Reassessing Productivity Growth in African Agriculture

May 18, 1999

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Selected paper for the annual meeting of the American Agricultural Economics Association, Nashville, Tennessee, August 8-11, 1999. Chan-Kang, Pardey, and Wood all work for the International Food Policy Research Institute, Washington D.C. Roseboom and Cremers are at the International Service for National Agricultural Research, The Hague.

Food security, hunger, and malnutrition are problems that still bedevil much of Sub-Saharan Africa (hereafter, Africa). Over the past three decades, growth in African agricultural output failed to keep pace with rapid population growth. In 1993, agricultural GDP per capita was a mere $243 (1985 international prices)— ranging from $6,543 per capita in Mauritius to $298 in Ethiopia—, barely two-thirds of the corresponding 1961 figure ($336). Agriculture is still the predominant sector of most African economies: it collectively accounted for one quarter of total GDP in 1993, and provided employment for nearly two-thirds of the region's total labor force. Dealing effectively with the problems of agriculture is seen by many as the key to broad based economic development throughout Africa (Delgado, Hopkins, and Kelly).

Despite some gains in some crops in some areas (Maredia, Byerlee, and Pee), African agricultural productivity continues to lag well behind other regions of the world. For example, maize yielded 1.1 metric tons per hectare in Africa and China in 1961; by 1998, yields in China had grown five times but in Africa they barely budged, reaching only 1.4 metric tons per hectare (FAO). Moreover, a ranking of 161 maize producing countries based on their 1998 yield performance reveals that almost two thirds of the worst 24 performers were African countries. The situation is similar for rice. Since 1961, much of the region's production growth was due to area expansion. African yields grew slowly, averaging 0.82 percent per annum, and by 1998 were still among the lowest of all rice-producing regions. The use of purchased inputs and improved crop varieties—some of the technical changes that have helped transform agriculture in many other parts of the world—are not widespread throughout Africa. In 1997, chemical fertilizer consumption throughout the region averaged just 12 kilograms per hectare of arable and permanently cropped land, compared with an average of 60 kilograms per hectare in Latin America, and 127 kilograms per hectare in Asia.

For policy and other purposes, it is important to develop a sense of the contribution to production, and the productivity consequences, of conventional inputs (duly adjusted for quality differentials), publicly provided inputs like rural infrastructure and stocks of local research knowledge, and, especially for African agriculture, natural inputs like rain. Less tangible but, perhaps, equally important, aspects like social, political, and economic institutions and operating norms—often under the guise of good government, democratic institutions, or free and open markets—can also play a role. While this list of growth-promoting factors is familiar to many, getting data to meaningfully measure their effects is difficult, doubly so for a region like Africa where agricultural statistics are problematic. Here we draw on some new and some novel national data to describe and econometrically assess cross-country productivity change in African agriculture, paying particular attention to the roles of "non-conventional" inputs such as research and development (R&D) expenditures, education, and infrastructure.

Past Evidence of Productivity Growth and its Sources

Partial productivity measures such as output per unit of land or output per unit of labor provide useful but somewhat circumscribed indications of productivity developments. Until quite recently these were the only productivity measures available for African agriculture, and most were provided as part of a broader, multi-regional assessment of productivity (see, for example, Hayami and Ruttan , Antle, and Craig, Pardey and Roseboom). In 1993, Thirtle et al. provided the first published estimates of multi-factor productivity (MFP) growth in Africa using data for Zimbabwe. Block used period-to-period differences in the intercept terms taken from econometric estimates of a system of production equations as measures of “total factor productivity”growth rates for 39 African countries for the 1963-1988 period. Lugisi and Thirtle and Thirtle, Hardley and Townsend report Malmquist multi-factor productivity estimates for 47 and 22 countries respectively. There seemed to be a slower rate of productivity growth throughout the 1970s compared with the 1980s, and a wide discrepancy among countries in reported rates of productivity growth.[1]

Frisvold and Ingram , as well as Reardon et al., and Lusigi and Thirtle sought to account for differences in measured agricultural productivity in Africa. All used estimates of some traditional inputs such as land, labor, and livestock, and more modern inputs like chemical fertilizer and machinery. Some of these studies included additional explanatory factors: Frisvold and Ingram also used a land quality indicator developed by Peterson to account for land productivity growth, Lugisi and Thirtle used the same quality index to account for changes in agricultural output. Block and Thirtle, Hadley, and Townsend experimented with the use of education variables, local R&D and extension variables, and some measures of price protection to control for various other influences on productivity. However, a systematic treatment of unmeasured variations in input quality and errors-in-variables problems has been largely absent from this earlier literature.

Model and Data

To draw some statistical inferences about the sources of productivity growth in Africa we follow Craig, Pardey and Roseboom by estimating a labor productivity function. Our empirical equation is derived from a production function that makes explicit the errors-in-variables, missing-variable, and input quality problems which are a feature of virtually all such estimation exercises, but are especially problematic for African data. Our study includes a panel of 36 African countries with annual data spanning the 36 year period 1961-96. We begin by taking the production function for the ith country at time t to be of a Cobb-Douglas form, with k conventional inputs, $X_{ij}^{*}(t)$, m infrastructure inputs, $P_{ij}(t)$, a country specific democracy index, $F_i(t)$, and a country-invariant temporal shift variable, $A(t)$:

[1] As Lugisi and Thirtle point out, the magnitude of some of their reported productivity gains are difficult to comprehend; for example, they report annual rates of multi-factor productivity gains for Zaire and Uganda for the period 1961-91 of 8.1 and 7.8 percent respectively.

$$Y_i(t) = A(t)\ F_i(t) \prod_{j=1}^{k} X_{ij}^{\ *}(t)^{\beta_j} \prod_{j=1}^{m} P_{ij}(t)^{\gamma_j} \qquad \textbf{(1)}$$

If the conventional inputs are measured with error, there is a difference between observed and effective inputs. In this instance, the production function depends on measured inputs as well as the sources of errors in those inputs. Drawing from Binswanger et al., we define some of those errors to be quality shifters in input j, $Z_{ij}(t)$, which may vary over time in ways that are specific to country i. And, as in Lau and Yotopolous, we also allow for a country-specific but time-invariant measurement error α_{ij} in input j. Thus the relationship between observed input $X_{ij}(t)$ and effective input $X_{ij}^{\ *}(t)$ is given by

$$X_{ij}^{*}(t) = \alpha_{ij}\ Z_{ij}(t)\ X_{ij}(t) \qquad \textbf{(2)}$$

To understand the sources of differences in output per worker, equations (1) and (2) were combined and both output and conventional inputs were divided by the number of workers, $X_{i1}(t)$, to yield

$$\frac{Y_i(t)}{X_{i1}(t)} = A(t)\ X_{i1}(t)^{\delta}\ F_i(t) \prod_{j=2}^{k} \left[\frac{X_{ij}(t)}{X_{i1}(t)}\right]^{\beta_j} \prod_{j=1}^{k} \left[\alpha_{ij}\ Z_{ij}(t)\right]^{\beta_j} \prod_{j=1}^{m} P_{ij}(t)^{\gamma_j}$$
$$\text{where} \quad \delta = \sum_{j=1}^{k} \beta_j - 1 \qquad \textbf{(3)}$$

Notably, labor still appears on the right hand side of equation (3) unless constant returns to scale in the scaled inputs is imposed on the production function so that $\delta = 0$.

The logarithmic form of equation (3) estimated in this study is given by

$$\begin{aligned} y_i(t) = & \sum_{i=1}^{n-1} \mu_i CD_i + \sum_{s=1}^{t-1} a_s TD_s + \sum_{i=1}^{n} \alpha_i F_i(t) + \sum_{j=2}^{k} \beta_j\ x_{ij}(t) + \delta x_{i1}(t) \\ & + \sum_{j=1}^{k} \lambda_j\ z_{ij}(t) + \sum_{j=1}^{m} \gamma_j\ p_{ij}(t) + \epsilon_{ij}(t) \end{aligned} \qquad \textbf{(4)}$$

where the lower case letters indicate logs; output and the conventional inputs are scaled by the total agricultural workforce; and $\epsilon_{ij}(t)$ represents random shocks to output that are uncorrelated with the other variables. Dummy variables for each year, $TD(t)$, appear in the empirical specification to allow for temporal shifts in the production function that are common to all countries. Dummy variables for each of the countries, CD_i, were also included to account for time-invariant measurement errors. In this instance, the country dummy is a composite measurement error and as such conveys no information about which inputs are actually mis-measured.

Much, but not all, of our production-related data were taken from FAO. Obtaining internationally comparable statistics is difficult. Many African countries have limited data collection and processing capacities, and the sometimes shifting, subsistence, communal, and intercropped production systems that are a feature of the region make it difficult to generate meaningful measures of agricultural inputs and outputs.

In the absence of a comprehensive set of agricultural output prices, our output measure was obtained from an unpublished FAO net output series. This series takes the reported quantity produced of a comprehensive basket of agricultural commodities for each country for each year and scales each commodity by the corresponding international agricultural price (calculated by the Gary-Khamis method) for the base period 1989-91 (Rao). Output is measured net of feeds and seeds used in the production process.

Conventional and Modern Inputs

Our agricultural labor series is the number of economically active population in agriculture, agricultural land consists of the unweighted sum of arable and permanent cropland and permanent pasture, chemical fertilizer inputs are measured in metric tons of plant nutrients, and we proxied capital services with a tractor count series. All of these variables are less than ideal input measures, as described in some detail by Craig, Pardey, and Roseboom. For instance, total tractors in use in agriculture provide, at best, a crude indicator of total services from capital because they omit many types of harvesting and forage equipment, all buildings, and even two-wheeled tractors. Moreover, tractor counts do not indicate the range of quality and intensity of use of tractors either over time or across countries.

Livestock serve many different purposes in agriculture, and so care must be taken in measuring and interpreting stocks of animals as inputs in agriculture. We partitioned animals into those used primarily for traction and those that provide breeding services. Any livestock that serve neither function are properly treated as part of output but not inputs.

Land Quality

Countries' agroecological and biophysical endowments, including land attributes and climate clearly account for some of the observed differences in productivity. The spatial (including cross-country) variation in land attributes can be quite pronounced, as can be the year-to-year variability in climate (see, for example, Mundlak, Larson, and Butzer). To represent variations in land quality, we used three indicators: (a) the share of total agricultural area classified as arable or permanently cropped land, (b) the share of irrigated land in total agricultural land, and (c) the amount of annual rainfall.

Total agricultural land for each country includes heterogeneous land types of various quality. Cross-sectional differences in land productivity measures will tend to be exaggerated when output is not scaled by hectares of constant quality. For instance, if a hectare of irrigated cropland is effectively more than one hectare of non irrigated cropland, one overstates the output per hectare of cropland by failing to weight non-irrigated and irrigated land differently in the cropland total.

The amount of rainfall has a direct effect on agriculture and approximates water availability in the largely rainfed production systems that typify African agriculture. In addition, rainfall affects soil attributes and thereby also land quality. We constructed a rainfall variable using three spatially referenced (GIS) data sets. By intersecting digital maps of national boundaries, area suited for rainfed agriculture, and annual rainfall across Africa we generated national time-series of annual rainfall averaged over the (potentially) rainfed agriculture extent of each country.[2]

Labor Quality

Indicators of the quality of labor used in agriculture are not available, so we used two variables that apply to the total population, namely life expectancy at birth and illiteracy rates. These variables may reflect public spending on education and health care but may also be thought of as human capital characteristics. While there may be significant differences within a country between the health and educational status of rural and urban workers, the cross-country differences in workforce characteristics appear to be much larger. Hence, these measures should suit our purpose of trying to explain some of the systematic differences in agricultural labor productivity. Life expectancy at birth and adult illiteracy rates (15 years old and over) were taken from the World Bank.

Democracy

There has been much empirical attention given recently to the growth promoting consequences of democratic institutions and effective and well-managed public agencies. The often gradual process of accumulating physical, human, and knowledge capital, that is central to sustaining productivity gains, relies on public and private incentives shaped by the reality and the expectations of stable and corruption free institutions. The African continent has seen more than its share of civil and military strife during the past three decades. Aside from the more immediate destruction of potentially productive assets, the lack of democratic processes that accompanies such strife can have a profound effect on growth and productivity. For example, Dasgupta attributes between 30-50 percent of the decline in food production

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[2] Areas suited for rainfed agriculture were assumed to be anywhere in which the length of growing season was greater than 90 days. The annual rainfall series for Sub-Saharan Africa was obtained from the National Center for Atmospheric Research (Dai, Fung, and del Genio 1997). These data comprised a monthly time series from 1960-95 on a 2.5 degree grid for the whole of SSA.

in Eritrea to its on-going war.

Barro (and others[3]) have used the "freedom" measures developed by Freedom House in Washington D.C. to proxy the impacts of democracy on growth. Here we draw on that same (admittedly incomplete, and in some respects inadequate) indicator of "democracy" to represent the impacts of political and civilian institutions on agricultural productivity. This democracy variable is formed by a simple average of the annual scores given to a range of criteria reflecting political rights and civil liberties. Countries are then grouped according to whether they are deemed not free, partly free, or free, and it is this group assignment that is used as a right-hand-side variable in our statistical model.

Infrastructure and Knowledge Stocks

Cross-sectional differences in infrastructure as well as knowledge stocks arising from public R&D spending may well explain part of the variability of labor productivity. Real, annual R&D expenditures since 1961 were summed to form a Fulginiti and Perrin-like stock-of-knowledge variable. Infrastructure was proxied by a road density variable measuring the length of paved road per hectare of agricultural land. Investing in R&D generates new knowledge, some of which has a direct effect on productivity, some of which is embodied in new and improved inputs and outputs. Better roads and transportation, may improve the timing of agricultural operations, facilitate access to markets, and make productivity gains from specialization possible. Kilometers of paved road were obtained from a comprehensive database developed by Canning, annual real expenditures on public agricultural R&D (measured in 1985 international dollars) were taken from Pardey, Roseboom, and Anderson.

Regression Results

A sample of the regression results, with (model 3) and without (models 1 and 2) the stock-of-

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[3] See, for example, the reviews by Sirowy and Inkeles as well as Prezworski and Limongi.

knowledge and infrastructure variables, are reported in table 1. Well over 96 percent of the variation in labor productivity is accounted for by the conventional inputs and other measures included in the regressions.

Variations in labor productivity in Africa are still largely driven by variations in conventional inputs. When the knowledge stock is absent from the regression, land and livestock inputs are highly significant and associated with higher productivity of labor. When the knowledge stock is included, land still has a positive but no longer statistically significant effect on labor productivity; livestock's effect is little altered. In all specifications, an increase in the number of tractors—our proxy for capital in agriculture— significantly increased labor productivity. Chemical fertilizers have a positive and significant, but comparatively smaller, effect on labor productivity. Including knowledge stocks in the regression substantially raises the production elasticity of fertilizer, from 0.005 percent (without R&D capital) to 0.023 percent (with R&D capital).

The output elasticities of conventional inputs, specifically land and livestock, were consistently higher than those of purchased inputs like fertilizer and machinery; for example, increasing land per unit labor by one percent increases labor productivity between 0.2 to 0.3 percent. In contrast, a one percent increase in the number of tractors per unit labor increases labor productivity by only 0.06 to 0.09 percent. These results suggest that traditional inputs continue to be a dominant source of labor productivity growth throughout Africa. They also lend support to the impression that new technologies have yet to have a pervasive impact on African agriculture.

The animal traction variable was insignificant in all specifications, a result consistent with findings from other studies. According to Reardon et al., evidence on the yield-promoting consequences of animal traction is mixed. Constraints to adopt animal traction technology include the comparatively high costs of purchasing and maintaining animals (for example, veterinary services), while the susceptibility to trypanosomiasis still limits the use of animals in significant parts of the continent. In addition, Pingali, Bigot, and Binswanger point out that the transition from hand hoe to animal traction depends on the farming systems in place. For example, a permanent cropping system (often involving a short fallow period) increases farming intensity, which, in turn, increases labor requirements and thus makes animal-draw technology more attractive economically. Under the forest- or bush-fallow systems that still characterize a good deal of African production systems, hand-hoe cultivation generally remains the most cost-effective approach to land preparation.

The coefficient on the labor variable equals the sum of the β coefficients on the conventional inputs minus one, thus it's consistently negative sign (and significance in models 1 and 2) points to decreasing returns to scale in the conventional inputs. However, our measure of labor was more akin to a stock than a flow variable (i.e., a head count not an hours worked in agriculture measure), and typically the reported annual data involved interpolations of occasional census estimates such that the smoothness in the reported series is probably more apparent than real.

All our land-quality measures have the expected signs, but only the share of arable and cropland in total agricultural land is consistently significant in explaining variations in labor productivity. The more irrigated area, the higher is the output per worker, but our irrigated area variable was generally only significant at the 90 percent confidence interval (and lost significance when R&D effects were included). African agriculture is principally rainfed, so it is not surprising that rainfall has a positive and generally significant, but hitherto econometrically unmeasured, effect on labor productivity.

The results regarding the labor quality variables are less clear cut. If R&D capital is omitted from the regression, improved life expectancy and literacy rates enhance labor productivity (although only the literacy variable was significant at the 90 to 95 percent confidence intervals). When R&D capital is included, neither variable was significant in explaining labor productivity.

Increasing either knowledge stocks or the density of paved roads increased labor productivity, but not statistically so. In this specification, both variables may be reflecting the direct effects of research and transportation on productivity, but they may also be proxies of a broader set of public resources targeted to agriculture. The limitations in data once again limit our scope to properly measure these factors. The road density variable relates to total paved road length (be they rural or urban roads) and does not distinguish between roads of different qualities. The R&D lag structure implicit in our stock-of-knowledge variable was largely dictated by the data (in particular it is probably too short— see, for example, Alston, Craig, and Pardey). A further limitation was that the inclusion of an R&D variable meant reducing the number of countries and shortening the time period in the sample used in our regression, thereby reducing degrees of freedom and reducing the variability in our data.

The various democracy dummies were jointly significant around the 99 percent confidence interval. By construction, the non-democratic regime in Angola in 1972 was the reference (i.e., omitted) observation. We discerned that a modicum of democracy (as indexed by the "partly free" variable) had a significant and positive effect on labor productivity in Africa. More extensive democratic institutions (as indexed by the "free" variable) had a positive but not significant effect on productivity in models 1 and 2. Greater democracy was associated with diminished productivity in model 3, but this may well be an anomalous result due to a lack of variation in this variable in this sample—the inclusion of R&D capital and other infrastructure variables eliminates four years from our sample (1972-91 instead of 1972-96, as in the other models) and reduces the number of countries to 17. Very few countries were classified as free for any of the years in this smaller sample. Even with the new variables included in our statistical analysis, there clearly remain a good number of unmeasured or mis-measured inputs into African agriculture. The country and year dummies, which in our model jointly measure these effects, were each jointly significant at the 99 percent confidence interval in all specifications.

Conclusion

The objective of this study was to improve our regional perspective on the sources of productivity growth in African agriculture. The extent of land per unit of labor is still a dominant source of variation in labor productivity. The more land that is irrigated or is arable and permanently cropped (compared with land that is simply used as range and pasture land) the higher the productivity. Increased precipitation leads to increased productivity in the principally rainfed agricultural production systems throughout Africa. We also found a smaller but statistically significant productivity effect from the use of modern inputs such as fertilizer and tractors. There were also indications that enhanced labor quality (as proxied by literacy rates) led to gains in productivity. In keeping with results found for other regions of the world, increased stocks of knowledge and higher road density were associated with higher productivity, but contrary to many prior studies, neither variable was statistically significant once other, often previously unmeasured, influences on productivity were included.

Finally, the inclusion of a simple "democracy" variable provides some preliminary, but by no means definitive, indications that the existence of democratic institutions has a positive effect on productivity, even after accounting for country- and time-specific effects not otherwise included in the statistical model.

Table 1: *Labor Productivity Regressions*

	Model 1	Model 2	Model 3
Intercept	7.103[a]	6.917[a]	6.880[c]
	(7.362)	(6.830)	(1.739)
Conventional and modern inputs			
Land	0.214[a]	0.249[a]	0.352
	(3.266)	(3.664)	(1.361)
Labor	-0.170[a]	-0.160[a]	-0.141
	(-3.626)	(-3.267)	(-0.618)
Livestock	0.421[a]	0.415[a]	0.343[a]
	(13.729)	(12.888)	(6.076)
Animal traction	0.003	0.002	0.006
	(1.248)	(1.046)	(1.555)
Tractor	0.091[a]	0.085[a]	0.061[c]
	(7.193)	(5.905)	(1.815)
Chemical fertilizer	0.004[a]	0.005[a]	0.023[c]
	(2.994)	(2.960)	(1.791)
Land quality			
Percent arable and permanently cropped	0.214[a]	0.198[a]	0.351[a]
	(3.871)	(3.461)	(3.400)
Percent irrigated	0.011[c]	0.012[c]	0.034
	(1.620)	(1.768)	(0.792)
Rainfall	0.036[c]	0.034[c]	0.025
	(1.807)	(1.669)	(1.196)
Labor quality			
Life expectancy	0.115	0.122	-0.007
	(0.959)	(0.959)	(-0.022)
Illiteracy rate	-0.079[b]	-0.071[c]	-0.137[a]
	(-2.109)	(-1.863)	(-2.372)
R&D and infrastructure			
Road density	___	0.013	0.011
		(0.676)	(0.399)
Knowledge capital	___	___	0.034
			(0.805)
Democracy			
Free	0.033	0.031	-0.118[a]
	(1.448)	(1.326)	(-3.320)
Partly free	0.025[b]	0.022[c]	-0.008
	(2.190)	(1.774)	(-0.431)
Adjusted R^2	0.9649	0.9646	0.9806
Number of observations	862	828	355
Number of countries	36	35	17

Note: The figures in brackets are t-values. All regressions included a set of country dummies and models 1 and 2 include time dummies, the coefficients of which are not reported here for brevity sake. Model 3 excludes time dummies, which are jointly insignificant in this sample.

[a] Significant at the 99 percent confidence level.
[b] Significant at the 95 percent confidence level.
[c] Significant at the 90 percent confidence level.

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