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Most economists since Adam Smith seem to have regarded it as axiomatic that productivity grows less rapidly in agriculture than in the manufacturing sector. Smith (1937, p6) himself viewed this difference as an inherent consequence of difficulties in extending the division of labor to the extent possible in manufacturing --".. the impossibility of making so complete a separation of all the different branches of labor is perhaps the reason why the improvement of the productive powers of labor in this art does not always keep pace with the improvement in manufactures."

This basic assumption pervades much subsequent writing on economic development. Ricardo's fundamental model assumes a fixed level of agricultural technology. As Rima (1971) notes, even though Ricardo did recognize the possibility of improvements in agricultural technology, he clearly believed them to be greatly inferior to those available in manufacturing. Marx certainly dismissed the rural sector as a source of growth, viewing the development of cities as rescuing people from the "idiocy of rural life".

The notion of relatively slow productivity growth in agriculture has been central to many theories of economic development. The dual economy models inspired by the work of W. A. Lewis (1954) typically feature a distinction between a stagnant, traditional rural sector and a dynamic modern manufacturing sector (Hayami and Ruttan 1985). Prebisch (1984, p184) believed that productivity growth did not spread from the center to peripheral countries because the periphery focussed on the supply of primary products. These theories imply both low productivity growth and a lack of convergence in productivity growth between developed and developing countries.

There are, however, many reasons for optimism about the potential for productivity growth in modern agriculture. Schultz (1964) argued that the agricultural sector in developing countries was not stagnant. In his view, small farmers and other small businessmen typically made very efficient use

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of the technologies available to them. The problem was a lack of the collective inputs needed to make high-payoff inputs of the right type available to these producers. Hayami and Ruttan (1985) examined a number of successful instances of rapid technological change in agriculture, and emphasized the importance of institutions and policies in modern, science-based agricultural development.

Estimates of productivity growth for the economy as a whole abound, as do estimates for the individual sectors. However, there is a paucity of comparable estimates for agriculture and manufactures, particularly in developing countries.. Information about rates of technical change in these major sectors is likely to be useful for a number of reasons, including policy, forecasting, and the insights that it might provide into the overall process of economic growth and development.

The belief that productivity growth rates differ substantially across sectors has had extremely important implications for policy. In many developing countries, the belief that TFP growth is higher in manufacturing appears to have contributed to strong policy biases against agriculture and towards manufacturing (Krueger, Schiff and Valdés 1992). The widespread failure of this approach to development might have been expected to raise questions about the underlying assumption of relative productivity differences, but this does not always appear to have been the case. Academic analysis of the problem, in particular, has frequently continued to use the Ricardian assumption of zero productivity growth in agriculture (eg Matsuyama 1991).

Comparisons of productivity growth between agriculture and manufacturing are also instructive for policy on the allocation of research resources and on the definition of intellectual property rights. In agriculture, much of the research underlying the development of high yielding varieties of rice and other crops was the result of a conscious policy choice to fund the development of such varieties and their adaptation to the particular environments of developing countries. In industry, direct public funding plays a relatively smaller, but not insignificant, role. In both sectors, important public policy issues arise in the definition and enforcement of intellectual property rights; because of the TRIPS agreement reached under the Uruguay Round (Braga 1996), these issues are much more strongly an international concern than was previously the case.

Information about differences in rates of technical change between sectors is vitally important for any understanding of the process of structural change so central to the development process. Recent model-based studies have highlighted the importance of differences in productivity growth between sectors for determining the pattern of trade in rapidly growing economies (Gehlhar, Hertel and Martin 1994; Anderson, Dimaranan, Hertel and Martin 1996).

Finally, an understanding of sectoral differentials in productivity growth and in productivity convergence appears to provide a useful complement to aggregate economic growth studies. If these differentials should prove to be substantial, then the structural change associated with economic growth can be expected to create a distinct growth profile not explicable at the aggregate level. Further, such a growth rate profile might contribute to convergence or divergence in the aggregate growth rate of economies. Convergence in aggregate productivity can come about either through changes in the sectoral composition of different economies or through convergence across countries in their sectoral total factor productivity levels.

Since the rate of productivity growth in agriculture is considerably more important to overall economic performance in developing countries, the omission of developing countries from the available studies is particularly unfortunate. The purpose of this paper is to provide some basic estimates on TFP growth in agriculture and manufacturing in a relatively wide range of countries and to investigate the extent to which productivity growth converges in each of these sectors.

In the next section of the paper, we survey some of the relevant literature on estimates of productivity in agriculture and manufacturing. Then, in Section III, we outline the methodology used in the analysis. The data are discussed in Section IV. Some interpretations are presented in Section V, prior to the conclusions of the study.

II. Some Relevant Literature

The direct empirical evidence on differences in the rate of productivity growth between agriculture and manufacturing involves two types of studies: firstly, studies based on production or cost functions for individual studies, and secondly, studies based on the apparent bias of technical changes between sectors.

Syrquin (1986) surveyed the evidence on partial and total factor productivity in agriculture and manufacturing. He observed a pattern where labor productivity in agriculture increases more rapidly than in manufactures during an important phase in the growth process. However, this appeared to have been achieved primarily by substituting capital for labor in agriculture. The empirical evidence on total factor productivity growth presented in his study focussed on those cases where data were available from the 19^{tth} century and generally found higher productivity growth in industry than in agriculture.

While there are many studies of productivity growth in agriculture, there are surprisingly few studies using more recent data that provide comparisons between productivity in agriculture and the rest of the economy. Jorgenson, Gollop and Fraumeni (1987) used a cost function approach for each major sector of the US economy to estimate rates of sectoral productivity growth and concluded that productivity growth had been more rapid in agriculture than in other sectors. Lewis, Martin and Savage (1988) used a production function approach to calculate productivity growth rates for agriculture and for the remainder of the Australian economy (industry plus services), and concluded that the rate of productivity growth in agriculture had been higher than for the remainder of the economy. Martin and Warr (1993) found a bias toward agriculture consistent with higher TFP growth in their profit function study of Indonesia.

Two recent studies allow comparisons of total factor productivity growth by sector for a large number of industrial countries (OECD 1995; Bernard and Jones 1996a). These studies use data from the early 1970s to the late 1980s, a much more recent sample period than was used in earlier multi-country studies, such as those surveyed by Syrquin (1986, p250). A striking feature of both of these studies is the much higher rates of growth in total factor productivity that they report for agriculture relative to other sectors. Bernard and Jones (1996a) report average TFP growth of 2.6 percent per year in agriculture, as against 1.2 percent in industry; in only one out of their 14 sample countries was TFP growth higher in industry than in agriculture. Clearly, these results suggest a need to reconsider the view that TFP growth in modern agriculture is always low.

Experience with simulation models used to project changes in the structure of economies under economic growth provides some suggestive indications. In studies using global general-equilibrium projections with the Global Trade Analysis Project (GTAP) model, such as Gehlhar, Hertel and Martin (1994), it has typically been found necessary to include a higher rate of productivity growth in agricultural sectors than in other sectors. Unless this is done, the model typically projects rises in agricultural product prices because of Rybczynski effects that withdraw resources from labor-intensive agricultural sectors as capital deepens during economic development.

III. Methodology

In this paper, we follow a simple production function approach in which the quantity of value added in each sector is explained by the volumes of land, labor and capital employed in the sector. Because the decomposition of total factor returns is fraught with difficulty in sectors such as agriculture, where unincorporated enterprises tend to dominate, we rely primarily upon estimates of the parameters of the production functions. However, we also provide a set of estimates using factor shares taken from the GTAP model database, which incorporates corrections for this problem (Hertel 1997).

In estimating the parameters of the production functions, we utilized a fixed-effects treatment because we are primarily interested in the changes over time within the panel of countries.

This approach, with a large panel dataset, should mitigate the problems of multicollinearity that otherwise bedevil inferences about productivity growth obtained solely from time series data. The panel data approach to productivity analysis also uses more information and increases the degrees of freedom, thereby making the estimates more efficient. The use of information from both time series and cross section enables us to control better for the effects of missing or unobserved variables. Moreover, use of panel data allows the estimation of long run relationships with fewer problems than with time series data; in particular, it mitigates the problems otherwise involved in estimating relationships between integrated series. (See Hsiao (1989) and Greene (1993) for detailed discussions of the merits of using panel data.)

The functional forms we use are the popular Cobb-Douglas and Translog production functions. In the estimation, we follow a general to specific approach by first estimating Translog functions and then testing whether Cobb-Douglas functions can be nested within them. As a check for robustness of the estimates, we also present estimates of total factor productivity growth estimated using standard growth accounting techniques with factor share estimates obtained from sources extraneous to the dataset used for estimation.

Consider the following production function augmented to allow for neutral technical change:

(1) $$Y_t = A_t F(L_t, K_t)$$

where Y_t, L_t, K_t and A_t denote output, labor employed, capital employed and the technology parameter (also called total factor productivity (TFP)) respectively at time t. In the case of agriculture, we also include land as a factor.

The widely-used Cobb-Douglas production function is frequently estimated in percentage changes, with the growth in output regressed directly on the percentage growth in labor and capital and the rate of growth of total factor productivity obtained from the intercept term. This specification is undesirable given our interest in the long run structural relationship between these variables, rather than the response of output to changes in inputs (Granger 1993). Thus, we preferred to write the Cobb-Douglas production function for manufacturing as a log-linear function in the levels as follows:

$$(2)\quad \ln Y_t = \ln A_0 + rt + a \ln L_t + b \ln K_t$$

where the parameter r is the TFP growth rate and A_0 is initial TFP level.

With this formulation, we can estimate the total factor productivity growth rate r by regressing the log of output on the time trend, the log of capital and the log of labor. We allow $\ln A_0$ and r to vary across countries, while a and b must be assumed to be common across countries if meaningful estimates of productivity differences are to be obtained (Bernard and Jones 1996b).[1] At the high level of aggregation at which we work, it seems reasonable to impose constant returns to scale by imposing the restriction that $\alpha+\beta=1$.

We believe that the Cobb-Douglas production function is too restrictive in that it imposes constancy of factor shares across countries and over time. To correct for this problem, we rely primarily on estimates from the translog form, which is simply a quadratic version of the linear-in-logarithms equation (1). With the translog, the factor shares and output elasticities, become functions of the quantities of factors used,[2] allowing factor shares to vary across countries and over time, while

[1] As an indication of the problems that arise in comparing productivity where the functions have different coefficients, let us compare the following two Cobb-Douglas production functions:

(i) $\ln Y = 1 + 0.9 \ln K + 0.1 \ln L$

(ii) $\ln Y = 0.5 + 0.1 \ln K + 0.9 \ln L$

If K=L=1, the intercept term gives an unambiguous indication of which function yields higher output. However, if L is higher than K, say K=0.1 and L=0.9, then equation (ii) will yield more output than (i) even though (i) has the higher intercept. The reverse will be true for low L and high K. If the growth rates of factors differ, then estimates of productivity growth rates, as well as levels, will be confounded.

[2] Christensen, Jorgenson and Lau (1973) have shown that the translog functional form provides a second order approximation to an arbitrary functional form. They also show that the well-known Constant Elasticity of Substitution. and Cobb-Douglas functions can be viewed as special cases of the translog form. They suggest that the translog function should be employed in the absence of correct information on the specific functional form.

maintaining the consistency of fundamental parameters needed for the productivity terms to have a clear economic interpretation. As with the Cobb-Douglas, we impose constant returns to scale for each sector.

As a check on our results, we also estimated total factor productivity growth as a residual obtained using data on factor shares. Let T (=25) be the length of the period under consideration. Under a Cobb-Douglas specification, TFP growth in the manufacturing sector can be written as

(3) $r = \frac{(\ln Y_T - \alpha \ln K_T - \beta \ln L_T) - (\ln Y_0 - \alpha \ln K_0 - b \ln L_0)}{T}$ where α and β are measured either using observed factor shares, or the coefficients estimated from previous studies.

Finally, we looked at convergence in the levels and growth rates of TFP across countries. Let $\ln A_{it}$ be the TFP level in a sector (say, manufacturing) in the i'th country at time t and be given by

(4) $\ln A_{it} = \ln Y_{it} - (a \ln L_{it} + b \ln K_{it} + g \frac{(\ln L_{it})^2}{2} + d \frac{(\ln K_{it})^2}{2} + m \ln L_{it} \ln K_{it})$

All the parameter values used above are the estimated coefficients from the Constant Returns to Scale translog production function regressions. Similarly, we can measure $\ln A_{it}$ for agriculture. It must be noted that the observed TFP ($\ln A_{it}$ calculated above in equation 12) is the sum of the estimated TFP level (estimated from the initial TFP level and the trend rate of growth) and the error term of our production function.

Our reference country for analyzing convergence is the United States. We define a new variable that measures the technology gap between the US and the ith country as follows:

$$D_{it} = \ln A_{Rt} - \ln A_{it}$$

Productivity in country i is considered to be converging with the reference country if D_{it} is stationary , that is if it tends to move over time to a certain expected level $\underline{D}_i$.

Let us consider the following model:[3]

$$(5) \qquad D_{it} = a_i + rD_{it-1} + e_{it}$$

If $r < 1$, then D_{it} is stationary and is expected to go to $\frac{a_i}{1-r}$ in the steady state, irrespective of the initial productivity gap. The reason here is that under $r < 1$, only a part of any shock to this variable applies in the next period, so that its effect disappears over time. Therefore, under the expectation of no further shocks, the variable should move to its steady state value. On the other hand, when $r > 1$, the effect of a shock is magnified in subsequent periods.

In this paper, following Bernard and Durlauf (1995) and Bernard and Jones (1996a), we focus on the null hypothesis of no convergence, which means that the expected steady state growth rates of TFP are not equal across countries and shocks to relative productivity are permanent. The alternative will be that of convergence meaning relative productivity shocks are transitory and countries have the same long run rate of growth. The productivity level in each country will in the

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[3] It is assumed $e_{it} \sim iid(0, s_e^2)$ and $a \sim iid(\bar{a}, s_a^2)$. We further assume that e_{it} has $2 + D$ moments for some $\Delta > 0$ and that $Ea_i e_{it} = 0$ for all i and t. We also assume that other standard regularity conditions hold. We invoke the following proposition derived by Bernard and Jones (1996a) as an extension of West (1988) and Levin and Lin (1992).

Proposition: Let $\hat{r}$ be the OLS estimate from a regression of D_{it} on D_{it-1} including country specific intercepts. $\hat{r}$ is asymptotically unbiased. Under the null hypothesis of a unit root with non zero drift, $t_{r=1} = \frac{\hat{r}-1}{SE(\hat{r})}$ asymptotically goes to N(0,1).

long run be expected to converge to the US level plus a country specific constant. In other words, in the long run the productivity gap with respect to the US is expected to remain constant for each country. However, this definition of convergence does not preclude the rise in the productivity gap from a level lower than the steady state to the steady state level. Therefore, checking for the time trend of this productivity gap is necessary if we are to satisfy the more restrictive definition of convergence, i.e., the productivity gap is moving from levels above the steady down to the steady level. However, Bernard and Jones (1996a) define time-series convergence only in terms of stationarity (irrespective of whether the convergence is from above or below).

For at least two reasons, there may be a problem of cross-sectional correlation in the TFP gap data series. Firstly, there might be common technology shocks across countries. Secondly, the fact that the gap for each country is being calculated relative to the USA makes idiosyncratic shocks to the USA common to all of the gaps. O'Connell (1998) has shown that, in the absence of correction, this correlation may seriously bias the results from tests of this type. We deal with this econometric problem using two different approaches - (i) time dummies in addition to our country specific fixed effects (see Frankel and Rose (1996)), and (ii) feasible GLS incorporating a non-zero cross-sectional covariance parameter in the variance-covariance matrix of the error terms in the fixed effects panel regression (see O'Connell (1998)).

After doing the panel convergence tests, we perform the same convergence tests country by country, thereby allowing the ρ parameter to differ across countries. In other words, while the panel analysis allows us to calculate the average rate of convergence (through a common ρ parameter) of TFP gap levels of the different countries to their respective steady state levels, the country-by-country analysis looks for the individual country-level rates of convergence or divergence. The country-by-country analysis, however, is not able to exploit the panel properties of the data set, i.e., it cannot take advantage of the cross-sectional variation. We report the number of countries which show convergence in agriculture and manufacturing and the mean and standard deviation of the estimated ρ's (by sector) from this country-by-country analysis.

We also examined the convergence question by looking at the number of countries that exhibit a higher TFP growth rate than that of the US. A country that grows faster than the US is catching up. This is done in addition to the more sophisticated convergence exercises as its is simpler to understand.

IV. Data

The data series used in this study were drawn primarily from the Larson-Mundlak dataset developed at the World Bank (Crego, Larson, Butzer and Mundlak 1998), which provides data for around 50 countries at a wide range of stages of development for the period from 1967 to 1992. This database brings together data from national sources on a consistent basis. The only other large cross-country database of which we are aware is the OECD sectoral database used by Bernard and Jones (1996a, 1996b), but this covers only industrial countries.

We need data on real value added, real capital, labor force and land use by sector. We chose 1990 as the base year for all countries and converted their data for that year into US dollars using market exchange rates[4]. Changes over time in value added at constant prices were then calculated by dividing the World Bank data on value added in domestic currency by the sectoral GDP deflators (base year = 1990) obtained from the Larson-Mundlak data set (Larson, Mundlak and Butzer 1997; Crego, Larson, Butzer and Mundlak 1998).

Real capital stock data in 1990 domestic prices for manufacturing and for agriculture are

[4] Since these two sectors mainly involve production of traded goods, market exchange rates seem more appropriate than the Purchasing Power Parity exchange rates, which are designed to deal with complications arising from the impacts of differences in consumer prices on volumes of consumption.

calculated from the Larson-Mundlak data set.[5] As in the case of the value added series, this series was also multiplied by the base year (1990) official exchange rate (US dollar per local currency) to get the values in terms of base-period US dollars.[6]

The agricultural labor data are also from the Larson-Mundlak data set. They interpolate the five yearly ILO data using annual data on the ratio of the agricultural labor to total labor, and the overall workforce participation rate. The Larson-Mundlak data set does not include data on manufacturing labor. The ILO provides data on the manufacturing labor force for most countries at between one and three points in time within our sample. We used the changes in the annual UNIDO labor series for manufacturing to infer annual changes in the manufacturing labor force.

The data on the area of agricultural land are obtained from the FAO database. We used the series on arable land plus land under permanent crops.

The period we consider is 1967 to 1992. For Manufacturing, we have data for 38 countries - 23 developing countries and 15 developed countries, while for agriculture, we have data for 49 countries - 32 developing countries and 17 developed countries. We started with 53 countries for Agriculture, but ended up dropping 4 countries (Argentina, Guatemala, Iran and Syria) because of problems with the quality of their data series. For all countries in both industries, we have data for the period 1967-92.

V. Results

[5] We needed to modify the data on real capital stock for our specific needs. Larson and Mundlak arrive at the real capital stock series by first using the annual exchange rates to obtain the nominal dollar value of the capital stock for each year and then the US deflator to calculate the real value in 1990 dollars. This was not satisfactory for our purposes, since such a series would capture not only volume changes but also international price and exchange rate movements. Therefore, we worked backwards using the Larson-Mundlak series on the real dollar capital stock, annual exchange rate and the US deflator to construct capital stock estimates in 1990 local prices . These series were then converted into 1990 dollar values using the 1990 exchange rates.

[6] The capital stock series is estimated using the Ball method, which assumes a proportional decay function for the asset. Mundlak, Larson and Butzer (1997) show that the Larson-Mundlak capital stocks generated using this method are quite robust to alternative methods of calculation.

Table 1 shows the TFP growth estimates for manufacturing and agriculture respectively.[7] The overall average growth rate of TFP in manufacturing varies between 1.13 per cent and 1.86 per cent depending on the specification used. The intersection of the manufacturing and the agriculture samples (from now on the intersection sample) shows an average growth rate of between 0.93 and 1.74 per cent per year depending on the methodology used. The developing country average varies between 0.62 and 0.92 per cent, while the developed country average varies between 1.91 and 3.29 per cent. Splitting the developing country sample, we have an average between 0.22 and 0.93 per cent for low income countries and 0.76 to 0.97 per cent for middle income countries. This shows that TFP grew very slowly in manufacturing in developing countries.[8]

In agriculture, the overall average TFP growth lies between 2.34 and 2.91 per cent. The intersection sample shows average growth rates of 2.26 to 2.69 percent. For developing countries, the range is between 1.76 and 2.62 per cent, while for developed countries, this range is between 3.35 and 3.46 per cent. Splitting the developing country sample, we have an average growth rate of 1.44 to 1.99 per cent for low-income countries and 1.78 to 2.91 per cent for middle income countries. Bernard and Jones (1996a) did not use land in their TFP growth measurement and put all the weight on capital and labor growth. Since land is the slowest growing factor in most cases, its exclusion leads to underestimation of TFP growth . Its inclusion contributes to our finding of higher growth rates in agricultural productivity growth.

Comparing the two sectors, it is very clear that agriculture generally had faster TFP growth than manufacturing. Table 2(a) summarizes the comparisons between TFP growth in

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[7] We present the estimates using both the CRS Translog and the CRS Cobb-Douglas production functions, even though we reject the null that the Cobb-Douglas restrictions within the Translog jointly hold. However, the Cobb-Douglas TFP estimates are not very different from the Translog ones in most cases and allow a fair comparison with most other studies that begin with the Cobb-Douglas assumption.

[8] It should be pointed out that there are differences between our estimates and those of Mundlak, Larson and Butzer (1997) for two reasons. Firstly, we have modified the capital stock data for our purposes as discussed earlier. Secondly, given the nature of our question, we have imposed constancy of production function parameters other than the TFP levels and growth rates.

manufacturing and in agriculture and we find that in most countries, TFP growth in agriculture is higher. We first do an informal t test to see whether the mean TFP growth in agriculture for the entire population of countries in the world equals that in manufacturing against the alternative hypothesis that the mean world TFP growth in agriculture is higher. We cannot reject the null hypothesis in the CRS translog case, but reject the null hypothesis by a large margin in the other two cases. The assumption here is that the intersection sample of countries is unbiased and representative of the entire population of countries in the world.

We then performed a more formal, sophisticated test by pooling the agriculture and the manufacturing data for the 36 countries in the intersection sample and estimating a CRS translog production function. We used dummy variables to allow the parameters to differ between agriculture and manufacturing. With this model, we rejected the null hypothesis by a wide margin. The results and the methodology are summarized in Table 2(b). TFP growth turns out to be higher by 0.54 percent per year in agriculture than in manufacturing. Similar and even stronger results are obtained using the CRS Cobb-Douglas.

Table 3 shows that the capital elasticity in the constant returns Cobb-Douglas production function turns out to be close to 0.69, implying a 69 per cent share of capital in value added under perfect competition. This appears on first sight to be an overestimate. Young (1993) argues that the estimated elasticity of output with respect to capital will be an overestimate, since the capital-labor ratio may be correlated with any kind of technology shocks.

Such high estimates for the share of capital in the aggregate economy were found necessary by Chari, Kehoe and McGrattan (1996) in their attempts to explain international income disparities. Barro and Sala-i-Martin (1992) and Mankiw, Romer and Weil (1992) also arrive at such high estimates for the aggregate economy when human capital is omitted. One of the reasons often given for this high coefficient is that human capital is somewhat proportional to the level of physical capital because formation of human capital takes place through things like on-the-job-training and therefore, depends on how much of capital each worker can work with. Moreover, both the level of human and physical capital are inversely related to the marginal rate of time preference and therefore, positively related to each other. Therefore, when human capital is excluded from the regression, the estimated coefficient of physical capital would to a large extent also include part of the elasticity with respect to human capital.

Table 3 also shows that in agriculture, under the assumption of constant returns to scale and a Cobb-Douglas specification, we also obtain low estimated capital shares. This may represent, in part, genuinely low capital input levels, as well as the measurement error problem in the case of agricultural capital especially in developing countries.

Table 4 gives us the results of the test for convergence. We first regress the TFP gap in logs (D_{it} as defined in section II) on country specific dummies and a common time trend and we find that the time trend is positive and significant for manufacturing and negative and highly significant for agriculture. This shows evidence of convergence in agriculture. We do a fixed effects regression of D_{it} on D_{it-1} to get the estimated value of ρ, i.e., $\hat{r}$. This estimate is asymptotically unbiased and with the long time period - 25 years—included in our panel should approach its true value. We see that $\hat{r}$ is less than one and the t statistic rejects the unit root null hypothesis both for manufacturing and agriculture. These results are more or less the same when we take care of the cross-sectional correlation by two alternative methods, namely the time dummy approach and feasible GLS. Thus we have stationarity and therefore, convergence as defined more broadly. However, convergence in the more restrictive sense (i.e., reduction in the productivity gap) is found only in the case of agriculture. The manufacturing sector in our study behaves similarly to the mining sector in Bernard and Jones (1996a) where they also find a positive time trend but stationarity and hence an absence of unit roots. However, for both manufacturing and agriculture, the expected steady state growth rates tend to equalize across countries.

Though $\hat{r}$ should be close to being unbiased, the expression in Nickel (1981) can be used to obtain the estimates $\tilde{r}$ corrected for asymptotic bias.[9] These results show very high rates of convergence =(1 -$\tilde{r}$) in manufacturing and agriculture (24 and 10 per cent respectively). This convergence measures the speed at which the productivity gap diminishes. Our estimated convergence rate for agriculture is less than the 21 per cent that Bernard and Jones (1996a) found for OECD agriculture. They do not find convergence for manufacturing while utilities and construction have convergence rates of 12 and 9 per cent respectively in their study. On the other hand Barro and Sala-i-Martin (1992) and Mankiw, Romer and Weil (1992) get rates of convergence in labor productivity for the aggregate economy of the order of only 2 per cent.

We also do a country-by-country convergence analysis. As can be seen from the third part of table 4, the mean of the individual estimated country-specific ρ's is significantly below one. For six out of 37 countries (excluding the US), the no convergence null is rejected against the convergence alternative in the case of manufacturing, while the corresponding figures for agriculture are 28 out of 48. As far as TFP growth is concerned, only eight countries do better than the US in manufacturing, while 30 do better in agriculture.

From all the results that we have, it is clear that the evidence for convergence in TFP levels was much stronger in agriculture than in manufacturing.

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[9] For reasonably large values of the number of time periods T, the Nickel asymptotic bias is given by

$$\underset{N\to\infty}{p\lim}(\hat{r}-r)\approx\frac{-(1+r)}{T-1} \qquad \text{(A)}$$

where N is the number of cross sectional units. We, then, calculate

$$\tilde{r}=\frac{(T-1)\hat{r}+1}{T-2} \qquad \text{(B)}$$

Using the Nickel result (A), it is easy to show that $\underset{N\to\infty}{p\lim}(\tilde{r}-r)\approx 0$. However, the variance of this estimator is

VI. Some implications for policy and growth prospects

The findings of this study further weaken the case for policies that discriminate against the agricultural sector in favor or the supposedly more dynamic manufacturing sector. They should also allay the fears expressed by authors such as Matsuyama (1991), Sachs and Warner (1995) and Rodriguez and Rodrik (1999) that countries with large agricultural sectors face diminished growth prospects. There may, in fact, be a tendency for the growth prospects of these countries to be higher at lower income levels, when agriculture represents a larger share of the economy, than at higher income levels.

Although the results of this study imply increases in the competitiveness of the agricultural sector, they do not imply that the agricultural sector can be expected to increase its share of output over time. At the global level, Engel's Law will clearly operate strongly, reducing the share of final spending on agriculture, and hence the share of agricultural output in global income. In individual high-growth developing economies, the share of agriculture can be expected to fall even more rapidly because capital deepening will tend to pull resources out of agriculture and into more capital-intensive sectors. For the world as a whole, rapid technical advances in agriculture facilitate the flow of resources out of agriculture and into other sectors.

Since agriculture is typically an atomistic industry, with little incentive for individual farmers to undertake research, the high rates of productivity growth reported in this study reflect effective systems for developing and disseminating innovations in agriculture. The fact that the dataset we use begins in 1967, very shortly after the establishment of a large scale system for international agricultural research, is probably an important influence on our results. Continuing efforts to develop and improve research and development systems in agriculture, and perhaps also

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given by $V(\tilde{r}) = \left[\frac{T-1}{T-2}\right]^2 V(\hat{r}) > V(\hat{r})$. For large values of T, $V(\tilde{r})$ is very close to $V(\hat{r})$.

in manufacturing, will be needed if the high productivity gains reported over the sample period are to continue into the future. Recent work by Craig, Pardey and Roseboom (1998) to assess the contribution of research and other factors in determining productivity is important as a guide to the allocation of resources towards improving efficiency.

VII. Conclusions

Using a new panel data for around 50 countries over the period 1967 to 1992, we found evidence of quite high rates of technical progress in both agriculture and manufacturing. At all levels of development, however, technical progress appears to have been faster in agriculture than in manufacturing. Moreover, there is strong evidence of convergence in levels and growth rates of TFP in agriculture, suggesting relatively rapid international dissemination of innovations.

We used a range of different techniques to calculate productivity growth, and examined a range of subsets of countries. The difference was generally substantial— most frequently in the range from 0.5 percent to 1.5 percent per year—and in evidence for low, middle and high income countries. The difference in productivity growth rates was strongly statistically significant. Further, the results suggested a tendency for relatively rapid convergence in agricultural productivity across countries, implying relatively efficient transmission of knowledge in modern agriculture.

These results have important policy implications both for development policy generally, and for research and development policies. They suggest that a large agricultural sector need not be a disadvantage, and may be an advantage in terms of growth performance. They weaken the case for the frequently-advocated policies of discrimination against agriculture on the grounds that it is a stagnant sector. They potentially provide an explanation for growth convergence at the macroeconomic level where growth rates slow down as the share of the agricultural sector declines. They highlight the need for continuing efforts to develop and disseminate innovations if the high rates of productivity growth are to be maintained.

TABLE 1. TFP growth (in % per year) in manufacturing and agriculture

Countries	TL-CRS		CD-CRS		SHARES	
Developing countries	**MAN**	**AGRI**	**MAN**	**AGRI**	**MAN**	**AGRI**
Low Income countries						
Egypt	4.15	1.86	2.63	1.23	3.68	1.47
Honduras	-	1.28	-	1.60	-	2.51
India	-0.20	1.90	-0.33	1.52	-0.39	2.29
Kenya	1.50	2.36	0.68	1.69	0.61	2.22
Sri Lanka	-2.00	2.38	-2.00	1.94	-0.11	1.77
Madagascar	-	-0.06	-	-0.18	-	1.20
Malawi	-	0.68	-	0.30	-	0.73
Pakistan	2.33	2.30	1.40	1.7	1.85	3.05
Tanzania		5.67		5.22		6.19
Zimbabwe	-0.20	-0.36	-1.04	-0.67	-1.49	-1.51
Low Income Average	**0.93**	**1.80**	**0.22**	**1.44**	**0.69**	**1.99**
Middle Income Countries						
Chile	2.36	2.73	2.83	2.70	3.38	3.45
Colombia	1.83	2.97	1.52	2.90	2.88	4.20
Costa Rica	1.21	-2.82	0.54	-3.03	2.90	-1.55
Czechoslovakia	-	0.84	-	0.99	-	0.98
Dominican Republic	-	2.49	-	2.89	-	3.61
Greece	1.17	2.91	-0.59	3.1	1.34	3.49
Indonesia	3.79	2.94	5.63	2.74	5.12	4.3
Iran	1.77	-	5.11	-	6.75	-
Jamaica	-1.39	0.93	-1.4	0.48	-1.36	1.65
Korea	5.87	2.89	4.01	3.42	4.92	3.18
Malta	-	5.67	-	5.89	-	4.73
Mauritius	-1.14	-0.12	-1.98	0.06	-2.52	0.58
Morocco	-	1.02	-	1.31	-	2.81
Peru	1.87	1.99	2.42	2.06	0.53	3.34
Philippines	1.80	1.64	0.95	1.57	1.22	2.07
Poland	-	1.30	-	1.35	-	2.84
El Salvador	-2.70	1.43	-2.10	1.05	-1.44	3.55
Trinidad & Tobago	-1.35	-2.92	-2.34	-2.52	-0.70	-0.74
Tunisia	0.51	2.93	0.33	2.99	1.56	5.23
Turkey	2.65	3.37	2.06	3.46	1.82	4.97
Uruguay		1.58		2.10		4.73
Venezuela	-3.83	2.61	-4.03	2.95	-10.39	3.83
South Africa	1.28	2.76	-0.10	3.40	0.43	2.75
Middle Income Average	**0.92**	**1.78**	**0.76**	**1.9**	**0.97**	**2.91**
Developing Country Average	**0.92**	**1.79**	**0.62**	**1.76**	**0.9**	**2.62**
Developed Countries						
Australia	2.65	0.84	2.01	2.58	2.23	2.74
Austria	2.92	3.92	2.23	3.89	2.99	3.12
Belgium	6.17	-	4.44	-	4.87	-
Canada	1.54	2.52	0.14	2.38	0.70	2.87

Countries	**TL-CRS**		**CD-CRS**		**SHARES**	
Developing countries	**MAN**	**AGRI**	**MAN**	**AGRI**	**MAN**	**AGRI**
Cyprus	-	5.37	-	5.30	-	5.72
Denmark	1.27	5.34	0.24	5.32	0.61	5.25
Finland	3.45	2.65	1.79	2.54	2.92	0.92
France	2.31	6.74	1.54	6.65	2.33	7.11
UK	2.56	2.70	1.10	2.90	2.16	3.36
Israel	-	2.74	-	2.90	-	3.36
Italy	4.28	4.38	1.95	4.00	3.35	4.50
Japan	5.21	3.46	4.60	2.97	4.68	2.58
Netherlands	4.82	2.20	2.64	2.30	4.02	2.34
New Zealand	-	3.54	-	2.97	-	6.75
Norway	1.68	-	-0.08	-	1.26	-
Sweden	2.31	4.32	1.03	4.03	2.05	1.96
Taiwan, China	5.41	2.64	3.86	2.49	5.50	2.25
USA	2.73	1.80	1.19	2.23	2.33	3.01
Developed Country Average	**3.29**	**3.38**	**1.91**	**3.35**	**2.80**	**3.46**
Overall Average	**1.86**	**2.34**	**1.13**	**2.31**	**1.65**	**2.91**
Intersection Sample Average	**1.74**	**2.29**	**0.93**	**2.26**	**1.41**	**2.69**

TL-CRS: Estimates of TFP growth using Translog production function with constant returns to scale imposed.
CD-CRS: Estimates of TFP growth using Cobb-Douglas production function with constant returns to scale imposed.
SHARES: Estimates of TFP growth using actual factor shares.
Note: The parameters other than TFP levels and growth rates are assumed constant across countries. The capital and labor shares in manufacturing estimated using CD-CRS were 69 and 31 per cent respectively. The capital, land and labor shares in agriculture estimated using CD-CRS were 12, 24 and 64 per cent respectively.

<u>Summary of TFP growth comparisons</u>:<u>Testing from our sample</u>

<u>Table 2(a) (Informal Test)</u>
Null Hypothesis: Mean Agriculture TFP Growth = Mean Manufacturing TFP Growth
Alternative Hypothesis: Mean Agriculture TFP Growth > Mean Manufacturing TFP Growth

Method of TFP Growth Estimation	t ratio
Translog-CRS	1.42
Cobb-Douglas-CRS	3.6
Using factor shares	2.41

Total number of countries compared = 36

Method of TFP Growth Estimation	Number of countries for which TFP growth in Agriculture > TFP growth in Manufacturing
Translog-CRS	22
Cobb-Douglas-CRS	26
Using factor shares	23

<u>Table 2(b) (Formal Test)</u>

$$\ln Y_t = a_{US} + \sum_{i\neq US} a_i D_i + \sum_{i\neq US} r_i D.D_i + g_{US} t + \sum_{i\neq US} r_i D_i t + r_D D.t + a \ln L_t + b \ln K_t$$
$$+ a_M D \ln L_t + b_M D \ln K_t + p(1-D)\ln N_t + g\frac{(\ln L_t)^2}{2} + g_M D\frac{(\ln L_t)^2}{2} + d\frac{(\ln K_t)^2}{2} + d_M D\frac{(\ln K_t)^2}{2}$$
$$+ q(1-D)\frac{(\ln N_t)^2}{2} + m \ln L_t \ln K_t + m_M D \ln L_t \ln K_t + l(1-D)\ln L_t \ln N_t + j(1-D)\ln K_t \ln N_t$$

$D = 0$ for agriculture
$= 1$ for manufacturing
$D_i = 1$ for country i
$= 0$ otherwise   Reference country : United States
We impose the constant returns to scale restrictions

Null Hypothesis $H_O: r_D = 0$
Alternative Hypothesis $H_A: r_D < 0$
OLS estimate of r_D = -0.0054, *t statistic* = -3.79, *F statistic* = 14.4> $F_{critical\ 1,\ 1722}$ (0.01) = 6.37
Therefore, we reject the null hypothesis.
A similar test was done using the CRS Cobb-Douglas for which we obtained the following values:
OLS estimate of r_D = -0.011, *t statistic* = -7.89, *F statistic* = 62.4> $F_{critical\ 1,\ 1725}$ (0.01) = 6.37

<u>Table 3.</u> OTHER COEFFICIENTS CORRESPONDING TO THE TFP ESTIMATES IN TABLE 1

RESTRICTED TRANSLOG - CONSTANT RETURNS TO SCALE
Dependent Variable lnY - lnL

Variable	Manufacturing	Agriculture
lnK - lnL	1.674 (16.466)	-1.440 (-5.872)
lnN - lnL	-	2.443 (5.249)
$\frac{(\ln K)^2}{2}+\frac{(\ln L)^2}{2}-\ln K \ln L$	-0.140 (-10.184)	-0.065 (-4.730)
$\frac{(\ln K)^2}{2}+\frac{(\ln N)^2}{2}-\ln K \ln N$	-	0.138 (6.442)
$\frac{(\ln N)^2}{2}+\frac{(\ln L)^2}{2}-\ln N \ln L$	-	-0.017 (-0.553)
R^2	0.979	0.998
ADJUSTED R^2	0.977	0.998

RESTRICTED COBB-DOUGLAS - CONSTANT RETURNS TO SCALE
Dependent Variable lnY - lnL

Variable	Manufacturing	Agriculture
lnK - lnL	0.687 (21.29)	0.124 (8.347)
lnN - lnL	-	0.240 (8.509)
R^2	0.977	0.998
ADJUSTED R^2	0.975	0.997

Table 4
Tests of Convergence

Sector	T (time trend)	t ratio	$\hat{r}$	t($r = 1$)	$\tilde{r}$ (adjusted)
Manufacturing	0.009	8.128	0.691	-15.550	0.76
Agriculture	-0.005	-7.970	0.819	-10.588	0.90

Sector	$\hat{r}_{\text{time dummy}}$	t ($r = 1$)	$\hat{r}_{\text{FGLS}}$	t ($r = 1$)
Manufacturing	0.667	-15.857	0.687	-15.095
Agriculture	0.864	-9.786	0.862	-9.857

Individual country-level convergence tests

Sector	Mean $\hat{r}$	SD	Total number of countries (excl. US)	Number of countries rejecting no convergence null	Number of countries with higher TFP growth than US
Manufacturing	0.807	0.164	37	6	8
Agriculture	0.678	0.219	48	28	30

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