International R&D Spillovers and Productivity Growth in the Agricultural Sector. A Panel Cointegration Approach

by

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Contributed paper selected for presentation at the 25th International Conference of Agricultural Economists, August 16-22, 2003, Durban, South Africa

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Abstract

This paper analyses, within the new growth theory framework and using panel cointegration techniques, the effect of agricultural international technological spillovers on total factor productivity growth for a sample of 47 countries during the period 1970-1992. The analysis shows that total factor productivity is influenced by domestic as well as foreign public R&D spending in agricultural sector and geographical factors matters. Countries located in temperate zones benefit more than countries located in tropical zones from technological spillovers. Finally, the analysis shows that the rate of return to agricultural R&D spending is higher in tropical countries and this could justify new support and an even greater investment of funds for agricultural R&D for these countries.

Key words **:** Technology spillover, agricultural productivity, panel cointegration.

JEL classification: C14, O30, Q16.

1. Introduction

Much research has been done in recent years to assess the importance of research and development (R&D) and trade in influencing output growth and total factor productivity. There is now a large body of literature that provide theoretical as well as empirical models where cumulative R&D is the main engine of technological progress and productivity growth (see Aghion and Howitt (1998), Grossman and Helpman (1991) and Romer (1990)). The empirical evidence has been provided by Coe and Helpman's (1995) seminal contribution where they find that accumulated spending on R&D by a country and by its trade partners helps to explain the growth of total factor productivity.

R&D investments are still central to agricultural productivity growth. Alston *et al.* (1999) in the introduction of their recent book on the theme underline that "Throughout the twentieth century improvements in agricultural productivity have been closely linked to investments in agricultural R&D and to policies that affect agricultural R&D".

Given the importance of agricultural R&D to the growth of the sector, many works have been devoted to reporting measures of the returns to domestic agricultural R&D (see recently Esposti (2000) and for a survey Alston *et al.* (2000)). But in a world where the international trade of agricultural products and the dissemination of knowledge are widespread, domestic agricultural productivity depends not only on domestic R&D but also on foreign R&D efforts. This point has been fully recognised, among others, by Hayami and Ruttan (1985) where they emphasise that a country can acquire substantial gains in agricultural productivity by borrowing advanced technology which exists in other countries.

Recent works by Evenson and Singh (1997), Schimmelpfennig and Thirtle (1999) and Johnson and Evenson (1999) analyse the effects of international public and/or private agricultural R&D on domestic agricultural productivity growth. They find, firstly, the presence of strong international spillovers in the agricultural sector and secondly that, without recognising knowledge spillovers, researchers will end up with biased estimates of R&D elasticities. In addition, as underlined in Alston and Pardey (2001), without recognizing the effect of international spillovers researchers "will overstate own-state research for state-level productivity growth and, thus, state-specific rates of return to research will be overstated".

However, the international transfer of agricultural technology is more difficult than that of industrial technology, Hayami (1997), Hayami and Ruttan (1985) and Sachs (2001). Modern agricultural technology has mainly been improved in developed countries located in temperate zones. Thus, without appropriate adaptive research which helps to assimilate and exploit externally available information, countries located in other ecological zones, for example tropical zones, may not benefit from technological spillovers.

In the next section, because the analysis of the links that connect the total factor productivity and the cumulative spending on R&D represents the point of departure in this paper, we will briefly review the theoretical underpinning.

In the third section, we introduce and review the recent results on estimation and inference in panel cointegration. As is well known, cointegrating regression enables us to exploit the relationship among the variables in levels without transforming the data, such as by differencing, to avoid spurious regression problems.

In section four, we provide three different estimates for total factor productivity. First, we use panel cointegration techniques to estimate a simple Cobb-Douglas production function for a sample of 47 countries during the period 1970-1992 by using panel cointegration. We also split the sample and estimate two production functions, one for the countries in the sample located in temperate zones, and one for the countries in the sample located in tropical zones. The assumption of constancy of factor elasticities may be too restrictive. For this reason we estimate total factor productivity from a translog production function. Finally, in order to compare the previous parametric estimates with non parametric estimates, we provide the Malmquist index computed by data envelopment analysis.

Using these estimates and following Coe and Helpman's (1995) empirical model, we adopt panel cointegrating techniques to estimate the relationship between total factor productivity and domestic as well as foreign public R&D capital stocks. We calculate the effect of a change in public R&D spending in a country on the change of total factor productivity in that country as well as in partner countries. Some evidence for a sample of OCDE countries on the effect of total agricultural R&D expenditures (which includes private expenditures) on total factor productivity follows. Summarising, we find that domestic R&D as well as foreign R&D influences total factor productivity. International spillovers of agricultural R&D are higher for countries located in temperate zones than tropical countries. Secondly, the rate of return on agricultural R&D investments is higher in tropical countries. Finally, section five concludes.

2. Theoretical Framework

As is well known, by contrast with the neoclassical growth model, where per capita output or productivity only grows in the long run because of exogenous technological progress, endogenous growth theory, initiated by Romer (1990) and extended by Grossman and Helpman (1991) and Aghion and Howitt (1992) explains long-term growth as resulting from innovation efforts. Endogenous models assume that output is a function of a bundle of horizontally or vertically differentiated intermediate inputs (see chap. 3 and 4). In the first case, horizontally differentiated inputs, they show, under simple hypothesis, that total factor productivity is a function of the number of intermediate inputs used in the production process. If they expand as a result of R&D investment, cumulative spending on domestic R&D can explain a large fraction of the total factor productivity variations within and between countries. The same approach is used when analysing vertically differentiated inputs. In this case, total factor productivity is a function of the quality of intermediate inputs. As before, if quality is a function of cumulative R&D spending Grossman and Helpman postulate a second channel which links domestic R&D spending to total factor productivity.

Recent developments in the theory of international trade and economic growth have, in addition, identified a number of channels through which a country's external relationships might affect its productivity performance. Grossman and Helpman (1991, Ch. 9) identify four distinct channels. First, international trade opens channels of communication that facilitate the transmission of technical information. This helps the spread of new production methods and the employment of domestic resources more efficiently. Second, trade reduces duplication of research by encouraging producers in each country to pursue new and distinctive ideas and technologies. Third, international trade enlarges the size of the market which influences the incentives to innovate. Finally, when countries' research experience differ, or when the composition of their endowment bundles differ, international trade induces patterns of specialisation that has implications for productivity growth in each of the trading partners. Thus, total factor productivity can be influenced not only by the domestic R&D spending but also by the foreign R&D spending of a country's trade partners.

However, international transfer of agricultural technology is not easy. The sector is strongly constrained by geographical conditions and consequently it is difficult, without adaptive research, to transfer advanced technologies developed in the temperate zones to the tropical zones. This issue is well known in economic literature. Hayami and Ruttan (1985, pg. 255) highlight that "Less developed countries can acquire substantial gains in agricultural productivity by borrowing advanced technology existing in developed countries…. (but) the direct transfer of agricultural technology from other agro-climatic regions have been largely unsuccessful". Recent works by Hayami (1997), Johnson and Evenson (2000), Sachs (2001) and Gutierrez (2002) analyse this point. In the empirical section, we will address these issues by using Coe and Helpman's (1995) empirical model for a sample of 47 countries.

3. Panel unit roots and cointegration: theoretical background.

Several studies have examined whether the time series behaviour of economic variables is consistent with a unit root (see for a survey Diebold and Nerlove, 1990; Campbell and Perron 1991). In general, the analysis has been carried out by using tests such as the augmented Dickey-Fuller's (ADF) (Dickey and Fuller, 1981) test or semi-parametric tests, as in the case of Phillips-Perron tests (Phillips and Perron, 1988). The main problem here is that, in finite sample, any unit roots process can be approximated by a trend-stationary process. For example, the simple difference stationary process $y_t = fy_{t-1} + e_t$ with $f = 1$ can be arbitrarily well approximated by a stationary process with f less than but close to one. The result is that unit root test statistics have limited power against the alternative. Campbell and Perron (1991) show that when 100 observations are generated by a stationary process but with a root close to unity, then the unit root tests have very little power. They compare the case $f = 1$ with the stationary case $f = 0.98$ and find that the rejection rate is no more that 1% greater for the stationary case than for the unit root case.

Recently, starting from the seminal works of Quah (1990, 1994), Breitung and Meyer (1991) and Levin and Lin (1992, 1993), many tests have been proposed which attempt to introduce unit root tests in panel data. They show that combining the time series information with that from the cross-section, the inference about the existence of unit roots can be made more straightforward and precise, especially when the time series dimension of the data is not very long and similar data may be obtained across a cross-section of units such as countries or industries. A second advantage when using panel unit root tests is that, whereas many of the estimators and statistics for unit root processes in time series are complicated distributions of Wiener processes, the former estimators are normally distributed. This result is still robust when heterogeneity is introduced across the units comprising the panel.

The problem now is that we need new multivariate central limit theorems in order to analyse the asymptotic properties of estimators and tests. Recently, Phillips and Moon (1999a) have presented the formal and general treatment of the asymptotic behaviour of a double indexed integrated process. The limit of the process may depend on which index, N (the units) or T (the time), tend to infinity. We can fix N and allow T to tend to infinity and then pass N to infinity or permit T and N to tend to infinity at a given controlled rate. For example, Levin and Lin (1992, 1993) show that their panel unit root statistics have limiting normal distributions as N and T tend to infinity with $N/T \to 0$ and Im *et al.* (1997) propose a set of normally distributed test statistics for N and T sufficiently large and $N/T \to k$, where k is a positive constant. In the following, we shall present a short review of the Levin-Lin tests and their extension by Im *et al.* (1997) which have been used in the empirical literature on panel unit root tests and will be proposed in the empirical section.

3.1 The Levin–Lin and Im, Pesaran and Shin unit root tests. [1]

Levin and Lin (1993), (LL), consider a sample of N cross-sections observed over T time periods. They suppose that the stochastic process $\{y_{it}\}$ for i=1,…,N and t=1,…,T can be generated by one of the following three models:

model 1: $\Delta y_{it} = b_i y_{it-1} + e_{it}$

model 2: $\Delta y_{it} = a_i + b_i y_{it-1} + e_{it}$

model 3: $\Delta y_{it} = a_i + dt + b_i y_{it-1} + e_{it}$,

where $\Delta y_{it} \equiv y_{it} - y_{it-1}$ follows a stationary ARMA process for each cross-section unit and e_{it} are independently and identically distributed both across i and t with finite variance. If we consider model 1, the null hypothesis of unit roots can be expressed as

$$\mathrm{H}_0 : b_i = 0 \text{ for all } i, \tag{1.1}$$

against the alternatives,

$$\mathrm{H}_A : b_i = b < 0 \text{ for all } i. \tag{1.2}$$

Note from (1.1) and (1.2) that LL tests require b to be homogenous across *i*. This means to test the null hypothesis that all series in the panel are generated by a unit root process against the alternative that each of the series are stationary with a common b .

It is useful to underline here that, as for the univariate process, when a deterministic component is present in the observed data but it is not included in the regression procedure, the unit root test will be inconsistent, and when included in the regression analysis but not present in the observed data, the statistical power of the unit root test will be reduced. LL procedure to test panel unit roots is presented in Levin and Lin (1993, pg. 8-14) and they show that the test has a standard normal limiting distribution.

Im, Pesaran and Shin (1997) (IPS) introduce t-statistics for unit roots in panel where the alternative hypothesis allows for b_i to differ across groups. Then the hypothesis of unit roots becomes

$$\mathrm{H}_0 : b_i = 0 \text{ for all } i, \tag{2.1}$$

against the alternatives,

$$\mathrm{H}_\mathrm{A} : b_i < 0 \;\; i = 1,2,\ldots,N_1, \;\; b_i = 0, \;\; i = N_1 + 1, N_1 + 2, \ldots, N. \tag{2.2}$$

They show in the paper that both their t-statistics have a standard normal distribution.

Note that the null hypothesis in both panel unit root tests is that each series in the panel contains a unit root, and thus is difference stationary. The alternative hypothesis is specified differently. In the LL approach the alternative is that *all* individual series in the panel are stationary (see 1.2). In IPS the alternative is that *at least one* of the individual series in the panel is stationary (see 2.2). The presence or absence of power against alternatives, where a subset of the series are stationary, can have serious implications for the empirical work. If the test has low power it may be erroneously concluded that the panel contains a common unit root even if a majority of series are stationary. To investigate this issue, Karlsson and Löthgren's (2000) analyse by Monte Carlo simulations the power properties of LL and IPS tests when a subset of the equations are stationary and the remainder have unit roots. They show that the power increases when the number of stationary equations rise and the IPS test is more powerful than the LL test for all subsets of stationary equations in the panel. The power of panel unit root tests is higher than unit root tests for the univariate case, where for small-T the power of the tests is approximately equal to the size. Similar results have been extended to panel cointegration tests by Gutierrez (2003).

In conclusion, panel unit roots or panel cointegration tests have higher power than univariate unit root tests, especially for small-T dimension. Nevertheless, when using panel data the researcher can model all the series as non-stationary even if only a fraction of the series are actually non-stationary and vice versa. Thus a substantial amount of simulation work is necessary to establish systematically the effect on cointegration tests and slope parameters of erroneously modelling as non-stationary some series, or non-cointegrated some relationships. However some results have already been produced. For example it has been shown that, by contrast with the pure time series case, in spurious panel regression slope estimators are consistent but the *t*-statistics diverge. These results will be presented in the following section.

3.2 Panel cointegration tests.

One difficulty that can arise when regressing two non-stationary series is the problem of *spurious regression*: when using two unrelated integrated series, regressing one on the other tend to produce a not consistent but apparently significant structural coefficient, Granger and Newbold (1974).

By contrast with the pure time series spurious regression, in the case of non-stationary panel data, Phillips and Moon (1999a) show that for the spurious panel regression, and under quite weak regularity conditions, the pooled least squares estimator of the structural coefficient is consistent and has a limiting normal distribution. The reason is that independent cross-section data in the panels introduce information and this leads to a stronger signal than the pure time series case. The problem here is that while the structural parameters that link the variables converge to the true values, their t-statistics diverge, so inferences are wrong with probability that goes to one asymptotically, Kao *et al.* (1999).

In the empirical analysis we will use two sets of cointegration tests. The first set of tests have been proposed by Kao *et al.* (1999), and can be seen as a generalisation of the Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests in the context of panel data. The second set of tests used have been proposed by Pedroni (1995, 1999).

All the tests consist of taking the hypothesis of no cointegration as null and using the residuals derived from a panel static regression to construct the test statistics and tabulate the distributions. After appropriate standardisation, all tests have asymptotic distributions that converge to a standard normal distribution.

4. Empirical Results.

4.1 Total factor productivity estimation.

The purpose now is to provide some basic estimate of total factor productivity in agriculture in a relatively wide range of countries using the methodology presented in the previous section. We first follow a simple and widely used approach where total factor productivity is computed as

$$TFP_{i,t} = Y_{i,t} / \left(K_{i,t}^{a} L_{i,t}^{b} T_{i,t}^{d} \right), \tag{3}$$

where $Y_{i,t}$ is the value added in the agricultural sector for country i in time period t, $K_{i,t}$ is the capital stock, $L_{i,t}$ is the quantity of labour, $T_{i,t}$ is the quantity of land, a , b and d are respectively the elasticity of capital, labour and land with respect to value added and $TFP_{i,t}$ is the total factor productivity variable. Naturally we have that when $a+b+d=1$ the production function shows constant returns to scale (which later will be tested) and constancy of factor elasticities across countries and over time. The assumption of constant returns has recently received empirical support from Mundlak *et al.* (1997) and has extensively been used by Bernard and Jones (1996) when testing for productivity convergence between countries and sectors and Gutierrez (1999, 2000) for EU and US agricultural sectors. In any case, the assumption of constancy of factor elasticities may be too restrictive. We first try to correct for this problem by estimating a, b and d for two different sets of countries, in our case countries located in temperate and tropical zones. Secondly, we estimate a translog production function and test for constant returns to scale. In this case, total factor productivity has been calculated as

$$\Delta \ln\left(TFP_{i,t}\right) = \Delta \ln Y_{i,t} - \overline{v}_{K,i\,t}\Delta \ln\left(K_{i,t}\right) - \overline{v}_{L\,i\,t}\Delta \ln\left(L_{i,t}\right) - \overline{v}_{T\,i\,t}\Delta \ln\left(T_{i,t}\right) \tag{4}$$

where $\overline{v}_{s,it} = 0.5\left(v_{s\,i\,t} + v_{s,it-1}\right)$ and $v_{s,it}$ is the factor share for input *s*, in country *i* at the time *t*.

Finally, since we have panel data, we use data envelopment analysis to compute the Malmquist total factor productivity change index. The aim here is to be able to compare parametric with non parametric estimates of total factor productivity. Following Färe *et al*. (1994), Malmquist total factor productivity change index (MTFP) is defined as

$$MTFP_{i,t} = \left[\frac{d_i^t\left(x_{t+1}, y_{t+1}\right)}{d_i^t\left(x_t, y_t\right)} \frac{d_i^{t+1}\left(x_{t+1}, y_{t+1}\right)}{d_i^{t+1}\left(x_t, y_t\right)}\right]^{1/2} \tag{5}$$

where $d_i^t\left(x_t, y_t\right)$ indicates the distance function for country i at the time t is function of the bundle of inputs x_t and output y_t.

Subsequent levels of total factor productivity variables are constructed by cumulating growth rates calculated by (4) and (5).

In brief, the data for output comes from the World Bank and are given by the gross value added in the agricultural sector. Fixed capital stock measures were kindly supplied by Donald Larson and referenced in Crego et al. (1997). Both variables, originally expressed in current local currency units, were deflated to base year 1985 using agricultural deflator provided by Crego et al. (1997) and then converted to 1985 international dollars by using the corresponding purchase power parity index reported in Penn World Table (Mark 5.6a). Hectares of arable and permanent cropland are used for land input and labour is given by the economically active population in agriculture. Both variables come from the FAO data set. The availability of data determined which countries were included in the study and details about data sources and the construction of the variables are provided in the appendix.

We do not correct for the effects of quality changes of capital, labour and land inputs on total factor productivity. Adjusting labour input for shifting from unskilled to more skilled workers, where the latter have a higher productivity, or capital services for improvements, for example in the horsepower of tractors, can result in a lower estimated productivity growth rate. However in the absence of information, especially on capital services, we do not correct productivity measurement for input quality changes and leave these important issues to further research.

We start the analysis determining whether the logarithm of the variables included in (3) is stationary or non-stationary, i.e. whether the series contain unit roots. We use the Im, Pesaran and Shin (1997) (IPS) tests and the Levin and Lin (1993) (LL) tests presented in the previous section. The results are reported in Table 1.

Table 1 about here

LL tests are one-sided tests from a N(0,1) distribution, thus a statistic less than -1.65 or -2.33 would case rejection respectively at 5 percent and 1 percent of the null hypothesis of non-stationarity. Im *et al.* (1997) provide exact sample critical values. Null hypothesis will be rejected for a panel of N=50 and T=25, when IPS statistic is less than –1.73 or –1.82 (5% and 1% critical values respectively) for ADF regressions that contain only an intercept and -2.37 or –2.45 for ADF regressions that contain an intercept and a linear trend.

Looking at Table 1, we note that for all variables, with one exception, both tests fail to reject the null of non-stationarity. The exception is the fixed capital variable. In this case, only IPS test when a constant is included in the process, rejects the null of non-stationarity. From these results, we assume that all the variables are non-stationary variables and we proceed by estimating the production function and testing for cointegration. Note that in Table 1 are presented tests for unit roots for the three total factor productivity variables estimated and for domestic and foreign R&D expenditure which will be used in the analysis. Also in these cases, all tests reject the null of non-stationarity.

We can now re-write equation (3) in logarithm and compute the factor elasticity estimates for the full sample of countries and for a subset of twenty-five countries located in temperate area and twenty-two countries located in tropical area. We decide whether to include a country in the tropical or temperate subset depending on whether more than 50% of land area is located inside or outside the tropics. The results are presented in Table 2.

The asymptotic properties of the estimators and associated statistical tests in cointegrated panel models are quite different from those of the time series regression models. Kao and Chiang (1995) and Chen, McCoskey and Kao (1999) show that the OLS estimator is asymptotically normal but asymptotically biased and propose a method to correct the estimates. [2] Secondly, they found that different estimators based on fully modified (FM) estimator or dynamic OLS (DOLS) estimator can be more promising in cointegrated panel regressions. The first estimator is a panel generalisation of the Phillips and Hansen (1990) time series estimator and has been proposed for the first time by Pedroni (1995). The second one has been used in Kao, Chiang and Chen (1999) and was built as panel generalisation of the Stock and Watson (1993) time series estimator. In Table 2 we present biased-corrected OLS, FM and DOLS estimates. [3] Finally, Phillips and Moon (1999b, pg.12) suggest detrending variables in order to obtain consistent estimation of long-run average estimates, so that all our variables have been previously detrended using OLS regression.

Following these results, in Table 2 each column reports the factor price elasticities obtained from the bias-corrected OLS estimator, FM estimator and finally DOLS estimator. All the estimates have been carried out under the assumption of homogeneous long-run covariance across cross-sectional units.

Table 2 about here

Many interesting results emerge from Table 2. The production elasticities and their levels of statistical significance are satisfactory and the three methods provide quite similar results. Capital elasticities are generally higher than labour and land estimates both for the total sample of countries as well as for the sample of temperate and tropical countries. The two subsets of countries seem to have the same values for capital elasticities but show differences when comparing labour and land elasticities. Table 2 reports an higher value for labour elasticity and a lower value for land elasticity in temperate countries. Looking at the elasticities for the total sample of countries it is interesting to note that their sum is near one, revealing the possible presence of constant returns to scale. We tested the null hypothesis of constant returns to scale by using the Wald test proposed in Kao and Chiang (1995).[4] They show that in cointegrated panel regressions, the test, when FM and DOLS methods are used, converges in distribution to a chi-squared random variable with m degrees of freedom, where m is the total number of restrictions, in our case one. The test statistics do not reject the null hypothesis of constant returns to scale for the total sample of countries and for the subsets of tropical countries. Evidence of increasing return to scale is testified to by the Wald statistics for the sample of temperate countries when using FM and DOLS method. Finding increasing return of scale in the agricultural sector is not new. Griliches (1963) reports increasing return in cross-regions analysis for the United States. Hayami and Ruttan (1985) provides evidence of increasing returns for a sample of developed countries and they find that for a sample of less developed countries the sum of conventional input coefficients is not significantly different from one. This finding may support our results. The sample of countries located in temperate zones is mainly constituted by developed countries whereas many countries which we label tropical countries are defined by the

World Bank as less developed countries. Thus, we use equation (3) to estimate total factor productivity and applying the two different sets of estimated elasticities to factor inputs for countries located in temperate zones and countries located in tropical zones.

As is well known, a Cobb-Douglas production function implies strong restrictions on factor input elasticities. Thus we estimate a physical production function which expresses the logarithm of output as a generalized quadratic function of the logarithm of the inputs, i.e. we estimate a translog production function. [5] It is important to note, especially when analysing unit roots processes, that a translog production function requires a nonlinear, square, transformation of, in our case, integrated I(1) variables. We test the square of factor inputs for unit roots, as well as the series resulting from the product of factor inputs. All the tests, not reported for brevity, do not reject the null of unit roots. Nonetheless, it is useful to note that, in the context of time series analysis, Granger and Hallman (1988) show that while some properties of I(1) process still remain after transformation, heteroskedasticity usually arises, reducing the power of unit root tests.

Table 3 contains the results when the translog production function is estimated by using OLS corrected, FM and Dynamic Ordinary Least Squares methods. Note that, by contrast with factor input levels, the estimates related to square and product variables are not significant. As before, we report in the table the Wald tests on the null hypothesis of constant returns to scale and their p-values.

Table 3 about here

Here, FM estimates do not reject the null of constant returns but DOLS estimates strongly reject the null hypothesis.

Finally, we have to analyse the cointegration test statistics. We do not report their values for brevity, but is worth mentioning that all the test statistics, with one exception, reject the null hypothesis of non cointegration. The exception is given by the test statistics for tropical countries. Here the null of non cointegration is not rejected by Kao et al.'s (1999) tests. As previously stated, total factor productivity for the Cobb-Douglas specification has been estimated by using different values for input elasticities. Specifically, we use the elasticity values reported in Table 2 for countries located in temperate and tropical zones. Thus, when finding that total factor productivity estimated from Cobb-Douglas production function show unit roots (see Table 1), we infer that this result could be attributable to the absence of cointegration in the regression for the countries located in tropical zones.[6] As previously stated, panel estimates are still unbiased when the variables are not cointegrated but t-statistics have to be read with care.

In order to compare our results with some previous ones, in Table 4 we collect factor input elasticities obtained from Cobb-Douglas and translog production functions when using DOLS estimation and four previous attempts to estimate intercountry production functions. All the estimates have been scaled by their sums in order to obtain comparable values and translog factor input elasticities are equal to the average for all countries and time.

Table 4 about here

Looking at the table, it emerges that capital elasticity estimates are usually higher than the labour or land elasticities. Only Mundlak *et al.* (1997) propose a land elasticity estimate higher than labour elasticity. Finally, our Cobb-Douglas labour estimate is halfway between the highest value of 0.45 proposed by Hayami and Ruttan (1985) and the lowest value of 0.09 proposed by Mundlak *et al.* (1987). While labour translog and Cobb-Douglas estimates are quite similar, a lower (higher) value for capital (land) estimate is showed by translog specification relatively to Cobb-Douglas specification.

As previously seen, we calculate the Malmquist index by using data envelopment analysis (DEA). As is well known, DEA involves the use of linear programming methods to construct a non-parametric piecewise frontier over the data. In this case we are able to calculate productivity change and decompose it into technical change and technical efficiency change. [7]

In Table 5, we compare the dynamics of the three estimated TFP indexes during the period 1970-1992.

Table 5 about here

In the first row the unweighted annual average TFP growth of rates during the period 1970-1992 are presented. We note first that all the indexes show a higher growth rates for the countries located in tropical zones and secondly that while TFP indexes estimated from the Cobb-Douglas specification and Malmquist index present similar values, and that TFP productivity estimated from the translog specification shows lower values and a negative annual average growth rate for the countries located in temperate zones. These results can mainly be attributed to the different factor shares used in the Cobb-Douglas specification to calculate TFP productivity for temperate and tropical countries by comparison with the same factor elasticities, which vary smoothly during the period, used in the translog specification. Thus, given that the Malmquist index shows similar aggregate dynamics to the Cobb-Douglas specification, one can infer that it takes differences in the factor shares in the two climate zones into account. In the table we report the average annual growth rate for public R&D expenditure during the period for the two subsets of countries and for the total sample of countries. Agricultural public R&D investments have grown more, on average, in countries located in tropical zones than countries located in temperate zones, but at the same time it is important to note that the aggregate data masks more variation of the annual average growth rates among tropical countries than temperate countries.

4.2 International R&D spillovers and productivity growth in agricultural sector.

The panel cointegration approach can be usefully used in estimating the long-run relationship between total factor productivity and the domestic and foreign R&D capital stocks. The aim of the section is twofold. First, we estimate the effects of a rise in a country's R&D capital stock on the country's total factor productivity. As seen in the introductory section, this issue has been long debated in the literature as testified by the large number of works published on this theme, which are however mainly devoted to calculating the rates of return of agricultural R&D. Second, we are interested in analysing the effect of foreign R&D capital stock on total factor productivity in order to introduce new evidence on the effects of new technology from one country on its trade partners and between different climate zones. This point has been debated at length in literature. For example, Thirtle and Bottomley (1989, pg. 1082), studying the effect of public UK R&D on total factor productivity, recognised that "spillover of new technology from one jurisdiction to others is an even more insoluble problem".

In this section, extending Coe and Helpman's (1995) aggregate empirical model to the agricultural sector, we attempt to provide evidence on this issue. We find that foreign agricultural R&D capital stock has a strong effect on a country's total factor productivity. This effect is stronger for countries located in homogeneous climate zones. For example an increase of US agricultural R&D has a larger effect on countries located in temperate zones and less on tropical countries. Once more these results paint the agriculture sector as strongly constrained by environmental conditions where, by contrast with industrial sector, transferring technologies developed in the temperate zones to tropical zones is difficult.

As previously underlined, Coe and Helpman's (1995) empirical model provides a source for analysing the relationship between a country's own R&D as well as the R&D efforts of its trade partners and productivity growth. Using their model, we estimate the following log linear equation, i.e. the long-run equilibrium relationship between total factor productivity and public R&D capital stock in the agricultural sector: [8]

$$\log TFP_i = a_{0i} + a_d \log SRD_{di(t-1)} + a_f \left(m_{i(t-1)} \log SRD_{fi(t-1)} \right), \qquad (6)$$

where a_{0i} are country-specific constants that can differ across countries, SRD_{di} represents the domestic R&D capital stock of country *i,* and SRD_{fi} represents the foreign R&D capital stock.

Domestic capital stock is built following a perpetual inventory model,

$$SRD_{dt} = (1-d)SRD_{dt-1} + RD_{t-1}$$

where RD_t are the agricultural R&D expenditure at the time t and d is the depreciation rate. The starting value for SRD_{di} was calculated following Griliches (1980) as

$$SRD_{d0} = RD_0 / (d+g)$$

where g is the average annual logarithmic growth of R&D expenditure over the period of analysis.[9]

The reason why we use a perpetual inventory model, is connected to the need to absorb, in a single observation, a complex time-lag structure between current productivity and the flow of past R&D investments. Usually data are not sufficient to estimate the R&D time-lag structure accurately. Some econometric studies have found that more than 30 years may be necessary to approximate the right time-lag structure. The perpetual inventory model is a way of introducing an infinite time-lag structure in the regression, with decreasing weights applied to R&D investments made further in the past. Naturally bias can be introduced if we choose a low (high) depreciation rate that gives too much econometric weight to the recent (past) time-lags, but the interesting thing that emerges from the econometrics analysis is that, modifying the depreciation rate inside a range of [0.01-0.10], does not strongly alter the R&D elasticity estimates in equation (6).

The variable SRD_{fi} in (6), the foreign R&D capital stock, is defined as a weighted average of the domestic R&D capital stock of trade partners. Coe and Helpman (1995) use as weights the bilateral total import share provided by the IMF's *Direction of Trade*. Agricultural bilateral imports for our full sample of countries and period are unavailable. So we define foreign R&D capital stock in country i as the bilateral total import-share-weighted average of agricultural domestic R&D capital stock of the remaining $i-1$ countries.[10]

In equation (6) the log of foreign R&D is multiplied by the variable m_i, which in this case stands for the fraction of agricultural imports relative to agricultural GDP for country *i*. The hypothesis is that the country where agricultural imports are higher relative to its GDP may benefit more from foreign R&D. Therefore, the composite variable $m_i \log SRD_{fi}$ can account for the interaction between foreign agricultural R&D capital stocks and the international level of agricultural trade. Finally all variables TFP, SRD_{di}, and SRD_{fi} have been indexed to 1985=1.

Table 6 reports the FM, DOLS pooled cointegrating estimates, i.e. long-run equilibrium estimates, based on equation (6) when total factor productivity is computed from a Cobb-Douglas production function specification, a translog production function specification and the Malmquist index computed by DEA.

Table 6 about here

When TFP from Cobb-Douglas and DEA are used, the slope estimates have the expected sign, are significant, and, moreover, have similar values. In this case the long-run estimated elasticities of TFP with respect to domestic R&D capital stock vary inside a range of [0.25-0.28]. When a translog production function is used to compute TFP, slope estimates are still positively related to domestic R&D capital stock but their values are lower when compared to previous estimates and, moreover, DOLS estimates are not significant.

Similar results have been obtained for foreign R&D capital stock estimates. In the case of the Cobb-Douglas and DEA specification, the variable has a strong effect. The elasticity values range inside [0.60-0.64]. When TFP from a translog production function is used, foreign R&D capital stock shows a lower impact on TFP and the estimates are not significant.

Note that in all cases the model explains more than 45 per cent of the variance of the 1081 observations. Finally, in the second section of Table 6 the values of the cointegration test statistics are reported. All statistics strongly reject the null of no cointegration.

Before describing the impact of domestic and foreign R&D expenditure on countries located in temperate and tropical zones, it is useful to analyse and compute a robustness test proposed by Keller (1998). He noted that when randomly created bilateral import shares are used to calculate foreign R&D expenditure instead of actual import shares, estimates are positive, and explain more of the variation in productivity across countries than if true bilateral trade patterns are employed. Naturally, this finding introduces doubts about the hypothesis that international R&D spillovers are trade related. We follow the same approach as Keller (1998) and create random bilateral import shares from a uniform distribution, then apply these weights to calculate, for each country, the cumulative foreign R&D stock variable. We replace this variable in equation (6) and calculate for 1000 replications the mean value of the parameters a_d, a_f and R^2. Both regression fit methods, FM and DOLS, were used. While we find on average pretty similar and significant mean values for a_d, a_f estimates, R^2 are lower and equal to 0.31 for Cobb-Douglas and DEA specifications and 0.28 for translog specification. This means that, contrary to Keller (1998) results, the true bilateral import trade weights help to explain a large part of the variance in the relationship between total factor productivity and domestic-foreign R&D expenditure in the agricultural sector.

Secondly, the presence of cointegration is consistent with causality running just in one or in all possible directions. Once a long-run relationship has been detected between total factor productivity and R&D expenditure, it is important to identify the actual direction of causality and usually this involves providing Granger-non-causality tests. Although Granger-non-causality is concerned with short-run forecasting, whereas our aim is only to estimate a long-run relationship [11], we run two regressions where the change in domestic (foreign) R&D stock is used as dependent variable and lagged changes of total factor productivity and foreign (domestic) R&D capital stocks are included as independent variables. Up to four lags were used in the regressions. We test whether total factor productivity estimates are jointly equal to zero. All the Wald tests, not reported for brevity but available upon request from the authors, do not reject the null of non-causality both for the domestic and foreign R&D variables. Thus this result could provide evidence in favour of the existence of a long-run relationship running from domestic-foreign R&D capital stocks to total factor productivity.

We can now analyse the international spillovers in the agricultural sector by looking at Table 7. Each entry in Table 7 presents the estimated elasticity of total factor productivity in the countries indicated in the row with respect to the R&D capital stock in the country indicated in the column. [12]

Table 7 about here

The United States R&D capital stock has the strongest effect on total factor productivity of its trade partners. A 1 per cent increase in the R&D capital stock in this country increases total factor productivity by an average of 0.087 per cent for the full sample of 47 countries. The effect is stronger for the subset of countries located in temperate zones, where the elasticity rises to 0.123, whereas tropical countries are less influenced by R&D in the United States. Looking at the values for single countries, the United States has the strongest effect on the Netherlands and UK (the elasticity are 0.71 and 0.52, respectively). European countries are well integrated. A 1 per cent increase in the R&D capital stock in France increases total factor productivity in Italy by 0.09 per cent, in the Netherlands by 0.14 per cent, in UK by 0.08 per cent. Japan and the USA are less influenced, with elasticities respectively of 0.003 and 0.005 per cent. Similar effects are easily verifiable for an increase in R&D capital stock in Italy, in the Netherlands and in UK. We compute elasticities also for a set of countries located in tropical zones. Note now that a rise in the R&D capital stock in the column countries has a lower effect on total factor productivity in India, Pakistan, Philippines, Kenya and Zimbabwe. Similar values can be reported for the other countries located in the same zones.

The results support the hypothesis that both domestic and foreign R&D have a significant impact on TFP in the agricultural sector, and that the latter increases with the degree of openness of the country. Thus agricultural trade is an important mechanism through which knowledge and technological progress is transmitted across countries. Second, when computing foreign R&D elasticities for countries located in temperate zones and countries located in tropical zones we show that they are higher in the former group. In synthesis, countries more open to agricultural trade and located in temperate zones will experience higher R&D spillovers than more closed ones especially if these are located in tropical zones. It would be of interest to analyse whether the true distinction is between developing and developed countries rather than between temperate and tropical countries. All of the tropical countries in the sample are developing countries while only six out of twenty-five temperate countries, specifically Argentina, Chile, Peru, South Africa, Turkey and Uruguay, can be included inside the group of developing countries. Interestingly, when averaging foreign elasticity for the six countries mentioned above and the sample of tropical/developing countries, we find that the former have a larger elasticity of 0.09 compared to the latter where the value is 0.04. This result must be treated with caution, given the small sample of developing-temperate countries, but at the same time it could shed light on the importance of climate in determining international agricultural spillovers.

Finally, we inspect Coe and Helpman's (1995) findings that smaller countries benefit more from foreign R&D. Our results [15], not reported for brevity, give a mixed response. When analysing the total sample of 47 countries, the six larger countries, the USA, UK, France, Italy, Japan and Canada, the un-weighted average of foreign R&D elasticity is 0.39 against a value of 0.25 for the smaller countries. Interestingly, inside the latter group, some countries, mainly EU members, have an elasticity greater than or similar to the larger ones. These findings may be explained by regional integration which, by spurring trade inside a larger common market, can be a vehicle to acquire new knowledge created in the area. These results do not change when the sub-sample of temperate countries are analysed but a completely different picture arises for tropical countries. In this case, larger tropical countries have, on average, a lower value of foreign R&D elasticity than smaller countries. In synthesis, Coe and Helpman's (1995) results which show that smaller countries have a greater foreign R&D elasticity are not fully confirmed for the agricultural sector.

Finally, we can estimate the rates of return on public investment in R&D. Instead of calculating the rate of return for the full set of countries, we concentrate attention on the average rates of return for the two groups of countries: countries located in temperate zones and countries located in tropical zones. The average rate of return for the first set of countries in 1990 was 71 per cent in the temperate countries and 120 per cent in the tropical countries.[13] Values above 100 percent for the rate of return of agricultural R&D are not new (as summarised in Alston *et al.* (2000)) but our results must be treated with care. They are sensitive to the level of R&D capital stock which is influenced, for example, by the depreciation rate used to compute the initial value for R&D capital stock. We note, using different of values of the depreciation rate to compute R&D capital stock inside a range of [0.01-0.10], that lower values increases the R&D capital stock and reduces the rate of return. Elasticities are less influenced by this problem due to the presence of country dummies in the regressions.

In the previous model, only public sector R&D expenditure can generate new technology and influence total factor productivity. But as shown in the works of Schimmelpfenning and Thirtle (1999) and Johnson and Evenson (1999), ignoring private expenditure can bias public R&D estimates. [16] Unfortunately, private expenditure and/or patent data, which have been used in the previously cited papers, are not available for the full sample of countries used in this work. Alston and al. (1999) provide data for private agricultural R&D during the period 1981-1992 for a sample of OECD countries. The series include private R&D expenditure by agricultural, food and chemical and pharmaceutical industries.

Given the short period of analysis, the total domestic capital stock (from public plus private expenditure) as well as the total foreign R&D capital stocks variables were built by using the same method adopted previously for public R&D expenditure. Table 8 presents the results of equation (11) where now the R&D capital stock variables correspond to the total sum of funds in R&D. [14]

Table 8 about here

In this case, comparing the new estimates with the previous one, foreign R&D elasticities are now always lower, by contrast with domestic R&D elasticities, where we find upper or lower estimates.

These findings can be compared with Coe and Helpman's (1995) results computed for a sample of 22 developed countries for the aggregate economy and during the period 1971 - 1990. They report, for the best regression, an elasticity of 0.078 of domestic R&D, and this rises to 0.234 for the sample of G7 countries. Our results show similar values, around 0.11, when DOLS estimation method is used and a higher elasticity, around 0.32, when adopting the FM method. When comparing agricultural foreign R&D capital stock elasticity, we find values which range from 0.31 and 0.56 against a value of 0.294 for the aggregate economy proposed by Coe and Helpman (1995). Thus the agricultural sector seems to benefit more from international spillovers than the total economy.

However, looking at table 8 when total R&D is used, mixed responses are obtained from cointegration tests where Pedroni's tests reject the null of no-cointegration while some Kao tests do not reject the null. These results indicate that there is a great need for further research to enlarge the database for private R&D expenditure and supply better estimates on the impact of public and private R&D expenditure on agricultural economic activity.

5. Conclusions

This paper, focusing a previous study by Coe and Helpman (1995) for the total economy on the agricultural sector, investigates the question of how R&D spending and trade affects total factor productivity in the agricultural sector. Although this is not a new question, only recently has the new economic growth literature provided theoretical as well as empirical models to analyse this field of research.

This paper addresses the problem by computing total factor productivity in the agricultural sector for a sample of 47 countries during the period 1970-1992 and uses this variable to analyse its relationship with domestic and foreign public R&D spending in agriculture. New panel cointegration econometrics has been adopted to compute sound long-run estimates.

Many results emerge from the analysis. First, extending Coe and Helpman's (1995) aggregate results on the effect of total R&D spending on total factor productivity for a sample of 22 developed countries, we show that productivity in the agricultural sector is positively and significantly influenced by its domestic R&D capital stock and by the foreign R&D capital stock of its trade partners. Interestingly, elasticities for both variables are larger than whose reported by Coe and Helpman's (1995) for the total economy. This could means both that productivity in the agricultural sector is strongly influenced by domestic R&D investments and that agricultural trade can boost productivity by augmenting the total amount of R&D available for a country. Second, geographical factors influence international spillovers in the agricultural sector. Countries located in temperate zones will benefit more than countries located in tropical zones from technological spillovers. Thus temperate countries need to make less effort to develop technological capability, i.e. less investments in adaptive research are needed to make effective use of technological knowledge and generate sizeable spillover benefits. In other words, by contrast with countries located in temperate zones, it is more difficult for countries located in tropical zones to boost their productivity by trading and thus acquiring knowledge created in countries located in temperate zones. So in the agricultural sector a firm's "absorptive" capacity (Cohen and Levinthan, 1989) to acquire new knowledge can be reduced by the substantial learning and adapting costs connected to the use of technologies developed in other climate zones. In 1951, John Kenneth Galbraith, when he was an agricultural economist, [17] underlined "[If] one marks off a belt a couple of thousand miles in width encircling the earth at the equator one finds within it *no* developed countries". Finding that agricultural R&D spillovers are higher for countries located in temperate zones than for countries located in tropical zones could at least partially explain the lack of convergence of agricultural productivity between the two climate zones.

Third, the USA is the country that exerts the major impact on the world-wide transfer of agricultural R&D. A one per cent increase in the R&D capital stock in this country increases total factor productivity by an average of 0.087 per cent for the full sample of 47 countries. The effect is stronger for the countries located in temperate zones, 0.123 cent, than for the countries located in tropical zones, 0.026 per cent. The Netherlands and the UK are the two countries in Europe that benefit most from agricultural R&D spending in the US. R&D investment in EU countries mainly influences agricultural productivity and output in these countries and there is less impact on US or Japanese total factor productivity. Finally, the average rate of returns for agricultural public R&D spending is higher for countries located in tropical zones than countries located in temperate zones. Taken together, these findings could provide evidence to justify new support and an even greater investment of funds for agricultural R&D in tropical zones.

Acknowledgements

An earlier version of this paper was presented at the CYMMIT International Conference on the "Impacts of Agricultural Research and Development" San Josè, Costarica, February 2002 and at the X Congress of European Association of Agricultural Economists, Zaragoza, Spain, August 2002. The research on which much of this paper is based was supported by a grant from the MIUR, Italy.

Note

[1] Both tests were implemented in GAUSS 3.2. The routines are freely available and can be downloaded from http://www.gutierrezluciano.net.
[2] By contrast with the FM method, where dependent variables are corrected using long-run covariance matrices to remove the nuisance parameters, the bias corrected OLS method consists of subtracting nuisance parameters from the OLS estimates.
[3] The Bartlett's kernel window was used to compute long-run covariance matrices.
[4] The Wald test is computed under the hypothesis of homogeneous long-run covariance structure. See Kao and Chiang (1995), remark 9, pg.13.
[5] The form of the estimated translog production function is

$$\ln Y_{kt} = c_k + \sum_i a_i \ln X_{ikt} + 0.5 \sum_{i,j} b_{i,j} \ln X_{ikt} \ln X_{jkt}$$

where, as before, Y is the value added of the agricultural sector in country k, c_k represents an index of technology and X_{ik} is the factor of production i in country k.
[6] From (8), when cointegration is detected, by definition the log of total factor productivity must be a stationary variable or, in other words, test of unit roots must reject the null of non stationarity.
[7] The DEAP 2.1 program was used to compute the Malmquist index, Coelli (1996).
[8] Coe and Helpman's (1995) model is based on aggregate variables instead of, as in our case, sectoral variables. Because our paper focuses on the long-run relationship between total factor productivity and R&D capital stock, we assume that the empirical aggregate model can be used to mimic the sector model.
[9] In order to compare our results with Coe and Helpman's (1995) findings, we assume, computing R&D capital stock variables, $d = 0.05$. In any case different values as $d = 0.01$ or $d = 0.10$ do not strongly alter the regression results.
[10] We still compute, as some studies in this field, the foreign R&D capital stock variable as the sum of domestic R&D capital stock in other countries for each country and period. We do not report estimates because the results are worse than those of the weighted scheme.
[11] Hendry (1995), pg. 176, introduces some warnings on the use of Granger-non-causality tests.
[12] We use the same formula as in Coe and Helpman (1995). When the R&D capital stock of country i, SRD_{dj}, increases by 1%, the foreign R&D capital stock for country j, SRD_{fj}, rises by $m_i^j SRD_{di} / \sum_{k \neq j} m_k^j SRD_{dk}$ per cent and county j's TFP rises by $m^j a_f m_i^j SRD_{di} / \sum_{k \neq j} m_k^j SRD_{dk}$ per cent, where m^j is country j's import share and m_i^j is the fraction of j's imports coming from country i. We use the value obtained from the Cobb-Douglas specification as an estimate for a_f, DOLS model.
[13] The average rate of return for a set C of homogeneous country equals $r_C = a_{dC}\left(\sum_{j \in C} Y_j / \sum_{j \in C} SRD_{dj}\right)$, where a_{dC} is the domestic elasticity and Y_j is the output (value added in our case) in country j.

[14] We tried to produce estimates for domestic public and private R&D as well as for foreign public and private R&D, but we obtained poor results. Some coefficients had the wrong sign and implausible magnitude. Assuming that this problem can be attributed to collinearity between variables, instead of introducing public and private R&D variables in the regression separately, we estimated the coefficient for domestic and foreign total R&D capital stock.

[15] Following Coe and Helpman's (1995), the ratio of agricultural imports to agricultural value added was multiplied to 0.603 in order to find a variable across countries and time elasticity of TFP to foreign R&D. Full results are freely available upon request from the authors.

[16] The same could be said for R&D investments from other sectors which can influence agricultural productivity growth. Given the lack of international data, note what was said in note 8.

[17] "Conditions for Economic Change in Underdeveloped Countries," *Journal of Farm Economics,* 33, (November 1951), p. 693.

Dataset Appendix.

Countries : Argentina, Australia, Austria, Belgium-Luxembourg, Canada, Chile, Colombia, Costa Rica, Cyprus, Denmark, Dominican Republic, El Salvador, Finland, France, Greece, Guatemala, Honduras, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Kenya, Malawi, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Portugal, South Africa, South Korea, Sri Lanka, Sweden, Syria, Tanzania, Trinidad & Tobago, Tunisia, Turkey, United Kingdom, United States, Uruguay, Venezuela, Zimbabwe.

Variables:

Value Added, local currency units: World Bank, World Development Indicators (2000, 2001). Deflated to base year 1985 using agricultural deflator provided by Crego *et al*. (1997) and then converted to 1985 international dollars using the corresponding purchase power parity index reported in Penn World Table (Mark 5.6a).

Capital stock, local currency units : kindly supplied by D. Larson and referenced in Crego *et al*. (1997). Deflated to base year 1985 using agricultural deflator provided by Crego *et al*. (1997) and then converted to 1985 international dollars using the corresponding purchase power parity index reported in Penn World Table (Mark 5.6a).

Labour : Economically Active Population in the Agricultural Sector, Faostat (1998).

Land : Hectares of arable and permanent cropland, Faostat (1998).

R&D expenditure:

Public R&D expenditure, local currency units where available. Deflated to base year 1985 using agricultural deflator provided by Crego *et al*. (1997) and then converted to 1985 international dollars using the corresponding purchase power parity index reported in Penn World Table (Mark 5.6a).

Sources:

OCDE countries: Alston *et al*. (1999).

Africa countries : Pardey, Roseboom, and Beintema (1995), and CGIAR, Agriculture Science and Technology Indicators database.

Latin America: Cremers and Roseboom (1997), and CGIAR, Agriculture Science and Technology Indicators database.

Asia : Tabor, Janssen and Bureau (1998), and CGIAR, Agriculture Science and Technology Indicators database.

OCDE Private R&D expenditure, 1985 international dollars: Alston *et al*. (1999).

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Tables

Table 1. Panel Data Unit Roots Tests Results (a)

Variables	Levin and Lin (1993) tests		Im et al. (1997) tests	
	without a time trend	with a time trend	without a time trend	with a time trend
Value-added	1.456	0.339	4.361	0.143
Capital stock	2.117	-0.073	-2.861	-0.870
Labour	8.236	1.299	5.844	3.259
Land	3.424	2.430	1.255	0.173
TFP Cobb-Douglas specification	1.103	-1.003	3.394	0.565
TFP Translog specification	0.268	-1.239	0.433	-1.039
TFP Malmquist index	1.011	-0.947	4.665	0.189
Domestic R&D capital stock	4.236	6.020	6.710	4.048
Foreign R&D capital stock	15.935	4.724	20.478	3.356

Notes : (a) Two lags included in the ADF process
Source: Authors' calculations

Table 2. Cobb- Douglas production function estimation results : pooled sample 1970-1992 (a)(b)

Variables	OLS (c)	FM	DOLS
Total sample (47 countries)			
Log Fixed Capital	**0.6010**	**0.5918**	**0.5818**
	(26.24)	(25.79)	(21.90)
Log Labour	**0.2683**	**0.2792**	**0.2902**
	(7.11)	(6.67)	(5.99)
Log Land	**0.1276**	**0.1334**	**0.1366**
	(3.64)	(2.96)	(2.62)
Sum elasticities	**0.9969**	**1.0044**	**1.0086**
Wald $\chi^2(1)$ test: $(\alpha+\beta+\gamma)=1$		0.056	0.220
p-value		0.81	0.64
N	1081	1081	1081
R^2 adjusted	0.99	0.99	0.99
Temperated countries (25 countries)			
Log Fixed Capital	**0.5629**	**0.5496**	**0.5262**
	(17.37)	(17.36)	(14.35)
Log Labour	**0.3922**	**0.4121**	**0.4430**
	(7.88)	(7.12)	(6.61)
Log Land	**0.0930**	**0.0982**	**0.1084**
	(2.74)	(2.15)	(2.05)
Sum elasticities	**1.0481**	**1.0599**	**1.0776**
Wald $\chi^2(1)$ test: $(\alpha+\beta+\gamma)=1$		8.278	13.927
p-value		0.004	0.000
N	575	575	575
R^2 adjusted	0.99	0.99	0.99
Tropical countries (22 countries)			
Log Fixed Capital	**0.5774**	**0.5726**	**0.5604**
	(16.28)	(16.02)	(15.68)
Log Labour	**0.2260**	**0.2309**	**0.2370**
	(2.65)	(2.50)	(2.57)
Log Land	**0.2022**	**0.2057**	**0.2202**
	(2.33)	(1.97)	(2.12)
Sum elasticities	**1.0056**	**1.0092**	**1.0176**
Wald $\chi^2(1)$ test: $(\alpha+\beta+\gamma)=1$		0.257	0.943
p-value		0.968	0.815
N	506	506	506
R^2 adjusted	0.99	0.99	0.99

Notes: Dependent variable: log value added agricultural sector
(a) conventional *t*-statistics are reported in parentheses.
(b) all equations include unreported, country-specific constants.
(c) bias-corrected OLS estimates.

Table 3. Translog production function estimation results : pooled sample 1970-1992 (a)(b)

Variables	OLS (c)	FM	DOLS
Total sample (47 countries)			
Log Fixed Capital	**0.5865**	**0.5608**	**0.5072**
	(22.09)	(21.19)	(17.42)
Log Labour	**0.2999**	**0.3076**	**0.3156**
	(6.88)	(6.39)	(5.96)
Log Land	**0.1148**	**0.1568**	**0.3140**
	(2.93)	(2.97)	(5.42)
(1/2) Log (Fixed Capital)^2	**0.0319**	**0.0082**	**-0.0140**
	(1.48)	(0.44)	(-0.68)
(1/2) Log (Labour)^2	**0.1273**	**0.1018**	**0.1300**
	(1.35)	(1.12)	(1.295)
(1/2) Log (Land)^2	**0.0411**	**0.0195**	**0.0046**
	(1.06)	(0.55)	(011)
Log (Fixed Capital)*Log(Labour)	**-0.0487**	**-0.0256**	**-0.0012**
	(-1.80)	(-1.05)	(-0.42)
Log (Fixed Capital)*Log(Land)	**-0.0062**	**0.0130**	**-0.0451**
	(-0.07)	(0.41)	(1.28)
Log (Labour)*Log(Land)	**-0.0365**	**-0.0505**	**-0.1035**
	(-0.70)	(-0.85)	(-1.59)
Wald $c^2(4)$ test : null hypothesis constant returns		3.38	42.32
p-value		0.49	0.00
N	1081	1081	1081
R^2 adjusted	0.99	0.99	0.99

Notes: Dependent variable: log value added agricultural sector
(a) conventional *t*-statistics are reported in parentheses.
(b) all equations include unreported, country-specific constants.
(c) bias-corrected OLS estimates.

Source: Author's calculation

Table 4. Comparisons of the estimates of the intercountry agricultural production function

Source	Capital	Labour	Land
Hayami and Ruttan (1985)	0.46	0.45	0.09
Mundlak *et al*. (1997)	0.47	0.09	0.45
Mundlak and Hellinghausen (1982)	0.40	0.40	0.20
Evenson and Kislev (1975)	0.65	0.20	0.10
Cobb-Douglas Production Function, DOLS estimates	0.58	0.29	0.13
Translog Production Function, DOLS estimates	0.48	0.27	0.25

Sources : Hayami and Ruttan (1985) Table 6-4; Crego *et al* . (1997) Table 4.

Table 5. Total factor productivity comparisons for the sample of countries, 1970-1992

	Temperate countries	Tropical countries	Total sample
Unweighted annual average growth rates:			
Cobb-Douglas specification	1.03	1.94	1.45
Translog specification	-0.13	0.84	0.32
Malmquist index	1.25	1.92	1.56
Public R&D expenditure	3.08	4.07	3.52

Sources : Authors' calculation and various sources for R&D expenditures (see Appendix)

Table 6. Total Factor Productivity Estimation Results : pooled data
1970-1992 for 47 countries (a)(b)

Variables :	**Cobb-Douglas**		**Translog**		**Malmquist**	
	FM	**DOLS**	**FM**	**DOLS**	**FM**	**DOLS**
$\log SRD_{d(t-1)}$	0.2745	0.2497	0.2067	0.1895	0.2590	0.2486
	(3.423)	(2.669)	(2.126)	(1.671)	(3.157)	(2.598)
$m_{i(t-1)} \log SRD_{f(t-1)}$	0.6396	0.6320	0.1573	0.2458	0.6437	0.6009
	(3.321)	(2.814)	(0.673)	(0.902)	(3.268)	(2.614)
N	1034	1034	1034	1034	1034	1034
R^2 adjusted	0.50	0.51	0.46	0.45	0.51	0.51
Cointegration tests :						
Pedroni (1995) PC_1	-24.57	-24.48	-24.68	-24.70	-23.95	-23.86
Pedroni (1995) PC_2	-24.00	-23.93	-24.12	-24.13	-23.40	-23.31
Kao (1999) DF_ρ	-2.56	-2.58	-2.09	-2.08	-2.39	-2.41
Kao (1999) DF_t	-1.84	-1.87	-2.08	-2.06	-1.68	-1.69
Kao (1999) DF*_ρ	-11.95	-11.90	-11.26	-11.22	-11.62	-11.65
Kao (1999) DF*_t	-4.11	-4.12	-4.26	-4.24	-3.99	-4.00
Kao (1999) ADF	-3.12	-3.11	-3.04	-3.00	-3.19	-3.21

Notes: dependent variable log total factor productivity
(a) conventional t-statistics are reported in parentheses.
(b) all equations include unreported, country-specific constants.

Source: Authors' calculation

Table 7 **Cross-Countries estimated elasticity of Total Factor Productivity with respect to R&D capital stock – 1990.**

	France	Italy	Japan	Netherlands	U.K.	U.S.A.
France	-	0.0372	0.0720	0.0259	0.0627	0.2660
Italy	0.0929	-	0.0370	0.0192	0.0334	0.1835
Japan	0.0025	0.0009	-	0.0004	0.0031	0.2050
Netherlands	0.1389	0.0276	0.1516	-	0.1870	0.7096
U.K.	0.0836	0.0237	0.1580	0.0417	-	0.5182
U.S.A.	0.0045	0.0021	0.0996	0.0010	0.0064	-
India	0.0003	0.0001	0.0030	0.0001	0.0008	0.0035
Pakistan	0.0018	0.0014	0.0485	0.0007	0.0008	0.0360
Philippines	0.0008	0.0002	0.0238	0.0002	0.0099	0.0588
Kenya	0.0040	0.0011	0.0243	0.0010	0.0071	0.0145
Zimbabwe	0.0025	0.0010	0.0089	0.0010	0.0010	0.0313
Avg. Temperated Countries	0.0187	0.0056	0.0624	0.0074	0.0168	0.1227
Avg. Tropical Countries	0.0019	0.0007	0.0130	0.0004	0.0017	0.0255
Avg. 47 Countries	0.0126	0.0038	0.0442	0.0049	0.0113	0.0869

Notes : Estimated elasticity of total factor productivity in the row countries with respect to the R&D capital stock in the column country, (TFP from Cobb-Douglas, DOLS estimates, value = 0.632).

Averages are calculated using agricultural GDP weights

Table 8. Total Factor Productivity Estimation Results : pooled data
1981-1992 OCDE countries (a)(b)

Variables :	**Cobb-Douglas**		**Translog**		**Malmquist**	
	FM	**DOLS**	**FM**	**DOLS**	**FM**	**DOLS**
$\log SRD_{d(t-1)}$	0.3081	0.1136	0.0780	0.2457	0.3440	0.1668
	(5.115)	(1.857)	(1.256)	(1.439)	(4.929)	(1.303)
$m_{i(t-1)} \log SRD_{f(t-1)}$	0.4293	0.3689	0.3169	0.3323	0.3224	0.5650
	(5.245)	(2.049)	(3.475)	(1.325)	(3.400)	(3.250)
N	216	216	216	216	216	216
R^2 adjusted	0.77	0.82	0.47	0.29	0.77	0.75
Cointegration tests :						
Pedroni (1995) PC_1	-7.35	-10.37	-17.30	-7.50	-6.93	-8.03
Pedroni (1995) PC_2	-7.04	-9.93	-16.57	-7.18	-6.64	-7.69
Kao (1999) DF_ρ	1.04	-0.83	-3.16	1.07	-2.39	1.43
Kao (1999) DF_t	2.37	-0.04	-2.94	2.40	1.27	2.77
Kao (1999) DF*_ρ	-2.28	-4.81	-6.47	-2.12	2.58	-1.61
Kao (1999) DF*_t	0.10	-1.62	-3.78	0.18	-1.84	0.43
Kao (1999) ADF	-1.37	-2.15	-3.23	-1.38	-1.17	-1.01

Notes: dependent variable log total factor productivity
(a) conventional t-statistics are reported in parentheses.
(b) all equations include unreported, country-specific constants.

Source: Authors' calculations