INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

IFPRI

ASTI AGRICULTURAL SCIENCE & TECHNOLOGY INDICATORS

led by IFPRI

IFPRI Discussion Paper 01432

March 2015

Inputs, Productivity, and Agricultural Growth in Africa South of the Sahara

Alejandro Nin-Pratt

Environment and Production Technology Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI), established in 1975, provides evidence-based policy solutions to sustainably end hunger and malnutrition and reduce poverty. The Institute conducts research, communicates results, optimizes partnerships, and builds capacity to ensure sustainable food production, promote healthy food systems, improve markets and trade, transform agriculture, build resilience, and strengthen institutions and governance. Gender is considered in all of the Institute's work. IFPRI collaborates with partners around the world, including development implementers, public institutions, the private sector, and farmers' organizations, to ensure that local, national, regional, and global food policies are based on evidence. IFPRI is a member of the CGIAR Consortium.

AUTHOR

Alejandro Nin-Pratt (a.ninpratt@cgiar.org) is a research fellow in the Environment and Production Technology Division of the International Food Policy Research Institute, Washington, DC.

Notices

[1.] IFPRI Discussion Papers contain preliminary material and research results and are circulated in order to stimulate discussion and critical comment. They have not been subject to a formal external review via IFPRI's Publications Review Committee. Any opinions stated herein are those of the author(s) and are not necessarily representative of or endorsed by the International Food Policy Research Institute.

[2.] The boundaries and names shown and the designations used on the map(s) herein do not imply official endorsement or acceptance by the International Food Policy Research Institute (IFPRI) or its partners and contributors.

Contents

Tables

Figures

ABSTRACT

The evidence of improved performance of agriculture in Africa south of the Sahara (SSA) in recent years has indeed been quite striking when compared with the past. For the first time, the sector has maintained a real growth rate of 3.4 percent per year, well above the population growth rate of 2.5 percent. Despite this improved performance, agricultural productivity growth in SSA continues to lag behind every other region of the world, growing at rates that are roughly half of the average rate of developing countries. Previous studies concluded that SSA should increase investment in agricultural research and development (R&D), highlighting the need to facilitate farmers access to technology, markets, and the necessary support services for raising agricultural productivity. This study introduces a new dimension to the puzzle of agricultural productivity growth in SSA: the role of the input mix and the need to increase capital and inputs per worker not only to boost output per worker but also to accelerate technology adoption and total factor productivity (TFP) growth. According to the appropriate technology hypothesis, advanced countries invent technologies that are compatible with their own factor mix, but these technologies are less productive with the very different factor mix of poor countries. This potential dependence of productivity on inputs could explain differences in income levels and the lack of convergence in labor productivity. This study revisited past performance of agriculture in SSA using a growth-accounting approach to get a better understanding of the role of inputs on TFP gaps. Our findings show that differences in labor productivity among SSA countries are explained mostly by differences in input per worker, that low levels of input per worker are associated with less productive technologies, and that technical change in the last 30 years has shifted the world frontier unevenly, increasing the distance between SSA countries and those countries with the right input mix. We also found that SSA countries using higher levels of input per worker have benefited more from technological progress than poorer countries, suggesting that technical change has done little to reduce the gap in labor productivity between countries. The need of an appropriate technology for SSA could have significant implications in terms of policy, allocation of R&D investment, the type of technologies to promote, and the growth path that countries should follow to sustain growth.

Key words: agriculture, appropriate technology, total factor productivity, Africa south of the Sahara

ACKNOWLEDGMENTS

This work was undertaken as part of the Agricultural Science and Technology Indicators (ASTI) and the CGIAR Research Program on Policies, Institutions, and Markets (PIM) led by the International Food Policy Research Institute (IFPRI). Funding support for this study was provided by the Bill & Melinda Gates Foundation, the Canada Department of Foreign Affairs, and PIM. I thank Markus Eberhardt for sharing STATA code he developed and I adapted and used in the econometric analysis of this study. This paper has not gone through IFPRI's standard peer-review procedure. The opinions expressed here belong to the author, and do not necessarily reflect those of PIM, IFPRI, or CGIAR.

ABBREVIATIONS AND ACRONYMS

2FE	two-way fixed effects
AEZ	agroecological zone
AMG	augmented mean group
CCEP	Pesaran (2006) common correlated effects pooled estimator
CD	Pesaran cross-section dependence test for panel data
CMG	Heterogeneous version of the common correlated effects estimator
CRS	constant returns to scale
DEA	Data Envelopment Analysis
FAO	Food and Agriculture Organization of the United Nations
FD	first difference
FE	fixed effects
GDP	gross domestic product
MG	Pesaran and Smith (1995) mean group
OLS	ordinary least squares
POLS	pooled ordinary least squares
R&D	research and development
SSA	Africa south of the Sahara
TFP	total factor productivity
TGR	technology gap ratio
USDA	US Department of Agriculture

1. INTRODUCTION

The evidence of improved performance of agriculture in Africa south of the Sahara (SSA) in recent years has indeed been quite striking when compared with the past. For the first time, the sector has maintained a real growth rate of 3.4 percent per year, well above the population growth rate of 2.5 percent. Recent studies (for example, Alene 2010; Block 1995, 2010; Fuglie 2011; Fuglie and Rada 2012; Nin-Pratt and Yu 2008, 2012) have shown how African agricultural performance improved in the aftermath of political, policy, and institutional reforms since the 1990s, increasing public investment and reducing the heavy taxation on agriculture. On the other hand, most of these studies concluded that the region should increase its efforts to accelerate total factor productivity (TFP) growth and technical change.

For example, Fuglie and Rada (2012) showed that despite recent improvement, agricultural productivity growth in SSA continues to lag behind every other region of the world, growing at rates that are roughly half of the average rate of developing countries. They concluded that SSA should increase its accumulated knowledge capital from long-term national and international investments in agricultural research and development (R&D), which are gradually delivering improved technologies to farmers. At the same time, they highlight the need to strengthen the broader enabling environment for farmers to access technology, markets, and the necessary support services for raising agricultural productivity in SSA. Similarly, Nin-Pratt and Yu (2012) concluded that several warning signs still exist, calling for more efforts to sustain TFP growth in the coming years, arguing that without increases in the rate of growth of technical change, TFP growth is expected to slow down in the coming years as countries catch up with efficiency levels at the production frontier.

Acknowledging the need to accelerate technical change through increasing investments in agricultural R&D and to improve the enabling environment for technology adoption, this study introduces a second dimension to the puzzle of agricultural growth in SSA countries: the role of the input mix and the need to increase capital and inputs per worker not only to boost output per worker but also to accelerate technology adoption and TFP growth. This has significant implications in terms of policy, allocation of R&D investment, the type of technologies to promote, and the growth path that countries could follow depending on how we interpret the role of capital in the process of technical change and its effect on productivity levels.

The level and combination of labor, capital, and inputs has not been central to the discussion of technical change and TFP growth in part because the conceptual framework normally used to analyze these issues assumes a uniform technology frontier for all countries. This means that a poor country using mostly labor and land and very little capital can produce at similar levels of output per unit of input than richer countries using a different combination of inputs (for example, high levels of capital per worker). If observed TFP levels in poor countries are low, these differences in productivity reflect inefficiency or a gap from the frontier that can be closed if poor countries have access to technologies used by frontier countries. Why do improved technologies not diffuse across borders, allowing SSA to catch up? According to this view, the reason is that barriers to the adoption of technology might exist, such as those resulting from agroecological differences, institutional differences, or inefficient social arrangements (for example, lack of competitive markets). These differences could result in lack of technologies due to barriers to adoption and also in the inefficient use of technologies already in place. If countries are able to reduce these barriers (such as by adapting technologies to their agroecologies and improving institutions and infrastructure), TFP levels should converge to those of richer countries. The assumption is that large gains can be made in terms of TFP by closing the technological gap even by poor countries at low levels of capitalization, and that technical change is “neutral,” so innovations from rich countries should benefit poor countries after some investment is done to adapt these technologies to a different economic environment.

What happens if the technological frontier is not uniform and not every country can reach the same TFP level? Or as Jerzmanowksi (2007) puts it, what if countries choose the best technologies available to them but their choice is limited by the fact that not all existing technologies are equally suited to every economy? Then the relevant question becomes, what determines whether certain technologies are appropriate for a particular economy? One possible answer to this question is provided by the literature on appropriate technology, which argues that depending on the country's relative stocks of physical and human capital, some technologies may be more or less productive than others. Formally, this means that TFP is a function of factor endowments. Recent theoretical contributions have emphasized the potential dependence of productivity on inputs such as physical or human capital, invoking the appropriate technology paradigm to explain differences in income levels and the lack of convergence (for example, Basu and Weil 1998; Acemoglu and Zilibotti 2001). In these models, rich countries invent technologies that are compatible with their own factor mix, but these technologies do not work well with the very different factor mix of poor countries. For example, some agricultural technologies require the intensive use of capital (irrigation and mechanization) or an appropriate match of land and machines (such as tractors). Consequently, these technologies are "inappropriate" for poor countries with high capital costs and when adapted to their economic conditions will not result in the same gains in TFP as those observed in richer countries.

In summary, the appropriate technology theory argues that low TFP is a result of the technology frontier being lower for some factor endowments. On the other hand, what Jerzmanowski (2007) calls the "efficiency" view maintains that the frontier is the same everywhere, but some countries operate below it. A better understanding of the role of inputs on TFP gaps could have important policy implications. Should SSA countries promote commercial agriculture so that a group of producers could converge faster to production conditions in richer countries to overcome technology "inappropriateness"? Should governments invest in agricultural R&D to develop technologies appropriate for poor households that are producing with low levels of capital, assuming that new productive techniques can always be developed? Or, is there a limit to increase productivity at a certain level of capital per worker especially if this level is very low, meaning that the oxcart can only be improved so much? Can we still expect large gains in productivity from improvements in efficiency and adoption of existing technologies? Is the slow pace of technology adoption and TFP growth in SSA the result of inappropriateness of technology given the very particular conditions and low levels of capitalization of agriculture in these countries? Looking for answers to these questions is important because different strategies can have different costs in terms of investment, time, and welfare for SSA economies.

Unlike previous papers that have looked at agricultural growth in SSA, in this study we decompose levels and growth in output per worker using a growth-accounting approach to analyze the explanatory power of the efficiency versus the appropriate technology hypothesis to explain productivity differences between SSA and other countries. In the next section we present the conceptual framework and methodological approach used in this study. Our approach requires the estimation of the world's technological frontier and of the technical efficiency of the SSA countries in our sample. Efficiency measures together with econometric estimates of input elasticities of a Cobb–Douglas production function are the main components of our model. Section 3 describes the data used, as well as technical aspects and results of the efficiency and input elasticities estimation. Section 4 revisits the analysis of past performance of agriculture in SSA, looking at growth of output per worker and its decomposition into efficiency, technical change, and input growth. Section 5 shows results of the decomposition of the levels of output per worker into levels of efficiency, technology, and inputs and how the efficiency and appropriate technology explain differences in labor productivity and TFP levels. The last section concludes and derives policy implications.

2. CONCEPTUAL FRAMEWORK AND APPROACH

An accepted view on the analysis of agricultural productivity adopts a Cobb–Douglas production function with constant returns to scale to estimate TFP assuming that countries have access to a common technology represented as $y = A\Pi x^{\alpha}$, where y and x are output and input per worker, respectively, and A represents TFP or the part of output not explained by inputs x. This view implies a uniform technology frontier for all countries; that is, all countries face the same A in the production function, and differences in TFP reflect inefficiency or a gap from the frontier due to barriers to the adoption of technology, natural resources, or lack of competitive markets or other efficient social arrangements (Jerzmanowski 2007). Basu and Wail (1998, 1025) provide a good example on the implications of the model's assumptions: "Do all countries in the world use the same technology? Many would view even the posing of this question as absurd. In India, fields are harvested by bands of sweating workers, bending to use their scythes. In the United States one farmer does the same work, riding in an air-conditioned combine. Yet an economist might argue that the two countries do have access to the same technology and simply choose different combinations of inputs (points along an isoquant) due to differences in factor prices. But this stance raises a new problem when one considers technological change: do technology improvements that raise the productivity of combines in America also improve the productivity of farmers in India? The answer obviously seems to be No. However, standard models of economic growth, which index technology by a single coefficient that is independent of factor proportions, would say yes. In these models, technology improvements in the United States should immediately improve total factor productivity in India—which seems counterfactual."

An alternative view to the standard growth-accounting analysis asserts that the technology frontier is not uniform (that is, not every country faces the same A in the production function above) and that countries choose the best technologies available to them; however, their choice is limited by the fact that not all existing technologies are equally suited to every economy. One explanation for this is that appropriateness depends on the mix of inputs. That is, depending on the country's relative stocks of labor, skills, and physical capital, some technologies may be more or less productive than others. Under this assumption the A in the Cobb–Douglas production function becomes $A = A(x)$ (Jerzmanowski 2007). As discussed in Basu and Weil (1998) and Acemoglu and Zilibotti (2001), the appropriate technology paradigm explains differences in income levels and the lack of convergence. For example, in the paper by Acemoglu and Zilibotti (2001), rich countries invent technologies that are compatible with their own factor mix, but these technologies do not work well with the very different factor mix of poor countries, and consequently the most productive technologies are inappropriate for developing countries and, even if adopted, do not raise their TFP levels.

In this section we present a model of appropriate technology adapted from Jerzmanowski (2007), which is part of a large literature—including Basu and Weil (1998), Parente and Prescott (1994), Segerstrom, Anant, and Dinapoulos (1990), Grossman and Helpman (1991), and Barro and Sala-i-Martin (1997), among others—that examines barriers to the transfer of technology across countries. We start by presenting the basic elements of the growth-accounting method, followed by the nonparametric approach to productivity analysis. We then combine elements of these two approaches to define a hybrid model where the Cobb–Douglas production function is defined as a frontier function and TFP is decomposed into an efficiency component that is independent of the level of inputs and a technology component expressed as a function of input per worker.

Growth-Accounting Approach

Much of the literature on agricultural productivity assumes a Cobb–Douglas production function with constant returns to scale to estimate TFP since the seminal agricultural studies by Griliches (1964) and Hayami and Ruttan (1985). Eberhardt and Teal's (2013) review of the literature refers to several studies applied to agriculture using the Cobb–Douglas function, including Craig, Pardy, and Roseboom (1997); Cermeno, Maddala, and Trueblood (2003); Bravo-Ortega and Lederman (2004); and Fulginiti, Perrin, and Yu (2004). Recent work looking specifically to SSA agriculture includes Block (2010) and Fuglie (2011). Under this approach, the output per worker in country i is given by

$$y_i = F_i(x) = A_i \prod x_{ij}^{\alpha_j}, \tag{2.1}$$

where y_i is agricultural output per worker, x_j is a set of observed inputs per worker, and A_i is unobserved TFP with technology parameters α_j constant over time. The production function shifter A_i can be modeled borrowing from Fuglie (2011) as

$$ln(A_i) = T_i + \eta_i + \sum \beta_{ki} Z_{ki} + \varepsilon_i, \tag{2.2}$$

where T represents technology levels, η_i is a random and unobserved country-specific effect, Z_{ki} are observed differences in resource quality, and ε_i is a random component capturing measurement error. Changes in A_i over time shift the production function and are interpreted as factor-neutral improvements in technology or production efficiency.

As discussed in Fuglie (2011), production elasticities α_j can be interpreted as the share of output that each input receives in payment for its contribution to the production process, and under certain assumptions this share indicates the payments that the owners of these resources receive when inputs are paid their value-marginal product. In this way, econometric estimation of the parameters of the production function are used instead of input prices, which are normally not available, to define TFP and an index of TFP growth expressed in terms of growth rates:

$$ln(TFP_i) = ln(y_i) - \sum \alpha_j ln(x_{ij}) \tag{2.3}$$

$$T\dot{F}P = \dot{Y}_i - \sum \alpha_j \dot{x}_{ij} \tag{2.4}$$

One of the disadvantages of this approach is that it involves strong technical and economic assumptions, like profit maximization and imposing a functional form. On the other hand, Fuglie (2011) argues that imposing more structure could be an advantage when dealing with data with a high degree of measurement error as it can help produce more plausible results.

Nonparametric Approach

The nonparametric approach, also known as Data Envelopment Analysis (DEA) and based on distance functions, has become especially popular because it is easy to compute and does not require information about input or output prices or assumptions regarding economic behavior, such as cost minimization and revenue maximization. The method has been extensively applied to the international comparison of agricultural productivity. See, for example, Bureau, Färe, and Grosskopf (1995); Fulginiti and Perrin (1997); Lusigi and Thirtle (1997); Prasada Rao and Coelli (2004); Arnade (1998); Fulginiti and Perrin (1999); Chavas (2001); Suhariyanto, Lusigi, and Thirtle (2001); Suhariyanto and Thirtle (2001); Trueblood and Coggins (2003); Nin, Arndt, and Preckel (2003); and Ludena et al. (2007).

In general, the nonparametric approach assumes that agricultural output per worker in country i is given by a production function of the form

$$y_i = E_i \times F(x), \tag{2.5}$$

where y is output per worker, x is a vector of inputs used in production, and E measures efficiency in the use of inputs and takes values between 0 and 1. The production function $F(x)$ satisfies free disposal and constant returns to scale and represents the production possibility frontier or the maximum attainable output given inputs. Actual output y results from the product of potential output and efficiency. In this context the production set S is defined as

$$S = \{(x, y): y \leq F(x)\}. \tag{2.6}$$

The output distance function $D(x,y)$ expresses the maximum proportional expansion of output given inputs, or the maximum increase in output (within S) given that inputs remain constant, which is captured by θ as follows:

$$D(x, y) = [sup\{\theta: (x, \theta y) \in S\}]^{-1} \tag{2.7}$$

where D(x,y) ≤ 1 if and only if (x,y) ϵ S, and D(x,y) = 1 implies that production takes place on the frontier. The distance function for a particular country i^* is estimated using linear programming as described in Section 3.

Growth in output per worker between periods 0 and 1 can be represented, adapting notation from Kumar and Russell (2002), as

$$\frac{y_1}{y_0} = \frac{E_1 \times F_1(x_1)}{E_0 \times F_0(x_0)}, \tag{2.8}$$

where y_1 and y_0 represent output per worker in the final and initial periods, respectively; $F_1(x_1)$ is potential output that can be achieved using technology of the final period and the amount of inputs used in that same period; and E_1 is efficiency of country i in the final period. Multiplying the top and bottom by $F_0(x_1)$ or potential output that can be obtained using the technology of the initial period with inputs used in the final period, we obtain

$$\frac{y_1}{y_0} = \frac{E_1}{E_0} \times \frac{F_1(x_1)}{F_0(x_1)} \times \frac{F_0(x_1)}{F_0(x_0)} \tag{2.9}$$

Equation (2.9) is a decomposition of change in the output–labor ratio between two periods for country i. The first term on the right-hand side is the change in efficiency or the change in the distance to the frontier; the second term is the shift of the frontier between the two periods measured relative to the coordinates of country i in output space in the final period (potential output is measured with respect to x1); and the last term is a measure of the change in potential output as a result of a change in the level of inputs, or movement along the frontier in the initial period.

The effect of changes in technology and inputs is path dependent, which means that we can build a similar index by multiplying the top and bottom in (2.8) by $F_1(x_0)$ instead of using $F_0(x_1)$ as before to obtain

$$\frac{y_1}{y_0} = \frac{E_1}{E_0} \times \frac{F_1(x_0)}{F_0(x_0)} \times \frac{F_1(x_1)}{F_1(x_0)}. \tag{2.10}$$

In this case, the shift in the frontier is measured with respect to country i's coordinates in the production space in the initial period, and the last term represents movement along the frontier in the final period. The only time (2.9) and (2.10) are equal is when technological change is Hicks neutral, in which case the shift in the frontier is independent of the value of the input–labor ratio. To avoid the problem of path dependence, Caves, Christensen, and Diewert (1982) adopted the "Fisher ideal" decomposition based on the geometric averages of the two measures of the effects of technological change and capital accumulation multiplying the top and bottom of (2.9) by $[F_1(x_0)\, F_0(x_1)]^{1/2}$:

$$\frac{y_1}{y_0} = \frac{E_1}{E_0} \times \left[\frac{F_1(x_1)}{F_0(x_1)} \times \frac{F_1(x_0)}{F_0(x_0)}\right]^{1/2} \times \left[\frac{F_0(x_1)}{F_0(x_0)} \times \frac{F_1(x_1)}{F_1(x_0)}\right]^{1/2} \tag{2.11}$$

This approach has the advantage of imposing minimum restrictions on the production structure. On the other hand, because of its deterministic character, it is not possible to evaluate the precision of the predicted efficiency levels if inputs and outputs are subject to stochastic variation. As the method constructs the production frontier based on efficient points, it is naturally sensitive to outliers and measurement error.

The Hybrid Approach: Appropriate Technology

The hybrid approach goes along the lines of neoclassical growth accounting in defining TFP growth as the ratio of output and input growth, with the aggregate production function being defined as Cobb–Douglas with constant returns to scale (CRS). Within this neoclassical framework, it also disentangles technical change along the technological frontier from changes in technical efficiency. Starting from equation (2.5), we impose the Cobb–Douglas functional form to the generic expression *F(x)* representing potential output:

$$y_i = E_i \times \left[T_i \prod x_{ij}^{\alpha_j}\right] \; where\, A_i = E_i \times T_i. \tag{2.12}$$

Notice that this hybrid model, unlike neoclassical growth accounting, deals exclusively with the best practice technology, not the average practice technology. In other words, the Cobb–Douglas production function is a frontier production function where TFP is decomposed into efficiency and available technology levels. Using growth-accounting approach (dropping country index) we can express the output growth decomposition between period 0 and 1 as

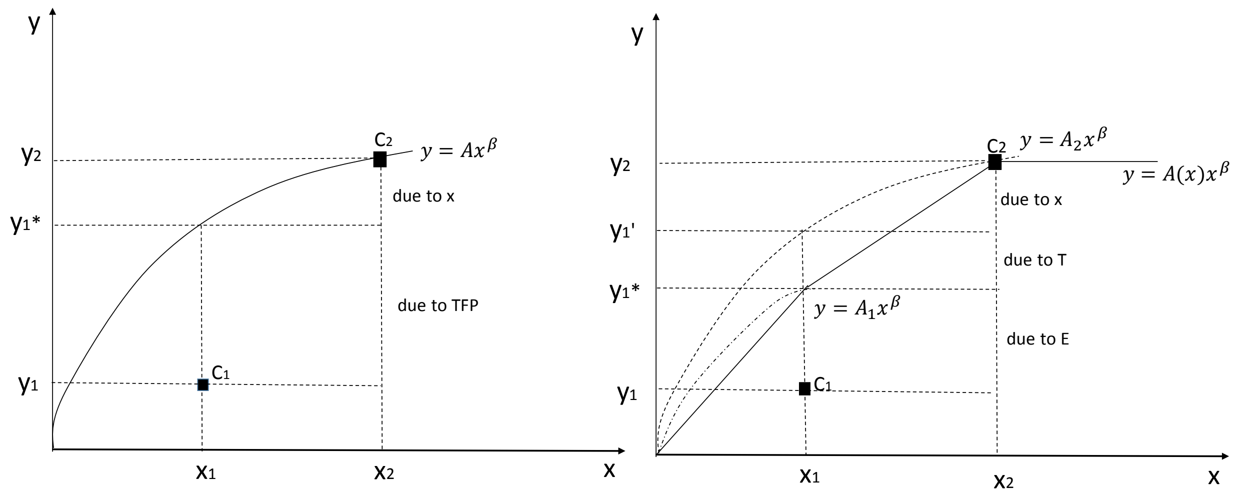
$$\frac{y_1}{y_0} = \frac{E_1}{E_0} \times \frac{\bar{T}_1}{T_0} \times \prod \left(\frac{x_{j1}}{x_{j0}}\right)^{\alpha_j}. \tag{2.13}$$

The expression in (2.13) is known in the growth-accounting literature as the "appropriate technology vs. efficiency" output growth decomposition (Basu and Weil 1998; Jerzmanowski 2007; Growiec 2012). This specification allows for two determinants of TFP differences: country-specific levels of efficiency and country-specific levels of available technology, which is allowed to be factor specific: $T_i(x)$ (Figure 2.1).

The right panel of Figure 2.1 represents a model of production where all countries have access to the same technology represented by the production function $y = Ax^{\alpha}$. In this setting differences in output per worker between an efficient country (C_2) and an inefficient country (C_1) are explained first by TFP levels, which result from inefficiency measured as the distance of C_1 to the frontier given the level of input x_1 used. Second, differences are due in part to the level of input x used, so increasing inputs from x_1 to x_2 will reduce the difference in output per worker to differences in efficiency only.

The left panel represents production with appropriate technology. In this case, the true frontier is a function of input per worker. For each input–labor combination there is a particular production function (*A* is a function of *x*). The difference is that the left panel shows an intermediate level of output y_1' that C_1 cannot achieve with its present level of inputs. The difference $y_1' - y_1^*$ is due to appropriate technology. This means that to achieve productivity levels of C_2, C_1 can increase efficiency up to a certain point; but to catch up with C_2, C_1 needs to increase input per worker to operate on C_2 production function and face TFP levels A_2 instead of A_1. The oxcart can be improved only so much.

Figure 2.1 Standard and appropriate technology levels accounting decomposition



Source: Adapted from Jerzmanowski (2007).
Note: Left panel assumes that technology $y = Ax^{\alpha}$ is available to all countries and differences are due to input–labor level and total factor productivity. Right panel: Technology is a function of input per worker and country 1 cannot access country 2's technology.

The empirical application of the appropriate technology model used in this study implies the estimation of the global production frontier for agriculture using a DEA approach and the parameters of the Cobb–Douglas function, discussed in the next section.

3. EMPIRICAL MODEL AND IMPLEMENTATION

Data

Output and input data to estimate the parameters of the global production function used in this study are from the Food and Agriculture Organization of the United Nations (FAO 2014) covering a period of 51 years from 1961 to 2012. The final database includes 134 countries (Table 3.1), one output (total agricultural production), and six inputs (fertilizer; feed; capital used in livestock production, or livestock capital; capital used in crop production, or crop capital; agricultural land; and labor). Results and discussion in sections 4 and 5 will focus on the period that goes from 1971 to 2012 covering the post-independence policies, the period of structural adjustment and the accelerated growth of recent years.

Table 3.1 Countries in data used by FAO to define the global agricultural production technology, by region

Africa south of the Sahara
Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Republic of the Congo, Côte d'Ivoire, Democratic Republic of Congo, Ethiopia (former), Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sudan (former), Swaziland, Togo, Uganda, Tanzania, Zambia, Zimbabwe
Latin America and the Caribbean
Argentina, Bahamas, Barbados, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Trinidad and Tobago, Uruguay, Venezuela
Asia
Afghanistan, Bangladesh, Bhutan, Cambodia, China, Democratic People's Republic of Korea, India, Indonesia, Japan, Lao People's Democratic Republic, Malaysia, Mongolia, Myanmar, Nepal, Pakistan, Philippines, Republic of Korea, Sri Lanka, Thailand, Vietnam
North Africa and West Asia
Algeria, Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, Turkey, United Arab Emirates, Yemen
Europe
Albania, Austria, Belgium-Luxembourg, Bulgaria, Cyprus, Czechoslovakia (former), Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Romania, Spain, Sweden, Switzerland, United Kingdom, Yugoslavia (former)
Other
Australia, Canada, New Zealand, United States of America (USA), USSR (former)

Source: Elaborated by authors based on FAO 2014.
Note: FAO = Food and Agriculture Organization of the United Nations.

Output: The value of gross agricultural production expressed in constant 2004–2006 International dollars (I$). It includes crop and livestock production. In Nigeria, output available from FAO since 2000 did not correspond to growth measured at the country level, so output for 2001–2012 was adjusted using agricultural gross domestic product (GDP) figures from World Development Indicators (World Bank 2014).

Animal Feed: The amount of edible commodities (cereals, bran, oilseeds, oilcakes, fruits, vegetables, roots and tubers, pulses, molasses, animal fat, fish, meat meal, whey, milk, and other animal products from FAOSTAT food balance sheets) fed to livestock during the reference period. Quantities of the different types of feed are transformed into metric tons of maize equivalents using information of energy content for each commodity.

Fertilizer: The quantity of nitrogen, phosphorus, and potassium (N, P, K) in metric tons of plant nutrient consumed in agriculture by country and year as used in Fuglie and Rada (2012) available from the US Department of Agriculture (USDA 2014).

Labor: Total economically active population in agriculture (in thousands) engaged in or seeking work in agriculture, hunting, fishing, or forestry, whether as employers, own account workers, salaried employees, or unpaid workers. This measure of agricultural labor input, also used in other cross-country studies, is an uncorrected measure that does not account for hours worked or labor quality (education, age, experience, and so forth). The data on labor are originally from FAO, which currently reports the number of economically active adults in agriculture from 1980 onward. For our analysis we used the labor data from USDA (2014) that uses annual growth rates from 1961 to 1979 previously reported by FAO to derive estimates for 1961–1979, extrapolating backward from FAO's 1980 figures. Labor figures for Nigeria were adjusted following Fuglie and Rada (2012) assuming 2 percent annual growth in agricultural labor for subsequent years.

Land: Expressed in thousands of hectares and includes land under temporary crops (doubled-cropped areas are counted only once); temporary meadows for mowing or pasture; land under market and kitchen gardens; land temporarily fallow (less than five years); and land cultivated with permanent crops such as flowering shrubs (coffee), fruit trees, nut trees, and vines; but excludes land under trees grown for wood or timber. Pasture land includes land used permanently (five years or more) for herbaceous forage crops, either cultivated or growing wild (wild prairie or grazing land).

Capital stock: We use FAO's new series of capital stock covering the period 1975–2007 valued at 2005 constant prices as the base year, which was developed by multiplying unit prices by the quantity of physical assets "in use" compiled from individual countries. The physical assets include assets used in the production process covering land development, irrigation works, structures, machinery, and livestock. In this study we use gross fixed capital stock, defined as the value, at a point of time, of assets held by the farmer with each asset valued at "as new" prices, at the prices for new assets of the same type, regardless of the age and actual condition of the assets. We divide capital stock into two components, as follows:

Crop capital (land developments and equipment): Includes (a) *land development*—result of actions that lead to major improvements in the quantity, quality, or productivity of land or prevent its deterioration including (i) on field land, improvement undertaken by farmers (includes work done on a field such as making boundaries, irrigation channels, and so forth) and (ii) other activities such as irrigation works, soil conservation works, flood control structure, and so forth undertaken by government and other local bodies; (b) *plantation crops*—trees yielding repeated products (including vines and shrubs) cultivated for fruits and nuts, for sap and resin, for bark and leaf products, and so forth; and (c) *machinery and equipment*—tractors (with accessories), harvesters and thrashers, and hand tools.

Livestock capital (livestock fixed asset and inventory): Includes (a) *animal stock*—stock of cattle and buffalo, camels, horses, mules, asses, pigs, goats, sheep, and poultry; (b) *structures for livestock*—the concept includes sheds constructed for housing cows, buffalo, horses, camels, and poultry birds—structures have been provided for only part of the total stocks that are held by commercial concerns; and (c) *milking machines.*

As the capital series are available until 2007 we project them to 2012 using values of their different components from FAO: machinery, area of permanent crops, and animal stock.

Efficiency Estimates

As discussed in Section 2, we use distance functions to measure output-oriented technical efficiency for our sample of countries including information on agroecologies for the different countries to account in part for resource quality. We do this in two steps. We first estimate distance function pooling all countries in our sample to measure the distance of each country to the world frontier in each year. We then group countries by agroecology and estimate the distance of all countries to the frontier of their respective group. The distance function of a country in the *k*th group is defined as follows:

$$D^k(x, y) = [sup\{\theta: (x, \theta y) \in S^k\}]^{-1}. \tag{3.1}$$

Technical efficiency with respect to the world metafrontier is

$$D^*(x,y) = [sup\{\theta: (x,\theta y) \in S^*\}]^{-1}. \quad (3.2)$$

The metafrontier envelopes the group frontiers, which means that $D^k(x,y) \geq D^*(x,y)$ for all k. Following Rambaldi, Rao, and Dolan (2002), we define the technology gap ratio (TGR) in year t as the ratio of the two distances:

$$TGR^k = \frac{D(x,y)^*}{D(x,y)^k} \leq 1. \quad (3.3)$$

Rearranging terms, we define the distance to the metafrontier as the product of the technology gap between group k's frontier and the metafrontier (TGR^k) and distance to the group's frontier:

$$D^*(x,y) = TGR^k \times D^k(x,y). \quad (3.4)$$

To estimate the distance function for a particular country $i*$ we solve the following linear programming problem:

$$D(x_{i*}, y_{i*}) = \max_{\theta,\lambda} \theta_{i*} \quad (3.5)$$

subject to

$$\theta_{i*} y_{i*} \leq \sum_{i=1}^{I} \lambda_i y_i \text{ and } x_{i*,j} \geq \sum_{i=1}^{I} \lambda_i x_{i,j} \text{ for inputs } j=\{1,\ldots J\}, \lambda_i \geq 0. \quad (3.6)$$

Table 3.2 presents a summary of efficiencies and TGR of SSA countries for different decades and by agroecological zone (AEZ). Definitions of AEZ and SSA country grouping by AEZ can be found in the Appendix. On average, technical efficiency of SSA countries has remained around 0.85 between 1971 and 2012, with a decline during the 1980s and a recovery in recent years. The technology gap of the region is 0.90, which means that TFP level at the frontier of the agroecologies where SSA countries produce is 10 percent lower than TFP level at the metafrontier.

Table 3.2 Average efficiency and technology gap ratios for SSA countries by agroecological zone

	Efficiency				TGR			
Zone	1971–1980	1981–1990	1991–2000	2001–2012	1971–1980	1981–1990	1991–2000	2001–2012
SSA	0.84	0.80	0.81	0.85	0.90	0.89	0.89	0.90
Temperate—arid, semiarid	0.90	0.86	0.84	0.87	0.80	0.84	0.81	0.75
Tropical—arid, semiarid, subhumid	0.80	0.75	0.78	0.81	0.89	0.89	0.90	0.94
Tropical—humid	0.88	0.88	0.86	0.91	0.94	0.91	0.90	0.91

Source: Author's estimation.
Note: SSA = Africa south of the Sahara; TGR = technology gap ratio.

Input Elasticities and the Cobb–Douglas Production Function

The empirical framework to estimate input elasticities of the Cobb–Douglas production function follows Eberhardt and Teal (2013) and builds on a common factor representation of the log-linearized production function, allowing to accommodate nonstationarity and correlation across panel members. Borrowing notation from Eberhardt and Teal (2013) we represent the model as follows:

$$y_{it} = \beta_i{}' x_{it} + \mu_{it} \tag{3.7}$$

$$\mu_{it} = \alpha_i + \lambda_i' f_t + \varepsilon_{it} \tag{3.8}$$

$$x_{ijt} = \pi_{ij} + \delta'_{ij} g_{jt} + \phi_{ij} f_t + v_{ijt} \tag{3.9}$$

$$f_t = \varrho' f_{t-1} + \epsilon_t \; and \, g_t = \kappa' g_{t-1} + \epsilon_t \tag{3.10}$$

The Cobb–Douglas production function (3.7) has observed output (y_{it}) and observed inputs (x_{it}) including labor, crop capital stock, livestock capital stock, fertilizer, feed, and agricultural land (all in logarithms). The constant term μ_{it} is represented by a combination of country-specific effects (α_i) and a set of common factors f_t, which can have different effects across countries (i). The model allows for endogeneity, as the input variables x_{it} are driven by a set of common factors g_{jt} and by the subset of factors f_t influencing output in equations (3.8) and (3.9), which means that some unobserved factors driving agricultural production are likely to drive, at least in part, the evolution of the inputs. Finally, equation (3.4) indicates that the latent factors are persistent over time, which allows for the setup to accommodate nonstationarity in factors ($\varrho = 1$, $\kappa = 1$).

The parameter of interest is the vector of elasticities β. As in Eberhardt and Teal (2013) we consider different models to estimate β that deal with unobserved heterogeneity, cross-section dependence, and dependence due to latent common factors. We divide these models into two groups. Pooled models assume parameter homogeneity: All countries share the same slope parameters ($y_{it} = \beta' x$). Within this group we estimate pooled standard ordinary least squares (POLS) in levels and first difference (FD-OLS), two-way fixed effects (2FE) including country and year dummy variables, and the Pesaran (2006) common correlated effects (CCEP) pooled estimator. Pesaran's estimator uses the cross-section averages of the observed variables (for example, averages of y and x) as proxies for the latent factors f_t, assuming that unobserved factors that influence productivity are common to all countries. This model is extended as in Eberhardt and Teal (2013) using different weight-matrices to calculate the cross-section averages: CCEPn uses averages of contiguous neighbors for each country; in CCEPd, cross-section averages are calculated using the inverse of the population-weighted distance between countries; in CCEPc, weights for every country pair are constructed based on the share of cultivated land within each of 12 climatic zones as defined in Jaffe (1986) and used in Eberhardt and Teal (2013), a more detailed climatic classification than the four AEZs defined here to control for natural resource quality in the efficiency comparisons. Finally CCEPoc (not included in Eberhardt and Teal 2013) uses weights to measure distance between countries by comparing agricultural output composition (shares of different commodities in total output).

The second group of models allows for heterogeneous slopes ($y_{it} = \beta_i' x$) and is able to accommodate the type of endogeneity presented in the original model (equations 3.1 to 3.4) to arrive at consistent estimates for common slope coefficients calculated as the mean of heterogeneous β_i. Simulations studies (for example, Coakley, Fuertes, and Smith 2006) show that results from these models are robust even when the cross-section dimension is small, when variables are nonstationary, and in the presence of weak unobserved common factors (spatial spillovers). Within this group we estimate the Pesaran and Smith (1995) mean group (MG), and heterogeneous versions of the different CCE estimators, including the heterogenous version of the common correlated effects or mean group common correlated effects (CMG) and its extensions using different weights: contiguous neighbors (CMGn), distance

(CMGd), climate (CMGc), and output composition (CMGoc). We also include Eberhardt and Bond (2009) augmented mean group (AMG) estimator.

The MG estimator assumes away cross-section dependence ($\lambda_i = 0$) and estimates separately individual country regressions. Estimated coefficients at the country level are then averaged across panel members to obtain β. The heterogeneous version of the CCE models estimate individual country regressions augmented by cross-section averages of dependent and independent variables using the data for the entire panel. The estimated β_i coefficients are averaged across panel members using different weights. Finally, the AMG estimator is implemented in three steps: (1) a pooled regression model augmented with year dummies is estimated by FD-OLS and the coefficient on the year when dummies are collected (common dynamic process); (2) the country-specific regression model is then augmented with estimates from step 1; and (3) country-specific parameters are averaged across the panel (see Eberhardt 2012 for details on the empirical aspects of estimating heterogeneous models using STATA).

Results

First- (Maddala and Wu 1999, not reported) and second-generation (Pesaran 2007) panel unit root tests applied to output and input data used in this study suggest that nonstationarity cannot be ruled out in this dataset. There is also strong evidence of the presence of cross-section dependence within the full sample dataset, based on the Pesaran (2004) cross-section dependence test (CD test). Eberhardt and Teal (2012) arrived to the same conclusions using a dataset similar to the one used in this study. It is then important to evaluate different models according to how they deal with nonstationarity and cross-section dependence. Results of the different estimated models are presented in Table 3.3 (pooled models) and Table 3.4 (heterogeneous models).

Table 3.3 Pooled regressions

	POLS	Two-way FE	FD-OLS	CCEP	CCEPn	CCEPd	CCEPc	CCEPoc
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Labor	–0.0555***	0.174***	–0.0593	0.107	0.0138	0.134	–0.120	0.0723
	(0.00304)	(0.0176)	(0.0997)	(0.151)	(0.156)	(0.132)	(0.110)	(0.131)
Crop capital	0.265***	0.179***	0.283***	0.364***	0.237***	0.323***	0.194***	0.362***
	(0.00867)	(0.00968)	(0.0635)	(0.0614)	(0.0670)	(0.0542)	(0.0434)	(0.0673)
Livestock capital	0.219***	0.280***	0.235***	0.328***	0.190***	0.335***	0.347***	0.357***
	(0.00733)	(0.0101)	(0.0565)	(0.0680)	(0.0679)	(0.0630)	(0.0923)	(0.0757)
Fertilizer	0.111***	0.0513***	0.00454	0.0136***	0.0202**	0.0140***	0.0124***	0.0129**
	(0.00498)	(0.00259)	(0.00277)	(0.00426)	(0.00913)	(0.00416)	(0.00427)	(0.00543)
Land	2.52e–05	0.515***	0.344***	0.288**	0.232	0.334***	0.253**	0.253**
	(0.00571)	(0.0200)	(0.0829)	(0.130)	(0.144)	(0.117)	(0.108)	(0.117)
Feed	0.174***	0.118***	0.0922***	0.109***	0.154***	0.1000***	0.0951***	0.104***
	(0.00795)	(0.00478)	(0.0246)	(0.0263)	(0.0457)	(0.0277)	(0.0319)	(0.0272)
Constant	6.994***			–2.43***	–2.426**	1.937	4.489***	0.208
	(0.0456)			(4.24e–06)	(1.127)	(1.337)	(0.856)	(1.140)

Table 3.3 Continued

Variable	POLS (1)	Two-way FE (2)	FD-OLS (3)	CCEP (4)	CCEPn (5)	CCEPd (6)	CCEPc (7)	CCEPoc (8)
Implied labor coefficient	0.175	0.031	–0.018	0.003	0.181	0.028	–0.022	–0.016
Returns	DRS	IRS	DRS	CRS	CRS	CRS	CRS	CRS
RMSE	0.412	0.154	0.079	0.071	0.088	0.071	0.072	0.072
Stationarity [a]	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Mean ρij [b]	0.416	0.388	0.124	0.173	0.131	0.159	0.143	0.152
CD(p) [c]	0.28	0.19	–0.99	–2.92	1.47	–0.08	–2.43	–2.15
CD p value	0.783	0.852	0.323	0.003	0.141	0.935	0.015	0.031
Observations	6,834	6,834	6,700	6,834	6,834	6,834	6,834	6,834
R-squared	0.917	0.777	0.465	0.976	0.963	0.976	0.975	0.975
Number of countries	134	134	134	134	134	134	134	134

Source: Author's estimation.

Notes: CCEP = Pesaran common correlated effects; CCEPn= common correlated effects where cross-section averages are averages of contiguous neighbors for each country; CCEPd= common correlated effects where cross-section averages are calculated using the inverse of the population-weighted distance between countries; CCEPc, common correlated effects where weights for every country pair are constructed based on the share of cultivated land within each of 12 climatic zones; CCEPoc= common correlated effects where weights for every country pair are constructed based on the share of different commodities in total output; MG= Pesaran's mean group; CMG= heterogenous version of the common correlated effects or mean group common correlated effects and its extensions using different weights: contiguous neighbors (CMGn), distance (CMGd), climate (CMGc), and output composition (CMGoc); AMG= Eberhardt and Bond (2009) augmented mean group estimator ; CD = Pesaran cross-section dependence test for panels ; CRS = constant returns to scale; DRS = decreasing returns to scale; FE = fixed effects; IRS = increasing returns to scale ; RMSE = root-mean-squared error. [a]. Pesaran (2007) CIPS test results: I(0) stationary, I(1) nonstationary. [b]. Mean absolute correlation coefficient. [c]. Pesaran CD test, H0: no cross-section dependence. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable is log output per worker in all models except for the transformation in (2) (see Coakley et al. 2006) and in (3), which is the model in first differences.

Table 3.4 Mean group type estimations

Variable	MG (9)	CMG (10)	CMGn (11)	CMGd (12)	CMGc (13)	CMGoc (14)	AMG (15)
Labor	–0.0134	0.135	0.0674	0.0359	0.0722	0.0286	0.0953
	(0.128)	(0.133)	(0.129)	(0.128)	(0.132)	(0.127)	(0.123)
Crop capital	0.147**	0.159***	0.183***	0.147***	0.141***	0.164***	0.194***
	(0.0598)	(0.0498)	(0.0581)	(0.0520)	(0.0491)	(0.0520)	(0.0626)
Livestock capital	0.205***	0.207***	0.182***	0.201***	0.193***	0.206***	0.232***
	(0.0303)	(0.0283)	(0.0298)	(0.0297)	(0.0305)	(0.0276)	(0.0320)
Fertilizer	0.0207***	0.0180***	0.0216***	0.0187***	0.0153***	0.0196***	0.0261***
	(0.00546)	(0.00562)	(0.00513)	(0.00521)	(0.00471)	(0.00521)	(0.00566)
Land	0.263***	0.262***	0.243***	0.221***	0.290***	0.267***	0.231***
	(0.0857)	(0.0896)	(0.0768)	(0.0827)	(0.0895)	(0.0943)	(0.0864)
Feed	0.164***	0.182***	0.206***	0.188***	0.182***	0.189***	0.167***
	(0.0172)	(0.0178)	(0.0186)	(0.0172)	(0.0181)	(0.0177)	(0.0175)
Constant	6.922***	–1.237	0.252	1.768	2.852	–7.476**	6.118***
	(0.975)	(3.706)	(1.361)	(3.566)	(2.327)	(3.545)	(0.915)

Table 3.4 Continued

Variable	MG (9)	CMG (10)	CMGn (11)	CMGd (12)	CMGc (13)	CMGoc (14)	AMG (15)
Implied labor coefficient	0.19	0.31	0.232	0.26	0.25	0.183	0.25
Returns	CRS	CRS	CRS	CRS	CRS	CRS	CRS
RMSE	0.064	0.051	0.052	0.051	0.050	0.051	0.064
Stationarity [a]	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Mean ρij [b]	0.132	0.132	0.124	0.129	0.124	0.127	0.133
CD(p) [c]	5.41	–1.08	0.1	1.94	–2.31	–1.04	0.77
CD p value	0.000	0.282	0.921	0.053	0.021	0.297	0.440
Observations	6,834	6,834	6,834	6,834	6,834	6,834	6,834
Number of countries	134	134	134	134	134	134	134

Source: Author's estimation.

Notes: MG= Pesaran's mean group; CMG = heterogeneous version of the common correlated effects or mean group common correlated effects and its extensions using different weights: contiguous neighbors (CMGn), distance (CMGd), climate (CMGc), and output composition (CMGoc); AMG = Eberhardt and Bond (2009) augmented mean group estimator; CRS = constant returns to scale. [a.] Pesaran (2007) CIPS test results: I(0) stationary, I(1) nonstationary. [b.] Mean Absolute Correlation coefficient. [c.] Pesaran CD test, H0: no cross-section dependence. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Dependent variable is log output per worker in all models.

Looking first at diagnostic tests of nonstationarity and cross-section dependence of residuals, we observe that the pooled OLS and FE models cannot rule out nonstationarity, but all other models show residuals that reject the null hypothesis of nonstationarity using the Pesaran CD test. The presence of nonstationary residuals reduces the precision of parameter estimates, and t-statistics are invalid, which makes the POLS and FE models unreliable.

As in Eberhardt and Teal (2013), the CD test for cross-section dependence yields very mixed results. The models that do not reject the null hypothesis of no cross-section dependence are FD-OLS and the pooled distance (CCEPd) and neighbor (CCEPn) CCE among the pooled models, and four of the MG models (CMG, CMGn, CMGoc and the AMG model). Pooled OLS and FE show relatively high mean absolute residual correlation (0.4) compared with correlation in other models ranging from 0.12 to 0.17. However, the CD test does not reject the null of cross-section independence in these models. Two of the 15 estimated models emphatically reject CRS: POLS and two-way FE.

We conclude from our results that heterogeneous parameter models seem to perform better than the traditional pooled models, with the neighbor and the crop share CMG showing the best performance. These models reject nonstationarity, show no evidence of cross-section dependence, and do not reject CRS. Table 3.5 presents results for these two models and the best-performing pooled model (neighbor CCE) compared with estimates of the same models with CRS imposed. The CMG output composition model (CMGoc) performs better than all other models when CRS are imposed with no significant changes in coefficient values. In contrast, the coefficient for labor in the CMGn model doubles, and other coefficients also change significantly when CRS are imposed

Table 3.5 Best-performing models, unrestricted and with CRS imposed

Model	CCEPn (5) Unrestricted	CRS imposed	CMGn (11) Unrestricted	CRS imposed	CMGoc (14) Unrestricted	CRS imposed
Labor	0.0138		0.0674		0.0286	
	(0.156)		(0.129)		(0.127)	
Crop capital	0.237***	0.236***	0.183***	0.239***	0.164***	0.179***
	(0.0670)	(0.0631)	(0.0581)	(0.0537)	(0.0520)	(0.0463)
Livestock capital	0.190***	0.188***	0.182***	0.196***	0.206***	0.227***
	(0.0679)	(0.0682)	(0.0298)	(0.0307)	(0.0276)	(0.0276)
Fertilizer	0.0202**	0.0204**	0.0216***	0.0243***	0.0196***	0.0201***
	(0.00913)	(0.00913)	(0.00513)	(0.00542)	(0.00521)	(0.00540)
Land	0.232	0.222**	0.243***	0.168**	0.267***	0.239***
	(0.144)	(0.0906)	(0.0768)	(0.0734)	(0.0943)	(0.0585)
Feed	0.154***	0.154***	0.206***	0.234***	0.189***	0.184***
	(0.0457)	(0.0455)	(0.0186)	(0.0191)	(0.0177)	(0.0181)
Constant	–2.426**	–2.341***	0.252	4.274***	–7.476**	3.198***
	(1.127)	(0.600)	(1.361)	(0.306)	(3.545)	(0.592)
Implied labor coefficient	0.181	0.180	0.232	0.139	0.183	0.150
Returns	CRS	—	CRS	—	CRS	—
RMSE	0.088	0.088	0.052	0.057	0.051	0.054
Stationarity [a]	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Mean ρij [b]	0.131	0.129	0.124	0.125	0.127	0.131
CD(p) [c]	1.47	1.33	0.1	0.28	–1.04	–0.41
CD p value	0.141	0.184	0.921	0.776	0.297	0.682
Observations	6,834	6,834	6,834	6,834	6,834	6,834
Number of countries	134	134	134	134	134	134

Source: Author's estimation.

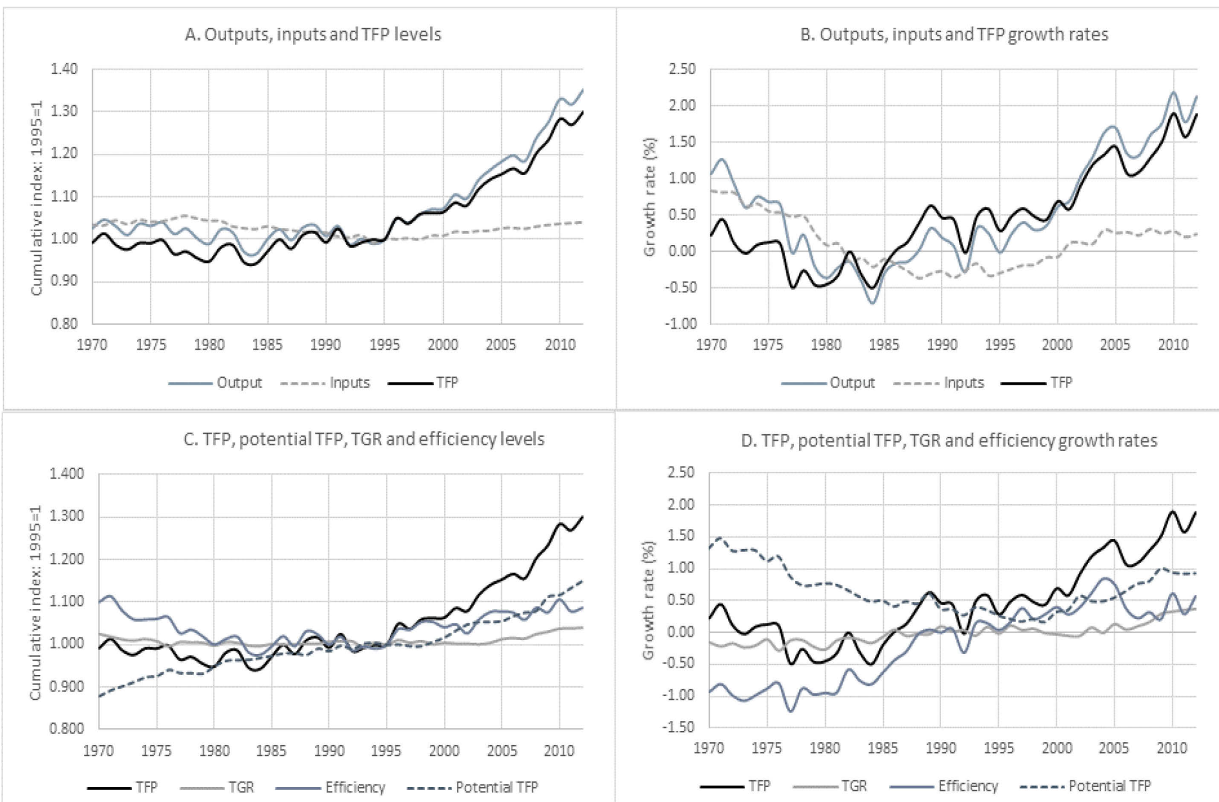
Notes: CRS =constant returns to scale; CCEPn = common correlated effects, contiguous neighbors; CMGn mean group common correlated effects contiguous neighbors = ; eCMGoc = mean group common correlated effects output composition; RMSE = root-mean-square error. CD = Pesaran cross-section dependence test. [a.] Pesaran (2007) CIPS test results: I(0) stationary, I(1) nonstationary. [b.] Mean absolute correlation coefficient. [c.] Pesaran CD test, H0: no cross-section dependence. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Dependent variable is log output per worker in all models.

4. TOTAL FACTOR PRODUCTIVITY GROWTH AND PERFORMANCE OF AGRICULTURE, 1971–2012

Aggregated Results Using a Simple Average of 38 SSA Countries

Results of the growth decomposition analysis for a sample of 38 Sub-Saharan African countries[1] shows that annual growth per worker for the period 1971–2012 was 0.7 percent, or equivalently, that agricultural output per worker in SSA was 30 percent higher in 2012 than its level in 1971. Two periods with contrasting results can be distinguished in Figure 4.1 and Table 4.1. A first period of poor performance and decline stretches from the beginning of the period to the mid-1980s, during which growth in SSA was close to zero: –0.4 and 0.2 percent in 1971–1980 and 1981–1990, respectively. The period of recovery and improved performance starts in the mid-1990s and extends to 2012, the last year for which information is available. During this period, output per worker grows at an annual rate of 1.8 percent, with 0.6 percent growth in 1991–2001 and accelerating to 2.0 percent in the last decade (2001–2012).

Figure 4.1 Evolution of levels and growth rates of output per worker and its components, 1971–2011



Source: Author's calculations.
Note: TFP = total factor productivity; TGR = technology gap ratio.

[1] South Africa and Mauritius are not included.

Table 4.1 Growth rates of output and inputs per worker and TFP and its components, different periods

Variable	1971–1980	1981–1990	1991–2000	2001–2012	1971–2012	2001–2006	2006–2012	Growth rate 1995–2012	Contribution to growth [a]
Output	–0.4	0.2	0.6	2.00	0.7	1.9	2.1	1.8	100
Efficiency	–1.2	0.1	0.4	0.7	0.00	0.7	0.6	0.7	41
Technical change	0.8	0.4	0.3	1.0	0.6	0.8	1.2	0.8	43
TFP	–0.5	0.5	0.7	1.7	0.7	1.6	1.8	1.5	84
Inputs	0.1	–0.3	–0.1	0.3	0.0	0.3	0.2	0.3	16
Land	–1.5	–1.9	–1.7	–1.3	–1.6	–1.2	–1.3	–1.3	–220
Crop capital	–0.2	–0.7	–0.4	–0.7	–0.5	–0.7	–0.6	–0.5	–64
Livestock capital	0.3	–0.4	–0.4	0.8	0.1	0.4	1.2	0.6	98
Fertilizer	3.0	0.7	–0.5	0.3	0.9	0.5	0.1	–0.3	–4
Feed	1.2	1.2	2.1	2.1	1.7	2.9	1.3	2.4	289
Labor [b]	1.8	2.2	2.0	1.8	1.9	1.8	1.8	1.9	n.a.

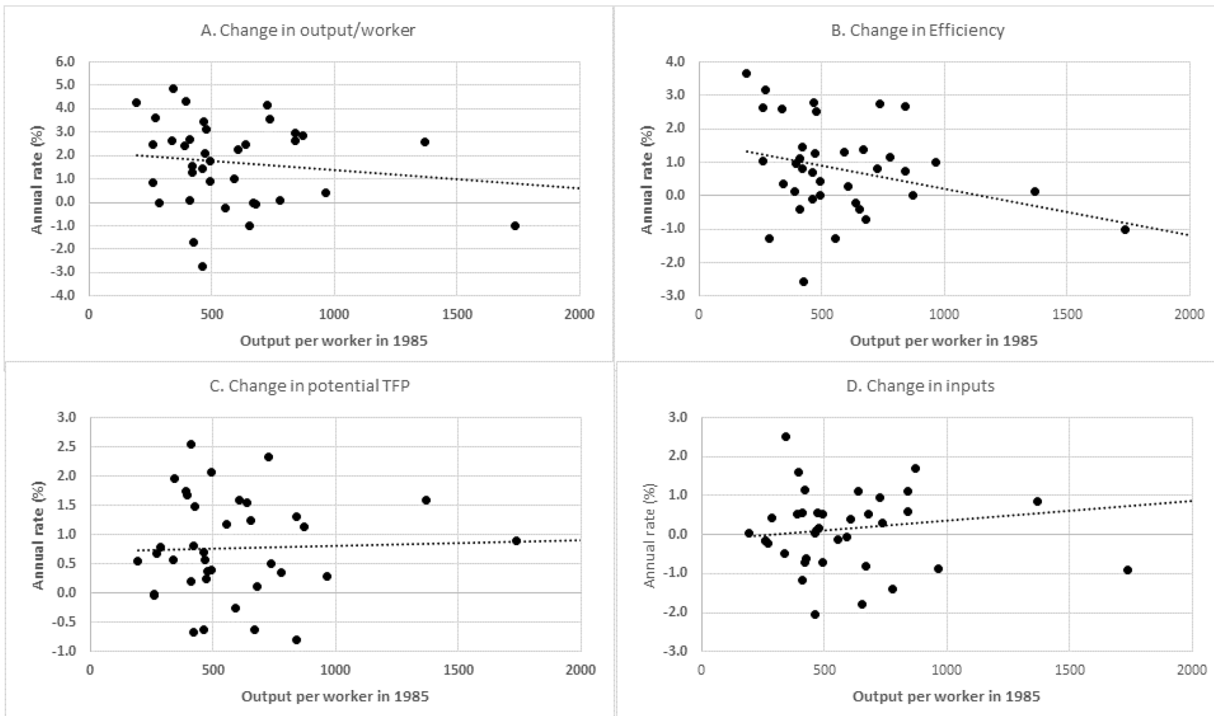
Source: Author's estimation.
Notes: TFP = total factor productivity. [a]. For inputs, contribution is to growth in total inputs. [b]. growth in the number of economically active people in agriculture.

The decomposition of growth in output per worker into inputs, efficiency, and technical change shows that 84 percent of growth in output per worker is explained by TFP growth, with inputs explaining the remaining 16 percent (Table 4.1). Both increased efficiency and technical change have contributed to TFP growth in the last 15 years. The region started catching up to the world frontier in 1995 after falling behind from 1971 to 1990. The period of improved performance has also seen accelerated growth of the technological frontier (1.0 percent yearly, compared with 0.3–0.4 percent in 1981–2000). Notice that in 2012 the region is still below the 1971 levels of efficiency and that growth in efficiency has remained below 0.7 percent during the period of improved performance. Inputs have also contributed to output growth since 1995, at an average rate of 0.3 percent. However, with low growth in inputs and with labor still growing at average rates of 1.9 percent between 1995 and 2012, the level of input per worker in the region is almost the same as in 1971.

Among inputs, we observe that rapid population growth has resulted in negative growth of agricultural land per worker. We also observe a sharp decline in fertilizer use from 3.0 percent growth in the 1970s to negative growth in the 1990s as most countries adjust their economies. Positive growth in fertilizer per worker is observed in the twenty-first century, although growth is low and negative on average between 1995 and 2012, the period of improved performance in the region. Capital used for livestock production also grew at negative rates during the 1980s and 1990s but started recovering in the twenty-first century. On the other hand, capital in crop production shows negative growth rates during the whole period of analysis (–0.5 percent). This means that on average SSA is using at present 20 percent less capital per worker in agricultural production than it did in 1971. Overall input growth after 1995 was driven by growth in feed and livestock capital. Modest growth in fertilizer and decreases in crop capital and agricultural land per worker indicate that the process of intensification in crop production is driven by labor use, with little contribution of inputs and capital.

Figure 4.2 plots average annual growth rates of the four productivity components against output per worker in 1985. Panel A shows a negative relationship between the level of output per worker in 1985 and growth during 1995–2012. However, the coefficient of the trend line is not significant as the result of two different forces explaining growth. First, the negative and significant relationship between the level of output per worker in 1985 and efficiency growth (panel B) implies that growth after 1995 has benefited low-labor-productivity (poorer) countries. On the other hand, technical change and increased use of inputs is positively related to higher initial levels of output per worker. This can be seen in Panels C and D of Figure 4.2. The positive slope in Panel C indicates that relatively richer countries (higher labor productivity) in 1985 tend to benefit more from technological progress than those countries with low output per worker in 1985, while Panel D suggests that increases in the use of capital and inputs have done little to reduce the gap in labor productivity between countries.

Figure 4.2 Average annual growth rate between 1995 and 2011 in output per worker, efficiency, technology, and inputs against output per worker in 1985

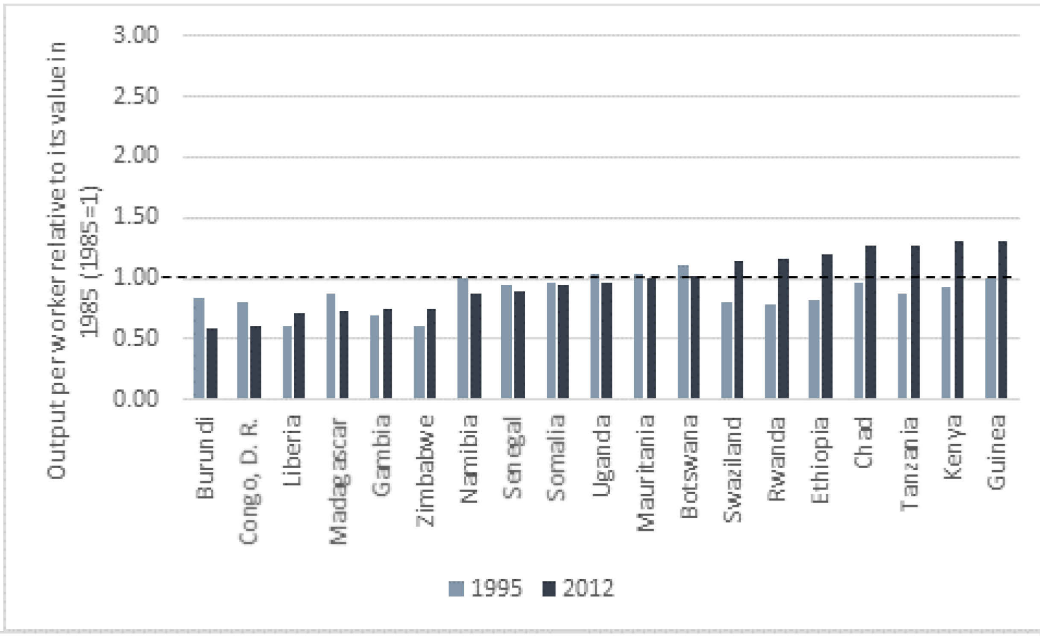


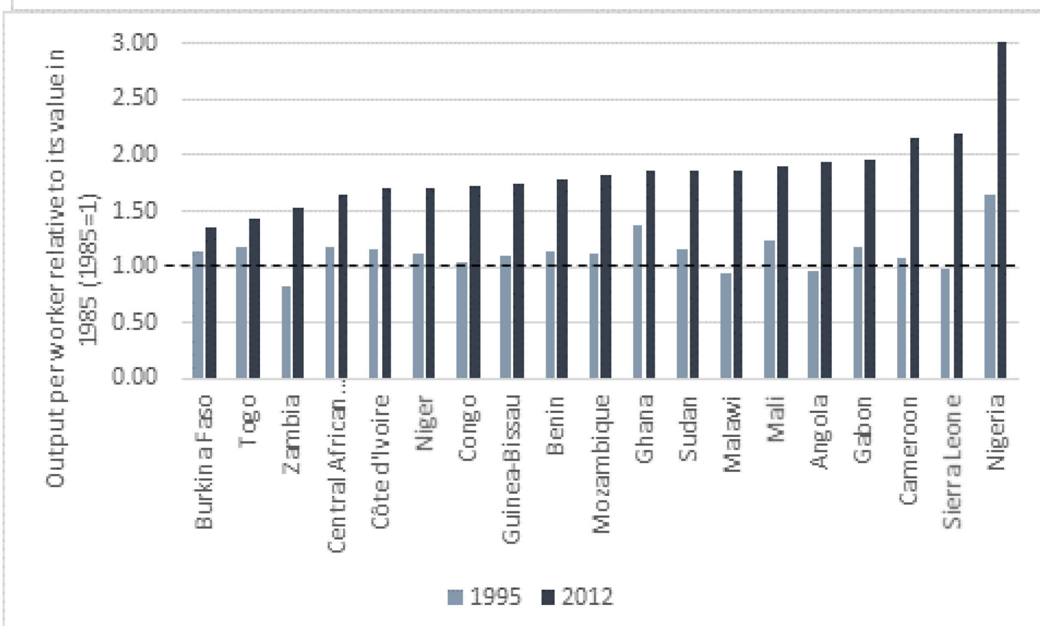
Source: Author's estimation.

Results at the Country Level

The performance and the contribution of different countries to total TFP growth in SSA vary greatly. Figure 4.3 shows levels of output per worker in 1995 and 2012 relative to 1985, and Figure 4.4 presents the contribution of different countries to total growth of output per worker between 1995 and 2012. For one-fourth of the countries in our sample, output per worker in 2012 was lower than in 1985. Half of the countries show output per worker in 2012 that was less than 30 percent higher than in 1985 (less than 1.0 percent annual growth). The 10 best-performing countries—Nigeria, Sierra Leone, Cameroon, Gabon, Angola, Mali, Malawi, Sudan, Ghana, and Mozambique—on average doubled output per worker between 1985 and 2012. Note that except for Nigeria and Ghana, two countries that show significant growth between 1985 and 1995, most of the observed growth occurred after 1995.

Figure 4.3 Output per worker in 1995 and 2011 relative to 1985 levels (1985 = 1)

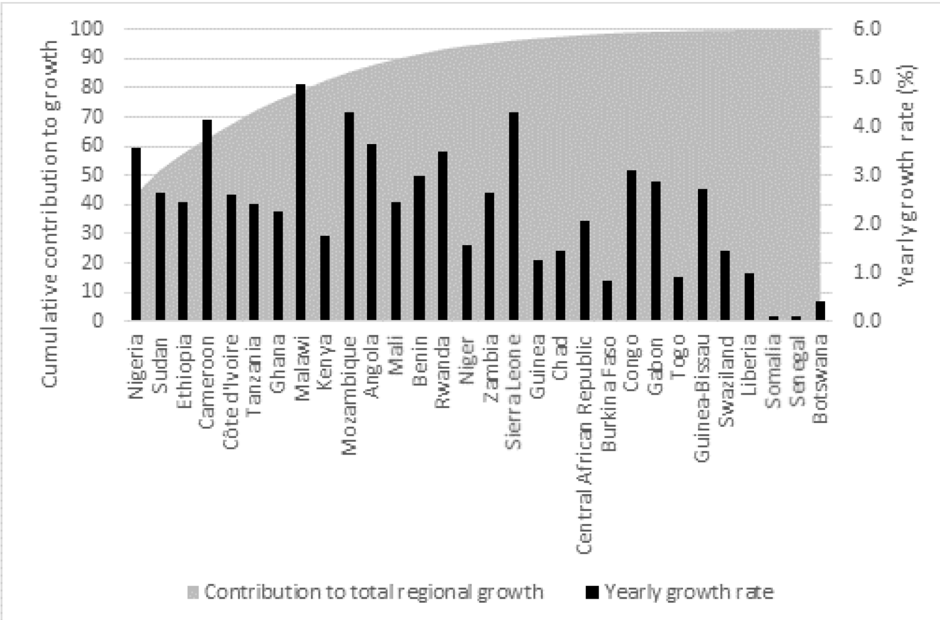




Source: Author's estimation.

Figure 4.4 presents average growth rates and the contribution of different countries to growth in output per worker in SSA between 1995 and 2012 calculated as the growth rate of each country weighted by the country's share in SSA's agricultural labor. Five countries—Nigeria, Sudan, Ethiopia, Cameroon, and Côte d'Ivoire—explain two-thirds of the total growth. If we extend the list to 12 countries by including Tanzania, Ghana, Malawi, Kenya, Mozambique, Angola, and Mali, we explain 90 percent of total growth in output per worker in SSA.

Figure 4.4 Average growth rates and contribution of different countries to total growth[a] in output per worker, 1995–2012



Source: Author's estimation.
Note: [a]. Cumulative contribution of countries. For example, Nigeria contributes 44% of total SSA growth, and Sudan's contribution is 8%, so the contribution of Nigeria and Sudan is 52%.

Table 4.2 looks at agricultural performance of individual countries presenting growth rates of output per worker, aggregated inputs, and TFP and its components for the period 1995–2012 with countries sorted by growth rate in output per worker. Table 4.3 complements information presented in Table 4.2 by showing the contribution of inputs and TFP and its components to total growth in output per worker. Results show that output per worker in the best-performing countries (countries with average growth greater than 1 percent) grew at an average rate of 2.8 with most of this growth explained by growth in TFP: 2.2 percent yearly growth (Table 4.2) or 78 percent of total growth in output per worker (Table 4.3), with a higher contribution of efficiency (43 percent) than of technical change (36 percent).

Total input per worker increased at only 0.6 percent for the group of best performers while showing negative growth on average for poor performers (countries where output per worker grew by less than 1 percent yearly). Among the group of 24 best-performing countries, only 7 countries (Malawi, Swaziland, Gabon, Sierra Leone, Guinea, Mali, and Benin) show growth rates in input per worker greater than 1.0 percent. Most countries with poor growth performance show negative growth in inputs per worker and in many cases a reduction in efficiency.

The slow growth in inputs per worker observed between 1995 and 2012 (last five columns of Table 4.2) is the result of a reduction in agricultural land and crop capital per worker, an increase in the use of fertilizer and livestock capital, and fast growth in the use of feed per worker. On average for the region, feed per worker increased at an annual rate of 2.3 percent, and fertilizer and livestock capital increased at 1.0 and 0.6 percent, respectively. Fast-growing countries increased feed per worker at a yearly rate of 3.5 percent and fertilizer at 0.7 percent, compared with 0.6 percent and –1.0 percent, respectively, in countries growing at 1 percent or less. Capital for crop production remained stagnated in rapidly growing countries, increasing proportionally to the labor force (0.0 percent annually) while growth was negative on average for slowly growing countries.

Table 4.2 Yearly growth rate of output and input per worker, productivity, and its components, 1995–2012, in percentage

Country	Output and input per worker, TFP, and components					Inputs				
	Output	Inputs	TFP	Efficiency	Technology	Feed	Fertilizer	Livestock capital	Crop capital	Agricultural land
Best performers	***2.8***	***0.6***	***2.2***	***1.2***	***1.0***	***3.5***	***0.7***	***1.1***	***0.0***	***–1.1***
Malawi	4.9	2.5	2.3	0.3	2.0	7.2	7.6	4.8	0.4	–0.3
Sierra Leone	4.3	1.6	2.7	1.0	1.7	2.6	–11.0	3.9	3.3	–0.5
Mozambique	4.3	0.0	4.2	3.7	0.6	3.1	13.1	–0.3	–1.2	–2.0
Cameroon	4.1	0.9	3.2	0.8	2.3	6.0	0.7	–0.4	0.0	–0.2
Angola	3.6	–0.2	3.9	3.2	0.7	6.8	–4.5	–0.5	–3.2	–2.7
Nigeria	3.6	0.3	3.3	2.8	0.5	1.1	4.5	1.9	–0.2	–1.6
Rwanda	3.5	0.1	3.4	2.8	0.6	5.6	–1.1	0.1	–1.5	–2.6
Congo, Republic of the	3.1	0.2	2.9	2.5	0.4	0.4	–5.1	2.0	–0.3	–0.7
Benin	3.0	1.1	1.8	2.7	–0.8	7.0	–30.7	1.1	1.2	0.6
Gabon	2.9	1.7	1.2	0.0	1.1	5.1	3.4	1.6	0.8	0.8
Guinea-Bissau	2.7	0.6	2.1	–0.4	2.6	0.2	12.4	1.1	1.3	–0.8
Sudan	2.7	0.6	2.1	0.8	1.3	4.8	0.4	0.5	–0.8	–1.1
Zambia	2.7	–0.5	3.2	2.6	0.6	–0.6	–3.4	–0.8	1.1	–1.4
Côte d’Ivoire	2.6	0.8	1.7	0.1	1.6	2.9	–0.5	0.6	0.7	0.3
Ethiopia	2.5	–0.1	2.6	2.6	0.0	1.3	5.3	0.6	–0.6	–2.1
Mali	2.4	1.1	1.3	–0.2	1.5	2.0	10.9	1.8	2.6	–1.4
Tanzania	2.4	0.5	1.9	0.1	1.8	5.8	3.7	0.1	–1.1	–1.6
Ghana	2.3	0.4	1.9	0.3	1.6	2.4	9.2	0.4	0.1	–1.4
Central African Republic	2.1	0.6	1.5	1.3	0.2	1.8	3.4	2.1	–0.8	–0.7
Kenya	1.8	–0.7	2.5	0.4	2.1	0.2	–0.4	–0.2	–0.9	–2.2
Niger	1.6	–0.7	2.3	1.5	0.8	0.5	–1.6	0.6	–2.4	–1.9
Swaziland	1.5	2.4	–1.0	–1.7	0.7	12.7	2.4	0.0	0.4	0.3
Chad	1.4	0.0	1.4	0.7	0.7	0.4	3.1	1.4	0.1	–1.7
Guinea	1.3	1.1	0.1	0.8	–0.7	3.5	–4.1	4.1	0.3	–1.6

Table 4.2 Continued

Country	Output and input per worker, TFP, and components					Inputs				
	Output	Inputs	TFP	Efficiency	Technology	Feed	Fertilizer	Livestock capital	Crop capital	Agricultural land
Poor performers	***–0.3***	***–0.6***	***0.4***	***0.0***	***0.4***	***0.6***	***–1.0***	***–0.2***	***–1.3***	***–1.7***
Liberia	1.0	0.0	1.0	1.3	–0.3	6.5	2.1	–0.4	–2.4	–3.0
Togo	0.9	0.5	0.4	0.0	0.4	4.8	–19.8	2.1	–0.6	–1.0
Burkina Faso	0.8	–0.2	1.0	1.0	0.0	0.3	1.2	0.8	0.0	–1.8
Botswana	0.4	–0.9	1.3	1.0	0.3	0.4	6.7	0.1	–3.6	–2.0
Senegal	0.1	–1.2	1.3	1.1	0.2	–0.9	–4.1	–1.0	–1.1	–2.0
Somalia	0.1	–1.4	1.5	1.2	0.4	–1.5	–4.6	–1.3	–1.8	–1.7
Mauritania	0.0	–0.8	0.8	1.4	–0.6	2.8	–2.8	–0.4	–2.9	–2.6
Gambia	0.0	0.4	–0.5	–1.3	0.8	4.0	4.9	–0.5	1.0	–1.9
Zimbabwe	–0.1	0.5	–0.6	–0.7	0.1	–0.8	–4.1	1.3	1.3	1.0
Uganda	–0.3	–0.1	–0.1	–1.3	1.2	1.3	9.4	0.6	–1.5	–1.6
Madagascar	–1.0	–1.8	0.8	–0.4	1.2	0.7	–5.4	–3.1	–3.0	–2.3
Namibia	–1.0	–0.9	–0.1	–1.0	0.9	–4.9	8.5	0.3	–0.1	–0.8
Burundi	–1.7	–0.6	–1.1	–2.6	1.5	–1.4	–3.1	1.7	–1.2	–1.9
Congo, Democratic Republic of	–2.7	–2.0	–0.7	–0.1	–0.6	–2.7	–2.9	–2.8	–2.4	–1.8
Average	***1.7***	***0.2***	***1.5***	***0.7***	***0.8***	***2.3***	***1.0***	***0.6***	***–0.3***	***–1.3***

Source: Author's estimation.
Note: TFP = total factor productivity.

Table 4.3 Contribution of inputs per worker, productivity, and its components to growth in output per worker and contribution of individual inputs to aggregated input, 1995–2012, in percentage

	Contribution of input per worker, TFP, and components to output per worker					Contribution to aggregated input					
Country	Output	Inputs	TFP	Efficiency	Technological change	Input	Feed	Fertilizer	Livestock capital	Crop capital	Agricultural land
Best performers	***100***	***22***	***78***	***43***	***36***	***100***	***152***	***39***	***58***	***–26***	***–123***
Malawi	100	52	48	7	41	100	50	6	44	3	–3
Sierra Leone	100	37	63	23	40	100	30	–15	56	37	–8
Mozambique	100	1	99	86	13	100	1,813	810	–199	–733	–1,591
Cameroon	100	23	77	20	57	100	114	2	–11	0	–5
Angola	100	–6	106	88	19	100	–453	35	42	223	253
Nigeria	100	8	92	78	14	100	70	31	151	–15	–138
Rwanda	100	3	97	80	17	100	1060	–24	35	–297	–674
Congo, Republic of the	100	6	94	82	12	100	34	–56	240	–31	–87
Benin	100	38	62	89	–27	100	111	–67	23	20	13
Gabon	100	59	41	1	40	100	54	4	21	8	12
Guinea-Bissau	100	21	79	–15	94	100	7	41	46	41	–35
Sudan	100	22	78	29	49	100	152	2	22	–27	–48
Zambia	100	–19	119	97	21	100	22	14	37	–40	68
Côte d'Ivoire	100	33	67	6	61	100	62	–1	16	15	8
Ethiopia	100	–6	106	107	–1	100	–156	–70	–88	73	340
Mali	100	46	54	–10	63	100	33	18	36	42	–30
Tanzania	100	22	78	5	73	100	198	14	4	–40	–76
Ghana	100	17	83	13	70	100	113	47	22	6	–88
Central African Republic	100	27	73	61	12	100	58	12	87	–26	–32
Kenya	100	–40	140	24	117	100	–4	1	5	23	75
Niger	100	–45	145	93	52	100	–14	4	–20	63	66
Swaziland	100	166	–66	–118	52	100	92	2	0	3	3
Chad	100	3	97	48	49	100	150	138	731	32	–952
Guinea	100	90	10	62	–52	100	55	–7	82	4	–34

Table 4.3 Continued

	Contribution of input per worker, TFP, and components to output per worker					Contribution to aggregated input					
Country	Output	Inputs	TFP	Efficiency	Technological change	Input	Feed	Fertilizer	Livestock capital	Crop capital	Agricultural land
Poor performers	100	236	–136	14	–150	***100***	***–87***	***–20***	***5***	***79***	***123***
Liberia	100	–5	105	130	–26	100	–1436	–52	116	560	912
Togo	100	58	42	0	42	100	161	–84	91	–22	–46
Burkina Faso	100	–21	121	124	–4	100	–34	–14	–109	3	254
Botswana	100	–217	317	246	71	100	–9	–15	–4	74	53
Senegal	100	–1,070	1,170	988	181	100	14	7	20	17	41
Somalia	100	–1,464	1,564	1,189	375	100	19	7	21	23	30
Mauritania	100	1,966	–1,866	–3,385	1,519	100	–60	7	10	64	79
Gambia	100	–1,030	1,130	2,987	–1,857	100	168	23	–25	43	–108
Zimbabwe	100	–767	867	1,041	–175	100	–25	–15	55	43	43
Uganda	100	46	54	496	–441	100	–181	–141	–102	215	309
Madagascar	100	182	–82	43	–124	100	–7	6	40	30	31
Namibia	100	87	13	100	–88	100	102	–19	–7	2	22
Burundi	100	35	65	150	–85	100	43	10	–64	35	76
Congo, Democratic Republic of	100	74	26	3	22	100	24	3	31	21	21
Average	100	9	91	44	46	***100***	***64***	***17***	***38***	***13***	***–33***

Source: Author's estimation.
Note: TFP = total factor productivity.

We compare patterns of growth between best-performing countries by dividing them into two groups. The first group includes countries for which growth is driven mainly by improvements in efficiency (yearly efficiency growth between 1995 and 2012 greater than 1 percent), and the second group includes countries where growth is driven mainly by input growth and technical change. The efficiency-driven group includes 10 countries: Mozambique, Angola, Rwanda, Nigeria, Benin, Ethiopia, Zambia, Republic of the Congo, Niger, and Central African Republic. The second group includes 14 countries: Sierra Leone, Cameroon, Guinea, Sudan, Chad, Kenya, Malawi, Ghana, Côte d'Ivoire, Tanzania, Gabon, Mali, Guinea-Bissau, and Swaziland. Average values of growth rates and contribution to growth in output and input per worker for these two groups of countries are presented in Table 4.4.

Table 4.4 Growth decomposition, best-performing countries, in percentage

Country	All best performers	Efficiency driven	Technological change driven
Output per worker	2.8	3.0	2.7
Inputs	0.6	0.1	1.0
Total factor productivity (TFP)	2.2	2.9	1.7
Efficiency	1.2	2.5	0.2
Technical change	1.0	0.3	1.4
Contribution to growth in output per worker			
Output per worker	100	100	100
Inputs	22	1	39
TFP	78	99	61
Efficiency	43	86	7
Technical change	36	13	54
Contribution to growth in aggregated input			
Input	100	100	100
Feed	152	255	79
Fertilizer	39	69	18
Livestock capital	58	31	77
Crop capital	–26	–76	11
Agricultural land	–123	–178	-84

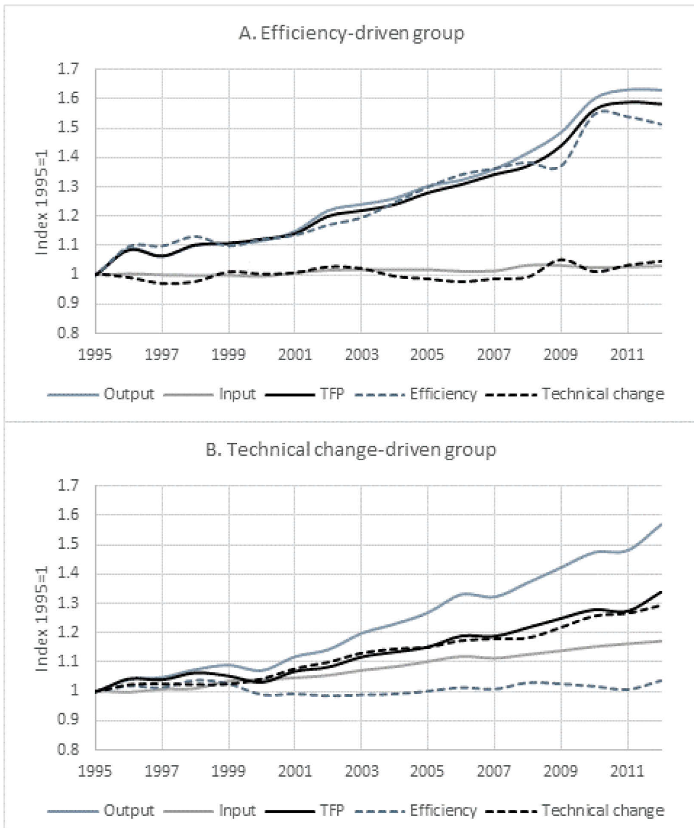
Source: Author's estimation.

Note: Both groups include countries with growth in output per worker bigger than 1 percent on average. Countries in the efficiency-driven growth group are those that increased efficiency by at least 1 percent per year on average: Mozambique, Angola, Rwanda, Nigeria, Benin, Ethiopia, Zambia, Republic of the Congo, Niger, and Central African Republic. The technical-change-driven group includes best-performing countries not included in the efficiency-driven group: Sierra Leone, Cameroon, Guinea, Sudan, Chad, Kenya, Malawi, Ghana, Côte d'Ivoire, Tanzania, Gabon, Mali, Guinea-Bissau, and Swaziland.

The efficiency-driven group and the technology-driven group show similar growth rates in output per worker for the analyzed period (3.0 and 2.7 percent, respectively). Despite similar performance between groups in terms of growth in output per worker, the composition of this growth is very different. For example, only 1 percent of total growth in output per worker in the efficiency-driven group is contributed by input growth, while 86 percent of total growth is explained by catching up to the frontier. Growth in output per worker in the input-technology group on the other hand is explained by increased inputs (39 percent of total growth). This growth in inputs is associated with increases in productivity through technical change (54 percent of total growth). The contribution of efficiency in this group is 7 percent. Most of the increase in inputs in this group is the result of growth in the use of feed and increased livestock capital. Countries in this group also increased fertilizer and, in contrast with the efficiency-driven group, also increased crop capital, although its contribution is small relative to that of other inputs.

The different growth patterns in the efficiency-driven and technology-driven countries is better visualized in Figure 4.5. In the efficiency-driven group (Figure 4.5A), the output per worker and efficiency curves follow almost the same path. In contrast, growth in output per worker in the technical-change-driven group was driven by increased potential output (technical change) and increased inputs per worker, which follow a very similar path (correlation 0.84 compared to –0.38 in the efficiency-driven group.

Figure 4.5 Decomposition in growth of output per worker for groups of best-performing countries with different growth patterns, 1995–2012

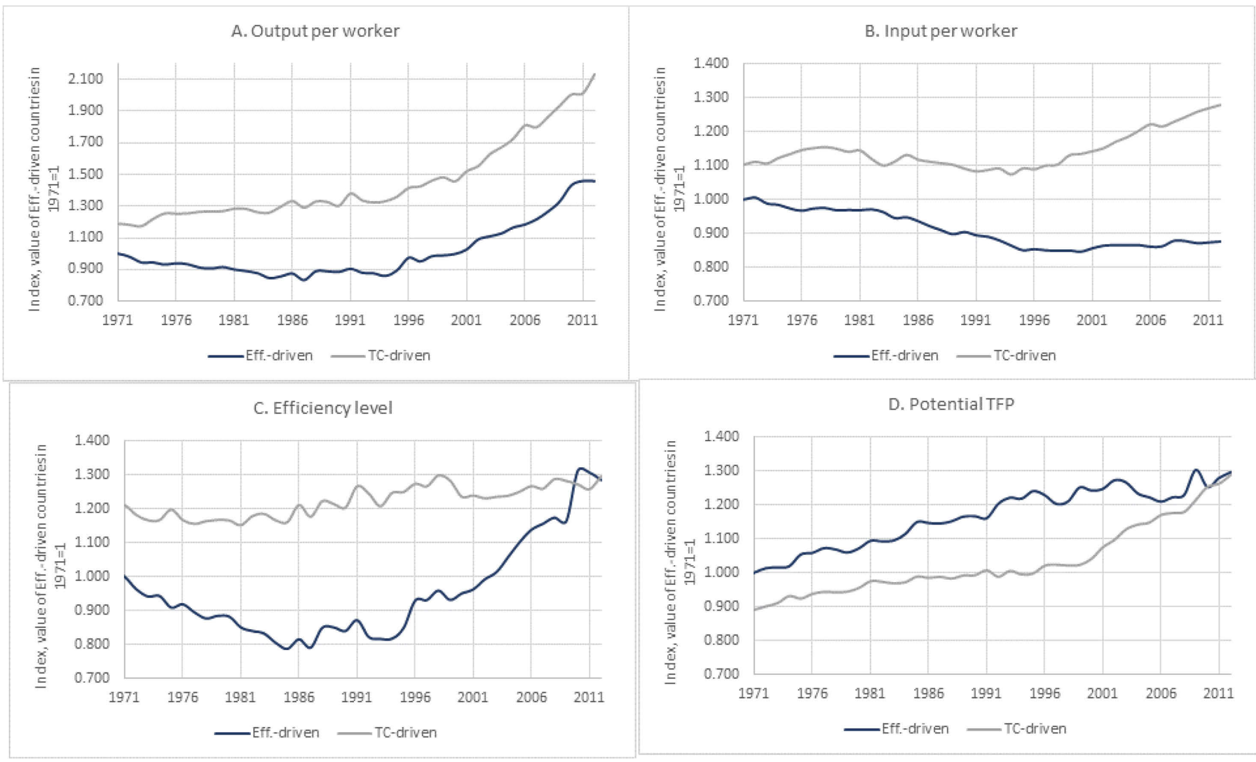


Source: Author's estimation.

Note: Both groups include countries with growth in output per worker bigger than 1 percent on average. Countries in the efficiency-driven growth group are those that increased efficiency by at least 1 percent per year on average: Mozambique, Angola, Rwanda, Nigeria, Benin, Ethiopia, Zambia, Republic of the Congo, Niger, and Central African Republic. The technical-change-driven group includes best-performing countries not included in the efficiency-driven group: Sierra Leone, Cameroon, Guinea, Sudan, Chad, Kenya, Malawi, Ghana, Côte d'Ivoire, Tanzania, Gabon, Mali, Guinea-Bissau, and Swaziland.

Figure 4.6 offers a partial explanation for the observed growth patterns in the different groups of countries by comparing levels of output per worker, efficiency, inputs per worker, and potential TFP. There are differences in initial levels of the different variables between the efficiency-driven and technical-change-driven groups. The efficiency-driven group produced almost 20 percent less output per worker than the technical-change-driven group at the beginning of the period. This difference was explained by 20 percent higher efficiency and 10 percent more inputs per worker. On the other hand, the efficiency-driven group had a more productive technology, with potential production 10 percent higher than that in the technical-change-driven group. During the 1970s and 1980s, the period of poor performance of agriculture in the region, countries in the efficiency-driven group saw a drastic reduction in efficiency, which means that they fell behind the world's technological frontier as agriculture in these countries couldn't keep pace with growth in other regions. As Figure 4.6 shows in Panel C, by 1986 the average efficiency for this group of countries was 20 percent lower than its level in 1971. The reaction of these countries to this loss in efficiency was to reduce the level of input per worker (possibly a consequence of structural adjustment and policy changes), an adjustment that starts precisely in 1986 (Figure 4.6, Panel B). Ten years later, input per worker in the efficiency-driven group was 15 percent lower than in 1971 and has remained at that level until the present time. It is only after this reduction in the level of input per worker that growth in efficiency takes off, catching up with the world technological frontier and with the efficiency level of the technical-change-driven countries.

Figure 4.6 Levels of output per worker, input per worker, efficiency, and potential TFP for groups of countries with different growth patterns



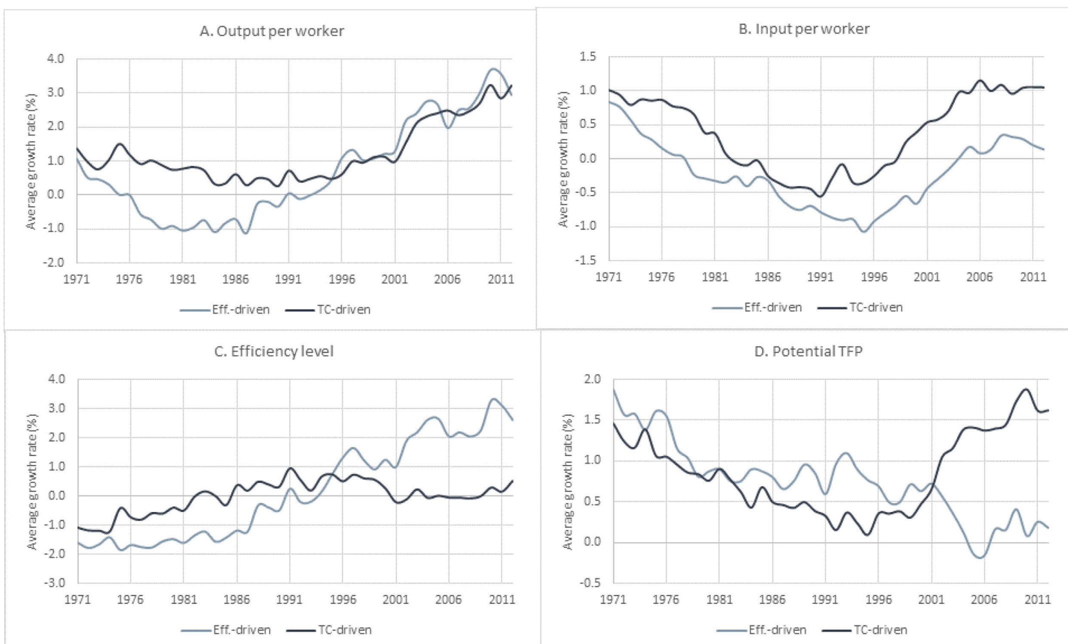
Source: Author’s estimation.

Note: TFP = total factor productivity. Both groups include countries with growth in output per worker bigger than 1 percent on average. Countries in the efficiency-driven growth group are those that increased efficiency by at least 1 percent per year on average: Mozambique, Angola, Rwanda, Nigeria, Benin, Ethiopia, Zambia, Republic of the Congo, Niger, and Central African Republic. The technical-change-driven group includes best-performing countries not included in the efficiency-driven group: Sierra Leone, Cameroon, Guinea, Sudan, Chad, Kenya, Malawi, Ghana, Côte d’Ivoire, Tanzania, Gabon, Mali, Guinea-Bissau, and Swaziland.

In contrast, we do not observe a reduction in efficiency in the technical change-driven countries. These countries were able to grow at rates similar to those of countries at the world technological frontier. Improved performance in this case is the result of accelerated technical change that started in the mid-1990s (Figure 4.6, Panel D), which coincides with fast-growing levels of input per worker (Figure 4.6, Panel B). In other words, countries in the technical-change-driven group increased potential output per worker by increasing levels of input per worker. By 2012, countries in both groups show the same levels of efficiency and potential output, with differences in output per worker explained only by the higher level of inputs per worker used by countries in the technical-change-driven group

Figure 4.7 shows average growth rates of output per worker and its components between 1971 and 2012, looking for changes in growth speed and in the contribution of inputs and TFP to output growth in the efficiency- and technical-change-driven countries. First, we observe that both groups of countries still show strong growth in output per worker at the end of the period: 3.1 and 2.9 percent between 2008 and 2012 in the efficiency- and technical-change-driven groups, respectively. The main difference is that the technical-change-driven group shows a stable 1.0 percent growth in input per worker, while this rate for the efficiency-driven group is below 0.5 percent and fluctuating close to 0.0 percent. At the same time, the speed of technical change has been growing for the technical-change-driven group, reaching 1.5 percent in 2012, and is close to 0.0 percent in the efficiency-driven group. Note that efficiency growth should slow down as countries catch up to the technological frontier, which means that the efficiency-driven group will need to change to technical-change-driven growth to be able to sustain growth in the future.

Figure 4.7 Average growth rates of output per worker, input per worker, efficiency, and potential TFP for groups of countries with different growth patterns



Source: Author's estimation.
Note: TFP = total factor productivity. Both groups include countries with growth in output per worker bigger than 1 percent on average. Countries in the efficiency-driven growth group are those that increased efficiency by at least 1 percent per year on average: Mozambique, Angola, Rwanda, Nigeria, Benin, Ethiopia, Zambia, Republic of the Congo, Niger, and Central African Republic. The technical-change-driven group includes best-performing countries not included in the efficiency-driven group: Sierra Leone, Cameroon, Guinea, Sudan, Chad, Kenya, Malawi, Ghana, Côte d'Ivoire, Tanzania, Gabon, Mali, Guinea-Bissau, and Swaziland.

To conclude, we find great variation in the performance and growth patterns of SSA countries after policy and institutional changes of the 1990s. Twenty-four of the 38 countries in our sample have increased output per worker at rates higher than 1 percent per year; 8 countries show low growth or remained virtually stagnated, growing at rates between 0 and 1 percent, while 6 countries experienced negative growth. Improved technical efficiency is the main driver of growth in output per worker for 10 of the 24 best-performing countries during 1995–2012. Given that the speed of catching up decreases when countries reduce the distance to the technological frontier, we expect to observe a slowdown in efficiency-driven countries unless they switch to a different growth pattern. We also found that 14 countries showing relatively strong growth during the period follow a very different growth pattern. Growth in these countries is driven by increases in input per worker and technical change and has accelerated in recent years.

5. PRODUCTIVITY LEVELS AND FUTURE GROWTH

Output Decomposition in Levels

After 15 years of growing at an average rate of 3.3 percent or 1.7 percent per worker, where are SSA countries compared with other countries? How productive is agriculture in SSA compared with agriculture in other regions, and what explains labor productivity differences between SSA and other developing regions? What effort in terms of inputs and TFP is needed to increase labor productivity? In this section we discuss possible answers to these questions.

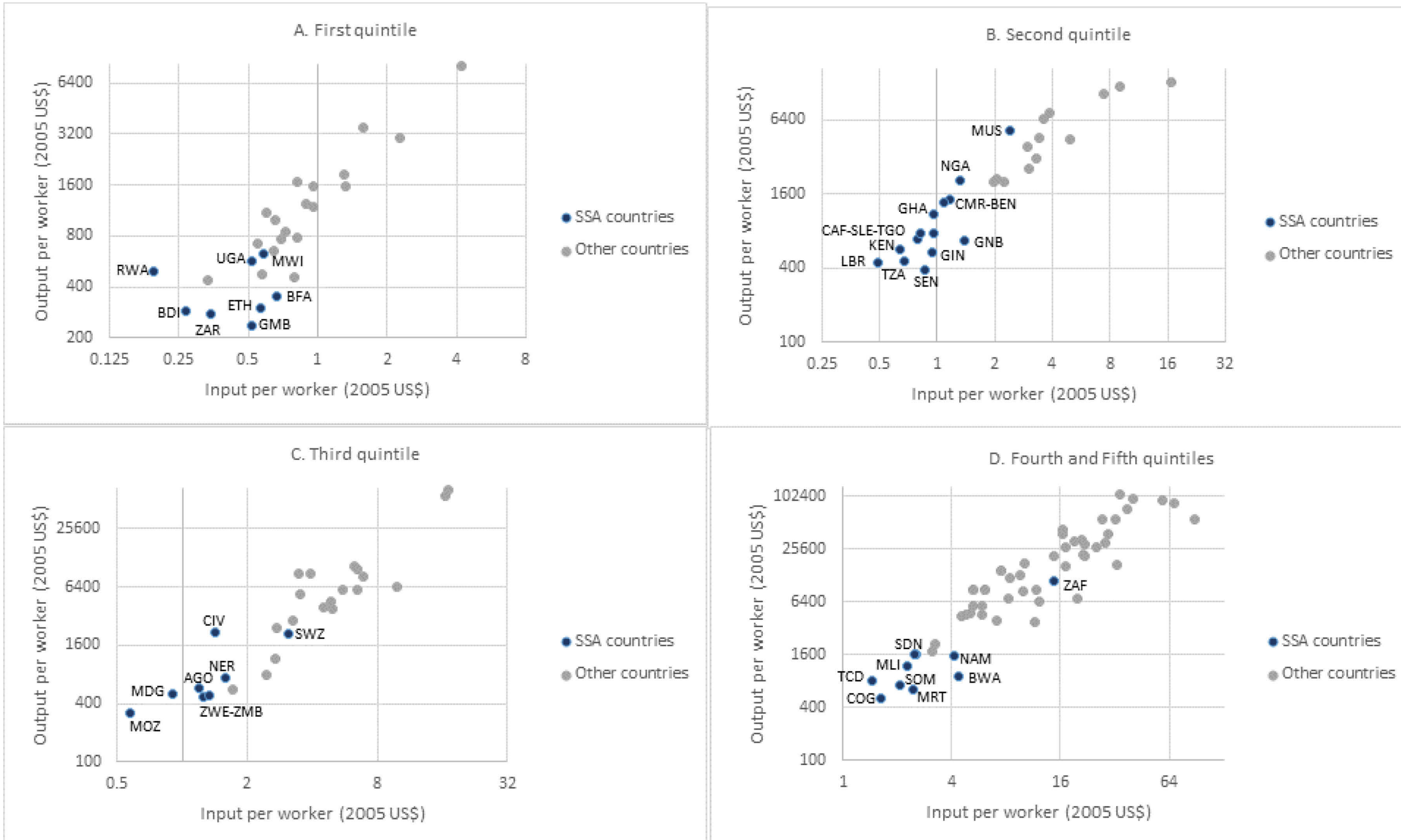
Figure 5.1 plots levels of total input per worker against output per worker for SSA and other countries, grouping countries by quintile of land–labor ratio. For example, Panel A shows land-scarce countries or countries with a very low land–labor ratio. Rwanda, Burundi, Uganda, Malawi, Gambia, Burkina Faso, and Ethiopia are SSA's most land-scarce, labor-abundant countries. At the other end of the spectrum, countries with a very high land–labor ratio include the Republic of the Congo and Gabon in a tropical-humid agroecology and several arid and semiarid countries (Sudan, Namibia, Botswana, Mali, Somalia, Mauritania, and Chad).

The first thing to notice in Figure 5.1 is the very low level of input per worker used by SSA countries at all levels of land–labor ratio. In Panel A, all SSA countries use inputs below US$0.6 per worker when most countries show values between $0.6 and $4.0. On average, input per worker in other countries (not including Korea, the country with the highest level of inputs) is twice the average level of SSA countries (0.46 and 0.92 respectively). This difference increases as we move up to countries in higher land–labor quintiles. In the second quintile, use of inputs in SSA countries concentrates around $0.9 per worker (not including Mauritius), while other countries on average use $5.0 per worker and $2.5 per worker in Mauritius. Ghana appears as an average SSA country in terms of input use in the second quintile, with Liberia, Tanzania, and Senegal on the low end and Nigeria, Benin, and Cameroon on the high end of input use. In quintile 3, SSA countries average $1.4 of inputs per worker, while average input level in other countries is $6.0. Similarly, SSA countries in quintiles 4 and 5 show average values of $2.6 per worker (not including South Africa), compared with $15.0 in South Africa and $19.0 in other countries. Also notice in quintiles 1 to 3 are what we can describe as "absolute outliers," or countries with extremely low levels of input per worker, even when compared with other SSA countries. These are Rwanda, Burundi, and the Democratic Republic of Congo in the first quintile; Liberia in the second quintile; Mozambique and Madagascar in the third quintile; and Chad and Republic of the Congo in the fourth and fifth quintiles.

What explains differences in output per worker between countries? Following Jerzmanowski (2007) we summarize the contribution of efficiency (E), factor endowments (F), and available technology or potential TFP (T) to output differences using the variance decomposition. Aggregating inputs, the Cobb–Douglas production function can be expressed as Y = TFP × F, where TFP is equal to TFP = E × T, or the product of efficiency and available technology. The variance of log output per worker expressed in logs can be decomposed as follows:

$$Var(lnY)= Var(lnT)+Var(lnE)+Var(lnF)+2Cov(T,E)+2Cov(T,F)+2cov(E,F). \qquad (5.1)$$

Figure 5.1 Input and output per worker by quintile of land–labor ratio for SSA countries and other countries, average 2009–2011 (log scale)



Source: Author’s calculations.

Note: SSA = Africa south of the Sahara; AGO = Angola, BDI = Burundi, BFA = Burkina Faso, BWA = Botswana, CAF = Central African Republic, CIV = Côte d’Ivoire, CMR = Cameroon, COG = Republic of the Congo, ETH = Ethiopia, GAB = Gabon, GHA = Ghana, GIN = Guinea, GMB = Gambia, GNB = Guinea-Bissau, KEN = Kenya, LBR = Liberia, MDG = Madagascar, MLI = Mali, MOZ = Mozambique, MRT = Mauritania, MUS = Mauritius, MWI = Malawi, NAM = Namibia, NER = Niger, NGA = Nigeria, RWA = Rwanda, SDN = Sudan, SEN = Senegal, SLE = Sierra Leone, SOM = Somalia, SWZ = Swaziland, TCD = Chad, TGO = Togo, TZA = Tanzania, UGA = Uganda, ZAR = Democratic Republic of Congo, ZMB = Zambia, ZWE = Zimbabwe.

Table 5.1 presents the contribution of factors, efficiency, and technology to the variation of output per worker in agriculture calculated for SSA countries only and for all countries including SSA countries.

Table 5.1 Contribution of factors, efficiency, and technology to the variation of output per worker in agriculture in different periods, between SSA countries only and between all countries including SSA countries

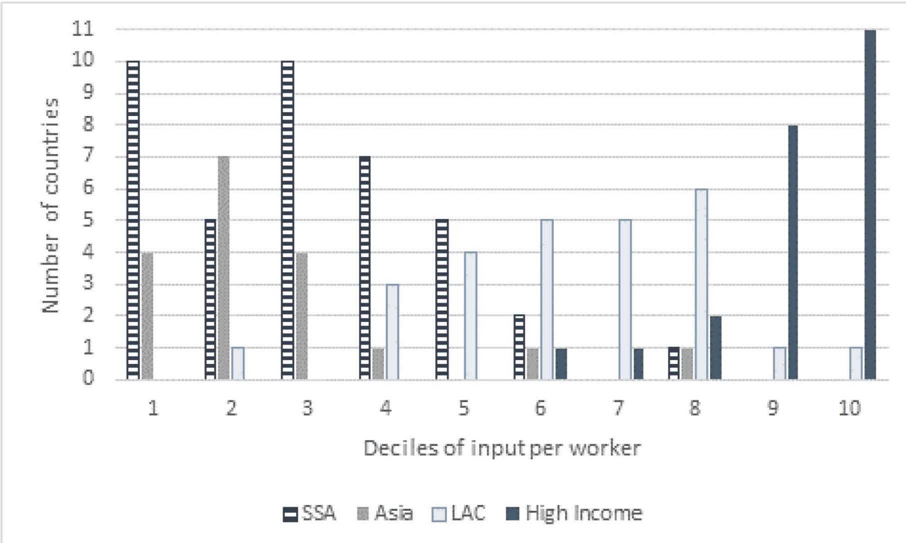
	SSA countries only				All countries			
Values	**Efficiency**	**Inputs**	**Technology**	**Total**	**Efficiency**	**Inputs**	**Technology**	**Total**
1981–1990	0.06	0.32	0.05	0.42	0.14	1.52	0.28	1.94
1991–2000	0.05	0.40	0.07	0.51	0.12	1.75	0.38	2.25
2000–2011	0.04	0.47	0.08	0.60	0.08	1.95	0.43	2.46
Composition								
1981–1990	13%	75%	12%	100%	7%	78%	14%	100%
1991–2000	10%	77%	13%	100%	5%	78%	17%	100%
2000–2011	7%	79%	14%	100%	3%	79%	17%	100%

Source: Author's calculations.
Note: SSA = Africa south of the Sahara.

Results in Table 5.1 show that differences in labor productivity between countries in 2001–2012 are explained in all cases mostly by differences in input levels and that these differences increased through time. Adding direct and indirect input effects (through technology) we find that inputs explain more than 90 percent of labor productivity differences between SSA countries and between all countries including SSA. Comparing values in different periods we observe two interesting results: First, the contribution of efficiency to differences in labor productivity has decreased with time, which coincides with growth patterns in SSA in recent years, when countries that experienced large losses of efficiency during the 1980s were able to catch up to efficiency levels of other countries in the region. Second, the importance of inputs explaining labor productivity has increased with time, not only because of its direct effect but also through its indirect effect, appropriate technology. In other words, differences in labor productivity are in part the result of low intensity in the use of inputs per worker but also result from low productivity of the mix of inputs used.

Is technology used by SSA countries less productive than technology used in other countries? Or equivalently, is the level of technology (T) or potential TFP affected by the input mix? Figure 5.2 shows the distribution of countries in different regions by decile of input per worker. All SSA countries (with the exception of South Africa) are in deciles 1–5, and two-thirds are in deciles 1–3 along with the majority of Asian countries (South Asia and Asia-Pacific). Most Latin American countries are in deciles 5–8, while high-income countries are in deciles 9 and 10.

Figure 5.2 Distribution of countries of different regions across deciles of input per worker, 2008–2012



Source: Author's calculations.
Note: LAC = Latin American countries; SSA = Africa south of the Sahara.

We now compare levels of potential TFP between deciles of input per worker in two periods: 1971–1975 and 2008–2012 (Figure 5.3). The first thing to notice is that in 1971–1975, differences in potential productivity between deciles 1–5 and the rest are small (less than 10 percent). However, if we compare potential TFP in 2008–2012, the differences between deciles 1–5 and deciles 6–10 are statistically significant. Differences between deciles 6–8 and deciles 9 and 10 are not significant. The figures for 2008–2012 suggest an "appropriate technology" or some level of input per worker that results in higher productivity levels. Technologies available to countries using low levels of input per worker (deciles 1–5) are significantly less productive than those technologies available for countries in deciles 6 or higher.

Figure 5.3 Comparison of potential TFP levels by decile of input per worker, 1971–1975 and 2008–2012

Source: Author's calculations.
Note: TFP = total factor productivity.

The change from no difference in potential TFP between countries using different levels of input per worker in 1971–1975 to significant differences at present in Figure 5.3 suggest biased technical change occurring between the 1970s and the twenty-first century. The difference in potential TFP by decile of input per worker and between periods shows that technical change between 1971–1975 and 2008–2012 shifted the frontier unevenly, with TFP in deciles 1 to 4 increasing only 23 percent in 37 years compared with more than 50 percent for deciles 6–8 and 76 percent for deciles 9 and 10. The largest shift of the frontier in 2001–2011 corresponds to the factor mix of high-income countries like Canada, the United States, France, Belgium, and the Netherlands. These results suggest that technological divergence is taking place in agriculture, increasing the distance between countries with the "right" input mix and those producing at very low levels of input per worker (like SSA countries).

Exercise on Future Growth

In this section we use the information on global agricultural technology developed in this study to determine possible growth paths for SSA countries. We define these paths by the contribution of inputs, efficiency, and technical change to growth, and the input mix that will be needed to achieve a specific growth target. To do this we compare each SSA country with a reference frontier country. The reference country is selected from the same land–labor quintile and from the same agroecological zone as the SSA country being analyzed. All SSA countries are then compared with their respective reference countries to determine the relative growth of inputs and productivity required by each SSA country to converge to the same levels of productivity and inputs and the same input mix of the reference country. Note that the goal of this exercise is not to recommend specific productivity or input growth targets but (a) to look at differences in labor productivity between SSA countries and other developing countries with similar characteristics, and (b) to see how TFP and the use of inputs contribute to explain those differences.

Table 5.2 shows the extent of the gap in labor productivity, TFP, and input use between SSA countries and countries with similar agroecologies and land–labor ratios. Labor productivity in SSA is only 16 percent of that in reference countries, while the level of input per worker is 34 percent and TFP is 48 percent of productivity in reference countries. Notice that the product of the relative levels of TFP and inputs per worker (0.48 × 0.34) equals the relative level of output per worker (0.16). On the input side, fertilizer per worker is only 2 percent of the reference value, while crop capital is 14 percent, feed is 7 percent, and livestock capital is 43 percent. The differences in agricultural land per worker are small because reference countries were chosen to be in the same decile of land per worker as the SSA country being compared. Countries with low land–labor ratios (quintiles 1 and 2 in Table 5.2) are closer to their references than countries with high land–labor ratios, as labor productivity is 20–23 percent of that in the reference country, compared with only 11–12 percent in quintiles 3 to 5. Low land–labor countries show higher TFP and higher input per worker relative to reference countries than land-abundant countries.

We use information in Table 5.2 to calculate the growth rate of inputs, technology, and efficiency needed by each country to increase output per worker at a yearly rate of 3.0 percent if countries were to converge to the input-productivity structure of the reference countries. Table 5.3 summarizes results of the projections; Figure 5.4 compares projected growth rates for the region with average growth rates for the period 1995–2012. To increase output per worker at 3.0 percent, TFP will need to increase at a yearly rate of 1.2 percent while inputs per worker will need to increase at 1.8 percent per year. Most of projected growth in TFP will need to come from technical change or increased potential output (0.9 percent), while efficiency gains could contribute on average with 0.3 percent per year. To achieve 1.8 percent growth in total inputs, fertilizer per worker will need to increase at an average rate of 6.4 percent, feed at 4.5 percent, crop capital at 3.2 percent, and livestock capital at 1.4 percent. This growth in TFP and inputs should result in 3.0 percent growth in output per worker and in 2.7 percent growth in land productivity (last column in Table 5.3). Figure 5.4 shows that the projected TFP growth of 1.5 percent is not far from the 1.2 percent growth observed between 1995 and 2012. The major difference is in input growth, which was only 0.3 percent in recent years and needs to increase to 1.8 percent, with substantial increases needed in fertilizer, feed, and crop capital if the region is to catch up to levels of output per worker in the reference countries.

Table 5.2 Average levels of output and inputs per worker and productivity relative to levels of reference countries for SSA countries grouped by quintile of land: Labor ratio, in percentage

Quintile	Output	TFP	Potential TFP	Efficiency	Inputs	Land	Fertilizer	Crop capital	Feed	Livestock capital	Output per hectare
Q1	23	50	62	80	47	103	3	13	16	99	24
Q2	20	53	60	88	38	112	2	20	6	64	27
Q3	12	43	53	81	28	107	4	14	4	26	16
Q4–Q5	11	43	52	83	25	103	1	9	7	18	11
SSA	***16***	***48***	***57***	***84***	***34***	***107***	***2***	***14***	***7***	***43***	***19***

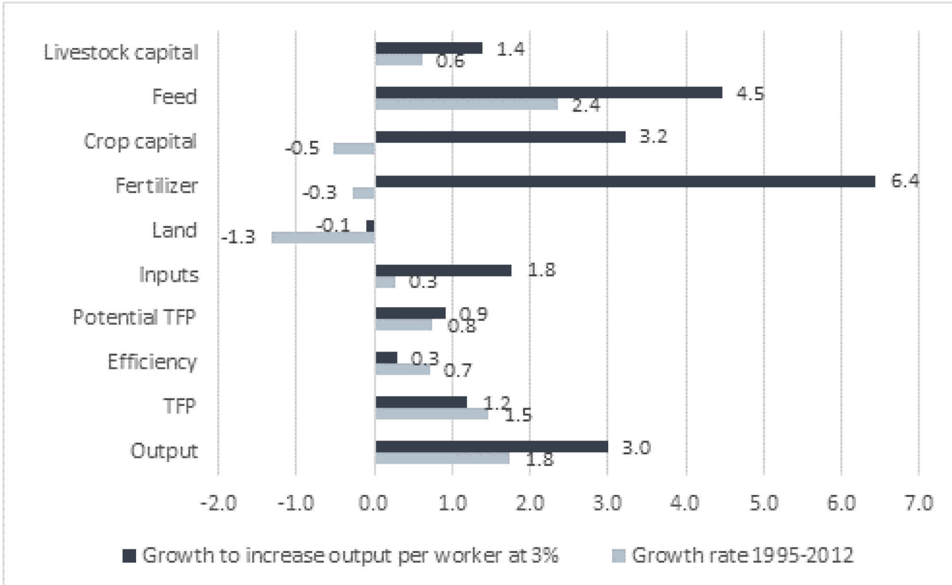
Source: Author's calculations.
Note: SSA = Africa south of the Sahara; TFP = total factor productivity.

Table 5.3 Growth percentage in levels of productivity, efficiency, and inputs needed to increase output per worker at a yearly rate of 3.0 percent

Quintile	Output	TFP	Potential TFP	Efficiency	Inputs	Land	Fertilizer	Crop capital	Feed	Livestock capital	Output per hectare
Q1	3.0	1.4	1.0	0.5	1.6	–0.1	7.1	4.2	3.8	0.0	3.0
Q2	3.0	1.2	0.9	0.2	1.8	–0.2	7.8	3.0	5.5	0.8	2.4
Q3	3.0	1.2	0.9	0.3	1.8	–0.1	4.5	2.8	4.7	1.9	2.5
Q4–Q5	3.0	1.1	0.9	0.3	1.8	0.0	6.3	3.3	3.6	2.3	3.0
SSA	3.0	1.2	0.9	0.3	1.8	–0.1	6.4	3.2	4.5	1.4	2.7

Source: Author's calculations.
Note: SSA = Africa south of the Sahara; TFP = total factor productivity.

Figure 5.4 Historical and projected annual growth rates of productivity, efficiency, and inputs needed to increase output per worker at a yearly rate of 3.0 percent in SSA



Source: Author's calculations.
Note: SSA = Africa south of the Sahara; TFP = total factor productivity.

Table 5.4 presents calculated growth rates of inputs, technology, and efficiency needed by 20 major agricultural-producing countries in SSA to increase output per worker at a yearly rate of 3.0 percent. How should we interpret these results? Take Nigeria for an example, where almost all growth is projected to come from growth in inputs. This does not mean that there is no need for Nigeria to increase TFP in the future but rather that TFP in Nigeria is high compared with that of the reference country (almost the same as in the reference country) and that the difference in output per worker is mostly the result of low levels of input per worker in Nigeria relative to the reference. The need to increase crop capital at 6.1 percent and fertilizer at 4.3 percent means that Nigeria is using significantly less crop capital than the reference country and that this difference is bigger than the difference in the use of fertilizer. Similarly, Nigeria needs to increase livestock capital by 2.7 percent, but faster growth in feed is needed (6.3 percent yearly). If productivity and inputs per worker are related as postulated by the appropriate technology hypothesis, we expect to see an increase in potential TFP in Nigeria if inputs increase by these amounts, something that is not reflected in Table 5.4, where growth rates result from relative distances between Nigeria and the reference country.

A contrasting country is Ethiopia, where comparisons to a reference country in the same agroecology show that potential TFP is low in Ethiopia, so most growth should come from increased potential TFP (2.0 percent) with inputs growing at 1.0 percent. When we look at growth rates of individual inputs we find that this low projected growth of inputs is the result of negative growth in livestock capital (–2.2 percent), relatively low growth in fertilizer (1.6 percent), and high growth in crop capital and feed (4.5 and 4.0 percent, respectively). This is not surprising given Ethiopia's large animal stock, mostly specialized in the production of draft animals, which implies low crop capital (machinery), low use of feed, and low animal productivity. A possible interpretation of these results is that Ethiopia uses inputs efficiently (0.0 percent projected growth in efficiency), but the particular combination of inputs and technology used is less productive (lower potential TFP) than the one used in other countries. Substitution of machinery for draft animals and a more productive livestock sector, using more feed to produce more meat and milk rather than draft animals, should result in a higher potential TFP (a more productive technology).

Table 5.4 Growth in levels of productivity, efficiency, and inputs needed to increase output per worker at a yearly rate of 3.0 percent for major agricultural producers in SSA, in percentage

Country	Output	Input	TFP	Efficiency	Potential TFP	Crop capital	Feed	Fertilizer	Livestock capital	Output per hectare
Angola	3.0	1.3	1.6	0.2	1.4	2.2	3.0	4.5	1.4	3.8
Burkina Faso	3.0	0.4	2.6	0.5	2.1	2.9	1.7	1.9	–2.1	3.6
Cameroon	3.0	2.3	0.7	0.0	0.7	3.9	6.5	8.5	1.4	1.3
Congo, Democratic Republic	3.0	2.0	0.9	0.1	0.8	3.6	3.7	6.8	2.6	4.5
Côte d'Ivoire	3.0	2.1	0.9	0.0	0.8	1.1	5.6	4.5	3.6	3.4
Ethiopia	3.0	1.0	1.9	0.0	1.9	4.5	4.0	1.6	–2.2	3.7
Ghana	3.0	1.5	1.5	0.0	1.5	2.6	2.7	5.1	1.8	3.0
Guinea	3.0	1.4	1.5	0.4	1.2	3.3	3.7	6.8	0.2	2.8
Kenya	3.0	2.1	0.9	0.0	0.9	3.6	7.4	4.7	0.2	1.8
Madagascar	3.0	2.1	0.9	0.2	0.7	2.2	6.7	5.8	1.9	1.8
Malawi	3.0	0.9	2.1	0.0	2.1	3.9	1.0	3.3	–0.2	2.7
Mali	3.0	2.1	0.9	0.4	0.5	3.7	4.0	5.7	2.9	2.0
Mozambique	3.0	2.3	0.8	0.1	0.7	3.3	5.1	3.5	3.1	2.0
Niger	3.0	1.8	1.2	0.2	1.0	2.8	5.4	4.3	1.2	2.4
Nigeria	3.0	2.9	0.2	0.0	0.2	6.1	6.3	4.3	2.7	2.7
Senegal	3.0	1.3	1.6	0.5	1.1	2.8	5.1	4.5	–0.7	2.2
Tanzania	3.0	2.2	0.8	0.1	0.7	3.3	5.3	7.2	2.4	2.3
Uganda	3.0	1.8	1.1	0.4	0.8	2.6	5.7	5.9	1.0	2.0
Zambia	3.0	2.2	0.7	0.9	–0.1	5.9	5.7	12.1	–0.2	4.3
Zimbabwe	3.0	1.8	1.3	0.7	0.6	2.7	4.8	2.2	1.7	2.1
Average	***3.0***	***1.5***	***1.5***	***0.5***	***0.9***	***4.2***	***2.6***	***3.9***	***0.9***	***3.1***

Source: Author's calculations.
Note: SSA = Africa south of the Sahara; TFP = total factor productivity.

Between the two extremes of Nigeria and Ethiopia we find Cameroon, Mozambique, Tanzania, Zambia, Mali, Madagascar, Côte d'Ivoire, Kenya, and the Democratic Republic of Congo closer to Nigeria (a relatively productive technology but low inputs); and Ghana, Guinea, Angola, Senegal, Malawi, and Burkina Faso closer to Ethiopia (less-productive technology and input mix). Independently of the projected growth rate for inputs and TFP, most SSA countries need to increase crop capital, while countries using low levels of input per worker need to significantly increase fertilizer and feed. Even though comparisons are made within the same agroecology, some of the differences in potential TFP between SSA and reference countries could reflect differences in natural resource potential, particularly in the arid, semiarid, and subhumid zone, which still includes significant differences in precipitation.

6. CONCLUSIONS

We revisited past performance of agriculture in SSA and found that TFP through improved technical efficiency and technical change has been the main driver of growth in recent years. Improved efficiency benefited mainly poorer, low-labor-productivity countries. On the other hand, we observed that countries with higher output and input per worker have benefited much more from technological progress than poorer countries, suggesting that technical change has done little to reduce the gap in labor productivity between countries.

A possible explanation of these results can be found in a literature that has emphasized the potential dependence of productivity on inputs to explain differences in income levels and the lack of convergence in labor productivity. Under this approach, the technological frontier is not the same for all countries as some technologies may be more or less productive than others, depending on the country's relative input mix. This is because advanced countries invent technologies that are compatible with their own factor mix, but these technologies do not work well with the very different factor mix of poor countries. To get a better understanding of the role of inputs on TFP gaps, this study used a growth-accounting approach to analyze the explanatory power of the appropriate technology hypothesis to explain differences in productivity levels between SSA and other countries.

Our findings show that the levels of input per worker used in SSA's agriculture at present are extremely low and that differences in labor productivity among 134 developing and high-income countries are explained mostly by differences in input per worker. Difference in input per worker is also the main explanation of difference in output per worker between SSA countries. We also found that the importance of inputs in explaining labor productivity has increased with time, not only because of the direct effect of inputs but because of a growing gap in the productivity of inputs as the result of low productivity of the input mix in poor countries. Countries using the most productive input mix can produce 60 percent more output per unit of input than SSA countries. These differences in TFP can increase in the future, as we found that technical change shifts the frontier unevenly, with TFP in those portions of the frontier at higher levels of input per worker growing much faster than those portions at low levels of input per worker (where SSA countries are located). A possible interpretation of the growing importance of technology explaining differences in output per worker is that technological divergence is taking place in agriculture, increasing the distance between countries with the "right" input mix and countries (like SSA countries) producing at very low levels of input per worker.

Comparisons between SSA countries and similar countries in the same agroecology show that to increase output per worker at a yearly rate of 3.0 percent, SSA countries need to increase TFP at an annual rate of 1.2 percent, which is similar to that observed between 1995 and 2012, while inputs per worker need to increase at 1.8 percent, six times the growth rate of the last 15 years. For inputs per worker to grow at 1.8 percent, fertilizer and feed per worker will need to increase at 6.4 and 4.5 percent, respectively, and crop capital at more than 3.0 percent per year.

The existence of an appropriate technology could have significant implications for policy and development strategies pursuing this goal of doubling output per worker in the coming years. Is the slow pace of technology adoption and TFP growth in SSA the result of inappropriateness of technology, given the very particular conditions and low levels of capitalization of agriculture in these countries? Should countries adapt technologies produced by advanced countries to their own input mix, or should they "adapt" their agricultural sector to use modern technologies more efficiently (for example, the debate of the poor smallholders versus commercial agriculture)? The appropriate technology hypothesis could bring a different perspective to this debate already taking place in SSA.

APPENDIX: AGROECOLOGICAL ZONES

Classification of countries in four main agroecologies was done using information from Lee et al. (2005), who worked with lengths of growing period and three climatic zones: tropical, temperate, and boreal. Table A.1 details the definition of global agroecological zones (AEZs) used in the Global Trade Analysis Project (GTAP) land use database, with the first six AEZs corresponding to tropical climate, the second six to temperate, and the last six to boreal.

Table A.1 Definition of global agroecological zones (AEZs)

Length of growing period in days	Moisture regime	Climate zone	GTP class
0–59	Arid	Tropical	AEZ1
		Temperate	AEZ7
		Boreal	AEZ13
60–119	Dry semiarid	Tropical	AEZ2
		Temperate	AEZ8
		Boreal	AEZ14
120–179	Moist semiarid	Tropical	AEZ3
		Temperate	AEZ9
		Boreal	AEZ15
180–239	Subhumid	Tropical	AEZ4
		Temperate	AEZ10
		Boreal	AEZ16
240–299	Humid	Tropical	AEZ5
		Temperate	AEZ11
		Boreal	AEZ17
>300 days	Humid; year-round growing season	Tropical	AEZ6
		Temperate	AEZ12
		Boreal	AEZ18

Source: Lee et al. (2005).

We used information of area of pasture and cropland in the different agroecologies to determine the predominant agroecology in each country. With this information we grouped countries in our sample in four major groups: temperate humid, temperate subhumid, tropical humid, and tropical subhumid. The humid groups include the humid and humid year-round growing season, and the subhumid groups include the subhumid, moist semiarid, and arid agroecologies. Only two countries were defined as belonging to the boreal climate zone, so they were assigned to the temperate groups.

Table A.2 SSA countries by agroecology

Agroecological zone		Country
Temperate	Arid, semiarid	Botswana, Namibia, South Africa, Swaziland, Zimbabwe
Tropical	Arid, semiarid, and subhumid	Benin, Burkina Faso, Cameroon, Central African Republic, Chad, Gambia, Guinea, Guinea-Bissau, Kenya, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Nigeria, Senegal, Sierra Leone, Somalia, Sudan (former), Tanzania, Togo, Zambia
	Humid	Angola, Burundi, Republic of the Congo, Côte d'Ivoire, Democratic Republic of Congo, Ethiopia (former), Gabon, Ghana, Liberia, Mauritius, Rwanda, Uganda

Source: Defined by authors.
Note: SSA = Africa south of the Sahara.

REFERENCES

Acemoglu, D., and F. Zilibotti. 2001. “Productivity Differences.” *The Quarterly Journal of Economics* 116 (2): 563–606.

Alene, A. D. 2010. “Productivity Growth and the Effects of R&D in African Agriculture.” *Agricultural Economics* 41 (3–4): 223–238.

Arnade, C. 1998. “Using a Programming Approach to Measure International Agricultural Efficiency and Productivity.” *Journal of Agricultural Economics* 49: 67–84.

Barro, R. J., and X. Sala-i-Martin. 1991. *Convergence across States and Regions*. Brookings Papers on Economic Activity. Washington, DC: Brookings Institute.

Basu, S., and D. N. Weil. 1998. “Appropriate Technology and Growth.” *Quarterly Journal of Economics* 113 (4):1025–1054.

Block, S. 1995. “The Recovery of Agricultural Productivity in Sub-Saharan Africa.” *Food Policy* 20: 385–405.

———. 2010. *The Decline and Rise of Agricultural Productivity in Sub-Saharan Africa since 1961.* NBER Working Paper Series No. 16481. Cambridge, MA, US: National Bureau of Economic Research.

Bravo-Ortega, C., and D. Lederman. 2004. “Agricultural Productivity and Its Determinants: Revisiting International Experiences.” *Estudios de Economia* 31(2): 133–163.

Bureau, C., R. Färe, and S. Grosskopf. 1995. “A Comparison of Three Nonparametric Measures of Productivity Growth in European and United States Agriculture.” *Journal of Agricultural Economics* 45: 309–326.

Caves, D. W., L. R. Christensen, and W. E. Diewert. 1982. “The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity.” *Econometrica* 50: 1393–1414.

Cermeno, R., G. Maddala, and M. Trueblood. 2003. “Modelling Technology as a Dynamic Error Components Process: The Case of the Inter-Country Agricultural Production Function.” *Econometric Reviews* 22: 289–306.

Chavas, J. P. 2001. “An International Analysis of Agricultural Productivity.” In *Agricultural Investment and Productivity in Developing Countries*, edited by L. Zepeda. Rome: Food and Agriculture Organization.

Coakley, J., A. M. Fuertes, and R. P. Smith. 2006. “Unobserved Heterogeneity in Panel Time Series Models.” *Computational Statistics & Data Analysis* 50 (9): 2361–2380.

Craig, B. J., P. G. Pardey, and J. Roseboom. 1997. “International Productivity Patterns: Accounting for Input Quality, Infrastructure, and Research.” *American Journal of Agricultural Economics* 79 (4): 1064–1076.

Eberhardt, M. 2012. “Estimating Panel Time-Series Models with Heterogeneous Slopes.” *Stata Journal* 12 (1): 61–71.

Eberhardt, M., and S. Bond. 2009. *Cross-Section Dependence in Nonstationary Panel Models: A Novel Estimator*. MPRA Paper 17692. University Library of Munich.

Eberhardt, M., and F. Teal. 2013. “No Mangoes in the Tundra: Spatial Heterogeneity in Agricultural Productivity Analysis.” *Oxford Bulletin of Economics and Statistics* 75 (6): 914–939.

FAO (Food and Agriculture Organization of the United Nations). 2014. “FAOSTAT” database. Accessed February 12, 2015. http://faostat3.fao.org/home/E.

Fuglie, K. O. 2011. “Agricultural Productivity in Sub-Saharan Africa.” In *The Food and Financial Crisis in Africa*, edited by D. L. Lee, 122–153. Wallingford, OX, UK: Commonwealth Agricultural Bureau International.

Fuglie, K. O., and N. Rada. 2012. “Constraints to Raising Agricultural Productivity in Sub-Saharan Africa.” In *Productivity Growth in Agriculture: An International Perspective,* edited by K. O. Fuglie, S. L. Wang and V. E. Ball, 273–292. Wallingford, OX, UK: Commonwealth Agricultural Bureau International.

Fulginiti, L., and R. K. Perrin. 1997. “LDC Agriculture: Nonparametric Malmquist Productivity Indexes.” *Journal of Development Economics* 53: 373–390.

———. 1999. “Have Price Policies Damaged LDC Agricultural Productivity?” *Contemporary Economic Policy* 17: 469–475.

Fulginiti, L. E., R. K. Perrin, and B. Yu. 2004. “Institutions and Agricultural Productivity in Sub-Saharan Africa.” *Agricultural Economics* 4: 169–180.

Griliches, Z. 1964. “Research Expenditures, Education, and the Aggregate Agricultural Production Function.” *American Economic Review* LIV (6): 961–974.

Grossman, G. M., and E. Helpman. 1991. “Trade, Knowledge Spillovers, and Growth.” *European Economic Review* 35(2): 517–526.

Growiec, J. 2012. “The World Technology Frontier: What Can We Learn from the US States?” *Oxford Bulletin of Economics and Statistics* 74 (6): 777–807.

Hayami, Y., and V. Ruttan. 1985. *Agricultural Development: An International Perspective*. Baltimore: Johns Hopkins University Press.

Jaffe, A. 1986. *Technological Opportunity and Spillovers of R&D: Evidence from Firms’ Patents, Profits and Market Value*. NBER Working Paper Series No. 1815. Cambridge, MA, US: National Bureau of Economic Research.

Jerzmanowski, M., 2007. “Total Factor Productivity Differences: Appropriate Technology vs. Efficiency. *European Economic Review* 51: 2080–2110.

Kumar, S., and R. R. Russell. 2002. “Technological Change, Technological Catch-Up, and Capital Deepening: Relative Contributions to Growth and Convergence.” *American Economic Review* 92(3): 527–548.

Lee, H. L., T. H. Hertel, B. Sohngen, and N. Ramankutty. 2005. *Towards an Integrated Land Use Data Base for Assessing the Potential for Greenhouse Gas Mitigation*. GTAP Technical Papers No. 26. West Lafayette, IN, US: Global Trade Analysis Project.

Ludena, C. E., T. W. Hertel, P. V. Preckel, K. Foster, and A. Nin. 2007. “Productivity Growth and Convergence in Crop, Ruminant, and Non-Ruminant Production: Measurement and Forecasts.” *Agricultural Economics* 37 (1): 1–17.

Lusigi, A., and C. Thirtle. 1997. “Total Factor Productivity and the Effects of R&D in African Agriculture.” *Journal of International Development* 9: 529–538.

Maddala, G. S., and S. Wu. 1999. “A Comparative Study of Unit Root Tests With Panel Data and a New Simple Test.” *Oxford Bulletin of Economics and Statistics* 61 (Special Issue): 631–652.

Nin, A., C. Arndt, and P. Preckel. 2003. “Is Agricultural Productivity in Developing Countries Really Shrinking? New Evidence Using a Modified Non-Parametric Approach.” *Journal of Development Economics* 71: 395–415.

Nin-Pratt, A., and B. Yu. 2008. *An Updated Look at the Recovery of Agricultural Productivity in Sub-Saharan Africa.* IFPRI Discussion Paper 787. Washington, DC: International Food Policy Research Institute.

———. 2012. “Agricultural Productivity and Policy Changes in Sub-Saharan Africa.” In *Productivity Growth in Agriculture: An International Perspective*, edited by K. O. Fuglie, S. L. Wang and V. E. Ball, 273-–292. Wallingford, OX, UK: Commonwealth Agricultural Bureau International.

Parente, S. L., and E. C. Prescott. 1994. “Barriers to Technology Adoption and Development.” *Journal of Political Economy* 102 (2): 298–321.

Pesaran, M. H. 2004. *General Diagnostic Tests for Cross Section Dependence in Panels.* CESifo Working Paper 1229; IZA Discussion Paper 1240. University of Cambridge.

———. 2006. “Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure.” *Econometrica* 74 (4): 967–1012.

———. 2007. “A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence.” *Journal of Applied Econometrics* 22 (2): 265–312.

Pesaran, M. H., and R. P. Smith. 1995. "Estimating Long-Run Relationships from Dynamic Heterogeneous Panels." *Journal of Econometrics* 68 (1): 79–113.

Prasada Rao, D. S., and T. J. Coelli. 2004. Catch-up and Convergence in Global Agricultural Productivity, 1980–1995. *Indian Economic Review* 39 (1): 123–148.

Rambaldi, A. N., D. P. Rao, and D. Dolan. 2007. *Measuring Productivity Growth Performance Using Metafrontiers with Applications to Regional Productivity Growth Analysis in a Global Contex*t. Paper presented at the 2007 Australasian Meeting of the Econometric Society, Queensland, Australia, July 4–6.

Segerstrom, P. S., T. C. A. Anant, and E. Dinapoulos. 1990. "A Schumpeterian Model of the Product Life Cycle." *American Economic Review* 80: 1077–1092.

Suhariyanto, K., A. Lusigi, and C. Thirtle. 2001. "Productivity Growth and Convergence in Asian and African Agriculture." In *Asia and Africa in Comparative Economic Perspective*, edited by P. Lawrence and C. Thirtle, 258–274. London: Palgrave.

Suhariyanto, K., and C. Thirtle. 2001. "Asian Agricultural Productivity and Convergence*." Journal of Agricultural Economics* 52: 96–110.

Trueblood, M. A., and J. Coggins. 2003. *Intercountry Agricultural Efficiency and Productivity: A Malmquist Index Approach*. Mimeo. Washington, DC: World Bank.

USDA (United States Department of Agriculture). 2014. Economic Research Service: Dataset on International Agricultural Productivity. Accessed August 12, 2014. http://www.ers.usda.gov/data-products/international-agricultural-productivity.aspx.

World Bank. 2014. "World Development Indicators." Accessed March 2014, 2015. http://data.worldbank.org/.

RECENT IFPRI DISCUSSION PAPERS

For earlier discussion papers, please go to www.ifpri.org/pubs/pubs.htm#dp.
All discussion papers can be downloaded free of charge.

1431. *When expectations become aspirations: Reference-dependent preferences and liquidity Constraints. Berber* Kramer, 2015.

1430. *Demand for complementary financial and technological tools for managing drought risk*. Patrick S. Ward, David J. Spielman, David L. Ortega, Neha Kumar, and Sumedha Minocha, 2015.

1429. *Examining gender inequalities in land rights indicators in Asia.* Caitlin Kieran, Kathryn Sproule, Cheryl Doss, Agnes Quisumbing, and Sung Mi Kim, 2015.

1428. Is reliable water access the solution to undernutrition?: A review of the potential of irrigation to solve nutrition and gender gaps in Africa south of the Sahara. Laia Domènech, 2015.

1427. *What will it take for biofortification to have impact on the ground?: Theories of change for three crop-country combinations.* Nancy Johnson, Hannah Guedenet, and Amy Saltzman, 2015.

1426. *Managing risk with insurance and savings: Experimental evidence for male and female farm managers in West Africa*. Clara Delavallade, Felipe Dizon, Ruth Vargas Hill, and Jean Paul Petraud, 2015.

1425. *The impact of "at-the-border" and "behind-the-border" policies on cost-reducing research and development*. Julien Berthoumieu and Antoine Bouët, 2015.

1424. *Market imperfections for tractor service provision in Nigeria:* International Perspectives and Empirical Evidence. Hiroyuki Takeshima, 2015.

1423. *Agriculture, nutrition, and the Green Revolution in Bangladesh*. Derek D. Headey and John Hoddinott, 2015.

1422. *Rural finance and agricultural technology adoption in Ethiopia: Does institutional design matter?* Gashaw Tadesse Abate, Shahidur Rashid, Carlo Borzaga, and Kindie Getnet, 2015.

1421. *Is more inclusive more effective? The "new-style" public distribution system in India*. Avinash Kishore and Suman Chakrabarti, 2015.

1420. E*xplicitly integrating institutions into bioeconomic modeling*. Kimberly A. Swallow and Brent M. Swallow, 2015.

1419. *Time allocation to energy resource collection in rural Ethiopia: Gender-disaggregated household responses to changes in firewood availability*. Elena Scheurlen, 2015.

1418. *Communities' perceptions and knowledge of ecosystem services: Evidence from rural communities in Nigeria*. Wei Zhang, Edward Kato, Prapti Bhandary, Ephraim Nkonya, Hassan Ishaq Ibrahim, Mure Agbonlahor, and Hussaini Yusuf Ibrahim, 2015.

1417. *2011 social accounting matrix for Senegal.* Ismaël Fofana, Mamadou Yaya Diallo, Ousseynou Sarr, and Abdou Diouf, 2015.

1416. *Firm heterogeneity in food safety provision: Evidence from Aflatoxin tests in Kenya*. Christine Moser and Vivian Hoffmann, 2015.

1415. *Mechanization outsourcing clusters and division of labor in Chinese agriculture*. Xiaobo Zhang, Jin Yang, and Thomas Reardon, 2015.

1414. *Conceptualizing drivers of policy change in agriculture, nutrition, and food security: The Kaleidoscope Model.* Danielle Resnick, Suresh Babu, Steven Haggblade, Sheryl Hendriks, and David Mather, 2015.

1413. *Value chains and nutrition: A framework to support the identification, design, and evaluation of interventions.* Aulo Gelli, Corinna Hawkes, Jason Donovan, Jody Harris, Summer Allen, Alan de Brauw, Spencer Henson, Nancy Johnson, James Garrett, and David Ryckembusch, 2015.

1412. *Climate change adaptation assets and group-based approaches: Gendered perceptions from Bangladesh, Ethiopia, Mali, and Kenya.* Noora Aberman, Snigdha Ali, Julia A. Behrman, Elizabeth Bryan, Peter Davis, Aiveen Donnelly, Violet Gathaara, Daouda Kone, Teresiah Nganga, Jane Ngugi, Barrack Okoba, and Carla Roncoli, 2015.

1411. *Information networks among women and men and the demand for an agricultural technology in India.* Nicholas Magnan, David J. Spielman, Kajal Gulati, and Travis J. Lybbert, 2015.

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

www.ifpri.org

IFPRI HEADQUARTERS

2033 K Street, NW
Washington, DC 20006-1002 USA
Tel.: +1-202-862-5600
Fax: +1-202-467-4439
Email: ifpri@cgiar.org