The Dynamics of International R&D Spillovers

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Abstract

Coe and Helpman (1995) 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 US appears to be a net loser in terms of international R&D spillovers. Our interpretation is that when competitors 'catch-up' technologically, they challenge US market shares and investments worldwide. This has implications for US productivity.

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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] In these models, technology spills over through international trade and triggers productivity increases in importing countries so long as there is a positive mark-up between the marginal product and the cost of imported intermediate goods.[2] 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 et al. (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) re-examines 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) scrutinizes the role of trade patterns in determining the extent of R&D spillovers. He focuses on the weights (actual import shares) used by CH to compute S^f and shows that randomly generated import ratios can lead to similar or even higher international spillovers. He further shows that ignoring the import ratios altogether and assigning equal weights to the R&D capital stocks of all trading partners also lead to larger spillover effects than those reported by CH. In a recent paper, however, Coe and Hoffmaister (1999) show that Keller's random weights are technically 'not random', and they suggest alternative randomisations which reconfirm that trade patterns are important for 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 spillovers 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 et al. (1999) re-examine 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 due to 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.[3]

II. Motivation

The multi-country panel tests reviewed above (CH; Engelbrecht, 1997; Keller, 1998; Lichtenberg and van Pottelsberghe, 1998; van Pottelsberghe and Lichtenberg, 2001; Kao et al., 1999), 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. This leaves scope for improvement and this is where we aim to contribute. For example, these panel tests imply that slope coefficients (the elasticity of TFP with respect to S^d and S^f), error variances and adjustment dynamics are identical across countries or groups of countries.[4] A disquieting outcome is that technology diffusion appears to generate equivalent productivity gains across countries irrespective of whether the country is a technological leader (e.g. the US) or follower (e.g. Canada).

In a world characterised by technological rivalry, knowledge diffusion can, in principle, be positive or negative.[5] If R&D strategy is designed to pre-empt competition, spillovers may be negative. Likewise, R&D competition may lead to duplicate R&D and may waste resources. Whether international knowledge spillover is indeed positive for all countries irrespective of their stage of technological sophistication is an interesting empirical question, which needs to be examined at country level. Nadiri and Kim (1996) point out, and we concur, that "R&D spillovers are likely to be country-specific even for the highly industrialised G7 countries". This diversity can be attributed to a host of country-specific factors including the heterogeneity of 'social capability' and technological infrastructure (see section IV).

Time series studies that do not impose any cross-country restrictions and that analyse knowledge spillovers at country level are conspicuously lacking.[6] This paper aims to fill this gap in the literature by offering, among other things, up-to-date country level analyses of knowledge spillovers taking a sample of 10 OECD countries (henceforth G10).[7] The long-run relationship between TFP, S^d and S^f (or mS^f)[8] is examined by employing Johansen's (1991) multivariate VAR, a well-established method in time series econometrics. This method also addresses possible multiple cointegrating vectors between TFP, S^d and S^f as well as the validity of normalisation on TFP. 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). Further contributions of this paper are as follows.

First, we extend the R&D data to 35 years (1965-1999) compared to the 20 years (1971-1990) analysed by all of the studies reviewed above. Second, the studies reviewed above only analyse business sector R&D. We analyse both business sector and total R&D activity (i.e., total R&D expenditure incurred within national boundries). The extension to total R&D is important because the non-business sector (i.e., higher education, government and private non-profit institutions) accounts for a non-trivial proportion of total R&D activities, although its share has tended to decline (see section III). Therefore, it is of interest to know whether the extent of knowledge spillovers is sensitive to data aggregation, a point emphasised by Griliches (1992). Griliches (1994, p.2) also remarked that advances in theory and econometric methods are 'wasted' unless they are applied to the right data set. We hope that the new data set and the econometric methods that we apply to examine spillover issues will go some way in addressing Griliches' point.

Third, we address the interesting empirical issue of whether or not global technology diffusion is beneficial to the US. A growing body of empirical literature that takes a distinctly different approach from CH doubts that it does. International spillovers appear asymmetrical: they flow from large R&D-intensive nations to small and less R&D-intensive nations, but not in the opposite direction (Park, 1995; Mohnen, 1999). The US and Japan trade heavily and Japan is a rich and technologically advanced country yet the bilateral spillovers between the US and Japan are either greatly in favour of Japan or are unidirectional from US to Japan (Bernstein and Mohnen, 1998). There is R&D spillover from Canada to Japan but not vice versa (Bernstein and Yan, 1995). Only a few OECD countries (the US, Germany and Japan) generate major spillovers (Eaton and Kortum, 1996). Inward FDI and Japanese new plant ('greenfield') investments do not contribute to US skills, nor do the imported inputs appear to upgrade US productivity levels (Blonigen and Slaughter, 2001).[9] These results, based on analyses of bilateral spillovers and/or disaggregated (micro) data, cast doubt on the thesis that international R&D spillovers benefit the US. However, as pointed out above, the macro effects of R&D may not be directly inferred from micro estimates, and the extent of R&D spillover may depend on the level of data aggregation (Griliches, 1992). We address this issue at a wider level by using two important aggregates of R&D data (business sector R&D and total R&D activities) and by modelling the R&D dynamics at country level. The US has been the technological leader of the capitalist world since World War II and there are ample grounds for believing that technological and industrial rivalries exist between the US, the EU and Japan. It is therefore of interest to enquire whether the US benefits or loses when its competitors (G10 partners) accumulate their own R&D stocks.[10]

Fourth, our time series results also 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'. Quah (1993) shows the difficulties associated with the lack of balanced growth paths across countries when pooling data; Pesaran and Smith (1995) point out the heterogeneity of coefficients across countries. Indeed, we find significant parameter heterogeneity of R&D dynamics across sample countries (see section IV). We provide estimates of country-specific parameters that are potentially of greater policy significance than cross-country 'average' parameters.

Finally, the issue of the stability of spillover elasticity has attracted considerable interest in the literature. CH address this issue by comparing the time varying elasticity of TFP with respect to S^f across different years (i.e., 1971, 1980 and 1990) and conclude that the impact of foreign R&D rose 'substantially' from 1971 to 1980.[11] Kao et al. (1999) follow the same approach. van Pottelsberghe and Lichtenberg (2001) conduct standard F tests by splitting the sample between 1971-80 and 1981-90 and report significant structural shifts in international spillovers. In this paper we address this issue through the tests of stability of cointegrating ranks and cointegrating parameters.

To preview our results, R&D dynamics across G10 countries are found to be heterogeneous. As a result, data cannot be pooled. In most cases, 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. This is consistent with the heterogeneous R&D dynamics discussed in section IV. We find a robust cointegrating relationship between TFP, S^d and S^f (or mS^f) under the Johansen method involving total R&D data; however, the evidence is not as robust for the business sector R&D data. This shows the importance of analysing total R&D data. All countries except Germany can be validly normalised on TFP.[12] For the US, 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, on the other hand, show either insignificant or significantly negative spillovers for the US. On balance, accumulation of R&D by G10 partners appears to hurt US TFP. Tests also reveal that cointegrating ranks and long-run parameters are stable over a considerably long period. Short-run parameters appear volatile but this squares well with the parameter instability reported by CH, Kao et al. (1999) and van Pottelsberghe and Lichtenberg (2001).

The rest of the paper is organised 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 summarises and concludes.

III. Data

Our sample consists of 10 OECD (G10) countries, viz., Canada, Denmark, France, Germany, Ireland, Italy, Japan, the Netherlands, 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 relevant data and their sources are given in Appendix A. Figure 1 plots the total factor productivity.[13]

Figure 1 about here

France, Italy, Japan and the Netherlands show more or less smooth increases in total factor productivity except for some reductions around 1974-75. 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 sizeable 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. UK productivity shows three episodes of decline: mid-1970s, early-1980s and late-1980s overlapping well into the 1990s. US total factor productivity appears stagnant for quite a long period from the mid-1960s to the early 1980s but shows improvements after 1984. In fact, our plot closely mirrors the discussion contained in a voluminous literature about the slowdown in US productivity. Griliches (1994) argues that the decline in US productivity may have started as early as the mid-1960s rather than in the mid-1970s in the aftermath of the first oil price shock, as is widely claimed, and productivity may not have recovered until the mid-1980s. The plot of US total factor productivity reflects Griliches' views.

Figure 2 about here

Figure 2 plots S^d. Canada, Denmark, France, Germany, Japan, the Netherlands, Ireland and Italy show a rise in their stocks of domestic R&D. The UK's plot is smooth but rather flat indicating a slow rate of accumulation. The US's stock of domestic R&D is quite flat and a prolonged slowdown from the late 1970s to the first half of 1980s is apparent. It recovers after 1985 and has since been on a slow upward trend.

Figure 3 about here

Figure 3 plots S^f. It is interesting to note that the S^f of Japan and Germany have been rather flat 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 1980-85. The latter is due to the continuous fall in the weights (m_{ij}/y_j ratio) used to calculate the stock of S^f. This ratio was 1.9 for Ireland in 1979 but fell continuously to 0.45 by 1985 and gradually recovered thereafter. The US, on the other hand, shows an upward trend in S^f (due to a rise in other countries' S^d), but flat TFP during most of the sample period. This raises the question of whether the build-up of R&D outside the US is at all beneficial to US productivity. We take up these issues in the empirical section. For the remaining countries, S^f and TFP both trend upwards.

Table 1 about here

Table 1 reports the relative importance of the business and non-business sectors in R&D activities. It is evident that business sector R&D dominates in Germany, Ireland, Japan, the UK and the US but it represents less than two-thirds in the other sample countries. For most countries, non-business sector R&D activities had a high share prior to 1979. Although their share has tended to decline over the years, it still accounted for 34.91% of overall R&D expenditure during 1990-98. It is therefore far from trivial and underlines the importance of focusing on total R&D.

IV. Heterogeneity

Technology gap theorists have long emphasised the heterogeneity of international R&D spillovers.[14] They argue that technology or 'know-how' is very much embedded in a country's organisational structures and contains a distinct 'national flavour'. This often makes technology transfer difficult and costly. Each country is perceived as a separate technological entity characterised by its own R&D dynamics and 'social capability' for absorbing international innovations. 'Social capability' is defined in terms of a country's technical, industrial, economic, financial and political ability. Abramovitz (1993), for example, argues that the lack of ‘technological congruence’ may have significantly delayed the adoption of US technology by European countries.

Table 2 presents some aggregate statistics. The table is self-explanatory and shows that: (i) the US is by far the dominant country in terms of economic activities and R&D ownership; and (ii) significant divergence exists across G10 countries in terms of the magnitude of economic activities, ownership of R&D capital stock, R&D intensity and trade intensity.[15] As a result, absorptive capacity and technological ‘congruence’ may differ across countries, thereby giving rise to the heterogeneity of R&D spillovers.

Formal tests of the dynamic heterogeneity of the TFP relationship across G10 countries are conducted as follows. 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 3; tests reject the null. Thus, the elasticity of TFP with respect to S^d and S^f (or mS^f) across G10 is not homogenous; this holds for both measures of R&D.

Further, as another measure of dynamic heterogeneity, we test if error variances across groups are homoskedastic. Both the LM-test and the White-test of group-wise heteroskedasticity are reported. The LM test is equivalent to the LR-test and assumes normality whereas White's test is robust to non-normality. Both tests 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 and therefore the data set cannot be pooled. This heterogeneity renders the tests implemented by CH and others inappropriate for this data set. 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

Specification

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

$$LogTFP_t = \beta_1 + \beta_1^d \log S^d{}_t + \beta_1^f \log S^f{}_t + \varepsilon_t \tag{1}$$

Equation (1) states that domestic total factor productivity is a function of domestic and foreign R&D capital stocks; β^d and β^f are (unknown) parameters which 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^f_t and specify the following equation:

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

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

Methods

Johansen's (1988) maximum likelihood (ML) method re-parameterises a k-dimensional and p^{th} order vector (X) to a vector error-correction model (VECM):

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

In our analysis $X_t = [TFP, S^d, S^f]_t$ is a 3x1 vector of the first order integrated [I(1)] variables; Γ_i are (3x3) short-run coefficient matrices; $\Pi_{(3x3)}$ is a 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. The steady-state of (3) is given by the rank of Π which is tested by the well known Maximal eigenvalue (λ-max) and Trace tests (Johansen, 1988). Asymptotic critical values of these test statistics are tabulated by Osterwald-Lenum (1992). A co-integrated system, X_t, implies that: (i) $\Pi = \alpha_{(3 \times r)}\beta'_{(r \times 3)}$ is rank deficient, i.e., r< k (r = number of distinct cointegrating vectors); and (ii)$\{\alpha_\perp \Gamma \beta_\perp\}$ has full rank, (k-r), where $\alpha_\perp$ and $\beta_\perp$ are (3 x (3-r)) orthogonal matrices to α and β.

A number of issues are important for the specification and testing of VAR models. The power of cointegration tests depends on the time span of the data rather than on the number of observations (Campbell and Perron, 1991).[16] 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. Further, in order to allow for finite samples, degrees of freedom adjustments are suggested by Reimers (1992), among others, and we adjust the test statistics accordingly.[17] The VAR lengths (p) are specified such that the VAR residuals are rendered non-autocorrelated.[18] Since variables in the VAR have non-zero mean we restrict 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, Johansen (1991) suggests identification through exactly identifying restrictions, whereas Pesaran and Shin (2002) suggest using tests of over-identifying restrictions. We follow the latter approach if two cointegrating vectors are found. The stock of foreign R&D for each country, a key conditioning variable, is a weighted sum of the rest of the world's (i.e., the other G10 countries') domestic R&D.

Therefore, S^f may be weakly exogenous to the system. We subject S^f to weak exogeneity tests and, where found to be weakly exogenous, we 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 multi-cointegration and normalisation. 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 super-consistent, asymptotically unbiased and normally distributed. The associated (corrected) t-ratios permit inference using standard tables (see Phillips and Hansen, 1990).[19] We examine the robustness of our results vis-à-vis both the Johansen and FMOLS estimators, particularly because of their different formulations for cointegration tests. 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:

$$y_t = \beta_0 + \beta_1^{'} x_t + u_t \qquad (4)$$

where y_t is a vector of I(1) dependent variable and x_t is (kx1) vector of I(1) regressors. Let x_t be a first difference stationary process with drift: $\Delta x_t = \mu + w_t$; where μ is a (kx1) vector of drift parameters and w_t is a (kx1) vector of stationary variables. FMOLS makes two adjustments over the OLS estimator of β in (4): (i) it adjusts y_t for the possible long-run interdependence between u_t and w_t and (ii) it corrects for the possible contemporaneous relation between u_t and w_t which rectifies the second order bias in the OLS estimator. Formally, let $\hat{\xi} = (\hat{u}_t, \hat{w}_t)'$. A hat indicates a consistent estimator of corresponding parameters. Define a long-run variance-covariance matrix of $\hat{\xi}$ ($\hat{V}$):

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

and further define,

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

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

where $\hat{\Gamma} = \frac{1}{T-1}\sum_{t=2}^{T}\hat{\xi}_t\hat{\xi}_t'$; $\hat{\Phi} = \sum_{s=1}^{m} w(s,m)\hat{\Gamma}_s$; $\hat{\Gamma}_s = T^{-1}\sum_{t=1}^{t-s}\hat{\xi}_t\hat{\xi}'_{t+s}$; w(s, m) is the lag turncation window. The adjustment in y_t is achieved by: $\hat{y}^*_t = y_t - \hat{v}_{12}v_{22}^{-1}\hat{w}_t$. The FMOLS estimator is:

$$\hat{\beta}_{fmols} = (W'W)^{-1}(W'\hat{y}^*) - TD\hat{Z}) \tag{8}$$

where $\hat{y}^* = (\hat{y}_1^*, \hat{y}_2^*, ..., \hat{y}_t^*)'$; $D = \begin{bmatrix} 0_{1xk} & I_k \end{bmatrix}'$ and $W_{(txk)}$ is matrix of regressors including a constant term. A consistent estimator of the variance-covariance matrix (ψ) is: $\Psi(\hat{\beta}_{fmols}) = \kappa_{11.2}(W'W)^{-1}$; where $\kappa_{11.2} = \hat{v}_{11} - \hat{v}_{12}\hat{v}_{22}^{-1}\hat{v}_{21}$. A test of cointegration is equivalent to the test of stationarity of the error correction term generated through $\hat{\beta}_{fmols}$.

VI. Empirical Results

Unit Root Tests

CH reported that TFP, S^d and S^f are clearly trended and contained unit roots. Plots of our data set in figures 1 to 3 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.[20] Results are reported in table 4. As expected, in most cases tests reject the null of stationarity of TFP, S^d, S^f and mS^f . The null of level stationarity is consistently rejected at a very high level of precision (1% or better) for all but Canadian TFP, Irish and Japanese S^f and Danish and German mS^f. The level stationarity of the latter is rejected at a conventional 5% and/or 10%.

Likewise, the null of trend stationarity is also overwhelmingly rejected at the conventional 5% level. However, there are a few exceptions. TFP of Denmark and the UK, S^f of Canada, Germany and the US and mS^f of Japan appear trend stationary although their level stationarity is clearly rejected at 1%. Nonetheless, in view of their level non-stationarity and slowly decaying autocorrelation functions, they appear closer to I(1) series than to I(0). Hence, we treat them as I(1) in further modelling. All series appear unequivocally stationary in their first differences.[21] Thus, the overall finding of KPSS tests is that TFP, S^d, S^f and mS^f are I(1), a result consistent with earlier findings (e.g., CH).[22]

Total R&D

Johansen rank tests and a range of VAR diagnostics obtained from total R&D under specifications (1) and (2) are reported in Tables 5A and 5B respectively. Tests show that S^f is clearly weakly exogenous in eight sample countries, marginal for Japan (weak exogeneity is rejected at 9%) and endogeneous for the US. Likewise, the weak exogeneity of mS^f holds for all but Canada and the US. Hence, we impose weak exogeneity of S^f and mS^f on all but the US in further estimations since this improves the efficiency of the estimates.[23]

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 normalisation and error-correction representation, the associated loading factors (α_s) must be negatively signed and significant. On this basis, we can normalise 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 normalised on TFP.[24] Therefore, Germany's cointegrating vector is normalised on S^d and the reported loading factors are now correctly signed and significant.[25] 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, i.e., a rise in total factor productivity causes an accumulation of the domestic R&D capital stock. Indeed, a formal implementation of Toda and Phillip'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.[26]

LM tests show an absence of serial correlation in VAR residuals in all cases except for the US in specification (2). The latter is marginal however. A second or third order lag length is sufficient to render the VAR residual uncorrelated. This is plausible in view of the low (annual) frequency of data. Residuals also pass normality tests.[27]

The last column of table 6 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 co-integrated in all cases. These results are consistent with those found using Johansen's approach.

The estimated cointegrating vectors (long-run parameters) are also reported in table 6. Most importantly, we find that for the US the 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 US is robust to VAR length (1-4), estimation methods and specifications. Thus, it appears that R&D accumulation by competitors hurts US TFP. This supports our conjecture and reinforces the findings of Bernstein and Mohnen (1998) and Blonigen and Slaughter (2001) from a macro perspective. Japanese results, on the other hand, are puzzling. International R&D spillovers appear insignificant for Japan in all but one estimate, i.e., FMOLS under 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; three (Denmark, Ireland and the UK) with statistically insignificant effects; and Germany can only be normalised on S^d. Germany shows a significant effect of TFP on S^d. FMOLS results, on the other hand, provide relatively more support for positive and significant spillover effects.[28] Seven of the sample countries show positive and significant elasticities of TFP with respect to S^f. The exceptions are the US, Germany and Denmark; spillover is negative and significant for the US but insignificant for Germany and Denmark.

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 coefficent for Ireland becomes significant whereas just the opposite occurs for the Netherlands; and (ii) the negative spillover coefficient for the US 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 that of Germany becomes significantly positive; and (ii) the negative spillover coefficient of the US increases by almost three-fold to –0.19.

The effect of S^d on TFP is more prevalent. Under the Johansen method, of the nine countries normalised 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 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 specification (1) and an insignificant effect under specification (2).

The country-specific results in table 6 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 extant panel tests.[29]

Table 7 presents the formal tests of the extent to which panel estimates obtained using the Johansen approach correspond to the country-specific estimates. Two sets of results are reported. Panel A contains p-values of the LR tests under the null that each country-specific parameter is equal to its respective panel estimate. Tests show that the null of the equality of panel and country-specific elasticity of TFP with respect to S^d is rejected by all but two countries in each specification. Denmark and the Netherlands do not reject the null in specification (1) whereas Italy and the Netherlands fail to reject it in specification (2). Likewise, tests reject the equality of the panel and country-specific estimates of spillover elasticity (semi-elasticity) in five (four) countries.[30]

Panel B of table 7 reports on the test that 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 up the individual χ^2 statistics (see Pesaran et al., 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 estimate. The test statistic is χ^2(N) distributed; where N is the number of countries in the panel. As is evident, these joint tests strongly reject the null of parameter equality.

Similar tests of the equality of country-specific and panel parameters pertaining to FMOLS estimates are reported in table 8. Panel A shows that five countries each reject the null of equality of panel and country-specific parameters of S^d and S^f in specification (1). In specification (2) nine countries reject the null of parameter equality involving S^d while five reject those of mS^f. Thus, FMOLS based country-by-country tests largely corroborate the parameter heterogeneity found earlier. Nonetheless, there are two important differences. First, unlike the earlier findings for the US, only the spillover coefficient differs from the panel estimates. Second, under FMOLS, the degree of parameter heterogeneity is quite high in specification (2) compared to specification (1). The joint tests (panel B), on the other hand, universally and strongly reject parameter homogeneity as before.

All in all, the statistical evidence suggests that panel estimates do not correspond to country-specific estimates and they conceal important cross-country differences. Therefore, any generalisations based on panel results may proffer incorrect inferences with respect to several countries of the panel. This appears true for most countries in this study, and the US appears to be distinctly different from the others.

Business Sector R&D

To assess the sensitivity of our results to data aggregation we report the cointegration tests involving business sector TFP, S^d and S^f (or mS^f) in tables 9A and 9B. Business sector results appear somewhat less robust than those obtained from total R&D. First, French TFP, S^d and S^f (or mS^f) show non-cointegation. Second, Italy and Japan show two cointegrating vectors in specification (1) whereas the other countries show only one. Third, Trace tests and λ-max tests show contradictory results for Denmark, Germany, the UK and the US in specification (1). These contradictions largely disappear in specification (2). Nonetheless, the λ-max test fails to reject non-cointegration for Germany, Japan and the US at the conventional 5% significance level. 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 non-cointegration. Nevertheless, Trace tests, shown to be preferable to λ-max tests (Kassa, 1992 and Cheung and Lai, 1993), consistently reject non-cointegration for all countries but France. Note also that the rejection for the Netherlands is at 7%. Overall diagnostics are well behaved.[31] As before, normalisation on TFP produces insignificant loading factors for Germany. Therefore, the cointegrating vectors for Germany (under the Johansen method) are normalised on S^d. All the associated loading factors are correctly signed and significant.

The last column of table 10 reports the KPSS tests of level stationarity of error correction terms obtained from FMOLS. Interestingly, the results show cointegration at 5% or better for all cases. Thus, FMOLS contradicts the sensitivity of cointegration between total and business sector R&D shown by the Johansen method. However, the system estimator shows multi-cointegration for Italy and Japan and the problem of normalisation for Germany, issues which FMOLS does not address. The FMOLS results should therefore be taken with some caution.

Table 10 also reports cointegrating parameters.[32] 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 UK (in specification (1)). This holds true under both estimators.[33] The insignificant and/or negative and significant elasticities of S^d found for Canada and the UK are rather puzzling.

With the Johansen method six countries show significant spillover effects (negative for the US and Denmark) in specification (1) but only three in specification (2). With FMOLS six countries show significant spillover effects (negative for Germany) in specification (1) and five countries in specification (2). It is also interesting that for business sector data the Johansen approach shows a significantly negative spillover for Denmark. It is evident that the point estimates of spillover coefficients differ across the two estimators.

A comparison between total and business sector R&D parameters (tables 6 and 10), obtained from the Johansen method, reveals that six countries (Germany, Denmark, Ireland, Japan, the Netherlands and the US) have qualitatively similar results with a positive and significant effect of S^d on TFP. The remaining four countries (Canada, France, Italy and the UK) show sensitivity of results to measures of R&D.

Five countries (Canada, Germany, Italy, Ireland and the US) show qualitatively similar spillover effects of S^f with respect to both measures of R&D; the other five show contradictory results. Likewise, six countries (Canada, Denmark, Germany, Italy, the Netherlands, and the UK) show qualitatively similar results for mS^f while the other four show contradictory results. Five countries exhibit a significant effect of S^f associated with total R&D (US negative) whereas six countries (Denmark and US negative) show 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 the 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 UK in 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 differ markedly. 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.

The last row of table 10 reports the panel (between-dimension) estimates of parameters associated with S^d, S^f and mS^f. Since CH's results are residual-based cointegration tests on business sector R&D, our FMOLS results involving business sector data are the closest for comparability. Indeed our panel results are extremely close to theirs.[34]

Table 11 reports the tests of equality of country-specific and panel estimates for business sector R&D. The results reflect our earlier findings for total R&D that most country-specific parameters differ significantly from their panel counterparts. Panel A (specification (1)) shows that five (out of eight) countries each reject the null that the parameters of S^d and S^f are equal to their panel counterparts. In specification (2), seven countries show different coefficients from panel estimates with respect to S^d (at 10%) and four countries differ with respect to the coefficients of mS^f. Results in panel B uniformly reject the null that country-specific parameters are jointly equal to their panel counterparts at a very high level of precision. Tests of parameter equality involving FMOLS estimates (not reported to conserve space) show a similar degree of heterogeneity.

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 quite sensitive to 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. A comparison of the Johansen and FMOLS results reveals that the estimated parameters for business sector R&D appear more disparate than those obtained for total R&D. Further, total R&D generally provides more evidence of significant spillover effects than business sector R&D. Our findings of significantly negative R&D spillovers for the US obtained from total R&D appear somewhat less strong vis-à-vis business sector data. Nevertheless, business sector results continue to show that R&D spillover for the US is either significantly negative or non-existent (statistically insignificant). These findings contrast sharply with those associated with the literature in the CH tradition. Further, significant heterogeneous productivity effects of S^d and S^f across countries remain despite different measures of R&D and the estimation methods employed.

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 $\prod$ matrix with its full sample estimate. If the sub-sample ranks of $\prod$ differ significantly from those of the full sample, this implies structural shifts in the cointegrating rank. Likewise, conditional on the identified cointegrating vectors, if sub-sample parameters significantly differ from those of the full sample, this signifies 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; Quintos, 1992; Luintel, 2000) and, 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) allowing both short-run and long-run parameters 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.[35] Thus, stability tests are carried out over a period of 20 years (1980-1999). Figure 4 plots the normalised LR statistics that test rank stability under specification (1) using the R-model.[36] 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.

Figure 4 about here

The time path of the scaled LR statistics shows that the null of non-cointegration (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: $r\leq1$ are below unity (i.e., less than the 5% critical value) for all but Italy and the US. Italy shows rank instability during much of the 1990s; the US shows a short period of instability in the early 1980s. It is tempting to associate US rank instability with the productivity slow down discussed in section III. Tests reveal stable cointegrating ranks for the rest of the sample countries.

Figure 5 about here

Figure 5 plots the normalised LR statistics, which test for the stability of cointegrating parameters. Two messages are clear. First, when short-run parameters are concentrated out the long-run parameters appear stable in all but two countries: the Netherlands shows instability during 1984-1987 whereas the UK shows instability during 1981-1983. Second, when short-run parameters are allowed to vary, the cointegrating vectors appear unstable, particularly prior to 1983/1984, and this generally holds for all countries. However, after1985 even the Z-model produces a stable cointegrating vector for all countries except Denmark and the Netherlands. Thus, we find the cointegrating ranks and the long-run parameters (the R-model) to be remarkably stable over the 20-year period for most countries analysed. The Z-model shows parameter instability especially prior to the mid-1980s, primarily owing to the volatility of short run parameters. In fact, the latter findings appear to corroborate the parameter instability reported by CH, Kao et al. (1999) and van Pottelsberghe and Lichtenberg (2001) since their tests do not distinguish between the short- and the long-run parameters and their sample runs only up to 1990.[37]

Bilateral and Multilateral Spillover elasticities

The estimates of bilateral international R&D spillovers based on the aggregate point elasticities of table 6 (specification (1)) are reported in Table 12. 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 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 12 shows that a 1% increase in US R&D would increase Japanese output by 0.017%. However, a 1% rise in Japanese R&D would reduce US output by 0.059%. The accumulation of R&D by Japan hurts US productivity the most. Given the negative elasticity of US TFP with respect to S^f, all bilateral spillover elasticities are negative. R&D accumulation by Canada is also rather costly for the US, but US R&D has its highest international productivity effect on Canada (0.058%).

The last row of table 12 reports the overall international productivity effect of domestic R&D. US R&D has the biggest output effect across other OECD members (a 1% increase in US R&D increases international output by 0.138%), followed by Germany (by 0.097%).[38] German R&D appears to enhance importantly the productivity of France, Italy and the Netherlands, while its effect on Japanese output is almost one-ninth of that of the US.

The total elasticity of domestic output with respect to foreign R&D is reported in the last column of table 12. A 1% rise in the R&D of other OECD countries in the sample would reduce US output by 0.178%. Canada, France, Italy and the Netherlands appear major beneficiaries of international R&D spillovers and the US and Germany appear to be the main generators of spillovers. Japan's major productivity gains accrue from the US.

Own Rates of Return

The average own rate of return of domestic R&D shows tremendous variation across sample countries.[39] Ireland shows the highest rate of return (453%) followed by Denmark (183%), the US (175%), the UK (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 real GDP to S^d ratio of 17.28. The sample average of this ratio is 8.09. van Pottelsberghe and Lichtenberg (2001, p. 494) estimate the 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. Since countries differ in terms of their stage of development, openness, stock and intensity of R&D, etc., we argue that knowledge diffusion is likely to be heterogenous across countries. Moreover, concerns over national competitiveness and world market share encourage countries to pursue aggressive policies to acquire and maintain technological leadership by pre-empting possible competitors. The EU's resolve to launch the Galileo satellite in competition with the US Global Positioning System (GPS) is a case in point, and several other rival R&D projects are well known. In a world characterised by technological rivalry, knowledge diffusion may, in principle, be positive or negative.

We model the dynamic heterogeneity of knowledge spillovers at country level. We adopt the behavioural specification of CH, as modified by Lichtenberg and van Pottelsberghe (1998), but take the empirical analysis forward through the use of more extensive data and new econometric methods. The data set is extended to 35 years and encompasses both total and business sector R&D (CH and others use a data set of 20 years and only business sector R&D). The proportion of R&D outside the business sector is not trivial, although it has tended to decline over the years.

The Johansen VAR approach and FMOLS are used for the estimations. We find a robust cointegrating relation between TFP, S^d and S^f (or mS^f) for total R&D data; all sample countries show a single cointegrating vector and results are robust to Trace and $\lambda_{\text{-max}}$ tests. However, under the system approach, cointegration results appear less robust when business sector R&D data are used – the results appear sensitive to the specifications and to the test statistics (Trace and $\lambda_{\text{-max}}$ tests) employed. FMOLS, on the other hand, shows cointegration in all cases. We attach more weight to results for total R&D since they are robust with respect to the system estimator.

Our results corroborate some of the stylised empirical regularities so far uncovered, and they also shed some new light on R&D spillover dynamics. One of those stylised findings is that international R&D spillovers are positive and do not differ in important respects across sample (OECD) countries (CH, footnote 10). Our results emphatically show this not to be the case. We show that data cannot be pooled; long-run spillover elasticities differ significantly among most sample countries. Panel estimates, in general, do not correspond to country-specific parameters and conceal important cross-country differences in knowledge diffusion.

Moreover, it is not always valid to normalise the relationship on TFP as we find in the case of Germany. Causality may run from TFP to S^d.

It is commonly observed that the US is the main generator of R&D spillovers, but a weak receiver. Our results confirm this, and we also find that the US is not only a weak receiver but a net loser. Significantly negative spillover elasticities are found for the US. This finding is consistent with our argument that the US, as the technology leader, may lose if competitors become technologically more sophisticated and take increased world market share.

Another stylised observation is that the output elasticity of S^d tends to be higher than that of S^f for large countries. This is broadly corroborated by our results.

It is also observed that Japan benefits significantly from spillover but generates a little. 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 US by 0.019% but hurts US output by 0.059% thus generating a net spillover of -0.040%.[40] Our finding that the US and Germany are the main generators of spillovers is consistent with that of Eaton and Kortum (1996); however, our finding about Japan differs from theirs.

We also find that spillover analyses of total R&D data produce more robust results than those of business sector R&D data only.

Finally, our results go some way towards reconciling 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 based on bilateral spillover analyses and/or 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 approach of CH - show positive spillover coefficients across sample countries 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.

The main implications of this study are two-fold. First, the extent and the dynamics of knowledge diffusion may differ depending on the stage of technological sophistication of the country concerned. Second, as bilateral spillover elasticities (table 12) indicate, the distribution of knowledge diffusion is hardly uniform. For example, the US is the sole spillover generator for Canada; and Germany is the main source of knowledge diffusion for France, Italy and the Netherlands. Japan mainly receives spillovers from the US; Germany and the US appear equally important for the UK. This may indicate some bonding between nations owing to technological congruence or geographical proximity or both.

Appendix A: 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 US dollars are obtained from International Financial Statistics (IFS) published by the International Monetary Fund.

A consistent series of 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.[41] A depreciation rate of eight percent 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 although the time span covered differs across countries. For example, the data for the UK are for 1985-1997, for Italy for 1981-97, for Japan for 1973-1997, etc. 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.[42] 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 1965-66; 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 is readily available from OECD for the sample period and we use the available data.[43]

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 (i.e., data mostly started from 1973 only), 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 (see CH):

$$S_0^d = \frac{E_0^R}{g+\delta} \tag{10}$$

where δ is the depreciation rate, assumed to be eight percent, [44] g is the average annual growth rate of E^{RD} over the sample, E^R_0 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:

$$S_i^f = \sum_{j \neq i} \frac{m_{ij} S_j^d}{y_j} \qquad (11)$$

where m_{ij} is imports of goods and services of country i from country j and y_j is country j's GDP. [45] The business sector domestic (S_b^d) and foreign (S_b^f) R&D capital stocks are computed following equations (10) and (11) and using E_b^{RD}. Finally, we compute total factor productivity (TFP) in the usual way (see CH):

$$\log TFP = \log Y - \gamma \log K - (1-\gamma)\log L \qquad (12)$$

Following the literature we set the value of the γ coefficient to 0.3. Business sector TFP is calculated as:

$$\log TFP_b = \log Y_b - \gamma \log K_b - (1-\gamma)\log L_b \qquad (13)$$

References:

Abramovitz, M., "The Search for the Sources of Growth: Areas of Ignorance, Old and New," *Journal of Economic History* 53(2) (June 1993), 86-125.

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

Aitken, B. J. and A. E. Harrison, "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela," *American Economic Review* 89(3) (June 1999), 605-618.

Akaike, H., "Information Theory and Extension of the Maximum Likelihood Principle," in B. Petrov and F. Caske edited, *Second International Symposium on Information Theory* (Budapest, Akademiai Kiado, 1973).

Ames, E. and N. Rosenberg, "Changing Technological Leadership and Industrial Growth," *Economic Journal* 73 (March 1963), 13-31.

Bernstein, J. I. and P. Mohnen, "International R&D Spillovers between US and Japanese R&D Intensive Sectors," *Journal of International Economics* 44(2) (April 1998), 315-338.

Bernstein, J. I. and X. Yan, "International R&D Spillovers between Canadian and Japanese Industries," NBER Working Paper No. 5401 (December 1995), www.nber.org

Blonigen, B. A. and M. J. Slaughter, "Foreign-Affiliate and U.S. Skill Upgrading," *The Review of Economics and Statistics* 83(2) (May 2001), 362-376.

Campbell, J. Y. and P. Perron, "Pitfalls and Opportunities: What Macroeconomists Should Know about Unit Roots", in *NBER Macroeconomics Annual*, edited by O. J. Blanchard and S. Fisher, Cambridge, MA: MIT Press, (1991).

Caner, M. and L. Kilian, "Size Distortions of Tests of the Null Hypothesis of Stationarity: Evidence and Implications for the PPP Debate," *Journal of International Money and Finance* 20 (2001), 639-657.

Caves, R.E., *Multinational Enterprise and Economic Analysis* (Second edition, Cambridge, Cambridge University Press, 1996).

Cheung. Y.-W. and K. S. Lai, "Finite-Sample Sizes of Johansen's Likelihood Ratio Tests for Cointegration," *Oxford Bulletin of Economics and Statistics* 55(3) (1993), 313-328.

Christiano, L. J., "Searching for a Break in GNP", *Journal of Business & Economic Statisitcs*, 10(1992), 237-249.

Coe, D.T. and E. Helpman, "International R & D Spillovers," *European Economic Review* 39(5) (1995), 859-887.

Coe, D. T., E. Helpman and A. W. Hoffmaister, “North-South R&D Spillovers,” *Economic Journal* 107 (January 1997), 134-149.

Coe, D. T. and A. W. Hoffmaister, “Are There International R&D Spillovers among Randomly Matched Trade Patterns? A response to Keller,” IMF Working Paper: WP/99/18 (February 1999).

Dosi, G., “Sources, Procedures, and Microeconomic Effects of Innovation,” *Journal of Economic Literature*, 26(3), (September 1988), 1120-1171.

Dunning, J. H., “Multinational Enterprises and The Globalization of Innovatory Capacity,” *Research Policy* 23(1) (1994), 67-88.

Eaton, J. and S. Kortum, “Trade in Ideas: Patenting and Productivity in the OECD,” *Journal of International Economics* 40 (May 1996), 251-278.

Engle , R. F. and C. Granger, "Cointegration and Error Correction: Representation, Estimation and Testing," *Econometrica* 55 (1987), 251-276.

Engelbrecht, H-J, “International R&D Spillovers, Human Capital and Productivity in OECD Economies: An Empirical Investigation,” *European Economic Review* 41(8) (1997), 1479-1488.

Griliches, Z., "Productivity, R&D and the Data Constraint," *American Economic Review*, 84(1) (1994), 1-23.

Griliches, Z., “The Search for R&D Spillovers,” *Scandinavian Journal of Economics* 94 (Supplement 1992), S29-S47.

Grossman, G. and E. Helpman, *Innovation and Growth in the Global Economy* (MIT Press, Cambridge MA and London UK, 1991).

Hakkio, C. S. and M. Rush, “Cointegration: How Short is the Long-Run?” *Journal of International Money and Finance* 10 (1991), 571-581.

Hansen, H. and S. Johansen, “Some Tests for Parameter Constancy in Cointegrated VAR-models,” *Econometrics Journal* 2 (1999), 306-333.

Johansen, S., “Determination of Cointegrated Rank in the Presence of a Linear Trend”, *Oxford Bulletin of Economics and Statistics* 54(3) (August 1992), 383-397.

Johansen, S., “Estimation and Hypothesis Testing of Cointegrating Vectors in Gausian Vector Autoregression Models”, *Econometrica* 59 (1991), 551-580.

Johansen, S., “Statistical Analysis of Cointegrating Vectors,” *Journal of Economic Dynamics and Control* 12 (1988), 231-254.

Kao, C., M-H Chiang and B. Chen, “ International R&D Spillovers: An Application of Estimation and Inference in Panel Cointegration”, *Oxford Bulletin of Economics and Statistics* (special issue, 1999), 691-709.

Kassa K., “Common Stochastic Trends in International Markets” *Journal of Monetary Economics* 29(1992) 95-124.

Keller, W., “Are international R&D spillovers trade-related? Analysing spillovers among randomly matched trade partners,” *European Economic Review* 42(8) (September 1998), 1469-1481.

Kwiatkowski, D., P. Phillips, P. Schmidt, and Y. Shin, “Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root,” *Journal of Econometrics* 54 (1992), 159-178.

Larsson, R., J. Lyhagen and M. Lothgren, “Likelihood-Based Cointegration Tests in Heterogeneous Panels,” *Econometrics Journal* 4(1) (2001), 109-142.

Lichtenberg, F. R. and B. van Pottelsberghe de la Potterie, “International R&D Spillovers: A Comment,” *European Economic Review* 42(8) (September 1998), 1483-1491.

Levine, R. and S. Zervos, "Stock Market Development and Long-Run Growth", *World Bank Economic Review*, 10(2) (May 1996), 323-339.

Luintel K. B., “Real Exchange Rate Behaviour: Evidence from Black Markets”, *Journal of Applied Econometrics*, 15 (2000), 161-185.

Luintel, K. and M. Khan, “A Quantitative Reassessment of Finance-Growth Nexus: Evidence from Multivariate VAR,” *Journal of Development Economics*, 60(2) (December 1999), 381-405.

Mairesse, J. and M. Sassenon, “R&D Productivity: A Survey of Econometric Studies at the Firm Level,” *Science-Technology-Industry Review*, OECD, Paris, No. 8 (1991), 9-43.

Mohnen, P., “International R&D Spillovers and Economic Growth”, *mimeo*, Department des Science économiques, université du Québec à Montrèal, (1999).

Nadiri, M. I. and S. Kim, “International R&D Spillovers, Trade and Productivity in Major OECD Countries,” *NBER Working Paper 5801* (October 1996), www.nber.org.

Navaretti, G. B. and D. G. Tarr, “International Knowledge Flows and Economic Performance: A Review of the Evidence,” *The World Bank Economic Review* 14(1) (January 2000), 1-15.

Nelson, R. R and G. Wright, “The Rise and Fall of American Technological Leadership: The Postwar Era in Historical Perspective,” *Journal of Economic Literature* 30(4) (1992), 1931-1964.

Nelson, R. R., *National Innovation Systems: A Comparative Analysis* (Oxford University Press, 1993).

Osterwald-Lenum M., "A Note with Quantiles of the Asymptotic Distribution of the ML Cointegration Rank Tests Statistics," *Oxford Bulletin of Economics and Statistics*, 54 (1992), 461-472.

Park, W. G., "International R&D Spillovers and OECD Economic Growth," *Economic Inquiry* 33(4) (October 1995), 571-591.

Pedroni, P., "Purchasing Power Parity Tests in Cointegrated Panels", *The Review of Economics and Statistics*, 83 (4) (2001), 727-731.

Pedroni, P., "Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors," *Oxford Bulletin of Economics and Statistics*, Special Issue, (1999), 653-670.

Perron, P., "Further Evidence on Breaking Trend Functions in Macroeconomic Variables", *Journal of Econometrics* 80 (1997), 355-385.

Pesharan, H. M. and Y. Shin, "Long-run Structural Modelling," *Econometrics Reviews* 21(2002), 49-87.

Pesaran, M. H., N. U. Haque, and S. Sharma, "Neglected Heterogeneity and Dynamics in Cross-Country Savings Regressions," in (eds) J. Krishnakumar and E. Ronchetti, *Panel Data Econometrics – Future Direction: Papers in Honour of Professor Pietro Balestra*, Elsevier Science (2000), 53-82.

Pesaran, H. M., Y. Shin and R. P. Smith, "Pooled Mean Group Estimation of Dynamic Heterogeneous Panels", *Journal of the American Statistical Association* 94 (1999), 621-634.

Pesaran, H. M, and R. Smith, "Estimating Long-run Relationships from Dynamic Heterogeneous Panels," *Journal of Econometrics* 68 (1995), 79-113.

Phillips, P. C. B. and B. E. Hansen, "Statistical Inference in Instrumental Variable Regression with I(1) Processes," *Review of Economics Studies*, 57(1) (January 1990), 99-125.

Quah, D., "Empirical Cross-section Dynamics in Economic Growth", *European Economic Review*. 37 (1993), 426-434.

Quintos C. E., "Sustainability of Deficit Process with Structural shifts", *Journal of Business & Economic Statistics*, 13(1995), 409-417.

Reimers, H. E., "Comparison of Tests for Multiple Cointegration," *Statistical Papers* 33 (1992), 335-359.

Reinsel, G. C. and S. K. Ahan, “Vector Autoregressive Models with Unit Root and Reduced Rank Structure: Estimation, Likelihood Ratio Tests and Forecasting,” *Journal of Time Series Analysis* 13 (1992), 353-375.

Romer, P.M., “Endogenous Technological Change,” *Journal of Political Economy*, 98(5) (October 1990), S71-S102.

Schwarz, G., “Estimating the Dimension of a Model,” *Annals of Statistics* 6 (1978), 461-465.

van Pottelsberghe de le Potterie, B. and F. Lichtenberg, "Does Foreign Direct Investment Transfer Technology Across Borders?," *The Review of Economics and Statistics* 83(3) (August 2001), 490-497.

Toda, H. Y., Phillips, C. B., “Vector Autoregression and Causality”, *Econometrica* 61(1993),1367-1393.

Table 1: Share of business sector R&D relative to total R&D

	CA	DK	FR	DE	IT	IRL	JP	NL	UK	US
Business sector R&D in total [1]										
1965-69	39.5	45.5	51.8	63.7	51.3	33.5	55.1	55.6	64.8	70.4
1970-79	37.6	46.7	59.0	64.2	55.4	33.5	57.8	53.2	63.6	68.4
1980-89	51.4	57.2	58.8	71.4	57.6	51.2	65.5	56.2	66.2	72.5
1990-99	59.8	60.3	62.0	68.4	53.6	69.6	77.5	52.5	74.2	73.0
Mean	54.9	57.5	60.5	68.6	54.8	64.1	70.8	53.9	70.2	72.3

1. Share of business sector R&D expenditure in total R&D expenditure. Total refers to the sum of business sector, government sector, higher education sector and private non-profit sector. Source: OECD, R&D database. 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.

Table 2: Some stylised aggregate statistics

	CA	DK	FR	DE	IT	IRL	JP	NL	UK	US
Share of total GDP (%) [1]										
1965-69	3.9	0.9	7.9	11.0	7.3	0.3	12.3	2.1	8.3	46.0
1970-79	4.1	0.9	8.2	10.7	7.5	0.3	15.5	2.2	7.5	43.2
1980-89	4.2	0.8	7.8	9.9	7.5	0.3	17.0	2.0	6.8	43.7
1990-99	4.1	0.7	7.2	10.3	6.9	0.4	17.6	2.0	6.5	44.4
Mean	4.1	0.8	7.7	10.3	7.2	0.3	16.5	2.0	7.0	44.1
Share of total R&D stock (%) [1]										
1965-69	1.8	0.3	6.2	7.8	2.1	0.1	6.7	2.0	11.8	61.0
1970-79	2.1	0.4	6.9	9.5	2.6	0.1	10.6	2.0	9.8	56.0
1980-89	2.3	0.4	7.1	10.9	3.0	0.1	15.4	1.9	8.1	50.7
1990-99	2.5	0.5	7.1	10.7	3.3	0.1	19.2	1.7	6.5	48.4
Mean	2.3	0.4	7.0	10.3	3.0	0.1	15.5	1.9	8.0	51.5
R&D intensity [2]										
1965-69	1.2	0.8	2.0	1.7	0.7	0.6	1.6	1.9	2.3	2.7
1970-79	1.1	1.0	1.7	2.1	0.8	0.7	2.0	1.8	2.2	2.2
1980-89	1.4	1.3	2.1	2.6	1.1	0.8	2.6	2.0	2.2	2.6
1990-99	1.6	1.8	2.3	2.4	1.1	1.2	2.6	2.0	1.7	2.6
Mean	1.4	1.5	2.2	2.4	1.1	1.0	2.5	2.0	1.9	2.5
Trade intensity [3]										
1965-69	27.9	25.8	10.3	16.1	12.4	323.1	7.2	37.1	13.1	4.0
1970-79	33.2	25.4	15.7	19.1	18.8	287.4	7.1	44.0	20.3	6.2
1980-89	36.6	29.3	19.2	25.2	19.0	151.2	8.0	52.3	24.1	7.5
1990-99	48.0	28.5	19.9	20.9	19.3	193.0	6.6	47.2	24.1	8.5
Mean	42.1	28.3	19.0	21.6	19.1	188.9	7.2	47.9	23.5	7.8

1. Based on constant 1995 PPP US dollars. The share refers to the percentage of the total of 10 OECD countries used in this study.
2. Research and development expenditure as a percentage of GDP.
3. Sum of the exports to and imports from the other 9 countries (used in this study) as a percentage of GDP. Source: R&D, ADB and International Trade Statistics databases of the OECD.

Table 3: 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:	14.10[a]	403.91[a]	66.66[a]	24.77[a]	219.80[a]	48.51[a]	21.643[a]	227.15[a]	121.77[a]	34.495[a]	197.50[a]	78.87[a]
BR&D:	19.90[a]	218.73[a]	67.36[a]	29.57[a]	134.24[a]	114.84[a]	20.82[a]	193.11[a]	48.00[a]	31.70[a]	124.80[a]	77.40[a]
	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: $\Delta tfp = \theta_0 + \sum_{i=1}^{2}\theta_{1i}\Delta tfp_{t-i} + \sum_{i=1}^{2}\theta_{2i}\Delta S^{d}{}_{t-i} + \sum_{i=1}^{2}\theta_{3i}\Delta S^{f}{}_{t-i} + \varepsilon_t$.

The specification for Panel B: $tfp = \lambda_0 + \sum_{i=1}^{2}\lambda_{1i} tfp_{t-i} + \sum_{i=1}^{2}\lambda_{2i} S^{d}{}_{t-i} + \sum_{i=1}^{2}\lambda_{3i} S^{f}{}_{t-i} + \varepsilon_t$.

The specification for panel C: $\Delta tfp = \beta_0 + \sum_{i=1}^{2}\beta_{1i}\Delta tfp_{t-i} + \sum_{i=1}^{2}\beta_{2i}\Delta S^{d}{}_{t-i} + \sum_{i=1}^{2}\beta_{3i} m * \Delta S^{f}{}_{t-i} + \varepsilon_t$.

The specification for Panel D: $tfp = \gamma_0 + \sum_{i=1}^{2}\gamma_{1i} tfp_{t-i} + \sum_{i=1}^{2}\gamma_{2i} S^{d}{}_{t-i} + \sum_{i=1}^{2}\gamma_{3i} m * S^{f}{}_{t-i} + \varepsilon_t$.

Row TR&D relates to total R&D capital stocks and the associated TFP; row BR&D represents business sector R&D. 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 whereas those in panels C and D involve interactions. Lagrange Multiplier (LM) and White's (WH) tests both reject that error variances are homoscedastic across sample countries. The latter are computed by regressing the square of residuals on original regressors, 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.

Table 4: KPSS unit root tests

Countries	TFP		S^d		S^f		mS^f	
	η_μ	ι_μ	η_μ	ι_μ	η_μ	ι_μ	η_μ	ι_μ
CA	0.718^b	0.126^c	1.259^a	0.190^b	1.242^a	0.103	1.029^a	0.158^b
DK	1.241^a	0.080	1.258^a	0.152^b	1.228^a	0.178^b	0.349^c	0.171^b
FR	1.227^a	0.226^a	1.257^a	0.198^b	1.194^a	0.296^a	1.087^a	0.268^a
DE	1.105^a	0.290^a	1.243^a	0.306^a	1.143^a	0.079	0.665^b	0.237^a
IT	1.225^a	0.246^a	1.250^a	0.183^b	1.232^a	0.301^a	0.830^a	0.262^a
IRL	1.236^a	0.183^b	1.244^a	0.190^b	0.542^b	0.126^c	0.900^a	0.120^c
JP	1.151^a	0.199^b	1.247^a	0.292^a	0.721^b	0.172^b	0.837^a	0.052
NL	1.180^a	0.264^a	1.252^a	0.272^a	1.111^a	0.276^a	0.749^a	0.235^a
UK	1.248^a	0.076	1.263^a	0.147^b	1.226^a	0.276^a	1.082^a	0.229^a
US	1.194^a	0.235^a	1.259^a	0.194^b	1.263^a	0.079	1.224^a	0.195^b

η_μ and ι_μ respectively test the null of level and trend stationarity. The critical values for η_μ are 0.739, 0.463 and 0.347 for 1%, 5% and 10%; the respective critical values for ι_μ are 0.216, 0.146 and 0.120. S^d and S^f pertain to total R&D.

Table 5A: Total R&D
Cointegration tests and VAR diagnostics between TFP, S^d and S^f (Johansen Method)

Specification: $LogTFP_t = \beta_1 + \beta_1^d \log S^d{}_t + \beta_2^f \log S^f{}_t + \varepsilon_t$ (1)

	Trace Statistics r = 0	r ≤ 1	r ≤ 2	Maximum Eigenvalue R = 0	r ≤ 1	r ≤ 2	Loading Factor (α)	Wexo	LM{3}	NOR	LAG
CA	38.11[a] [0.000]	7.24 [0.117]	-	30.87[a] [0.000]	7.24 [0.117]	-	-0.307[b] (0.144)	0.458	0.324	0.973	3
DK	22.70[b] [0.021]	3.74 [0.464]	-	18.96[b] [0.014]	3.74 [0.463]	-	-0.354[a] (0.126)	0.324	0.356	0.967	2
FR	26.24[a] [0.006]	6.75 [0.144]		19.49[a] [0.011]	6.75 [0.144]		-0.367[a] (0.107)	0.977	0.354	0.399	2
DE	19.41[c] [0.064]	3.51 [0.501]	-	15.90[a] [0.048]	3.51 [0.500]	-	-0.032[a] (0.007)	0.145	0.199	0.157	2
IT	34.60[a] [0.000]	6.56 [0.157]	-	28.05[a] [0.000]	6.56 [0.157]	-	-0.438[a] (0.070)	0.565	0.281	0.184	2
IRL	20.12[b] [0.051]	1.12 [0.920]	-	19.00[a] [0.013]	1.12 [0.920]	-	-0.398[b] (0.210)	0.315	0.254	0.936	3
JP	20.96[b] [0.038]	4.34 [0.376]	-	16.63[b] [0.036]	4.34 [0.375]	-	-0.497[a] (0.105)	0.087[c]	0.514	0.590	3
NL	26.70[a] [0.005]	6.78 [0.142]	-	19.92[a] [0.009]	6.78 [0.142]	-	-0.382[a] (0.077)	0.765	0.185	0.502	2
UK	23.80[b] [0.014]	7.26 [0.116]	-	16.54[b] [0.037]	7.26 [0.116]	-	-0.625[a] (0.135)	0.363	0.415	0.280	2
US	40.06[b] [0.01]	14.78 [0.24]	2.95 [0.60]	25.28[b] [0.02]	11.8 [0.202]	2.95 [0.60]	-0.320[b] (0.160)	0.006	0.556	0.618	3

Reported Trace and Maximal Eigenvalue statistics are adjusted for finite sample following Reimers (1992). Figures within brackets [.] are p-values under the H_0: r=0; r ≤ 1 and r ≤ 2. DE is normalised on S^d. Figures within parentheses (.) are standard errors. The column Wexo reports p-values of weak-exogeneity test of S^f, $\chi^2(r)$ 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. DK, FR and JP do not require any dummy. DE required unification dummy (1991-92). Other countries required impulse dummy around the first and/or second oil price shocks. Exclusion of these dummies does not change the results qualitatively except for the failure of the diagnostics (non-normality and/or autocorrelation). Dummies are not reported for the sake of brevity but are available on request. These dummies are entered unrestricted in the VAR.

Table 5B: Total R&D

Cointegration tests and VAR diagnostics between TFP, S^d and mS^f (Johansen Method)

Specification: $LogTFP_t = \beta_2 + \beta_2^{d} \log S^{d}{}_t + \beta_2^{f} m_t \log S^{f}{}_t + \varepsilon_t$ (2)

	Trace Statistics $r=0$	$r \le 1$	$r \le 2$	Maximum Eigenvalue $R=0$	$r \le 1$	$r \le 2$	Loading Factor (α)	Wexo	LM(3)	NOR	LAG
CA	29.91[a] [0.001]	7.11 [0.124]	-	22.80[a] [0.002]	7.11 [0.124]	-	-0.297[b] (0.117)	0.061[b]	0.805	0.735	2
DK	19.23[c] [0.068]	1.94 [0.786]	-	17.29[b] [0.028]	1.94 [0.785]	-	-0.462[a] (0.144)	0.163	0.233	0.849	2
FR	26.51[a] [0.005]	5.82 [0.212]		20.68[a] [0.006]	5.82 [0.212]		-0.385[a] (0.094)	0.333	0.377	0.446	2
DE	24.03[b] [0.013]	6.01 [0.197]	-	18.03[b] [0.02]	6.01 [0.197]	-	-0.018[a] (0.005)	0.463	0.858	0.011[b]	3
IT	39.77[a] [0.000]	7.16 [0.121]	-	32.61[a] [0.000]	7.16 [0.121]	-	-0.525 (0.070)	0.259	0.171	0.863	2
IRL	20.55[b] [0.044]	1.36 [0.886]	-	19.19[b] [0.012]	1.36 [0.885]	-	-0.376[c] (0.218)	0.200	0.228	0.923	3
JP	21.61[b] [0.031]	5.19 [0.273]	-	16.42[b] [0.039]	5.19 [0.273]	-	-0.461[a] (0.098)	0.260	0.375	0.405	3
NL	21.93[b] [0.027]	4.53 [0.350]	-	17.40[b] [0.026]	4.53 [0.350]	-	-0.243[a] (0.058)	0.656	0.392	0.350	2
UK	21.75[b] [0.03]	4.71 [0.328]	-	17.05[b] [0.03]	4.71 [0.330]	-	-0.646[a] (0.137)	0.690	0.437	0.461	2
US	38.15[b] [0.02]	13.87 [0.31]	3.33 [0.53]	24.28[b] [0.023]	10.5 [0.291]	3.33 [0.50]	-0.368[b] (0.182)	0.002[a]	0.095[c]	0.135	3

Reported Trace and Maximal Eigenvalue statistics are adjusted for finite sample following Reimers (1992). Figures within brackets [.] are p-values under the H_0: r=0; $r \le 1$ and $r \le 2$. DE is normalised on S^d. Figures within parentheses (.) are standard errors. The column Wexo reports p-values of weak-exogeneity test of mS^f, $\chi^2(r)$ 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. DK and FR do not require any dummy. DE required unification dummy (1991-92). Other countries required impulse dummy around the first and/or the second oil price shocks. Exclusion of these dummies does not change the results qualitatively except for the failure of the diagnostics (non-normality and/or autocorrelation). Dummies are not reported for the sake of brevity but are available on request. All dummies are entered unrestricted in the VAR.

Table 6: Total R&D
Estimated cointegrating parameters (Johansen and FMLOS methods)

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

(.) 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 30.

Table 7: Total R&D

Tests for the heterogeneity of cointegrating parameters across countries (Johansen estimates)

Panel: A Tests for each individual parameter

Specification: $LogTFP_t = \beta_1 + \beta_1^d \log S^d{}_t + \beta_1^f \log S^f{}_t + \varepsilon_t$ (1)

CA		DK		FR		IRL		IT		JP		NL		UK		US	
S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f
0.000	0.000	0.731	0.028	0.000	0.002	0.000	0.519	0.005	0.002	0.000	0.888	0.357	0.103	0.000	0.979	0.000	0.000

Specification: $LogTFP_t = \beta_2 + \beta_2^d \log S^d{}_t + \beta_2^f m_t \log S^f{}_t + \varepsilon_t$ (2)

CA		DK		FR		IRL		IT		JP		NL		UK		US	
S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	MS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f
0.000	0.110	0.001	0.354	0.000	0.000	0.000	0.001	0.429	0.000	0.000	0.838	0.939	0.556	0.000	0.275	0.003	0.003

Panel: B Joint tests

	S^d	S^f	S^d	m^*S^f
	80.855	40.771	81.836	55.325
Degree of freedom: $\chi^2(.)$	(9)	(9)	(9)	(9)
Critical Value (1%):	21.667	21.667	21.667	21.667

P-values are reported in panel A. Panel B reports χ^2 statistics. Since Germany could only be normalised on S^d it is excluded from this table.

Table 8: Total R&D
Tests for heterogeneity of cointegrating parameters across countries (FMOLS estimates)

Panel A: Tests for each individual parameter

Specification: $LogTFP_t = \beta_1 + \beta_1^d \log S^d{}_t + \beta_1^f \log S^f{}_t + \varepsilon_t$

CA		DK		DE		FR		IRL		IT		JP		NL		UK		US	
S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f
0.000	0.048	0.453	0.693	0.017	0.059	0.755	0.693	0.000	0.790	0.411	0.958	0.003	0.024	0.214	0.000	0.018	0.739	0.164	0.001

Specification: $LogTFP_t = \beta_2 + \beta_2^d \log S^d{}_t + \beta_2^f m_t \log S^f{}_t + \varepsilon_t$

CA		DK		DE		FR		IRL		IT		JP		NL		UK		US	
S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f
0.000	0.328	0.000	0.547	0.001	0.001	0.084	0.035	0.000	0.000	0.001	0.000	0.001	0.865	0.001	0.805	0.000	0.134	0.872	0.006

Panel: B Joint tests

	S^d	S^f	S^d	$m*S^f$
	162.340	55.392	513.607	933.806
Degree of freedom: $\chi^2(.)$	(10)	(10)	(10)	(10)
Critical Value (1%)	23.209	23.209	23.209	23.209

P-values are reported in panel A. Panel B reports χ^2 statistics. Germany is included under FMOLS.

Table 9A: Business Sector R&D
Cointegration tests and VAR diagnostics between TFP, S^d and S^f (Johansen Method)

Specification: $LogTFP_t = \beta_1 + \beta_1^d \log S^d{}_t + \beta_1^f \log S^f{}_t + \varepsilon_t$ (1)

	Trace Statistics $R=0$	$r \le 1$	$r \le 2$	Maximum Eigenvalue $r=0$	$r \le 1$	$r \le 2$	Loading Factor (α)	Wexo	LM{3}	NOR	LAG
CA	29.16[a] [0.00]	7.21 [0.12]	-	21.95[a] [0.00]	7.21 [0.12]	-	-0.329[a] (0.10)	0.708	0.123	0.891	3
DK	20.02[b] [0.05]	7.67 [0.10]	-	12.35 [0.17]	7.67 [0.10]	-	-0.285[a] (0.09)	0.786	0.118	0.791	2
FR	29.68 [0.18]	15.38 [0.21]	4.99 [0.30]	14.30 [0.44]	10.40 [0.31]	4.99 [0.30]	NA	0.129	0.147	0.845	3
DE	20.79[a] [0.04]	7.57 [0.11]	-	13.21 [0.13]	7.57 [0.11]	-	-0.035[a] (0.01)	0.209	0.668	0.001[a]	2
IT	45.23[a] [0.00]	23.40[b] [0.02]	6.76 [0.14]	21.83[b] [0.05]	16.64[b] [0.04]	6.76 [0.14]	-0.200[b] (0.104)	0.453	0.873	0.499	2
IRL	23.05[b] [0.02]	3.11 [0.57]	-	19.94[a] [0.01]	3.11 [0.57]	-	-0.602[a] (0.122)	0.869	0.092[c]	0.494	2
JP	44.84[b] [0.00]	23.02[b] [0.02]	5.06 [0.29]	21.82[b] [0.05]	17.96[b] [0.02]	5.06 [0.29]	-0.290[a] [0.086]	0.000[a]	0.160	0.572	2
NL	18.76 [0.07]	1.76 [0.82]	-	17.00[b] [0.03]	1.76 [0.82]	-	-0.238[a] (0.06)	0.789	0.048[b]	0.139	2
UK	37.48[b] [0.03]	18.01 [0.10]	6.47 [0.16]	19.47 [0.12]	11.55 [0.22]	6.47 [0.16]	-0.109[a] (0.02)	0.050[b]	0.247	0.791	2
US	20.40[b] [0.05]	6.90 [0.14]	-	13.50 [0.12]	6.90 [0.14]	-	-0.202[c] (0.12)	0.888	0.366	0.152	2

Reported Trace and Maximal Eigenvalue statistics are adjusted for finite sample following Reimers (1992). Figures within brackets [.] are p-values under the H_0: r=0; $r \le 1$ and $r \le 2$. DE is normalised on S^d. Figures within parentheses (.) are standard errors. The column Wexo reports p-values of weak-exogeneity test of S^f, $\chi^2(r)$ 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. DK, FR and UK do not require any dummy. Other countries required an impulse dummy around the first and/or second oil price shock. Exclusion of these dummies does not change the results qualitatively except for the failure of the diagnostics (non-normality and/or autocorrelation). Dummies are not reported for the sake of brevity but are available on request. All dummies are entered unrestricted in the VAR. The loading factor for France is not reported (NA) due to non-cointegration. 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.

Table 9B: Business Sector R&D
Cointegration tests and VAR diagnostics between TFP, S^d and mS^f (Johansen Method)

$$LogTFP_t = \beta_2 + \beta_2^{\,d} \log S^d{}_t + \beta_2^{\,f} m_t \log S^f{}_t + \varepsilon_t \quad (2)$$

	Trace Statistics			Maximum Eigenvalue			Loading Factor (α)	Wexo	LM{3}	NOR	LAG
	R = 0	$r \le 1$	$r \le 2$	r = 0	$r \le 1$	$r \le 2$					
CA	20.42^{b} [0.04]	4.13 [0.41]	-	16.28^{b} [0.04]	4.13 [0.41]	-	-0.299^{a} (0.07)	0.641	0.273	0.475	3
DK	21.98^{b} [0.03]	4.58 [0.34]	-	17.39^{b} [0.03]	4.58 [0.34]	-	-0.470^{a} (0.01)	0.396	0.284	0.776	3
FR	30.26 [0.156]	15.06 [0.22]	3.94 [0.43]	15.19 [0.37]	11.12 [0.25]	3.94 [0.43]	NA	0.126	0.518	0.943	3
DE	20.54^{b} [0.04]	6.18 [0.18]	-	14.36 [0.08]	6.18 [0.18]	-	-0.021^{a} (0.005)	0.835	0.689	0.001^{a}	2
IT	39.24^{a} [0.00]	3.98 [0.43]	-	35.26^{a} [0.00]	3.98 [0.43]	-	-0.545^{a} (0.067)	0.531	0.131	0.683	2
IRL	22.35^{b} [0.02]	2.98 [0.59]	-	19.38^{a} [0.01]	2.98 [0.59]	-	-0.544^{a} (0.118)	0.340	0.090^{c}	0.578	2
JP	38.64^{b} [0.02]	17.25 [0.13]	3.88 [0.44]	21.40^{c} [0.07]	13.37 [0.12]	3.88 [0.44]	-0.143^{b} (0.067)	$.005^{a}$	0.071^{c}	0.939	2
NL	20.75^{b} [0.04]	3.59 [0.49]	-	17.16^{b} [0.03]	3.59 [0.48]	-	-0.185^{a} (0.054)	0.551	0.475	0.122	2
UK	24.97^{a} [0.01]	8.27 [0.08]	-	16.70^{b} [0.04]	8.27 [0.08]	-	-0.240^{a} (0.065)	0.924	0.602	0.110	2
US	21.56^{b} [0.031]	7.29 [0.12]	-	14.27^{c} [0.08]	7.29 [0.12]	-	-0.575^{a} (0.178)	0.206	0.631	0.094^{c}	2

Reported Trace and Maximal Eigenvalue statistics are adjusted for finite sample following Reimers (1992). Figures within brackets [.] are p-values under the H_0: r=0; $r \le 1$ and $r \le 2$. DE is normalised on S^d. Figures within parentheses (.) are standard errors. The column Wexo reports p-values of weak-exogeneity test of mS^f, $\chi^2(r)$ 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. FR, IRL, JP and UK do not require any dummy. Impulse dummy for a period of 1974-1975 for DK and for a period of 1985-86 for NL proved important for cointegration. CA, IT and US required impulse dummy around the first and/or the second oil price shock. Exclusion of these dummies does not change the results qualitatively except for the failure of the diagnostics (non-normality and/or autocorrelation). All dummies are entered unrestricted in the VAR. The loading factor for France is not reported (NA) due to non-cointegration.

Table 10: Business Sector R&D
Estimated cointegrating parameters (Johansen and FMLOS methods)

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

(.) are respective standard errors . (#) no standard error since these parameters are imposed as part of the identification. Italy and Japan show two cointegrating vectors in specification (1). For identification details see footnote 34. The second cointegrating vector for Italy is: $S^d = 0.54S^f$; for Japan: S^d = 2.58 TFP + 2.95 S^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 non-cointegrated.

Table 11: Business Sector R&D
Tests for the heterogeneity of cointegrating parameters across countries (Johansen estimates)

Panel: A Tests for each individual parameter

Specification: $LogTFP_t = \beta_1 + \beta_1^d \log S^d{}_t + \beta_1^f \log S^f{}_t + \varepsilon_t$ (1)

CA		DK		IRL		IT		JP		NL		UK		US	
S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f	S^d	S^f
0.000	0.019	0.023	0.054	0.000	0.000	0.440	0.991	0.999	0.022	0.014	0.628	0.331	0.662	0.009	0.007

Specification: $LogTFP_t = \beta_2 + \beta_2^d \log S^d{}_t + \beta_2^f m_t \log S^f{}_t + \varepsilon_t$ (2)

CA		DK		IRL		IT		JP		NL		UK		US	
S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f	S^d	mS^f
0.000	0.598	0.043	0.357	0.001	0.000	0.001	0.005	0.041	0.018	0.041	0.018	0.075	0.905	0.512	0.238

Panel: B Joint tests:

	S^d	S^f	S^d	$m*S^f$
	51.210	36.268;	74.616	32.977
Degree of freedom: $\chi^2(.)$	(8)	(8)	(8)	(8)
Critical Value *1%)	20.09	20.09	20.09	20.09

France is non-cointegrated and Germany could only be normalised on S^d; hence both are excluded from these tests. P-values are reported in panel A. Panel B reports χ^2 statistics.

Table 12: 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 US 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 analysed in this study. The average effect on Japanese output is 0.003%.

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

[2] It should be noted that, in addition to international trade, knowledge is internationally diffused through channels such as foreign direct investment, international alliances between firms, migration of scientists and engineers, international collaborative research, conferences and publications etc.

[3] Our purpose is to add to the spillover literature initiated by CH and only briefly summarise the main papers in this area. Griliches (1992 and 1994), Mohnen (1999) and Mairesse and Sassenon (1991), to name but a few, provide extensive surveys.

[4] Recent advances in panel econometrics allow for such heterogeneity to a certain extent (see for example, Pesaran et al., 1999 and 2000). However these tests have not been used to assess the dynamics of knowledge spillovers. While previous studies have examined the group-specific elasticity by incorporating group dummies in the regressions, our argument for heterogeneity goes much deeper (see section IV).

[5] A number of high profile rival R&D projects exist. The EU's Galileo satellite programme, the Eurofighter, the Airbus, etc., are examples of competition between Europe and America.

[6] 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.

[7] Data constraints prevent modelling beyond G10 countries (see Appendix A for details). Section III provides the names of our sample countries.

[8] The term mS^f is import-interacted S^f ; where m is the time varying import ratio. For specification details see section V.

[9] Caves (1996) and Aitken and Harrison (1999) also point out that inward FDI can be costly for the productivity of domestic firms.

[10] A number of points can be put forward as to why international R&D spillover may not be positive for US productivity. If foreigners heavily imitate the US then the foreign R&D stock that the US faces may not be distinct from its domestic R&D stock. Hence, it can be argued that the foreign R&D stock, duplicated from the US, does not enhance US productivity. If spillover from the US accrues to its product-market rivals, this may cost the US in terms of productivity loss. Further, the accumulation of R&D by the EU and Japan may gradually replace US investments both at home and abroad and reduce US productivity. For empirical evidence on this see van Pottelsberghe and Lichtenberg (2001) and Dunning (1994).

[11] CH (pp. 884-885) also test for the stability of parameters by using dummy and trend variables and report instability. However, they do not report the standard errors, which makes it difficult to infer whether these shifts are indeed significant.

[12] The cointegrating vector for Germany is normalised on S^d. We explain why and discuss the implications for causal flows in section VI.

[13] Plots of TFP, S^d and S^f pertain to total R&D. Plots based on business sector R&D show a similar trend and are not reported to conserve space but are available on request. All plots are normalised at 1995=1. This is done for ease of comparison with CH's data set. Our data plots appear quite close to those of CH. However, following the suggestion of Litchenberg and van Pottelsberghe (1998), we do not use indexed data in our econometric analyses.

[14] Ames and Rosenberg (1963); Nelson and Wright (1992); Dosi (1988); and Nelson (1993), to name but a few.

[15] The extremely high Irish trade intensity is primarily due to trade deflection. US companies export to Ireland and then re-export to continental Europe. Further, the weight (m_{ij}/y_j) that we use to construct the stock of S^f is different from the trade and/or the import intensity. This feature of Irish data is inherent in previous studies. In short, the high trade intensity of Ireland does not make our empirical results incomparable with previous studies. An earlier version of this paper downloadable from the web page of the Department of Economics and Finance,

Brunel University excludes Ireland and analyses only G7 countries. It produces results similar to those of this paper.

[16] Hakkio and Rush (1991) point out that, unlike in the univariate tests, a multivariate VAR can use a shorter sample since it yields additional observations on long-run fluctuations. Luintel and Khan (1999) elaborate on this issue.

[17] Reinsel and Ahan (1992) and Cheung and Lai (1993) also suggest (equivalent) degree of freedom correction for small samples.

[18] It is common to specify lag lengths following some information criteria (for example, Akaike, 1973; Schwarz, 1978). However, Johansen (1992) suggests that the lag length in the VAR should be specified such that the VAR residuals are empirically uncorrelated. Cheung and Lai (1993) show that selection of lag length based on information criteria may not be adequate when errors contain moving average terms. Hence, we specify lag-length based on the test of serial correlation in VAR residuals.

[19] In short, FMOLS corrects the bias and non-normality inherent in the Engle-Granger (1987) OLS estimator of cointegrating parameters.

[20] Kwiatkowski et al. (1992) show that these tests are more powerful than the usual DF/ADF tests. Recently, however, Caner and Kilian (2001) warn against these power gains especially for high frequency data. Our data are low frequency.

[21] For the sake of brevity we do not report these results but they are available on request.

[22] S^d, S^f and TFP based on business sector R&D activities are also non-stationary. These unit root tests are not reported for the sake of brevity.

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

[24] When normalised on TFP the associated loading factor for Germany appears positive and significant. The loading for specification (1) is 0.097(0.049), whereas it is 0.058 (0.019) for specification (2). Numbers within parentheses are standard errors.

[25] Normalisation on S^f is conceptually problematic; nonetheless it is weakly exogenous as reported in tables 5A and 5B.

[26] Toda and Phillip's (1993) long run causality test is rooted in the Johansen VAR framework. For Germany, the LR test rejects the null of non-causality from TFP to S^d at very high precision (p-value of 0.006) whereas the null of non-causality from S^f to S^d is not rejected at any conventional level of significance (p-value = 0.143). For a formal derivation of this test see Toda and Phillips (1993) and for its illustration and implementation, see Luintel and Khan (1999).

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

[28] Under FMOLS Germany is normalised on TFP. Since Johansen's approach shows that this normalisation is not valid for Germany, we warn readers of this caveat regarding the FMOLS results for this country.

[29] The between-dimension panel estimates are obtained by averaging the country-specific parameters. Larsson et al. (2001) discuss the computations of these panel estimates under the Johansen approach and Pedroni (2001) derives them for the FMOLS. Details can also be found in the earlier version of this paper (see footnote 15).

[30] The coefficients of S^f directly measure elasticities whereas those of mS^f are semi-elasticities.

[31] Some exceptions are as follows. Ireland in both specifications and Japan in specification (2) show VAR residuals to be marginally correlated. The Netherlands, on the other hand,

shows significant residual autocorrelation in specification (1). Germany shows significant non-normality in both specifications whereas it is marginal for the US in specification (2) . These marginal failures of diagnostics (i.e., failure at lower precision) are less of a concern. However, the significant serial correlation found for the Netherlands in specification (1) should be borne in mind, and the results should be taken with some caution. See footnote 27 on German non-normality.

[32] Italy and Japan show two cointegrating vectors in specification (1). No over-identifying restriction could be sustained for Italy, and identification is therefore achieved through exactly identifying restrictions; hence they are not unique. The four restrictions imposed for exact identification are: the first and second cointegrating vectors are normalised on TFP and S^d respectively, forming two restrictions. A positive coefficient on S^f in the first cointegrating vector and a zero restriction on the coefficient of TFP in the second cointegrating vector are imposed as two further restrictions. Japan did not reject an overidentifying restriction. Two normalisation restrictions for Japan are similar to those imposed on Italy. Three further restrictions include a positive coefficient on S^d in the first cointegrating vector, and positive coefficients on S^d and S^f in the second cointegrating vector. It should be noted that the latter two coefficients appear with very high values when unrestricted. Thus, for both countries, the first cointegrating vector is a TFP relationship and the second is an S^d relationship. The second cointegrating vectors thus identified are reported in the footnotes of table 10. The p-value of the LR test of over-identifying restriction for Japan is 0.111.

[33] The two differences are that France shows cointegration under FMOLS but not under Johansen and that Germany is normalised on TFP under FMOLS.

[34] CH (p. 869) report the elasticity of TFP with respect to S^d and S^f to be 0.223 and 0.060 for G7 countries in their specification (ii). Our corresponding estimates for 10 OECD countries are 0.209 and 0.065. Likewise, CH's specification (iii) reports 0.234 and 0.294 as the coefficients of S^d and mS^f. Our corresponding estimates are 0.263 and 0.122. Although the latter coefficient differs in magnitude these results are nonetheless qualitatively quite close. This resemblance in panel coefficients indicates that the heterogeneity of estimated parameters that we find is not an artefact of the data set we use. Instead, it is the result of the estimation method that we follow.

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

[36] The R-model is more suitable for testing the stability of cointegrating ranks and long-run parameters (Hansen and Johansen, 1999). Nonetheless, results from the Z-model appear broadly similar and hence are not reported.

[37] Tests of the stability of cointegrating parameters (β^d and β^f) are also conducted under FMOLS by computing recursive Wald tests over the period 1980-1999. The null hypothesis is that the recursively computed sub-sample and full-sample parameters are equal. Canada, Japan and the UK did not reject the null for the whole period; Ireland and the US show robust stability over 1990s only; the rest of the countries did not reject the null under specification (1) but specification (2) shows episodes of parameter instability particularly prior to the 1990s. Overall, FMOLS corroborates the stability found by the VECM. To conserve space, we do not report these results but they are available on request.

[38] International output means output of the other members of the 10 OECD countries analysed in this study.

[39] The own rate of return from domestic R&D, $\theta_{jj} = \alpha^d{}_j \dfrac{y_j}{S^d{}_j}$, where $\alpha^d{}_j$ is the elasticity of TFP of country j with respect to its own domestic R&D capital Stock, S_j^d.

[40] Since the US commands 44% of the G10's real GDP this net negative spillover of -0.040% is not widely off the mark.

[41] Gross fixed investment was converted to constant prices by deflating by the gross fixed investment deflator.

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

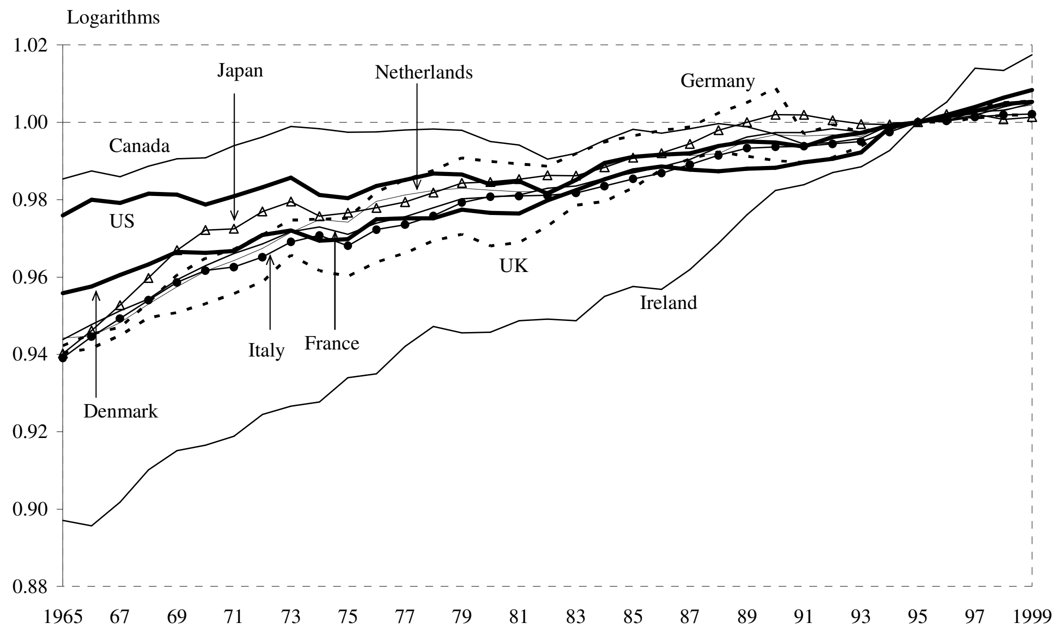
[43] As a check we computed the business sector physical capital stock (K_b) using the perpetual inventory method and business sector gross fixed investment. Our computed series compare

extremely closely with the OECD data. This lends further support to our measurement of total physical capital stock through the perpetual inventory method.

[44] Following CH, we also computed R&D capital stocks using a 15% depreciation rate. Our econometric results remain qualitatively the same on this alternative measure.

[45] Note that S^{d}_{j} is converted to a common currency (US dollars) using PPP equivalent exchange rates when calculating S_i^{f}.

Figure 1: Total Factor Productivity (1995=1)



Plots of TFP, S^d and S^f pertain to total R&D. Plots based on business sector R&D show a similar trend and are not reported to conserve space but are available on request. All plots are normalised at 1995=1. This is done for ease of comparison across countries. Our data plots appear quite close to those of CH. However, following the suggestion of Litchenberg and van Pottelsberghe (1998), we do not use indexed data in our econometric analyses.

Figure 2: Domestic R&D Capital Stocks (1995=1)

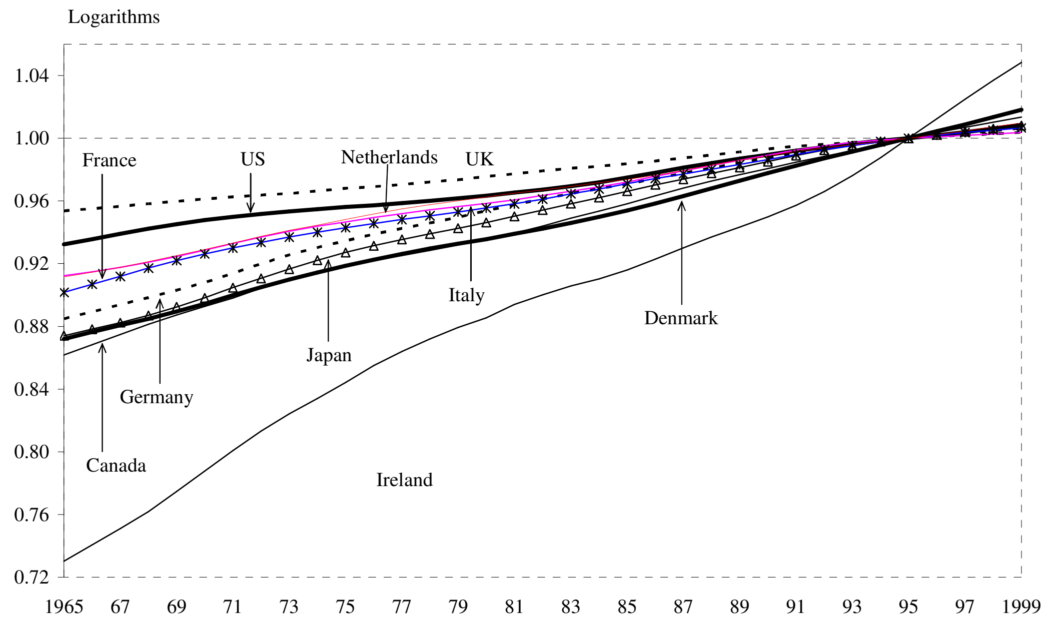


Figure 3: Foreign R&D Capital Stocks (1995=1)

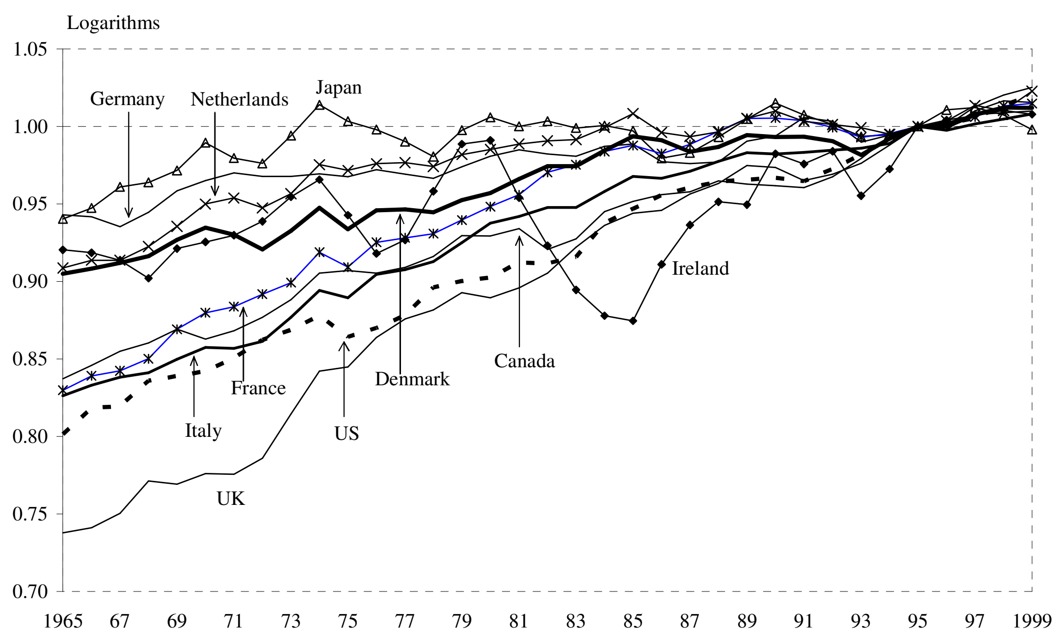


Figure 4: Plots of Scaled Recursive LR-Statistics (Rank Stability Tests)

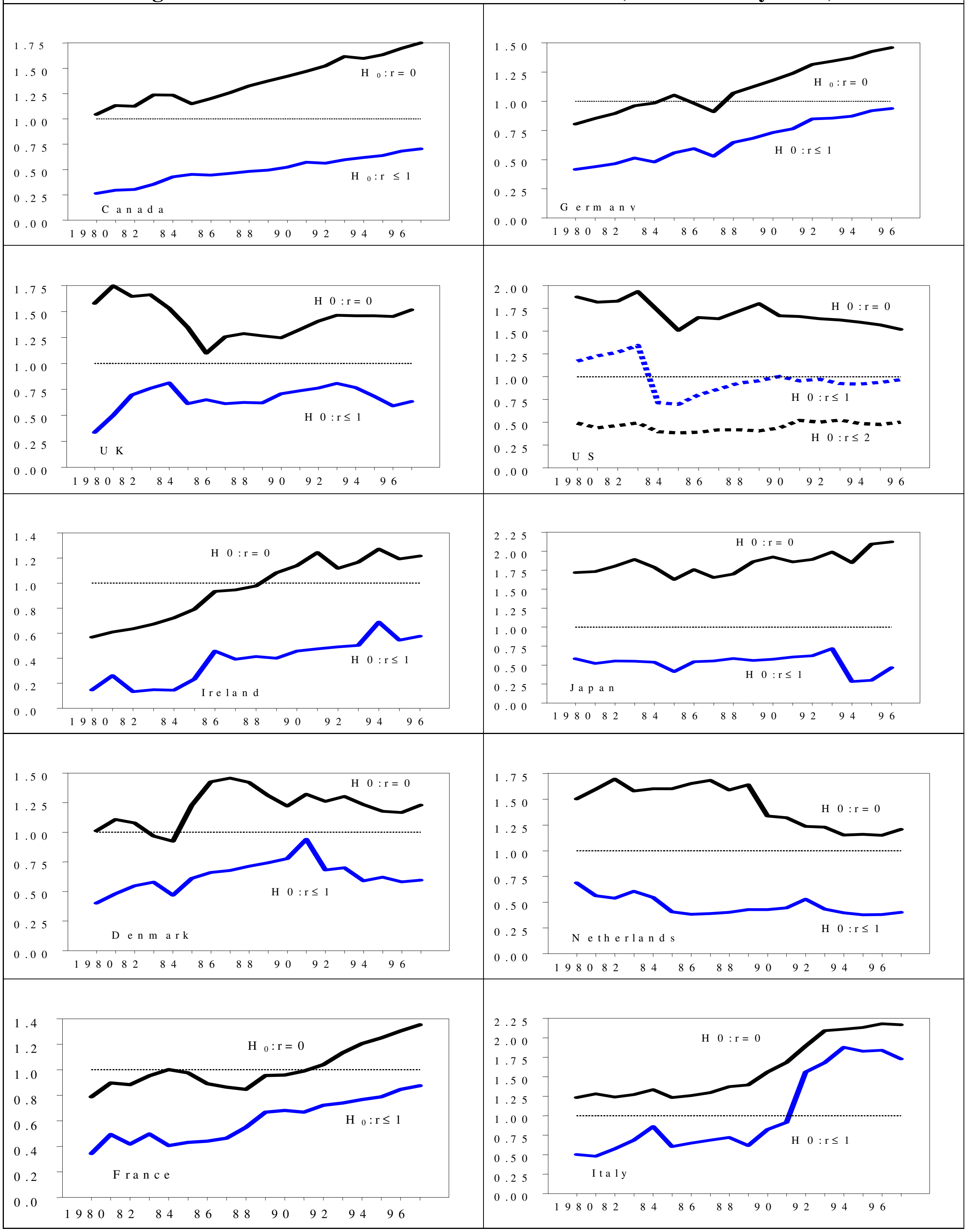


Figure 5: Plots of Scaled Recursive LR-Statistics (Parameter Stability Tests)