-1960s rather than in the aftermath of the first oil price shock in the mid-1970s (as is widely claimed), and productivity may not have recovered until the mid-1980s. The plot of U.S. TFP reflects Griliches's views.

Plots of S^d show a rise for Canada, Denmark, France, Germany, Japan, the Netherlands, Ireland, and Italy. The United Kingdom's plot is smooth but rather flat, indicating a slow rate of accumulation. The U.S. stock of domestic R&D is quite flat and shows a prolonged slowdown from the late 1970s to the first half of the 1980s. It recovers after 1985 and has since been on a slow upward trend.

Plots of S^f appear rather flat for Japan and Germany since 1975, while their TFP and S^d have been rising. This pattern is puzzling given the common belief that Japan, in particular, has increasingly benefited from international R&D spillovers. Ireland's S^f is less smooth and shows a decline in the aftermath of first oil shock followed by a deep slide during 1980–1985, which is due to the deep slide in the weights (m_{ij}/y_j ratios) used to calculate the stock of S^f. The United States, on the other hand, shows an upward trend in S^f (due to a rise in other countries' S^d), but a flat TFP during most of the sample period. This raises the question whether the buildup of R&D outside the United States is at all beneficial to U.S. productivity. For the remaining countries, S^f and TFP both trend upward.

IV. Heterogeneity

Technology gap theorists have long emphasized the heterogeneity of international R&D spillovers.[11] They argue that technology, or "know-how," is very much embedded in a country's organizational structures and has a distinct "national flavor." Each country is perceived as a separate technological entity characterized by its own R&D dynamics and "social capability" for absorbing international innovations. Abramovitz (1993), for example, argues that the lack of "technological congruence" may have significantly delayed the adoption of U.S. technology by European countries.

We formally test for the dynamic heterogeneity of the TFP relationship across G10 countries. First, we estimate a second-order autoregressive and distributed lag model, ADL(2), conditioning the level of TFP on the levels of S^d and S^f (or mS^f), and test for the equality of parameters across G10 countries. Second, we estimate ADL(2) on growth rates and perform tests of parameter equality. Chow-type F-tests under the null of parameter equality across G10 countries are reported in table 1; tests reject the null. Thus, the elasticity of TFP with respect to S^d and S^f (or mS^f) across G10 is not homogeneous; this holds for both measures of R&D. Further, as another measure of dynamic heterogeneity, we test if error variances across countries are homoskedastic. Both the LM test and the White test of groupwise heteroskedasticity confirm that error variances across G10 countries are significantly different; again this holds irrespective of the measures of R&D. The elasticity of TFP with respect to S^d and S^f (or mS^f) as well as the dynamics across G10 countries are thus significantly different. Therefore the data set cannot be pooled. In view of these results, empirical tests that do not explicitly allow for cross-country heterogeneity of knowledge diffusion raise some concerns.

V. Specification and Econometric Methods

A. Specification

We adopt the behavioral specification of CH, which was followed by numerous studies cited above, to examine the effects of S^d and S^f on domestic TFP. Their basic econometric specification is

$$LogTFP_t = \beta_1 + \beta_1^d \log S_t^d + \beta_1^f \log S_t^f + \varepsilon_t. \tag{1}$$

Equation (1) states that domestic TFP is a function of domestic and foreign R&D capital stocks; β^d and β^f are (unknown) parameters that directly measure the respective elasticities. To evaluate the role of trade patterns in international R&D spillovers, CH interact the time-varying import ratio (m_t) with S_t^f and specify the following equation:

$$LogTFP_t = \beta_2 + \beta_2^d \log S_t^d + \beta_2^f m_t \log S_t^f + \varepsilon_t. \tag{2}$$

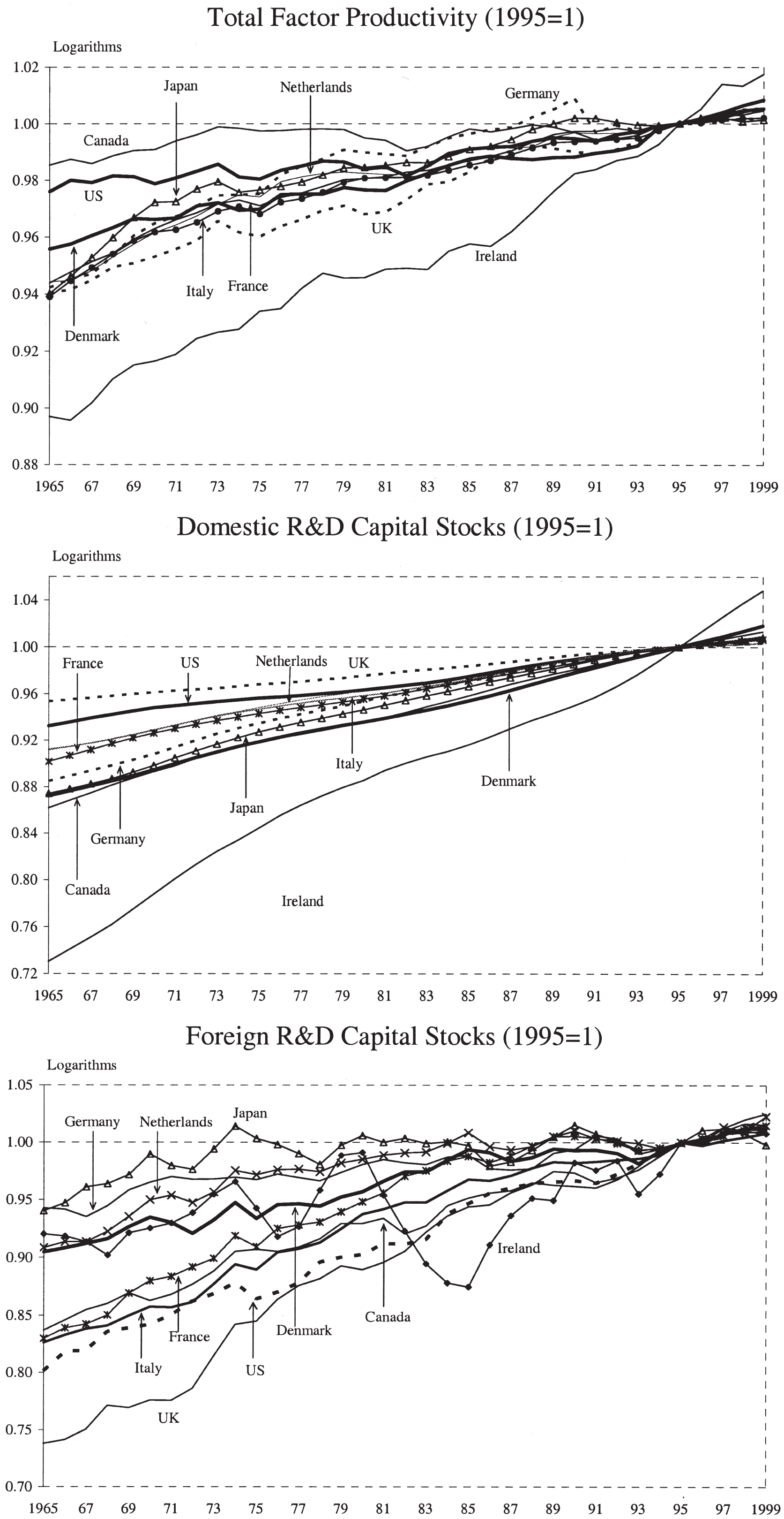
We estimate the long-run relationship between TFP, S^d, and S^f using both of these specifications.

B. Methods

Johansen's (1988) maximum likelihood (ML) method reparameterizes a k-dimensional and pth-order vector (X) to a vector error-correction model (VECM):

[11] See Nelson and Wright (1992), Dosi (1988), and Nelson (1993), to name but a few.

FIGURE 1.—PLOTS OF RAW DATA



These plots pertain to total R&D stocks. Plots involving business-sector R&D appear very similar.

TABLE 1.—HETEROGENEITY OF R&D AND TFP DYNAMICS ACROSS 10 OECD COUNTRIES

	Panel A			Panel B			Panel C			Panel D		
	Equality of θ	LM Test	WH Test	Equality of λ	LM Test	WH Test	Equality of β	LM Test	WH Test	Equality of γ	LM Test	WH Test
TR&D:	12.75[a]	41.88[a]	48.23[a]	25.81[a]	45.84[a]	50.28[a]	13.32[a]	40.04[a]	47.89[a]	26.72[a]	46.91[a]	52.67[a]
BR&D:	15.94[a]	56.84[a]	25.86[a]	33.69[a]	61.22[a]	27.54[a]	17.21[a]	61.41[a]	25.71[a]	33.01[a]	67.60[a]	28.75[a]
Test:	$F(7, 270)$	$\chi^2(9)$	$\chi^2(9)$	$F(7, 280)$	$\chi^2(9)$	$\chi^2(9)$	$F(7, 270)$	$\chi^2(9)$	$\chi^2(9)$	$F(7, 280)$	$\chi^2(9)$	$\chi^2(9)$

The specification for panel A: $\Delta tfp = \theta_0 + \Sigma_{i=1}^2 \theta_{1i}\Delta tfp_{t-i} + \Sigma_{i=1}^2 \theta_{2i}\Delta S^d_{t-i} + \Sigma_{i=1}^2 \theta_{3i}\Delta S^f_{t-i} + \varepsilon_t$.
The specification for panel B: $tfp = \lambda_0 + \Sigma_{i=1}^2 \lambda_{1i} tfp_{t-i} + \Sigma_{i=1}^2 \lambda_{2i} S^d_{t-i} + \Sigma_{i=1}^2 \lambda_{3i} S^f_{t-i} + \varepsilon_t$.
The specification for panel C: $\Delta tfp = \beta_0 + \Sigma_{i=1}^2 \beta_{1i}\Delta tfp_{t-i} + \Sigma_{i=1}^2 \beta_{2i}\Delta S^d_{t-i} + \Sigma_{i=1}^2 \beta_{3i}\Delta(mS^f)_{t-i} + \varepsilon_t$.
The specification for panel D: $tfp = \gamma_0 + \Sigma_{i=1}^2 \gamma_{1i} tfp_{t-i} + \Sigma_{i=1}^2 \gamma_{2i} S^d_{t-i} + \Sigma_{i=1}^2 \gamma_{3i}(mS^f)_{t-i} + \varepsilon_t$.
Row TR&D relates to total R&D capital stocks and the associated TFP; row BR&D represents business-sector R&D. Tests for equality of θ, λ, β, and γ are standard (Chow type) F-tests under the null of parameter equality across 10 OECD countries. Results in panels A and B pertain to models where S^f is not interacted with import ratios (m), whereas those in panels C and D involve interactions. Lagrange multiplier (LM) and White's (WH) tests both reject that error variances are homoskedastic across sample countries. The latter are computed by regressing the squares of residuals on original regressors and their squares and cross products. In this and subsequent tables superscripts a, b and c indicate significance (rejection of the null) at 1%, 5%, and 10%, respectively.

$$\Delta X_t = \mu + \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + \cdots + \Gamma_{p-1}\Delta X_{t-p+1} + \Pi X_{t-p} + \varphi D_t + \varepsilon_t. \tag{3}$$

In our analysis $X_t = [\text{TFP}, S^d, S^f]_t$ is a 3×1 vector of the first-order integrated [I(1)] variables, Γ_i are 3×3 short-run coefficient matrices, Π is a 3×3 matrix of long-run (level) parameters, D_t captures the usual deterministic components, μ is a constant term, and ε_t is a vector of Gaussian error. A cointegrated system X_t implies that $\Pi = \alpha_{(3\times r)}\beta'_{(r\times 3)}$ is rank-deficient, that is, $r < k$ (r = number of distinct cointegrating vectors). It is well known that the power of cointegration tests depends on the time span of the data rather than on the number of observations. Our data extend to 35 years; in our view this is sufficient to capture the long-run relationship between TFP, S^d, and S^f. In order to allow for finite samples, we adjust the test statistics [maximal eigenvalue ($\lambda_{\max}$) and trace tests] following Reimers (1992). The VAR lengths (p) are specified so that the VAR residuals are rendered nonautocorrelated. Because variables in the VAR have nonzero mean, we include a constant term in the cointegrating space. Our trivariate VAR can have two cointegrating vectors at most. If multiple cointegrating vectors are found in the system, we follow Pesaran and Shin (2002) and identify them through the tests of overidentifying restrictions. The S^f for each country, a key conditioning variable, is a weighted sum of the rest of the world's (that is, the other G10 countries') S^d. Therefore, S^f may be weakly exogenous to the system. We subject S^f to weak-exogeneity tests and, where we find it to be weakly exogenous, maintain it in further estimations. This improves the efficiency of the estimated cointegrating vectors.

The Johansen method is a reduced-form dynamic system estimator and addresses the issues of multicointegration and normalization. The fully modified OLS (FMOLS) of Phillips and Hansen (1990), on the other hand, is a single-equation estimator which estimates long-run parameters from static level regressions when variables are I(1). FMOLS corrects for both short- and long-run dependence across equation errors, and it is shown to be superconsistent, asymptotically unbiased, and normally distributed. The associated (corrected) t-ratios permit inference using standard tables. We examine the robustness of our results vis-à-vis both the Johansen and FMOLS estimators. In the event of contradictory results, we attach more weight to the results based on the system estimator. In the following we briefly outline the FMOLS estimator.

Consider the following linear static regression:

$$y_t = \beta_0 + \beta_1' x_t + u_t, \tag{4}$$

where y_t is a vector of the I(1) dependent variables and x_t is the $k \times 1$ vector of the I(1) regressors. Let $\Delta x_t = \mu + w_t$, where μ is a $k \times 1$ vector of drift parameters and w_t is a $k \times 1$ vector of stationary variables. Define $\widehat{\xi} = (\widehat{u}_t, \widehat{w}_t)'$. A hat indicates a consistent estimator of the corresponding parameters. The long-run variance-covariance matrix of $\widehat{\xi}(\widehat{V})$ is

$$\widehat{V} = \widehat{\Gamma} + \widehat{\Phi} + \widehat{\Phi}' = \begin{bmatrix} \widehat{v}_{11} & \widehat{v}_{12} \\ \widehat{v}_{21} & \widehat{v}_{22} \end{bmatrix}. \tag{5}$$

Further define

$$\widehat{\Delta} = \widehat{\Gamma} + \widehat{\Phi} = \begin{bmatrix} \widehat{\Delta}_{11} & \widehat{\Delta}_{12} \\ \widehat{\Delta}_{21} & \widehat{\Delta}_{22} \end{bmatrix}, \tag{6}$$

$$\widehat{Z} = \widehat{\Delta}_{21} - \Delta_{22}\widehat{v}_{22}^{-1}\widehat{v}_{21}, \tag{7}$$

where

$$\widehat{\Gamma} = \frac{1}{T-1}\sum_{t=2}^{T}\widehat{\xi}_t\widehat{\xi}_t', \quad \widehat{\Phi} = \sum_{s=1}^{m} w(s,m)\widehat{\Gamma}_s, \quad \widehat{\Gamma}_s = T^{-1}\sum_{t=1}^{t-s}\widehat{\xi}_t\widehat{\xi}_{t+s}',$$

and $w(s, m)$ is the lag truncation window. The adjusted y_t is $\widehat{y}_t^* = y_t - \widehat{v}_{12}v_{22}^{-1}\widehat{w}_t$. The FMOLS estimator is

$$\widehat{\beta}_{\text{FMOLS}} = (W'W)^{-1}(W'\widehat{y}^*) - TD\widehat{Z}, \tag{8}$$

where $\widehat{y}^* = (\widehat{y}_1^*, \widehat{y}_2^*, \ldots, \widehat{y}_t^*)'$, $D = [0_{1\times k} \quad I_k]'$, and W is a $t \times k$ matrix of regressors including a constant term. A consistent estimator of the variance-covariance matrix Ψ is $\Psi(\widehat{\beta}_{\text{FMOLS}}) = \kappa_{11.2}(W'W)^{-1}$, where $\kappa_{11.2} = \widehat{v}_{11} - \widehat{v}_{12}\widehat{v}_{22}^{-1}\widehat{v}_{21}$.

TABLE 2.—TOTAL R&D: COINTEGRATION TESTS AND VAR DIAGNOSTICS BETWEEN TFP, S^d, AND S^f (JOHANSEN METHOD)

	Trace Statistics			Maximum Eigenvalue			Loading				
	$r = 0$	$r \leq 1$	$r \leq 2$	$r = 0$	$r \leq 1$	$r \leq 2$	Factor α	Wexo	LM{3}	NOR	LAG
	A. Specification: $LogTFP_t = \beta_1 + \beta_1^d \log S_t^d + \beta_2^f \log S_t^f + \varepsilon_t$ [Equation (1)]										
CA[f]	38.11[a]	7.24	—	30.87[a]	7.24	—	−0.307[b]	0.458	0.324	0.973	3
	[0.000]	[0.117]		[0.000]	[0.117]		(0.144)				
DK[d]	22.70[b]	3.74	—	18.96[b]	3.74	—	−0.354[a]	0.324	0.356	0.967	2
	[0.021]	[0.464]		[0.014]	[0.463]		(0.126)				
FR[d]	26.24[a]	6.75	—	19.49[b]	6.75	—	−0.367[a]	0.977	0.354	0.399	2
	[0.006]	[0.144]		[0.011]	[0.144]		(0.107)				
DE[e]	19.41[c]	3.51	—	15.90[b]	3.51	—	−0.032[a]	0.145	0.199	0.157	2
	[0.064]	[0.501]		[0.048]	[0.500]		(0.007)				
IT[f]	34.60[a]	6.56	—	28.05[a]	6.56	—	−0.438[a]	0.565	0.281	0.184	2
	[0.000]	[0.157]		[0.000]	[0.157]		(0.070)				
IRL[f]	20.12[b]	1.12	—	19.00[b]	1.12	—	−0.398[b]	0.315	0.254	0.936	3
	[0.051]	[0.920]		[0.013]	[0.920]		(0.210)				
JP[d]	20.96[b]	4.34	—	16.63[b]	4.34	—	−0.497[a]	0.087[c]	0.514	0.590	3
	[0.038]	[0.376]		[0.036]	[0.375]		(0.105)				
NL[f]	26.70[a]	6.78	—	19.92[a]	6.78	—	−0.382[a]	0.765	0.185	0.502	2
	[0.005]	[0.142]		[0.009]	[0.142]		(0.077)				
UK[f]	23.80[b]	7.26	—	16.54[b]	7.26	—	−0.625[a]	0.363	0.415	0.280	2
	[0.014]	[0.116]		[0.037]	[0.116]		(0.135)				
US[f]	40.06[b]	14.78	2.95	25.28[b]	11.8	2.95	−0.320[b]	0.006[a]	0.556	0.618	3
	[0.012]	[0.245]	[0.599]	[0.016]	[0.202]	[0.598]	(0.160)				
	B. Specification: $LogTFP_t = \beta_2 + \beta_2^d \log S_t^d + \beta_2^f m_t \log S_t^f + \varepsilon_t$ [Equation (2)]										
CA[f]	29.91[a]	7.11	—	22.80[a]	7.11	—	−0.297[b]	0.061[b]	0.805	0.735	2
	[0.001]	[0.124]		[0.002]	[0.124]		(0.117)				
DK[d]	19.23[c]	1.94	—	17.29[b]	1.94	—	−0.462[a]	0.163	0.233	0.849	2
	[0.068]	[0.786]		[0.028]	[0.785]		(0.144)				
FR[d]	26.51[a]	5.82	—	20.68[a]	5.82	—	−0.385[a]	0.333	0.377	0.446	2
	[0.005]	[0.212]		[0.006]	[0.212]		(0.094)				
DE[e]	24.03[b]	6.01	—	18.03[b]	6.01	—	−0.018[a]	0.463	0.858	0.011[b]	3
	[0.013]	[0.197]		[0.02]	[0.197]		(0.005)				
IT[f]	39.77[a]	7.16	—	32.61[a]	7.16	—	−0.525[a]	0.259	0.171	0.863	2
	[0.000]	[0.121]		[0.000]	[0.121]		(0.070)				
IRL[f]	20.55[b]	1.36	—	19.19[b]	1.36	—	−0.376[c]	0.200	0.228	0.923	3
	[0.044]	[0.886]		[0.012]	[0.885]		(0.218)				
JP[f]	21.61[b]	5.19	—	16.42[b]	5.19	—	−0.461[a]	0.260	0.375	0.405	3
	[0.031]	[0.273]		[0.039]	[0.273]		(0.098)				
NL[f]	21.93[b]	4.53	—	17.40[b]	4.53	—	−0.243[a]	0.656	0.392	0.350	2
	[0.027]	[0.350]		[0.026]	[0.350]		(0.058)				
UK[f]	21.75[b]	4.71	—	17.05[b]	4.71	—	−0.646[a]	0.690	0.437	0.461	2
	[0.029]	[0.328]		[0.030]	[0.328]		(0.137)				
US[f]	38.15[b]	13.87	3.33	24.28[b]	10.5	3.33	−0.368[b]	0.002[a]	0.095[c]	0.135	3
	[0.022]	[0.305]	[0.531]	[0.023]	[0.298]	[0.530]	(0.182)				

Reported trace and maximal eigenvalue statistics are adjusted for finite sample following Reimers (1992). Values within brackets are p-values under H_0: $r = 0$, $r \leq 1$, and $r \leq 2$. DE is normalized on S^d. Values within parentheses are standard errors. The column Wexo reports p-values of a weak-exogeneity test of S^f (panel A) or mS^f (panel B), $\chi^2(r)$-distributed. LM{3} reports p-values of the third-order LM test of serial correlation in VAR residuals. NOR reports p-values of Bera-Jarque normality tests of VAR residuals, $\chi^2(2)$-distributed. LAG reports the VAR lag lengths. Dummies are not reported for the sake of brevity but are available on request. All dummies are entered unrestricted in the VAR. In panel A, exclusion of dummies does not change the results qualitatively except for the failure of the diagnostics (nonnormality and/or autocorrelation). The country mnemonics in this and subsequent tables are: CA = Canada; DK = Denmark; FR = France; DE = Germany; IT = Italy; IRL = Ireland; JP = Japan; NL = the Netherlands; UK = United Kingdom; US = United States.

[d] No dummy required.

[e] Unification dummy (1991–1992) required.

[f] Impulse dummy around the first and/or the second oil price shock required.

A test of cointegration is equivalent to the test of stationarity of the error correction term generated through $\hat{\beta}_{FMOLS}$.

VI. Empirical Results

CH reported that TFP, S^d, and S^f were clearly trended and contained unit roots. Plots of our data set in figure 1 also confirm this trending pattern. Nevertheless, we implement the univariate KPSS test (Kwiatkowski et al., 1992), which tests the null of stationarity, in order to evaluate the time series properties of the data formally. Tests confirm that TFP, S^d, S^f, and mS^f are I(1), a result consistent with earlier findings (for example, CH).[12]

A. *Total R&D*

Johansen rank tests and a range of VAR diagnostics obtained from total R&D under the specifications (1) and (2) are reported in table 2A and B, respectively. Tests show

[12] We do not report the results of unit root tests, due to space limitations. They are reported in Luintel and Khan (2003).

TABLE 3.—TOTAL R&D: ESTIMATED COINTEGRATING PARAMETERS (JOHANSEN AND FMOLS METHODS)

	Johansen			FMOLS			
	S^d	S^f	mS^f	S^d	S^f	mS^f	KPSS η_μ
CA	−0.051 (0.032)	0.066^{b} (0.031)		−0.130^{b} (0.057)	0.166^{b} (0.053)		0.100
	−0.001 (0.016)		0.036^{b} (0.016)	0.017 (0.015)		0.046^{b} (0.016)	0.108
DK	0.278^{a} (0.030)	−0.082 (0.050)		0.027^{a} (0.028)	0.045 (0.042)		0.089
	0.230^{a} (0.009)		−0.030 (0.041)	0.231^{a} (0.009)		0.038 (0.039)	0.073
FR	0.152^{a} (0.025)	0.102^{a} (0.016)		0.219^{a} (0.029)	0.070^{a} (0.019)		0.090
	0.225^{a} (0.016)		0.157^{a} (0.027)	0.258^{a} (0.017)		0.123^{a} (0.030)	0.091
DE	$S^d = 1.385^{a}\text{TFP} + 0.385S^f; S^d = 0.803^{b}\text{TFP} + 0.287mS^f$			0.354^{a} (0.053)	−0.170 (0.126)		0.342
	(0.328) (0.243) (0.443) (0.247)			0.222^{a} (0.019)		0.235^{a} (0.056)	0.201
IT	0.088 (0.058)	0.136^{a} (0.031)		0.279^{a} (0.062)	0.060^{b} (0.032)		0.217
	0.301 (0.011)^{a}		0.132^{a} (0.022)	0.323^{a} (0.011)		0.154^{a} (0.021)	0.081
IRL	0.352^{a} (0.008)	0.020 (0.017)		0.333^{a} (0.010)	0.057^{b} (0.020)		0.249
	0.367^{a} (0.009)		0.002^{b} (0.001)	0.370^{a} (0.014)		0.004^{b} (0.002)	0.264
JP	0.221^{a} (0.017)	0.024 (0.036)		0.183^{a} (0.015)	0.174^{a} (0.049)		0.209
	0.223^{a} (0.020)		0.030 (.108)	0.232^{a} (0.016)		0.031 (0.178)	0.347^{c}
NL	0.226^{a} (0.045)	0.141^{a} (0.047)		0.196^{a} (0.026)	0.231^{a} (0.029)		0.092
	0.292^{a} (0.036)		0.029 (0.035)	0.361^{a} (0.022)		0.068^{b} (0.029)	0.229
UK	0.583^{a} (0.098)	0.028 (0.021)		0.470^{a} (0.102)	0.055^{b} (0.022)		0.066
	0.654^{a} (0.046)		0.043 (0.029)	0.574^{a} (0.043)		0.102^{a} (0.028)	0.077
US	0.538^{a} (0.088)	−0.172^{a} (0.039)		0.346^{a} (0.085)	−0.065^{c} (0.038)		0.109
	0.300^{a} (0.037)		−0.330^{a} (0.082)	0.281^{a} (0.039)		−0.188^{b} (0.090)	0.095
Panel	0.265^{a} (0.009)	0.292^{a} (0.071)		0.228^{a} (0.010)	0.062^{a} (0.009)		
	0.288^{a} (0.006)		0.008^{a} (0.002)	0.287^{a} (0.006)		0.061^{a} (0.008)	

Values in parentheses are respective standard errors. Bartlet's window of second order is used for FMOLS estimates. The 10%, 5%, and 1% critical values for the KPSS η_μ (level stationarity) test are 0.347, 0.463, and 0.73, respectively. The last row reports between-dimension panel estimates of parameters. The relevant references associated with the derivation of these panel tests are given in footnote 18.

that S^f is clearly weakly exogenous in eight sample countries, marginal for Japan (weak exogeneity is rejected at 9%), and endogenous for the United States. Likewise, the weak exogeneity of mS^f holds for all but Canada and the United States. Hence, we impose weak exogeneity of S^f and mS^f on all but the United States in further estimations, because this improves the efficiency of the estimates.[13]

Trace and λ_{max} statistics, adjusted for the finite samples, show that TFP, S^d, and S^f (or mS^f) are cointegrated in all sample countries and exhibit a single cointegrating vector. This finding is robust to both tests (trace and λ_{max}) and specifications. For a valid normalization and error-correction representation, the associated loading factors α_s must be negatively signed and significant. On this basis, we can normalize all countries but Germany on TFP; their associated loading factors are negatively signed and significant at 5% or better, except for Ireland in specification (2), which is significant at 10%. Germany, on the other hand, shows a perversely (positively) signed loading factor in both specifications and hence cannot not be normalized on TFP.[14] Therefore, Germany's cointegrating vector is normalized on S^d and the reported loading factors are now correctly signed and significant. Thus, our findings suggest that in this trivariate system German TFP does not adjust (error-correct) to any long-run disequilibrium between TFP, S^d, and S^f (or mS^f); instead, S^d adjusts. This has implications for the econometrically defined causal flows. In Germany causal flow is from TFP to S^d, that is, a rise in TFP causes an accumulation of the domestic R&D capital stock. Indeed, a formal implementation of Toda and Phillips's (1993) test of long-run causality for Germany shows significant causality from TFP to S^d, but the causal flow from S^f to S^d is insignificant.[15] LM tests show an absence of serial correlation in VAR residuals in all cases except for the United States in the specification (2). The latter is marginal, however. Residuals also pass normality tests.[16]

The last column of table 3 reports the tests of stationarity of the error-correction term derived from FMOLS. KPSS tests show that, at 5% or better, all error-correction terms are level stationary and hence that TFP, S^d, and S^f (or mS^f) are

[13] Although the weak exogeneity of mS^f for Canada is rejected at 6.1%, we impose it because the precision of cointegration tests is thereby much improved.

[14] When normalized on TFP, the loading factors for Germany are 0.097 (0.049) for the specification (1), and 0.058 (0.019) for (2). Numbers within parentheses are standard errors.

[15] Toda and Phillips's (1993) long-run causality test is rooted in the Johansen VAR framework. For Germany, the LR test rejects the null of noncausality from TFP to S^d at very high precision (p-value of 0.006), whereas the null of noncausality from S^f to S^d is not rejected at any conventional level of significance (p-value = 0.143).

[16] The only exception is Germany in the specification (2). Inclusion of a unification dummy does not improve the nonnormality. Given the extremely low (or virtual lack of) sensitivity of the estimated parameters and their significance levels to the correction of nonnormality in this study, we are of the view that this rejection of normality should not be a serious concern.

TABLE 4.—TESTS FOR THE HETEROGENEITY OF COINTEGRATING PARAMETERS ACROSS COUNTRIES

	Johansen Estimates			FMOLS Estimates		
	S^d	S^f	mS^f	S^d	S^f	mS^f
Test statistics	80.855[a]	40.771[a]		162.340[a]	55.392[a]	
	81.836[a]		55.325[a]	513.607[a]		933.806[a]
Degrees of freedom of $\chi^2(\cdot)$	(9)	(9)	(9)	(10)	(10)	(10)
Critical values (1%)	21.667	21.667	21.667	23.209	23.209	23.209

χ^2 statistics are reported under the null that country-specific parameters are jointly equal to the panel estimates. Tests reject the null at a very high level of precision. Because Germany could only be normalized on S^d, it is excluded while conducting these tests under the Johansen method but included under the FMOLS. This explains the differences in the degrees of freedom.

cointegrated in all cases. These results are consistent with those found using Johansen's approach.

The estimated cointegrating vectors are also reported in table 3. Most importantly, we find that for the United States international R&D spillovers are significantly negative; the elasticity of TFP with respect to S^f is -0.17 under Johansen and -0.07 under FMOLS. The finding of negative spillovers for the United States is robust to VAR length (1–4), estimation methods, and specifications. Thus, it appears that R&D accumulation by competitors hurts U.S. TFP. The Japanese results, on the other hand, are puzzling. International R&D spillovers appear insignificant for Japan in all but one estimate, namely, FMOLS under the specification (1). Of the remaining eight countries, the Johansen approach shows four countries (Canada, France, Italy, and the Netherlands) with positive and significant effects of S^f on TFP, and three (Denmark, Ireland, and the United Kingdom) with statistically insignificant effects; Germany can only be normalized on S^d. Germany shows a significant effect of TFP on S^d. FMOLS results largely support the Johansen results.[17]

Interacting S^f with the import ratio does not change the results significantly. Under the Johansen method this produces two tangible differences: (i) the spillover coefficient for Ireland becomes significant, whereas the opposite occurs for the Netherlands; and (ii) the negative spillover coefficient for the United States almost doubles, to -0.33. The rest of the parameters are qualitatively similar. FMOLS also produces two tangible differences when the import ratio and S^f are interacted: (i) the Japanese spillover coefficient becomes insignificant, whereas the German one becomes significantly positive; and (ii) the negative spillover coefficient of the United States increases by almost threefold, to -0.19.

The effect of S^d on TFP is more prevalent. Under the Johansen method, of the nine countries normalized on TFP, all but Canada and Italy exhibit a positive and significant elasticity of TFP with respect to S^d. The insignificance of S^d for Canada (under both specifications) and Italy (under the specification (1)) is rather surprising. Likewise, FMOLS shows a significant positive effect of S^d on TFP for all countries except Canada, which shows a significantly negative effect under the specification (1) and an insignificant effect under (2).

The country-specific results in table 3 vividly show the considerable cross-country heterogeneity in the estimated point elasticity of S^d and S^f (or mS^f). Interestingly, however, the panel (between-dimension) estimates, reported in the last row of the table, show positive and significant effects of S^d and S^f (or mS^f) on TFP, results that closely resemble the findings of the previous panel tests.[18]

In order to assess the equivalence between panel and country-specific estimates, we formally test whether country-specific parameters are jointly equal to the corresponding panel estimates. This involves conducting a Wald or LR test for the restriction that each country-specific coefficient is equal to its panel counterpart and summing the individual χ^2 statistics (see Pesaran, Haque, and Sharma, 2000). Under the assumption that these tests are independent across countries, the sum of the individual χ^2 statistics can be used to test the null that country-specific coefficients are jointly equal to the respective panel estimates. The test statistic is $\chi^2(N)$ distributed, where N is the number of countries in the panel. Table 4 reports these results; as is evident, they strongly reject the null of parameter equality. This result is robust to specifications and estimation methods. Thus, the statistical evidence is that panel estimates do not correspond to country-specific estimates and they conceal important cross-country differences.[19] Therefore, any generalizations based on panel results may proffer incorrect inferences with respect to several countries of the panel.

B. *Business-Sector R&D*

We report the cointegration tests involving business-sector TFP, S^d, and S^f (or mS^f) in table 5A and B. Business-sector results appear somewhat less robust than those obtained from total R&D. First, the French TFP, S^d, and S^f (or

[17] Under FMOLS Germany is normalized on TFP. Because Johansen's approach shows that this normalization is not valid for Germany, we warn readers regarding the FMOLS results for that country. Apart from Germany, FMOLS shows significant spillover effects for seven countries, whereas Johansen's approach shows them for five countries.

[18] The between-dimension panel estimates are obtained by averaging the country-specific parameters. Larsson, Lyhagen, and Lothgren (2001) discuss the computations of these panel estimates under the Johansen approach, and Pedroni (2001) derives them for the FMOLS.

[19] Individual country level results also reject the null of equality in the majority of cases, and this holds true under both specifications and estimation methods. Due to space limitations, these results are not reported here; they are reported in Luintel and Khan (2003).

TABLE 5.—BUSINESS-SECTOR R&D: COINTEGRATION TESTS AND VAR DIAGNOSTICS BETWEEN TFP, S^d, AND S^f (JOHANSEN METHOD)

	Trace Statistics			Maximum Eigenvalue							
	$r = 0$	$r \leq 1$	$r \leq 2$	$r = 0$	$r \leq 1$	$r \leq 2$	Loading Factor α	Wexo	LM{3}	NOR	LAG
	A. Specification: $LogTFP_t = \beta_1 + \beta_1^d \log S_t^d + \beta_1^f \log S_t^f + \varepsilon_t$ [Equation (1)]										
CA[e]	29.16[a]	7.21	—	21.95[a]	7.21	—	−0.329[a]	0.708	0.123	0.891	3
	[0.002]	[0.118]		[0.004]	[0.118]		(0.102)				
DK[d]	20.02[b]	7.67[c]	—	12.35	7.67	—	−0.285[a]	0.786	0.118	0.791	2
	[0.052]	[0.097]		[0.172]	[0.097]		(0.093)				
FR[d]	29.68	15.38	4.99	14.30	10.40	4.99	NA	0.129	0.147	0.845	3
	[0.176]	[0.209]	[0.295]	[0.448]	[0.310]	[0.295]					
DE[e]	20.79[b]	7.57	—	13.21	7.57	—	−0.035[a]	0.209	0.668	0.001[a]	2
	[0.041]	[0.101]		[0.128]	[0.101]		(0.009)				
IT[e,f]	45.23[a]	23.40[b]	6.76	21.83[b]	16.64[b]	6.76	−0.200[b]	0.453	0.873	0.499	2
	[0.002]	[0.016]	[0.144]	[0.056]	[0.036]	[0.143]	(0.104)				
IRL[e]	23.05[b]	3.11	—	19.94[a]	3.11	—	−0.602[a]	0.869	0.092[c]	0.494	2
	[0.018]	[0.570]		[0.009]	[0.569]		(0.122)				
JP[e]	44.84[a]	23.02[b]	5.06	21.82[c]	17.96[b]	5.06	−0.290[a]	0.000[a]	0.160	0.572	2
	[0.003]	[0.019]	[0.287]	[0.056]	[0.021]	[0.286]	(0.086)				
NL[e]	18.76[c]	1.76	—	17.00[b]	1.76	—	−0.238[a]	0.789	0.048[b]	0.139	2
	[0.071]	[0.817]		[0.031]	[0.816]		(0.062)				
UK[d]	37.48[b]	18.01[c]	6.47	19.47	11.55	6.47	−0.109[a]	0.050[b]	0.247	0.791	2
	[0.026]	[0.099]	[0.163]	[0.121]	[0.221]	[0.163]	(0.021)				
US[e]	20.40[b]	6.90	—	13.50	6.90	—	−0.202[c]	0.888	0.366	0.152	2
	[0.046]	[0.135]		[0.116]	[0.135]		(0.126)				
	B. Specification: $LogTFP_t = \beta_2 + \beta_2^d \log S_t^d + \beta_2^f m_t \log S_t^f + \varepsilon_t$ [Equation (2)]										
CA[e]	20.42[b]	4.13	—	16.28[b]	4.13	—	−0.299[a]	0.641	0.273	0.475	3
	[0.046]	[0.405]		[0.041]	[0.404]		(0.072)				
DK[g]	21.98[b]	4.58	—	17.39[b]	4.58	—	−0.470[a]	0.396	0.284	0.776	3
	[0.027]	[0.344]		[0.026]	[0.343]		(0.099)				
FR[d]	30.26	15.06	3.94	15.19	11.12	3.94	NA	0.126	0.518	0.943	3
	[0.156]	[0.228]	[0.433]	[0.372]	[0.252]	[0.432]					
DE[d]	20.54[b]	6.18	—	14.36	6.18	—	−0.021[a]	0.835	0.689	0.001[a]	2
	[0.044]	[0.183]		[0.086]	[0.183]		(0.005)				
IT[e]	39.24[a]	3.98	—	35.26[a]	3.98	—	−0.545[a]	0.531	0.131	0.683	2
	[0.000]	[0.426]		[0.000]	[0.426]		(0.067)				
IRL[d]	22.35[b]	2.98	—	19.38[a]	2.98	—	−0.544[a]	0.340	0.090[c]	0.578	2
	[0.024]	[0.593]		[0.011]	[0.592]		(0.118)				
JP[d]	38.64[b]	17.25	3.88	21.40[c]	13.37	3.88	−0.143[b]	.005[a]	0.071[c]	0.939	2
	[0.019]	[0.125]	[0.442]	[0.065]	[0.122]	[0.441]	(0.067)				
NL[g]	20.75[b]	3.59	—	17.16[b]	3.59	—	−0.185[a]	0.551	0.475	0.122	2
	[0.041]	[0.488]		[0.029]	[0.487]		(0.054)				
UK[d]	24.97[a]	8.27[c]	—	16.70[b]	8.27[c]	—	−0.240[a]	0.924	0.602	0.110	2
	[0.009]	[0.084]		[0.035]	[0.084]		(0.065)				
US[e]	21.56[b]	7.29	—	14.27[c]	7.29	—	−0.575[a]	0.206	0.631	0.094[c]	2
	[0.031]	[0.115]		[0.088]	[0.114]		(0.178)				

Reported trace and maximal eigenvalue statistics are adjusted for finite sample following Reimers (1992). Values within brackets are p-values under H_0: $r = 0$, $r \leq 1$, and $r \leq 2$. DE is normalized on S^d. Values within parentheses are standard errors. The Wexo column reports p-values of weak-exogeneity test of S^f (panel A) or mS^f (panel B), $\chi^2(r)$-distributed. LM{3} reports p-values of the third-order LM test of serial correlation in VAR residuals. NOR reports p-values of Bera-Jarque normality tests of VAR residuals, $\chi^2(2)$-distributed. LAG reports the VAR lag lengths. All dummies are entered unrestricted in the VAR. The loading factor for France is not reported (NA) due to noncointegration. Dummies are not reported but are available on request.

[d] No dummy required.

[e] Impulse dummy around the first and/or the second oil price shock required.

[f] Note that the Π matrix for Italy displays full rank when S^f is treated as weakly exogenous. This is puzzling. We circumvent it by treating S^f as endogenous.

[g] Impulse dummy for 1974–1975 for DK and for 1985–1986 for NL proved important for cointegration.

mS^f) show noncointegration. Second, Italy and Japan show two cointegrating vectors in the specification (1), whereas the other countries show only one. Third, trace tests and λ_{max} tests show contradictory results for Denmark, Germany, the United Kingdom, and the United States in the specification (1). These contradictions largely disappear in the specification (2); nonetheless, the λ_{max} test fails to reject noncointegration for Germany, Japan, and the United States at the conventional 5% significance level. Trace tests, shown to be preferable to λ_{max} tests (Cheung and Lai, 1993), consistently reject noncointegration for all countries but France. Note also that the rejection for the Netherlands is at 7%.[20] Thus, the system estimator shows not only that the evidence of cointegration involving business-sector data is sensitive to the specifications and the test statistics employed, but also that there is evidence of noncointegration. Overall diagnostics are well behaved.[21] As before, normalization on TFP produces insignificant loading factors for

[20] UK and DK show marginal evidence of a second cointegrating vector; however, in view of their poor precision, we treat them as having only one cointegrating vector.

[21] Except for the significant serial correlation found for the Netherlands in the specification (1), only a few diagnostics show marginal failure. See footnote 16 on German nonnormality.

TABLE 6.—BUSINESS-SECTOR R&D: ESTIMATED COINTEGRATING PARAMETERS (JOHANSEN AND FMOLS METHODS)

	Johansen			FMOLS			
	S^d	S^f	mS^f	S^d	S^f	mS^f	KPSS η_μ
CA	−0.152[a] (0.037)	0.212[a] (0.038)		−0.138[a] (0.039)	0.207[a] (0.041)		0.222
	−0.034 (0.034)		0.089[b] (0.035)	0.020 (0.023)		0.048 (0.031)	0.104
DK	0.242[a] (0.047)	−0.150[c] (0.087)		0.147[a] (0.031)	0.042 (0.052)		0.183
	0.204[a] (0.015)		0.022 (0.056)	0.164[a] (0.008)		0.120[a] (0.050)	0.201
FR	NA	NA	NA	0.112[b] (0.060)	0.168[a] (0.040)		0.177
				0.225[a] (0.034)		0.279[a] (0.065)	0.264
DE	$S^d = 2.53tfp + 0.479S^f$; $S^d = 0.96tfp + 0.86^bS^f$;			0.295[a] (0.051)	−0.233[b] (0.106)		0.173
	(0.422) (0.224) (0.840) (0.43)			0.122[a] (0.021)		0.222[a] (0.062)	0.158
IT	0.074[a] (0.017)	0.100 (#)		0.266[a] (0.063)	0.014 (0.036)		0.409[c]
	0.203[a] (0.010)		0.140[a] (0.022)	0.228[a] (0.011)		0.160[a] (0.024)	0.195
IRL	0.349[a] (0.008)	0.002 (0.020)		0.361[a] (0.008)	−0.029 (0.021)		0.250
	0.351[a] (0.009)		0.000 (0.002)	0.351[a] (0.009)		−0.002 (0.002)	0.241
JP	0.100 (#)	0.401[a] (0.038)		0.140[a] (0.012)	0.194[a] (0.045)		0.076
	0.200[a] (0.025)		0.681[a] (0.238)	0.186[a] (0.014)		0.081 (0.161)	0.067
NL	0.338[a] (0.076)	0.077 (0.069)		0.385[a] (0.060)	0.126[a] (0.069)		0.123
	0.435[a] (0.048)		0.060 (0.052)	0.493[a] (0.034)		0.010 (0.042)	0.109
UK	−1.008 (0.705)	0.334[b] (0.152)		0.197 (0.133)	0.152[a] (0.029)		0.236
	0.675[a] (0.119)		0.054 (0.082)	0.549[a] (0.051)		0.267[a] (0.036)	0.209
US	0.523[a] (0.116)	−0.109[b] (0.050)		0.322[a] (0.068)	0.009 (0.029)		0.149
	0.315[a] (0.036)		−0.051 (0.089)	0.289[a] (0.034)		0.038 (0.803)	0.117
Panel	0.058[a] (0.003)	0.108[a] (0.022)		0.209[a] (0.009)	0.065[a] (0.013)		
	0.294[a] (0.009)		0.124[a] (0.029)	0.263[a] (0.006)		0.122[a] (0.006)	

Values in parentheses are respective standard errors. (#) No standard error, because these parameters are imposed as part of the identification. For Italy and Japan identification is achieved through two normalization restrictions on TFP and S^d, and further suitable constraints are imposed on S^f and TFP in the first and the second cointegrating vectors. Precise details are available on request. The second cointegrating vector for Italy is $S^d = 0.54S^f$; for Japan, $S^d = 2.58tfp + 2.95S^f$; the latter set of parameters are on the higher side. Bartlet's window of second order is used for FMOLS estimates. The 10%, 5%, and 1% critical values for the KPSS η_μ (level stationarity) tests are 0.347, 0.463, and 0.73, respectively. Under the Johansen method no parameter is reported for France (NA), as the French TFP, S^d, and S^f appear noncointegrated.

Germany. Therefore, the cointegrating vectors for Germany (under the Johansen method) are normalized on S^d. All the associated loading factors are correctly signed and significant.

The last column of table 6 reports the KPSS tests of level stationarity of error-correction terms obtained from FMOLS. Results show cointegration at 5% or better for all cases. These results corroborate the findings of trace tests. However, the system estimator shows multicointegration for Italy and Japan and the problem of normalization for Germany, issues which FMOLS does not address. The FMOLS results should therefore be taken with some caution.

Table 6 also reports cointegrating parameters. Estimates of the point elasticity of TFP with respect to S^d are positive and significant for all countries except Canada (in both specifications) and the United Kingdom [in the specification (1)]. The insignificant and/or negative and significant elasticities of S^d found for Canada and the United Kingdom are rather puzzling.

With the Johansen method six countries show significant spillover effects (negative for the United States and Denmark) in the specification (1), but only three in the specification (2). With FMOLS six countries show significant spillover effects (negative for Germany) in the specification (1) and five countries in the specification (2). It is also interesting that for business-sector data the Johansen approach shows a significantly negative spillover for Denmark.

A comparison of total and business-sector R&D parameters (tables 3 and 6), obtained with the Johansen method reveals that six countries (Germany, Denmark, Ireland, Japan, the Netherlands, and the United States) have qualitatively similar results with a positive and significant effect of S^d on TFP. The remaining four countries (Canada, France, Italy, and the United Kingdom) show sensitivity of results to measures of R&D. Five countries (Canada, Germany, Italy, Ireland, and the United States) show qualitatively similar spillover effects of S^f with respect to the two measures of R&D; the other five show contradictory results. Likewise, six countries (Canada, Denmark, Germany, Italy, the Netherlands, and the United Kingdom) show qualitatively similar results for mS^f, whereas the other four show contradictory results. Five countries exhibit a significant effect of S^f associated with total R&D (the United States negative), whereas six countries (Denmark and the United States negative) show a significant effect in relation to business-sector R&D. On the other hand, five coefficients of mS^f (four positive and one negative) are significant with respect to total R&D, whereas only three appear significant with respect to business-sector R&D.

The FMOLS estimates largely echo the differences shown by the Johansen method across the two measures of

R&D activities. Except for the United Kingdom in the specification (1), the elasticities of TFP with respect to S^d appear qualitatively similar across the two measures of R&D, but the spillover elasticities are somewhat different. All in all, under FMOLS, eight (six) spillover coefficients associated with S^f and seven (five) of those associated with mS^f appear statistically significant in relation to total (business-sector) R&D. On balance, total R&D shows relatively more point estimates of significant spillovers.

We also conducted tests of whether panel estimates correspond to country-specific estimates for business-sector R&D. Like our earlier findings for total R&D, the results show that there is no equivalence. Joint tests consistently reject the null that country-specific parameters are jointly equal to their panel counterparts at a very high level of precision. Individual country-level results also reject the null in most cases. These results are robust to specifications and the estimation methods. Due to space constraints, we do not report these results here, but the full set of results can be found in Luintel and Khan (2003).

Overall, the system approach shows a robust cointegrating relation between TFP, S^d, and S^f (or mS^f) for total R&D data. We consistently find a single cointegrating relation, and results are robust to trace and λ_{max} tests. Results involving business-sector data appear somewhat sensitive to the specifications and the test statistics employed. FMOLS, on the other hand, shows cointegration between TFP, S^d, and S^f (or mS^f) in all cases, thus corroborating the findings of the system estimator. Our finding of significantly negative R&D spillovers for the United States is robust to the measures of R&D stocks and the methods of estimation. The business-sector results continue to show that R&D spillovers for the United States are either significantly negative or nonexistent (statistically insignificant). Likewise, significant heterogeneous productivity effects of S^d and S^f across countries remain despite different measures of R&D and estimation methods. These findings contrast sharply with those associated with the literature in the CH tradition.[22]

C. Stability

The stability of cointegrating ranks and parameters is examined following the approach of Hansen and Johansen (1999), which compares the recursively computed ranks of the matrix Π with its full-sample estimate. If the subsample ranks of Π differ significantly from those of the full sample, this implies structural shifts in the cointegrating rank. Likewise, conditional on the identified cointegrating vectors, if subsample parameters significantly differ from those of the full sample, this signifies the instability of cointegrating parameters. It is well known that structural shifts should be identified endogenously rather than exogenously (see, among others, Perron, 1997; Christiano, 1992; Luintel, 2000); hence, we follow this recursive approach. The LR test for these hypotheses is asymptotically χ^2, with $kr - r^2$ degrees of freedom. Tests are carried out in two settings: (i) both short-run and long-run parameters are allowed to vary (the Z-model), and (ii) short-run parameters are concentrated out, and only long-run parameters are allowed to vary (the R-model).

We specify a base estimation window of the first 15 observations.[23] Thus, stability tests are carried out over a period of 20 years (1980–1999). Figure 2 plots the normalized LR statistics that test rank stability under the specification (1) using the R-model.[24] All LR statistics are scaled by the 5% critical value; hence, values greater than unity imply rejection of the null of stability and vice versa. In these plots the rank r is stable if the rank $r - 1$ is rejected. The time path of the scaled LR statistics shows that the null of noncointegration ($H_0 : r = 0$) is clearly rejected for all sample countries, as plots that test this hypothesis are all above unity or cross the critical threshold. The plots that test $H_0 : r \leq 1$ are below unity (that is, less than the 5% critical value) for all but Italy and the United States. Italy shows rank instability during much of the 1990s; the United States shows a short period of instability in the early 1980s. It is tempting to associate U.S. rank instability with the productivity slowdown discussed in section III. Tests reveal stable cointegrating ranks for the rest of the sample countries.

We also evaluated the stability of cointegrating parameters. Results show that the long-run parameters (the R-model) are remarkably stable over the 20-year period for almost all countries analyzed.[25] The Z-model, on the other hand, shows parameter instability especially prior to the mid-1980s, primarily owing to the volatility of short-run parameters. The latter findings appear to corroborate the parameter instability reported by CH, Kao et al. (1999), and van Pottelsberghe and Lichtenberg (2001), for their tests do

[22] One referee asked us to clarify the sources of the difference (data span or estimation methods) between our results and those of CH. It is not feasible to conduct country-by-country cointegration tests on CH's data set, as it contains only 20 data points for each country. Therefore, we first pooled our business-sector R&D data and ran CH's OLS regressions. We then extracted data from CH's database for our sample (G10) countries and ran identical regressions. The estimated point elasticities based on CH's data set are $0.23S_i^d$ and $0.02S_i^f$, whereas those based on our data set are $0.21S_i^d$ and $0.07S_i^f$. CH emphasize the theoretical plausibility of these estimated parameters rather than their significance and the test of cointegration (CH, p. 870). Thus, for the same set of countries CH's approach produces qualitatively similar results for the two sets of data. Hence we conclude that the data span may play a very marginal role; the main source of difference lies in the time series techniques that we use, which allow fully for cross-country heterogeneity. As the referee indicated, such a comparison between the coefficients of mS^f is invalid, due to the time variation in the import ratio.

[23] Hansen and Johansen (1999) specify an initial estimation window of 16 (monthly) observations.

[24] The R-model is more suitable for testing the stability of cointegrating ranks and long-run parameters (Hansen and Johansen, 1999). Nonetheless, the results from the Z-model appear broadly similar.

[25] The only two exceptions are that the Netherlands during 1984–1987 and the United Kingdom during 1981–1983 show instability in the long-run parameters. The full sets of results of parameter stability tests pertaining to both the R- and Z-models are reported in Luintel and Khan (2003).

FIGURE 2.—PLOTS OF SCALED RECURSIVE LR STATISTICS (RANK STABILITY TESTS)

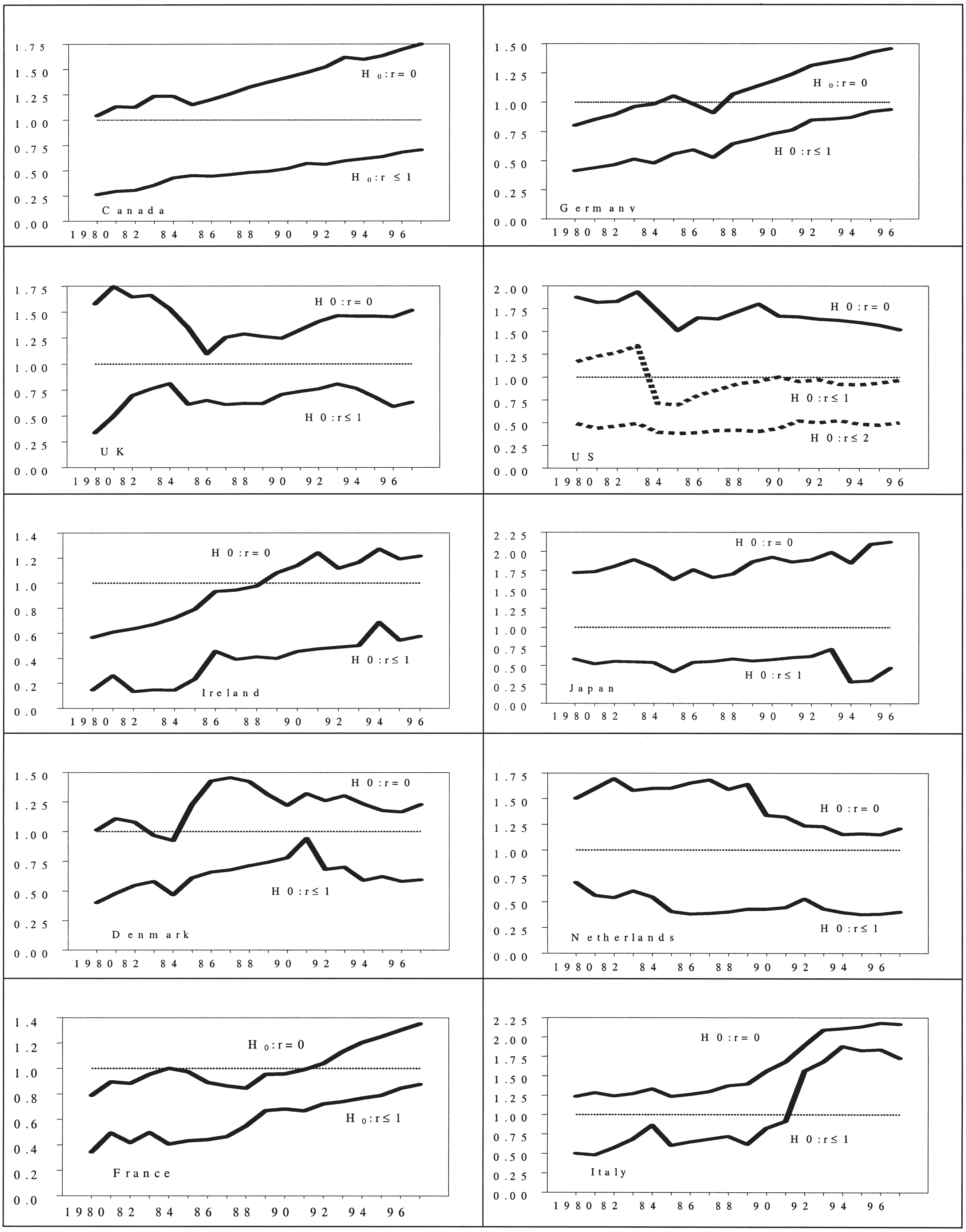


TABLE 7.—INTERNATIONAL OUTPUT ELASTICITIES OF DOMESTIC R&D CAPITAL STOCKS, 1965–1999

	CA	DK	FR	DE	IT	IRL	JP	NL	UK	US	Average	Total
CA	—	0.000	0.001	0.002	0.001	0.000	0.003	0.000	0.003	0.058	0.008	0.068
DK	0.000	—	−0.007	−0.029	−0.003	0.000	−0.004	−0.007	−0.018	−0.009	−0.009	−0.078
FR	0.001	0.001	—	0.035	0.013	0.001	0.006	0.009	0.022	0.019	0.012	0.106
IT	0.001	0.001	0.036	0.047	—	0.001	0.004	0.012	0.021	0.017	0.016	0.140
IRL	0.000	0.000	0.001	0.001	0.000	—	0.001	0.001	0.013	0.004	0.002	0.021
JP	0.001	0.000	0.001	0.002	0.001	0.000	—	0.000	0.002	0.017	0.003	0.025
NL	0.001	0.001	0.018	0.054	0.005	0.001	0.007	—	0.031	0.025	0.016	0.143
UK	0.001	0.001	0.005	0.007	0.002	0.001	0.002	0.003	—	0.008	0.003	0.029
US	−0.048	−0.001	−0.011	−0.022	−0.007	−0.001	−0.059	−0.003	−0.026	—	−0.020	−0.178
Average	−0.005	0.000	0.005	0.011	0.001	0.000	−0.005	0.002	0.006	0.017		
Total	−0.043	0.004	0.043	0.097	0.011	0.002	−0.040	0.014	0.048	0.138		

Bilateral output elasticities are calculated using equation (9) in the text. Their interpretation is as follows. The output elasticity of Japan with respect to U.S. R&D is 0.017. The average figures show that a 1% increase in Japan's R&D would on average reduce other G10 output by 0.005%; the total effect will be a reduction of 0.04%. Likewise, the column shows that Japan's output will increase by 0.025% following a 1% rise in the domestic R&D of the other nine members of the 10 OECD countries analyzed in this study. The average effect on Japanese output is 0.003%.

not distinguish between the short- and the long-run parameters, and their sample runs only up to 1990.[26]

D. Bilateral and Multilateral Spillover Elasticities

The estimates of bilateral international R&D spillovers based on the aggregate point elasticities of table 3 [from the specification (1)] are reported in table 7. Each entry is the estimated elasticity of TFP of country i (reported in columns) with respect to the S^d of country j (reported in rows). These bilateral spillover elasticities are calculated as

$$\beta^f_{ij} = \alpha^f_i \frac{m_{ij}}{y_j} \cdot \frac{S^d_j}{S^f_i}, \tag{9}$$

where β^f_{ij} is the bilateral spillover elasticity of the TFP of country i with respect to the S^d of country j; α^f_i is country i's elasticity of TFP with respect to S^f; other variables are as already defined. Table 7 shows that a 1% increase in U.S. R&D would increase Japanese output by 0.017%. However, a 1% increase in Japanese R&D would reduce U.S. output by 0.059%. The accumulation of R&D by Japan hurts U.S. productivity the most. Given the negative elasticity of U.S. TFP with respect to S^f, all bilateral spillover elasticities are negative. R&D accumulation by Canada is also rather costly for the United States, but U.S. R&D has its highest international productivity effect on Canada (0.058%).

The last row of table 7 reports the overall international productivity effect of domestic R&D. U.S. R&D has the biggest output effect across other G10 members (a 1% increase in U.S. R&D increases international output by 0.138%), followed by Germany (0.097%). German R&D appears to enhance significantly the productivity of France, Italy, and the Netherlands, and its effect on Japanese output is almost one-ninth that of U.S. R&D.

The total elasticity of domestic output with respect to foreign R&D is reported in the last column of table 7. A 1% rise in the R&D of other G10 countries in the sample would reduce U.S. output by 0.178%. Canada, France, Italy, and the Netherlands appear major beneficiaries of international R&D spillovers, and the United States and Germany appear to be the main generators of spillovers. Japan's major productivity gains accrue from the United States.

E. Own Rates of Return

The average own rate of return to domestic R&D shows tremendous variation across sample countries.[27] Ireland shows the highest own rate of return (453%), followed by Denmark (183%), the United States (175%), the United Kingdom (148%), the Netherlands (106%), Japan (100%), France (56.8%), Italy (4.9%), and Canada (−33.4%). The extremely high own rate of return for Ireland is due to its very high ratio of real GDP to S^d, which is 17.28. The sample average of this ratio is 8.09. van Pottelsberghe and Lichtenberg (2001, p. 494) estimate average rates of return of 68% for G7 countries, which is lower than our estimate of 132%. However, our estimate is close to that reported by CH (p. 874) for G7 countries (123%).

VII. Summary, Conclusion, and Implications

Coe and Helpman (1995) and a number of subsequent studies have provided empirical evidence in support of positive and equivalent R&D spillovers across groups of countries in a panel framework. However, the nature of these panel tests does not allow for the possible heterogeneity of knowledge diffusion across countries. Because countries differ in their stage of development, openness, stock and intensity of R&D, and so on, we argue that knowledge diffusion is likely to be heterogeneous across countries. Moreover, in a world characterized by technological rivalry, knowledge diffusion may, in principle, be positive or negative.

We model knowledge spillover dynamics at the country level by utilizing extended data set and time series methods. The Johansen VAR approach and FMOLS are used for the

[26] Tests of the stability of cointegrating parameters (β^d and β^f) were also conducted under FMOLS by computing recursive Wald tests over the period 1980–1999. Overall, FMOLS corroborates the stability found by the VECM.

[27] The own rate of return from domestic R&D is $\theta_{jj} = \alpha^d_j(y_j/S^d_j)$, where α^d_j is the elasticity of TFP of country j with respect to its own domestic R&D capital stock, S^d_j.

estimations. We find a robust cointegrating relation between TFP, S^d, and S^f (or mS^f) for total R&D data; all sample (G10) countries show a single cointegrating vector, and the results are robust to trace and λ_{max} tests. However, under the system approach, cointegration results appear slightly less robust when business-sector R&D data are used. FMOLS shows cointegration in all cases, thus mainly corroborating the findings of the system estimator. We attach more weight to results for total R&D because they are robust with respect to the system estimator.

Our results are interesting and shed some new light on R&D spillover dynamics. First, we find significant heterogeneity in the dynamics of knowledge diffusion across G10 countries. The results show that data cannot be pooled; long-run spillover elasticities differ significantly among sample countries; and panel estimates, in general, do not correspond to country-specific parameters. Thus, panel tests appear to conceal important cross-country differences in knowledge diffusion. This is in sharp contrast to the existing findings that international R&D spillovers are positive and do not differ in important respects across OECD countries (CH, note 10). Second, we find that it is not always valid to normalize the relationship on TFP, as the case of Germany shows. Causality may run from TFP to S^d. Third, we find that the spillover elasticities are significantly negative for the United States. This finding is robust to data measurements, specifications, and estimation methods. Fourth, it is generally observed that Japan benefits significantly from but generates few spillovers. Our results go a step further, as we find that Japan's net spillover generation is negative. A 1% rise in Japan's R&D stock increases the output of other members of G10 except the United States by 0.019%, but hurts U.S. output by 0.059%, thus generating a net spillover of −0.040%.[28]

Finally, our results may help reconcile two sets of seemingly conflicting findings. Studies in the tradition of CH report positive and equivalent R&D spillovers across groups of countries. However, studies on bilateral spillover flows and those that use micro data report international R&D spillovers to be asymmetrical, flowing from large R&D-intensive nations to small and less R&D-intensive nations. Our panel (between-dimension) estimates—methodologically close to the previous panel approach—show positive spillover coefficients, whereas country-level results show a diversity of spillover parameters across G10 countries. This study may therefore bridge the gap between these two sets of findings by showing that the dynamics of knowledge diffusion are country-specific and inherently heterogeneous.

In addition, our results corroborate the stylized finding that the output elasticity of S^d tends to be higher than that of S^f for large countries. We also find that the United States and Germany are the main generators of spillovers. This is consistent with Eaton and Kortum (1996); however, our finding about Japan differs from theirs.

[28] Because the United States commands 44% of the G10's real GDP, this net negative spillover of −0.040% is not widely off the mark.

The main implications of this study are twofold. First, the extent and the dynamics of knowledge diffusion may depend on the technological sophistication of the country concerned. Second, as bilateral spillover elasticities (table 7) indicate, the distribution of knowledge diffusion is hardly uniform. For example, the United States is the sole generator of spillovers for Canada; and Germany is the main source of knowledge diffusion for France, Italy, and the Netherlands. Japan mainly receives spillovers from the United States; Germany and the United States appear equally important for the United Kingdom. This may indicate some bonding between nations owing to technological congruence, geographical proximity, or both.

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APPENDIX

Sources and Construction of Data

The relevant data series and their sources are as follows. Gross domestic product (Y), gross fixed investment (I), level of employment (L), GDP deflator (P), business-sector GDP (Y_b), business-sector capital stock (K_b), business-sector employment (L_b), and business-sector GDP deflator (P_b) are obtained from the OECD's Analytical Database. Total gross domestic expenditure on research and development (E^{RD}) and business-sector gross expenditure on research and development (E_b^{RD}) are obtained from the OECD's R&D Database. Exports (X) and imports (M) of goods and services are obtained from the OECD's International Trade Statistics (ITS) Database; bilateral exchange rates with U.S. dollars are obtained from *International Financial Statistics* (IFS), published by the International Monetary Fund.

A consistent series of the total physical capital stock K for the whole sample period is lacking. Therefore we constructed it for each country in the sample from the respective gross fixed investment series, using the perpetual inventory method. A depreciation rate of 8% and the sample-average growth rate of real investment are used to generate the initial capital stock. The OECD has published total capital stock data for the OECD countries, but the time span covered differs across countries. For example, the data for the United Kingdom are for 1985–1997, for Italy for 1981–1997, and for Japan for 1973–1997. An alternative approach would be to extend this (published) data set to our sample (1965–1999) through backward and forward extrapolation using the perpetual inventory method and the gross fixed investment series.[29] Unfortunately this strategy proved problematic on two counts. First, the published total physical capital stock data are based on the Systems of National Accounts 1968 (SNA 68), whereas the available data on gross fixed investment are based on the Systems of National Accounts 1993 (SNA 1993) and are not compatible. Second, when we generated the total physical capital stocks by backward and forward extrapolation, strange data patterns emerged. Plots show that for most OECD countries total physical capital stocks fall in a rather sustained way during 1965–1985 (downward slope), Japanese total capital stock becomes negative for 1965–1966, and the plot of Italian total capital stock appears as a shallow V-shape. Because these patterns do not reflect the positive secular trend believed to exist in the total physical capital stocks of these countries, we decided to use the total capital stock that we constructed. The business-sector physical capital stock data are readily available from OECD for the sample period, and we use those data.

We would have liked to cover more than 10 OECD countries, but data constraints proved prohibitive. Countries that were excluded either did not have sufficiently long time series (data mostly started from 1973), or suffered from a large number of missing observations (data holes), or both. However, it is important to note that our sample countries account for 89% of total OECD R&D activities (expenditures) during the 1990s.

Following common practice (CH, 1995), the total domestic R&D capital stock (S^d) is calculated from E^{RD} using the perpetual inventory method. E^{RD} covers all the R&D expenditure carried out within the national territory of each sample country, converted to constant prices by deflating by the GDP deflator. The initial total domestic R&D capital stock (S_0^d) is calculated as

$$S_0^d = \frac{E_0^R}{g + \delta}, \tag{A-1}$$

where δ is the depreciation rate, assumed to be 8%, g is the average annual growth rate of E^{RD} over the sample, and E_0^R is the initial value of E^{RD} in the sample. We follow Lichtenberg and van Pottelsberghe (1998) and compute the total foreign R&D capital stock (S^f) as

$$S_i^f = \sum_{j \neq i} \frac{m_{ij} S_j^d}{y_j}, \tag{A-2}$$

where m_{ij} is the imports of goods and services to country i from country j and y_j is country j's GDP.[30] The business-sector domestic (S_b^d) and foreign (S_b^f) R&D capital stocks are computed following equations (A-1) and (A-2) and using E_b^{RD}. Finally, we compute the total factor productivity (TFP) in the usual way (see CH):

$$\log \mathrm{TFP} = \log Y - \gamma \log K - (1 - \gamma) \log L. \tag{A-3}$$

Following the literature, we set the value of the coefficient γ to 0.3. The business-sector TFP is calculated as

$$\log \mathrm{TFP}_b = \log Y_b - \gamma \log K_b - (1 - \gamma) \log L_b. \tag{A-4}$$

[29] We would like to thank one of the anonymous referees for pointing this out.

[30] Note that S_j^d is converted to a common currency (U.S. dollars) using PPP equivalent exchange rates when calculating S_i^f.