J Prod Anal (2010) 33:173–190
DOI 10.1007/s11123-009-0149-3

Technology capital: the price of admission to the growth club

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Published online: 29 August 2009

Abstract We assess long-run patterns of global agricultural productivity growth between 1970 and 2005 and examine the relationship between investments in technology capital and productivity. To measure agricultural total factor productivity (TFP) we employ a Solow-type growth accounting method to decompose output growth into input and TFP growth. For technology capital we construct two indexes reflecting national capacities in agricultural research and education-extension for 87 developing countries. We then correlate technology capital levels with long-term growth rates in agricultural TFP. Our findings show that global agricultural TFP growth as a whole accelerated since 1980, although performance was very uneven across developing countries. TFP growth rates were significantly influenced by technology capital. Marginal improvements to research capacity, given a minimal level of extension and schooling existed, were associated with faster TFP growth. However, marginal increases in extension-schooling without commensurate improvements in research capacity did not improve productivity performance.

Keywords Agricultural development · Agricultural extension · Agricultural research · Land quality · Agricultural cost shares · Growth accounting · Total factor productivity (TFP)

JEL Classification Q10 · O47 · O57

1 Introduction

For low income countries, most of which share an economic structure heavily dependent on agriculture, increasing agricultural productivity is a precondition for sustained economic growth. More than four decades ago Johnson and Mellor (1961) described how this comes about: improvement to agricultural productivity releases resources to other sectors, raises the nutritional status of workers, lowers the costs of raw materials for industry, earns foreign exchange, and increases the demand for other sectors' outputs. Since the onset of the "Green Revolution" era in the 1960s, many developing countries have successfully sustained productivity growth in agriculture, and some of these have since graduated to "newly industrialized country" status. However, many others have failed to do so. Some remain bound by traditional farming methods while others appear to have only been able to achieve short and unsustained spurts of productivity growth. Our hypothesis is that a key factor separating the growth from the non- (or unsustained)-growth club is domestic capacity to develop and extend locally-adapted agricultural technology, a capacity we broadly term "technology capital." While many studies have found high average returns from public investments in agricultural research and extension (see Evenson 2001, and Alston et al. 2000 for reviews of this literature), the evidence linking these investments to sector productivity growth remains fragmentary (Pingali and Heisey 2001). It may be that in many countries investments in agricultural

The views expressed do not reflect the official position of the U.S. Department of Agriculture.

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R&D have simply been too limited to make much dent in the overall sector performance. The relevant measures for making international comparisons possible have also proven difficult to assemble.

Our objectives in this paper are to develop internationally-comparable measures of technology capital and long-run growth in agricultural total factor productivity (TFP), and then examine the correlations between them. To measure productivity, we use a Solow-type decomposition of agricultural output growth into changes in inputs and TFP for nearly every country of the world from 1970 to 2005. Then, for 87 developing countries we construct two indexes of technology capital—one measuring capacity to invent or innovate new technologies (research) and one for the capacity to master the new techniques (agricultural extension and education). Regressing TFP growth against these measures of technology capital allows us to explore how they contribute to productivity as well as the degree to which these two forms of technology capital act as compliments or substitutes in the growth process.

Previous research on global agricultural TFP growth gives a mixed picture of long-run trends and considerable country-to-country variation. Because of limited production cost data, many studies have relied on distance function measures like the Malmquist Index to compare productivity among countries. Ludena et al. (2007) used this method to estimate agricultural productivity growth for 116 countries, and found that average agricultural TFP growth increased from 0.60% per year to 1.29% per year between 1961–1980 and 1981–2000. But results for individual countries from this methodology are sensitive to the set of countries and the number of variables included in the model, or the dimensionality issue (Coelli and Rao 2005; Lusigi and Thirtle 1997). Studies using index number methods, which require more data, have usually been limited to single countries. These also show mixed results regarding long-run trends. In a comparison of economic growth between India and China between 1978 and 2004 Bosworth and Collins (2008), show a decline in Indian agricultural TFP after 1993 while China's remained roughly constant. Fuglie (2004) found evidence of rapid TFP growth in Indonesian agriculture during the 1970s followed by stagnation in the 1990s. Latin American agriculture, according to Avila (2007), experienced generally higher productivity growth during 1981–2000 than during 1961–1980, but with mixed trends for individual countries. These country and regional studies provide little guidance for assessing long-run trends in global agricultural productivity growth.

Previous research has generally found positive correlations between national investments in research and extension-education and agricultural growth. In their seminal study of agriculture development, Hayami and Ruttan (1985) found schooling enrollment and the number of agricultural college graduates (a proxy for research capacity) to be positively correlated with agricultural output per worker across in a sample of developed and developing countries. Evenson and Kislev (1975) incorporated a direct measure of research (the number of agricultural publications) into the Hayami–Ruttan model and found a significant and positive influence of this variable on labor productivity, as well as strong correlations between research and the use of modern agricultural inputs like fertilizer and machinery. Using a longer time series and more countries, Craig et al. (1997) also found significant effects of human capital (literacy and life expectance) and public spending for agriculture on agricultural output per worker. None of these studies, however, developed estimates of agricultural TFP or examined interactions between research and extension-education in the growth process. The limitations have largely been empirical. Measures of national capacities in agricultural extension in particular are sparse and fragmented. A survey of by Judd et al. (1991) found that during the 1960s and 1970s, many developing countries gave more attention to expanding agricultural extension than agricultural research under the assumption that relevant technology could be borrowed from other countries. The Sasakawa Global 2000 program, a privately-funded agricultural extension program that operated in parts of Sub-Saharan Africa in the 1990s and early 2000s, is a testament that this belief persists. However, the main lessons from Evenson's (1997) review of 57 studies of the economic impacts of agricultural extension were that impacts were highly variable across time and space and seemed to be most effective where research systems were functioning and where farmers had access to basic schooling. We investigate these interactions by examining the growth performance of a broad set of developing countries that employed different combinations of research and extension-education capacities. The results have important implications for agricultural development policy, especially for poor countries with limited resources to invest in national research and extension systems.

In the next section of this paper we outline a practical approach for measuring growth in agricultural TFP across a broad set of countries given limited data on production costs. Considerable attention is given to data issues, including a method for adjusting agricultural land area for quality differences. We also describe how we construct our indexes of technology capital. Then, in Sect. 3, we report our productivity measurements of agricultural TFP growth for major global regions over the 1970–2005 period. In Sect. 4 we examine the contribution of technology capital to agricultural TFP growth for a group of 87 developing countries. In particular, we investigate the interaction between research and extension-education in the agricultural growth process.

The final section concludes with a summary of findings and implications.

2 Methodology and data

2.1 Method for TFP measurement

We define TFP as the ratio of total output to total inputs in a production process, or the average product of all inputs. Let total output be given by Y and total inputs by X. Then TFP is simply:

$$\mathrm{TFP} = \frac{Y}{X}. \quad (1)$$

Changes in TFP over time are found by comparing the rate of change in total output with the rate of change in total input. Expressed as logarithms, changes in Eq. 1 over time can be written as:

$$\frac{\mathrm{d}\ln(\mathrm{TFP})}{\mathrm{d}t} = \frac{\mathrm{d}\ln(Y)}{\mathrm{d}t} - \frac{\mathrm{d}\ln(X)}{\mathrm{d}t} \quad (2)$$

which simply states that the rate of change in TFP is the difference in the rate of change in aggregate output and input.

In agriculture, output is a composed of multiple commodities produced by multiple inputs, so Y and X are vectors. Chambers (1988) shows that when the underlying technology is represented by a Cobb–Douglas production function and where (1) producers maximize profits so that output elasticities equal input shares in total cost and (2) markets are in long-run competitive equilibrium so that total revenue equal total cost, then Eq. 2 can be written as:

$$\ln\left(\frac{\mathrm{TFP}_t}{\mathrm{TFP}_{t-1}}\right) = \sum_i R_i \ln\left(\frac{Y_{i,t}}{Y_{i,t-1}}\right) - \sum_j S_j \ln\left(\frac{X_{j,t}}{X_{j,t-1}}\right). \quad (3)$$

where R_i is the revenue share of the ith output and S_j is the cost-share of the *j*th input. Output growth is estimated by summing over the growth rates for each commodity weighted by its revenue share. Similarly, input growth is found by summing the growth rate of each input, weighted by its cost share. TFP growth is just the different between the growth in aggregate output and aggregate input. The principal difference between this index measure of TFP growth and a more general TFP productivity measure, such as the Tornqvist–Thiel index, is that here revenue and cost shares are held constant while in a Tornqvist–Thiel index these parameters may vary over time. Using fixed revenue and factor shares over a long period could potentially give rise to "index number bias" in cases where either the revenue or cost shares are changing significantly. It should be pointed out as well that cost shares are partly dependent on output prices themselves, since a part of agricultural output (seed and feed) is used as input in production.

A key limitation in using Eq. 3 for measuring agricultural productivity change is a lack of representative cost share data for most countries. Many types of agricultural inputs (such as land and labor) may not be widely traded and heterogeneous in quality, making price or cost determination difficult. Some studies have circumvented this problem by estimating a distance function, such as a Malmquist index, which measures productivity using data on input quantities alone (Coelli and Rao 2005). But this method is sensitive to the dimensionality problem and can give unbelievably high or negative growth rates. We extend an approach originally developed by Avila and Evenson (2004), who constructed careful estimates of input cost shares for two large developing countries (India and Brazil) from representative farm survey data and from these derived cost shares for other developing countries. For our analysis, we assembled cost share estimates for five additional countries (China, Indonesia, Japan, the UK and the United States). We then assigned the cost shares from these seven countries to other countries that are roughly similar in development level and geography in order to aggregate input quantity data from FAO. We describe this more thoroughly in the section on "input cost shares" below.

To summarize, the theory underpinning the TFP productivity index assumes that producers maximize profits so that the elasticity of output with respect to each input is equal to its factor share. It also assumes that markets are in long-run competitive equilibrium (where technology exhibits constant returns to scale) so that total revenue equals total cost. If the underlying production function is Cobb–Douglas, then our index is an exact representation of Hicks-neutral technical change.

2.2 Output and input data

To assess changes in agricultural productivity over time we use FAO (2008) annual data on agricultural outputs and inputs over 1970–2005 and in some cases augment these data with updated or improved statistics from other sources.

For output, FAO publishes data on production of crops and livestock and aggregates these into a production index using a common set of commodity prices based on the 1999–2001 period. What is important for estimating output growth are the *relative* prices of these commodities (since this determines the weights on the commodity growth rates used for deriving the growth rate for total output). In relative terms, the 1999–2001 FAO commodity prices are fairly close to the "wheat equivalent" prices developed by Hayami and Ruttan (1985, pp. 453–454) in their study on international agricultural productivity (the FAO prices have a correlation coefficient of 0.86 with the Hayami–Ruttan wheat-equivalent prices). The FAO index of real output excludes production of forages but includes crop production that may be used for animal feed.

To disentangle long-run trends from short-run fluctuations in output (due to weather and other disturbances), we smooth the output series for each country using the Hodrick–Prescott filter setting $\lambda = 6.25$ for annual data as recommended by Ravn and Uhlig (2002). This filter is commonly used to remove short-run fluctuations from macro economic time series in business cycle analysis. However, this process does not completely remove the effects of multi-year shocks, so it is still necessary to evaluate observed changes in the rate of TFP growth with auxiliary information about extended periods of unusual weather or other disturbances.

For agricultural inputs, FAO publishes data on cropland (rainfed and irrigated), permanent pasture, labor employed in agriculture, animal stocks, the number of tractors in use and inorganic fertilizer consumption. For selected large countries (China, Brazil, and Indonesia) we supplement FAO statistics with more recent data on agricultural inputs from national statistical agencies. A relatively comprehensive dataset on China's agriculture is available from the ERS (2008), with original data coming from the State Statistics Bureau of the People's Republic of China. For Brazil, we use results of the recently-published 2006 Brazilian agricultural census (IPGE 2008) and for Indonesia, we used Fuglie's (2004, 2007) improved data on agricultural land and machinery use. For fertilizer, we use the International Fertilizer Association (2008) database, which has more up-to-date and accurate statistics on fertilizer consumption by country than FAO.

Inputs are divided into five categories. *Farm labor* is the total economically active population (males and females) in agriculture (it is actually a measure of labor availability rather than actual labor input, but no better data are available). *Agricultural land* is the area in permanent crops (perennials), annual crops, temporary fallow, and permanent pasture. Cropland (area in permanent crops, annual crops and temporary fallow) is further divided into rainfed cropland and irrigated cropland. We derive a quality-adjusted measure of agricultural land that gives greater weight to irrigated cropland and less weight to permanent pasture in assessing agricultural land changes over time (see the next section on "land quality" below). *Livestock* is the aggregate number of animals in "cattle equivalents" held in farm inventories, and include cattle, camels, water buffalos, horses and other equine species (asses, mules and hinnies), small ruminants (sheep and goats), pigs, rabbits and poultry species (chickens, ducks and turkeys), with each species weighted by its size. The weights for aggregation from Hayami and Ruttan (1985, p. 450) are as follows: 1.38 for camels, 1.25 for water buffalo and horses, 1.00 for cattle and other equine species, 0.25 for pigs, 0.13 for small ruminants, 25 per 1,000 rabbits and 12.50 per 1,000 head of poultry. *Fertilizer* is the amount of major inorganic nutrients applied to agricultural land annually, measured as metric tons of N, P_2O_5, and K_2O equivalents. *Farm machinery* is the number of pedestrian and riding tractors in use.

While these inputs account for the major part of total agricultural input usage, there are a few types of inputs for which complete country-level data are lacking, namely, use of chemical pesticides, seed, prepared animal feed, veterinary pharmaceuticals, other farm machinery, energy and farm buildings. However, data on many of these inputs are available for the seven country case studies we use for constructing the representative input cost shares. To account for these inputs we assume that their growth rates are correlated with one of the five input variables described above and include their cost in the related input: service flows from farm structures are included with the agricultural land cost share; the cost of chemical pesticide and seed are included with the fertilizer cost share; costs of animal feed and veterinary medicines are included in the livestock cost share, and other farm machinery and energy costs are included in the tractor cost share. So long as the growth rates for the observed inputs and their unobserved counterparts are similar, then the model captures the growth of these inputs in the aggregate input index.

2.3 Land quality

The FAO agricultural database provides time series estimates of agricultural land by country and divides these estimates into cropland (arable and permanent crops) and permanent pasture. It also provides an estimate of irrigated area. Land quality between classes, and between countries, can be very different, however. For example, some countries count vast expanses of semi-arid lands as permanent pastures even though these areas produce very little agricultural output. Using such data for international comparisons of agricultural productivity can lead to serious distortions, such as significantly biasing downward the econometric estimates of the production elasticity of agricultural land (Peterson 1987; Craig et al. 1997). In two recent studies of international agricultural productivity, Craig et al. (1997) and Wiebe et al. (2003) made considerable effort to include in their regression models variables that could account for differences in land quality (such as indices of average rainfall and soil type, the proportion of irrigated or pastureland in total agricultural land, and fixed effect models with regional or country dummies) with some success.

In this study, because we only estimate productivity growth rather than productivity levels, differences in land quality across countries is less problematic. The estimates of TFP growth only depend on changes in agricultural land and other input use within a country over time. However, a bias might arise if changes occur unevenly among land classes. For example, adding an acre of irrigated land would likely have considerably more importance than adding an acre of rainfed cropland or pasture, and should therefore be given greater weight in measuring input changes. To account for differences in land type, we derive weights for irrigated cropland, rainfed cropland, and permanent pasture based on their relative productivity, and allow these weights to vary regionally. In order not to confound the land quality weights with productivity change itself, the weights are estimated using country-level data from prior to the period of study (i.e., we use average annual data for the 1961–1965 period, while our study period is 1970–2005). We first construct regional dummy variables (REGION$_i$, $i = 1\ldots5$, representing Asia–Pacific, Latin America and the Caribbean, Sub-Saharan Africa, Middle East and North Africa, and developed countries), and then regress the log of agricultural land yield against the proportions of agricultural land in rainfed cropland (CROP), permanent pasture (PASTURE), and irrigated cropland (IRRIG). Including slope dummy variables allows the coefficients to vary across regions:

$$\ln\left(\frac{\text{Ag output}}{\text{Cropland} + \text{Pasture}}\right) = \sum_i \alpha_i(\text{CROP} * \text{REGION}_i) + \sum_i \beta_i(\text{PASTURE} * \text{REGION}_i) + \sum_i \gamma_i(\text{IRRIG} * \text{REGION}_i). \tag{4}$$

The coefficient vectors α, β and γ provide the quality weights for aggregating the three land types into an aggregate land input index. Essentially, Eq. 4 asserts that countries with a higher proportion of irrigated land are likely to have higher average land productivity, as will countries with more cropland relative to pasture land, and that these differences provide a ready means of weighting the relative qualities of these land classes.

The results of this land quality adjustment are shown in Table 1. On average, one hectare of irrigated land was more than twice as productive as rainfed cropland, which in turn was 10–20 times as productive as permanent pastures. When summed by their raw values, total global agricultural land expanded by about 10% between 1961 and 2005, with nearly all of this expansion occurring in developing countries. When adjusted for quality, "effective" agricultural land expanded by nearly double this rate.

Table 1 Global agricultural land use changes

Region	Rainfed cropland			Irrigated cropland			Permanent pasture			Total agricultural land		
	1961	2005	% Change	1961	2005	% Change	1961	2005	% Change	1961	2005	% Change
1.1. Raw totals (millions of hectares)												
Developed countries	363	345	−5	27	44	63	886	805	−9	1,276	1,194	−6
Developing countries	626	685	9	99	209	111	1,871	2,215	18	2,596	3,109	20
Former USSR countries	279	226	−19	11	25	127	332	382	15	622	633	2
World	1,268	1,256	−1	137	278	103	3,089	3,402	10	4,494	4,936	10
1.2. Quality adjusted (millions of hectares of "rainfed cropland equivalents")												
Developed countries	363	345	−5	58	94	63	84	76	−9	504	515	2
Developing countries	626	685	9	247	522	111	53	63	18	926	1,270	37
Former USSR countries	279	226	−19	24	54	127	31	36	15	334	316	−5
World	1,268	1,256	−1	329	670	104	168	175	4	1,765	2,101	19

Source: Agricultural land area from FAO, with adjustments made for Indonesia, China and Brazil based on national statistical sources (see text). Land quality adjustments from authors' regressions (see text)

Globally, irrigated cropland expanded by 141 million hectares and this accounted for virtually all of the change in “effective” agricultural land over this period. For the purpose of our TFP calculation, accounting for the changes in the quality of agricultural land over time should increase the growth rate in aggregate agricultural input and commensurately reduce the estimated growth in TFP.

2.4 Input cost shares

To derive input cost shares we draw upon other studies that reported carefully measured input cost share calculations for selected countries and then we use these cost shares as “representative” of agriculture in other countries at a similar level of economic development or geography. In Table 2 we show the input cost shares from the seven country studies (four developing countries: India, Indonesia, China and Brazil, and three developed countries: Japan, the United Kingdom and the United States). The table also shows the regions to which the various cost-share estimates were applied for constructing the aggregate input index. For example, the estimates for Brazil were applied to Latin American and Caribbean countries, North African and Middle Eastern countries, and South Africa, and the estimates for India were applied to other countries in South Asia as well as countries in Sub-Saharan Africa other than South Africa. These assignments were based on judgments about the resemblance among the agricultural sectors of these countries. Countries assigned to cost shares from India, for example, tended to be low income countries using relatively few modern inputs. Countries assigned to the cost shares from Brazil tended to be middle income countries and having relatively large livestock sectors.

While assigning cost shares to countries in this manner may seem fairly arbitrary, an argument in favor is that there is a remarkable degree of congruence among the cost shares reported for the seven country studies shown in Table 2. For the four developing-country cases (India, Indonesia, China and Brazil), cost shares ranged from 0.40 to 0.46 for labor, 0.22–0.25 for land, and 0.14–0.25 for livestock, while cost shares for fertilizer and machinery inputs were not more than 14% of total output. There was a tendency for the labor cost share to fall and the fertilizer and machinery cost shares to rise with agricultural development, reflecting labor substitution and embodiment of new technology in these inputs. But the fact that for these four developing and three developed countries, the input cost shares show a consistent pattern lends support to using them as representative of global agriculture. The seven countries are also relatively large producers, together accounting for 53% of global agricultural output in 2004–2006, according to the FAO data.

Table 2 Agricultural input cost shares

Study	Country/period	Labor	Land and buildings	Livestock and feed	Machinery and energy	Chemicals and seed	Regions to which these factor shares are assigned	Global production share (%)
Developing countries								
Evenson et al. (1999)	India 1967, 1977, 1987 avg	0.46	0.23	0.25	0.01	0.04	South Asia Sub-Saharan Africa	16.4
Fuglie (2007)	Indonesia 1961–2005 avg	0.46	0.25	0.22	0.01	0.05	SE Asia, Oceania developing	5.2
Fan and Zhang (2002)	China 1961–1997 avg	0.40	0.22	0.23	0.06	0.09	NE Asia developing	16.7
Avila and Evenson (1995)	Brazil 1970, 1990 avg	0.43	0.22	0.14	0.14	0.07	LAC, MENA, South Africa	15.6
Developed countries								
Hayami and Ruttan (1985)	Japan 1965–1980 avg	0.39	0.23	0.10	0.05	0.23	NE Asia developed	2.0
Thirtle and Bottomley (1992)	UK 1967–1990 avg	0.30	0.17	0.26	0.17	0.10	EU-27	19.3
Ball et al. (1997)	USA 1961–2004 avg	0.20	0.19	0.28	0.14	0.18	N Amer, former USSR, Oceania developed	24.9
World		0.35	0.21	0.23	0.10	0.10	Average, weighted by production shares	100.0

Another argument in favor of using the cost-share estimates reported in Table 2 as representative is that they are reasonably close to econometrically-estimated production elasticities from studies that compared agricultural productivity across countries. An implication of profit-maximization and long-run competitive equilibrium is these should be equal. Antle (1983), Hayami and Ruttan (1985), Craig et al. (1997) and Wiebe et al. (2003) all found that labor had the highest production elasticity, followed by land and livestock. The Craig et al. (1997) and Wiebe et al. (2003) studies estimate production elasticities for land that are within the range of the land cost shares reported in Table 2, and about double those estimated by Antle (1983) and Hayami and Ruttan (1985). The difference between these econometric results can probably be attributed to the land quality variables included in the two more recent studies. However, econometric estimates of production elasticities from panel data on countries are not very robust and sensitive to model specification: all of the authors of these econometric studies mention significant multicollinearity among the production factors. Further, none of the studies imposed constant returns to scale, and their estimates of scale economies in agriculture are mixed. However, it is not altogether clear how to interpret estimates of "scale economies" using country-level data. Economies of scale is a firm-level concept that does not apply to nations and requires comparisons among firms to test (Coelli and Rao 2005).

One concern is that for very poor countries that use few modern inputs, assigning cost shares from China, India, Indonesia or Brazil may overstate the role of these inputs in agricultural growth in these countries. Fertilizer application in India during 1967–1987, for example, averaged 27 kg ha^{-1} of cropland compared with only 7 kg ha^{-1} in Sub-Saharan Africa. However, the effect of lower application rates on the input cost share is at least partially offset by higher average unit costs, particularly in Sub-Saharan Africa. In any case, the cost shares assumed for modern inputs are so low that the bias on TFP growth estimates for these countries is likely to be quite small.

2.5 Limitations to the TFP productivity index measure

Some limitations of these calculations should be noted, given the nature of the data on which they are based. The first limitation is that we only compute rates of change in TFP. TFP "levels" cannot be compared across countries with this method. A second limitation is that we do not make adjustments for input quality other than for land. A third limitation is that revenue and cost shares are held constant over time. An examination of the output data show that for major commodity categories (cereal crops, oilcrops, fruits and vegetables, meat, milk, etc.) the global output growth rates were similar over the 1970–2005 period. On the input side there has been more movement in cost shares among the major input categories, but these changes occur gradually over decades. Thus, the likelihood of major biases in productivity measurement over a decade or two is not large, although this does remain a potential source of bias for long-term comparisons. The principal advantage of these TFP growth estimates, however, is that the calculations have a standardized quality. We use a common method, a common period of time for all countries, and a consistent set of definitions for determining factor shares. Moreover, we include 156 countries in the assessment, a nearly complete accounting of global agricultural production of crops and livestock.[1] We assess growth in individual countries as well as regions, and while regional averages may mask differences in performance among the countries within a region, the choice of aggregation into regions does not affect individual country results, unlike distance function measures. See Table 3 for a complete list of countries included in the analysis and their regional groupings.

2.6 Defining technology capital

The circumstantial sensitivity of agricultural technology to specific agronomic conditions limits the degree to which new technology can be transferred from other regions. Therefore, at least some domestic capacity in technology capital is likely to be necessary in order to close the productivity gap between countries. Two broad types of national technology capital are (1) the capacity to develop or adapt new technology and (2) the capacity of users (farmers) to master the new techniques. Unfortunately, systematic information on investments in different kinds of technology capital is generally not available or exceedingly difficult to obtain on an aggregate basis (Evenson and Westphal 1995). What are available instead are various indicators related to distinct aspects of technological capacity. Weiss (1990) compiled several such indicators for a wide range of developing countries and from these assigned each country to one of a typology of "levels" of technology capability. We propose a similar approach for developing indexes for technology capital specific to agriculture.

[1] For the purpose of estimating long-run productivity trends, we aggregate some national data to create consistent political units over time. For example, data from the nations that formerly constituted Yugoslavia were aggregated in order to make comparisons with productivity before Yugoslavia's dissolution. Similarly for Czechoslovakia, Ethiopia, and the USSR. Because some small island nations have incomplete or zero values for some agricultural data, we constructed three composite "countries" by aggregating available data for island states in the Lesser Antilles, Micronesia and Polynesia. This also enables a more detailed examination of regional patterns of agricultural productivity growth.

Table 3 Countries included in productivity analysis and regional groupings

Region	Countries			
Sub-Saharan Africa, developed	South Africa			
Sub-Saharan Africa, developing	Angola	Côte d'Ivoire	Madagascar	Senegal
	Benin	Djibouti	Malawi	Seychelles
	Botswana	Equatorial Guinea	Mali	Sierra Leone
	Burkina Faso	Ethiopia, former	Mauritania	Somalia
	Burundi	Gabon	Mauritius	Sudan
	Cameroon	Gambia	Mozambique	Swaziland
	Cape Verde	Ghana	Namibia	Tanzania
	Central African Rep.	Guinea	Niger	Togo
	Chad	Guinea-Bissau	Nigeria	Uganda
	Comoros	Kenya	Réunion	Zambia
	Congo	Lesotho	Rwanda	Zimbabwe
	Congo, Dem. Rep.	Liberia	Sao Tome and Principe	
Latin America and the Caribbean (LAC)	Argentina	Cuba	Honduras	Puerto Rico
	Bahamas	Dominican Rep.	Jamaica	Suriname
	Belize	Ecuador	Lesser Antilles[a]	Trinidad & Tobago
	Bolivia	El Salvador	Mexico	Uruguay
	Brazil	French Guiana	Nicaragua	Venezuela
	Chile	Guatemala	Panama	
	Colombia	Guyana	Paraguay	
	Costa Rica	Haiti	Peru	
North America	Canada	United States		
Northeast Asia, developed	Japan	Korea, Rep.		
Northeast Asia, developing	China	Korea, DPR	Mongolia	
Southeast Asia	Brunei Darussalam	Laos	Philippines	Viet Nam
	Cambodia	Malaysia	Thailand	
	Indonesia	Myanmar	Timor-Leste	
South Asia	Afghanistan	Bhutan	Nepal	Sri Lanka
	Bangladesh	India	Pakistan	
Western Europe	Austria	France	Italy	Spain
	Belgium-Luxembourg	Germany	Malta	Sweden
	Cyprus	Greece	Netherlands	Switzerland
	Denmark	Iceland	Norway	United Kingdom
	Finland	Ireland	Portugal	
Eastern Europe	Albania	Czechoslovakia, former	Poland	Yugoslavia, former
	Bulgaria	Hungary	Romania	
Middle East and North Africa (MENA)	Algeria	Israel	Morocco	Tunisia
	Bahrain	Jordan	Oman	Turkey
	Egypt	Kuwait	Qatar	United Arab Emirates
	Iran	Lebanon	Saudi Arabia	Yemen
	Iraq	Libya	Syria	
Oceania, developed	Australia	New Zealand		
Oceania, developing	Fiji	New Caledonia	Polynesia[a]	Vanuatu
	Micronesia[a]	Papua New Guinea	Solomon Islands	

Table 3 continued

Region	Countries			
Former USSR countries (analysis of individual countries for 1992 and onward)	Armenia	Georgia	Lithuania	Turkmenistan
	Azerbaijan	Kazakhstan	Moldova	Ukraine
	Belarus	Kyrgyzstan	Russian Federation	Uzbekistan
	Estonia	Latvia	Tajikistan	USSR, former

[a] Lesser Antilles, Polynesia and Micronesia are composite countries each consisting of several island states

To represent the capacity to develop or adapt new agricultural technology we construct an "Invention–Innovation" (II) capital index based on two indicators, the number of public-sector agricultural scientists per thousand hectares of arable land and the UNESCO indicator of research and development as a percentage of GDP. Agricultural scientists per crop area represent capacity to breed and adapt appropriate varieties and agronomic practices for the range of crops and environments in a country. The UNESCO indicator is primarily an indicator of industrial R&D and should capture a country's capacity to adapt and manufacture appropriate industrial inputs for agriculture. The number of agricultural scientists per country is from Pardey et al. (1991) and updated from ASTI (2008).

Countries are given an II index value of 1, 2, or 3 based on the following "break points" or threshold values:

1. Agricultural Scientists per thousand hectares of arable land

   AgSci = 1 if value is .02 or lower
   AgSci = 2 if value is .021 to .06
   AgSci = 3 if value is greater than .06

2. R&D/GDP

   RD = 1 if value is .002 or lower
   RD = 2 if value is .0021 to .006
   RD = 3 If value is greater than .006

The threshold values for AgSci are based on subjective judgment but capture the range of capacities in agricultural research investment by developing countries. In 1970–1975, about one-fourth of the developing countries in our sample were at the AgSci = 1 level, while by 1990–1995 about one-third of the sample had achieved AgSci = 3. For R&D/GDP, the threshold values are taken from Weiss (1990) who classified countries into a typology of technology development levels based on a set of technology indicators. Weiss (1990)[2] classified countries having R&D/GDP at 0.2% or below (RD index = 1) as using "traditional technology", while countries having R&D/GDP of at least 0.6% (RD index = 3) were in transition to newly-industrialized status. Countries in between these thresholds were at an intermediate stage. The sum of the two indicators is the II index (II = AgSci + RD). Thus the minimum II index is 2, the maximum is 6.

Capacity to extend and adopt agricultural technology is represented by an index of "Technology Mastery" (TM) capital. Our TM index is also a composite of two indicators, the number of extension workers per thousand hectares of arable land and the average years of schooling of males over 25. Comprehensive statistics on national agricultural extension services are lacking, but we have compiled what information is available from Judd et al. (1991) with updates from Swanson et al. (1990). The average years of schooling for adult males in the labor force are from Barro and Lee (2001). Countries are given TM value of 1, 2, or 3 based on the following:

1. Extension workers per thousand hectares of cropland

   AgExt = 1 if value is .2 or lower
   AgExt = 2 if value is .21 to .6
   AgExt = 3 if value is higher than .6

2. Average schooling of males over 25.

   Sch = 1 if value is less than 4 years.
   Sch = 2 if value is 4–6 years.
   Sch = 3 if value is greater than 6 years.

The threshold value for AgExt is comparable to that of AgSci, since in developing countries extension workers are roughly 10 times as numerous as agricultural scientists (so the threshold values are 10 times larger). For schooling, achievement of basic literacy in the labor force is consistent with a Sch index value of 2, while Sch = 3 implies a substantial share of the labor force has acquired some additional technical skills. The sum of the two indicators is the TM index (TM = AgExt + Sch). The minimum TM index is 2, the maximum is 6.

The measurement of technology capital by these broad index measures circumvents many of the issues encountered when trying to construct such indicators from sparse data of variable quality. Unlike measures of program expenditure, the index values are stable over long periods of time and do not require assumptions about currency exchange rates for international comparability. Although simple counts of research and extension personnel do not

[2] See also Evenson and Westphal (1995), table 37.1, pp. 2242–2243.

reflect differences in staff quality, the general pattern is for quality (measured by education level of program staff) to improve along with the staff numbers in systems that are expanding, particularly for research (Pardey et al. 1991).

Changes in the index values represent significant improvements in a country's established capacity to invent and diffuse new technology. We have attempted to select threshold values that are robust to measurement errors in national science, technology and education statistics. One criterion for the selection of thresholds is to obtain adequate numbers of observations at each level (e.g., to divide observations roughly by $1/n$ across n levels). Another criterion is to pay attention to where there may be a natural gap in the data, so that country index values are not sensitive to small changes in threshold values. But there is no mechanical way to derive threshold values for indexes of this type, and some professional judgment is required. We did experiment with a number of perturbations of the model and feel that the results capture the broad dimensions of influences of technology capital on agricultural productivity growth and are robust to modest changes in model characteristics.

Table 4 reports II and TM indexes for two periods, 1970–1975 and 1990–1995, for 87 developing countries with a 2000 population of 750,000 or more.[3] The countries are grouped according to their II index scores in the two periods, with the TM index scores shown in parenthesis after the country name. For example, Afghanistan scored 22 for both the II and TM indexes. This means that Afghanistan achieved the lowest possible score (2) in 1970–1975 and again in 1990–1995 for both measures. Brazil, on the other hand, scored 56 (46), meaning that it's II score increased from 5 to 6 and its TM score from 4 to 6 between the two periods. By the early 1990s, Brazil had sufficient technology capital in agricultural research and extension to generate and rapidly diffuse a broad set of improved agricultural technologies.

If we consider an II index of 2 as a characterization of a country in "traditional agriculture," 21 of the 87 countries were in traditional agriculture in 1970–1975. By 1990–1995 nine of these countries remained in traditional agriculture while one country (Guinea Bissau) had reverted to traditional agriculture levels of technology capital between 1970–1975 and 1990–1995. Of the 12 countries that moved out of traditional agriculture, six moved to II class 3 and six to II class 4, by 1990–1995. All moves to II class 3 and most moves to II class 4 were based on an increase in public agricultural research rather than industrial R&D. In no case did the industrial R&D index move ahead of the agricultural scientist index. Thus, an II index of 5 means that the agricultural scientist index was 3 and the R&D/GDP index was 2. By 1990–1995, at least 31 of the 87 countries were investing in significant agricultural research (AgSci = 3). We point out that the components of each of the indexes are not perfect substitutes and are more likely to be complementary (e.g., extension services will be more efficient with a literate farm population). Most of the advances in the Technology Master index that occurred in our sample between the two periods were due to increases in schooling rather than extension.

2.7 Modeling influence of technology capital on TFP growth

To examine the relationship between technology capital and productivity growth, we hypothesize that technology capital in period t will influence TFP growth in that period and in subsequent years. Since we have the technology capital index measures for two periods, we effectively have a two-period panel dataset. We let the II–TM level in 1970–1975 explain average annual TFP growth during 1970–1989 and II–TM level in 1990–1995 explain TFP growth during 1990–2005. We establish causality between technology capital and productivity through the lag structure (i.e., present technology capital stock affects future growth performance). To examine the interaction between research and extension, we construct a series of dummy variables representing different combinations of II (research) and TM (extension-education) capacities. We also include road density (km of roads per km^2 of land area) to account for the effect of public infrastructure. The International Road Federation (2006) reports road density data for 64 of the 87 developing countries for at least 1 year during 1970–1989 and for all 87 countries at least once during 1990–2005, and we use the average road density over the period. For these observations, we estimate:

$$\mathrm{TFP}_{c,t} = \beta \log(\text{road density})_{c,t} + \sum_{\mathrm{II}=2}^{6} \sum_{\mathrm{TM}=2}^{6} \delta_{\mathrm{II,TM}} \mathrm{II} - \mathrm{TM}_{c,t}. \tag{5}$$

where $\mathrm{TFP}_{c,t}$ is the growth rate in country c's agriculture in period t and $\mathrm{II{-}TM}_{c,t}$ takes on a value of 1 if both $\mathrm{II}_{c,t} = 1$ and $\mathrm{TM}_{c,t} = 1$, and 0 otherwise for that country and period. Thus, in Eq. 5, there is a potential for 25 II–TM class combinations, although only 19 are present in the data. Each of these II-TM combinations is represented by a

[3] The set of 87 countries is fairly comprehensive, missing only nine developing countries with a population of more than 750,000 due to insufficient data on some of the technology capital variables. The nine are Cuba in the Caribbean, Fiji, Papua New Guinea, Lebanon and North Korea in Asia–Pacific, and Liberia, Namibia, Swaziland and Lesotho in Africa. We have excluded countries with less than a 750,000 people because these nations face a unique set of problems associated with very small country scale.

Table 4 Country index scores for innovation–invention (II) and technology mastery (TM) in 1970–1975 and 1990–1995 (II index underlined and TM index in parentheses)

22	23	24	
Afghanistan (22)	Benin (34)	Dominican Rep. (24)	
Angola (22)	Burkina Faso (43)	Ecuador (33)	
Cambodia (22)	Burundi (22)	Guinea (33)	
Congo (22)	Central African Rep. (33)	Mali (34)	
Congo, Dem Rep. (23)	Rwanda (44)	Nicaragua (34)	
Ethiopia (23)	Somalia (22)	Togo (34)	
Mongolia (44)			
Mozambique (22)			
Niger (22)			
32[a]	33	34	35
Guinea Bissau (22)	Chad (22)	Algeria (34)	Guatemala (44)
	Gabon (32)	Cameroon (34)	Kenya (45)
	Haiti (33)	Guyana (44)	Panama (56)
	Honduras (24)	Indonesia (25)	Peru (45)
	Laos (33)	Iran (23)	Venezuela (34)
	Madagascar (22)	Libya (34)	
	Mauritania (33)	Malawi (44)	
	Myanmar (33)	Morocco (44)	
	Paraguay (34)	Nepal (34)	
	Zambia (34)	Nigeria (34)	
		Senegal (33)	
		Sudan (22)	
		Syria (35)	
		Tanzania (34)	
		Tunisia (24)	
		Uganda (34)	
		Uruguay (44)	
		Vietnam (34)	
		Yemen (23)	
43[a]	44	45	46
Saudi Arabia (23)	Bangladesh (33)	Argentina (44)	India (24)
Zimbabwe (45)	Bolivia (33)	Botswana (45)	Pakistan (24)
	Colombia (44)	Egypt (35)	Turkey (25)
	Cote d'Ivoire (23)	Iraq (22)	
	Gambia (22)	Malaysia (35)	
	Ghana (34)	Mauritius (56)	
	Jamaica (45)	Mexico (35)	
	Jordan (45)	Sri Lanka (56)	
	Sierra Leone (44)	Thailand (45)	
	Trinidad & Tobago (45)		
55	56		
Costa Rica (44)	Brazil (46)		
El Salvador (25)	Chile (35)		
Philippines (46)	China (56)		
South Africa (46)			

Source: Authors' estimates based on data from ASTI (2008), Barro and Lee (2001), Judd et al. (1991) and UNESCO (2008)

The scores gives the value of the index in each period. For example, 22 means that Afghanistan's II index score was 2 in 1970–1975 and 2 in 1990–1995. Afghanistan also achieved the minimum TM index scores (22) in each of the periods

[a] Note that these countries had a reduction in II capital between periods

dummy variable. The coefficient β measures the effect of transportation infrastructure on productivity growth. The dummy variable coefficient's $\delta_{\mathrm{II,TM}}$ measure the average TFP growth rate for the countries with this II–TM combination. We also estimate Eq. 5 without the road density variable and include all 87 countries in both periods. This is more representative of all developing countries with a population of at least 750,000, since most of the countries lacking data on road density also have low levels of II-TM. To get a meaningful R^2 and F-statistic for the regression, a constant term was added to the model and one of the II–TM classes was left out.

Equations 3 and 5 describe a "two-stage" decomposition of output growth (Evenson and Pray 1991, pp. 81–91). In the first stage (Eq. 3), TFP growth is estimated as the difference between output growth and input accumulation. In the second stage (Eq. 5), this estimate of TFP growth is modeled as a function of technology capital and infrastructure. This two-stage framework helps to avoid the multicollinearity problem that arises when estimating an agricultural "metaproduction function," in which output growth is modeled econometrically as a function of both conventional inputs and non-conventional factors such as research and education. As mentioned previously, a high correlation between research and the use of modern inputs like fertilizer and machinery causes econometric estimates from multi-country agricultural metaproduction functions to be sensitive to model specification. In the two-stage approach, the contribution of modern inputs to output is accounted for by their cost share, and any increase in output over cost is attributed to productivity.

In addition to technology and human capital, TFP will be affected by errors in measurement, "left-out" factors of production, weather fluctuations, civil disturbances, economies of scale, gains in allocative efficiency from market liberalization and other variables. However, several of these omitted variables are probably not relevant to our model because of the long period over which we measure TFP change (i.e., we take average TPF growth over a 20 year period and a 16 year period). Thus, short-run fluctuations to output or TPF due to natural or civil disturbances will tend to be averaged out. Regarding scale economies Hayami and Ruttan (1985), found no evidence that scale economies accounted for differences in productivity among developing countries. Market liberalization and institutional reforms that improve allocative efficiency will also cause TFP to grow, although the effect may only be temporary. Once resources have been reallocated to realize the efficiencies, growth will again stagnate unless improved technology is also forthcoming.

An advantage of the model in Eq. 5 is that it allows us to examine the marginal effects of changes in the two types of technology capital, given levels of the other. Holding II (research capacity) at some level J and then examining how the coefficients $\delta_{J,2}\ldots\delta_{J,6}$ vary allows us to examine how marginal increases in TM (agricultural extension and schooling) affect TFP growth. Similarly, holding TM fixed at some level K and examining the values of coefficients $\delta_{2,K}\ldots\delta_{6,K}$ allow us to say something about the marginal effect of research capacity.

3 Trends in global agricultural productivity

The global picture of agricultural productivity growth since 1970, in 5 year averages, is described in Figs. 1 and 2. Figure 1 plots the average growth rates for global output, inputs and TFP. The long-run pattern shows that while growth in agricultural production inputs slowed through most of the period, the rate of increase in TFP accelerated to maintain real output growth at about 2% per annum. The exceptionally low rate of capital formation in global agriculture during the 1990s was due primarily to the rapid withdrawal of resources from agriculture in the countries of the former Soviet block. By the early 2000s agricultural resources in this region had stabilized and there was a slight increase in the rate of global input growth between the 1990s and early 2000s. Figure 2 shows agricultural TFP growth across three regions: developing countries, former Soviet-block transition countries, and other industrialized countries. The average TFP growth in developing countries accelerated throughout most of the period and by the 1990s was comparable to that of other industrialized countries. Agricultural TFP growth in former Soviet-block countries was negative until the late 1980s but has since caught up with the rest of the world. Productivity growth in the USSR and Eastern Europe was not sufficient to keep agricultural output from falling in the decade immediately after the breakup of the USSR, but output growth in this region resumed in the 2000s as inputs stabilized and TFP growth continued.

Table 5 shows the growth patterns in real agricultural output, inputs and TFP by decade since 1970, with more regional detail.[4] In the industrialized regions of Northeast Asia, North America and Western Europe, the agricultural resource base has been shrinking since 1980 and at an accelerating rate while TFP growth continued at historical levels. TFP growth in Western Europe and North America was sufficient to compensate for lower inputs and keep output growing, but in the developed countries of Northeast Asia real agricultural output has been gradually falling since around 1990. Output growth was also negative in Oceania (Australia, principally) in 2000–2005, but this largely reflects the impact of a prolonged drought in this period. In developing regions, productivity growth sharply accelerated in the 1980s and the decades following while input growth steadily slowed but was still positive. Two large developing countries in particular, China and Brazil,

[4] Annual indices of TFP growth were estimated for each country for the entire 1970–2005 period (except for countries that made up the former Soviet Union, for which TFP indices were estimated only for 1992–2006). For space limitations country results are not shown but are available from the authors on request.

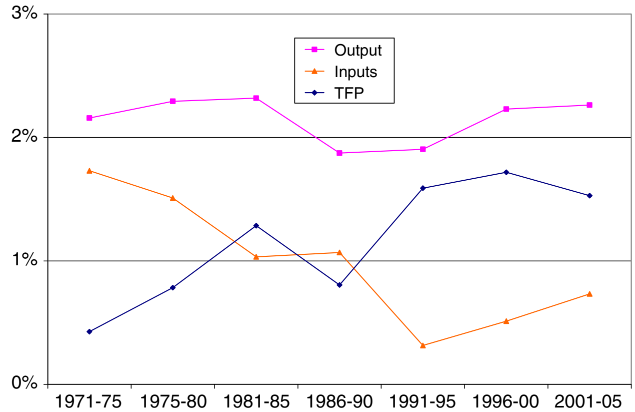

Fig. 1 Growth rates for global agricultural output, inputs and total factor productivity (TFP; 5 year average annual %) *Source:* Authors' estimates

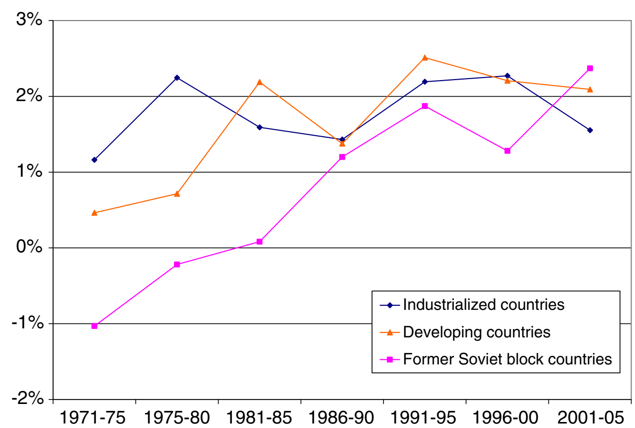

Fig. 2 Growth rates for agricultural total factor productivity (TFP) by region (5 year average annual %) *Source:* Authors' estimates

sustained exceptionally high TFP growth rates since the 1980s. Sub-Saharan Africa is a major exception to the general pattern, with TFP growth lagging significantly behind other developing regions.

Results at country level (not shown) give further evidence on where agricultural productivity was growing and where it was not. Among industrialized nations, agricultural TFP growth was robust nearly everywhere, with the exceptions of Switzerland and Norway. These two countries have stayed outside of the European Union's Common Agricultural Policy and maintain the highest levels of protection of their agricultural sectors among OECD countries. They have intentionally sought to keep resources (especially labor) employed in rural areas and as a result agricultural productivity growth has been notably slow. Among developing countries, there are a fair number of countries besides Brazil and China that achieved respectable levels of agricultural productivity growth: Malaysia, Vietnam, Peru, Chile, Colombia, and Iran all achieved average annual agricultural TFP growth rates of over 2.5% over 1990–2005. However, with a few exceptions, developing countries in Sub-Saharan Africa, the Caribbean, and Oceania continued to rely on resource-led agricultural growth rather than productivity, and as a consequence their agricultural sectors performed poorly.

The strong and sustained productivity growth described here for a number of large developing countries is broadly consistent with results from a number of other studies. Gasquez et al. (2008) estimated average annual agricultural TFP growth in Brazil to be 2.5% over 1975–2005, similar to our estimate of 2.6%, and both studies show an acceleration of TFP growth over time. China had success since the late 1970s with both institutional reform and technological change (Rozelle and Swinnen 2004). Fan and Zhang (2002) estimated average annual TFP growth for Chinese agriculture at 2.6% during 1970–1997 with relatively slow growth until 1980 after which TFP rapidly accelerated. Our estimates also show an accelerating pattern to TFP growth, although at a lower average annual rate of 1.9% over the same period. Our results for India during 1979–1994 are also slightly lower than Fan et al.'s (1999)—1.5% versus their 1.7% annual TFP growth. These studies all used the Tornqvist method in which factor shares vary over time. Our estimates of lower TFP growth for some countries may possibly reflect an "index number bias" arising from holding factor shares fixed. For Indonesia Fuglie's (2004), estimate of 1.7% average annual agricultural TFP growth between 1961 and 2000 is somewhat higher than our estimate of 1.3% over these years. Our method of adjustment for land quality may imply higher rates of input accumulation (and thus less TFP growth), especially in countries where irrigated area substantially increased.

4 Agricultural productivity and technology capital

The findings reported in the previous section showed that among industrialized countries, all of which have well-developed technology capital, agricultural TFP growth was robust and sustained over the past 35 years (except for two countries which deliberately kept resources employed in agriculture). But the results for developing countries were decidedly more mixed: some countries sustained rapid productivity growth while others did not. These countries also exhibited a wide range of technology capital, with some significantly expanding their capital stocks over time while others achieved little or no improvement or even regression.

Our findings on the relationship between technology capital and long-term growth in agricultural TFP in developing countries are reported in Tables 6 and 7.

Table 5 Agricultural output, input and TFP growth by region

Average annual growth rate (%) by period	Output index (smoothed with Hodrick–Prescott filter)				Input index (land adjusted for quality)				TFP index			
	1970–1979	1980–1989	1990–1999	2000–2005	1970–1979	1980–1989	1990–1999	2000–2005	1970–1979	1980–1989	1990–1999	2000–2005
Sub-Saharan Africa	1.31	2.60	3.10	2.20	1.68	1.66	1.63	1.59	−0.37	0.94	1.47	0.61
Latin America & Caribbean	3.07	2.37	2.87	3.13	2.46	1.07	0.49	0.65	0.61	1.30	2.38	2.48
Brazil	3.83	3.73	3.29	4.41	4.38	0.60	0.29	0.75	−0.54	3.13	3.00	3.66
Middle East & North Africa	2.94	3.37	2.73	2.34	2.52	1.64	1.14	0.78	0.42	1.73	1.59	1.56
Northeast Asia, developed	2.15	1.03	−0.01	−0.01	0.29	−1.20	−2.57	−3.09	1.86	2.22	2.55	3.08
Northeast Asia, developing	3.11	4.55	5.06	3.85	2.60	1.98	1.06	0.43	0.51	2.57	4.00	3.42
China	3.09	4.60	5.17	3.87	3.27	2.13	1.39	0.65	−0.19	2.47	3.78	3.22
Southeast Asia	3.68	3.59	3.13	3.54	1.67	2.63	1.52	1.37	2.01	0.97	1.60	2.16
South Asia	2.56	3.39	3.00	2.19	1.90	1.37	1.29	0.83	0.66	2.02	1.71	1.36
India	2.69	3.52	2.94	2.00	1.89	1.42	1.19	0.57	0.80	2.10	1.74	1.43
North America	2.17	0.73	2.03	1.10	0.72	−0.63	−0.10	−0.65	1.46	1.36	2.13	1.75
Oceania	1.79	1.25	2.93	−0.04	0.71	0.23	1.03	0.21	1.08	1.02	1.90	−0.25
Western Europe	1.54	0.94	0.46	−0.35	0.08	−0.71	−1.50	−1.74	1.46	1.65	1.97	1.39
Eastern Europe	1.80	0.25	−2.18	−0.19	1.22	−0.08	−3.21	−0.78	0.58	0.33	1.03	0.58
USSR, former	1.32	0.98	−4.62	2.70	2.07	0.69	−6.23	−0.57	−0.74	0.29	1.60	3.28
Developing countries	2.82	3.46	3.64	3.09	2.27	1.79	1.34	1.01	0.55	1.67	2.31	2.08
Developed countries	1.88	0.86	1.21	0.39	0.26	−0.62	−1.04	−1.37	1.62	1.48	2.25	1.76
USSR & Eastern Europe	1.47	0.77	−3.88	1.81	1.93	0.49	−5.48	−0.29	−0.46	0.27	1.59	2.10
World	2.23	2.13	2.04	2.22	1.62	1.18	0.44	0.66	0.60	0.94	1.60	1.55

Source: Authors' estimates

Table 6 shows results when the infrastructure variable is included in the regression but using a smaller sample due to missing data on this variable for some countries. Table 7 reports results for the full set of 87 countries observed in both the 1970–1989 and 1990–2005 periods but without the infrastructure variable. Since most countries lacking data on infrastructure also had the lowest levels of technology capital, there is a possibility of selectivity bias in the estimates for the group reported in Table 6. In any case the infrastructure variable was not significant in the regression. We also ran this regression adjusting the road density variable in terms of km of roads per km^2 of agricultural land (rather than total land area) but the variable was still not significant. Both Craig et al. (1997) and Wiebe et al. (2003) found road density to be correlated with growth in agricultural output per worker, but our results would suggest that the principal pathway for infrastructure to expand output is to encourage input intensification, since it does not appear to be correlated with TFP growth. Nor was infrastructure highly correlated with the technology capital variables. For these reasons we focus the discussion on the results using the more complete set of countries (with infrastructure excluded) reported in Table 7.

The regression coefficients are arrayed in a matrix corresponding to the II–TM class they refer to. The coefficient estimates reflect the average annual TFP growth rate (in percent) for all countries having technology capital in that II–TM class in either the 1970–1975 or 1990–1995 period. The numbers in parentheses below the coefficients indicate the number of observations that fell in that class. For example, in Table 7 there were 18 countries that fell in the class characterized by little or no technology capital (II class = 2 and TM class = 2) in one of the periods. These countries as a group achieved a mean annual TFP growth of 0.40%, which was not significantly different from zero. At the other end of the technology capital scale there were two countries in II–TM class 66, and they achieved an average annual TFP growth rate of 3.45%. These countries are Brazil and China, large countries that have invested heavily in agricultural research and extension. There is a clear progression of higher TFP growth as countries increase II–TM technology capital. However, countries needed a minimal capacity in both research and extension-schooling in order to sustain significant productivity growth. When either II capital or TM capital were at very low levels (class 2), mean TFP growth rates were not significantly different from zero. However, with one exception, II–TM levels of 33 and higher were all associated with positive and significant TFP growth. The exception is II-TM class 35, which consists of only two countries—Panama in 1970–1989 and Zimbabwe in 1990–2005. Both of these countries suffered from political

Table 6 Technology capital, infrastructure and agricultural TFP growth

Data sample: 64 developing countries during 1979–1989 and 87 developing countries during 1990–2005

Technology mastery (TM) class (Ag extension + schooling)	Invention–innovation (II) class (Ag research + industry R&D)[a] 2	3	4	5	6	F-test of marginal effect of II holding TM fixed
2	0.73 ($n = 10$)	0.28 ($n = 12$)	0.60 ($n = 7$)	0.42 ($n = 1$)		$F(3, 131) = 0.28$ ns
3	−0.75 ($n = 6$)	0.44 ($n = 18$)	1.01** ($n = 15$)	0.94 ($n = 2$)		$F(3, 131) = 3.27$^^
4	−0.37 ($n = 4$)	0.81* ($n = 10$)	1.16*** ($n = 29$)	1.76*** ($n = 8$)	1.40* ($n = 2$)	$F(4, 131) = 2.26$^
5		−0.55 ($n = 2$)	1.08** ($n = 7$)	1.16** ($n = 9$)	1.70** ($n = 2$)	$F(3, 131) = 1.46$ ns
6				1.13** ($n = 5$)	3.21*** ($n = 2$)	$F(1, 131) = 4.41$^^

log(road density): −0.0013, t-statistic = −1.24, $P > t = 0.218$

F-test of marginal effect of TM holding II fixed: $F(2, 131) = 3.30$ ns, $F(3, 131) = 0.87$ ns, $F(3, 131) = 0.43$ ns, $F(4, 131) = 0.54$ ns, $F(2, 131) = 1.35$ ns

Source: Authors' estimates

Number of observations = 151, $F(19, 130) = 1.970$, $P > F = 0.0139$; R-squared = 0.222, Adj R-squared = 0.110, Root MSE = 0.012

*, **, *** Coefficients are significant from zero at 10, 5, and 1% significance level

^, ^^ Rejection of hypothesis that all coefficients in row or column are equal at 10 and 5% significance level and 'ns' indicates not significant—cannot reject hypothesis of equal coefficients

[a] Coefficients show average annual TFP growth rate in percent (number in parenthesis is number of observations with II–TM combination)

Table 7 Technology capital and agricultural TFP growth

Data sample: 87 developing countries over two periods

Technology mastery (TM) class (Ag extension + schooling)	Invention–innovation (II) class (Ag research + industry R&D)[a]					F-test of marginal effect of II holding TM fixed
	2	3	4	5	6	
2	0.40 ($n = 18$)	0.54 ($n = 14$)	0.36 ($n = 8$)	0.50 ($n = 1$)		$F(3, 155) = 0.04$ ns
3	−0.09 ($n = 9$)	0.86*** ($n = 25$)	1.33*** ($n = 15$)	1.25* ($n = 2$)		$F(3, 155) = 2.53$^^
4	0.03 ($n = 4$)	0.83** ($n = 12$)	1.44*** ($n = 29$)	1.96*** ($n = 8$)	1.50* ($n = 2$)	$F(4, 155) = 2.16$^
5		−0.30 ($n = 2$)	1.19** ($n = 7$)	1.44*** ($n = 9$)	1.90** ($n = 2$)	$F(3, 155) = 1.29$ ns
6				1.24** ($n = 5$)	3.45*** ($n = 2$)	$F(1, 155) = 4.50$^^

F-test of marginal effect of TM holding II fixed: $F(2, 155) = 0.51$ ns, $F(3, 155) = 0.69$ ns, $F(3, 155) = 0.61$ ns, $F(4, 155) = 0.52$ ns, $F(2, 155) = 1.37$ ns

Source: Authors' estimates

Number of observations = 174, $F(18, 155) = 2.25$, $P > F = 0.004$; R-squared = 0.208, Adj R-squared = 0.116, Root MSE = 0.125

*, **, *** Coefficients are significant from zero at 10, 5, and 1% significance level

^, ^^ Rejection of hypothesis that all coefficients in row or column are equal at 10 and 5% significance level and 'ns' indicates not significant—cannot reject hypothesis of equal coefficients

[a] Coefficients show average annual TFP growth rate in percent (number in parenthesis is number of observations with II–TM combination)

instability and poor macroeconomic performance over these periods, which may likely account for their low agricultural productivity growth despite significant levels of extension-schooling and some research capacity.

The F-statistic tests reported in the final column and row of Tables 6 and 7 examine the marginal effects of research and extension holding the other fixed. Casual observation indicates that TFP growth rates tended to rise at higher levels of either II or TM capital (holding the other fixed), but the F-statistic tests the hypothesis that all of the row (or column) coefficients are equal. In other words, it tests the hypothesis that there was no significant increase in TFP growth with a marginal increase in one of the kinds of technology capital. Neither II capital (research) or TM capital (extension and schooling) was effective at raising agricultural TFP growth without at least a minimal capacity in the other. But in the case of research, TFP growth rose significantly with marginal increases in II capital in three of the four cases where TM capital was at level 3 or higher. TFP growth also rose in the fourth case—where TM capital equals 5—but the growth was not statistically significant. On the other hand, in no case did a marginal increases in TM capital significantly increase TFP growth when II capital remained constant. In other words, agricultural extension and schooling were not substitutes for research and development capacity. Improved capacity to invent and adapt new technology to country-specific conditions was a requisite for sustaining TFP growth in agriculture.

The results show a clear impact of research capacity on achieving long-term productivity growth in agriculture. It is also useful to examine whether some countries were able to achieve TFP growth without it. Among the 174 country-period combinations in our sample, there were only four cases in which countries with the lowest II level (II = 2) achieved average annual TFP growth of 1.4% or higher (in other words, that were in the top 40% of the sample). Three of these cases, Angola, Mozambique, and Cambodia during 1990–2005, reflect the influence of war recovery. The rapid increase in TFP measured in these countries was a return to pre-war productivity levels as labor once again became more fully employed on farms. The fourth case was Benin, which achieved a TFP growth rate of 1.9% per year during 1970–1989 despite having an II level of 2 during 1970–1975. This was one case that was sensitive to how we defined the variables in the model. Benin began to build its agricultural research capacity starting around 1970 and by the second half of the decade had graduated to an II class 3 country. Thus, for most of the 1970–1989 period Benin was no longer in "traditional agriculture." It is simply difficult to find a single example of a country that able to achieve long-run productivity growth in agriculture without first establishing domestic capacity in agricultural research.

5 Conclusions and implications

This new global assessment of agricultural productivity indicates that TFP growth accelerated in recent decades, due in no small part to rapid productivity gains in several developing countries and more recently to a recovery of agricultural growth in the countries of the former Soviet block. However, the results also show clear evidence of a slowdown in the growth in agricultural capital accumulation: the global agricultural resource base is still expanding but at a much slower rate than in the past. These two trends: accelerating TFP growth and decelerating input growth, have largely offset each other to keep the real output of global agriculture growing at about 2% per year at least since the 1970s.

Agricultural TFP growth has been robust in most industrialized countries but has been highly uneven among developing countries. The largest group of countries in the low growth club is in Sub-Saharan Africa, but also includes many countries in the Caribbean, Oceania and some others. We examined the relationship between average long-run TFP growth and national investments in technology capital and infrastructure for a set of 87 developing countries. To distinguish between two major forms of technology capital we constructed an index of Technology Mastery to capture national capacities in agricultural extension and labor-force schooling, and an index of Invention–Innovation to measure strengths in public agricultural research and industrial R&D. Our econometric results showed that rising agricultural TFP growth rates were correlated with increases in technology capital but not with improvements in transportation infrastructure. While infrastructure improvements may raise agricultural output by encouraging resource expansion, to sustain long-run growth in TFP requires technology capital. Among these two forms of technology capital, our results argue in favor of giving greater emphasis to strengthening research capacity as an economic growth strategy. While some countries have sought to achieve rapid improvements in agricultural productivity by expanding agricultural extension services at the expenses of agricultural research, our results show that marginal improvements to extension and schooling, without commensurate improvements in research capacity, were not associated with increased productivity growth, while marginal improvements to research capacity often were.

It should be emphasized that our model refers to productivity growth over the long run. Since the middle of the twentieth century, improvements in global agricultural productivity have caused international prices for agricultural commodities to decline in real terms. In an increasingly globalized economy, developing countries with low TFP gains in agriculture are "trapped" in a price–cost squeeze, with real prices falling more rapidly than their costs are falling. These countries are mostly those with minimal Invention–Innovation or Technology Mastery capital. On the other hand, many developing countries that increased their technology capital were able to achieve agricultural TFP gains at least as large as or larger than those of industrialized countries. These countries are moving toward an economic transformation that is raising the material well-being of their societies.

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