The Decline and Rise of Agricultural Productivity in Sub-Saharan Africa Since 1961

Steven Block

Fletcher School, Tufts University

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Abstract

Agricultural productivity growth in sub-Saharan Africa has been a qualified success. Total factor productivity growth has increased rapidly since the early 1980s. By the early 2000s, average annual TFP growth was roughly four times faster than it had been 25 years earlier. This period of accelerated growth, however, followed nearly 20 years of declining rates of TFP growth subsequent to independence in the early 1960s. Average agricultural TFP growth for sub-Saharan Africa was 0.14% per year during 1960 – 84, and increased to 1.24% per year from 1985 – 2002. The average over this period was approximately 0.6% per year, which accounts for 36% of the increase in total crop output over this period. These highly aggregated results conceal substantial regional and country-level variation. Expenditures on agricultural R&D, along with the reform of macroeconomic and sectoral policies shaping agricultural incentives, have played a substantial role in explaining both the decline and the rise in agricultural productivity. The case study of Ghana clearly reflects these broader findings.

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"Measuring technical change is of interest because, in a sense, it defines our wealth and puts limits on what we can accomplish...Since our ability to accumulate additional conventional resources...maybe limited, the growth of the economy and of per capita income and wealth depends on the rate at which technological knowledge is expanding..." (Zvi Griliches, 1987, p. 1010)

1. Introduction

Agricultural productivity is central to the lives of most Africans. Two-thirds of the population of sub-Saharan Africa is rural, and the FAO counts nearly half of sub-Saharan Africa's rural population as "economically active" in agriculture. For some countries, such as Burundi, Rwanda, Uganda, and Burkina Faso, the rural population share approaches 85-90%, with 45-50% the total population counted as economically active in agriculture. Even among the most urbanized countries of sub-Saharan Africa, such as South Africa, one-third of the population remains rural. In addition, up to 80% of Africa's poor live in rural areas, nearly all of whom work primarily in agriculture (World Bank, 2000). For these producer groups, agricultural productivity is the key determinant of welfare, and agricultural productivity growth is the key hope for poverty reduction (at least in the short- to medium-term). Non-farm rural employment, too, is often closely linked to agriculture -- either directly (as in the marketing of agricultural inputs and outputs), or indirectly (as in the provision of other services in rural markets). The indirect benefits of agricultural productivity growth, in the form of lower food prices, are also critical to the welfare of Africa's rapidly expanding urban populations, the poorest of whom devote 60-70% of total expenditures to food (Sahn, et. al., 1997).

From a macroeconomic perspective, as well, agriculture continues to play a central role in sub-Saharan Africa, accounting for 15% of total value added (20%, excluding South Africa). Of course, every generalization about sub-Saharan Africa and masks the region's vast heterogeneity. In Liberia, for example, agriculture accounts for 66% of total value added, while in other countries, such as oil-rich Angola, agriculture accounts for only 10% of the value added (World Bank, 2010).

African organizations, themselves, highlight these issues. The Comprehensive Africa Agriculture Development Program of the New Partnership for Africa's Development has stated that, "High and sustained rates of agricultural growth, largely driven by productivity growth, will be necessary if African countries are to accelerate poverty reduction. This is because agricultural growth has powerful leverage effects on the rest of the economy...The poor performance of the agricultural sector explains much of the slow progress towards reducing poverty and hunger in Africa." (CAADP, 2006) Current efforts to promote a "new Green Revolution" in Africa face myriad environmental, institutional, and physical challenges in their quest to promote agricultural productivity growth in the region.

This paper provides new estimates of cross-country agricultural productivity growth in sub-Saharan Africa. The resulting picture is one of qualified success. Total factor productivity growth in African agriculture has accelerated dramatically since the early 1980s. By the early 2000s, average annual total factor productivity growth in African agriculture was over four times faster than it had been 25 years earlier. The success is qualified by the finding that much of this acceleration represents a recovery from the substantial decline in TFP growth rates during the 1960s and early 1970s. In addition, levels of output per hectare and per worker in African agriculture remain low by global standards. Among a range of potential explanations for agricultural productivity growth in agriculture, expenditures on agricultural R&D play a dominant role, followed by policy distortions at both the macroeconomic and sectoral levels.

Improvements in the *quality* of the labor force, as indicated by average years of schooling, have also played a central role in driving productivity growth in African agriculture.

Many of these findings gleaned from cross-country analysis, are also evident in this paper's more detailed examination of agricultural productivity in Ghana.

This paper is organized as follows. Section 2 reviews related studies. Section 3 describes data used in the cross-country analysis, as well as the approach used to aggregate agricultural output across multiple commodities. Section 4 provides a preliminary perspective on agricultural productivity trends in the form of partial productivity ratios (output per worker and per hectare). Sections 5 and 6 describe, respectively, my methodology for estimating total factor productivity growth and my results. Section 7 explores various explanations for the productivity results presented in the previous section. Section 8 presents a brief case study of agricultural productivity in Ghana, while Section 9 concludes.

2. Related Studies

Within the broader literature on cross-country agricultural productivity, relatively few papers have focused specifically on sub-Saharan Africa. Block (1994) was the first to report a recovery of aggregate agricultural TFP in sub-Saharan Africa during the 1980s, a result confirmed by a number of subsequent studies. Block attributed up to two-thirds of this recovery to investments in agricultural R&D and to macroeconomic policy reform. Frisvold and Ingram (1995) provide an early growth accounting exercise for land productivity, concluding that most of it (up to 1985) resulted from increased input use (labor, in particular). Thirtle, Hadley, and Townsend (1995) highlight the role of policy choices, finding that an index of real agricultural protection played a significant role in explaining TFP growth in African agriculture for the period 1971-86. Lusigi and Thirtle (1997) highlight the role of agricultural R&D in explaining TFP growth in Africa. They also highlight the role of increasing population pressure in driving increased agricultural productivity in Africa. Chan-Kang, et. al. (1999) focus on the determinants of labor productivity in a cross-country African setting. They, too, find land per unit of labor to be an important determinant of labor productivity.

Fulginiti, Perrin, and Yu (2004) estimate agricultural TFP growth for 41 sub-Saharan African countries from 1960 to 1999, finding an average TFP growth rate of 0.83% per year, and confirming the finding from Block (1994) of an acceleration of the agricultural TFP growth since the mid-1980s. Their analysis concentrates on the role of institutions in explaining this growth. They conclude that former British colonies experienced greater rates of TFP growth, while former Portuguese colonies experienced lower rates. They also found negative effects for political conflicts and wars, and positive effects resulting from political rights and civil liberties. Three more recent papers conclude this review.

Nin-Pratt and Yu (2008) reconfirm the acceleration of African agricultural TFP growth since the mid-1980s. They find, however, a negative average growth rate of agricultural TFP (-0.15% per year) from 1964 to 2003, casting the recovery period as making up for negative productivity growth during the 1960s and 70s. Specifically, Nin-Pratt and Yu find that average TFP growth fell at the rate of -2% per year from the mid-1960s to the mid-1980s, then grew by 1.7% per year between 1985 and 2003. They, too, highlight the role policy change in explaining this reversal in performance. In particular, they find that an indicator of reforms associated with structural adjustment played a positive role. In addition, they find that agricultural productivity in East and Southern Africa benefited from the end of internal conflicts, and that agriculture in

West Africa benefited from the devaluation of the CFA franc. They also provide suggestive evidence of the positive effect of investments in agricultural R&D.

Alene (2010) also focuses on the contributions of R&D expenditures to productivity growth in African agriculture. In contrast to the average TFP growth rate reported by Nin-Pratt and Yu (2008), Alene finds an average TFP growth rate of 1.8% per year for the period 1970-2004 (a difference that he attributes to an improved estimation technique). Alene finds strong positive effects of lagged R&D expenditure on agricultural productivity growth, arguing that rapid growth in R&D expenditures during the 1970s helped to explain strong productivity growth after the mid-1980s, while slower growth of R&D expenditures in the 1980s and early 1990s led to slower productivity growth since 2000. Alene (2010) also notes a 33% annual rate of return on investments in agricultural R&D in Africa.

Most recently, Fuglie (2010) examines agricultural productivity growth in sub-Saharan Africa from 1961 to 2006. His findings are mixed. While he reports an increased rate of growth in agricultural *output* during the 1990s and early 2000s, Fuglie finds that most of this growth in output is explained by expanding crop land rather than improved productivity. Fuglie (2010) stands out in this literature for his critical assessment of the standard data sources, for which he proposes various corrections. In contrast to previous studies, Fuglie does not find a general recovery of agricultural productivity in recent decades. For the period 1961-2006, he reports an average TFP growth rate of 0.58% per year, with the lowest rate occurring during the 1970s (-0.18% per year), and the highest rate occurring during the 1990s (1.17% per year).

Thus, recent estimates of the rate of agricultural TFP growth in Africa differ widely, though there is a general consensus surrounding a decline in productivity during the first two decades following independence and a recovery during the past two decades. These studies applied different methodologies to essentially the same data set, which may explain some of the conflicting findings cited above. As described below, the methodology applied in the present study differs from all of the studies cited above.

3. Data and Output Aggregation

This study combines data from a variety of sources. The core data on agricultural outputs and inputs are drawn from the FAO online database. While often regarded as being of limited quality, these data are ubiquitous in studies of international agricultural productivity, as they are the only comprehensive and detailed source of cross-country data over a long period of time. The central challenge in constructing a data set suitable for estimating a cross-country agricultural production function lies in aggregating the output of multiple agricultural commodities in a way that is comparable across both time and space. The fact that national-level data on key agricultural inputs -- land, labor, fertilizer, tractors, and livestock -- are provided as national totals, and not disaggregated by the crops to which they are applied, requires that agricultural output also be aggregated to the national level.

The most comprehensive discussion of agricultural output aggregation for international comparison is Craig, Pardey, and Roseboom (1991). Drawing on index number theory, they note that the ideal approach to aggregating multiple commodities for a given country and year would be to multiply a vector of base-year local commodity prices expressed in dollars by a vector of quantities of individual commodities. In particular, they specify that the best price weights would be those most specific to the economic activity and agents in question. Yet, even in the absence of data constraints, there is no perfect way to implement this ideal. The key dimensions of the problem, in practice, lie in choosing appropriate deflator's for comparisons over time, and in choosing appropriate exchange rates for comparisons across countries. Severe constraints on the availability of commodity-specific price data over time for each country in sub-Saharan Africa add to these challenges of constructing internationally and inter-temporally comparable agricultural output aggregates.

Given the availability of commodity-specific local currency-denominated prices over time, the standard approach for converting aggregate output in a given year into internationally comparable units of measure is to select a numeraire currency, and to use Purchasing Power Parity exchange rates for conversion.[1] For its global agricultural data set, the FAO has calculated "agricultural exchange rates," or agricultural PPPs, that it applies in creating internationally comparable aggregates of agricultural output. In practice, virtually every study of international agricultural productivity (whether global or region-specific) simply uses these FAO data, based on PPP prices calculated from the global data set. In theory, however, as noted above, the best price weights to use in aggregating output are those that are most specific to the particular setting of concern.

The present study thus departs from standard practice by calculating a unique set of international commodity prices and PPP exchange rates specific to African agriculture.

In order to calculate the Africa-specific international prices and PPP exchange rates used to construct the data set for this study, I applied the Geary-Khamis method summarized by Rao (1993). This method requires calculating both a reference set of international commodity prices based on relevant PPP exchange rates, and calculating the PPP exchange rates based on the

[1] Craig, Pardey, and Roseboom (1991) provide an extensive discussion of the trade-offs involved in first deflating and then converting each year aggregate output versus first converting in any deflating.

reference set of international commodity prices. This problem is described by a system of two simultaneous equations. In the first equation, the international reference price for commodity i is calculated as a function of its local currency price in each country $j = 1,\ldots,m$ converted by the PPP exchange rate for country j. In the second equation, the PPP exchange rate for country j is calculated as a function of the quantities and international reference prices for each commodity $i = 1,\ldots,n$ in country j. This is done for a given base year. These two equations can be solved iteratively, ultimately converging on a unique set of reference prices and PPP exchange rates for the specific countries and commodities to be studied. For purposes of this study, I calculated international prices and PPP exchange rates using prices and quantities for the $n = 35$ commodities in the $m = 27$ sub-Saharan African countries for which data were available from the FAO.[2] I then applied these reference prices in aggregating output across these commodities for the full set of 44 sub-Saharan African countries for which commodity-specific output data were available. Output data for each commodity are net of quantities used for seed and feed.

The base year for these reference prices was 2006. I then created a Paasche-type output index, applying the 2006 prices to aggregate the commodity output data in each country for each year going back to 1961. The rationale for applying the Paasche approach was that the range and, in particular, the quality of the price data has tended to improve over time, and that the best data would thus be the most recent.[3]

Data for the other standard inputs to be used in estimating the agricultural production function are also drawn from the FAO database. The land measure is hectares of permanent and arable crop land; the labor measure is the number of economically active males and females in

[2] Appendix 1 presents the list of commodities and countries used in calculating the Africa-specific international prices. Resulting output data for each country-year are available on request from the author.
[3] I am grateful to Philip Pardey for suggesting this approach.

agriculture; capital is represented by the number of tractors; fertilizer is measured in tons of inorganic plant nutrient; and, livestock is measured as the number of “cattle equivalents” held on farms for productive use.[4]

Each of these indicators of agricultural inputs falls short of the ideal data for measuring agricultural productivity. In discussing the measurement problems generically associated productivity analysis, Griliches (1960, 1987) has noted that proper estimation of production functions should be based the flow of services of capital (accounting for vintage) in constant prices, as well as on the flow of labor services (e.g., hours worked) weighting different types of labor by their marginal prices. Clearly, the input data available for African agriculture, consisting of counts of the number of tractors and the number of agricultural workers (issues of data quality aside), fall far short of this ideal. In particular, the assumption in the data that all of what is counted as agricultural labor is specifically on-farm labor contradicts micro-based evidence of significant non-farm rural activity (Liedholm, McPherson, and Chuta, 1994). Over-counting labor in this way may impose a downward bias on estimated TFP growth. There must also be substantial measurement error in fertilizer data that capture only inorganic fertilizer in a setting where manure is the primary source of added soil nutrients.

In short, the methodological tradeoffs and measurement errors inevitably associated with constructing both the output and the input data for African agriculture are substantial, and suggest the potential for significant noise and bias in estimates of total factor productivity. Yet, as demonstrated in the seminal work of Jorgenson and Griliches (1967), it is possible to mitigate these problems by introducing explicit controls for the quality of inputs.

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[4] Craig, Pardey, and Roseboom (1997) note, for example, that up to 70% of total horsepower traction in African agriculture is provided by livestock.

As described below, the quality of inputs differs across countries and over time within countries. To the limited extent possible, it is important to control for these differences by including input quality adjustments in productivity estimates. Data used here to adjust for variations in land quality include the proportion of permanent and arable crop land that is irrigated, and annual rainfall. The former are drawn from data compiled by Sebastion (2007). The annual rainfall data used in this study are drawn from Mitchell, et. al. (2003) and Jefferson and O'Connell (2004), based on the crop-weighting scheme of Ramankutty and Foley (1998).[5] Quality adjustments to the agricultural labor force generally rely on literacy rates. This study takes advantage of newly-released data on average years of schooling from Barro and Lee (2010). Additional data used in trying to decompose the productivity residual are described below.

4. Partial Productivity Ratios

Partial productivity ratios (output per worker, and output per hectare) provide a useful initial overview of both the level and growth rate of agricultural productivity. While these ratios share the analytical limitation of not controlling for changes in other inputs, they have the virtue of reflecting the general nature of technical change and agriculture as being predominantly either land- or labor-saving. The simplicity of partial productivity ratios may also be a benefit in a preliminary analysis of noisy and often low-quality data.

Hayami and Ruttan (1985) present a useful and intuitive conceptual approach for analyzing joint trends in partial productivity ratios, based on the simple identity

[5] These rainfall data, along with detailed explanations of their construction, are available at: http://acadweb.swarthmore.edu/acad/rain-econ/Framesets/CountryAggregated.htm

(1) $$\frac{Y}{L} \equiv \frac{A}{L} \times \frac{Y}{A}$$

where Y is output, A is area, and L is labor. Taking logarithms of this identity facilitates thinking in terms of relative changes, as in

(2) $$\log\left(\frac{Y}{L}\right) \equiv \log\left(\frac{A}{L}\right) + \log\left(\frac{Y}{A}\right)$$

The welfare of Africa's agricultural labor force ultimately depends on increasing output per worker. Equation (2) illustrates the challenge to that process in an environment characterized by rapid population growth and limited land area. To the extent that population growth outpaces the rate of expansion of agricultural area, area per worker (A/L) declines, thus increasing the challenge of raising average labor productivity (Y/L) by means of increasing average yield (Y/A). This dynamic has been a major obstacle to agricultural development in sub-Saharan Africa.

Table 1 presents the growth rates of partial productivity ratios for sub-Saharan Africa and its sub-regions by decade from 1961 to 2007. For the region as a whole over this entire period the average annual growth rate of output per worker has been only 0.41%, despite an average annual growth rate of 1.24% in output per hectare. As suggested by equation (2), the limited ability of yield growth in African agriculture to drive growth in average labor productivity has been driven by the increasing population density of rural Africa, where the annual growth of the agricultural labor force has outpaced area expansion by 0.83% per year from 1961 to 2007. Yet, recent years demonstrate a more optimistic trend. For the period 2001 to 2007, the growth rate of average labor productivity in African agriculture has increased dramatically (to over 2% per year) relative to previous periods -- an advance aided by a reversal of the historical trend towards declining area per worker.

In their seminal study of agricultural development, Hayami and Ruttan (1985) also developed a useful and intuitive graphical presentation of partial productivity ratios. Their graphical representation of equation (2) simultaneously relates changes over time in average land and labor productivity by measuring average land productivity along the vertical axis and average labor productivity along the horizontal axis. Changes in output per hectare and output per worker over a given period can be illustrated by drawing an arrow between the relevant beginning and ending coordinates in that space. Scaling the axes in logarithms conveniently implies that movements along any 45° line represent equal rates of change in both land and labor productivity. From equation (2), it follows that such equal rates of change imply a constant level of area per worker. Thus, each 45° line in this space represents a unique and constant level of *A/L*. Partial productivity paths steeper than 45° reflect increased rural population density over time.

Timmer (1988) provides various interpretations of movements over time in this space. He notes, for example that a movement due north (indicating growth in yield with no growth in average output per worker) may indicate population growth matched by increased yields through higher labor inputs and technical change, but no improvement in rural living standards. Movements to the northwest might suggest population growth faster than technical change in raising yields, with a consequent deterioration in rural living standards. In contrast, movements due east in this space might reflect a declining agricultural workforce with no changes in yields, but with new mechanical technologies needed to maintain output with fewer workers, hence increasing average labor productivity and rural welfare.

Figure 1 implements this framework, placing African agriculture in a global context. The partial productivity paths depicted in Figure 1 illustrate changes from 1961/65 (period average) to 2001/05, distinguishing the coordinates also at 1981/85 for sub-Saharan Africa and other middle-income and advanced economies. The positions of these paths reflect different levels of land and labor productivity, while their lengths indicate rates of change. It is clear from Figure 1 that Africa begins and ends this period with levels of land and labor productivity that are quite low in comparison with those found in more advanced economies, as well as in comparison with the world averages. Stated differently, African agriculture falls well within the meta-production frontier defined here by Japan, Germany, USA, and Australia. Productivity growth in African agriculture, as reflected in these partial productivity ratios, has been driven almost entirely by increased yields per hectare, with little growth of output per worker. This results in a path substantially steeper than the 45° line, indicating that rural Africa has grown increasingly crowded.

While during the second half of this period sub-Saharan Africa reflects a slightly increased rate of growth in average labor productivity, that progress remains quite small by comparison with the other countries illustrated in Figure 1. Note as well, that those countries with the most rapid increases in agricultural labor productivity have followed paths shallower than the 45° lines, indicating increases in area per worker over time.

Figure 2 intensifies the focus on partial productivity ratios in Africa, disaggregating by five sub-regions and the averages of successive five-year periods.[6] Consistent with the data presented in Table 1, no region of sub-Saharan Africa experienced continuous growth in both land and labor productivity, though some regions were clearly more successful than others. Southern Africa, for example, began in the early 1960s at a relatively low level of output per

[6] For purposes of global comparison, output in Figure 1 was measured in constant agricultural value-added. Beginning with Figure 2, as discussed in the text, output is measured as aggregate crop output calculated for this study.

worker, yet experienced the fastest rate of subsequent growth (averaging 1.24% per year, per Table 1), though with a significant setback between 1986/90 and 1991/95. West Africa, too, made substantial progress in increasing agricultural labor productivity beginning in the early 1980s. In contrast, Sahelian countries began with the lowest level of average labor productivity in 1961/65, and saw that level decline consistently (along with yields) until at least the early 1980s. Similarly, countries in Middle Africa experienced slow declines in agricultural labor productivity until the early 1990s, while countries in Eastern Africa experienced consistent but relatively slow increases in both land and labor productivity over most of the period.[7] These contrasting experiences, even at the regional level, illustrate the great heterogeneity of African agriculture. This heterogeneity pertains both to conditions and to rates of progress over time. (Note, for example, the substantially greater level of average area per worker in southern Africa as compared with Eastern Africa.)

Figures 3 (a – d) underscore this country-level heterogeneity. Figure 3a presents country-level partial productivity paths for Western Africa over the period 1961/65 to 2001/05. Some countries, such as Nigeria, Côte d'Ivoire, and Benin experienced significant growth in average labor productivity accompanied by moderate growth in crop yield, while other countries, such as Togo, Niger, and Liberia experienced gains in crop yield accompanied by small reductions in average labor productivity. At the same time, Figure 3a depicts rapid declines in agricultural labor productivity in Senegal, Gambia, and Guinea-Bissau. Among countries in Eastern Africa (Figure 3b), there was the predominant tendency towards moderate gains in crop yield accompanied by slow growth in output per worker. Figures 3c and 3d depict a similar

[7] Note here that the East African countries begin with relatively high levels of rural population density (reflected in their position along a higher 45° line) follow a relatively steep path over time, indicating a tendency towards land-saving technical change. This is consistent with the Induced Innovation Hypothesis, associated with Hayami and Ruttan (1985).

heterogeneity of experience among the countries of Middle and Southern Africa, respectively. Table 2 presents partial productivity growth rates by country, and ranks countries in order of their growth rates of both land and labor productivity.

In general, these patterns (particularly at the level of regional disaggregation) conform to what is known of events on the ground. Gabre-Mahdin and Haggblade (2004) provide an interesting perspective on successes in African agriculture. They conducted a survey of over 100 experts working in various areas related to African agriculture (two-thirds of whom were Africans), asking them to identify the most important factors in advancing African agriculture. The majority (62%) pointed to successes tied to specific commodities; 21% identified activities such as policy reform and enhancement of soil fertility; and, 16% cited successful institution-building efforts as the primary drivers of African agriculture. Maize breeding (followed by cassava breeding) was the most widely-cited contributor. Byerlee and Jewell (1997) report that most of the successes in breeding, releasing, in adopting improved maize varieties was in East and Southern Africa. Between 1966 and 1990, Byerlee and Jewell note the release of over 300 improved varieties and hybrids by national maize research programs.

The release of hybrid maize in Africa dates back to the early 1930s in Zimbabwe (then Southren Rhodesia), though there were no major successes until the release in Zimbabwe of the variety SR52 in 1960. Successful hybrid maize releases followed shortly thereafter in Kenya. Byerlee and Jewell (1997) report widely varying results for the adoption of maize hybrids and improved open-pollinated varieties. By 1990, nearly all of Zimbabwe's maize area was planted to hybrids, as was 70% of Kenya's maize area, and 77% of Zambia's maize area. At the same time however, Malawian farmers had planted only 14% of maize area to improve varieties, similar to the 18% of Mozambique's maize area, and 13-29% of Ethiopia's maize area under improve varieties. Byerlee and Jewell also note that even in countries with substantial areas devoted to improved maize varieties, yield gains were often moderated by declining soil fertility combined with extremely limited application of chemical fertilizer. Kumwenda, et. al. (1997) cite declining soil fertility as the most widespread limitation on both yield improvement in the sustainability of the maize-based production systems in Southern and Eastern Africa.

Gabre-Madhin and Haggblade's (2004) survey reinforces the specific success of maize breeding programs in East and Southern Africa, where by the turn of the century, they reported that 58% of maize area planted to improved hybrids with yields gains of about 40% over local varieties. In contrast, only about 20% of total maize area in West and Central Africa were planted to improve varieties. Those regions were more dominated by improved open-pollinating varieties, with output gains of 15-45% over local varieties.

Evenson and Gollin (2003) track the annual rate of varietal releases for all improved crop varieties. While not disaggregating by regions within Africa, they do report a near doubling of the number of average annual releases between 1976-80 and 1981-85, from 23 to 43.2 (and to 50 per year by the early 1990s). This accelerated release of improved crop varieties coincides with the acceleration in the growth of both partial productivity ratios reported in Table 1.

Other important sources of success in African agriculture cited in the survey included breeding to combat mosaic virus in cassava, as well as improvements in the yield and drought-resistance of that crop (which is particularly important in West and Central Africa); expansion of horticultural and flower exports from East and Southern Africa; rapid growth of cotton production and exports from West Africa (the Sahelian countries in particular); and, improved breeding of bananas in Central Africa. Among activity-led successes, Gabre-Madhin and

Haggblade's survey noted soil fertility enhancement, such as alley cropping in West Africa and improved water management techniques in Southern Africa. Respondents also noted the positive effects of market reforms, currency devaluation, and improved institutions as contributors to Africa's improved agricultural performance.

Partial productivity ratios, while indicative of broad trends in the rate and nature of productivity growth, are limited by their lack of control for potentially confounding changes in other inputs. The remaining sections of this paper thus turn to the estimation of total factor productivity growth in African agriculture.

5. Measuring Total Factor Productivity Growth in Agriculture: Methodology

The rate of growth of total factor productivity (TFP) is conventionally defined as the difference between the rate of growth of real product and the rate of growth of real factor input. Assuming, as in Solow (1957), competitive factor markets and constant returns to scale in the aggregate production function, a change in total factor productivity can be measured as a vertical shift in the production function. A variety of methodological approaches have evolved for estimating total factor productivity growth, including the construction of TFP indices (such as the Tornquist-Theil), data envelopment analysis (based on the non-parametric Malmquist index), and stochastic frontier analysis, in addition to the econometric estimation of the aggregate production function. TFP estimation in the present study is based on the latter approach of estimating the aggregate agricultural production function for a panel of African countries.[8] One

[8] Tornquist-Theil indices require detailed factor price data that are unavailable for African agriculture. Stochastic frontier approaches derive their results entirely by imposing very strong conditions on the error structure of the estimated production function -- an approach that seems particularly ill-suited to the present setting, which is

key benefit of a parametric approach is that it helps to impose order in an otherwise noisy data set.

Specifying the aggregate agricultural production function requires numerous choices, beginning with functional form. I adopt the Cobb-Douglas functional form, which has been repeatedly validated in agricultural studies (Griliches, 1964; Hayami and Ruttan, 1985), as has been the assumption of constant returns to scale (Hayami and Ruttan, 1985). The "traditional" inputs included in virtually every cross-country study of agricultural productivity include: land, labor, fertilizer, tractors, and livestock. As noted above, available data for each of these inputs almost certainly include significant measurement error. In addition, as emphasized in the early studies of US agriculture by Griliches (1963, 1964), and for the US economy as a whole by Jorgenson and Griliches (1967), much of what might mistakenly be attributed to TFP growth may in reality be changes over time in the *quality* of inputs.

Whether one puts such adjustments for input quality in the production function or in the residual is an interesting question. Griliches (1960) takes an agnostic approach, suggesting "Whether or not we want the input measures to cover all possible quality changes is a semantic rather than a substantive issue. Hybrid seed corn can be viewed either as improvement in the quality of seed or as ‘technical change.’ Since we are interested in explaining the growth of agricultural output, it does not matter much whether we put it into the ‘input change’ category or the ‘productivity change’ category as long as we put it somewhere and know where it is."

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characterized by low quality and quite noisy data. The data envelopment analysis approach, while often used in recent studies of agricultural productivity (Lusigi and Thirtle, 1997; Fulginiti, Perrin, and Yu, 2004; and Nin-Pratt and Yu, 2008; and Alene, 2010, among others), is also problematic. Heady, Alauddin, and Prasada Rao (2010), along with Nin-Pratt, et. al. (2003), note that DEA studies of agricultural TFP often produce anomalous and implausible results. The DEA approach measures countries' progress relative to a productivity frontier, which depends arbitrarily on the number and selection of countries included in the sample, and which is poorly suited to distinguish between TFP growth, noisy data, and measurement error. Coelli, Prasada Rao, O’Donnell, and Battese (2005) discuss the relative merits of these approaches.

Specification

The dependent variable in my aggregate production function is crop output aggregated (as described above) based on the Africa-specific international commodity prices and PPP exchange rates calculated for this study. The resulting TFP estimates are thus limited to crop agriculture. This, too, reflects a departure from most of the literature, which typically includes both crop and livestock output (summed) for aggregate output. The median share by value of livestock output in total agricultural output over the entire sample is 0.21, though this share varies by region and country. The mean livestock share in total agricultural output is highest in the five countries included from southern Africa (0.48), and lowest among the ten included (non-Sahelian) countries of western Africa (0.17). For certain countries, including Botswana, Sudan, Mali, Mauritania, and Namibia, livestock output accounts for greater than half of the value of total agricultural output. For such countries, excluding livestock is a potentially significant omission. Yet, that omission brings with it the broader benefit of more accurate aggregation of output (based on Africa-specific data, which are not available for livestock output). On average this omission is relatively small. (Appendix 2 demonstrates the robustness of my main results compared against those derived from using a broader output aggregate that includes livestock.)

There is also a more theoretical reason for excluding livestock from the output aggregate, arising largely from the construction and interpretation of the production function itself. As typically specified, with inputs including tractors, fertilizer, livestock (used both for traction and as a source of manure), the production function conceptually describes specifically crop output. The estimated coefficients on these inputs are interpreted as production elasticities and serve as input weights for productivity measurement. This interpretation of estimated coefficients for tractors and fertilizer in particular is clouded by the inclusion of livestock in the dependent variable. Indeed, by comparison with crop agriculture, livestock production is less labor intensive and more land intensive, thus blurring the interpretation of those coefficients, as well. Yet, excluding livestock from the dependent variable does come at the cost of under-emphasizing integrated crop-livestock production systems that have become increasingly common in Africa. Available cross-country data on inputs and output in agriculture provide no perfect match between what is included on the left- and right-hand sides of the production function. For instance, while I can (and do) eliminate permanent pasture from my measure of land, the labor variable still includes labor applied to livestock production.[9]

Prior to specifying and estimating the cross-country production function, it is useful to present the growth rates of output and inputs. Table 3 presents these growth rates, distinguishing the periods before and after 1985. Crop output for the entire period 1961 to 2007 grew at an average rate of just over 2% per year, accelerating post-1985. Growth of the agricultural labor force was also stable, at about 1.65% per year. Agricultural area also expanded at a relatively stable 0.85% per year. What is striking, however, is the dramatic reversal in the growth rates of the number of tractors and tons of chemical fertilizers pre- and post-1985, a break-point that may reflect the widespread onset of structural adjustment and related reforms. From 1961 to 1984, the average growth rate for tractors and fertilizer were just over 7% and 6%, respectively; yet, post-1985, consumption of both *fell* at an average rate of 0.5% per year.

Loosely borrowing notation from Craig, Pardey, and Roseboom (1997), I specify the initial production function for country *i* at time *t* with *k* conventional inputs $X_{ij}^{*}(t)$, and a country-invariant temporal shift of variable *A(t)* as:

[9] Even if the FAO labor data were to distinguish between crop and livestock labor, they would likely grow at the same rate in any given country and year. As it is ultimately the growth rate of inputs that matters for TFP estimation, over-stating the level of labor may have little effect on estimated TFP growth.

(3) $$Y_i(t) = A(t)\prod_{j=1}^{k} X_{ij}^{*}(t)^{\beta_j}$$

The presence of both quality change and measurement error in the inputs creates a divergence between observed inputs and effective inputs. We can separate out measurable country-specific (but time-varying) quality shifters in input *j*, $Z_{ij}(t)$, and country-specific but time-invariant measurement error in input *j*, α_{ij}. In this case, Craig, Pardey, and Roseboom (1997) note that the relationship between observed input $X_{ij}(t)$ and effective input $X_{ij}^{*}(t)$ is given by

(4) $$X_{ij}^{*}(t) = \alpha_{ij}Z_{ij}(t)X_{ij}(t)$$

Substituting equation (4) into equation (3) and scaling the production function by dividing by input $X_{i1}(t)$ yields

(5) $$\frac{Y_i(t)}{X_{i1}(t)} = A(t)\prod_{j=2}^{k}\left[\frac{X_{ij}(t)}{X_{i1}(t)}\right]^{\beta_j}\prod_{j=1}^{k}\left[\alpha_{ij}Z_{ij}(t)\right]^{\lambda_j}$$

This production function imposes constant returns to scale across the conventional inputs. The production elasticity for variable X_1 can be recovered in estimation as $\hat{\beta}_1 = 1 - \sum_{i=2}^{k}\hat{\beta}_j$. In practice, the scaling variable will be labor.[10] Equation (5) provides the basic production function to be estimated in measuring TFP growth, where TFP growth is captured by the intertemporal shifts in the production function measured by *A(t)*. Once having estimated the rate of TFP growth, the second stage of the analysis will be to explain that growth. Towards that end, I add to the production function in equation (5) a vector of *m* potential explanations, $P_{ij}(t)$, for the observed productivity growth in African agriculture.

The final production function can thus be written as

[10] Scaling the production function substantially eliminates the heteroskedasticity that would otherwise result from combining countries of greatly differing size.

(6) $$\frac{Y_i(t)}{X_{i1}(t)} = A(t)\prod_{j=2}^{k}\left[\frac{X_{ij}(t)}{X_{i1}(t)}\right]^{\beta_j}\prod_{j=1}^{k}\left[\alpha_{ij}Z_{ij}(t)\right]^{\lambda_j}\prod_{j=1}^{m}P_{ij}(t)^{\gamma_j}$$

Following Craig, Pardey, and Roseboom (1997), in the empirical representation of equation (6) I replace *A(t)* with time period dummies, *TD(s).* These time dummies track vertical shifts of the production function over time, and thus provide a basis for estimating the rate of TFP growth. I also aggregate the input- and country-specific measurement error into composite time-invariant country-specific dummies, CD_h . Expressing all but the dummy variables in natural logs (as lower-case letters) in per worker terms leads to the estimating equation:

(7) $$y_i(t) = c + \sum_{j=2}^{k}\beta_j x_{ij}(t) + \sum_{\mathrm{j=1}}^{\mathrm{k}}\lambda_j z_{ij}(t) + \sum_{j=1}^{m}\gamma_j p_{ij}(t) + \sum_{s=2}^{T}\alpha_s TD(s) + \sum_{h}^{n-1}\varphi_h CD_h + \varepsilon_i(t)$$

In practice, data constraints limit the number of input quality adjusting variables to fewer than the number of inputs. Thus, the *Z* variables to be used include two adjustments for land quality (annual rainfall and percentage of land equipped for irrigation), and one variable to adjust for the quality of the labor force (average years of schooling, from Barro and Lee, 2010).

Estimation Strategy

I implement two different econometric approaches to deriving the rate of TFP growth from the estimation of equation (7).[11] The strategy will be first to estimate the production function including only conventional inputs and the country and period dummy variables (that is, imposing the constraints $\lambda_j = \gamma_j = 0$). I then derive the input quality-adjusted estimates of TFP

[11] In theory there is some risk of endogeneity in estimating production functions if for example farmers choose observed inputs as a function of unobserved inputs. Estimating fixed effects models, such as that proposed here, helps to the extent that these unobserved effects are constant over time. Fuglie (2010) estimates a cross-country agricultural production function both with and without instrumental variables, but finds little difference between the two approaches.

growth by re-estimating equation (7), this time including the Z variables (relaxing the constraint that $\lambda_j = 0$). The resulting quality-adjusted TFP estimates provide the baseline against which I decompose this productivity residual into various explanations for productivity growth.

A key practical consideration in deriving TFP growth estimates from equation (7) is to distinguish trends in true productivity from the substantial noise inherent in these data. Productivity growth is ultimately measured as a reflection of the deeper process of technical change, which in principle does not fluctuate dramatically from year to year (Griliches, 1987). Given the heavy reliance of African agriculture on rainfall in particular, some form of smoothing is essential. This study applies two alternative econometric approaches to address this problem.

The most common approach for addressing this problem, given the availability of panel data, has been to collapse the annual cross sections into successive five-year averages. While somewhat ad hoc and potentially sensitive to the starting and ending years chosen, this approach is effective in smoothing out annual fluctuations. In deriving TFP measures from the estimation of equation (7), I begin with this approach. Having annual data from 1961 – 2007 permits the creation of nine full cross sections of five-year averages. I then introduce a novel approach to deriving TFP estimates from annual data, based on semi-parametric estimation of the production function. The core idea shared by both approaches is that one can estimate the rate of TFP growth directly from vertical shifts in the production function.

The first approach applies seemingly unrelated regression (SURE) to a panel data set consisting of sequential five-year averages of the annual data. The strategy here is to specify the same production function for each cross section in the panel, using the SURE estimator to apply appropriate cross-equation constraints on the parameter estimates for conventional agricultural inputs, leaving the intercept terms unconstrained. Constraining similar slope terms to be equal across pairs of adjacent production functions ensures that the change in the intercepts of the production functions between periods reflects vertical shifts of the same production function over time.[12] In this case, we can derive estimates of TFP growth directly from changes in the intercept terms of adjacent production functions. My SURE system of production functions thus takes the form:

$$\begin{aligned}
y_{i,61/65} &= \alpha_{61/65} + \beta_{1,61/65}a_{i,61/65} + \beta_{2,61/65}tr_{i,61/65} + \beta_{3,61/65}f_{i,61/65} + \beta_{4,61/65}lv_{i,61/65} + \varepsilon_{i,61/65} \\
y_{i,66/70} &= \alpha_{66/70} + \beta_{1,66/70}a_{i,66/70} + \beta_{2,66/70}tr_{i,66/70} + \beta_{3,66/70}f_{i,66/70} + \beta_{4,66/70}lv_{i,66/70} + \varepsilon_{i,66/70} \\
&\vdots \\
y_{i,01/07} &= \alpha_{01/07} + \beta_{1,01/07}a_{i,01/07} + \beta_{2,01/07}tr_{i,01/07} + \beta_{3,01/07}f_{i,01/07} + \beta_{4,01/07}lv_{i,01/07} + \varepsilon_{i,01/07}
\end{aligned}$$

where (in logs) *y* is crop output per worker, *a* is area per worker, *tr* is tractors per worker, *f* is fertilizer per worker, and *lv* is livestock per worker.

Estimating the rate of TFP growth between 1961/65 and 1966/70 first requires imposing (and testing) the constraint $\beta_{k,61/65} = \beta_{k,66/70}$ jointly for all of the conventional inputs. The rate of TFP growth between these periods can then be calculated as

(8) $$Annual\ TFP\ growth\ rate = T^{-1}exp\{\alpha_{66/70} - \alpha_{61/65}\},$$

where (given this panel structure) T = 5. This econometric approach is not common in the literature, but was used in Block (1994, 1995).

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[12] Pair-wise equality constraints of the slope terms in adjacent production functions (e.g., the first two five-year periods out of nine, then the second and third periods, etc.) is the minimal requirement for this approach. The maximal approach would be to constrain the slope coefficients for a given inputs to be equal across all time periods simultaneously. Wald tests reject this maximal constraint, yet, as reported in the text, tend not to reject pair-wise constraints across adjacent periods.

I also introduce in this paper a novel approach to estimating TFP growth from annual panel data. As noted above, a key concern in estimating TFP growth is to distinguish productivity trends from noise. For this purpose, I propose a semi-parametric approach to estimating the production function in equation (7). This approach controls linearly for the conventional inputs while allowing the residual relationship between output and time to take an undefined functional form. This revised production function is thus

(9)

$$y_i(t) = c + \sum_{j=2}^{k} \beta_j x_{ij}(t) + \sum_{\mathrm{j=1}}^{\mathrm{k}} \lambda_j z_{ij}(t) + \sum_{j=1}^{m} \gamma_j \; p_{ij}(t) + g\big(TD(s)\big)$$
$$+ \sum_{h=1}^{n-1} \varphi_h CD_h + \varepsilon_i(t)$$

The difference between equation (7) and equation (9) lies in the specified functional relationship between output, $y_i(t)$, and the year dummies, *TD(s)*. Equation (7) is fully parametric and thus imposes a linear relationship between output and time, estimation of which would provide a basis for calculating a single average rate of TFP growth for the period. In contrast, equation (9) retains the linear parametric relationship between output and all other variables included in the production function with the exception of the year dummies. Rather than imposing linearity on the relationship between output and the year dummies, the semi-parametric specification of equation (9) allows this relationship to take an undefined functional form $g(\cdot)$.[13] This approach allows the estimated rate of TFP growth to vary freely over time, as defined by the data themselves, rather than imposing linearity (or any other pre-defined parametric specification).

[13] Yatchew (2003) provides comprehensive detail on semi-parametric regeression.

To clarify the estimation procedure, combine all the linear arguments in (9) into the matrix *x*, and write the semi-parametric regression as,

$$(10) \qquad y_i = g(z_i) + x_i\beta + \varepsilon_i$$

Yatchew (2003) describes that when the data are sorted by z in increasing order of size (and assuming that g is a smooth function), then first differencing the data tends to eliminate the nonparametric term, $g(z_i)$, since the first difference, $g\left[z_{i(n)}\right] - g\left[z_{i(n-1)}\right] \rightarrow 0$ as the sample size increases.[14] In this case, after first differencing, one can consistently estimate $\hat{\beta}_{diff}$ by OLS. Then, subtracting the estimated parametric portion of the model from both sides of (10) (as Lokshin, 2006, shows), one is left with

$$(11) \qquad y_i - x_i\hat{\beta}_{diff} = x_i\left(\beta - \hat{\beta}_{diff}\right) + g(z_i) + \varepsilon_i \cong g(z_i) + \varepsilon_i$$

since $\hat{\beta}_{diff}$ converges to β. What remains is a two-dimensional purely non-parametric relationship between y_i and z_i, which is estimated by a locally-weighted kernel density smoother (using Stata's *lowess* command).

Thus, estimation of equation (9) effectively partials out the linear effects of the conventional inputs and country dummies, leaving a non-parametric kernel regression of output on the annual time dummies. The resulting estimated function, $\hat{g}(TD(s))$, is a smoothed non-parametric representation of annual shifts in the production function, controlling linearly for all other variables in equation (9).

[14] Also see M. Lokshin (2006) for a detailed exposition of the *plreg* Stata command commonly used to implement this estimator.

Transforming this continuous function into estimates of the instantaneous rate of TFP growth requires a calculation analogous to that described by equation (8). Equation (8) converts discrete shifts over time in the intercept of the production function into a rate of change – an estimate of the average rate of TFP growth during the period of estimation. In the semi-parametric case, the analogous task is to convert the estimated non-parametric effect of time on output into rates of change (or estimates of the growth rate of TFP). In this case, $\hat{g}(TD(s))$ is a non-parametrically smoothed representation of the annual shifts of the production function, estimated from the year dummies. For arbitrarily small changes in time, the analogy to equation (8) is implemented by differentiating $\hat{g}(TD(s))$ with respect to time:

$$(12) \qquad Instantaneous\ rate\ of\ TFP\ growth = \frac{\partial \hat{g}(TD(s))}{\partial s}$$

That is, the slope of $\hat{g}(TD(s))$ with respect to time provides a point estimate of the instantaneous rate of TFP growth. Taking this derivative at every point of $\hat{g}(TD(s))$ thus results in a smoothed non-parametric path that describes the rate of TFP growth as a continuous function of time.

The following section presents estimates of TFP growth rates derived from both the SURE and semi-parametric approaches described above.

6. Measuring Total Factor Productivity Growth in Agriculture: Results

An African success emerges from Figure 4, which presents the rates of TFP growth in African crop agriculture, averaged over successive five-year periods from 1961/65 to 2001/06.

These results reflect vertical shifts in the successive production functions based on five-year averages of annual panel data, estimated by the SURE regression procedure described above.[15] Thus, for example, the first bar in Figure 4, marked 63-68 describes the average rate of TFP growth between "1963" (designating data averaged over the period 1961-65) and "1968" (designating data averaged over the period 1966-70). These baseline results control only for the conventional inputs, unadjusted for quality.

These preliminary results are encouraging in their reflection of a broad recovery of productivity growth in African crop agriculture beginning in the mid-1980s, re-confirming the results by Block (1994). Figure 4 depicts a history in which the early years of independence were characterized, on average, by a slow yet positive rate of productivity growth in African crop agriculture. This relatively auspicious start, however, was followed by 15 years of stagnation and decline, as TFP growth rates became increasingly negative on average from the late 1960s through the early 1980s. In contrast, TFP growth rates since the mid-1980s, at least in this preliminary view, reflect a substantial turnaround, approaching 2.8% per year on average between the five-year periods centered around 1998 and 2003. The challenge, then, is to explain this reversal of fortune for African agriculture. I begin by examining the effect of changes in the quality of inputs, in particular land and labor. First, however, it is useful to review estimates of the underlying production function.

Table 4 presents estimates of the basic production function for African crop agriculture described by equation (7). The estimates in column (1) include only the conventional inputs.

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[15] Estimating TFP growth based on vertical shifts of the production function, as noted above, requires equality of the production elasticities for given conventional inputs across the production functions for the beginning and ending of the period being measured. Joint tests of the quality of the estimated coefficients on conventional inputs, implemented pair-wise for each of the eight sets of adjacent production functions failed to reject the equality of the production functions for all but one period (1968-73), and in that case the rejection was only at the .10-level. These tests are thus highly supportive of this SURE approach to TFP estimation.

Column (2) adds controls for annual rainfall and the share of land equipped for irrigation to adjust for differences in land quality; and column (3) adds average years of schooling to control for changes in the quality of labor. In keeping with the inclusion of country dummies in equation (7) to control for, among other things, time-invariant measurement error, the production functions in Table 4 are estimated as fixed-effects models.

The coefficient estimates in column (1) are all statistically significant and have the expected signs. By comparison with estimates in other studies of African agriculture (such as Fuglie, 2010), the production elasticity of land is quite high (and by implication, that of labor, quite low). The higher estimate for land in the present study may reflect in part the exclusion of livestock production from the output aggregate (described above). Historically, much of the increase in African crop output has been the result of land extensification. The implication that a 10% increase in land area per worker would result in a roughly 8% increase in crop output is thus plausible. Rainfall and share of land equipped for irrigation (which often differs from the share of land actually irrigated in any given year due to water constraints), both present significant positive effects on per capita output (column (2)). In addition, column (3) demonstrates the significant positive effect of average years of schooling of the labor force on agricultural output, suggesting that improvements in the quality of the labor force has been an important positive factor for African agriculture.

Figure 5 illustrates the non-parametric pattern of TFP growth rates over time, estimated from annual data and controlling linearly for (only) the five conventional inputs. These smoothed continuous results are consistent with the initial results presented in Figure 4 in suggesting that the stagnation and decline of African crop productivity of the late 1960s through the early 1980s has been followed by two decades of substantial recovery and progress. While that progress appears to have stalled during the early and mid-1990s, average TFP growth rates for African crop agriculture have trended steeply upwards since the late 1990s. By 2005, this growth rate exceeded 2% per year.

The average TFP growth rate of the path illustrated in Figure 5 is 0.97% per year. This measurement is based on the period 1961 – 2000 for 29 countries in sub-Saharan Africa. It is not adjusted for differences in the quality of inputs. Over this same period and set of countries, crop output grew at the average rate of 1.68% per year. As a first cut, then, TFP appears to explain 58% of the growth in Africa's crop output (though this estimate will be revised downward with the incorporation of adjustments for input quality).

Is interesting, as well, to disaggregate this average SSA result to the regional level (as presented above in Figures 3a-d for the partial productivity analysis). Here too, Figure 6 demonstrates substantial heterogeneity across the regions of sub-Saharan Africa, though with a trend towards convergence in growth rates. Southern Africa has maintained a consistently high rate of TFP growth throughout this period, though the TFP growth rate for West Africa (excluding the Sahel) turned positive around 1975 and surpassed the growth rate for Southern Africa between 1980 and 1995. On the low end, Sahelian and Middle African countries began the post-independence period with negative rates of TFP growth, which turned positive only in the early and late 1980s, respectively. These results, summarized in Table 5, are consistent with those of the partial productivity analysis presented above. Comparing, in Table 5, the regional average TFP growth rates for the periods 1961-84 and 1985-2002, it is clear that every region except East Africa enjoyed a substantially greater rate of TFP growth in the later period.

Returning to the SSA average, the next step is to measure the contributions of changes in input quality to these initial estimates of TFP growth. Figure 7 repeats the semi-parametric procedure underlying Figure 5, adjusting first for changes in land quality, and then adjusting for labor quality as well.[16] Changes in the quality of land and labor emerge as significant contributors to TFP growth.

Table 6 quantifies these contributions by calculating the percentage change in the mean TFP growth rate over the entire period resulting from the inclusion of these additional explanatory variables. The mean TFP growth rate for the baseline estimates illustrated in Figure 5 (and in the highest path in Figure 7) for the period 1961 to 2000 was 0.97% per year.[17] After adjusting for land quality, this estimate falls to 0.87% per year. (This difference is significant at the .10-level in a one-sided t-test.) That is, adjustments for land quality explain just over 10% of the baseline growth rate of agricultural TFP. The non-parametric approach reveals that most of this difference has occurred since the mid-1980s, reflecting, in part, expansion of irrigation. Controlling in addition for improvements in the quality of the agricultural labor force reduces the mean TFP residual to 0.59% per year. Together, adjusting for changes in the quality of land and labor inputs thus account for 0.38 percentage points difference in, or 39% of, the baseline growth rate of agricultural TFP.

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[16] Note that the baseline (unadjusted) TFP growth path depicted in Figure 7 is shifted up relative to the baseline growth TFP path depicted in Figure 5. This difference results from the loss of observations, given the availability of data for the adjustments to land and labor. Figures 4 and 5 use the same set of all available observations; whereas the three TFP growth paths presented in Figure 7 all use the same, but more limited, sample of observations.

[17] Note that this growth is greater than the unadjusted growth rate reported in Table 5. This higher rate was estimated over a sample that was limited by the availability of data for land and labor quality adjustments, while the rate reported in Table 5 was for the largest possible sample.

In terms of the broader growth accounting, this adjusted baseline TFP growth rate estimate of 0.59% per year accounts for 36% of the 1.68% per year growth rate of aggregate crop output.

Even net of these adjustments, however, it is clear from Figure 7 that TFP growth in African crop agriculture has generally accelerated since reaching its nadir in the late 1970s. Despite a modest deceleration in TFP growth during the early and mid-1990s, aggregate TFP growth for African crop agriculture in 2000 was 4 to 5 times greater than it had been 25 years earlier.

The following section continues the task of decomposing and explaining the TFP residual measured here, expanding that task to consider a wider range of potential explanations. My starting point for these additional decompositions is the TFP residual estimated net of adjustments for input quality.

7. Explanations for Total Factor Productivity Growth in Agriculture

This section considers several potential explanations for productivity growth in African crop agriculture, including: expenditures on agricultural research and development, infrastructure (roads), the effects of civil war, and incentives (agricultural and macroeconomic policy distortions). Severe data constraints, however, preclude a complete decomposition in which all of these potential explanations are considered together. The best one can do, then, is to compare the baseline TFP residual (net of adjustments for input quality) individually against each of these potential explanations. In each case, it is necessary to re-estimate the "baseline" TFP growth rate based on the sample of observations available for each potential explanation of productivity growth. This approach provides estimates of the share of TFP growth explained by each of these factors; yet, these results will not be strictly additive across the potential explanations (as the explanatory variables are not orthogonal to one another), and the generalizability of these results must be qualified (as each decomposition must be estimated over a slightly different sub-sample of the full data set). It may be reasonable, then, to think of the following results as reflecting upper-bounds on the role of any individual explanation for productivity growth.

As in my previous accounting for input quality adjustments, my approach to measuring the contribution of a given explanatory variable to TFP growth is first to estimate the quality-adjusted production function with and without the additional variable, and then to calculate the percentage difference in the means of the resulting non-parametric TFP growth paths as the contribution of that variable to TFP growth.

Agricultural R&D

Ultimately, measured productivity growth is intended to reflect a deeper process of technological change. Expenditures on agricultural R&D are thus a potentially important driver of productivity growth, as numerous studies have shown for Africa and for other developing and developed regions (most recently for Africa, Alene, 2010). Data on agricultural research expenditures for 27 sub-Saharan African countries since 1971 have been collected by the Agricultural Science and Technology Indicators (ASTI) Initiative, housed at the International Food Policy Research Institute.[18] Beintema and Stads (2006) describe the rapid post-independence growth in funding for agricultural R&D in Africa, followed by slower growth in research expenditures during the 1980s, and near stagnation during 1990s. Table 7, from

[18] The ASTI data are available for download at http://www.asti.cgiar.org/data/.

Beintema and Stads (2006, p. 4), disaggregates agricultural R&D expenditures in Africa by region and decade. By region, the average growth rate of R&D expenditures from 1971 to 2000 has been greatest in East Africa -- exceeding the growth rate of expenditures in West Africa by a factor of nearly eight. These are annual expenditures by governments in each country. They thus reflect a flow of inputs into R&D. While much of the national funding for agricultural R&D in Africa is donor-funded, these data do not include the benefits for any given country of expenditures by the international agricultural research centers. Thus, to the extent that national funding and the benefits of international research are correlated, the present estimates may be biased upwards.

Substantial lags exist between the time expenditures on R&D occur and the time they affect productivity. Alene (2010) examines alternative lag structures on R&D expenditures, with lags ranging from 2 to 16 years. His finding that the maximum effect of agricultural R&D occurs around lag 10 leads him to conclude that the slowdown in agricultural TFP growth during the 1990s is partially explained by the reduced growth rate of agricultural R&D expenditures in the 1980s. This is consistent with the prediction by Block (1995), which also found that agricultural research expenditures, lagged by ten years, were significant in explaining the recovery of African agricultural productivity during the 1980s (but which expressed concern for the future impact of reduced R&D expenditures by the late 1980s).

Adding the 10-year lag of log agricultural R&D expenditures to the production function estimated above (net of input quality adjustments) results in a production elasticity of approximately 0.2 (P = 0.000), suggesting that doubling the level of agricultural R&D expenditures at time *t* would boost agricultural output per worker by 20% at time *t+10* -- a substantial effect, and one that is consistent with studies that find high rates of return to agricultural research expenditures in Africa (Alene, 2010).[19] Including the 10-year lag of R&D expenditures limits the estimation period to1981-2000. For that period, the 10-year lag of R&D expenditures explains 75% of estimated TFP growth. Extending the estimation period back to 1976-2000 by including only the 5-year lag of R&D expenditures results in only a small reduction in the estimated production elasticity (to 0.18). In this case, agricultural R&D expenditures still explain 45% of estimated TFP growth.

Roads

The potential benefits of increased road density for agricultural productivity have been explored in a variety of developing-country settings. These benefits, according to Zhang and Fan (2004) include: increased profitability of farming resulting from reduced transportation costs; greater purchases of inputs and marketing of output resulting from reduced transportation costs; and, the potential to shift land from low-value cereals to higher-value horticulture with reduced risks of perishability. Zhang and Fan (2004) demonstrate significant contributions of roads to crop TFP in rural India, as do Mendes, Teixeira, and Salvato (2009) for Brazil, and Suphannachart and Warr (2009) for Thailand, among many others. In a simulation model of Uganda, Gollin and Rogerson (2010) also find significant complementarities between road density and agricultural TFP. Most recently, Dorosh, et. al. (2010) provide evidence from sub-Saharan Africa that agricultural production is higher in areas with lower travel times to urban markets, and that adoption of modern technologies is negatively correlated with travel time to urban centers.

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[19] Including R&D expenditures in the production function required excluding the country dummies, as virtually all of the variation in R&D expenditure is in the cross-section dimension of the data (rendering the "within" estimator impractical).

Such findings are consistent with both intuition and with the broadly held presumption that roads are a critical ingredient for growth in agricultural productivity in Africa. For instance, in its Framework for African Agricultural Productivity, the Comprehensive African Agriculture Development Program (2006, p. 16) presents it as a given that, "... investment in infrastructure, particularly rural feeder roads, can also lead to large productivity growth and poverty reduction efforts." It is difficult, however, to demonstrate this contribution with available cross-country country data.

To account for the potential contributions of roads to agricultural TFP in Africa, I re-estimate my baseline semi-parametric production function to include countries' share of paved roads as a proportion of total roads. These roads data, drawn from the World Bank's World Development Indicators, are quite limited in their country coverage and only begin in 1990. The median paved road share for 1990-2007 was 16%. Perhaps owing to either the small sample size or to the general lack of paved roads, the estimated production elasticity for paved road share is effectively zero, and its inclusion makes virtually no difference to the estimated rate of TFP growth. Replacing the paved road share of total roads with the ratio of road kilometers to arable land does not change this result. One cannot conclude from this that the broad intuition regarding roads' potential contribution to agricultural TFP is wrong. Rather, available cross-country data and historical experience in Africa do not yet provide the expected statistical support for that intuition.

Civil War

Civil conflict has been endemic in much of sub-Saharan Africa in the post-independence period. Sambanis and Elbadawi (2000) report that between 1960 and 2000, 40% of sub-Saharan

African countries had experienced at least one period of civil war, and that in the year 2000 alone 20% of sub-Saharan Africa's population lived in countries that were formally at war (with endemic low-intensity conflict in any other countries). They attributed this problem to high levels of poverty, failed political institutions, and economic dependence on natural resources. It is reasonable to suppose that endemic civil war (and perhaps even the expectation of civil war) could negatively affect agricultural productivity. Physical destruction of crops, damaged infrastructure inhibiting both the purchase of inputs and the marketing of outputs, the diversion and destruction of human capital, and the potential reticence of households to invest in agricultural improvement given the threat of these disruptions, could all lead to reductions in agricultural productivity. I test this hypothesis by including in the production function data on the incidence of civil wars, carefully constructed by Sambanis (2006).[20]

A dummy variable equal to one during years of civil war enters the production function negatively, with a coefficient equal to -.04 (P = 0.11), suggesting that average crop output across the sample falls by 4% during years of civil war. Its effect on productivity is greater. Comparing the averages of the non-parametric TFP growth paths with and without the incidence of civil wars suggest that average TFP growth in African crop agriculture for the period 1960 to 2000 would have been over 11% greater in the absence of civil wars. This is the average effect based on the occurrence of civil war in 13% of the country-year observations included in the regression. A cautious interpretation of this result might consider the possibility that the incidence of civil war acts as a proxy for broader (and excluded) institutional failures.

Given this qualification, one can gain additional insight into the effect of civil war on agricultural productivity in Africa by dividing the sample into observations with and without

[20] I am grateful to Nicholas Sambanis and to Robert Bates for making these civil war data available.

civil war, observing their distinct experiences over time as opposed to the average effect of civil war across the entire sample. This approach reveals that the average rate of agricultural TFP growth was 0.74 percentage points lower (and negative on average) in the presence of civil war. Figure 8 illustrates these differences, which (given the inclusion of country fixed effects) are identified by countries moving in or out of the state of civil war.[21]

Macroeconomic Policy Distortions (Black Market Premium)

It is well-documented that African economies have historically experienced high degrees of distortion in macroeconomic policy. It has also been documented, first by Krueger, Schiff, and Valdes (1988), that macroeconomic distortions in developing countries have often imposed indirect taxes on agricultural producers in excess of their rates of direct taxation. That story highlighted the role of real exchange rates, which were often overvalued to the detriment of African farmers (who tended to produce import-competing tradables or exportables). By undermining agricultural incentives, macroeconomic policy distortions might also have affected agricultural productivity. To test that hypothesis, I use data on the black market premium for foreign currency, often employed as a proxy for such distortions. Over the period 1961-2004, the mean black market premium for sub-Saharan Africa was approximately 66% (though this mean falls to 30% if one excludes as outliers observations with black market premia greater than 500%).

The estimated coefficient on the log black market premium in the production function is not statistically different from zero, indicating that this proxy for macroeconomic distortions did

[21] It is possible that this over-estimates the difference between settings with and without civil war if TFP is under-estimated during civil wars. This could be the case if the data simply count the number of workers in the sector, some of whom are prevented from working by war. The author is grateful to Keith Fuglie for noting this.

not affect crop output, per se.[22] Yet, including the log black market premium in the specification accounts for 29% of measured TFP growth. Figure 9 illustrates this result. It is interesting to note that the productivity cost of this macroeconomic distortion diminishes over time relative to the baseline TFP growth path, given that black-market currency premia in Africa over this period fell on average by 12% per year (and was half the level post-1990 that had pertained pre-1990).

Agricultural Policy Distortions (Relative Rate of Assistance)

Producer incentives might also exert a substantial effect on agricultural productivity, particularly as regards farmers' choices on production intensity, crop mix, and input use. In a recent and major update to the earlier work by Krueger, Schiff, and Valdes (1988), the World Bank has released an extensive data set on trade-based agricultural price distortions (Anderson and Valenzuela, 2008). This data set provides commodity-specific indicators of the policy-induced divergence between domestic and international prices, covering 30 different commodities in 68 countries (including 13 countries from sub-Saharan Africa) since 1955. The key analytical building block of this data set is the nominal rate of assistance (NRA) for each commodity-year observation, essentially measuring the rate of tax or subsidy at the border. Anderson and Valenzuela (2008) also aggregate these nominal rates of assistance into agricultural and non-agricultural categories. By calculating the ratio of the rate of assistance to agricultural versus non-agricultural commodities, they create a relative rate of assistance (RRA) indicator, which measures the extent to which agriculture is either favored or disfavored by trade policy.[23] Historically, African governments have discriminated heavily against their agricultural sectors (Bates, 1981). This discrimination peaked around 1980, and though reduced during the

[22] This regression excludes outliers on black-market premia (over 500%).
[23] An RRA less than zero indicates relative discrimination against agriculture; an RRA greater than zero indicates a relative discrimination in favor of agriculture.

subsequent years of structural adjustment, was still present in 2005 (Masters and Garcia, 2010; Bates and Block, 2010).

Figure 10 juxtaposes the TFP growth paths (with and without controlling for RRA) with the nonparametric time path of the RRA, itself. The similarity of these patterns is striking. The RRA is negative throughout this period. The fact that TFP growth rates and the RRA decline and then rise together suggests the possibility that it is the first-difference (rather than the level) of the RRA that drives TFP growth. With this motivation, I include the first-difference of RRA in the semi-parametric production function. The RRA, however, is a policy choice and thus potentially vulnerable to reverse causation. This would require that governments choose to discriminate more heavily against sectors that perform worse over time, and discriminate less heavily against sectors as their performance improves. Such a perspective runs contrary to the logic found in much of the political economy literature on this subject (Bates, 1981), and ignores the external pressures for reform that characterized much of the 1980s and 1990s in Africa. Nonetheless, to provide at least some degree of protection against the potential for reverse causation, I specify the production function to include the lagged first-difference of the RRA. The point estimate (as expected) is positive, yet not statistically different from zero (0.037, P = .62).

The effect of RRA on TFP growth, however, is statistically significant (P = .016), as the lagged first-difference of RRA explains 16% of TFP growth over this period (as illustrated in Figure 10).[24, 25]

[24] Headey, Alauddin, and Prasada Rao (2010) find positive contributions to agricultural TFP growth with the same RRA indicator in a broader sample of mostly non-African developing countries. This is consistent, as well, with earlier evidence based on the use of the nominal protection coefficient in a small sample of non-African developing countries by Fulginiti and Perrin (1999).

Table 8 summarizes the results described in this section. This list of potential explanations for agricultural productivity growth in Africa is far from comprehensive, yet it represents the broad categories that have been addressed in the literature. Ideally, one would incorporate all of these potential explanations into a single decomposition. In practice, data constraints preclude such a comprehensive approach, requiring instead the pair-wise comparisons presented above. I take at least a small step towards that ideal by estimating the contributions of each potential explanation for productivity growth against baseline estimates that are adjusted for variations in the quality of land and labor. Nonetheless, this approach supports only broad statements regarding the relative importance of various explanations for productivity growth. As Table 8 reflects, expenditures on agricultural R&D, albeit with substantial lags, play the largest role in explaining agricultural TFP growth. Policy distortions, both at the macroeconomic and sectoral level, have also played an important, though smaller, role. Africa's agricultural TFP growth, on average, would have been 11% faster in the absence of civil wars (though the difference is much greater in the specific comparison of country-year observations with and without civil wars). And, contrary to expectations, available data suggest that infrastructure as represented by paved roads has contributed little to Africa's agricultural TFP growth.

Ghana, in many ways, reflects the experience of sub-Saharan Africa over this period. The following section draws on the broader cross-country analysis to highlight key aspects and determinants of Ghana’s agricultural productivity.

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[25] The black market premium and the first difference of the RRA are only loosely correlated ($\rho = -0.11$). While this negative correlation suggests that countries with distorted currency regimes also tended to discriminate against agriculture, the small magnitude of this correlation suggests that these two indicators do indeed reflect different impacts on agricultural productivity.

8. The Case of Ghana

This brief review is not intended to be a comprehensive analysis of Ghana's agricultural productivity experience. Rather, the primary objective is to explore in greater detail key findings from the cross-country analysis regarding the drivers of productivity growth. A secondary objective of this brief review of Ghana is to highlight some the issues that arise in country-level analysis – issues that are generally invisible at the cross-country level, but which may suggest caution in interpreting of cross-country findings.

Partial & Total Factor Productivity in Ghana

Ghana typifies the decline and rise pattern of agricultural productivity seen in the broader African sample. Figure 11 summarizes Ghana's experience as reflected in the time path of its partial productivity ratios. The first decade of independence saw small gains in crop yield combined with declining output per worker. The country's decline into economic chaos during the 1970s is reflected in the rapid deterioration of both land and labor productivity depicted in Figure 11. For agriculture, the country's economic nadir in 1983 was exacerbated by severe drought (starting in 1981), widespread bushfires, and the forced repatriation of one million Ghanaians from Nigeria.

These negative trends were strikingly reversed in the early 1980s, leading to a sustained (and continuing) period of growth in the productivity of both land and labor. Clearly, looking only at a path connecting the first and last periods (from which we would conclude that the annual growth rates of average land and labor productivity were 1.35% and 0.6%, respectively) would obscure the dramatic decline and resurgence seen by tracing out successive 5-year period averages. The narrative of Ghana's agricultural productivity is thus much more complex than would be implied by the moderate rates of growth in land and labor productivity observed on average over the period 1961 – 2007. The challenge is to explain the decline and rise.

The semi-parametric estimation approach developed above is not well-applied to a single country time series of only 40 observations. The estimated (input quality-adjusted) production elasticities are not statistically significant. Yet, controlling linearly for the conventional inputs results in a TFP growth path, depicted in Figure 12, which is statistically different from zero and suggests an average rate of crop TFP growth of 1.03% per year from 1961 – 2000. This pattern of TFP growth rates is also consistent with the pattern of partial productivity ratios for Ghana shown in Figure 11.

For the period 1961 – 2000, aggregate crop output in Ghana grew at the average annual rate of 2.37%. Growth accounting thus suggests that a TFP growth rate of 1.03% accounts for approximately 43% of the growth in crop output.

One way to summarize the current levels of crop productivity is to compare current yields against potential yields. Such analysis by Ghana's Ministry of Agriculture (2007) suggests that the yields gaps remain substantial. For example, average maize yield of 1.5 MT/Ha is reported to be 40% short of the achievable yield. Yield gaps calculated for other staple grains are reported on the same order of magnitude, while the yield gap for cassava in Ghana is reported to be 57.5% (Breisinger, et. al., 2008). The challenge is to identify the constraints to reducing these yield gaps.

One critical constraint to reducing the yield gap is the great heterogeneity of conditions that characterize agriculture in Ghana (and virtually every other country in sub-Saharan Africa). Figure 13 shows that Ghanaian agriculture is spread across six distinct agro-ecological zones, each listed here with its mean annual rainfall in millimeters: Rain Forest (2,200), Deciduous Forest (1,500), Transitional (1,300), Coastal (800), Guinea Savanna (1,100), and Sudan Savanna (1,000). These zones differ in their average annual rainfall by a factor of nearly four (Figure 14); unlike the first four zones, which have two growing seasons, the two Savanna zones have only one. Ghana's agro-ecological zones also differ in their soil types and in the length of their growing seasons, as a result of which they also differ widely in the mix of crops produced. In addition, the productivity levels and growth rates for individual crops also vary widely across agro-ecological zones.

Figures 15 (a – d) illustrate this diversity for maize, cassava, sorghum, and plantains. Maize is grown widely across Ghana, yet maize yields also vary widely across agro-ecological zones. The greatest concentration of relatively high-yield maize production is in the southern Guinea savanna in transitional zones, while the greatest concentration of relatively low-yield maize production lies just south of there in the forest zone. Average yields in the former are approximately twice those of the latter. Cassava production is similarly widespread (with the exception of the northernmost savanna areas), with a spatial distribution of yields similar to that of maize. In contrast, sorghum is grown exclusively in the Guinea and Sudan savanna zones, and districts with vastly different yields border one another; while plantain is grown exclusively in the forest and coastal zones, with somewhat less spatial variation in yields.

R&D

The cross-country analysis identified expenditure on agricultural R&D as a key determinant of productivity growth. The diversity of agricultural conditions within Ghana multiplies the technical challenges to increasing agricultural productivity. Broadly, however, the relationship between R&D expenditures and TFP growth in Ghana is consistent with the cross-country evidence.

While the poor estimation of the underlying production function renders the estimated TFP growth rates for Ghana as merely suggestive, their conformity with a 10-year lag of expenditures on agricultural R&D is striking.[26] Figure 12 juxtaposes the growth path of crop TFP with R&D expenditures. The transition to positive rates of TFP growth in the early 1980s follows by roughly 10 years the increased expenditures on agricultural R&D of the early 1970s; the peak in TFP growth rates seen in the mid-1990s similarly follows the peak of R&D expenditures of the mid-1980s; and, the decline in TFP growth rates in the late 1990s also lags by approximately 10 years the reduced R&D expenditures of the late 1980s. The main anomaly to this pattern is that the reduced expenditures of the late 1970s and early 1980s are not reflected in the estimated TFP growth path.

R&D expenditure is a blunt proxy for specific research outputs. The main research output of interest here is improved varieties of staple grains. As Figure 15a demonstrates, maize is grown is all of Ghana's agro-ecological zones. The diversity of growing conditions, however, implies that improved maize varieties must be adapted to specific settings. Ghana's Crop Research Institute takes the lead in developing and releasing improved varieties. During the critical period of reversal in crop productivity trends, the Crop Research Institute, in collaboration with the International Maize and Wheat Improvement Center (CIMMYT), the International Institute of Tropical Agriculture (IITA), and the Canadian International Development Agency (CIDA) implemented the Ghana Grains Development Project. Between

[26] The TFP growth path for Ghana is not statistically different from zero when lagged R&D expenditures are included in the production function (though the sample falls to 19 years).

1984 and 1996, this project developed and released twelve improved varieties of maize (Morris, Tripp, and Dankyi, 1999). The project also promoted use of chemical fertilizers to complement these improved varieties, and recommended new planting strategies.

While these research advances created the potential for improved maize productivity, the real benefits came only with their widespread adoption. By 1997, a nation-wide survey found that 54% of farmers planted modern varieties of maize, though adoption rates varied widely across agro-ecological zones (the highest adoption rate, 69%, was in the coastal savanna, while the lowest rate, 38%, was in the Forest zone). Adoption of recommended planting strategies followed a similar pattern. Yet, only 21% of farmers adopted the recommended fertilizers (ranging from 36% in the Guinea Savanna to 9% in the Forest zone), and only 26% of the national maize crop (by area) received fertilizer. (Morris, Tripp, and Dankyi, 1999.) In 1997, approximately half of Ghana's maize area was planted to modern varieties (ranging from 75% in the Coastal Savanna, to 33% in the Forest).[27]

Adoption of improved maize was thus reasonably widespread, if unevenly so, across the country. On the supply side, one constraint to more widespread adoption of improved maize varieties was an inability of the Ghana Seed Company (a government entity) to multiply the improved seeds in sufficient quantity (Morris, et. al., 1999). On the demand side, Doss and Morris (2001) found that the key constraints to adoption were lack of access to land, labor, and credit. Jatoe, Al-Hassan, and Abatania (2005) found similar constraints to the adoption of improved sorghum varieties in northern Ghana, where 40% of farmers had adopted improved sorghum, but only 0.1% of total sorghum area was planted to modern varieties.

[27] The survey also found that 9% of farmers who adopted modern varieties subsequently "disadopted" them, along with nearly one-third of those who had tried fertilizer, and 13% of those who had adopted recommended management techniques.

More recently, Kwadzo, Ansah, Kuwornu, and Amegashie (2010) surveyed farmers in Ghana's Eastern Region. They found that 83% of farmers had adopted improved maize, which covered 78% of maize area planted in the region. Yet, they also found that the yield potential of this adoption was not maximized because only 34% of farmers had also adopted nitrogen fertilizer, and that only 30% of maize area received fertilizer. They also found that the likelihood of adoption of improved maize was a positive function of both road access by farmers and the number of visits by extension agents.

Policy Interventions

Policy interventions – both macroeconomic and sectoral – were also found to play important roles in shaping agricultural productivity patterns in the African cross-section. In this regard, too, Ghana is representative.

Ghana's post-independence economic and policy experience is divided into two distinct periods. Following its auspicious emergence into independence in 1957 as an essentially middle-income country, Ghana's economy spiraled gradually downward into chaos, reaching its nadir in the crisis of 1983. With the adoption of its well-known Economic Recovery Program in that year, the country entered an extended (and continuing) period of stable growth. The macroeconomic environment that ended in crisis was characterized by high inflation, large fiscal deficits, declining exports, and a black market premium on its currency that grew from 35% in the early 1970s to 367% in the late 1970s, to nearly 1300% in the early 1980s (World Bank data cited in Brooks, Croppenstedt, and Aggrey-Fynn, 2009).

This history coincides cleanly with the sharp reversal of the partial productivity path depicted in Figure 11, as well as with the transition to positive rates of TFP growth depicted in

Figure 15. The potential connections between macroeconomic distortions and agricultural productivity are direct. The dramatically overvalued exchange rates that characterized the late 1970s and early 1980s in Ghana directly undermined incentives for domestic producers of import-competing crops (such as maize and rice), as well as for export-crop producers (cocoa). The 90% real depreciation of the cedi between 1983 and 1987 helped to relieve prior macroeconomic discrimination against agriculture, improving incentive on the output side, yet also increasing the cost of imported inputs. In addition, economic reform included the elimination of numerous input subsidies that had contributed to the unsustainable fiscal deficits. Thus, for example, the removal of fertilizer subsidies in 1990 led to a 36% increase in the real price of fertilizer, while the prices of insecticides and fungicides tripled in real terms with the removal of their subsidies (Seini, 2002).

Policy reforms at the sectoral level were less ambiguous in their benefits for Ghana's farmers. The period from independence to 1983 was characterized by high rates of agricultural taxation – both indirect (arising largely from the overvalued exchange rate), and direct. Subsequent to the liberalization of Ghana's foreign exchange market and the devaluation of the cedi in 1984, agricultural taxation was primarily direct taxation. The example of cocoa taxation is notorious. The combination of an overvalued exchange rate and direct taxation in the form of low producer prices paid by the monopsonistic Ghana Cocoa Board was such that by 1983, farmers received about one-fifth of the FOB price of cocoa (Seini, 2002). With the subsequent devaluation and the reform of agricultural policies that accompanied the Economic Reform Program, cocoa farmers' share of the FOB price had increased to 40% by 1995, and to 50% by 2001 (Brooks, Croppenstedt, and Aggrey-Fynn, 2009).

The nominal and relative rates of assistance (described above) provide a more general indicator of agricultural policy in Ghana. Average rates of taxation (measured relative to international prices) for agricultural tradables increased from approximately 17% in the early 1960s to 50% by the late 1970s. With the period of reform, these rates of taxation fell back to 17% by the late 1980s, and averaged just over 3% for 2000-04 (Brooks, Croppenstedt, and Aggrey-Fynn, 2009). Comparing this indicator to similar measures for non-agriculture provides an indicator of price discrimination of agriculture relative to non-agriculture (the “relative rate of assistance”). From this broader perspective, as well, one finds substantial and increasing discrimination against agriculture in the pre-reform period, with declining but persistent discrimination against agriculture in the post-reform period. Relative discrimination against agriculture averaged just over 6% in the early 1960s, increasing to approximately 25% in the late 1970s. While falling substantially during the period of economic reform, this indicator of relative discrimination was still 8% for 2000-04.

Figure 16 highlights the close association between the TFP growth path for Ghana’s crop agriculture with the (non-parametrically smoothed) path of the relative rate of assistance for agriculture versus non-agriculture in Ghana. As in the broader cross-section, the RRA remains negative throughout the period (indicating relative discrimination against agriculture); yet, it is clear from Figure 16 that reductions in this rate of discrimination were associated with increases in the rate of TFP growth. The potential for this association to be explained by reverse causation, in which improved TFP growth led to reduced discrimination against agriculture, is strongly limited by the fact that the severity of Ghana’s economic crisis (and its multiple sectoral and macroeconomic adjustment agreements with the IMF and World Bank) left the government no choice but to implement its broad program of economic reforms.

This brief review demonstrates that agricultural productivity growth in Ghana broadly reflects the cross-country experience of sub-Saharan Africa. The general pattern of post-independence decline followed by renewed productivity growth since the 1980s is clear in Ghana. The important roles of agricultural R&D expenditure and policy interventions seen in the broader cross-section are also clear in Ghana.

Cautionary Note

Even a brief country case study can serve the purpose of providing a cautionary note for the interpretation of cross-country findings. In particular, Ghana's agro-ecological diversity is common in sub-Saharan Africa. From a technological perspective, this diversity greatly complicates current efforts to promote a new green revolution for Africa. As seen in Figure 14(a – d), different crops are specific to different agro-ecological zones; and for ubiquitous crops such as maize, an improved variety that thrives in humid Evergreen zones of south-western Ghana may be inappropriate for planting in the arid zones of the northern savanna. An analysis that explains aggregate agricultural productivity at the country level based on total expenditures on agricultural R&D inevitably obscures the fact that both expenditures and productivity growth are likely to be quite unevenly distributed across the country.[28] This diversity is even more obscured when that aggregate country-level analysis is merely part of a broader cross-country panel data set.

Looking within a particular country also enables a closer examination of the sources and quality of agricultural data. In the case of Ghana, Obirih-Opareh (2004) provides a critical examination of the methods applied by the Ministry of Food and Agriculture in compiling its

[28] Indeed, regional disparities between Ghana's northern and southern zones are a source of considerable tension.

national area and production data. He notes, for example, that most Ghanaian farmers do not keep their own records of area and production. In addition, Obirih-Opareh notes that most farmers mix numerous crops in a single field, further complicating the calculation of area and yield of individual crops, and that many farms are not accessible by road. As a result, production and area surveys must rely on limited and potentially poorly-measured samples. For export crops, such as cocoa, the situation is better. Similarly, consumption data for imported inputs such as chemical fertilizer, are also more reliable. Yet, Obirih-Opareh in general finds that the limited ability of the Government to undertake annual nation-wide surveys of complex and remote production systems often leads to statistical anomalies in the published data. He also notes that different international and national sources of published data on agricultural area and production in Ghana provide conflicting information. In this respect, too, Ghana is undoubtedly not unique in sub-Saharan Africa.

9. Conclusions

Agricultural productivity growth in sub-Saharan Africa has been a qualified success. Total factor productivity growth has increased rapidly since the early 1980s. By the early 2000s, average annual TFP growth was roughly four times faster than it had been 25 years earlier. This period of accelerated growth, however, followed nearly 20 years of declining rates of TFP growth subsequent to independence in the early 1960s. Average agricultural TFP growth for sub-Saharan Africa was 0.14% per year during 1960 – 84, and increased to 1.24% per year from 1985 – 2002. The average over this period was approximately 0.6% per year, which accounts for 36% of the increase in total crop output over this period.

These highly aggregated results conceal substantial regional and country-level variation. While regional TFP growth rates have tended to converge over time, and most rapid rate of TFP agricultural growth over the entire period 1960 – 2002 was in Southern Africa (1.25% per year), while the slowest rate was in the Sahel (-1.17%). With the exception of East Africa, every region's TFP growth rate was higher between the years1985 – 2002 than it had been during 1960 – 1984.

From among the long list of potential explanations for these trends, this paper considers several leading contenders. Data constraints on individual explanations preclude a unified and comprehensive decomposition of the productivity residual. It is clear, however, that expenditures on agricultural R&D, along with the reform of macroeconomic and sectoral policies shaping agricultural incentives have played a substantial role in explaining both the decline and the rise in agricultural productivity found in this paper.

The case study of Ghana clearly reflects these broader findings, and permits a more nuanced view of their effects. The case study also provides a brief window into the vast complexity of agricultural development in any single country, and in doing so, provides a cautionary note for the interpretation of aggregate cross-country results.

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Figure 1. Partial Productivity Ratios for Africa and Global Comparisons

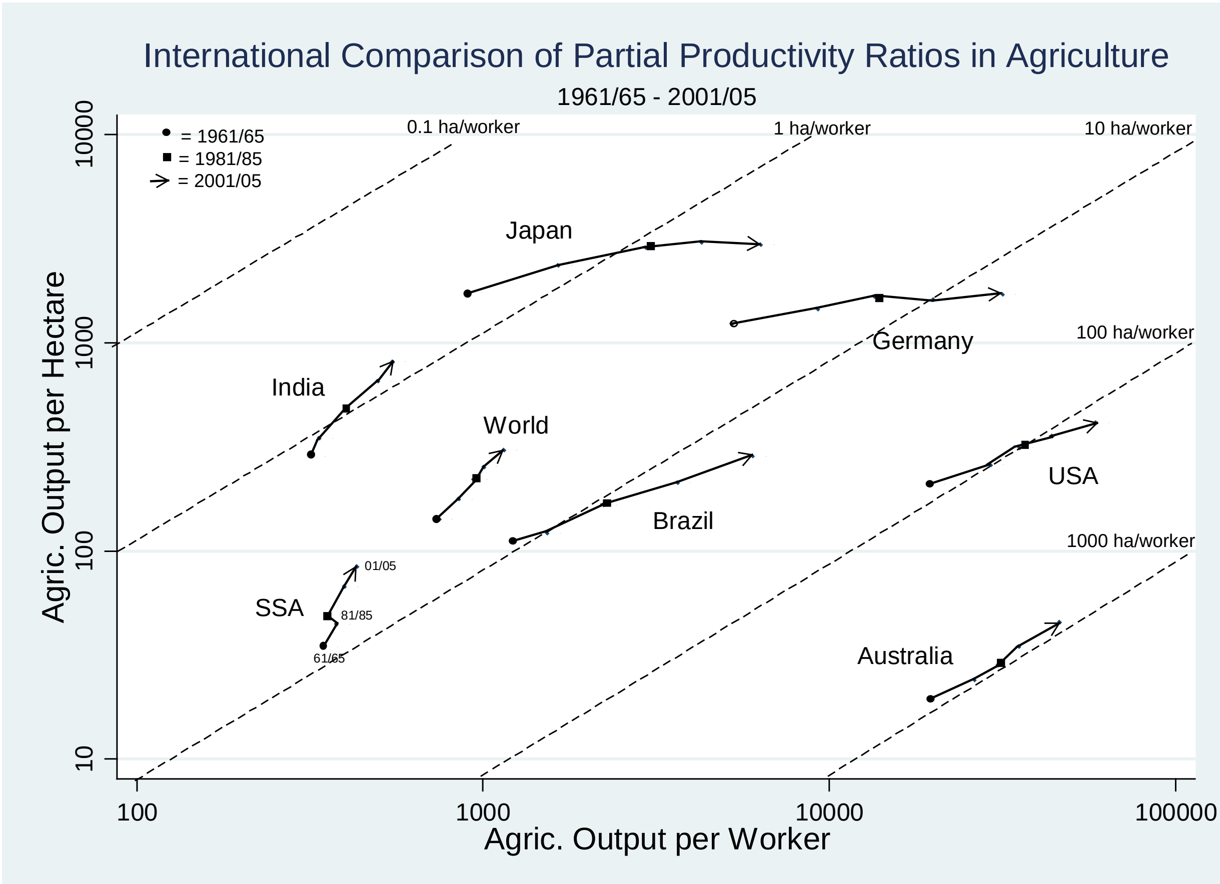


Figure 2. Regional Disaggregation of African Partial Productivity Ratios (Crop Output)

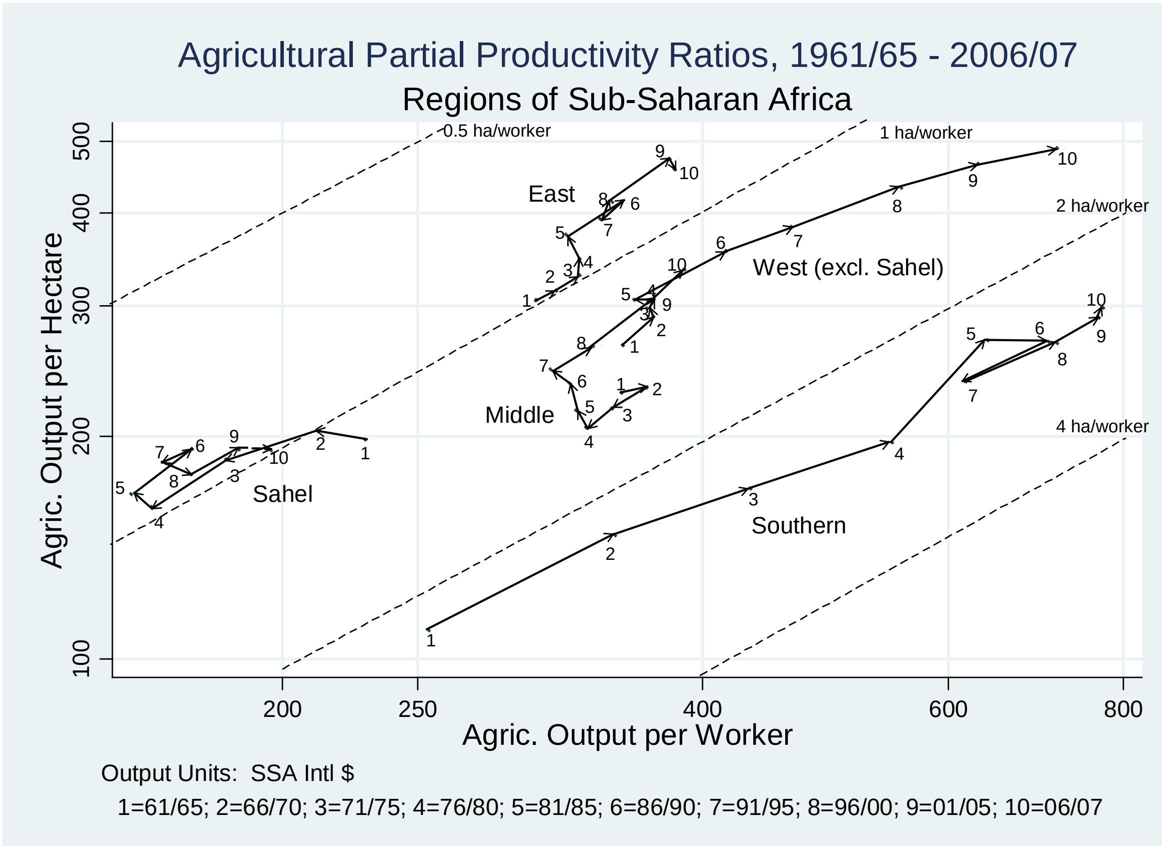
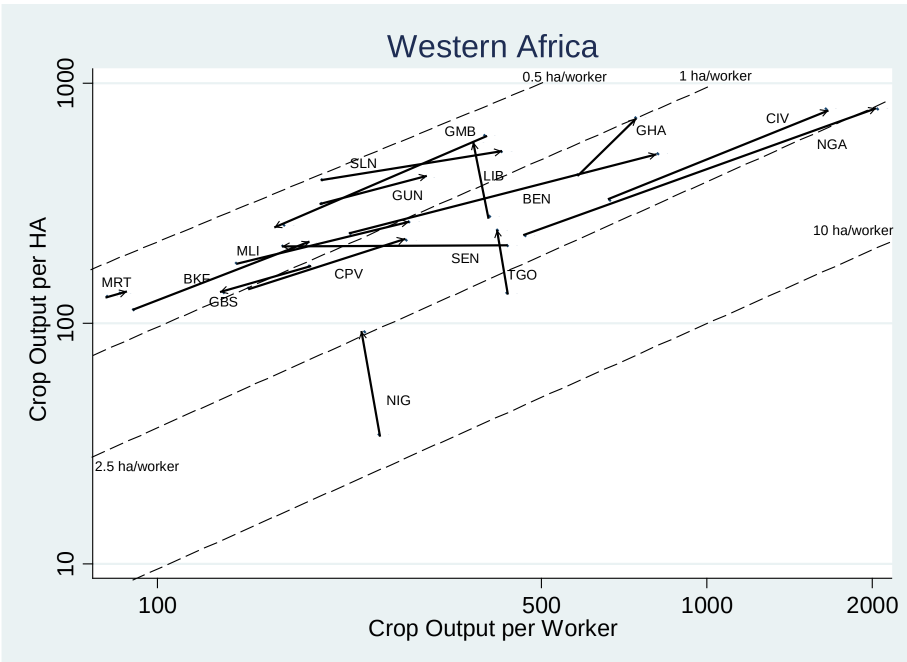
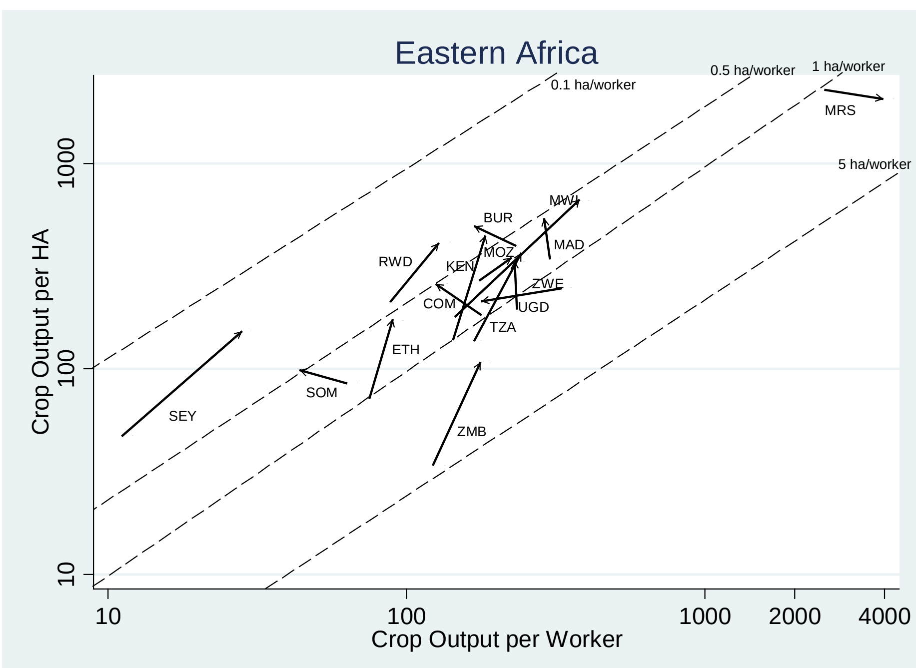
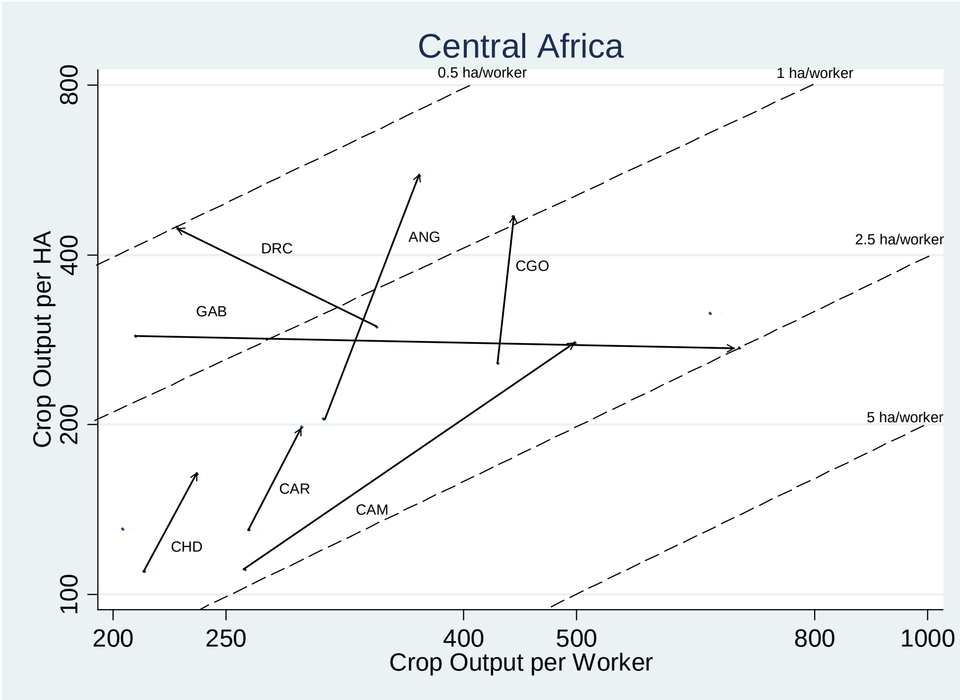


Figure 3a – d. Country-Specific Partial Productivity Ratios (a. West, b. East, c. Middle, d. Southern)






Central Africa
0.5 ha/worker
1 ha/worker
2.5 ha/worker
5 ha/worker
DRC
ANG
CGO
GAB
CAR
CAM
CHD
Crop Output per HA
Crop Output per Worker
800
400
200
100
200
250
400
500
800
1000

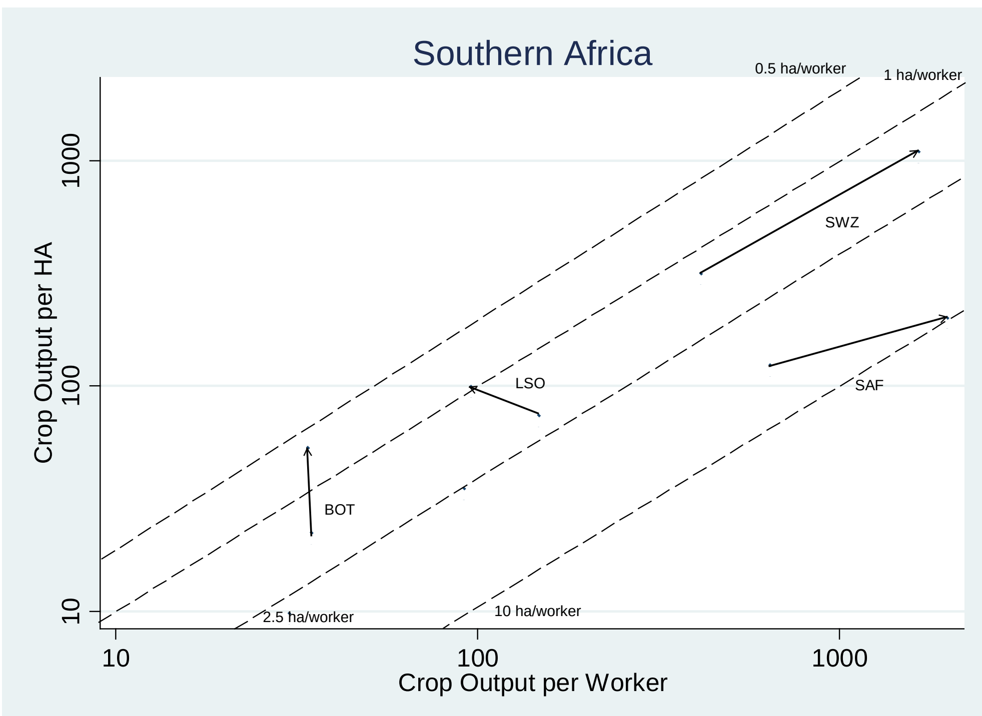

Southern Africa
0.5 ha/worker
1 ha/worker
2.5 ha/worker
10 ha/worker
SWZ
LSO
SAF
BOT
Crop Output per HA
Crop Output per Worker
1000
100
10
10
100
1000

Figure 4. Baseline TFP Growth Estimates for 5-Year Periods (from SURE approach)

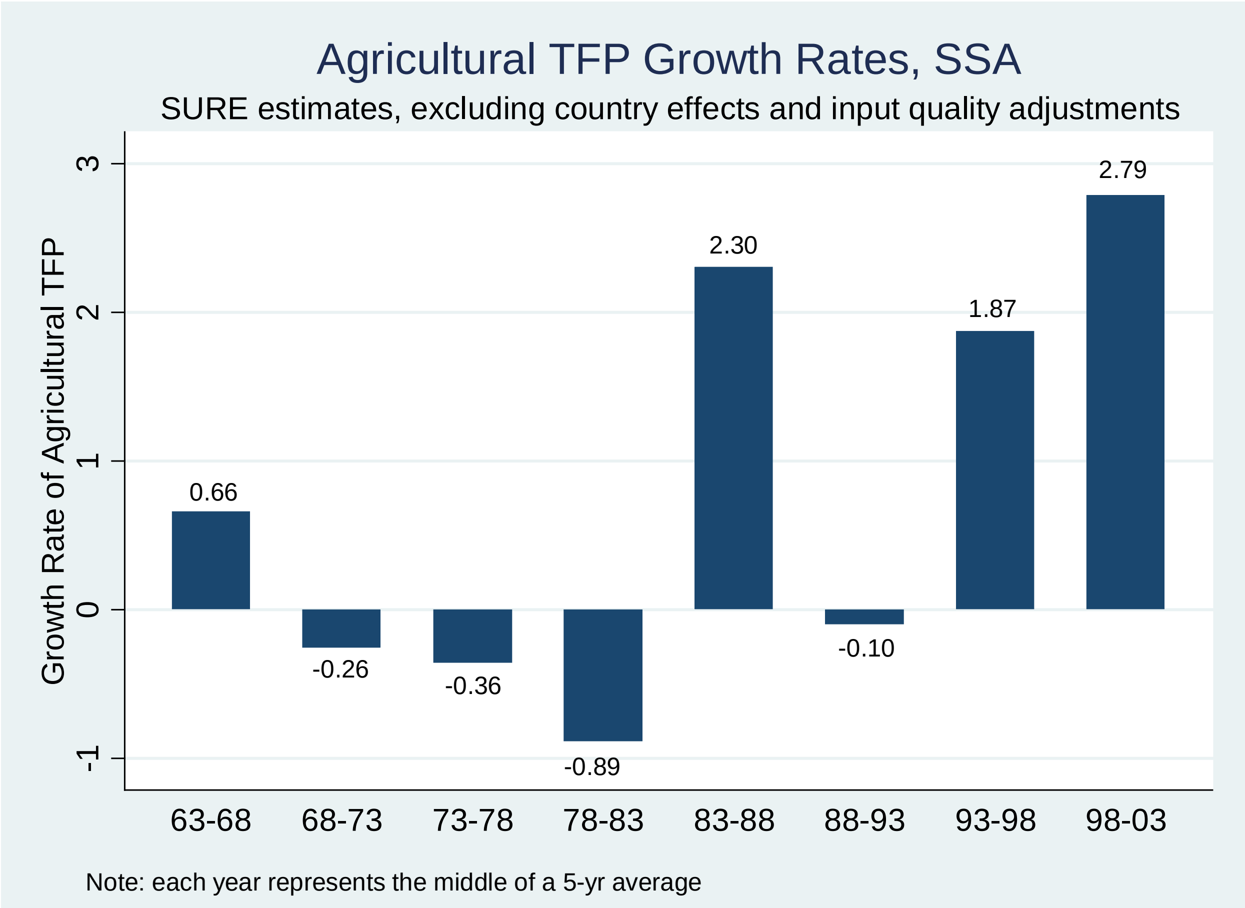


Figure 5. Baseline TFP Growth Rates (from Semi-Parametric Regression)

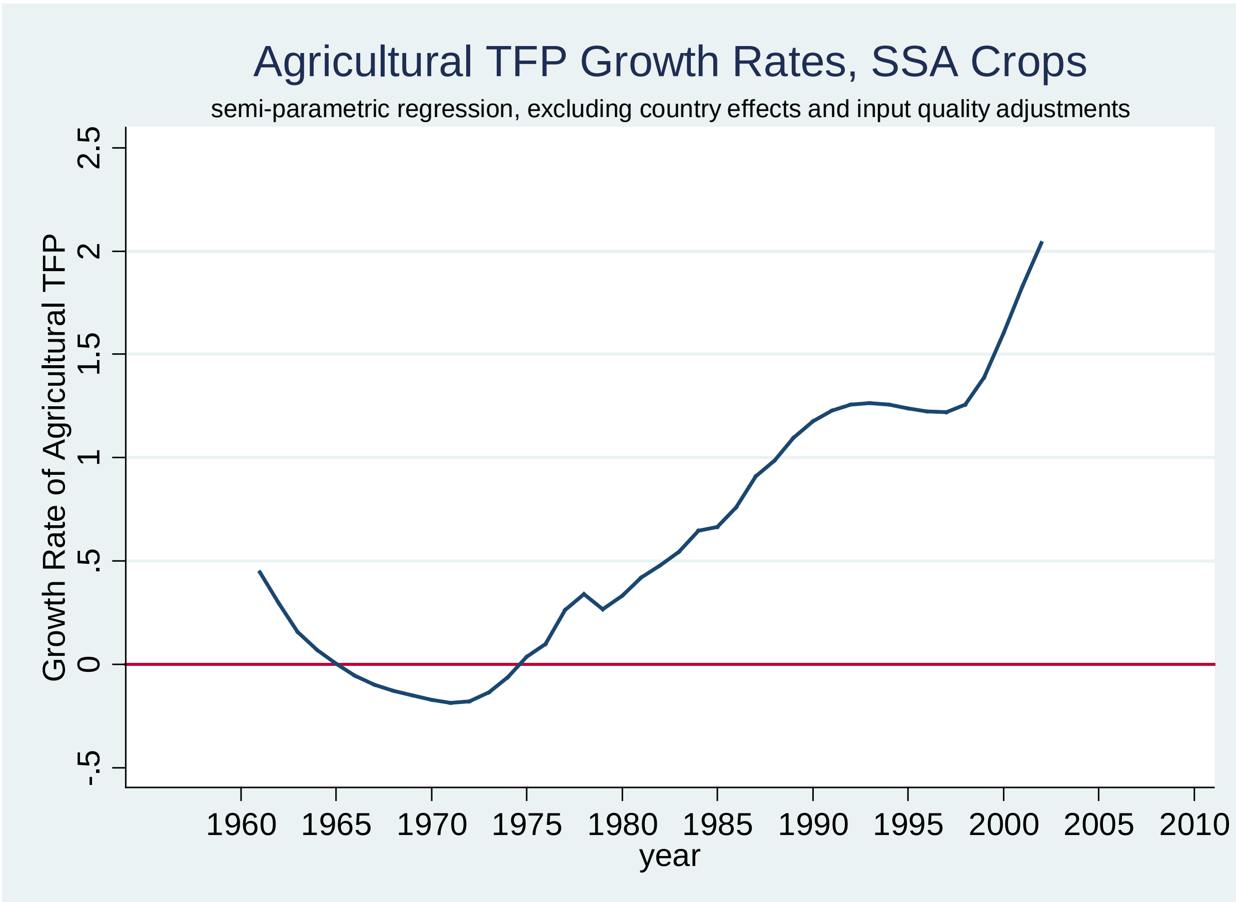


Figure 6. Regional Disaggregation of TFP Growth Rates

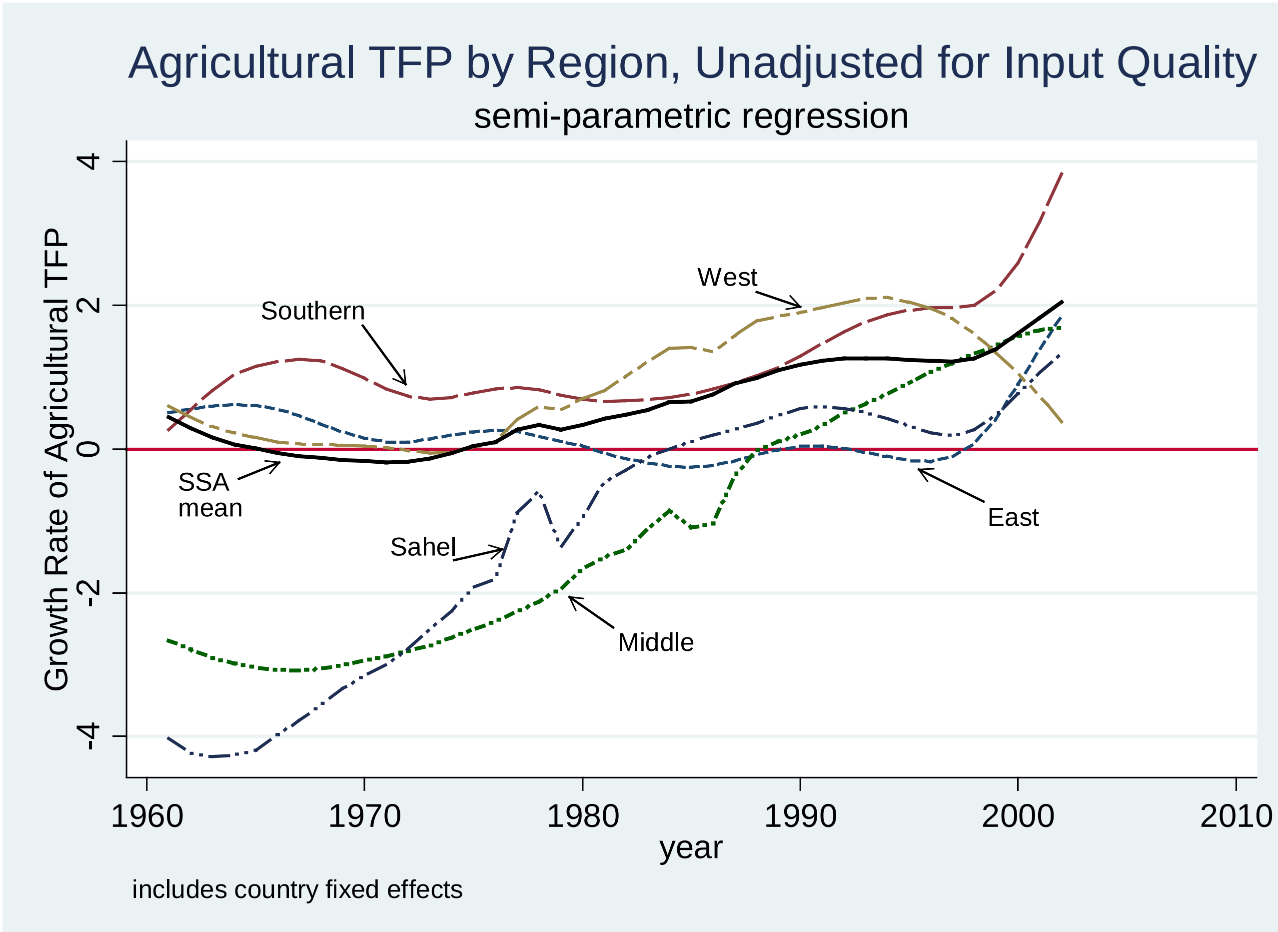


Figure 7. Agricultural TFP Growth Rates Adjusted for Input Quality

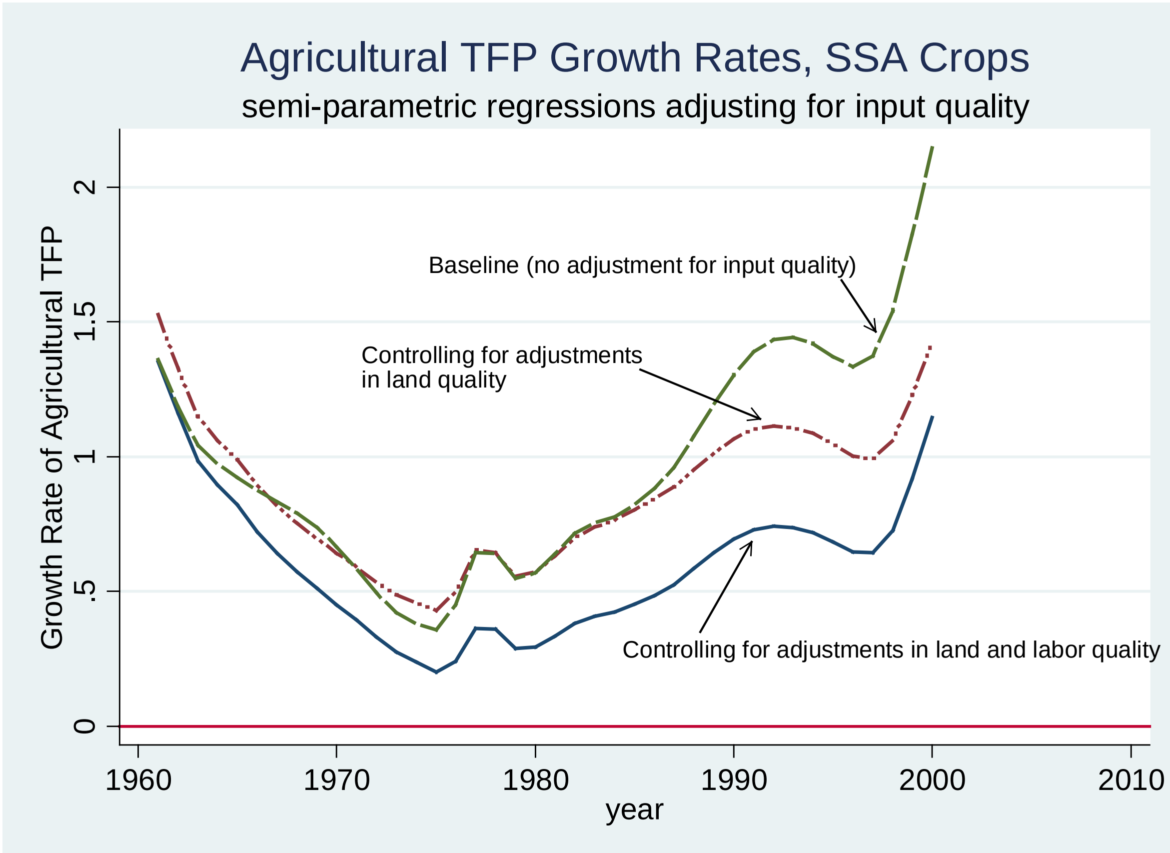


Figure 8. Effect of Civil War on Agricultural TFP

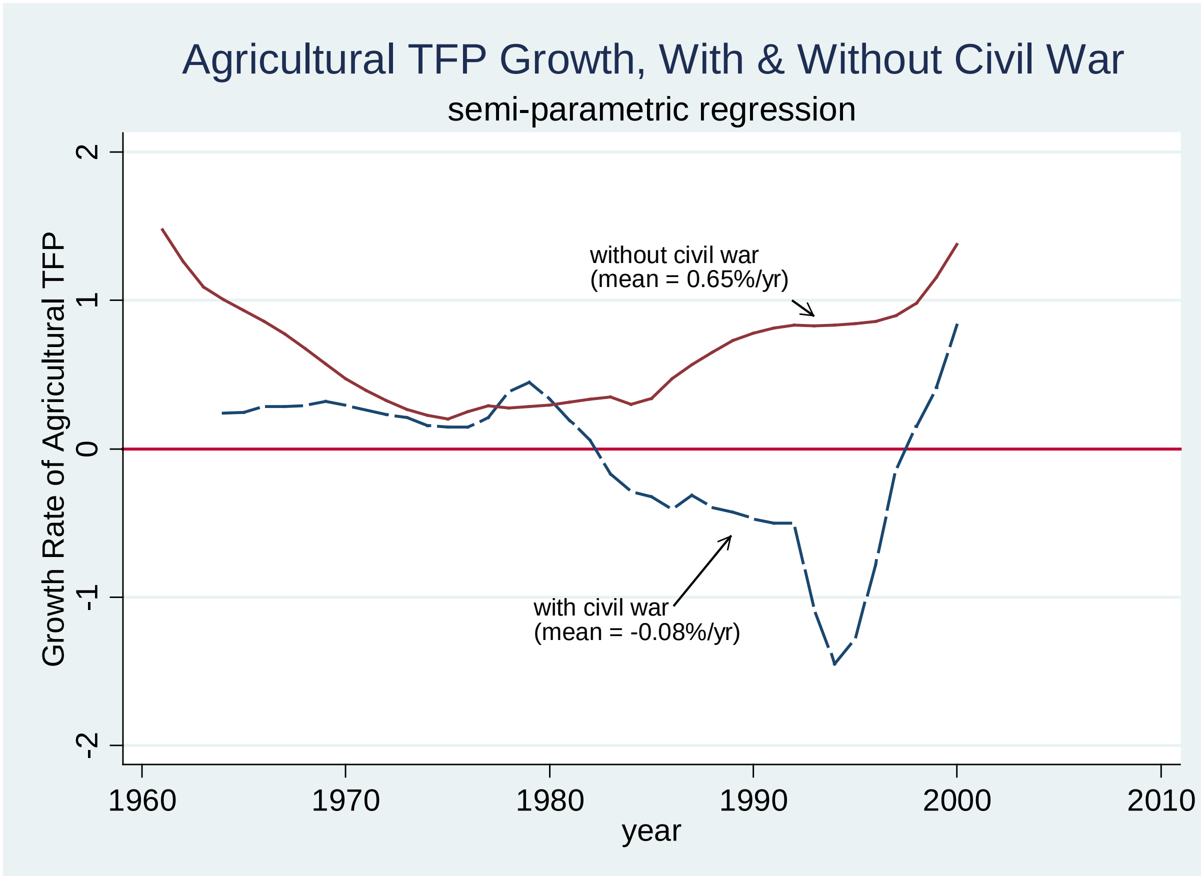


Figure 9. Effect of Black Market Premium on TFP Growth Rates

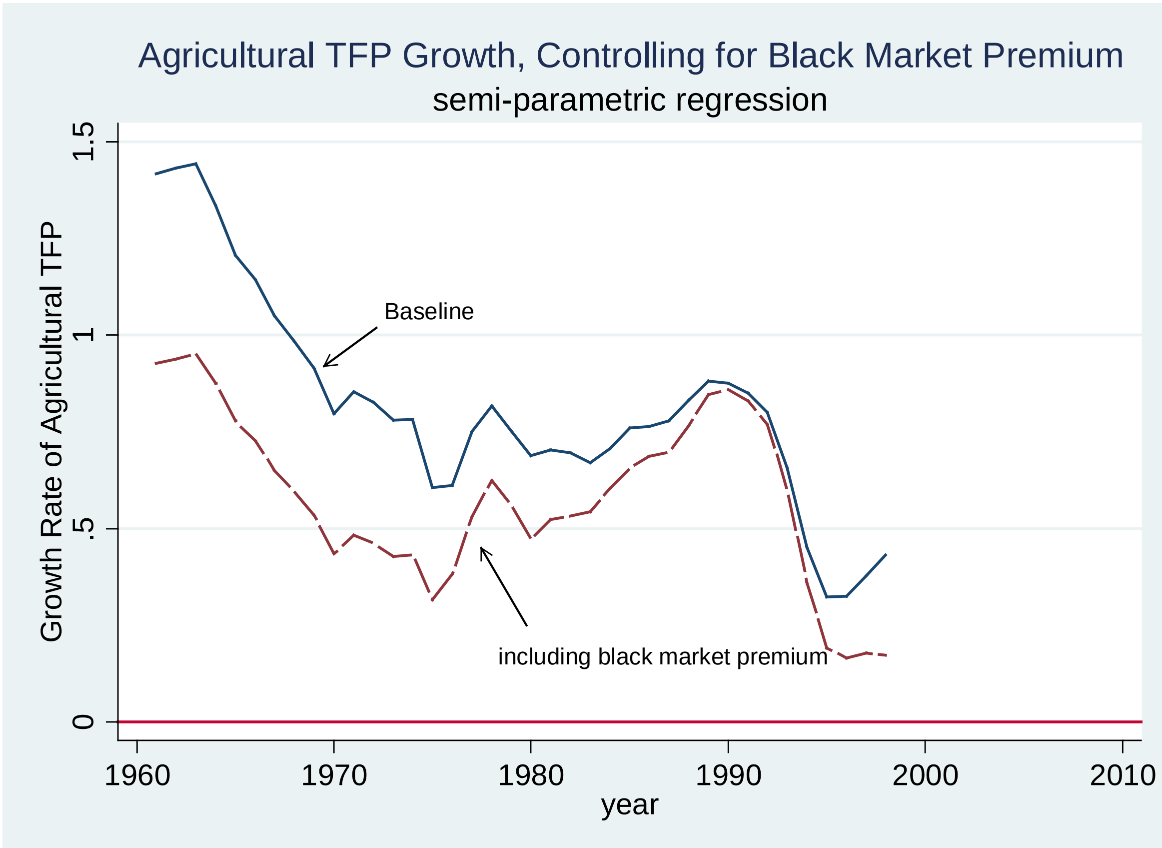


Figure 10. Effect of Agricultural Price Policy Distortions on Agricultural TFP

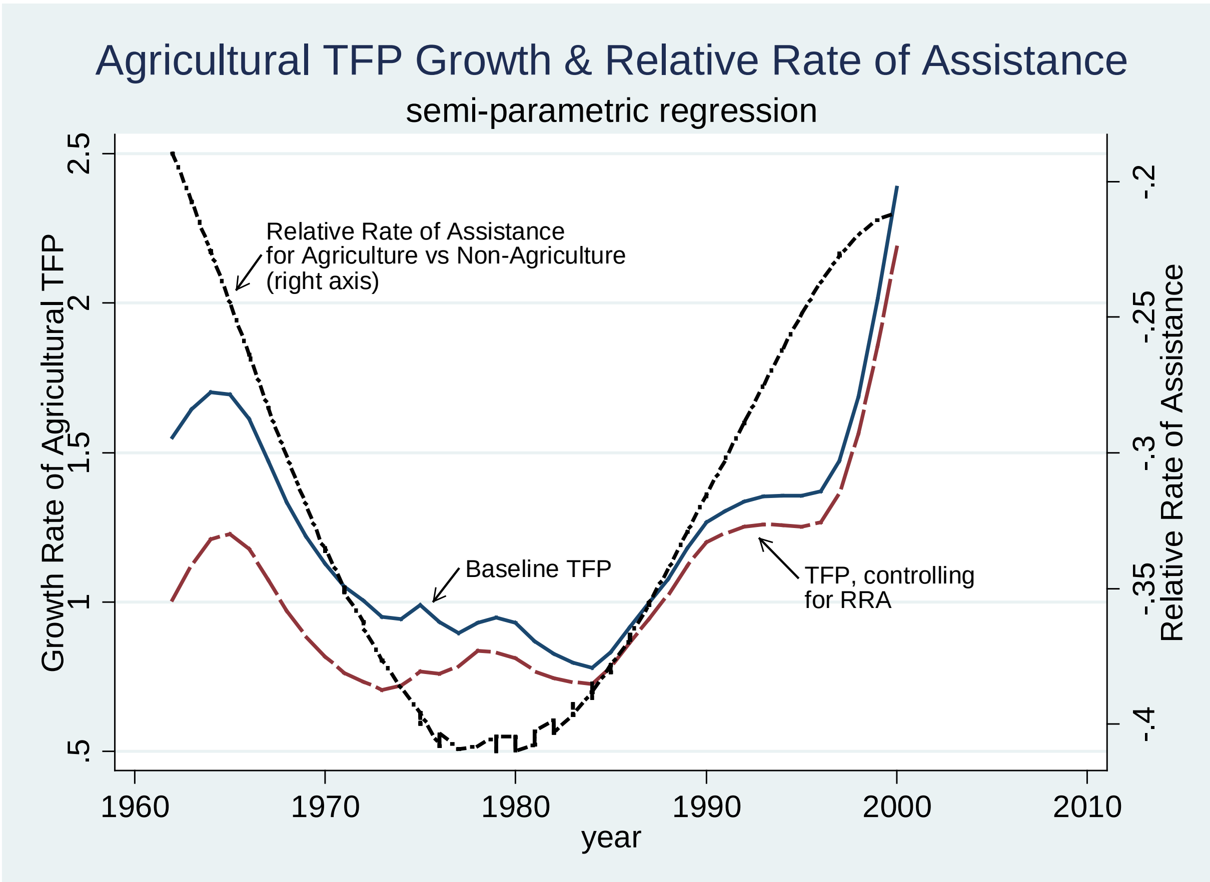


Figure 11. Partial Productivity Ratios for Ghana

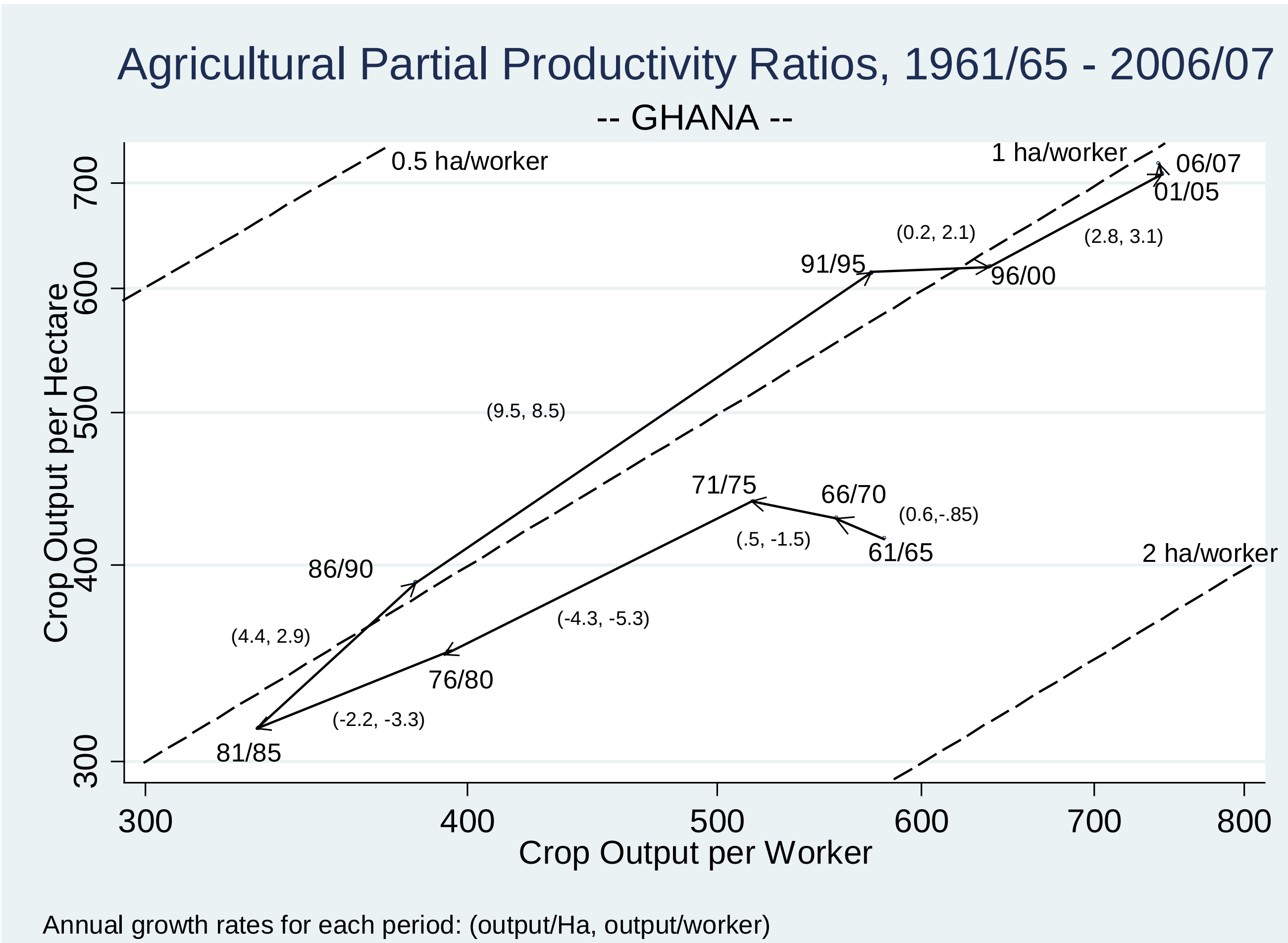


Figure 12. Agricultural TFP Growth and R&D Expenditures, Ghana

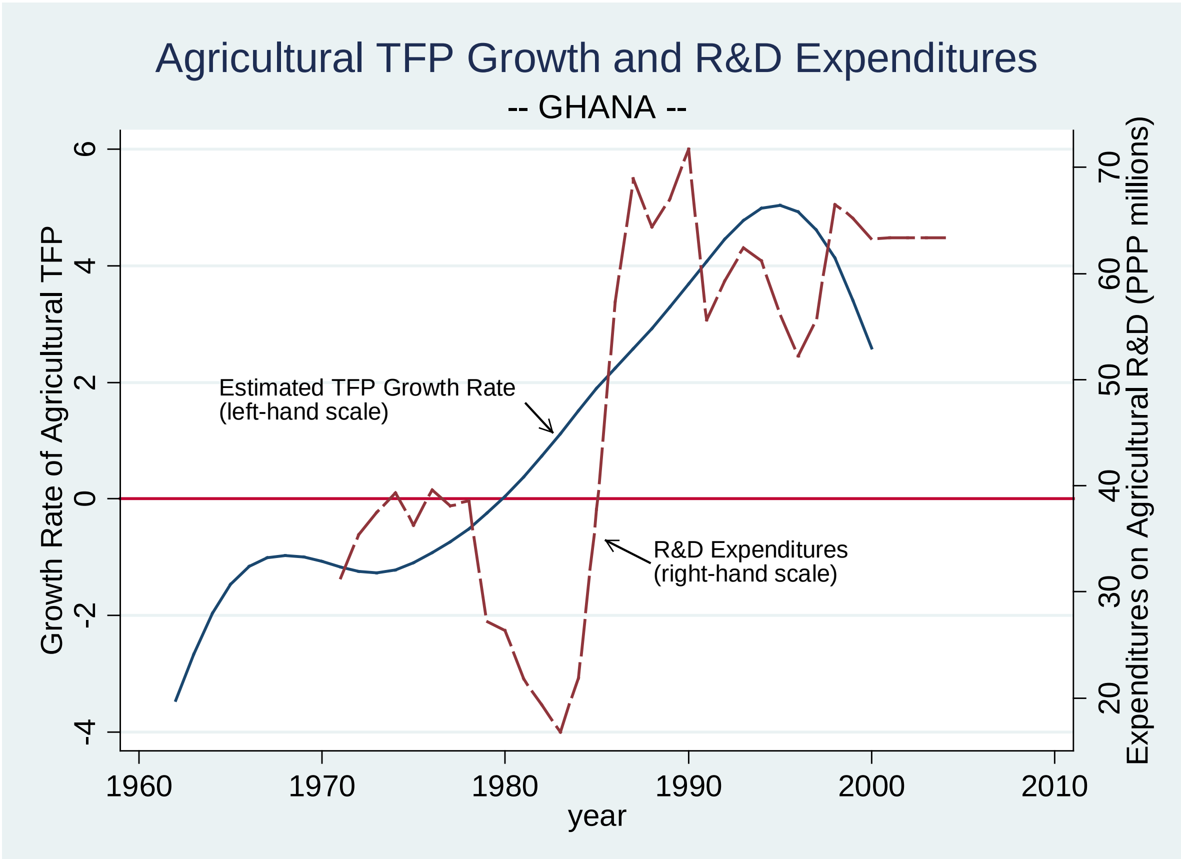


Figure 13. Agro-Ecological Zones of Ghana

Figure 14. Rainfall Patterns in Ghana

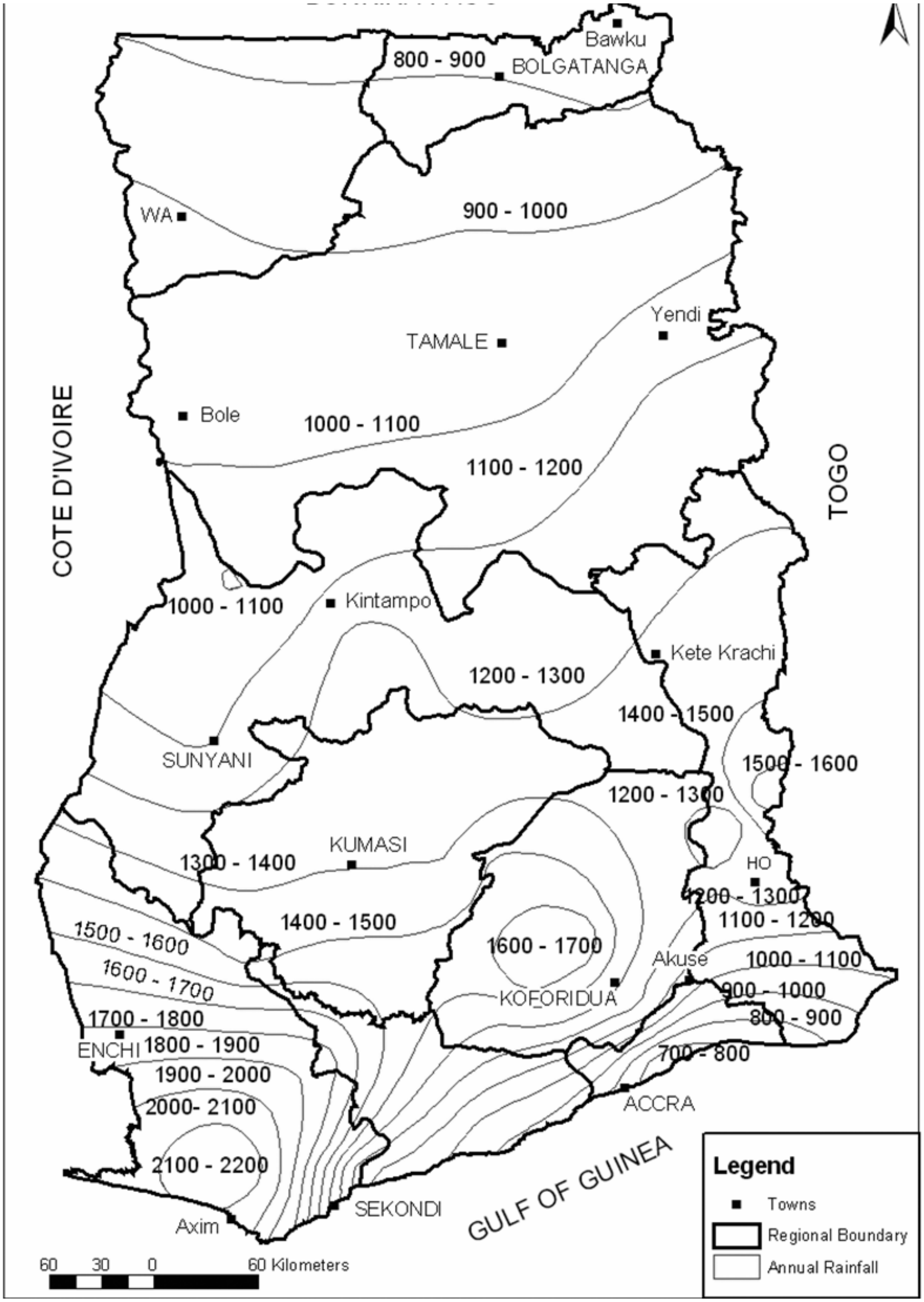


Figure 15 (a – d). Yield, by District, for Maize, Cassava, Sorghum, and Plantain (2008)

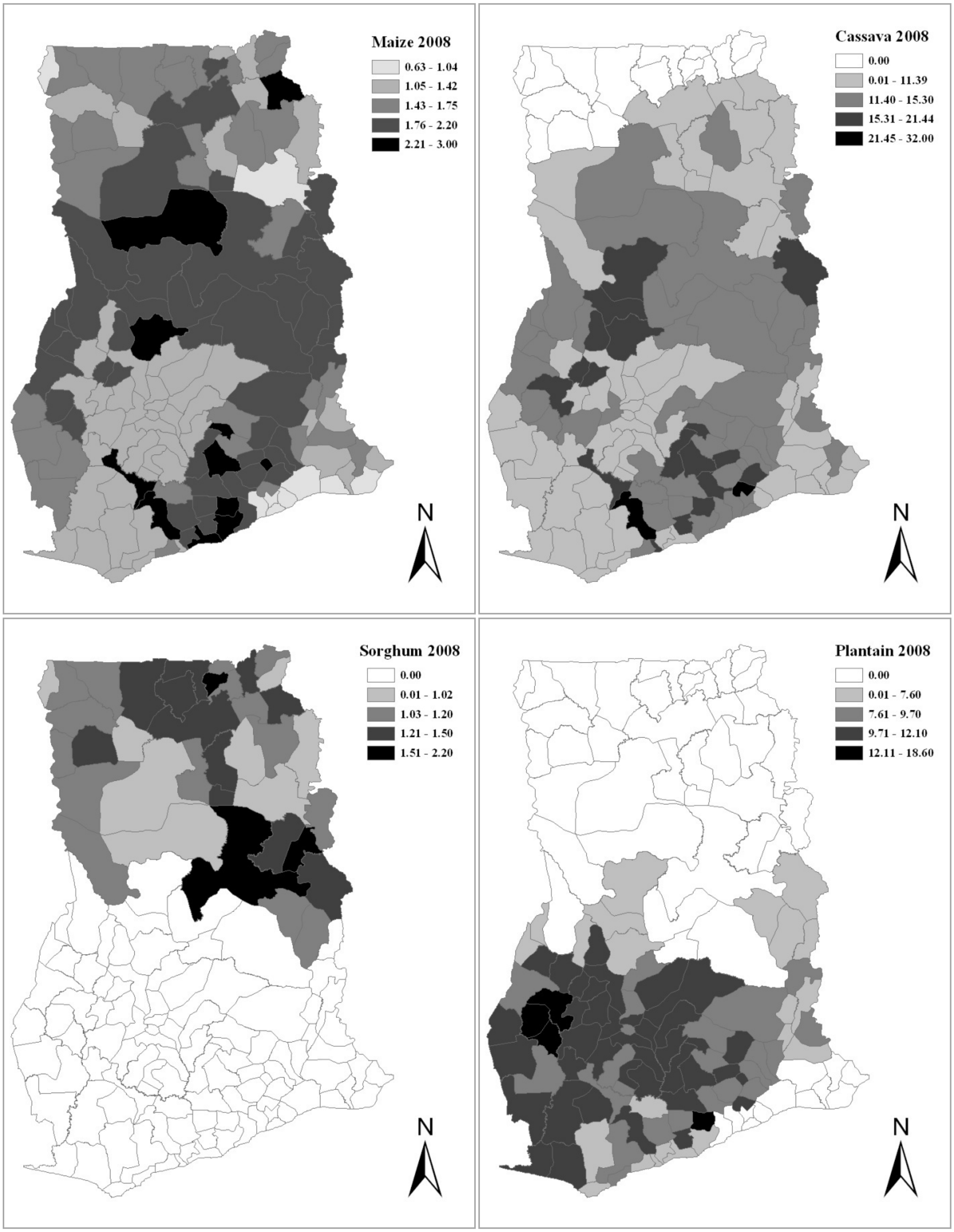


Figure 16. TFP & Relative Rate of Assistance to Agriculture vs Non-Agriculture in Ghana

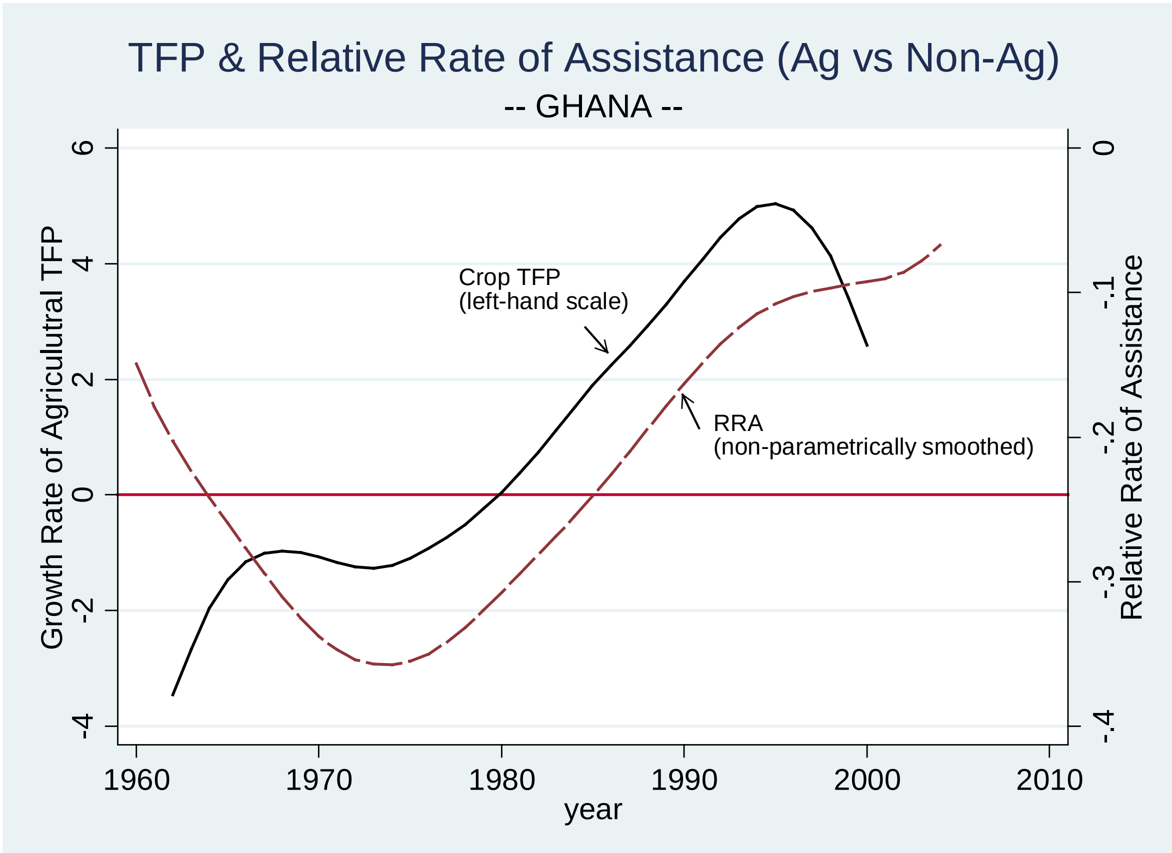


Figure A1. Comparison of TFP Estimates with Alternative Output Aggregates

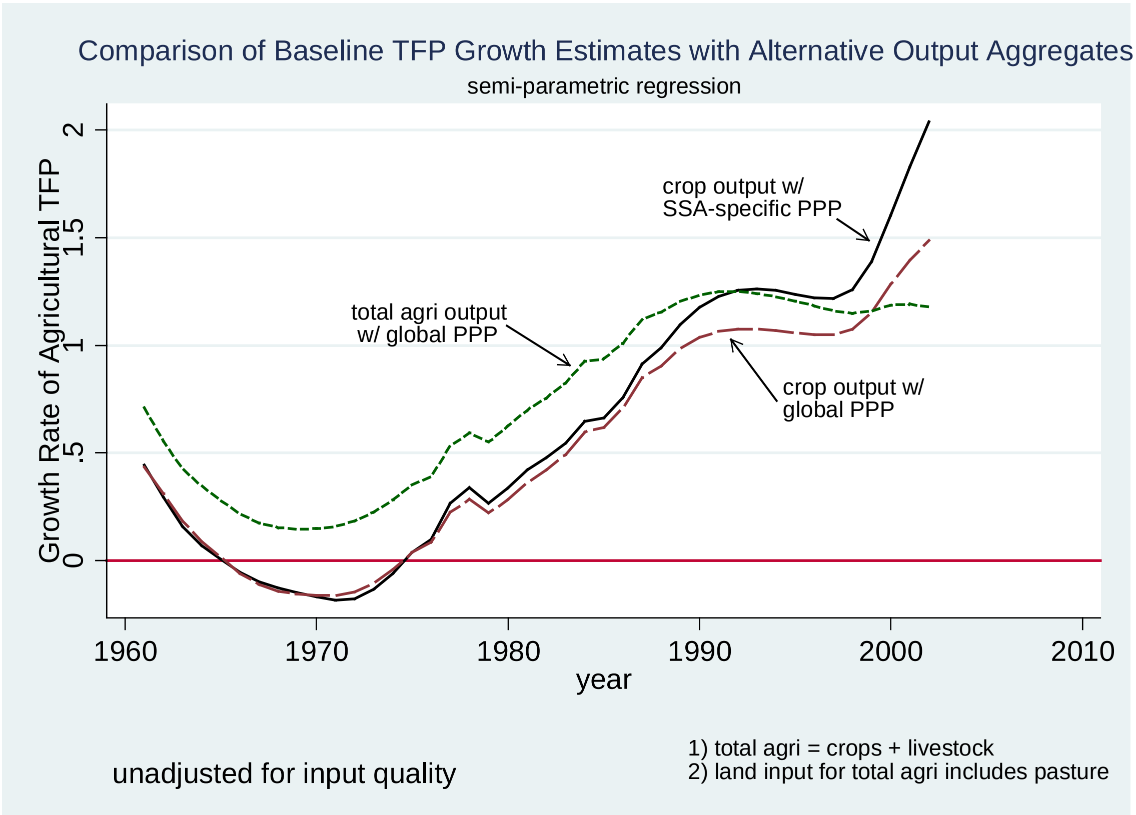


Table 1. Partial Productivity Ratio Growth Rates by Region

Region	1961-70	1971-80	1981-90	1991-2000	2001-07	1961-2007
East						
Output/Worker	1.06	-0.73	1.3	-0.03	1.16	0.26
Output/Ha	1.81	1.22	2.56	1.38	1.16	1.59
Ha/Worker	-0.75	-1.95	-1.26	-1.41	0	-1.33
Central						
Output/Worker	0.97	-0.76	-0.58	1.2	1.67	-0.09
Output/Ha	0.55	-1.43	1.09	2.3	2.19	0.65
Ha/Worker	0.42	0.67	-1.67	-1.1	-0.52	-0.74
Southern						
Output/Worker	3.14	1.98	3.72	2.68	1.09	1.24
Output/Ha	3	1.87	3.32	3.39	1.74	1.14
Ha/Worker	0.14	0.11	0.4	-0.71	-0.65	0.1
Western						
Output/Worker	0.4	1.31	3.16	2.77	4.67	1.05
Output/Ha	1.14	1.46	3.61	2.14	2.69	1.27
Ha/Worker	-0.74	-0.15	-0.45	0.63	1.98	-0.22
Sahel						
Output/Worker	-0.99	-0.95	1.92	0.96	2.34	-0.05
Output/Ha	0.38	0.24	0.23	0.42	1.71	0.56
Ha/Worker	-1.37	-1.19	1.69	0.54	0.63	-0.61
SSA						
Output/Worker	0.81	-0.02	1.79	1.12	2.18	0.41
Output/Ha	1.38	0.78	1.79	1.79	1.65	1.24
Ha/Worker	-0.57	-0.8	0	-0.67	0.53	-0.83

Source: FAO and author's calculations

Table 2. Growth Rates of Partial Productivity Ratios by Country

1961 - 2007	Growth Rate of:		Ranked by:	
	Output/Worker	Output/Ha	Output/Worker	Output/Ha
Angola	-0.98	1.25	Nigeria	Nigeria
Benin	3.03	2.09	Benin	Seychelles
Botswana	-.625	1.52	Gabon	Swaziland
Burkina Faso	1.74	1.65	Swaziland	Malawi
Burundi	-0.47	0.79	South Africa	Zambia
Cameroon	1.09	1.81	Seychelles	Namibia
Cape Verde	1.91	1.51	Cape Verde	Ethiopia
Cent Afr Rep	-.107	0.684	Côte d'Ivoire	Kenya
Chad	0.35	1.43	Namibia	Benin
Comoros	-0.62	0.803	Burkina Faso	Niger
Congo	-0.29	1.19	Mali	Côte d'Ivoire
Congo, Dem. Rep.	-0.63	1.15	Malawi	Cameroon
Côte d'Ivoire	1.88	1.82	Mauritania	Tanzania
Djibouti	6.17	10.61	Cameroon	Burkina Faso
Equatorial Guinea	-2.75	-2.01	Mauritius	Botswana
Eritrea	-3.99	-3.78	Guinea	Cape Verde
Ethiopia	-0.18	2.25	Sierra Leone	Chad
Gabon	3.02	0.47	Ghana	Ghana
Gambia	-2.86	-2.09	Rwanda	Angola
Ghana	0.6	1.41	Zambia	Rwanda
Guinea	0.78	0.81	Chad	Congo
Guinea-Bissau	-0.65	-0.44	Tanzania	Congo, Dem. Rep.
Kenya	0.15	2.17	Kenya	Lesotho
Lesotho	-0.54	1.12	Central African Rep	Togo
Liberia	-0.79	0.9	Mozambique	South Africa
Madagascar	-0.41	0.62	Ethiopia	Liberia
Malawi	1.46	2.62	Congo	Uganda
Mali	1.73	0.67	Togo	Guinea
Mauritania	1.12	0.17	Madagascar	Comoros
Mauritius	1.06	-0.09	Burundi	Burundi
Mozambique	-0.15	0.2	Uganda	Central African Republic
Namibia	1.87	2.39	Niger	Mali
Niger	-0.52	1.87	Lesotho	Madagascar
Nigeria	3.43	3.16	Zimbabwe	Zimbabwe
Rwanda	0.56	1.19	Comoros	Gabon
Senegal	-1.93	0.33	Botswana	Sierra Leone
Seychelles	2.54	2.78	Congo, Dem. Rep.	Senegal
Sierra Leone	0.65	0.42	Guinea-Bissau	Mozambique

Somalia	-1.1	-0.02	Liberia	Mauritania
South Africa	2.6	1.01	Angola	Somalia
Swaziland	2.91	2.63	Somalia	Mauritius
Tanzania	0.28	1.73	Senegal	Guinea-Bissau
Togo	-0.35	1.05	Equatorial Guinea	Equatorial Guinea
Uganda	-0.48	0.83	Gambia	Gambia
Zambia	0.36	2.46	Eritrea	Eritrea
Zimbabwe	-0.6	0.48	(excluding Djibouti, as too small and an outlier)	
AVERAGE (excl. Djibouti)	0.441	1.21		

Source: FAO and author's calculations

Table 3. Annual Growth Rates of Crop Output and Conventional Inputs

	1961-84	1985-2007	1961-2007
Crop Output	1.66	2.22	2.09
Labor	1.60	1.64	1.63
Land	0.84	0.90	0.85
Livestock	2.28	1.67	1.88
Tractors	7.14	-0.5	3.47
Fertilizer	6.28	-0.5	3.35

Source: FAO and author's calculations

Table 4. Production Function Estimates (with Country Fixed Effects), 1961 – 2000. Dependent variable: aggregate crop output

	(1)	(2)	(3)
Log land per worker	0.821***	0.822***	0.923***
	(17.07)	(17.22)	(18.12)
Log tractors per worker	0.025*	0.028**	0.031**
	(1.81)	(2.08)	(2.34)
Log livestock per worker	0.149***	0.106***	0.009
	(3.96)	(2.90)	(0.22)
Log fertilizer per worker	0.033***	0.034***	0.034***
	(4.05)	(4.30)	(4.37)
Log irrigated land share		0.050***	0.067***
		(3.09)	(4.10)
Log rainfall		0.365***	0.366***
		(8.67)	(8.80)
Avg years schooling			0.058***
			(5.21)
Constant	5.123***	2.813***	2.774***
	(95.55)	(10.03)	(9.48)
Includes Year dummies	X	X	X
Observations	1038	1038	1038
Number of countries	30	30	30
R-squared	0.40	0.45	0.46

Absolute value of t statistics in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Regional TFP Growth Rates (Unadjusted for Input Quality)

Region:	1960 - 1984	1985 - 2002	1960 - 2002
East	0.23	0.19	0.21
Southern	0.84	1.80	1.25
Middle	-2.43	0.61	-1.13
West	0.37	1.61	0.90
Sahel	-2.41	0.48	-1.17
SSA	0.14	1.24	0.61

Table 6. Accounting for Changes in Land and Labor Quality

	(1) Baseline TFP	(2) Adjusting for Land Quality	(3) Adjusting for Land and Labor Quality
Mean Growth Rate	0.97	0.87	0.59
% Change Relative to Baseline		10%	39%
t-test (P-value)		vs (1): 0.103[a*]	vs (2): 0.000[***]

a. one-sided test

Table 7. Trends in Agricultural Research Spending by Sub-Region, 1971-2000. Originally, Table 1 in Beintema and Stads (2006).

	Total spending (million 1993 international dollars)				Annual growth rate (percent)[a]			
Subregion	**1971**	**1981**	**1991**	**2000[b]**	**1971–81**	**1981–91**	**1991–2000**	**1971–2000[b]**
East Africa (7)	136.5	185.6	292.7	341.4	2.21	5.07	0.88	3.17
Southern Africa (6)	371.3	370.2	398.2	427.9	–0.19	0.30	1.20	1.25
West Africa (14)	224.0	358.2	345.5	315.3	4.62	0.14	0.06	0.39
Total (27)	731.8	914.0	1,036.4	1,084.7	2.02	1.32	0.77	1.43
Nigeria	62.5	127.9	68.3	106.0	5.64	–6.71	6.27	–1.84
South Africa	287.5	300.3	313.3	365.6	0.11	0.14	1.85	1.65
Total excluding Nigeria and South Africa (25)	381.8	485.8	654.8	613.1	2.46	3.31	–0.30	1.89

Source: Appendix Table C.1.

Notes: Figures in parentheses indicate the number of countries in each category. The 7 East African countries are Burundi, Eritrea, Ethiopia, Kenya, Sudan, Tanzania, and Uganda; the 6 southern African countries are Botswana, Madagascar, Malawi, Mauritius, South Africa, and Zambia; the 14 West African countries are Benin, Burkina Faso, Republic of Congo, Côte d'Ivoire, Gabon, Gambia, Ghana, Guinea, Mali, Mauritania, Niger, Nigeria, Senegal, and Togo. Data were not available prior to 1991 for 6, mainly small, countries; hence, they were estimated using trends for the other countries in the respective subregions.

[a] Annual growth rates are calculated using the least-squares regression method, which takes into account all observations in a period.

[b] For West Africa, total spending data are for 2001 and the growth rate is for 1991–2001.

Table 8. Pair-Wise Decompositions of Agricultural TFP

l	% Change vs baseline TFP[a]	T-test vs baseline	Sample size of regression[c]	No. of years included	No. of countries included
R&D (*t-10*)	75	P = .044	219	11	11
R&D (*t* – *5*)	45	P = .06[b]	274	16	11
Paved Road Share	3	P = .47	237	11	28
Civil War	11	P = .13[b]	1037	37	28
Black Mkt Prem.	29	P = 0.00	737	37	28
ΔRRA(*t-1*)	16	P = .016	387	38	10

a. Baseline net of input quality adjustments b. One-sided t-test.

c. Refers to underlying estimation of production function from which TFP growth path is derived.

Appendix 1 – Commodities and International Prices Included in Aggregate Crop Output

Commodity	Price ($I)*
wheat	157.0241
rice_paddy	274.6291
barley	146.3894
maize	98.85061
oats	129.3321
millet	227.9305
sorghum	183.9405
potatoes	183.828
sweet_potatoes	147.4281
cassava	170.8198
yams	348.0107
sugar_cane	39.34161
cow_peas_dry	253.0388
pulses_nes	233.8105
nuts_nes	2186.915
soybeans	207.6962
groundnuts_with_shell	509.03
oil_palm_fruit	57.23346
sunflower_seed	290.227
sesame_seed	485.4894
seed_cotton	315.2179
lettuce_chicory	363.9961
tomatoes	816.665
beans_green	557.1413
leguminous_vegetables_nes	342.7727
carrots_turnips	393.2994
bananas	208.0983
citrus_fruit_nes	337.675
avocados	1002.395
dates	879.3388
coffee_green	1179.314
cocoa_beans	1421.738
tea	1500.892
tobacco	2541.928
natural_rubber	1197.116

* Base year = 2006

Appendix 2 – Comparison of Baseline TFP Growth Rates with Alternative Output Aggregates

The main results presented in the paper are based on an output aggregate that includes only crops, and that uses international prices that were calculated specifically for this African sample to aggregate those crops. This appendix compares the baseline TFP growth rate estimates derived from that crop aggregate output with two alternative output aggregates – one using only crop output but using the FAOs global international prices for aggregation, and another using total agricultural output (from FAO) – the sum of crop and livestock output – aggregated with global FAO international prices. In the latter case, I include permanent pasture land in the measure of land input.

As Figure A1 illustrates, the resulting sets of TFP growth paths tell a broadly similar story, though with different average TFP growth over the period.

Mean TFP Growth Rate Estimates:

- crop output with African international prices = 0.61%/yr
- crop output with FAO global international prices = 0.52%/yr
- total agricultural output with FAO global international prices = 0.74%/yr