International R&D Spillovers: An Application of Estimation and Inference in Panel Cointegration*

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Abstract

In this paper, we apply the asymptotic theory of panel cointegration developed by Kao and Chiang (1997) to Coe and Helpman's (1995) international R&D spillovers regression. The OLS with bias-correction, the fully-modified (FM) and the dynamic OLS (DOLS) estimations produce different predictions about the impact of foreign R&D on total factor productivity (TFP) although all the estimations support the result that domestic R&D is related to TFP.

Key Words: *International R&D Spillovers, Panel Data, OLS; FM, DOLS, Cointegration.*

JEL Classification: C22, C23.

1 Introduction

In this paper, we consider the application of recent results on the estimation and inference in panel cointegration to the study of empirical economic growth. The emergence of endogenous growth theory in the 1980s has led to a resurgence of interest in the sources of economic growth. Among the current researchers, Coe and Helpman (1995), among other researchers, state that commercially oriented innovation efforts which respond to economic incentives are the major engine of technological progress and productivity growth. Coe and Helpman (1995) argue that, in a global economy, a country's productivity depends on its own R&D efforts as well as the R&D efforts of its trading partners. Using data from 21 OECD countries plus Israel

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during 1971-1990, they find that both domestic and foreign R&D capital stocks have important effects on total factor productivity (TFP). We intend to re-examine the econometric foundation of Coe and Helpman's paper.

Coe and Helpman (1995) discovered that all of their data exhibit a clear trend and unit root tests on these data indicate that the TFP and both the domestic and foreign R&D capital stocks are non-stationary. They then confirm the presence of cointegration for TFP and the domestic and foreign R&D capital stocks by testing for a unit root in the residuals. In other words, although all the variables are individually non-stationary, there exists a linear combination of these variables so that the regression containing these variables has a stationary error term.

Coe and Helpman's use of a cointegrating regression enables us to exploit the relationship among the variables in levels, without tediously transforming the data by an extra process, such as differencing, to avoid the spurious regression problem. Unfortunately, at the time of their article the econometrics of panel cointegration had not yet been resolved. Among the various issues that now need to be addressed are two directly associated with Coe and Helpman's empirical interpretations. First, we need to know the asymptotic distribution of the estimated cointegrating vector in panel data. It is well known that the asymptotic distributions of estimators in pure time-series regression are dramatically affected by the presence of unit roots and the cointegration Accordingly, we expect that the asymptotic distributions of estimators in panel regression might also be affected by the presence of unit roots and cointegration. Indeed, Coe and Helpman chose not to report the t-ratio, because the asymptotic distribution of the t-ratio was unknown. Given that the estimated coefficients are relatively small, we are not sure whether these estimators are significantly different from zero. Second, although it is well known that the time series regression estimates are super consistent, it has been found that the estimation bias may remain substantial for moderate sample sizes. We have no reason to presume that this bias will become negligible in panel regression due to the introduction of the cross-section dimension. Given that the estimated coefficients in Coe and Helpman are relatively small in magnitude, one even wonders whether those estimates are correctly signed after the bias-correction. The issues presented above cast serious doubts on Coe and Helpman's conclusion that TFP is closely linked to domestic and foreign R&D.

Recently, Kao and Chiang (1997) found that the limiting distributions of OLS estimators are normally distributed with non-zero means and proposed Fully-Modified (FM) and Dynamic OLS (DOLS) estimators in panel data. While the limiting distribution of the OLS estimator is normal with a nonzero mean, the FM and DOLS estimators are asymptotically normal with zero means. Therefore, we apply Kao and Chiang's result to Coe and Helpman's international R&D spillovers regressions, and we compare the empirical consequences of the different estimation approaches.

The paper is organized as follows. Section 2 briefly reviews Coe and Helpman's model. Section 3 reviews the asymptotic theory developed by Kao and Chiang (1997). Section 4 presents the empirical results. Concluding remarks are made in Section 5.

A word on notation should be mentioned. We write the integral $\int_0^1 W(s)ds$ as $\int W$ when there is no ambiguity over limits. We define $\Omega^{1/2}$ to be any matrix such that $\Omega = \left(\Omega^{1/2}\right)\left(\Omega^{1/2}\right)'$. We use $\|A\|$ to denote $\left\{tr\left(A'A\right)\right\}^{1/2}$, $|A|$ to denote the determinant of A, $\xrightarrow{d}$ to denote convergence in distribution, $[x]$ to denote the largest integer $\leq x$, $I(0)$ and $I(1)$ to signify a time series that is integrated of order zero and one, respectively, and $BM(\Omega)$ to denote Brownian motion with covariance matrix Ω.

2 Coe and Helpman's Theory and Model

Coe and Helpman's model is built on recent theories of innovation-driven growth (e.g., Grossman and Helpman, 1991). Contrary to most cross-country studies of economic growth that focus on explaining output growth as determined by the accumulation of labor, capital, and some additional economic and political variables, Coe and Helpman choose to focus on the growth of TFP, which is the component of output growth that is not attributable to the accumulation of inputs. By this account, in an economy with two factors of production, the log of TFP is measured as

$$\log TFP \equiv \log Y - \theta \log K - (1-\theta)\log L, \tag{1}$$

where $Y =$ final output, $L =$ the available labor force, $K =$ the capital accumulation, and $\theta =$ the share of capital in GDP.

In a simple closed economy, the production function of final output is assumed to be a linearly homogenous function in the employed inputs. Because a country's R&D investment either expands the measure of available inputs or improves the qualities of inputs, one can establish a linkage between the TFP and the domestic R&D capital stock. International trade in intermediate goods enables a country to gain access to all inputs available in the rest of the world. From this aspect, the foreign R&D capital stocks of a country's trading partners become relevant to this country's TFP:

$$\log TFP_i = \alpha_i^0 + \alpha^d \log S_i^d + \alpha^f \log S_i^f, \tag{2}$$

where i is the country index, S^d represents the domestic R&D capital stock, and S^f represents the foreign R&D capital stocks defined as the import-share-weighted average of the domestic R&D capital stocks of trade partners. Note that this specification allows the constant α_i^0 to differ across countries to account for country-specific effects. However, the specification may not capture the role of international trade. Although the foreign R&D capital stocks S_i^f have been weighted by import shares, these weights are fractions that add up to one and, therefore, do not properly reflect the level of imports. Whenever two countries have the same composition of imports and face the same composition of R&D capital stocks among trade partners, the country that imports more relative to its GDP may benefit more from foreign R&D. Therefore, a modified specification of (2) that accounts for the interaction between the foreign R&D capital stocks and the level of international trade may be preferable:

$$\log TFP_i = \alpha_i^0 + \alpha^d \log S_i^d + \alpha^f \left(m_i \log S_i^f \right), \tag{3}$$

where m_i stands for the fraction of imports relative to GDP for country i.

One salient feature that distinguishes Coe and Helpman's work from most other empirical works on economic growth is that Coe and Helpman pay close attention to the time-series behavior of the data set. They detect that TFP and domestic and foreign R&D capital stocks all exhibit a clear upward trend over time. The unit root tests on the panel data confirm that all the variables are non-stationary with unit roots. To avoid the 'spurious' correlation problem, they conduct cointegration tests on the estimation equations. Even though those tests tend to suggest the presence of cointegration, Coe and Helpman fail to interpret their estimation results within a cointegration framework. As already noted, while they report the estimated coefficients, they do not discuss the accuracy of the results and whether those estimates are statistically significant. Consequently, the results do not strongly support the argument that domestic and foreign R&D capital stocks are closely linked to TFP, even though the estimated parameters seem to be plausible and consistent with the theoretical model. For example, the estimates have the expected sign and estimated elasticities of TFP with respect to the domestic R&D stock are in the range of .06 and .1 which are typically found in single country studies. Coe and Helpman simply did not have appropriate econometric foundation available for them to draw such a conclusion.

For this reason, the role of the asymptotic theory of panel cointegrating regressions becomes important. Kao and Chiang's work enables us to estimate and make inference on the cointegrating vector in Coe and Helpman's regression.

3 A Brief Review of OLS, FM, and DOLS in Panel Data

In this section, we provide a brief review of the OLS, FM, and DOLS estimation methods with cointegration discussed by Kao and Chiang (1997). The reader is referred to the cited paper for further details and discussions.

Consider the following fixed effect panel regression:

$$y_{it} = \alpha_i + x_{it}^{'}\beta + u_{it}, \; i = 1, ..., N, \; t = 1, ...T, \tag{4}$$

where $\{y_{it}\}$ are 1×1, β is a $k \times 1$ vector of the slope parameters, $\{\alpha_i\}$ are the intercepts, and $\{u_{it}\}$ are the stationary disturbance terms. We assume that $\{x_{it}\}$ are $k \times 1$ integrated processes of order one for all i, where

$$x_{it} = x_{it-1} + \varepsilon_{it}.$$

Under these specifications, (4) describes a system of cointegrated regressions, i.e., y_{it} is cointegrated with x_{it}. The initialization of this system is $y_{i0} = x_{i0} = O_p(1)$ for all i.

Assumption 1 *$\{y_{it}, x_{it}\}$ are independent across i.*

Assumption 2 *The asymptotic theory employed in this paper is a sequential limit theory established by Phillips and Moon (1997) in which $T \to \infty$ followed by $N \to \infty$.*

Next, we characterize the innovation vector $w_{it} = \left(u_{it}, \varepsilon_{it}^{'}\right)^{'}$. We assume that w_{it} is a linear process that satisfies the following assumption.

Assumption 3 *(e.g., Phillips, 1995)*

(a) $w_{it} = \Pi(L)\epsilon_{it} = \sum_{j=0}^{\infty} \Pi_j \epsilon_{it-j}, \sum_{j=0}^{\infty} j^a \|\Pi_j\| < \infty, |\Pi(1)| \neq 0$ *for some* $a > 1$.

(b) *ϵ_{it} is i.i.d. with zero mean, variance matrix Σ_ϵ, and finite fourth order cumulants.*

Assumption 3 implies that (e.g., Phillips and Solo, 1992) the partial sum process $\frac{1}{\sqrt{T}} \sum_{t=1}^{[Tr]} w_{it}$ satisfies the following multivariate invariance principle:

$$\frac{1}{\sqrt{T}} \sum_{t=1}^{[Tr]} w_{it} \xrightarrow{d} B_i(r) \equiv BM_i(\Omega) \text{ as } T \to \infty, \tag{5}$$

where

$$B_i = \begin{bmatrix} B_{ui} \\ B_{\varepsilon i} \end{bmatrix}.$$

The long-run covariance matrix of $\{w_{it}\}$ is given by

$$\Omega = \sum_{j=-\infty}^{\infty} E\left(w_{ij} w_{i0}^{'}\right)$$

$$
\begin{aligned}
&= \Pi(1)\Sigma_{\epsilon}\Pi(1)^{'} \\
&= \Sigma + \Gamma + \Gamma^{'} \\
&\equiv \begin{bmatrix} \Omega_{u} & \Omega_{u\varepsilon} \\ \Omega_{\varepsilon u} & \Omega_{\varepsilon} \end{bmatrix},
\end{aligned}
$$

where

$$\Gamma = \sum_{j=1}^{\infty} E\left(w_{ij}w_{i0}^{'}\right) \equiv \begin{bmatrix} \Gamma_{u} & \Gamma_{u\varepsilon} \\ \Gamma_{\varepsilon u} & \Gamma_{\varepsilon} \end{bmatrix} \tag{6}$$

and

$$\Sigma = E\left(w_{i0}w_{i0}^{'}\right) \equiv \begin{bmatrix} \Sigma_{u} & \Sigma_{u\varepsilon} \\ \Sigma_{\varepsilon u} & \Sigma_{\varepsilon} \end{bmatrix} \tag{7}$$

are partitioned conformably with w_{it}.

Assumption 4 *Ω_{ε} is non-singular, i.e., $\{x_{it}\}$ are not cointegrated.*

Define

$$\Omega_{u.\varepsilon} = \Omega_{u} - \Omega_{u\varepsilon}\Omega_{\varepsilon}^{-1}\Omega_{\varepsilon u}. \tag{8}$$

Then, B_i can be rewritten as

$$B_{i} = \begin{bmatrix} B_{ui} \\ B_{\varepsilon i} \end{bmatrix} = \begin{bmatrix} \Omega_{u.\varepsilon}^{1/2} & \Omega_{u\varepsilon}\Omega_{\varepsilon}^{-1/2} \\ 0 & \Omega_{\varepsilon}^{1/2} \end{bmatrix} \begin{bmatrix} V_{i} \\ W_{i} \end{bmatrix},$$

where $\begin{bmatrix} V_{i} \\ W_{i} \end{bmatrix} = BM(I)$ is a standardized Brownian motion. We then define the one-sided long-run covariance

$$
\begin{aligned}
\Delta &= \Sigma + \Gamma \\
&= \sum_{j=0}^{\infty} E\left(w_{ij}w_{i0}^{'}\right)
\end{aligned}
$$

with

$$\Delta = \begin{bmatrix} \Delta_{u} & \Delta_{u\varepsilon} \\ \Delta_{\varepsilon u} & \Delta_{\varepsilon} \end{bmatrix}.$$

Kao and Chiang (1997) derive limiting distributions for the OLS, FM, and DOLS estimators in a cointegrated regression and shows they are asymptotically normal. Kao and Chiang (1997) also investigate the finite sample proprieties of the OLS, FM, and DOLS estimators. They find that (i) the OLS estimator has a non-negligible bias in finite samples, (ii) the FM estimator does not improve over the OLS estimator in general, and (iii) the DOLS estimator may be more promising than OLS or FM estimators in estimating the cointegrated panel regressions.

The OLS estimator of β is

$$\widehat{\beta}_{OLS} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \overline{x}_i)(x_{it} - \overline{x}_i)' \right]^{-1} \left[\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \overline{x}_i)(y_{it} - \overline{y}_i) \right], \tag{9}$$

where $\overline{x}_i = \frac{1}{T} \sum_{t=1}^{T} x_{it}$ and $\overline{y}_i = \frac{1}{T} \sum_{t=1}^{T} y_{it}$.

The FM estimator is constructed by making corrections for endogeneity and serial correlation to the OLS estimator $\widehat{\beta}_{OLS}$ in (9). Let $\widehat{\Omega}_{\varepsilon u}$ and $\widehat{\Omega}_{\varepsilon}$ be consistent estimates of $\Omega_{u\varepsilon}$ and Ω_{ε}. Define

$$u_{it}^{+} = u_{it} - \Omega_{u\varepsilon}\Omega_{\varepsilon}^{-1}\varepsilon_{it},$$

$$\begin{aligned} \widehat{u}_{it}^{+} &= u_{it} - \widehat{\Omega}_{u\varepsilon}\widehat{\Omega}_{\varepsilon}^{-1}\varepsilon_{it}, \\ y_{it}^{+} &= y_{it} - \Omega_{u\varepsilon}\Omega_{\varepsilon}^{-1}\varepsilon_{it}, \end{aligned}$$

and

$$\widehat{y}_{it}^{+} = y_{it} - \widehat{\Omega}_{u\varepsilon}\widehat{\Omega}_{\varepsilon}^{-1}\varepsilon_{it}.$$

Note that

$$\begin{bmatrix} u_{it}^{+} \\ \varepsilon_{it} \end{bmatrix} = \begin{bmatrix} 1 & -\Omega_{u\varepsilon}\Omega_{\varepsilon}^{-1} \\ 0 & \mathbf{I}_k \end{bmatrix} \begin{bmatrix} u_{it} \\ \varepsilon_{it} \end{bmatrix},$$

which has the long-run covariance matrix

$$\begin{bmatrix} \Omega_{u.\varepsilon} & 0 \\ 0 & \Omega_{\varepsilon} \end{bmatrix},$$

where $\mathbf{I}_k$ is a $k \times k$ identity matrix. The endogeneity correction is achieved by modifying the variable y_{it} in (4) with the transformation

$$\begin{aligned} \widehat{y}_{it}^{+} &= y_{it} - \widehat{\Omega}_{u\varepsilon}\widehat{\Omega}_{\varepsilon}^{-1}\varepsilon_{it} \\ &= \alpha_i + x_{it}'\beta + u_{it} - \widehat{\Omega}_{u\varepsilon}\widehat{\Omega}_{\varepsilon}^{-1}\varepsilon_{it}. \end{aligned}$$

The serial correlation correction term has the form

$$\begin{aligned} \widehat{\Delta}_{\varepsilon u}^{+} &= \begin{pmatrix} \widehat{\Delta}_{\varepsilon u} & \widehat{\Delta}_{\varepsilon} \end{pmatrix} \begin{pmatrix} 1 \\ -\widehat{\Omega}_{\varepsilon}^{-1}\widehat{\Omega}_{\varepsilon u} \end{pmatrix} \\ &= \widehat{\Delta}_{\varepsilon u} - \widehat{\Delta}_{\varepsilon}\widehat{\Omega}_{\varepsilon}^{-1}\widehat{\Omega}_{\varepsilon u}, \end{aligned}$$

where $\widehat{\Delta}_{\varepsilon u}$ and $\widehat{\Delta}_{\varepsilon}$ are kernel estimates of $\Delta_{\varepsilon u}$ and Δ_{ε}. Therefore, the FM estimator is

$$\widehat{\beta}_{FM} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \overline{x}_i)(x_{it} - \overline{x}_i)' \right]^{-1} \left[\sum_{i=1}^{N} \left(\sum_{t=1}^{T} (x_{it} - \overline{x}_i) \widehat{y}_{it}^{+} - T \widehat{\Delta}_{\varepsilon u}^{+} \right) \right]. \tag{10}$$

Before constructing the DOLS estimator, $\widehat{\beta}_D$, we need the following additional assumptions:

Assumption 5 *The process $\{u_{it}\}$ can be projected on to $\{\varepsilon_{it}\}$ to get*

$$u_{it} = \sum_{j=-\infty}^{\infty} c_{ij} \varepsilon_{it+j} + v_{it}, \tag{11}$$

where

$$\sum_{j=-\infty}^{\infty} \|c_{ij}\| < \infty,$$

$\{v_{it}\}$ is stationary with zero mean, and $\{v_{it}\}$ and $\{\varepsilon_{it}\}$ are uncorrelated not only contemporaneously but also in all lags and leads.

Remark 1 *Assumption 5 can be guaranteed by following the conditions in Saikkonen (1991, p. 11).*

Remark 2 *In practice, the leads and lags may be truncated while retaining Assumption 5 approximately, so that*

$$u_{it} = \sum_{j=-q_1}^{q_2} c_{ij} \varepsilon_{it+j} + v_{it}.$$

This is because $\{c_{ij}\}$ are assumed to be absolutely summable, i.e., $\sum_{j=-\infty}^{\infty} \|c_{ij}\| < \infty$.

We also need to require that q_1 and q_2 tend to infinity with T at a suitable rate, i.e.,

Assumption 6 $\frac{q_1^3}{T} \to 0, \frac{q_2^3}{T} \to 0,$ *and*

$$T^{1/2} \sum_{|j| > q_1 \ or \ q_2} \|c_{ij}\| \to 0. \tag{12}$$

We then substitute (11) into (4) to get

$$y_{it} = \alpha_i + x_{it}'\beta + \sum_{j=-q_1}^{q_2} c_{ij} \varepsilon_{it+j} + v_{it}.$$

Therefore, we obtain the DOLS of β, $\widehat{\beta}_D$, by running the following regression:

$$y_{it} = \alpha_i + x_{it}'\beta + \sum_{j=-q_1}^{q_2} c_{ij} \triangle x_{it+j} + v_{it}. \tag{13}$$

The asymptotic theory for OLS, FM, and DOLS estimators is as follows.

Theorem 1 *If Assumptions* $1-6$ *hold, then*

(a) $\sqrt{N}T\left(\widehat{\beta}_{OLS}-\beta\right)-\sqrt{N}\delta_{NT}\xrightarrow{d}N\left(0,6\Omega_{\varepsilon}^{-1}\Omega_{u.\varepsilon}\right),$

(b) $\sqrt{N}T\left(\widehat{\beta}_{FM}-\beta\right)\xrightarrow{d}N\left(0,6\Omega_{\varepsilon}^{-1}\Omega_{u.\varepsilon}\right),$

(c) $\sqrt{N}T\left(\widehat{\beta}_{D}-\beta\right)\xrightarrow{d}N\left(0,6\Omega_{\varepsilon}^{-1}\Omega_{u.\varepsilon}\right),$

where

$$\delta_{NT}=\left[\frac{1}{N}\sum_{i=1}^{N}\frac{1}{T^2}\sum_{t=1}^{T}\left(x_{it}-x_{it}\right)\left(x_{it}-\overline{x}_i\right)'\right]^{-1}\left[\frac{1}{N}\sum_{i=1}^{N}\Omega_{\varepsilon}^{1/2}\left(\int\widetilde{W}_i dW_i'\right)\Omega_{\varepsilon}^{-1/2}\Omega_{\varepsilon u}+\Delta_{\varepsilon u}\right].$$

Remark 3 *See Kao and Chiang (1997) for the proof of the theorem.*

Remark 4 *We notice that* $\delta_{NT}\xrightarrow{p}-3\Omega_{\varepsilon}^{-1}\Omega_{\varepsilon u}+6\Omega_{\varepsilon}^{-1}\Delta_{\varepsilon u}$*.*

Remark 5 $\Omega_{\varepsilon}^{-1}\Omega_{u.\varepsilon}$ *can be seen as the long-run signal-to-noise ratio.*

Remark 6 *The normality of the OLS estimator comes naturally. When summing across* i*, the nonstandard asymptotic distribution due to unit root in the time dimension is smoothed out. However, it is important to note that the OLS estimator is asymptotically biased. The asymptotic bias is*

$$\widehat{\beta}_{OLS}-\beta\cong\frac{\delta_{NT}}{T}\cong\frac{-3\Omega_{\varepsilon}^{-1}\Omega_{\varepsilon u}+6\Omega_{\varepsilon}^{-1}\Delta_{\varepsilon u}}{T}$$

which decreases as T *increases. This also indicates that we can propose a bias-corrected OLS*

$$\widehat{\beta}_{OLS}^{*}=\widehat{\beta}_{OLS}-\frac{\delta_{NT}}{T}=\widehat{\beta}_{OLS}-\frac{-3\Omega_{\varepsilon}^{-1}\Omega_{\varepsilon u}+6\Omega_{\varepsilon}^{-1}\Delta_{\varepsilon u}}{T}$$

which is asymptotically unbiased.

We now consider a linear hypothesis that involves the elements of the coefficient vector β. We show that hypothesis tests constructed using the FM and DOLS estimators have asymptotic chi-squared distributions. The null hypothesis has the form:

$$H_0: R\beta=r, \tag{14}$$

where r is a $m\times 1$ known vector and R is a known $m\times k$ matrix describing the restrictions. A natural test statistic of the Wald test using $\widehat{\beta}_{FM}$ or $\widehat{\beta}_{D}$ for homogeneous panels is

$$Wald=\frac{1}{6}NT^2\left(R\widehat{\beta}_{FM}-r\right)'\left[R\widehat{\Omega}_{\varepsilon}^{-1}\widehat{\Omega}_{u.\varepsilon}R'\right]^{-1}\left(R\widehat{\beta}_{FM}-r\right). \tag{15}$$

Hence, we establish the following theorem:

Theorem 2 *If Assumptions* $1-8$ *hold, then under the null hypothesis (14),*

$$Wald \xrightarrow{d} \chi^2_k,$$

Remark 7 *Because the FM and the DOLS estimators have the same asymptotic distribution, it is easy to verify that the Wald statistics based on the FM estimator share the same limiting distributions with those based on the DOLS estimator.*

4 Data and Estimation Results

We use annual data for 22 countries listed in Coe and Helpman (1995) from 1971 to 1990. The variables include TFP, domestic R&D capital stocks $\left(S^d\right)$, foreign R&D capital stocks $\left(S^f\right)$, and the fraction of imports in GDP (m). See Coe and Helpman's appendix for the definition and construction of these variables.

Table 1 is simply a reproduction of Table 3 of Coe and Helpman (1995), except that we augment it by adding regression (iv). In regression (iv), the estimated coefficient on the domestic R&D capital stocks is constrained to be the same for all countries and the foreign R&D capital stocks are interacted with the ratio of imports to GDP for allowing country-specific and time-varying elasticities on foreign R&D capital stocks. The rationale for this specification is obvious since it is explicitly suggested by equation (3). All regressions include unreported country specific effects. The conventional t-ratio statistics are shown in parentheses.

Although the estimated coefficients reported in Table 1 have the expected signs and the values of all the t-ratios are significantly large, as shown in the previous section, these OLS estimates are generally biased and the corresponding t-statistics do not have usual t-distributions. Consequently, it is unwise to place too much faith in the estimation results of Table 1.

Tables 2, 3, and 4 present the coefficient estimates based upon the OLS with bias-correction, the FM, and the DOLS estimators respectively (with their t-ratio statistics in parentheses). Observe that the coefficient estimators by the OLS with bias-correction are similar to those of the FM estimator. That might result from the fact that FM estimation corrects the dependent variable using the long-run covariance matrices for the purpose of removing the nuisance parameters and applies the usual OLS estimation method to the corrected variables. On the other hand, the estimated coefficient coefficients of the DOLS estimator are quite different from those of the FM estimator, even though the limiting distributions of the DOLS estimator is the same as of the FM estimator as shown in Kao and Chiang (1997). The DOLS estimator includes lead and lag terms to correct the nuisance parameter in order to obtain coefficient estimates with nice limiting distribution properties.

First, we would like to examine the magnitude of the estimation bias by the OLS in comparison with those bias-correction method. At first glance, the estimated elasticities on the domestic and the foreign R&D capital stocks are correctly signed for all regressions in all Tables 1-4. However, the estimated elasticities on the domestic and the foreign R&D capital stocks vary considerably with different methods. It is interesting to see that the estimation bias by the OLS may be upward or downward, depending upon which method you make the comparison. The OLS estimator overestimates the elasticity on the domestic R&D capital stocks in comparison with the estimation results of the OLS with bias-correction and the FM methods. On the other hand, it underestimates the elasticity on the domestic R&D capital stocks in comparison with the DOLS. Overall, the bias remains within the range of 20%. The estimation bias of the elasticity on the foreign R&D capital stocks spreads even wider among different estimation methods. For example, the estimated coefficient on ($m \log S^f$) by the OLS is 0.266, but 0.068 by the DOLS based on regression (iv).

It is more troublesome when we turn to inferences made by the OLS. As can be seen from the tables, showing the values of t-ratios in all the OLS with bias-correction, the FM and the DOLS estimators are significantly reduced in comparison with those in the OLS without bias corrections. All the estimations confirm that the elasticity on the domestic R&D capital stocks is significant at a 5% level. In addition, the estimated coefficient on the domestic R&D capital stocks with the G7 dummy (G7$\cdot \log S^d$) in all regressions is significant at a 5% level, which supports the argument that the impact of the domestic R&D differs between the largest seven economies and the remaining fifteen small countries. However, these methods disagree on the impact of foreign R&D capital stocks. The OLS with bias-correction and the FM estimators confirm that the impact of the foreign R&D capital stock is significant at a 5% level, but the DOLS indicates that the impact is statistically insignificant even at a 10% level. The Monte Carlo simulations in Kao and Chiang (1997) suggest that the DOLS estimator outperforms the OLS and FM estimators. Consequently, we lean to rejecting the linkage between TFP and the foreign R&D via trade in Coe and Helpman (1995).

Our finding is in line with recent criticisms of Coe and Helpman's results. Lichtenberg and Van Pottesberghe (1996) suggest that Coe and Helpman's functional form of how foreign R&D affects domestic productivity via imports is probably incorrect. They claimed the construction of foreign R&D capital stocks in Coe and Helpman is subject to the aggregation bias. Using an improved measure of foreign R&D capital stock, Lichtenberg and Van Pottesberghe (1996) were able to produce improved results. Keller (1997) argued that Coe and Helpman's results are not sufficient to support their hypothesis that international R&D spillovers are trade related. Using the same model as Coe and Helpman used, Keller (1997) found large international R&D spillovers by randomly generated bilateral trade shares to construct foreign R&D capital stocks. However, they were silent about the nonstationarity of the variables in their regressions. Applying

Kao and Chiang (1997) to their models may provide further insight of the relationship of foreign R&D and TFP. However, this goes beyond the scope of this paper.

Although inferences about the impact of foreign R&D capital stocks are different between the FM and the DOLS methods, the impact of foreign R&D capital stocks on the TFP is still of interest to us. Tables 5 and 6 compute the estimated elasticities [1] of TFP with respect to the foreign R&D capital stocks based on regression (iii) of the FM and the DOLS methods, respectively. The estimated impacts of foreign R&D capital stocks increase from 1971 to 1980 as found by Coe and Helpman (1995). Most of the 15 small countries have larger impacts generated from changes of foreign capital stocks than G7 countries, which confirms that the small countries with open economy benefit larger than large countries. As expected, the magnitudes of estimated impacts are much smaller in Table 6 than in Table 5.

Tables 7 and 8 present the estimates of the international R&D spillovers[2] from the FM and the DOLS methods, respectively. While the conclusions drawn from these tables are basically consistent with conclusions made by Coe and Helpman qualitatively, one can observe some quantitative differences. Tables 7 and 8 confirm that international R&D spillovers from the major countries (U.S.A., Japan) are the largest.

Tables 9 and 10 show estimates of the average own rate of return[3] from investment in R&D in 1990. The average own returns from investment in R&D are 120 (118) percent in the G7 countries and 79 (99) percent in the remaining 15 countries. While these estimates are a little smaller than those in the Coe and Helpman, they indicate that the R&D capital investment in G7 countries generates higher rates of return than in smaller countries. In addition, the spillover effect of R&D capital investment in G7 countries through trades is 29 (16) percent assuring that G7 countries contributes larger proportions to its trade partners.

5 Concluding Remarks

We have reexamined Coe and Helpman's international R&D spillovers regressions by applying different estimation methods of cointegrating regressions in panel data proposed by Kao and Chiang (1997). Our

[1] The estimated elasticities of total factor productivity with respect to the foreign R&D capital stocks are calculated as the prodcut of the estimated coefficient of $m \cdot \log S^f$ and the import share.

[2] The estimated elasticities of total factor productivity with respect to R&D capital stocks in the G7 countries are calculated using the formula: $m^j \alpha^f m_i^j S_i^d / \Sigma_{k \neq j} m_k^j S_k^d$, where m^j is country $j's$ import share and m_i^j is the fraction of $j's$ imports from country i.

[3] The average own rate of return for a group, N, is computed as $\rho_{NN} = \sum_{j \in N} \rho_j S_j^d / (\sum_{i \in N} S_i^d)$, where ρ_j is calculated as $\sum_i \rho_{ij} = \alpha_j Y / S_j^d$ in which $Y = \sum_i Y_i$ is a aggregate GDP and $\alpha_j = \sum_i \alpha_{ij} Y_i / Y$ is the GDP weighted average elasticity of output with respect to country $j's$ R&D capital stock. α_{ij} represents the elasticity of country $i's$ output with respect to $j's$ domestic R&D capital stock.

empirical results indicate that the estimated coefficients in the Coe and Helpman's regressions are subject to estimation bias. However, in all cases the estimates are correctly signed.

All estimation confirms the existence of the linkage between TFP and domestic capital stock. In addition, there exists strong evidence supporting Coe and Helpman's argument that the impact of the domestic R&D capital stocks on TFP differs between the G7 countries and the other small countries. However, these estimations do not seem to agree on the impact of the foreign R&D capital stocks on TFP. The OLS with bias-correction and the FM support the idea that foreign R&D is related to TFP. However, the DOLS method suggests that the impact of foreign R&D on TFP is insignificant. Given the superiority of the DOLS over the FM as suggested by Kao and Chiang (1997), we lean to rejecting Coe and Helpman's hypothesis that international R&D spillovers are traded-related.

We also remeasured the magnitude of international R&D spillovers, and found the small countries benefit more from international R&D spillovers than the larger countries do. In addition, international R&D spillovers from the major countries (U.S.A. and Japan) are the largest, which means that R&D in the largest countries may lead the world trend. Our estimates suggest that the rates of return on R&D capital stock are very high, both in terms of domestic and international spillovers, although not so large as Coe and Helpman's estimates.

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Table 1: TFP Estimation Results Using OLS

	(i)	(ii)	(iii)	(iv)
$\log S^d$	0.097	0.090	0.078	0.105
	(10.98)	(10.86)	(10.32)	(13.24)
$G7 \cdot \log S^d$		0.135	0.157	
		(8.58)	(10.71)	
$\log S^f$	0.092	0.060		
	(6.00)	(4.06)		
$m \cdot \log S^f$			0.289	0.266
			(7.23)	(5.94)
R^2	0.558	0.622	0.650	0.558
$Adjusted R^2$	0.556	0.620	0.647	0.556

Note:

(a) Estimations are based on pooled data from 1971-90 for 22 countries (440 observations). The dependent variable is log TFP. All regressions include unreported, country-specific constants. The conventional t-ratios are reported in parentheses. Note that our estimated coefficients in regression (iii) are slightly different from Coe and Helpman's.

(b) S^d= domestic research and development capital stock, beginning of the year.

(c) S^f= foreign research and development capital stock, beginning of the year.

(d) $G7$= dummy variable equal to 1 for the seven major countries and equal to 0 for the other 15 countries.

(e) m=ratio of imports of goods and services to GDP, both in the previous year.

Table 2: TFP Estimation Results With Bias-corrected OLS

	(i)	(ii)	(iii)	(iv)
$\log S^d$	0.084	0.078	0.065	0.095
	(4.571)**	(4.533)**	(4.199)**	(5.715)**
$G7 \cdot \log S^d$		0.131	0.163	
		(3.653)**	(4.874)**	
$\log S^f$	0.125	0.090		
	(4.071)**	(3.1103)**		
$m \cdot \log S^f$			0.395	0.358
			(5.285)**	(4.153)*
R^2	0.558	0.622	0.641	0.551
$Adjusted R^2$	0.556	0.620	0.647	0.556

Note:

(a) Estimations are based on the pooled data from 1971-90 for 22 countries (440 observations). The dependent variable is log TFP. All regressions include unreported, country-specific constants. The bias-corrected t-ratios are reported in parentheses. * (**) denotes that the coefficient is significantly different from zero at a 10 percent (5 percent) level.

(b) S^d= domestic research and development capital stock, beginning of the year.

(c) S^f= foreign RD capital stock, beginning of the year.

(d) $G7$= dummy variable equal to 1 for the seven major countries and equal to 0 for the other 15 countries.

(e) m=ratio of imports of goods and services to GDP, both in the previous year.

Table 3: TFP Estimation Results Using FM estimator

	(i)	(ii)	(iii)	(iv)
$\log S^d$	0.084	0.077	0.072	0.100
	(4.372)**	(4.27)**	(4.451)**	(5.72)**
$G7 \cdot \log S^d$		0.127	0.156	
		(3.378)**	(4.449)**	
$\log S^f$	0.103	0.075		
	(3.184)**	(2.452)**		
$m \cdot \log S^f$			0.264	0.244
			(3.354)**	(2.696)*
R^2	0.506	0.574	0.581	0.494
$Adjusted R^2$	0.554	0.617	0.645	0.554

Note:

(a) Estimations are based on pooled data from 1971-90 for 22 countries (440 observations). The dependent variable is log TFP. All regressions include unreported, country-specific constants. The t-ratios are reported in parentheses. * (**) denotes that the coefficient is significantly different from zero at a 10 percent (5 percent) level.

(b) S^d= domestic research and development capital stock, beginning of the year.

(c) S^f= foreign RD capital stock, beginning of the year.

(d) $G7$= dummy variable equal to 1 for the seven major countries and equal to 0 for the other 15 countries.

(e) m=ratio of imports of goods and services to GDP, both in the previous year.

Table 4: TFP Estimation Results Using DOLS Estimator

	(i)	(ii)	(iii)	(iv)
$\log S^d$	0.107	0.091	0.091	0.124
	(4.672)**	(4.248)**	(4.705)**	(5.957)**
$G7 \cdot \log S^d$		0.116	0.135	
		(2.597)**	(3.221)**	
$\log S^f$	0.056	0.044		
	(1.450)	(1.215)		
$m \cdot \log S^f$			0.145	0.068
			(1.555)	(0.633)
R^2	0.511	0.572	0.579	0.502
$Adjusted R^2$	0.305	0.378	0.393	0.295

Note:

(a) Estimations are based on the pooled data 1971-90 for 22 countries with 1 lead and 2 lags of first differenced independent variables, 440 observations. The dependent variable is log TFP. All regressions include unreported, country-specific constants. The t-ratios are reported in parentheses. * (**) denotes that the coefficient is significantly different from zero at a 10 percent (5 percent) level.

(b) S^d= domestic research and development capital stock, beginning of the year.

(c) S^f= foreign RD capital stock, beginning of the year.

(d) $G7$= dummy variable equal to 1 for the seven major countries and equal to 0 for the other 15 countries.

(e) m=ratio of imports of goods and services to GDP, both in the previous year.

Table 5: Country-Specific, Time-Varying Estimates of the Impact of Foreign Research and Development Capital Stocks on TFP Using FM Estimators: Based on Regression (iii) in Table 3

	1971	1980	1990
United States	0.015	0.027	0.030
Japan	0.025	0.033	0.024
West Germany	0.051	0.064	0.069
France	0.040	0.054	0.060
Italy	0.041	0.060	0.052
United Kingdom	0.057	0.072	0.073
Canada	0.053	0.070	0.067
Australia	0.039	0.044	0.049
Austria	0.081	0.095	0.103
Belgium	0.116	0.162	0.233
Denmark	0.082	0.085	0.082
Finland	0.071	0.079	0.067
Greece	0.045	0.056	0.085
Ireland	0.111	0.161	0.148
Israel	0.132	0.139	0.137
Netherlands	0.119	0.131	0.142
New Zealand	0.067	0.077	0.060
Norway	0.120	0.112	0.099
Portugal	0.089	0.105	0.118
Spain	0.039	0.039	0.056
Sweden	0.060	0.078	0.083
Switzerland	0.103	0.095	0.101

Table 6: Country-Specific, Time-Varying Estimates of the Impact of Foreign Research and Development Capital Stocks on TFP Using DOLS Estimators: Based on Regresion (iii) in Table 4

	1971	1980	1990
United States	0.008	0.015	0.016
Japan	0.014	0.018	0.013
West Germany	0.028	0.035	0.038
France	0.022	0.030	0.033
Italy	0.023	0.033	0.028
United Kingdom	0.031	0.040	0.040
Canada	0.029	0.039	0.037
Australia	0.021	0.024	0.027
Austria	0.045	0.052	0.057
Belgium	0.064	0.089	0.128
Denmark	0.045	0.047	0.045
Finland	0.039	0.043	0.037
Greece	0.025	0.031	0.047
Ireland	0.061	0.089	0.082
Israel	0.073	0.076	0.076
Netherlands	0.066	0.072	0.078
New Zealand	0.037	0.043	0.033
Norway	0.066	0.061	0.055
Portugal	0.049	0.058	0.065
Spain	0.021	0.021	0.031
Sweden	0.033	0.043	0.046
Switzerland	0.057	0.052	0.056

Table 7: Elasticiities of TFP with Respect to Research and Development Capital Stocks in G7 Countries in 1990 Using Fully Modified Estimators: Based on Regression (iii) in Table 3

	U.S.	Japan	Germany	France	Italy	U.K.	Canada
United States	...	0.0196	0.0035	0.0012	0.0005	0.0022	0.0022
Japan	0.0228	...	0.0007	0.0003	0.0001	0.0003	0.0001
West Germany	0.0417	0.0087	...	0.0073	0.0022	0.0054	0.0001
France	0.0331	0.0044	0.0140	...	0.0022	0.0044	0.0001
Italy	0.0228	0.0024	0.0149	0.0068	...	0.0029	0.0001
United Kingdom	0.0475	0.0062	0.0117	0.0042	0.0010	...	0.0002
Canada	0.0643	0.0017	0.0005	0.0002	0.0001	0.0005	...
Australia	0.0367	0.0082	0.0017	0.0004	0.0002	0.0016	0.0001
Austria	0.0270	0.0092	0.0548	0.0036	0.0030	0.0027	0.0001
Belgium	0.0834	0.0104	0.0728	0.0304	0.0035	0.0206	0.0004
Denmark	0.0403	0.0056	0.0224	0.0033	0.0011	0.0059	0.0001
Finland	0.0320	0.0092	0.0148	0.0024	0.0011	0.0047	0.0001
Greece	0.0260	0.0124	0.0258	0.0058	0.0051	0.0063	0.0001
Ireland	0.0926	0.0084	0.0085	0.0026	0.0007	0.0339	0.0001
Israel	0.1066	0.0040	0.0109	0.0027	0.0015	0.0074	0.0001
Netherlands	0.0746	0.0067	0.0386	0.0075	0.0014	0.0101	0.0002
New Zealand	0.0415	0.0117	0.0018	0.0004	0.0002	0.0032	0.0002
Norway	0.0577	0.0075	0.0166	0.0029	0.0010	0.0086	0.0005
Portugal	0.0486	0.0084	0.0264	0.0140	0.0044	0.0115	0.0003
Spain	0.0321	0.0042	0.0088	0.0054	0.0016	0.0033	0.0001
Sweden	0.0445	0.0082	0.0183	0.0032	0.0010	0.0062	0.0001
Switzerland	0.0406	0.0072	0.0359	0.0077	0.0029	0.0051	0.0001
Average elasticity of foreign TFP	0.0379	0.0124	0.0081	0.0029	0.0009	0.0030	0.0010

Table 8: Elasticiities of TFP with Respect to Research and Development Capital Stocks in G7 Countries in 1990 Using Dynamic OLS Estimators: Based on Regression (iii) in Table 4

	U.S.	Japan	Germany	France	Italy	U.K.	Canada
United States	...	0.0108	0.0019	0.0007	0.0003	0.0012	0.0012
Japan	0.0126	...	0.0004	0.0002	0.0001	0.0002	0.0001
West Germany	0.0230	0.0048	...	0.0040	0.0012	0.0030	0.0001
France	0.0182	0.0024	0.0077	...	0.0012	0.0024	0.0001
Italy	0.0126	0.0013	0.0082	0.0038	...	0.0016	0.0001
United Kingdom	0.0262	0.0034	0.0065	0.0023	0.0006	...	0.0001
Canada	0.0354	0.0010	0.0003	0.0001	0.0001	0.0003	...
Australia	0.0202	0.0045	0.0010	0.0002	0.0001	0.0009	0.0001
Austria	0.0149	0.0051	0.0302	0.0020	0.0016	0.0015	0.0001
Belgium	0.0459	0.0057	0.0401	0.0168	0.0019	0.0114	0.0002
Denmark	0.0222	0.0031	0.0124	0.0018	0.0006	0.0033	0.0001
Finland	0.0176	0.0051	0.0081	0.0013	0.0006	0.0026	0.0001
Greece	0.0143	0.0068	0.0142	0.0032	0.0028	0.0035	0.0001
Ireland	0.0510	0.0046	0.0047	0.0014	0.0004	0.0187	0.0001
Israel	0.0587	0.0022	0.0060	0.0015	0.0009	0.0041	0.0001
Netherlands	0.0411	0.0037	0.0212	0.0041	0.0008	0.0056	0.0001
New Zealand	0.0228	0.0064	0.0010	0.0002	0.0001	0.0018	0.0001
Norway	0.0318	0.0041	0.0091	0.0016	0.0006	0.0047	0.0003
Portugal	0.0268	0.0046	0.0145	0.0077	0.0024	0.0063	0.0002
Spain	0.0177	0.0023	0.0049	0.0030	0.0009	0.0018	0.0001
Sweden	0.0245	0.0045	0.0101	0.0018	0.0005	0.0034	0.0001
Switzerland	0.0224	0.0040	0.0198	0.0042	0.0016	0.0028	0.0001
Average elasticity of foreign TFP	0.0209	0.0068	0.0045	0.0016	0.0005	0.0016	0.0006

Table 9: Rates of Return on Investment in Research and Development in 1990 Using FM Estimator: Based on Regression (iii) in Table 3

Average own return of research and development investment	
in G7 countries	1.20
in the remaining 15 OECD countries	0.79
worldwide	1.17
Average worldwide return of reseach and development investment in G7 countries	1.49

Table 10: Rates of Return on Investment in Research and Development in 1990 Using DOLS Estimator: Based on Regression (iii) in Table 4

Average own return of research and development investment	
in G7 countries	1.18
in the remaining 15 OECD countries	0.99
worldwide	1.17
Average worldwide return of reseach and development investment in G7 countries	1.34