Chapter 2

INTERTEMPORAL TRENDS IN AGRICULTURAL PRODUCTIVITY

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Introduction

Changes or trends in agricultural productivity over time can shed light on the relative sources of agricultural growth as well as on resource and factor constraints to increasing agricultural production sustainably. Because improvements in agricultural productivity are important for reducing poverty and achieving other development objectives, it is essential to use the appropriate indicator and measure of agricultural productivity—partial factor productivity (PFP) or total factor productivity (TFP). However, because productivity embodies many different components, changes in productivity can catalyze a wide range of direct and indirect effects on the pathways to achieving different development objectives.

For example, output per worker or labor productivity, as indicators of PFP, may be better measures of productivity to identify linkages to nonagricultural growth, because it encapsulates the additional ways farm households earn income (Mellor 1999). Byerlee, Diao, and Jackson (2009) show that countries with the highest agricultural growth per worker experienced the greatest rate of rural poverty reduction. Other measures of PFP have been found to be significant determinants of poverty. Datt and Ravallion (1998), for example, find that higher land productivity (measured by agricultural output per unit area) had greater effect in reducing absolute poverty than in reducing the poverty gap or squared poverty gap, suggesting that the gains from higher land productivity were via rising average living standards, rather than improved distribution. Because changes in PFP could be caused by change from a variety of reasons, including change in the use of other inputs or change in output mix, the policy implications of changes in PFP measures are often unclear. Furthermore, changes in output and productivity also do not necessarily have similar impacts, and sometimes move in different directions, with differential consequences for poverty (Schneider and Gugerty 2011), and productivity

gains, depending on the distribution of assets, may have limited impact on poverty reduction (Thirtle, Lin, and Piesse 2003).

Unlike these PFP measures, TFP measures provide a better sense of the changes in agricultural productivity that are attributable to technological change, which, for many policymakers and the Comprehensive Africa Agriculture Development Programme (CAADP), is a critical means of improving African agriculture. Known as the Solow residual, TFP measures the part of growth that is not accounted for by changes in conventional factors of production, such as land, labor, or capital. As a residual, however, the source of TFP growth is varied. Fan, Hazell, and Thorat (2000) found that investments in roads, agricultural research and development, and education were significant determinants of TFP, which in turn had a substantial effect on reducing poverty via reduced prices and increased wages, but at the cost of increased landlessness. Rahman and Salim (2013) show that the different sources can have different effects on the various components of TFP, which, similar to the case with the PFP measures, also suggests that the policy implications of changes in TFP can be complex.

Deciding what indicator and measure of agricultural productivity to use is complicated by knowledge gaps across several dimensions of the different components embodied in productivity, including

- Composition of agriculture—sector (all agriculture), subsector (crops, livestock, fisheries, forestry), commodity group (such as cereal, export crops, meat), and commodity (such as maize, rice, beef, tilapia);
- Type of factor (land, labor, capital), input (seed, fertilizer, feed), or husbandry (plant spacing, weeding, intensive livestock management);
- Measure of output and input—physical quantity or monetary value, which is important when aggregating across several subcomponents, because summing over weights or volumes may not be meaningful;
- Time (annual, long-term average, most recent years) and space (countries, regions, agroecologies, stage of development, endowment, etc.); and
- Level of aggregation (plot, farm, household, subnational, national, regional, continental).

The objective of this chapter is to assess changes over time and across different parts of Africa, in both partial and total measures of agricultural productivity, to understand the relative sources of productivity growth. We begin the next section with a presentation of the partial and total measures

of productivity, in addition to the data used in estimating the indicators and in conducting the analysis. This is followed by trends analysis of the indicators and key drivers, and then conclusions and implications for using different measures and indicators.

Productivity Measures and Methodology

Partial factor productivity is a ratio of output to a subset of the inputs, usually one input, described as single-factor productivity. Two commonly used measures of PFP are land productivity (defined as the ratio of output to total harvested area) and labor productivity (the ratio of output to total number of hours worked). Obviously, these two PFP measures differ from one another by the variables they measure, as well as by the variables they exclude. PFP measures make it possible to focus on a given variable (that is, land or labor in the two examples above), to assess how that variable is changing relative to the output.

Total factor productivity, conceptually also a measure of output to inputs, is commonly measured as an index of the ratio of total agricultural outputs to total agricultural inputs. As such, TFP analysis can be seen as an extension of PFP analysis, since the variables used in measuring PFP are included in the variables used in measuring TFP. Use of TFP is favored in the analysis of productivity, because long-run agricultural growth depends on TFP growth, which can be decomposed into finer measures, including the three that are commonly estimated or presented in the literature: *technical change*, arising from movement of the technological frontier; *technical-efficiency change,* arising from movement of observations toward or away from the technological frontier; and *scale-efficiency change,* arising from movement of observations about the technological frontier to capture economies of scale.[1]

In principle, measuring PFP is straightforward, and the data requirements are not complicated. Measuring TFP, however, can be challenging, especially for developing countries that lack data on prices to use in aggregating outputs and inputs. Several methods for and approaches to measuring TFP are available, differing mainly in how outputs and inputs are aggregated. The methods can be classified into two broad groups: (1) nonparametric methods, including

1 Some studies have tried to decompose finer measures of efficiency change, distinguishing, for example, allocative efficiency change for inputs, allocative efficiency change for outputs, residual scale-efficiency change, etc. (for example, Rahman and Salim 2013). Details of the TFP decomposition in general, as well as the changes analyzed in the study (that is, technical-efficiency change and technical change), are presented in the appendix to this chapter.

index-based growth accounting (for example, the Törnqvist-Theil index) and data envelopment analysis (DEA); and (2) parametric methods, including econometric estimation of the technology, often by stochastic frontier analysis. (See, for example, Coelli, Prasada Rao, and Battese [1998] and Coelli and Prasada Rao [2001] for review of the different methods and measurement issues.) This study uses the Malmquist index approach, where the index is calculated by DEA, using one output and six inputs, and assuming sequential technology that rules out technological regression or negative growth rates in technical change. This method, referred to as the DEA-Malmquist index, is fully documented in Nin-Pratt and Yu (2010), so we present the main aspects of it in Appendix 2A of this chapter.

The literature has identified some issues with use of DEA methods to calculate distance functions. The major drawbacks include nonstochastic functions—that is, lack of including a random-error term to account for statistical noise; determination of implicit or shadow prices used in aggregating inputs; and dimensionality, or the number of inputs and outputs used relative to the number of observations in the cross-section. These issues and how they are dealt with in this study are also discussed in Appendix 2A.

To generate greater confidence in the findings associated with this method, however, we compare the results with those obtained using three other approaches that differently address the issues with DEA. These include two other versions of the DEA-Malmquist index: one is calculated by using two outputs to deal with the dimensionality issue, and the other is calculated by including lower and upper bounds on the shadow prices. The third method is the more conventional growth-accounting TFP index, where inputs are aggregated using fixed-input shares for all countries and periods. A brief comparison of the results is presented in Appendix 2B. Overall, the different methods yield similar TFP growth patterns, with the DEA-Malmquist–2-output-index giving higher growth rates, followed by the DEA-Malmquist–1-output-index, the DEA-Malmquist-bounds-index, and the growth-accounting-TFP-index.

Data and Sources of Data

The data used in the measurements of the different PFP and TFP indicators are drawn mostly from the Food and Agriculture Organization of the United Nations FAOSTAT database on agricultural production (FAO 2014), which covers the period 1961–2012. The data, which are detailed in Table 2.1, include one output (total agricultural production) and six inputs (land, labor, fertilizer, animal feed, crop capital, and livestock capital). The two PFP

TABLE 2.1 Description of variables and data used in estimating partial and total factor productivity

Variable	Description
Output	Value of gross crop and livestock production expressed in constant 2004–2006 international dollars. In the case of Nigeria, output for 2001–2012 was adjusted using agricultural value-added data from the World Development Indicators (World Bank 2014) to better reflect recent growth measured at the country level.
Land	Hectares of land, including land under temporary crops (doubled-cropped areas are counted only once); temporary meadows for mowing or pasture, such as land used permanently (five years or more) for herbaceous forage crops, either cultivated or growing wild (wild prairie or grazing land); land under market and kitchen gardens; land temporarily under fallow (less than five years); land cultivated with permanent crops, such as flowering shrubs (coffee), fruit trees, nut trees, and vines, but excluding land under trees grown for wood or timber.
Labor	Total economically active population engaged in or seeking work in agriculture, hunting, fishing, or forestry, whether as employers, their own account workers, salaried employees, or unpaid workers assisting in the operation of a family farm or business. This is an uncorrected measure of labor that does not account for actual hours worked or labor quality (education, age, experience, etc.). Data for Nigeria were adjusted following Fuglie (2011).
Fertilizer	Metric tons of nitrogen, phosphorus, and potassium nutrients consumed.
Animal feed	Metric tons (maize equivalent) 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) fed to livestock.
Crop capital	Sum of gross fixed capital stock in constant 2005 US$: • *Land development:* major improvements in the quantity, quality, or productivity of land to prevent its deterioration, including (1) on-field land improvement undertaken by farmers (includes work done on the field, such as making boundaries and irrigation channels); and (2) other activities, such as irrigation works, soil conservation works, and flood control structure, undertaken by government and other local bodies. • *Plantation crops:* trees yielding repeated products (including vines and shrubs) cultivated for fruits and nuts, sap and resin, bark and leaf products, etc. • *Machinery and equipment:* tractors (with accessories), harvesters and thrashers, and hand tools.
Livestock capital	Sum of gross fixed capital stock in constant 2005 US$: • *Animal stock:* stock of cattle and buffalo, camels, horses, mules, asses, pigs, goats, sheep, and poultry. • *Structures for livestock:* sheds constructed for housing cows, buffalo, horses, camels, and poultry. • *Milking machines:* machinery and related equipment used for milking animals.

Source: Authors' representation based on FAO (2014).

Notes: Crop and livestock capital cover 1975–2007. The values were developed by multiplying the quantity of physical assets in use by unit prices compiled from individual countries. Each asset held at a point in time is valued at the price at the same time, regardless of the age or actual condition of the asset.

measures of land productivity and labor productivity were obtained by dividing output by land and labor, respectively. TFP was calculated using the Malmquist index presented in Appendix 2A.

The results for each PFP and TFP indicator are presented at an aggregate level for the entire continent (which includes 45 of the 55 African countries because of data issues),[2] Africa south of the Sahara (SSA), and the five geographic regions of the African Union (central, eastern, northern, southern, and western). Table 2.2 presents the distribution of countries. The other type of aggregation or grouping used in the analysis and on which results are presented derives from the concept that different countries, depending on their resource endowments and stage of development, are on different trajectories toward achieving their development objectives (Diao et al. 2007). We use a four-category economic development typology based on three factors: agricultural potential, alternative (or nonagricultural) sources of growth, and income level (Benin et al. 2010; Appendix Table 2C.1).

We also present in Appendix Table 2C.2 the results of aggregation based on Regional Economic Communities (RECs). In general, we use the three different regional aggregations (geographic region, economic development classification, and REC) to generate greater confidence in the results of the analysis. However, the aggregations based on the latter two seem more rational, because they are based on economic criteria that are appropriate to the subsequent economic analysis of PFP and TFP. The aggregation based on geographic region seems more of a convenience or convention following the African Union. Therefore, apart from the political rationale and some economic ties in the case of western Africa (which also constitutes the Economic Community of West African States [ECOWAS] REC), the analyses of PFP and TFP that draw on a geographic perspective are relatively less significant. In all cases, the aggregated values of an indicator are estimated using the weighted sum approach, where the weight for each country is the share of that country's value of output relative to the total value of output for all countries in the region or group. To assess the effect of size and growth path as conditioning performance, we also present trends separately for the large and small agricultural economies and for the fast-growing and slow-growing agricultural economies (Appendix Table 2C.3).

2 Excludes Cape Verde, Comoros, Djibouti, Equatorial Guinea, Eritrea, Lesotho, Mayotte, São Tomé and Príncipe, Seychelles, and South Sudan for lack of data on all the relevant variables used in calculating TFP.

TABLE 2.2 Countries by geographic region and country's share in region's total agriculture value-added (%)

Central Africa (5.3)	East Africa (23.6)	North Africa (26.7)	Southern Africa (8.0)	West Africa (36.4)
Burundi (5.0)	Comoros (–)	Algeria (22.5)	Angola (21.0)	Benin (2.6)
Cameroon (35.7)	Djibouti (0.1)	Egypt (50.7)	Botswana (1.7)	Burkina Faso (3.6)
Central African Rep. (7.8)	Eritrea (–)	Libya (–)	Lesotho (0.8)	Cape Verde (0.1)
Chad (8.5)	Ethiopia (29.2)	Mauritania (1.5)	Malawi (9.4)	Côte d'Ivoire (5.3)
Congo, Dem. Rep. (37.4)	Kenya (13.7)	Morocco (18.3)	Mozambique (14.9)	Gambia, The (0.4)
Congo, Rep. (2.8)	Madagascar (5.1)	Tunisia (7.0)	Namibia (3.8)	Ghana (7.1)
Equatorial Guinea (2.6)	Mauritius (0.8)		South Africa (37.5)	Guinea (1.4)
Gabon (–)	Rwanda (3.6)		Swaziland (1.3)	Guinea-Bissau (0.4)
São Tomé & Príncipe (0.2)	Seychelles (0.0)		Zambia (9.6)	Liberia (0.6)
	Somalia (–)		Zimbabwe (–)	Mali (3.5)
	South Sudan (2.8)			Niger (2.4)
	Sudan (21.2)			Nigeria (67.4)
	Tanzania (15.3)			Senegal (2.2)
	Uganda (8.2)			Sierra Leone (1.3)
				Togo (1.6)

Source: Authors' calculations based on World Bank (2012).

Notes: The figures in parentheses are the regions' percentage shares in Africa's total agriculture value-added, and the countries' percentage shares in their respective regions' totals (2003–2010 annual average). Dashes indicate data are not available. Data for South Sudan and Sudan are based on 2008–2010 values.

Results

Annual trends in land and labor productivity

Annual trends in land and labor productivity are detailed in Tables 2.3a and 2.3b, Figure 2.1, and Appendix Figures 2C.1–2C.3 for the aggregations and for selected countries. The graphics are quite revealing and offer a quick overview of the comparative growth in land versus labor productivity or changes in land–labor intensity over time. There are three aspects to the plots in comparing the trends: their position in the quadrant space, their slope, and their length.

- The plot's *position* shows the magnitude, which is increasing in both land and labor productivity, going from the origin in a northeasterly direction.

- For a particular plot, the *slope* reflects the relative growth rates of labor and land productivity. With land productivity plotted on the *y*-axis and labor productivity on the *x*-axis, a slope steeper than the 45-degree line reflects a higher land productivity growth rate relative to the labor productivity growth rate and, therefore, a decreasing land-to-labor ratio. Conversely, a plot flatter than the 45-degree line means the labor productivity growth rate is higher than the land productivity growth rate and, therefore, has an increasing land-to-labor ratio. (This can be extended to compare different plots. For any two plots, the steeper one has a higher labor-to-land ratio, irrespective of the position of the plots in the quadrant.)
- The *length* of a plot reflects the magnitude of the combined growth rates, with a longer plot depicting a larger combined growth rate and a shorter plot depicting a smaller combined growth rate, again irrespective of the position of the plot in the quadrant.

AFRICA AND GEOGRAPHIC SUBREGIONS

Table 2.3a and Table 2.3b, Figure 2.1, and Appendix Figures 2C.1–2C.3 show that the trends in land and labor productivity are highly variable in different dimensions across different parts of the continent. For Africa as a whole, land productivity increased on average by 3.3 percent per year in 1961–2012, compared with a 2.0 percent increase per year for labor productivity, starting from 1961–1970 average levels of $256 per hectare (ha) and $892 per worker.[3] Compared with the entire continent, SSA realized lower growth rates in both land productivity (2.8 percent) and labor productivity (1.7 percent) over the same periods. These rates reflect the higher growth rates achieved in northern Africa, which experienced an annual average rate of growth of 3.2 percent in land productivity and 3.0 percent in labor productivity.

Northern and southern Africa have the highest annual average labor productivities, at $1,953 per worker in northern Africa and $3,333 per worker in southern Africa, compared with only $561 in central Africa, $612 in eastern Africa, and $999 in western Africa. Comparing the northern and southern Africa regions shows some significant differences, however. First, land productivity is much higher in northern Africa: $1,942/ha on average in 1961–2012, compared with only $92/ha in southern Africa over the same period. The relatively low land productivity in the southern region reflects the much higher

3 All currency is in constant 2004–2006 "international dollars," unless specifically noted as US dollars.

land-to-labor ratios associated with large plantations, with more mechanized agricultural operations. Second, whereas labor productivity has risen much faster than land productivity in southern Africa (with annual averages of 2.6 and 2.2 percent, respectively, in 1961–2012), land and labor productivities in northern Africa have risen at a roughly equal rate (3.2 and 3.0 percent, respectively). The trends observed in northern and southern Africa are driven by Egypt and South Africa, respectively: Egypt accounts for 51 percent of the total agriculture value-added in northern Africa, while South Africa accounts for about 44 percent in southern Africa (Table 2.2).

Figure 2.1 shows that the trends in central and eastern Africa are fairly similar, with land and labor productivity much lower than the levels for Africa as a whole. In 1961–2012, the annual average growth in land productivity in the two subregions was about 1.6 percent, compared with the range of 0.5–0.8 for labor productivity. The trend in western Africa is closer to the trend for Africa as a whole, although western Africa experienced a higher growth rate in land productivity (3.6 percent) and lower growth rate in labor productivity (1.8 percent) in 1961–2012.

Looking at the trends by subperiods (1961–1970, 1971–1980, 1981–1990, 1991–2000, and 2001–2012), Table 2.3b shows that labor productivity in Africa as a whole and in SSA increased more rapidly in 2001–2012 than in any of the preceding decades since 1961. While the patterns for the five geographic subregions differ, the general trend remains.

Many of the above results are consistent with the findings of other studies, but some are different. For example, whereas the findings of higher land than labor productivity growth rates in Africa as a whole are consistent with the results of previous studies on Africa (for example, Thirtle and Piesse 2008; Fuglie and Nin-Pratt 2013), the growth rates obtained in this chapter are larger, and are especially so for labor productivity. For example, Thirtle and Piesse (2008) estimate respective land and labor productivity growth rates at 2.0 and 0.4 percent for 1961–2003,[4] whereas Fuglie and Nin-Pratt (2013) estimate respective land and labor productivity growth rates at 2.3 and 0.6 percent for 1971–2009. Although we use more updated data in this study, country composition in this and other studies accounts for the bulk of the differences. In the Thirtle and Piesse (2008) study, for example, South Africa, which experienced a much higher growth rate in labor productivity than land productivity (Table 2.3b), was excluded. The results obtained here for the

4 The estimated average slope coefficient for the plots in Thirtle and Piesse (2008), however, is almost exactly unity, suggesting equal growth rates in land and labor productivity.

TABLE 2.3a Land and labor productivity (annual average level, 1961–2012)

	Subperiods			
	1961–1970		1971–1980	
Aggregations	Land	Labor	Land	Labor
Africa	256	892	323	1,102
Africa, south of the Sahara	104	863	124	1,063
Geographic location				
Central	136	488	152	518
Eastern	117	560	147	605
Northern	923	1,010	1,186	1,261
Southern	52	1,697	75	2,533
Western	115	768	125	736
Economic group				
LI–1	82	434	99	451
LI–2	98	466	131	506
LI–3	124	605	145	577
MI	362	1,167	460	1,516
Regional Economic Community				
CEN-SAD	379	807	484	886
COMESA	528	637	647	727
EAC	208	710	260	932
ECCAS	138	483	167	501
ECOWAS	115	768	125	736
IGAD	89	550	124	615
SADC	85	1,250	101	1,776
UMA	74	1,075	96	1,450
Other economic groups				
Large	374	1,061	476	1,357
Small	553	1,105	542	1,262
Fast-growing	125	700	145	632
Slow-growing	196	816	206	1,063
Selected countries				
Large				
Egypt	1,889	933	2,394	1,050
Ethiopia	57	335	62	299
Kenya	66	460	94	494
Morocco	94	924	107	1,019

Subperiods (continued)							
1981–1990		1991–2000		2001–2012		1961–2012	
Land	Labor	Land	Labor	Land	Labor	Land	Labor
456	1,271	685	1,557	935	2,078	547	1,407
142	1,189	208	1,315	328	1,771	187	1,261
177	526	202	536	266	706	189	561
149	553	175	575	236	742	168	612
1,685	1,580	2,390	2,414	3,261	3,242	1,942	1,953
90	3,347	100	3,663	137	5,077	92	3,333
155	770	275	1,086	460	1,531	235	999
123	451	135	417	143	434	117	437
135	451	181	436	249	482	162	469
174	574	163	586	220	687	167	609
669	1,811	965	2,155	1,287	2,856	769	1,938
692	1,006	981	1,465	1,296	1,975	787	1,257
938	804	1,450	1,234	1,966	1,687	1,139	1,044
267	921	309	1,195	401	1,237	293	1,008
207	495	221	502	303	641	211	529
155	770	275	1,086	460	1,531	235	999
115	555	152	597	204	813	139	633
118	2,189	131	2,372	160	3,349	121	2,232
123	1,857	164	2,562	219	3,294	138	2,095
697	1,601	1,035	1,905	1,360	2,585	811	1,736
511	1,422	545	1,534	592	1,779	550	1,434
186	655	305	1,023	522	1,510	267	927
230	1,081	263	1,457	289	1,770	239	1,258
3,398	1,275	4,425	2,263	5,901	3,191	3,690	1,798
75	279	121	224	203	274	107	282
130	507	161	457	239	521	142	489
137	1,258	172	1,576	252	2,447	156	1,483

(continued)

TABLE 2.3A (continued)

	Subperiods			
	1961–1970		1971–1980	
Aggregations	Land	Labor	Land	Labor
Nigeria	133	858	140	749
South Africa	58	2,586	79	3,939
Sudan	22	677	31	796
Tanzania	72	364	83	379
Small				
Botswana	6	844	7	957
Gabon	21	524	27	689
Gambia, The	176	574	164	450
Guinea-Bissau	66	394	65	353
Mauritius	1,933	2,244	1,975	2,331
Swaziland	78	982	128	1,508
Fast-growing				
Angola	17	503	17	432
Cameroon	154	525	196	668
Malawi	147	284	203	349
Mozambique	24	290	27	277
Nigeria	133	858	140	749
Rwanda	384	376	485	418
Sierra Leone	112	365	130	408
Zambia	18	340	27	410
Slow-growing				
Burundi	418	465	386	469
Congo, Dem. Rep.	100	455	119	447
Liberia	82	520	116	597
Mauritius	1,933	2,244	1,975	2,331
Namibia	9	2,001	11	2,330
Tunisia	114	1,536	173	2,397
Zimbabwe	73	576	106	708

Source: Authors' calculation and representation based on FAO (2014).

Notes: Land productivity is in constant 2004–2006 international dollars (I$) per hectare, and labor productivity is in constant 2004–2006 I$ per worker. LI–1 = low income, more favorable agriculture, and mineral rich; LI–2 = low income, more favorable agriculture, and nonmineral rich; LI–3 = low income and less favorable agriculture; MI = middle income. CEN-SAD = Community of Sahel-Saharan States; COMESA = Common Market for Eastern and Southern Africa; EAC = East African Community; ECCAS = Economic Community of Central African States; ECOWAS = Economic Community of West African States; IGAD = Intergovernmental Authority on Development; SADC = Southern African Development Community; UMA = Union du Maghreb Arabe. Large agricultural economies have at least 3.0 percent of Africa's total agricultural output; small agricultural economies have less than 0.1 percent of Africa's total agricultural output; fast-growing agricultural economies surpass the CAADP agricultural growth rate target of 6.0 percent per year; and slow-growing agricultural economies have an agricultural growth rate of less than 1.0 percent per year.

Subperiods (continued)							
1981–1990		1991–2000		2001–2012		1961–2012	
Land	Labor	Land	Labor	Land	Labor	Land	Labor
176	777	334	1,223	586	1,807	286	1,111
90	5,236	97	6,039	123	9,334	91	5,577
35	796	45	1,005	78	1,556	44	988
105	384	123	339	186	426	117	380
8	970	8	917	10	827	8	900
36	898	44	1,091	52	1,401	37	939
159	324	158	214	228	230	179	354
92	413	116	477	162	613	103	456
2,045	2,635	2,309	3,496	2,721	4,805	2,217	3,168
197	1,974	208	1,760	229	1,999	170	1,658
14	273	19	275	45	480	23	396
216	704	283	781	452	1,185	267	788
238	337	296	359	465	537	277	379
23	209	29	214	47	283	30	256
176	777	334	1,223	586	1807	286	1111
587	422	608	391	937	435	613	409
145	407	145	393	231	626	156	447
32	345	37	323	54	413	34	368
432	418	450	366	457	308	430	401
151	459	166	397	148	286	137	404
134	586	108	453	154	489	120	527
2,045	2,635	2,309	3,496	2,721	4,805	2,217	3,168
9	1,814	10	1,672	11	1,618	10	1,877
216	2,794	295	3,852	348	4,349	234	3,038
115	598	118	522	100	505	102	579

TABLE 2.3B Land and labor productivity (%, annual average growth rate, 1961–2012)

	Subperiods			
	1961–1970		1971–1980	
Aggregations	Land	Labor	Land	Labor
Africa	2.20	1.87	3.01	2.26
Africa, south of the Sahara	3.05	1.85	–0.08	2.49
Geographic location				
Central	1.82	0.66	0.32	0.22
Eastern	3.22	1.45	–0.82	–1.07
Northern	2.32	1.98	4.04	1.31
Southern	3.26	2.35	3.49	5.99
Western	3.29	1.70	–0.67	–1.50
Economic group				
LI–1	1.98	0.36	1.41	–0.18
LI–2	3.82	1.47	–0.75	–1.34
LI–3	2.48	1.13	0.95	–0.75
MI	2.01	2.05	3.73	3.17
Regional Economic Community				
CEN-SAD	1.91	1.85	3.60	0.01
COMESA	1.87	1.65	3.21	0.42
EAC	3.56	1.24	–0.93	–0.31
ECCAS	2.60	0.91	1.65	–0.38
ECOWAS	3.29	1.70	–0.67	–1.50
IGAD	4.83	1.82	–2.32	–1.26
SADC	1.39	2.10	2.02	5.03
UMA	1.89	2.16	1.56	1.66
Other economic groups				
Large	1.93	2.11	3.62	3.26
Small	–0.29	1.47	–0.25	0.78
Fast-growing	3.81	1.97	0.56	–2.69
Slow-growing	0.50	0.76	0.61	0.36
Selected countries				
Large				
Egypt	1.58	1.80	3.82	0.95
Ethiopia	1.97	0.06	1.07	–0.66
Kenya	2.96	0.38	3.78	0.77
Morocco	3.21	3.66	0.26	–0.62

Subperiods (continued)							
1981–1990		1991–2000		2001–2012		1961–2012	
Land	Labor	Land	Labor	Land	Labor	Land	Labor
3.86	1.25	3.53	2.14	2.16	3.18	3.31	2.04
3.16	0.32	3.27	1.65	5.20	3.32	2.82	1.67
2.53	0.17	–0.15	0.29	4.81	4.80	1.63	0.81
2.01	–0.18	1.30	1.07	2.96	1.59	1.59	0.54
2.99	3.93	3.45	3.02	1.63	3.19	3.20	2.96
1.24	0.78	2.64	1.27	3.36	3.58	2.22	2.56
4.73	2.28	4.60	2.66	5.75	4.02	3.59	1.81
2.51	0.38	–1.22	–1.74	2.35	1.98	1.37	–0.06
2.68	–0.03	2.99	0.17	2.75	1.15	2.21	–0.04
1.52	0.44	–2.20	0.67	4.81	2.30	1.26	0.32
3.73	1.13	3.21	1.90	1.89	3.15	3.25	2.14
3.48	2.98	3.04	2.84	1.88	3.19	3.13	2.30
4.22	2.31	3.76	4.44	1.84	2.38	3.41	2.47
1.74	1.74	0.94	0.27	2.86	1.48	1.49	1.29
1.83	0.00	–0.32	0.04	4.89	4.41	1.85	0.61
4.73	2.28	4.60	2.66	5.75	4.02	3.59	1.81
2.73	–0.22	2.34	1.80	2.58	1.74	1.89	0.79
1.85	0.32	0.62	1.92	2.49	3.51	1.52	2.27
4.63	3.89	1.18	1.69	4.03	3.71	2.67	2.77
3.89	0.90	3.51	2.24	1.69	3.17	3.32	2.13
1.66	2.02	0.10	–0.35	–0.70	1.50	0.16	1.13
3.63	3.20	4.20	2.68	5.90	4.70	3.63	2.06
2.44	1.74	–0.21	1.07	1.45	2.92	1.01	1.81
3.21	3.84	2.22	4.76	2.13	2.72	2.87	3.22
0.98	–2.74	6.66	–1.08	4.63	3.10	3.21	–0.60
3.88	0.92	1.25	–2.04	4.67	2.85	3.11	0.20
5.76	5.71	1.10	0.73	4.83	5.65	2.48	2.43

(continued)

TABLE 2.3B (continued)

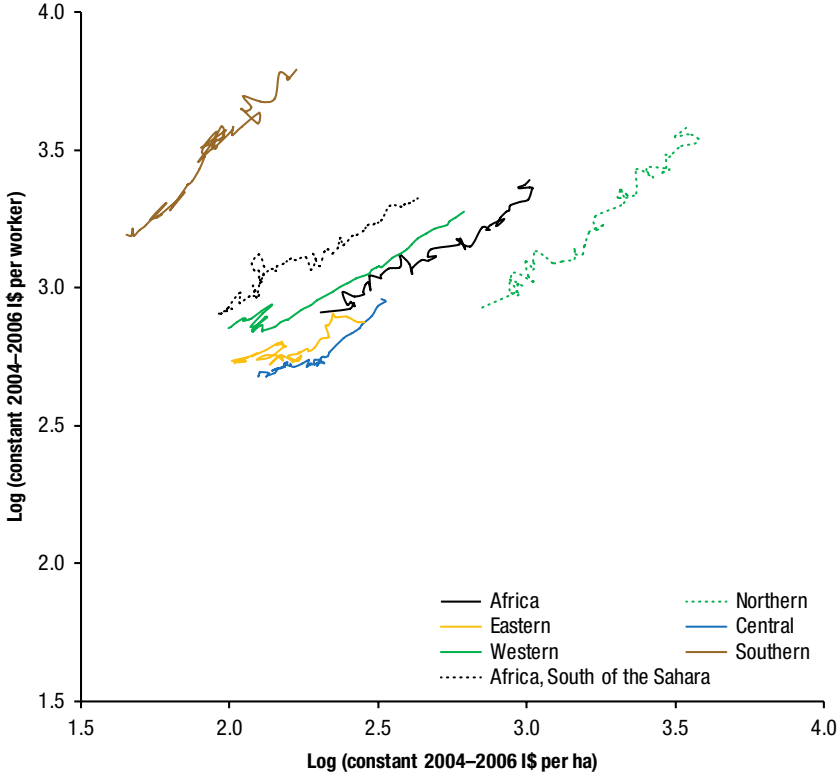
	Subperiods			
	1961–1970		1971–1980	
Aggregations	Land	Labor	Land	Labor
Nigeria	3.74	1.85	–1.20	–3.08
South Africa	3.63	2.49	2.86	5.97
Sudan	2.62	1.50	2.88	0.96
Tanzania	1.67	0.80	2.81	1.10
Small				
Botswana	3.32	2.72	–0.61	–1.31
Gabon	1.68	2.08	3.49	3.84
Gambia, The	2.21	0.25	–4.69	–6.66
Guinea-Bissau	–3.07	–2.88	2.78	0.45
Mauritius	–0.06	0.52	0.20	–0.46
Swaziland	4.21	4.39	5.11	3.61
Fast-growing				
Angola	2.97	1.97	–4.33	–6.24
Cameroon	3.17	2.60	0.42	1.11
Malawi	1.76	1.67	3.58	1.38
Mozambique	2.78	1.16	–1.76	–3.84
Nigeria	3.74	1.85	–1.20	–3.08
Rwanda	4.40	2.77	1.71	0.43
Sierra Leone	2.87	2.71	1.20	0.58
Zambia	2.78	1.13	3.10	0.46
Slow-growing				
Burundi	0.40	0.81	–0.77	–0.58
Congo, Dem. Rep.	1.72	–0.21	1.42	–0.58
Liberia	4.37	2.09	1.73	–0.38
Mauritius	–0.06	0.52	0.20	–0.46
Namibia	3.27	2.30	–1.32	–1.62
Tunisia	0.18	1.54	2.92	1.66
Zimbabwe	2.63	1.18	1.71	–0.23

Source: Authors' calculation and representation based on FAO (2014).

Notes: Annual average growth rates are calculated using the "LOGEST" function in Microsoft Excel. LI–1 = low income, more favorable agriculture, and mineral rich; LI–2 = low income, more favorable agriculture, and nonmineral rich; LI–3 = low income and less favorable agriculture; MI = middle income. CEN-SAD = Community of Sahel-Saharan States; COMESA = Common Market for Eastern and Southern Africa; EAC = East African Community; ECCAS = Economic Community of Central African States; ECOWAS = Economic Community of West African States; IGAD = Intergovernmental Authority on Development; SADC = Southern African Development Community; UMA = Union du Maghreb Arabe. Large agricultural economies have at least 3.0 percent of Africa's total agricultural output; small agricultural economies have less than 0.1 percent of Africa's total agricultural output; fast-growing agricultural economies surpass the CAADP agricultural growth rate target of 6.0 percent per year; and slow-growing agricultural economies have an agricultural growth rate of less than 1.0 percent per year.

Subperiods (continued)							
1981–1990		1991–2000		2001–2012		1961–2012	
Land	Labor	Land	Labor	Land	Labor	Land	Labor
5.40	3.58	4.91	2.67	6.15	4.66	3.87	2.03
0.93	1.05	1.25	2.36	2.57	4.81	1.73	3.00
–1.01	–0.61	4.89	3.63	3.62	2.53	2.87	1.91
2.37	–0.25	1.25	–1.23	4.09	2.75	2.30	0.25
1.14	1.15	–1.49	–4.76	3.71	2.13	1.03	–0.12
2.21	1.89	2.00	2.00	1.94	3.18	2.27	2.41
0.31	–3.48	4.12	0.81	0.17	–1.14	0.51	–2.42
3.39	2.15	2.44	2.12	3.86	2.50	2.37	1.20
1.84	4.33	0.78	1.73	1.02	2.64	0.84	1.93
2.38	0.39	–0.76	–1.42	1.64	2.33	2.57	1.54
0.89	–1.79	4.55	1.80	8.55	5.52	2.11	–0.35
1.75	0.13	3.33	2.08	5.67	5.96	2.54	1.81
0.61	–1.25	5.11	4.90	4.32	3.43	2.68	1.34
–0.84	–0.80	6.60	3.37	5.38	3.51	1.54	–0.18
5.40	3.58	4.91	2.67	6.15	4.66	3.87	2.03
0.55	–1.65	1.06	–1.76	4.92	3.01	2.05	0.25
1.65	0.02	–1.92	–1.38	9.59	8.40	1.57	1.08
4.00	0.35	0.83	–0.22	5.87	4.29	2.48	0.22
2.91	–0.52	–2.36	–2.31	1.56	–1.94	0.33	–1.07
2.85	0.62	–2.08	–4.31	0.43	–1.39	1.03	–1.09
0.22	–0.18	5.97	3.67	0.34	–2.11	1.24	–0.37
1.84	4.33	0.78	1.73	1.02	2.64	0.84	1.93
–0.21	–2.39	–0.34	–1.54	0.42	–0.16	0.44	–0.73
3.04	3.40	1.29	0.38	2.52	2.34	2.68	2.47
2.21	–0.86	2.02	2.14	–2.43	–1.35	0.67	–0.54

FIGURE 2.1 Line plots of land and labor productivity by geographic region (1961–2012)



Source: Authors' calculation and representation based on FAO (2014).
Note: I$ = international dollar.

different subperiods are consistent with the finding of a decline in the poverty rate in Africa from the long-standing average of 50 percent to 47 percent in 2008, and also in the decline in the number of the extreme poor since 2005—the first time ever (World Bank 2012).

OTHER GROUPINGS

The trends in land and labor productivity analyzed by the other aggregations (that is, by economic classification, regional economic communities, or size and growth of the agricultural sector) are presented in Tables 2.3a and 2.3b and Appendix Figures 2C.1–2C.3. Looking at the trends by economic classification (Figure 2C.1), the *middle-income* (MI) category clearly outperformed the others in both measures of productivity. In the MI countries, land

and labor productivity increased at 3.2 percent and 2.1 percent, respectively, in 1961–2012. The performance of the MI group as whole is heavily influenced by the performance of Egypt and Nigeria, which accounted for about 24 and 27 percent, respectively, of the group's total agriculture value-added (Table 2.2). However, while the land productivity growth rate was higher in Nigeria (3.9 percent) than in Egypt (2.9 percent), the labor productivity growth rate was higher in Egypt (3.2 percent) than in Nigeria (2.0) in 1961–2012 (Table 2.3b).

The other three categories of countries are *low income, more favorable agriculture, and mineral rich* (LI–1); *low income, more favorable agriculture, and nonmineral rich* (LI–2); and *low income and less favorable agriculture* (LI–3). For these groups, we see negative or stagnant growth in labor productivity in the LI–1 and LI–2 groups and little increase in the LI–3 group for 1961–2012, compared with moderate increase in land productivity (annual average growth rate of 1.3–2.2 percent for the same period). Average land and labor productivity in the LI–1 group was the lowest, with a respective annual average of only $117/ha and $437/worker in 1961–2012. Note that the LI–1 group has favorable agriculture production potential and is also rich in minerals—dominated by the Democratic Republic of the Congo, which accounts for about 41 percent of the group's total agriculture value-added. The poor performance thus seems consistent with the "resource curse" thesis. The trends by subperiods (1961–1970, 1971–1980, 1981–1990, 1991–2000, and 2001–2012) reveal that, for all four economic categories, the growth rates in both land and labor productivity were generally lower (and negative in many cases) on average in the 1970s and 1990s than in the other three subperiods. Overall, labor productivity increased more rapidly in 2001–2012 than in any of the preceding decades since 1961.

Appendix Figure 2C.2 shows the trends by REC. Two of the RECs outperformed the others in land productivity: (1) the Common Market for Eastern and Southern Africa (COMESA) REC, dominated by Egypt in total agriculture value-added, shown in Appendix Table 2C.1, with an average level of $1,139/ha; and (2) the Community of Sahel-Saharan States (CEN-SAD) REC, dominated by Nigeria and Egypt, with an average level of $787/ha for the entire period (Table 2.3a). The Southern African Development Community (SADC), dominated by Tanzania and South Africa, and the Union du Maghreb Arabe (UMA), dominated by Algeria and Morocco, outperformed the other RECs in labor productivity, with an average of $2,232/worker for SADC and $2,095/worker for UMA. The lowest-performing RECs in levels of both land and labor productivity are the Economic Community of

Central African States (ECCAS) and the Intergovernmental Authority on Development (IGAD), with respective average land and labor productivity values in the range of $139–$211/ha and $529–$633/worker. With respect to the UMA REC, where labor productivity increased faster than land productivity in 1961–2012, land productivity increased relatively faster than labor productivity in the other RECs. The East African Community (EAC) and SADC RECs experienced the most variability in land and labor productivity, as reflected in the tortuous shape of their plots in Appendix Figure 2C.2.

SELECTED COUNTRIES

Turning now to the selected countries representing the large and small agricultural economies as well as the fast-growing and slow-growing agricultural economies in Africa, Appendix Figure 2C.3a shows the plots for the four different groups, and Appendix Figures 2C.3b and 2C.3c show the results for the individual countries. Two distinct characteristics stand out. First, the plots are longer for the large or fast-growing agricultural economies and shorter for the small or slow-growing agricultural economies. This indicates more rapid combined growth in land and labor productivities in the large or fast-growing agricultural economies, which is confirmed in the individual country plots in Figure 2C.3b and the results in Table 2.3b. Second, the plots are flatter for the large or fast-growing agricultural economies and seemingly steeper but tortuous for the small or slow-growing agricultural economies. This indicates a relatively higher land-to-labor productivity growth ratio in the large or fast-growing agricultural economies. The small or slow-growing agricultural economies are dominated by Mauritius, which has extremely high levels of land and labor productivity, and whose labor productivity increased more rapidly than land productivity in 1961–2012 (Tables 2.3a and b). Unfortunately, most of the countries in these two groups experienced average negative growth rates in labor productivity.

Looking at the performance of individual selected countries, we see that Egypt leads the group of countries in both levels and growth rates of land and labor productivity (Appendix Figure 2C.3b). Whereas Mauritius, Morocco, Namibia, Nigeria, South Africa, Swaziland, and Tunisia have similar or higher labor productivity values, averaging more than $2,000/worker in 1961–2012, Egypt clearly outperformed all of the other selected countries in land productivity, with an average of $3,690/ha in the same periods, compared with the next-highest levels of $2,217/ha in Mauritius and $613/ha in Rwanda (Table 2.3a). Egypt, South Africa, and Mauritius also stand out among the group of countries in terms of having higher average growth rate in labor productivity than in land productivity in 1961–2012.

Other countries with high average growth rates in land productivity in 1961–2012 include Kenya (3.1 percent), Ethiopia (3.2 percent), and Nigeria (3.9 percent), whereas others with high average growth rates in labor productivity include Gabon (2.4 percent), Morocco (2.4 percent), and South Africa (3.0 percent). Countries with the lowest average levels of land productivity (less than $50/ha) in 1961–2012 include Angola, Botswana, Gabon, Mozambique, Namibia, Sudan, and Zambia, whereas those with the lowest average levels of labor productivity (less than $400/worker) include Angola, Ethiopia, The Gambia, Malawi, Mozambique, and Zambia.

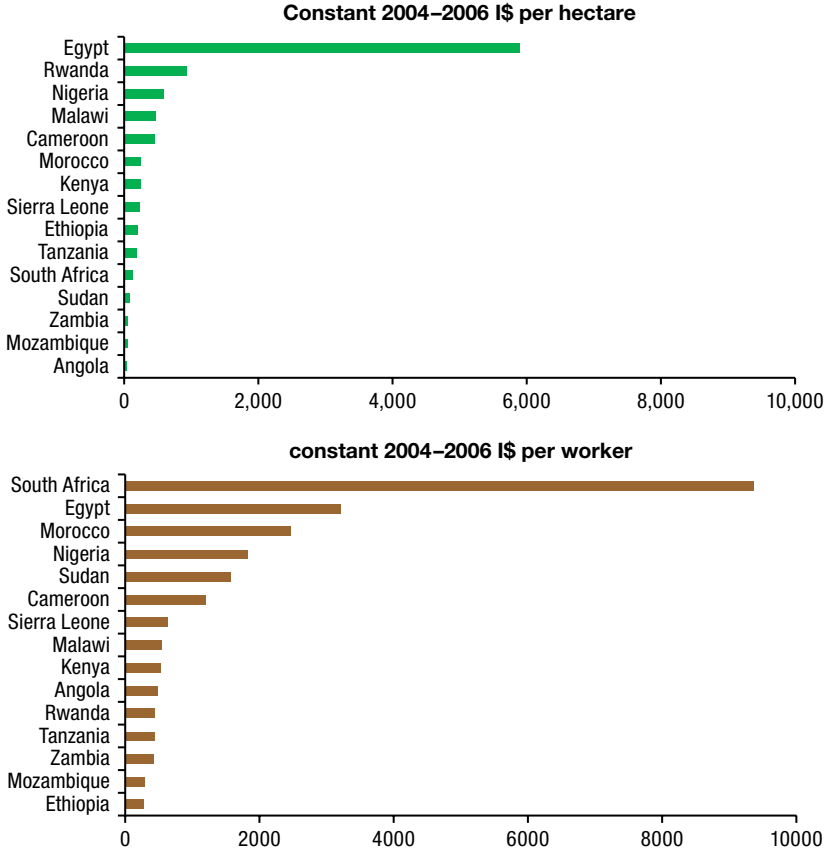
Countries with the lowest annual average growth rates in land productivity (less than 1.0 percent) in 1961–2012 include Burundi, The Gambia, Mauritius, Namibia, and Zimbabwe, whereas those with negative annual average growth rates in labor productivity include Angola, Botswana, Burundi, Democratic Republic of the Congo, Ethiopia, The Gambia, Liberia, Mozambique, Namibia, and Zimbabwe. Several of the countries classified recently as fast-growing agricultural economies (particularly Angola, Mozambique, and Rwanda—reflected in their high land and labor productivity growth rates in 2000–2012) show worse performance in the overall 1961–2012 trend, because of their initial low levels of land and labor productivity emerging from civil war.

It is clear from the results that high performance in one indicator of PFP does not mean equally high performance in other PFP indicators. South Africa, for example, is the top performer in labor productivity (with an average of $5,577/worker in 1961–2012), but has very low land productivity (with an average of only $91/ha in the same period). Figure 2.2 shows countries' relative rankings in the two indicators, using the average annual levels in 2000–2012 for illustration. Only Mozambique and Zambia have the same ranking in both measures, as the second- and third-lowest performers. Analyzing the trend by subperiods (1961–1970, 1971–1980, 1981–1990, 1991–2000, and 2001–2012), the 2000s saw strong positive growth in both land and labor productivity in many countries, headed by Sierra Leone and followed by Angola, Cameroon, Nigeria, and Morocco. These four countries experienced roughly equal average annual growth rates in land and labor productivity (Figure 2.3a and b).

SUMMARY OF FINDINGS ON TRENDS IN LAND AND LABOR PRODUCTIVITY

To summarize, we find that the trends in land and labor productivity are highly variable in different dimensions across different parts of Africa. High performance in one indicator does not necessarily mean equally high performance in the other indicator. Looking at the annual trends over the entire

FIGURE 2.2 Land and labor productivity for selected countries (average 2000–2012)

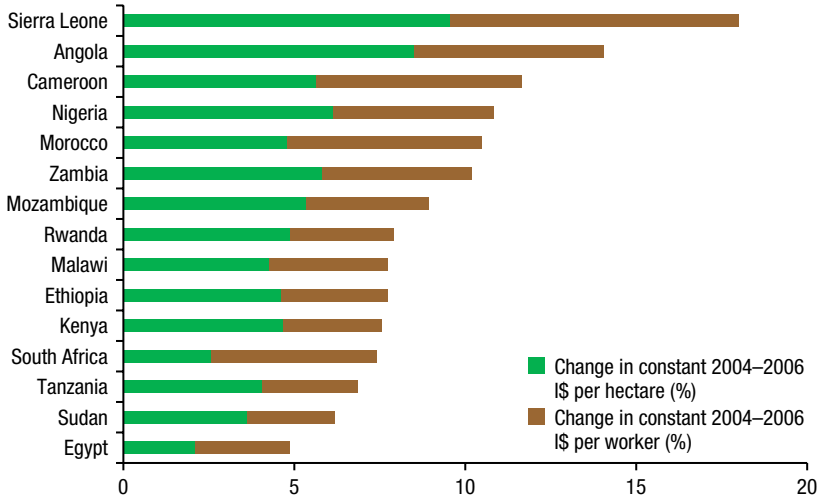


Source: Authors' calculation and representation based on FAO (2014).

Notes: Countries are large agricultural economies with at least 3 percent of Africa's total agricultural output, or fast-growing agricultural economies surpassing the CAADP agricultural growth rate target of 6 percent per year. I$ = international dollar.

1961–2012 period, we find that land productivity has risen much faster than labor productivity in Africa as a whole and in the majority of the subregions and countries analyzed. Looking at the trends by subperiods (1961–1970, 1971–1980, 1981–1990, 1991–2000, and 2001–2012), we find a mostly slower or declining rate of increase in both land and labor productivity in the 1970s and 1990s. The 2000s saw strong positive growth, especially in labor productivity, which is consistent with the finding of a decline in the poverty rate in Africa from the long-standing average of 50 percent to 47 percent in 2008 (World Bank 2012).

FIGURE 2.3 Growth rate in land and labor productivity for selected countries (annual average 2000–2012)



Source: Authors' calculation and representation based on FAO (2014).

Notes: Countries are large agricultural economies with at least 3 percent of Africa's total agricultural output, or fast-growing agricultural economies surpassing the CAADP agricultural growth rate target of 6 percent per year. I$ = international dollar.

However, the analysis for Africa as a whole hides significant differences across different subregions and countries. For example, the northern and southern regions have the highest annual labor productivities. In Egypt, Gabon, Mauritius, and South Africa (and many of the subregions and groups to which these countries belong), labor productivity has risen much faster than land productivity. Egypt stands out as a high performer in both level and growth of land and labor productivity. These differences reflect differences in factors that are not analyzed in the PFPs, including high capital endowment and use of other inputs (for example, fertilizer and irrigation) in those countries and subregions, compared with the largely rainfed average observed in many parts of Africa. Such shortcomings with the PFP measures are addressed in the TFP measures in the next section.

Trends in total factor productivity

By accounting for all factors and inputs used in production, TFP better captures the overall performance of agricultural production than PFP. In this study, TFP growth is decomposed into *technical-efficiency change*, or movement of observations toward the technological frontier, and *technical change*,

or movement of the technological frontier. The results are shown in Table 2.4, Figure 2.4, and Appendix Figures 2C.4–2C.6 for the different aggregations and selected countries. Table 2.4 shows the average annual growth rates of TFP and its decomposed parts for the period 1961–2012 and for the same five subperiods (1961–1970, 1971–1980, 1981–1990, 1991–2000, and 2001–2012). Although useful from a quantitative perspective, because the annual averages shown in the table can hide significant variations across time, Figure 2.4 and Appendix Figures 2C.4–2C.6 based on the plots of the underlying TFP index (indexed at 1961=1) give a bird's-eye view of such variations.

TFP GROWTH AT THE AGGREGATE LEVELS

For Africa as a whole, TFP increased at an annual average growth rate of 0.71 percent in 1961–2012 (Table 2.4). For SSA, TFP increased at an annual average growth rate of 0.5 percent during the same period. These findings are consistent with previous estimates, including Headey, Alauddin, and Prasada Rao (2010), who estimated TFP growth for SSA to be less than 0.5 percent in 1970–2001, and Fuglie and Nin-Pratt (2013), who estimated it to be 0.5 percent in 1971–2009. Compared with other developing regions of the world, SSA has an annual average TFP growth rate similar to that of Latin America and the Caribbean, higher than that of South and Southeast Asia, and lower than that of China and Northeast Asia (Fuglie and Nin-Pratt 2013). Headey, Alauddin, and Prasada Rao (2010) show that the estimate for SSA is lower than those for other developing regions when the DEA method is used, but comparable when the stochastic frontier analysis is used.

The above analysis, however, hides the significant variation in TFP growth over time and across different parts of the continent. For Africa as a whole, for example, the results show that TFP remained stagnant until the mid-1980s, when it started to rise steadily at an annual average rate of 0.8 percent in 1981–1990, 1.4 percent in 1991–2000, and 2.0 percent in 2001–2012. The trend for SSA is similar, where TFP also stagnated until the mid-1980s, and then started to rise steadily at an annual average rate of 0.5 percent in 1981–1990, 1.1 percent in 1991–2000, and 2.0 percent in 2001–2012. The rapid growth in TFP in 2001–2012 is consistent with the earlier finding of rapid growth, especially in labor productivity within the same period.

Looking at the trends in the index for the different subregions—geographic region (Figure 2.4), income group (Appendix Figure 2C.4), and REC (Appendix Figure 2C.5)—we find some significant differences across different parts of Africa. We can distinguish three broad categories in terms of the pattern of TFP growth: (1) TFP, as observed for Africa as a whole, stagnated

initially until the mid-1980s and then increased—observed in the majority of the subregions and groups; (2) TFP declined initially and then increased and has caught up with or surpassed the 1961 initial level in northern and western Africa, in the LI–3 and MI economic groups, and in the ECOWAS and UMA RECs; and (3) TFP consistently increased, rising slowly initially, in southern Africa and in the COMESA, EAC, and SADC RECs.

TFP GROWTH DECOMPOSITION AT THE AGGREGATE LEVELS

Decomposition of TFP growth into technical-efficiency change (or simply, efficiency change) and technical change, presented in Figure 2.5, shows that the stagnation of or decline in TFP observed in most parts of Africa prior to the mid-1980s was the result of negative efficiency change (Figure 2.5a). This is typically characterized by using more inputs to obtain the same amount of output—as occurs, for example, when inputs are distributed freely to farmers to replace lost harvest (Irz and Thirtle 2004). The negative efficiency change was largest in central and western Africa and in the ECOWAS and UMA RECs, averaging more than –1.4 percent per year. In general, the estimated negative efficiency change associated with the periods prior to the mid-1980s is consistent with the low overall economic growth in the continent in the 1970s and 1980s, and when agricultural output in SSA, for example, grew by only 1.0 percent per year on average (see Chapter 1 of this book).

From the mid-1980s onward, both efficiency change and technical change contributed positively to TFP growth. Figure 2.5b shows that technical change accounted for about 50 percent of the growth in TFP in many parts of the continent, with the contribution being more than 70 percent in northern Africa, the LI–3 economic group, and the EAC and COMESA RECs. The TFP growth decomposition results for the LI–1 economic group and the EAC REC for 1985–2012 stand out: in the LI–1 economic group, technical change accounted for only 7 percent of the growth in TFP; and in the EAC REC, efficiency change was negative.

TRENDS IN TFP AND TFP GROWTH DECOMPOSITION AT THE COUNTRY LEVEL

Appendix Figure 2C.6 shows considerable variation in the trends in levels of TFP, efficiency, and technology across the selected countries, representing the large or small agricultural economies and fast-growing or slow-growing agricultural economies. Nigeria and Egypt are the top two largest agricultural economies. For Nigeria, TFP was stagnant initially, and then declined rapidly until the mid-1980s when it began to rise, and is only recently catching up with the 1961 initial level. Egypt, however, has realized consistent increase in TFP, with more rapid growth since the late 1980s.

TABLE 2.4 Total factor productivity growth, efficiency change, and technical change (%, annual average, 1961–2012)

	Subperiods					
	1961–1970			1971–1980		
Aggregations	TFP	Eff	Tech	TFP	Eff	Tech
Africa	–0.07	–0.88	0.83	–0.29	–1.10	0.83
Africa, south of the Sahara	0.13	–0.71	0.86	–0.37	–1.24	0.91
Geographic location						
Central	–0.44	–1.25	0.82	–0.59	–2.24	1.85
Eastern	0.37	–0.68	1.10	0.86	–0.22	1.07
Northern	–0.87	–1.68	0.75	–0.02	–0.58	0.51
Southern	0.14	–0.37	0.52	1.43	0.99	0.42
Western	0.05	–0.78	0.84	–3.47	–4.10	0.67
Economic group						
LI–1	–0.17	–0.86	0.70	–0.12	–1.90	2.07
LI–2	0.16	–0.75	0.97	0.21	–0.67	0.88
LI–3	–0.45	–1.93	1.47	1.25	0.27	0.90
MI	–0.11	–0.81	0.70	–0.74	–1.35	0.63
Regional Economic Community						
CEN-SAD	–0.14	–0.97	0.84	–1.00	–1.63	0.62
COMESA	0.28	–0.80	1.11	0.78	–0.33	1.19
EAC	0.89	–0.07	0.96	1.26	–0.44	1.84
ECCAS	–0.11	–0.98	0.87	–0.39	–2.02	1.71
ECOWAS	0.05	–0.78	0.84	–3.47	–4.10	0.67
IGAD	0.07	–1.13	1.26	1.28	0.08	1.21
SADC	0.25	–0.27	0.54	0.73	–0.08	0.95
UMA	–2.40	–3.10	0.63	–0.85	–1.52	0.56
Other economic groups						
Large	0.09	–0.70	0.83	–0.46	–0.91	0.50
Small	1.01	–0.24	1.26	0.37	–1.21	1.71
Fast-growing	0.47	–0.28	0.74	–3.71	–4.34	0.69
Slow-growing	–0.01	–1.06	1.08	–0.30	–1.99	1.88
Selected countries						
Large						
Egypt	0.48	–0.38	0.86	0.57	0.11	0.46
Ethiopia	–1.07	–3.08	2.08	–0.67	–0.73	0.06
Kenya	0.62	–0.05	0.67	1.68	1.42	0.26
Morocco	–1.75	–2.32	0.58	–0.99	–1.42	0.43

Subperiods (continued)									All		
1981–1990			1991–2000			2001–2012			1961–2012		
TFP	Eff	Tech	TFP	Eff	Tech	TFP	Eff	Tech	TFP	Eff	Tech
0.77	0.24	0.44	1.38	0.56	0.77	1.98	1.16	0.82	0.71	–0.02	0.70
0.47	0.05	0.32	1.11	0.76	0.37	1.98	1.18	0.73	0.50	–0.09	0.56
0.73	0.54	0.18	1.16	1.11	0.00	1.71	0.61	1.03	0.57	–0.01	0.62
1.11	0.63	0.39	0.97	1.03	0.17	1.91	0.28	1.45	0.85	0.20	0.67
1.67	0.82	0.84	2.02	–0.09	2.02	2.18	1.19	1.22	1.36	0.21	1.13
0.73	0.05	0.60	0.95	–0.20	1.17	2.27	2.12	0.27	0.94	0.16	0.75
0.26	0.07	0.21	2.02	1.51	0.38	2.28	1.81	0.45	0.12	–0.33	0.42
0.58	0.35	0.18	1.01	0.94	–0.07	0.66	0.75	0.26	0.36	–0.15	0.54
1.10	0.61	0.34	–0.13	–0.02	0.08	2.03	0.81	1.08	0.50	–0.01	0.51
0.52	0.11	0.40	1.16	0.64	0.42	1.73	0.47	1.15	0.55	–0.27	0.76
0.71	0.10	0.54	1.93	0.72	1.13	2.04	1.36	0.73	0.81	0.00	0.77
0.89	0.37	0.46	1.93	0.93	0.90	2.05	1.07	0.96	0.75	–0.02	0.71
1.28	0.48	0.70	1.81	0.90	0.98	1.81	0.18	1.55	1.18	0.17	1.01
1.77	1.02	0.69	–0.48	–1.23	0.84	1.91	0.27	1.36	0.95	–0.15	1.13
0.63	0.29	0.32	1.43	1.13	0.26	2.41	1.52	1.12	0.79	0.07	0.76
0.26	0.07	0.21	2.02	1.51	0.38	2.28	1.81	0.45	0.12	–0.33	0.42
1.37	0.77	0.45	1.07	1.40	0.03	2.14	0.34	1.60	0.99	0.32	0.70
0.59	0.10	0.41	0.91	0.18	0.68	1.52	1.29	0.24	0.67	0.03	0.62
1.68	1.72	0.13	0.95	–0.52	1.34	2.81	2.97	0.04	0.94	0.31	0.64
0.73	0.03	0.58	1.82	0.74	0.98	1.99	1.13	0.85	0.82	0.03	0.73
0.90	0.41	0.31	–0.96	–1.13	0.23	0.87	0.41	0.44	0.28	–0.35	0.63
–0.36	–0.66	0.30	2.10	2.00	0.09	2.99	2.57	0.44	0.06	–0.34	0.40
0.93	0.76	0.20	0.90	0.31	0.59	–0.62	–1.06	0.36	0.35	–0.42	0.78
1.72	0.14	1.57	2.23	–0.04	2.27	2.08	–0.05	2.13	1.57	0.08	1.49
–0.65	–0.65	0.00	1.71	1.57	0.13	2.76	1.98	0.77	0.57	0.36	0.21
1.41	0.69	0.72	–0.06	–0.25	0.19	2.81	–0.02	2.83	1.34	0.45	0.89
3.27	3.27	0.00	–0.15	–0.96	0.82	4.10	4.06	0.04	1.15	0.76	0.39

(continued)

TABLE 2.4 (continued)

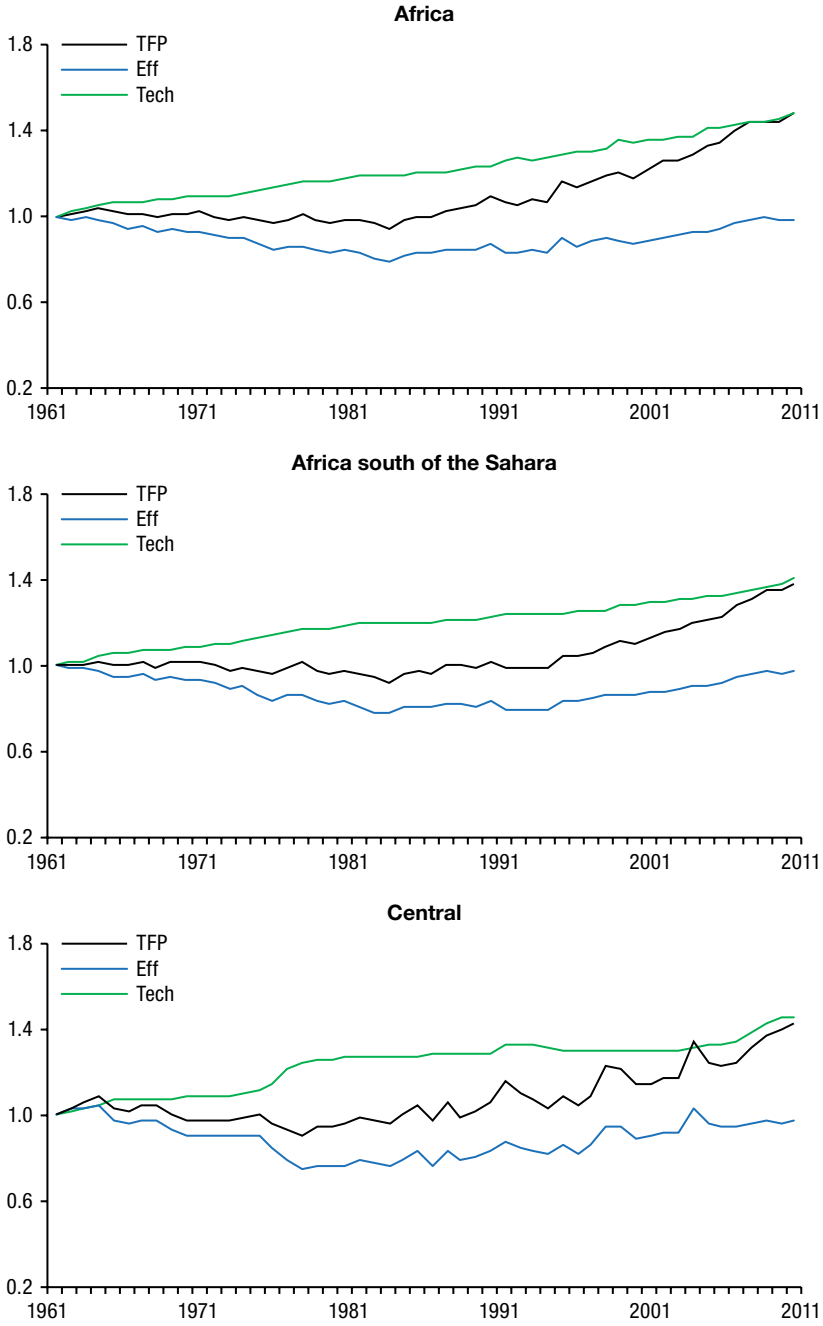
	Subperiods					
	1961–1970			1971–1980		
Aggregations	TFP	Eff	Tech	TFP	Eff	Tech
Nigeria	0.50	–0.29	0.79	–6.44	–7.25	0.88
South Africa	0.17	–0.23	0.41	2.61	2.05	0.55
Sudan	–0.64	–1.70	1.07	0.95	0.32	0.63
Tanzania	0.82	0.65	0.17	–1.14	–1.19	0.06
Small						
Botswana	1.47	0.78	0.68	–4.20	–4.93	0.76
Gabon	1.11	0.00	1.11	0.23	–0.19	0.42
Gambia, The	2.11	–0.40	2.52	–6.13	–6.13	0.00
Guinea-Bissau	–3.03	–3.76	0.76	0.51	0.51	0.00
Mauritius	1.34	–0.34	1.69	3.09	–2.08	5.29
Swaziland	1.14	0.30	0.84	2.37	2.05	0.31
Fast-growing						
Angola	–0.42	–0.46	0.04	–3.50	–3.61	0.11
Cameroon	0.66	–0.18	0.84	–1.69	–1.81	0.13
Malawi	–0.14	–0.79	0.66	0.97	0.97	0.00
Mozambique	–0.23	–0.24	0.01	–3.13	–3.13	0.00
Nigeria	0.50	–0.29	0.79	–6.44	–7.25	0.88
Rwanda	3.59	1.31	2.25	1.70	0.71	0.98
Sierra Leone	0.08	–0.61	0.69	–0.42	–0.44	0.02
Zambia	–0.93	–1.25	0.32	1.88	1.80	0.08
Slow-growing						
Burundi	–0.27	–1.01	0.75	–0.73	–2.10	1.40
Congo, Dem. Rep.	–0.09	–0.93	0.85	–0.20	–3.49	3.40
Liberia	1.44	–0.06	1.50	–0.18	–0.50	0.33
Mauritius	1.34	–0.34	1.69	3.09	–2.08	5.29
Namibia	2.10	0.49	1.61	–1.31	–2.63	1.36
Tunisia	–1.24	–2.12	0.90	–1.00	–1.45	0.46
Zimbabwe	0.14	–1.69	1.85	0.27	0.27	0.00

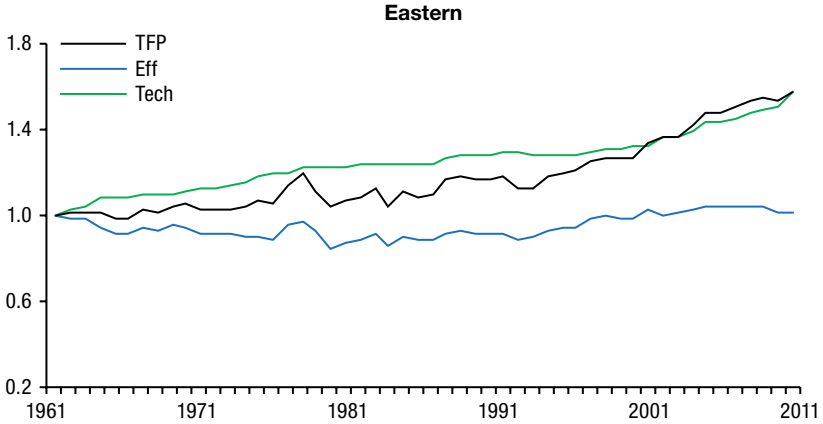
Source: Authors' calculation based on the Malmquist index model results.

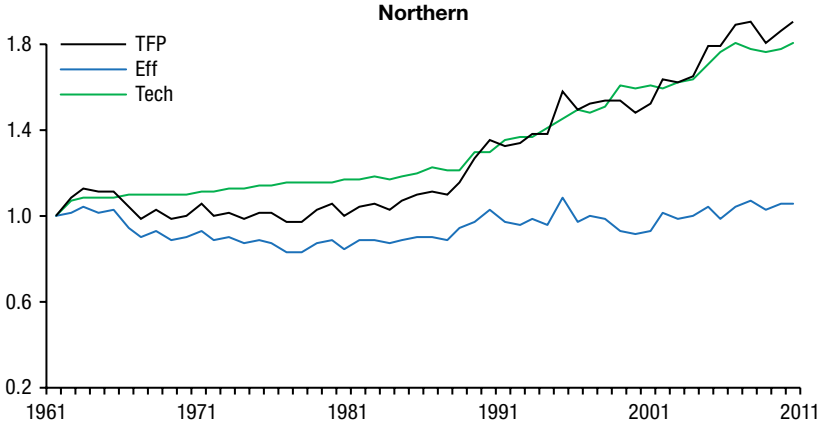
Notes: TFP = total factor productivity growth; Eff = efficiency change; Tech = technical change. LI-1 = low income, more favorable agriculture, and mineral rich; LI-2 = low income, more favorable agriculture, and nonmineral rich; LI-3 = low income and less favorable agriculture; MI = middle income. CEN-SAD = Community of Sahel-Saharan States; COMESA = Common Market for Eastern and Southern Africa; EAC = East African Community; ECCAS = Economic Community of Central African States; ECOWAS = Economic Community of West African States; IGAD = Intergovernmental Authority on Development; SADC = Southern African Development Community; UMA = Union du Maghreb Arabe. Large agricultural economies have at least 3.0 percent of Africa's total agricultural output; small agricultural economies have less than 0.1 percent of Africa's total agricultural output; fast-growing agricultural economies surpass the CAADP agricultural growth rate target of 6.0 percent per year; and slow-growing agricultural economies have an agricultural growth rate of less than 1.0 percent per year.

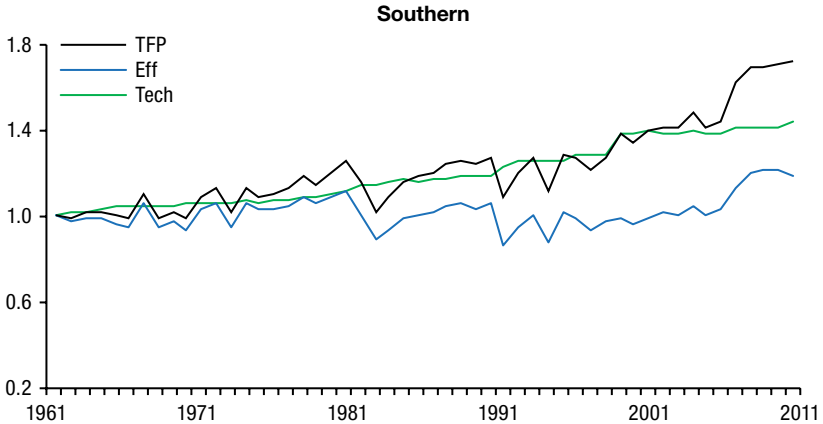
Subperiods (continued)									All 1961–2012		
1981–1990			1991–2000			2001–2012					
TFP	Eff	Tech	TFP	Eff	Tech	TFP	Eff	Tech	TFP	Eff	Tech
0.26	0.00	0.25	3.01	2.97	0.04	2.73	2.69	0.04	–0.16	–0.50	0.33
0.92	–0.01	0.94	1.24	–0.85	2.10	2.50	1.84	0.65	1.40	0.22	1.18
–0.11	–0.11	0.00	5.28	5.27	0.01	2.35	–0.52	2.89	1.43	0.77	0.65
0.96	0.81	0.15	0.62	0.59	0.02	0.62	–0.11	0.73	0.18	0.04	0.14
–0.56	–0.56	0.00	–2.61	–2.61	0.00	2.19	2.18	0.01	–0.65	–0.91	0.27
0.18	0.09	0.09	1.36	0.25	1.11	1.00	0.05	0.94	0.69	–0.08	0.77
–0.64	–0.64	0.00	1.09	1.09	0.00	–1.42	–2.42	1.02	–1.24	–1.49	0.26
2.09	2.07	0.02	1.02	0.91	0.11	2.51	0.32	2.19	0.66	0.38	0.27
0.85	0.85	0.00	–2.33	–2.33	0.00	0.33	0.30	0.03	0.25	–0.82	1.09
1.84	0.31	1.53	–1.69	–2.40	0.73	0.59	0.35	0.23	1.02	0.10	0.91
–1.46	–1.46	0.00	3.09	3.09	0.00	5.23	5.02	0.20	0.40	0.33	0.07
0.57	0.57	0.00	0.06	0.02	0.05	4.67	1.85	2.76	0.72	0.36	0.36
–0.26	–0.26	0.00	2.83	2.32	0.50	1.11	0.04	1.07	0.77	0.30	0.47
–2.46	–2.46	0.00	2.80	2.80	0.00	3.69	3.46	0.22	–0.61	–0.63	0.02
0.26	0.00	0.25	3.01	2.97	0.04	2.73	2.69	0.04	–0.16	–0.50	0.33
0.89	–0.49	1.38	3.72	1.06	2.63	2.18	0.42	1.76	2.07	0.13	1.94
–0.37	–0.39	0.01	–0.40	–0.40	0.00	6.15	2.29	3.77	0.37	–0.11	0.48
1.65	1.65	0.00	–0.05	–0.12	0.07	4.38	4.21	0.16	0.76	0.69	0.07
1.48	0.74	0.73	0.58	–0.25	0.83	–3.97	–4.28	0.32	–0.14	–1.04	0.91
0.71	0.62	0.09	1.92	1.66	0.26	–1.90	–2.21	0.32	0.44	–0.42	0.86
2.16	0.16	1.99	1.78	1.69	0.09	–1.69	–1.71	0.02	0.12	–0.70	0.83
0.85	0.85	0.00	–2.33	–2.33	0.00	0.33	0.30	0.03	0.25	–0.82	1.09
–0.63	–0.63	0.00	–0.83	–0.83	0.00	0.34	0.16	0.19	–0.11	–0.63	0.53
0.85	0.69	0.16	–0.16	–2.10	1.99	1.68	1.50	0.18	0.59	–0.31	0.90
1.75	1.75	0.00	1.20	1.20	0.00	–1.18	–1.23	0.05	–0.07	–0.18	0.12

FIGURE 2.4 Levels of total factor productivity, efficiency, and technology by geographic region (1961–2012: indexed at 1961=1)



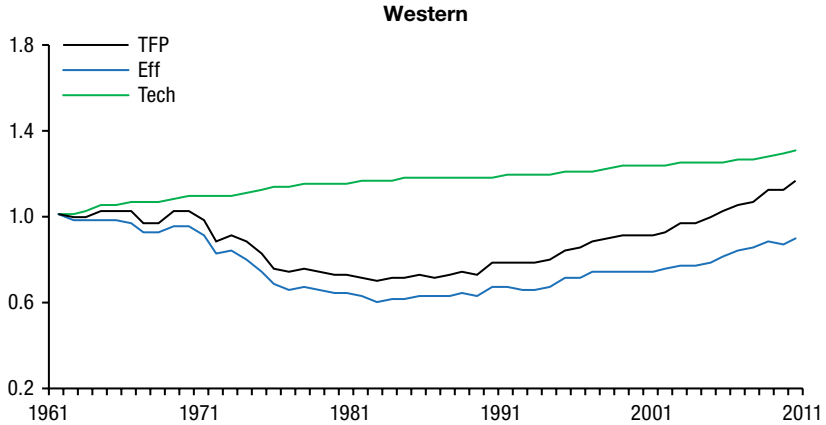

Eastern
TFP
Eff
Tech
1.8
1.4
1.0
0.6
0.2
1961
1971
1981
1991
2001
2011


Northern
TFP
Eff
Tech
1.8
1.4
1.0
0.6
0.2
1961
1971
1981
1991
2001
2011


Southern
TFP
Eff
Tech
1.8
1.4
1.0
0.6
0.2
1961
1971
1981
1991
2001
2011

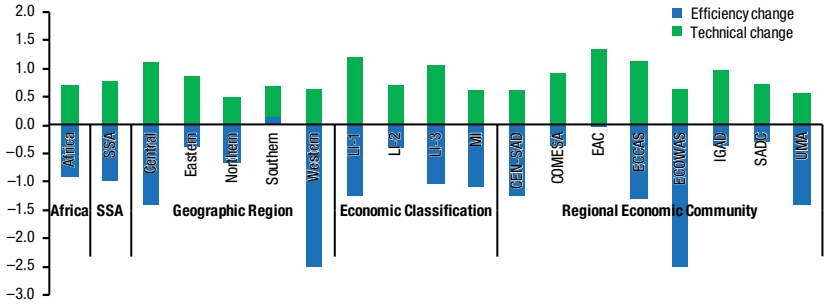
(continued)

FIGURE 2.4 (continued)



Source: Authors' calculation and illustration based on TFP model results.
Notes: TFP = total factor productivity; Eff = efficiency; Tech = technology.

FIGURE 2.5A Total factor productivity growth decomposition by group (%, annual average 1961–1985)

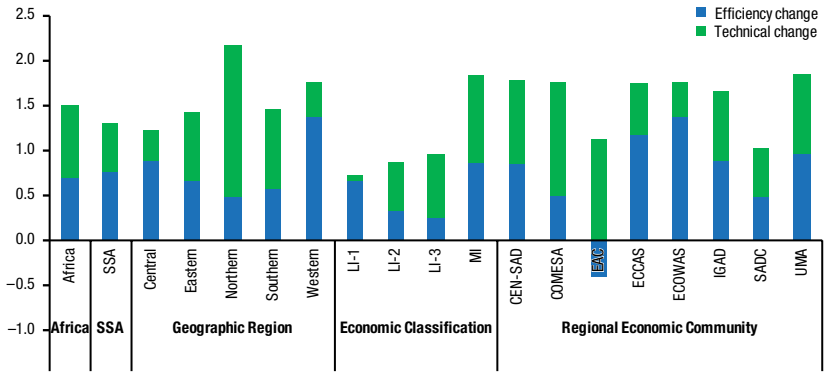


Source: Authors' calculation and illustration based on TFP model results.

Notes: LI–1 = low income, more favorable agriculture, and mineral rich; LI–2 = low income, more favorable agriculture, and nonmineral rich; LI–3 = low income and less favorable agriculture; MI = middle income. CEN-SAD = Community of Sahel-Saharan States; COMESA = Common Market for Eastern and Southern Africa; EAC = East African Community; ECCAS = Economic Community of Central African States; ECOWAS = Economic Community of West African States; IGAD = Intergovernmental Authority on Development; SADC = Southern African Development Community; SSA = Africa south of the Sahara; UMA = Union du Maghreb Arabe.

As most of the observations are on or close to the technological frontier, TFP growth is dominated by technical change. Malawi and Angola are the fastest-growing agricultural economies in the recent past decade in terms of overall agricultural growth. Whereas there has been little technical change in Angola, its remarkable agricultural growth starting in the mid-1990s reflects its emergence

FIGURE 2.5B Total factor productivity growth decomposition by group (%, annual average, 1985–2012)



Source: Authors' calculation and illustration based on TFP model results.

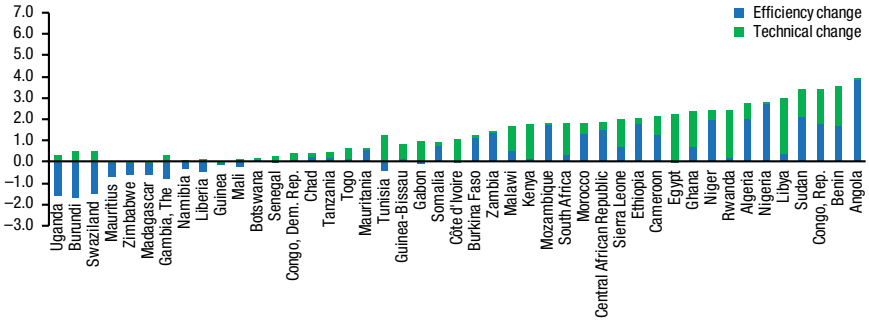
Notes: LI–1 = low income, more favorable agriculture, and mineral rich; LI–2 = low income, more favorable agriculture, and non-mineral rich; LI–3 = low income and less favorable agriculture; MI = middle income. CEN-SAD = Community of Sahel-Saharan States; COMESA = Common Market for Eastern and Southern Africa; EAC = East African Community; ECCAS = Economic Community of Central African States; ECOWAS = Economic Community of West African States; IGAD = Intergovernmental Authority on Development; SADC = Southern African Development Community; SSA = Africa south of the Sahara; UMA = Union du Maghreb Arabe.

from war and catching up rapidly with and surpassing the initial 1961 level. In Malawi, TFP remained at the initial 1961 level until the late 1990s, when it increased as a result of both positive technical change and efficiency change.

The trends in The Gambia and Botswana, representing Africa's two smallest agricultural economies, are very similar, with TFP declining initially and then becoming stagnant over time in the remaining periods. Mauritius and Namibia, the two slowest-growing agricultural economies, also have similar trends in TFP growth, increasing initially, declining toward the 1961 level, and then remaining stagnant or fluctuating around the 1961 level.

Several of our findings are consistent with previous estimates. For example, Headey, Alauddin, and Prasada Rao (2010) find acceleration (2.5–5.5 percent) in TFP growth in 1985–2001 for Angola, Egypt, and Malawi, compared with sluggish growth in 1970–1985 for Egypt and Malawi (0.3–0.5 percent) or negative growth for Angola (–0.5 percent). Our finding for Nigeria, however, differs from that of Headey, Alauddin, and Prasada Rao (2010), who find positive TFP growth (0.5 percent) for Nigeria in 1970–1985 compared with our negative growth rate in the 1970s (–6.4 percent) and sluggish growth rate in the 1980s (0.3 percent) (Table 2.4 and Appendix Figure 2C.6). Our finding of rapid TFP growth for Nigeria from 1985 onward is consistent with that of Headey, Alauddin, and Prasada Rao (2010). Irz and Thirtle (2004) find negative TFP

FIGURE 2.6 **Total factor productivity growth decomposition at country level (%, annual average 1985–2012)**



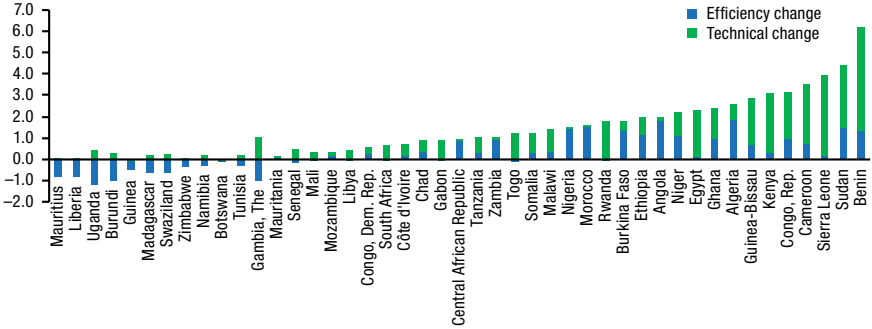
Source: Authors' calculation and illustration based on TFP model results.

growth (–2.3 percent) in Botswana's traditional agriculture sector in 1979–1996, but positive TFP growth (1.2 percent) in the commercial agriculture sector. They also find significant technological regression (–2.9 percent) in Botswana's traditional agriculture sector—a finding that is fundamentally different from the findings in this study because of differences in methodologies used.[5]

Whereas the above analysis shows the patterns in TFP growth over the entire 1961–2012 period considered here, the patterns in more recent years better reflect the current trajectory of the countries in agricultural transformation. We analyze two subperiods: 1985–2012, representing the general period following the recovery or turnaround in the decline in TFP growth (Figure 2.6), and 2000–2012 (Figure 2.7). For the first subperiod, the year 2000 is when African countries signed the Millennium Declaration that

5 The DEA-Malmquist index used in this study assumes *sequential technology* instead of *contemporaneous technology* in the sense that there is dependence between the production sets across time. This approach is based on the assumption that "production units can always do what they did before" in the production process, ruling out the possibility of technological regression or negative technical change (see Appendix 2A for details). This is captured in the efficiency change component, which in Botswana we find to be negative in the 1970s (–4.9 percent), 1980s (–0.6 percent), and 1990s (–2.6 percent) (Table 2.4 and Appendix Figure 2C.6). Therefore, our overall result of declining TFP in Botswana in 1971–2000 is consistent with the "technological regression" of Irz and Thirtle (2004). In general, differences in the decomposition from using the sequential versus contemporaneous technology are more pronounced in the 1970s and 1980s for SSA countries with a low-capital agriculture sector (particularly Angola, Botswana, Ethiopia, Mozambique, and Namibia). This is reflected by the largely zero technical change and negative efficiency change for those countries in those periods (Table 2.4). The technology frontier collapses in those periods, which would result in technological regression or negative technical change when the contemporaneous technology assumption is used in calculating the Malmquist index.

FIGURE 2.7 Total factor productivity growth decomposition at country level (%, annual average 2000–2012)



Source: Authors' calculation and illustration based on TFP model results.

defined the Millennium Development Goals; it also represents the start of the most recent decade of rapid growth in labor productivity seen earlier.

During 1985–2012, Figure 2.6 shows that about one-third of the 45 countries achieved an annual average TFP growth rate of at least 2.0 percent, with Angola in front (at 3.9 percent), followed by Benin, Republic of the Congo, Sudan, and Libya (at 3.0 percent or higher). Technical change accounted for less than one-half of the TFP growth in the majority of all of the countries. For the period 2000–2012, Figure 2.7 also shows that about one-third of the countries achieved an average annual TFP growth rate of at least 2.0 percent. However, the ranking of countries shifts, with Benin, Sudan, Sierra Leone, Cameroon, Republic of the Congo, and Kenya taking over the lead, with at least a 3.0 percent annual average growth rate in TFP. Many more countries also show positive and large rates of technical change.

SUMMARY OF FINDINGS ON TFP TRENDS AND TFP GROWTH DECOMPOSITION

For Africa as a whole, TFP increased at an annual average growth rate of 0.71 percent in 1961–2012, and in SSA by 0.5 percent. These figures are consistent with previous estimates, but hide the significant variation in TFP growth over time and across different parts of the continent. For Africa as a whole, TFP remained stagnant between 1961 and the mid-1980s, when it started to rise steadily at an annual average rate of 0.8 percent in 1981–1990, 1.4 percent in 1991–2000, and 2.0 percent in 2001–2012. The rapid growth in TFP in 2001–2012 is consistent with the earlier finding of rapid growth, especially in labor productivity, within the same period.

TABLE 2.5 Input and capital per worker and technical change, annual average (1995–2012)

Technical change (average %)	Land (ha)	Crop capital (2005 US$)	Livestock capital (2005 US$)	Fertilizer (kg)	Feed (kg)
High (2.0%)	21.4	6.9	2.3	94.6	1.6
Medium (0.6%)	14.5	3.4	3.4	83.0	1.0
Low (0.1%)	33.2	0.8	2.8	12.0	0.3

Source: Authors' calculation and illustration based on TFP model results.
Note: ha = hectare; kg = kilogram.

TFP growth decomposition shows that the widespread stagnation or decline in TFP observed prior to the mid-1980s was due to loss in efficiency or negative efficiency change, also consistent with previous findings. The rate of negative efficiency change was largest in central and western Africa and in the ECOWAS and UMA RECs, averaging more than –1.4 percent per year. From the mid-1980s onward, however, efficiency change and technical change contributed positively and equally to TFP growth. During the periods of recovery and turnaround, technical change contributed more than 70.0 percent of TFP growth in northern Africa, the LI–3 economic group, and the EAC and COMESA RECs, but only 7.0 percent in the LI–1 economic group.

At the country level, Nigeria and Egypt, which are the two largest agricultural economies in Africa in terms of their share of Africa's total agriculture value-added, show distinct TFP growth paths, particularly prior to the mid-1980s. For example, compared with the U-shaped pattern observed in Nigeria, Egypt realized a consistent increase in TFP, with more rapid growth since the late 1980s; however, as most of the observations are on or close to the technological frontier, TFP growth in Egypt is dominated by technical change. Considering the period 1985–2012, about one-third of the 45 countries analyzed achieved annual average TFP growth rates of at least 2 percent, with countries in the lead, including Angola, Benin, Congo, Sudan, and Libya (at 3 percent in 1985–2012), and Benin, Sudan, Sierra Leone, Cameroon, Congo, and Kenya taking over the lead in the more recent periods of 2000–2012.

A key question then is, what is driving the strong role of technical change in TFP growth in northern Africa, the LI–3 economic group, and the EAC and COMESA RECs compared with, for example, countries in the LI–1 economic group? In calculating the Malmquist index, countries with similar input and capital intensities below and at the frontier are compared, which results in different speeds of frontier expansion for the different groups of comparable countries. We find that the frontier for low-input and low-capital countries, mostly in SSA, has been moving slowly or not at all (under the sequential-technology

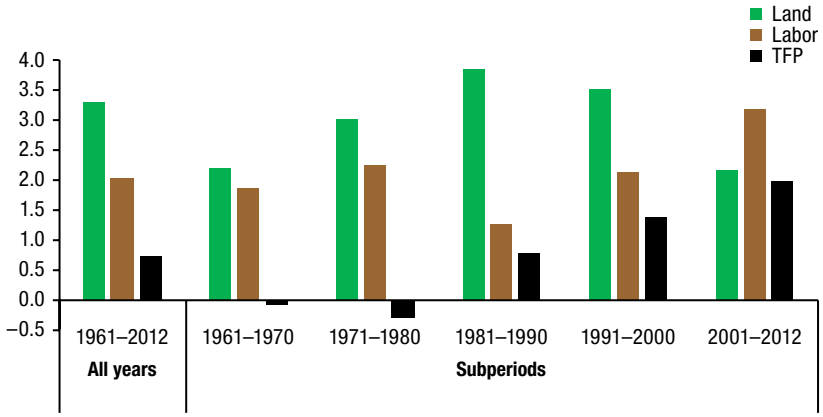
assumption) or collapsing (under the contemporary-technology assumption). On the other hand, the frontiers for the high-input and high-capital countries have been moving steadily and faster. Table 2.5 shows that countries with larger endowments of crop capital and using more fertilizer and feed per worker (likely also those with more commercial-oriented agriculture) are those experiencing rapid technical change.

Correlation between PFP and TFP measures

From the above analysis of PFP and TFP measures, we have seen that whereas TFP measures can provide a better sense of the changes in agricultural productivity, measuring TFP can be challenging (especially for developing countries), compared with measuring PFP, which is straightforward and has uncomplicated data requirements. A key question, therefore, concerns not which measure to use instead of the other, but how they complement each other.

Figure 2.8 shows that the patterns of growth in the PFP and TFP measures are quite different. Growth in land productivity increased from an initial average rate of 2.2 percent achieved in the 1960s to 3.0 percent in the 1970s, reached a high of 3.9 percent in the 1980s, and then declined in the 1990s and 2000s to the average rate achieved in the 1960s. Growth in labor productivity also increased from its initial average rate of 1.9 percent achieved in the 1960s to 2.3 percent in the 1970s, then dropped rapidly to 1.2 in the 1980s, and then increased to 2.1 percent in the 1990s and 3.2 percent in

FIGURE 2.8 Land, labor, and total factor productivity growth in Africa (%, annual average 1961–2012)



Source: Authors' calculation and illustration based on FAO (2014) and TFP model results.
Note: TFP = total factor productivity.

TABLE 2.6 Correlation coefficients between land, labor, and total factor productivity (TFP) growth by technical change and input intensity (1961–2012)

	1961–1985					
Coefficients	Land	Labor	Land	TFP	Labor	TFP
All Africa	0.98	***	0.84	***	0.82	***
Technical change (%)						
Low (0.00)	0.98	***	0.84	***	0.88	***
Medium (0.07)	0.97	***	0.86	***	0.84	***
High (2.94)	0.98	***	0.72	***	0.68	***
Input per worker						
Land (ha)						
Low (2.04)	0.98	***	0.86	***	0.85	***
Medium (6.87)	0.99	***	0.84	***	0.83	***
High (52.66)	0.98	***	0.83	***	0.81	***
Crop capital (2005 US$)						
Low (350)	0.96	***	0.86	***	0.84	***
Medium (900)	0.98	***	0.77	***	0.74	***
High (6,160)	0.98	***	0.87	***	0.86	***
Livestock capital (2005 US$)						
Low (420)	0.97	***	0.80	***	0.79	***
Medium (1,260)	0.98	***	0.83	***	0.81	***
High (5,190)	0.98	***	0.85	***	0.84	***
Fertilizer (kg)						
Low (0.85)	0.97	***	0.68	***	0.65	***
Medium (6.23)	0.98	***	0.85	***	0.84	***
High (142.71)	0.98	***	0.91	***	0.91	***

Source: Authors' calculation based on FAO (2014) and TFP model results (2011).

Notes: *** = significant at 1% level; ha = hectare; kg = kilogram. Figures in parentheses are average values for the respective category, where low, medium, and high are terciles of the indicator.

the 2000s. Annual average TFP growth rates were negative in the first two decades, and then increased to 0.8 percent in the 1980s, 1.4 percent in the 1990s, and 2.0 percent in the 2000s As such, for Africa as a whole from 1961 to 1980, we observe a U-shaped trend for growth in land and labor productivity, but a declining trend for TFP growth. From the 1980s onward, there was an increasing trend for growth in labor productivity and TFP, but a declining trend for growth in land productivity.

	1986–2012					
Coefficients	Land	Labor	Land	TFP	Labor	TFP
All Africa	0.96	***	0.74	***	0.74	***
Technical change (%)						
Low (0.00)	0.96	***	0.81	***	0.80	***
Medium (0.07)	0.94	***	0.82	***	0.84	***
High (2.94)	0.96	***	0.58	***	0.57	***
Input per worker						
Land (ha)						
Low (2.04)	0.94	***	0.64	***	0.66	***
Medium (6.87)	0.98	***	0.87	***	0.87	***
High (52.66)	0.97	***	0.78	***	0.77	***
Crop capital (2005 US$)						
Low (350)	0.95	***	0.82	***	0.84	***
Medium (900)	0.96	***	0.54	***	0.54	***
High (6,160)	0.97	***	0.85	***	0.84	***
Livestock capital (2005 US$)						
Low (420)	0.97	***	0.72	***	0.72	***
Medium (1,260)	0.92	***	0.60	***	0.61	***
High (5,190)	0.98	***	0.89	***	0.88	***
Fertilizer (kg)						
Low (0.85)	0.97	***	0.57	***	0.57	***
Medium (6.23)	0.94	***	0.85	***	0.87	***
	0.97	***	0.85	***	0.85	***

Looking at the correlation between the growth rates of the three productivity measures, the results presented in Table 2.6 show differences in the correlation coefficients, which differ by periods—for example, from 1961 to 1985 (during the periods of TFP decline) and from 1986 to 2012 (during the periods of TFP recovery and increase). In general or for Africa as a whole, the coefficients for the correlation between land and labor productivity growth (which are close to 1) are larger than those for the correlations between land productivity and TFP growth and between labor productivity and TFP growth. These patterns hold for the different periods, as well as for different observations grouped according to technical change and input and capital intensities.

Furthermore, the coefficients for the correlation between land and labor productivity growth are the same across the different groups of technical change and input and capital intensities. There are differences, however, in the coefficients for the correlations between land productivity and TFP growth and between labor productivity and TFP growth across the different groups of technical change and input and capital intensities. For example, going from low to high within any group, the coefficients are declining for technical change, increasing for land and fertilizer use per worker, and U-shaped for crop and livestock capital per worker.

Together, the above results suggest that analysis of agricultural productivity in Africa involving analysis of both PFP and TFP measures will provide strong complementarity. Because growth in land and labor productivity is strongly correlated (which is confirmed by the plots in Figure 2.1 and Appendix Figures 2C.1–2C.3 for different parts of the continent), using either of the PFP measures for a rapid assessment of changes in agricultural productivity is likely to be acceptable. But, because there are differences in the productivity effects of different factors and inputs, analysis of which are excluded in PFP measures, the policy implications of PFP analysis are not likely to be strong. To get a better sense of the long-term changes in agricultural productivity that are attributable to technological change, such as required for CAADP, analysis of TFP and TFP decomposition will be necessary and critical.

Conclusions and Implications

This chapter assessed changes in indicators of both PFP and TFP (using the DEA-Malmquist index) measures over time (1961–2012) and across different parts of Africa at the aggregate, subregional, and country levels. The results shed light on the relative sources of agricultural growth, on the resource and factor constraints for increasing agricultural production sustainably, and on the relative usability of the different indicators in strategic monitoring of agriculture sector performance. Between 1961 and 2012, we find that for Africa as a whole, land productivity increased the fastest, at a 3.3 percent annual average, followed by labor productivity at an annual average of 2.0 percent, and then TFP at an annual average of 0.7 percent, with technical change accounting for nearly all of the TFP growth. These findings are consistent with the literature, but hide significant differences across different subregions and countries, as well as over different subperiods of time.

Looking at differences across different parts of Africa, we found that the southern region, for example, had relatively high labor productivities but

relatively low land productivities compared with other geographic regions. This finding is consistent with the high land–labor and capital–labor intensities associated with large plantations and more mechanized, commercial agricultural operations that take place there. Land productivities in northern Africa are as high as in southern Africa, but whereas labor productivity has risen much faster than land productivity in southern Africa, land and labor productivities in northern Africa have risen at roughly equal rates. The trends observed in western Africa are closer to those observed for Africa as a whole, compared with the generally lower average levels and growth rates observed in central and eastern Africa. For TFP, three broad patterns of growth were found: (1) TFP, as observed for Africa as a whole, stagnated initially until the mid-1980s and then increased, as observed in the majority of the subregions and groups; (2) TFP declined initially and then increased and has caught up with or surpassed the 1961 initial level in northern and western Africa, the LI–3 and MI economic groups, and the ECOWAS and UMA RECs; and (3) TFP consistently increased, rising slowly initially, in southern Africa and the COMESA, EAC, and SADC RECs.

Looking at differences over different subperiods of time, we found that from 1961 until the mid-1980s there was a U-shaped trend for growth in land and labor productivity, but a declining trend for TFP growth. From the mid-1980s onward, there was an increasing trend for growth in labor productivity and TFP, but a declining trend for growth in land productivity. TFP growth decomposition shows that the widespread stagnation or decline in TFP observed prior to the mid-1980s was the result of negative efficiency change, especially in central and western Africa and in the ECOWAS and UMA RECs. From the mid-1980s onward, however, efficiency change and technical change contributed positively and equally to TFP growth for Africa as a whole, although technical change contributed more than 70 percent of TFP growth in northern Africa, the LI–3 economic group, and the EAC and COMESA RECs, and only 7 percent in the LI–1 economic group.

The findings from both the PFP and the TFP analyses suggest that different policies and investments will be needed in different parts of the continent to increase and sustain high agricultural productivity and growth. However, only the TFP analysis sheds light on the relative sources of agricultural productivity growth to help inform specific strategies to accelerate the expansion of Africa's technical frontier and improve efficiency in production systems. For example, we found that the technological frontier for countries with relatively low-input and low-capital intensities have been moving slowly or not at all, compared with the faster-moving frontier for those with relatively

high-input and high-capital intensities. In particular, countries with larger endowment of crop capital and using more fertilizer and feed per worker (likely also those with more commercial-oriented agriculture) are experiencing rapid technical change. Therefore, policies and investments that help farmers to intensify and capitalize their agricultural production processes will be critical for increasing and sustaining high technological advancement in the sector. This support will be particularly important in places with a slowdown in land availability, to help improve rural incomes and further reduce poverty.

Depending on data availability, one important area for additional work that could help sharpen the policy implications of the TFP analysis is using data at the firm or farm level, rather than at the country level as done here and in the literature, which loses the heterogeneity of production systems and decisionmaking units or farms within the country. In general, considering the data and analytical challenges associated with measuring TFP compared with the relatively easy requirements for measuring PFP, analysis of changes in agricultural productivity that involves analysis of both PFP and TFP measures will provide strong complementarity. This will be especially important when comparing production units or systems with different input and factor use intensities, as their respective patterns of growth in PFP and TFP measures are likely to be different.

Appendix 2A: Measuring Total Factor Productivity: The Malmquist Index

The Malmquist index, pioneered by Caves, Christensen, and Diewert (1982) and based on distance functions, became extensively used in the measure and analysis of productivity, after Färe et al. (1994) showed that the index can be estimated using data envelopment analysis (DEA), a nonparametric approach. The nonparametric Malmquist index has been 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. This ease of use is attractive in the context of African agriculture, where usually market prices for the inputs are either nonexistent or insufficiently reported to provide any meaningful information for land, labor, and livestock. In addition, the nonparametric approach can be applied in a multiple-input, multiple-output setting. Also important is its ability to decompose productivity growth into two mutually exclusive and

exhaustive components: changes in technical efficiency over time (catching up) and shifts in technology over time (technical change).

We adopt the following notations and definitions: t=1, ...,T is time period in years; j=1, ..., J is an index of production points or units or countries; m=1, ... , M is an index of outputs; n=1, ..., N is an index of inputs; x_j is a column vector of inputs used by production unit j $(x_{j1}, x_{j2}, ..., x_{jN})$; y_j is a column vector of outputs of production unit j $(y_{j1}, y_{j2}, ..., y_{jM})$; k is the number of country groups k=1, ..., K, where each group corresponds to an agroecological zone; z_j is a row vector of nonnegative weights; and Θ is a scalar "contraction" or "shrinking" factor.

To calculate the output-based Malmquist index, we define the production possibility set (PPS), which contains all the correspondences of input and output vectors that are feasible and within which the production units operate. In our analysis, we will refer to these production units as countries. Denote the PPS for a particular period t (t=1, ..., T) as S^t, such that:

$$S^t = \left\{(x^t, y^t) \in \Re_+^{n+m} \mid x^t \text{ can produce } y^t\right\} \tag{2A.1}$$

The PPS contains all feasible correspondence of inputs $x^t \in \Re_+^N$ capable of producing output levels $y^t \in \Re_+^M$. The set S^t is also referred to as the production technology and can also be represented from the input or output perspective:

$$L^t(y) = \left\{x^t \middle| (x^t, y^t) \in S^t\right\} \tag{2A.2}$$

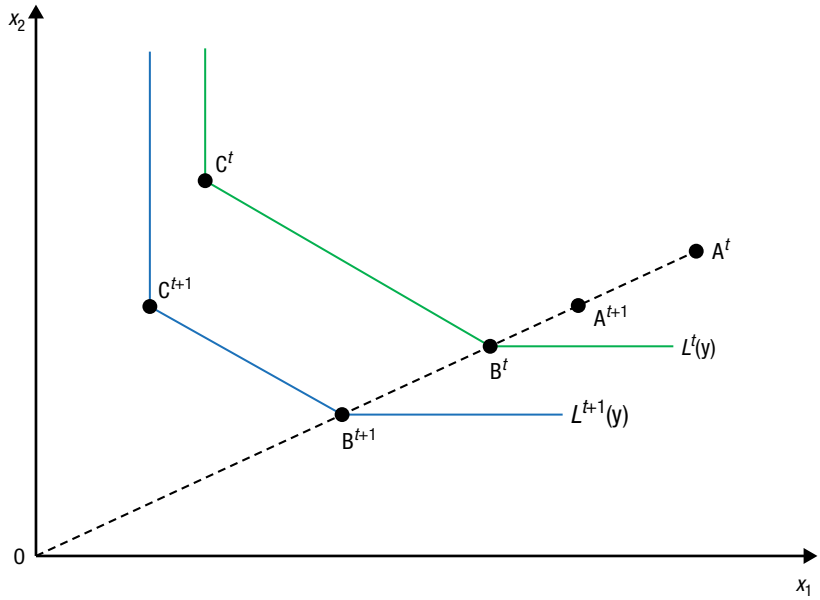
$$P^t(x) = \left\{y^t \middle| (x^t, y^t) \in S^t\right\} \tag{2A.3}$$

These are alternative ways of describing the possibilities for the transformation of inputs x into outputs y. Figure 2A.1 illustrates the technology in the form of an input possibility set (for periods t and t+1), as defined in equation 2A.2. This is the set of input vectors that can produce output vector y, for the technology in period t and with $x^t \in \Re_+^N$ inputs and $y^t \in \Re_+^M$ outputs.

In the figure, the frontier is defined by two production points (B and C) representing efficient combinations of inputs x_1 and x_2 used by production points B and C in period t (B^t, C^t) and in period t+1 (B^{t+1}, C^{t+1}) to produce, respectively, y^t and y^{t+1}. The frontier of the input possibilities for a given output vector in a particular period is defined as the input vector that cannot be reduced by a uniform factor without leaving the set. Formally, the frontier in input space is represented by the isoquant, such that:

$$I(y) = \left\{x \middle| L(y), \Theta x \notin L(y), \Theta < 1\right\} \tag{2A.4}$$

FIGURE 2A.1 Input possibility set, periods *t* and *t*+1



Source: Authors' illustration based on literature review.

In Figure 2A.1, the input set $L^t(y)$ is the space to the right of and above the isoquant defined by B^t and C^t. The efficient subset for this technology is the segment of the isoquant between points B^t and C^t: efficiency is attained at the technological frontier, when a decrease in any input requires an increase in at least another input.

In Figure 2A.1, the technical efficiency of country A is the distance from the production point A to the frontier and can be expressed as the ratio $TE^t(x^t,y^t) = OB^t/OA^t<1$. This is a measure of how far the production point A is from the frontier in period *t*. We can also define efficiency between the production point in *t*+1 and the frontier in *t* $TE^t(x^{t+1}, y^{t+1})$ as the ratio OB^t/OA^{t+1}. In the same way, the efficiency of the production point in *t* with respect to the frontier in *t*+1 is calculated as $TE^{t+1}(x^t, y^t) = OB^{t+1}/OA^t$. Finally, the distance from the production point in *t*+1 to the frontier in *t*+1 is $TE^{t+1}(x^{t+1}, y^{t+1}) = OB^{t+1}/OA^{t+1}$. The efficiency measure equals 1 when the production point in period *t* is on the frontier for period *t*, as is the case for point B in Figure 2A.1. (When evaluating the distance function for a production point *t* relative to some other period's frontier, the distance measure can exceed 1.)

The input-oriented measures of efficiency defined using Figure 2A.1 can be expressed in terms of input-distance functions, which are used to define the Malmquist productivity index. The efficiency of a production unit with respect to the frontier in t is defined using distance functions as:

$$T_i^t(x^t, y^t) = \frac{1}{D_i^t(x^t, y^t)} = 1/sup\left\{\Theta: \left[x_j^t/\Theta, y_j^t\right] \in L^t(y)\right\} \tag{2A.5}$$

where θ is the coefficient representing the maximum feasible contraction of the input vector x^t at period t given y^t for production unit j, and i indicates that this is an input-oriented distance measure. The analysis that follows will use only input-oriented measures for ease of notation and thus drop the i index in the equations. Distances for points in t with respect to the frontier in t+1 or points in t+1 with respect to the frontier in t are defined similarly. Depending on the technology used as reference, we can define a period t-based or a period t+1-based input-oriented Malmquist index. The period t-based Malmquist index is defined as:

$$M^t = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \tag{2A.6}$$

Using the technology at t+1 as the reference, the period t+1-based Malmquist index is defined as:

$$M^t = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \tag{2A.7}$$

We can apply these definitions to measure productivity growth in the frontier country B in Figure 2A.1, recalling that, for a frontier country, $D^t(x^t, y^t) = D^{t+1}(x^{t+1}, y^{t+1}) = 1$. For this particular case, the Malmquist indexes defined in equations 2A.6 and 2A.7 are $M_i^t = (OB^t/OB^{t+1}) > 1 = M_i^{t+1} = 1/(OB^{t+1}/OB^t) > 1$. An index greater than 1, as in this example, means that productivity is growing. For a frontier country like B, productivity growth is equivalent to a shift in the frontier. A shift in the frontier upward and to the right, as in Figure 2A.1, can indicate technical progress. In the particular example presented here, the period t-based and period t+1-based Malmquist indexes both result in the same estimate of productivity growth.

The two Malmquist indexes in equations 2A.6 and 2A.7 give the same result only if, as pointed out by Färe et al. (1997), either of the conditions in (i) holds in conjunction with any of those in (ii):

1. $y^{t+1} = \lambda y^t, \lambda > 0$, or technology exhibits implicit Hicks output neutral technical change;

2. $x^{t+1} = x^t$ or $x^{t+1} = \lambda x^t, \lambda > 0$ and technology exhibits constant returns to scale, or technology exhibits constant returns to scale and implicit Hicks-input neutral technical change.

As the choice between either of the two indexes is arbitrary, Färe et al. (1994) defined their Malmquist index as the geometric mean of M_i^t and M_i^{t+1}:

$$M = [M^t \times M^{t+1}]^{1/2} = \left[\frac{D^t(x^{t+1},y^{t+1})}{D^t(x^t,y^t)} \times \frac{D^{t+1}(x^{t+1},y^{t+1})}{D^{t+1}(x^t,y^t)}\right]^{1/2} \quad (2A.8)$$

Growth decomposition

Färe et al. (1994) showed that the Malmquist index could be decomposed into a technical-efficiency change (or simply, efficiency change) component and a technical change component, and that these results applied to the different period-based Malmquist indexes. It follows that:

$$M = \frac{D^{t+1}(x^{t+1},y^{t+1})}{D^t(x^t,y^t)} \left[\frac{D^t(x^{t+1},y^{t+1})}{D^t(x^t,y^t)} \times \frac{D^{t+1}(x^{t+1},y^{t+1})}{D^{t+1}(x^t,y^t)}\right]^{1/2} \quad (2A.9)$$

The ratio outside the square brackets measures the efficiency change between periods t and t+1, or the change in how far observed input is from the minimum potential input that can be used to produce y between periods t and t+1. The technical change component captures the shift of technology (the frontier) between the two periods.

Note that if we decompose the two Malmquist indexes in equations 2A.6 and 2A.7 into their efficiency change and technical change components, the efficiency change index will be the same for both, but they will differ in the way they measure the shift in the frontier (technical change). The index M^t measures the shift in the frontier along a ray through the origin and the production point in t+1. The index M^{t+1} measures the shift in the frontier through the production point in t. The technical change component of the Malmquist index in equation 2A.9 is just the geometric mean of the technical change components in M^t and M^{t+1}.

A value of the efficiency change component of the Malmquist index greater than 1 means that the production unit is closer to the frontier in period t+1 than it was in period t: the production unit is catching up to the frontier. A value of less than 1, which is negative efficiency change, indicates efficiency regress. The same range of values is valid for the technical change component, meaning technical progress when the value is greater than 1 and technical regress when the index is less than 1. Notice that in our example of Figure 2A.1, the efficiency change component of the productivity indexes for country B equals 1, because this country is on the frontier in periods t and in

t+1, implying that there is no change in efficiency. In that case, the Malmquist indexes for country B are equivalent to the technical change component, measuring the shift in the frontier.

The Malmquist index owes some of its popularity to these productivity change decompositions. However, the Malmquist index represents a correct measure of productivity only if the reference technology exhibits constant returns to scale (CRS), as assumed here for country comparisons. This relates to two main problems with the initial definition of the Malmquist index by Caves, Christensen, and Diewert (1982). First, the Malmquist index did not comply with the definition of an "adequate" measure of productivity change because it did not fulfill the property of proportionality. This property states that if outputs are increased in the same proportion from one period to the next while inputs remain the same (that is, output-oriented measure of productivity), then the productivity index should increase in the same proportion. In the case of the Malmquist index, this property requires that the distance functions be linearly homogeneous of degree +1 in outputs and –1 in inputs, which means that the benchmark technology is characterized by CRS.

If the technology exhibits variable returns to scale (VRS), then the Malmquist index does not comply with the proportionality properly; however, most important, it is an inaccurate measure of productivity change, because it ignores the contribution of scale change to productivity change (Grifell-Tatjé and Lovell 1995). In the case of equation 2A.9, if VRS is present, then the efficiency change and technical change components are not actual measures of "pure" efficiency change and technical change, but they both include a scale-efficiency change. There is a discussion in the literature about how to correctly introduce and measure the effect of scale economies in the decomposition of the Malmquist index. A good summary of this discussion and the conceptual interpretation of different decompositions of the Malmquist index can be found in Zofio (2007). Decomposition of technical change into biased and magnitude components is proposed in Färe et al. (1998), for which several variations have been proposed (for example, Balk [2001]).

Because a common CRS technology is assumed for all African countries in calculating the Malmquist index, we are not able to identify efficiency change or technical change resulting from differences in structural characteristics of production in different regions, like natural resource quality and agroecologies. These effects can be obtained by measuring the Malmquist index and decomposition separately for different groups of countries that are grouped according to geographic or agroecological location or other relevant criteria. These effects can then be compared with the results obtained from pooling

all countries in a metafrontier Malmquist index (MM). By representing the distance to the frontier of the kth group of a country in this group as $D_k^t(x^t, y^t)$ and the distance of this same country to the metafrontier as $D_F^t(x^t, y^t)$, we can define a technology gap ratio (TGR) at period t as the ratio of the two technical efficiencies. Following Rambaldi, Prasada Rao, and Dolan (2007), the TGR for group k is:

$$TGR_k^t\left(x^t, y^t\right) = \frac{D_F^t(x^t, y^t)}{D_k^t(x^t, y^t)} \tag{2A.10}$$

As the metafrontier envelops the group frontiers, we have that $D_F^t(x^t, y^t) \leq D_k^t(x^t, y^t)$, which means that $TGR_k^t \leq 1$. Using the distance functions calculated with respect to the group and the metafrontier, Rambaldi, Prasada Rao, and Dolan (2007) show that the efficiency change and technical change components of the Malmquist index can be decomposed as follows:

$$E_F^{t,t+1} = E_k^{t,t+1} \times \frac{TGR_k^{t+1}(x^{t+1}, y^{t+1})}{TGR_k^t(x^t, y^t)} \tag{2A.11}$$

$$TC_F^{t,t+1} = TC_k^{t,t+1} \times \left[\frac{TGR_k^t}{TGR_k^{t+1}} \times \frac{TGR_k^t(x^{t+1}, y^{t+1})}{TGR_k^{t+1}(x^t, y^t)}\right]^{1/2} \tag{2A.12}$$

$E_F^{t,t+1}$ and $TC_F^{t,t+1}$ are measures of efficiency change and technical change between t and t+1, respectively, measured with respect to the metafrontier (as represented in equation 2A.9). Equation 2A.11 shows that efficiency change for a particular country relative to the metafrontier is equal to efficiency change within the kth group, times the change in the technology gap between group k and the metafrontier. Similarly, equation 2A.12 shows that technical change for a particular country relative to the metafrontier is equal to the technical change relative to the group frontier, times the geometric mean of the inverse of the technology gap growth index evaluated at (x^t, y^t) with respect to period t+1 technology, and at (x^{t+1}, y^{t+1}) with respect to period t technology. According to Rambaldi, Prasada Rao, and Dolan (2007), this term can be interpreted as the inverse of the relative improvement in the technology gap of a specific country between t and t+1.

In sum, productivity growth measures that result from assuming a common technology will be the same as those obtained by using multiple technologies. The difference is that, with the single-technology assumption, we cannot separate the efficiency change and technical change effects related to changes between the different technologies. With the assumption of different technologies, technical change for countries located in southern Africa, for example, could be decomposed into growth of the southern Africa technology frontier and a reduction in the gap between the southern Africa frontier and the metafrontier. The same decomposition could be applied for countries

located in the different geographic locations (Table 2.2), economic groups (Appendix Table 2C.1), or agroecological zones or farming systems (Chapters 3 and 4 of this book). With a single technology, we cannot observe these differential effects, which are beyond the scope of this study.

Estimation by data envelopment analysis

To measure the Malmquist index and decompose efficiency change and technical change based on the concepts of PPS presented earlier, we use DEA. In DEA, the PPS is deduced from observed input–output correspondences by making assumptions as to the nature of the PPS. These assumptions are included as constraints in the different linear programs used to estimate four different distance functions. As presented in Charnes, Cooper, and Rhodes (1978), frequent assumptions made are:

(i) Convexity of the PPS: If $(x,y) \in S$ and $(x',y') \in S$, then $(\lambda(x,y) + (1-\lambda)(x',y')) \in S$

(ii) Monotonicity or strong disposability of inputs and outputs:
   a. If $(x,y) \in S$ and $x' \geq x$, then $(x',y) \in S$
   b. If $(x,y) \in S$ and $y' \leq y$, then $(x,y') \in S$

(iii) CRS: If $(x,y) \in S$ and $(x',y') \in S$, then $(\lambda x,\lambda y) \in S$ for any $\lambda \geq 0$.

Notice that under CRS and efficient production, scaling of inputs by a certain factor leads to the outputs being scaled by the same factor. Because of this, when assuming CRS, we obtain the same results using input- or output-oriented distance functions. In what follows, we define input-oriented problems under CRS.

We need to solve four different linear programming (LP) problems to determine the distance functions needed to calculate the Malmquist index for a particular production point (country) C between t and t+1. The distance of production point C in t to the frontier in t is:

$$D_c^t(x^t,y^t) = \max \Theta^c \; s.t. \; y_c^{t,m} \leq \sum_{j=1}^{J} z_j^t y_j^{t,m} \text{ and } (1/\Theta^c)x_c^{t,n} \geq \sum_{j=1}^{J} z_j^{t,n} x_j^{t,n}, \text{ and } z_j^t \geq 0 \quad (2A.13)$$

Where c is one of the j production units: j = 1,..,c,...,J; Similarly, the distance of production point c in t+1 to the frontier in t is:

$$D_c^t(x^{t+1},y^{t+1}) = \max \Theta^c \; s.t. \; y_c^{t+1,m} \leq \sum_{j=1}^{J} z_j^t y_j^{t,m} \text{ and } (1/\Theta^c)\, x_c^{t+1} \geq \sum_{j=1}^{K} z_j^t x_j^t, \text{ and } z_j^t \geq 0 \quad (2A.14)$$

Computation for $D_c^{t+1}(x^{t+1}, y^{t+1})$ is like in $D_c^t(x^t, y^t)$, but with t+1 substituted for t. Finally, $D_c^{t+1}(x^t, y^t)$ is calculated as in $D_c^t(x^{t+1}, y^{t+1})$ (equation 2A.13), but the t and t+1 subscripts are transposed (Färe et al. 1994). All these problems assume CRS. To impose VRS, we need to include one more constraint: $\sum_{j=1}^{J} z_j^t = 1$.

Problems with DEA

OUTLIERS

Several problems have been pointed out in the literature that result from the use of DEA methods to calculate distance functions. One of these problems is that the DEA frontier defined in the linear problems above is not stochastic—that is, it does not contain a random-error term to account for statistical noise. This means that the efficiency of a production unit measured using DEA methods is typically defined by a small proportion of the observations—those at the frontier of the PPS. In practice, some of the frontier units are atypical, either because of a much stronger performance than other units in the sample or as the result of an atypical mix of inputs and outputs (Thanassoulis, Portela, and Despić 2008). For this reason, it is important that the data for these particular units be reliable.

To detect outliers in our sample of countries, we use the method suggested by Tran, Shively, and Preckel (2010), based on two scalar measures. The first is the relative frequency with which an observation appears in the construction of the frontier when testing the efficiency of other observations. The second measure is the cumulative weight of an observation in the construction of the frontier. For example, using constraints in the dual-optimization problem (equation 2A.10), we define z-count (C_j) as the number of times an observation appears during the construction of the DEA hull (the DEA problem is solved $_j$ times, the number of production units that define the PPS):

$$C_j = \sum_{j \text{ if } z_j^n > 0} 1 \qquad (2A.15)$$

We define z-sum (S_j) as the cumulative weight of an observation in all constructed efficient sets (when solving the LP problem for a particular country C). It is computed as:

$$S_j = \sum_j z_j^t \qquad (2A.16)$$

The DEA model yields nonzero values for z-count and z-sum for all efficient observations (the ones that appear with values z_j>0 in the solution to the LP problems), while all inefficient firms have zero values of both z-count and

z-sum. We followed the procedure suggested by Tran, Shively, and Preckel (2010) to detect outliers. First, and based on the values of C_j and S_j, we identify potential outliers: observations in the dataset that exert an especially strong influence on the construction of the efficient frontier. After identifying observations with a high frequency or level for their weights, we drop these observations, and with the remaining observations we repeat the DEA to obtain new values for C_j and S_j, exclusive of the dropped observations. We drop observations in an iterative fashion, and the process stops once we reach a desired degree of convergence in the observed weights. Given that we work with a limited sample of countries, we do not drop observations identified as likely outliers. These observations are not included in the sample when we calculate the distance for other observations, so reported results are not influenced by these observations. However, we still calculate distance functions separately for these potential outliers, and report these results with results for other countries.

INAPPROPRIATE SHADOW PRICES

One of the reasons for the popularity of the DEA method approach to international comparisons of productivity is that it does not require market prices as weights (normally not available) to obtain an index of total inputs or outputs to measure total factor productivity (TFP). However, even though a priori price information is not needed, the DEA approach still uses implicit price information derived from the shape of the production surface, which allows the estimation of efficiency measures and nonparametric Malmquist indexes. This implicit determination of shadow prices entails potential problems, because these methods are susceptible to the effect of data noise, and shadow prices can prove to be inconsistent with prior knowledge or accepted views on relative prices or cost shares. This is the case when linear programming problems used in DEA methods to calculate distance functions assign a zero or close-to-zero price to some factors because of the particular shape of the production possibility set. As a consequence, inputs considered important a priori could be all but ignored in the analysis, or could end up being dominated by inputs of secondary importance (Pedraja-Chaparro, Salinas-Jimenez, and Smith 1997).

We check our results for the incidence of zero shadow input prices in the standard estimation of the nonparametric Malmquist index, and use a modified procedure to calculate the index that constrains the values of shadow prices in the DEA approach, introducing a priori information on the expected values of shadow input shares.

Constraints to implicit shadow prices are introduced by using the dual-optimization problem in equation 2A.10. This dual problem can be thought of as minimizing shadow cost subject to the constraint that shadow revenue is normalized to 1, and subject to the constraints that when these multipliers are assigned to all producers in the sample, no producer earns positive shadow profit (Thanassoulis, Portela, and Despić 2008). This dual problem is defined for a particular production unit c as:

$$D_c^t(x^t, y^t) = \min\left[\sum_{n=1}^{N} w^n x_c^{t,n}\right], \text{ s.t. } \sum_{m=1}^{M} \rho^m y_c^{t,m} = 1,$$
$$\left(\sum_{n=1}^{N} w^n x_j^{t,n} - \sum_{m=1}^{M} \rho^m y^{t,m}\right) \geq 0 \qquad (2A.17)$$

With ρ^m, $w^n \geq 0$ being shadow prices of outputs and inputs, respectively, and the set of production units *j*, outputs *m,* and inputs *n,* as defined above.

The optimization problem shown in equation 2A.10 and its dual counterpart in 2A.17 allow for total flexibility in choosing shadow prices. To define suitable limits to the value that input shares take, we introduce additional constraints to the original formulation in 2A.14 that set upper and lower bounds (a^n,b^n) to the input share. We define the standard distance function, where ρ and w are, respectively, the output and input shadow prices, and $w^{t,n} \times x_c^{t,n}$ (the input shadow prices multiplied by the input quantities) is equal to the implicit input shares, as shown in Coelli and Prasada Rao (2001). Then, constraints to shadow shares are expressed as:

$$b_c^{t,n} \leq w_c^{t,n} x_c^{t,n} \leq a_c^{t,n} \qquad (2A.18)$$

Restricted and unrestricted models will provide the same results only if all the additional restrictions imposed are nonbinding. In general, the narrower the imposed bounds, the larger the expected differences between the outcomes of each model. To define the bounds for the input shares, we first solve the model to obtain average shadow shares for each input, and then define a range of two standard deviations around the mean within which we allow solutions to the LP problems. In this way, we still take advantage of the flexibility of the DEA approach to define shadow prices, while controlling for extreme and zero values in the solution.

THE CURSE OF DIMENSIONALITY

Suhariyanto and Thirtle (2001) called attention to two main difficulties that may result from dimensionality, or the number of inputs and outputs relative to the number of observations in the cross-section, when using DEA for international comparisons: (1) the greater the number of input and output variables, the higher the probability that a particular decisionmaking unit will

appear as efficient; and (2) the technology frontiers may be unstable, with the frontier for different periods intersecting and introducing unlikely levels of technological regression.

Estimation approach

In this study we follow Suhariyanto and Thirtle (2001) and Nin, Arndt, and Preckel (2003), who suggest the use of a *sequential technology* instead of the *contemporaneous technology* frequently used in DEA analysis. A contemporaneous technology is the technology defined by the equation 2A.2: $L^t(y) = \{x^t | (x^t, y^t) \in S\}$. With this definition, successive production sets are essentially unrelated to one another—that is, they may or may not overlap in any possible way. The sequential production set, on the other hand, assumes that there is some form of dependence between the production sets across time. This dependence stems from the assumption that "production units can always do what they did before in the production process." For each time period t=1, ..., T, rewrite the technology as:

$$L^{(1,t)}(y) = \{x^{t-g} | (x^{t-g}, y^{t-g}) \in S\} \qquad \text{(2A.19)}$$

With this technology, the input–output mix used in previous years (t-g) is always available and is part of the technology in period t, which means that successive sequential reference production sets are nested into one another. Using this definition of technology instead of the contemporaneous technology definition, we increase the number of observations defining the PPS, reducing the dimensionality problem while ruling out the possibility of technical regress: contractions of the frontier are not allowed.

We calculate a Malmquist index for one output and six inputs, as described in the main text, using the sequential technology, thus ruling out the possibility of technical regress. Constraints to implicit shadow prices are introduced by using the dual-optimization problem, as described above. Before calculating the different components of the Malmquist index, the method suggested by Tran, Shively, and Preckel (2010) is used to detect outliers.

Sensitivity analysis

To generate greater confidence with the findings associated with the one-output, six-inputs constrained or bounded DEA-Malmquist index method used here, we compare our results with those obtained using three other approaches that differently address the problems with the DEA discussed above: (1) DEA-Malmquist index calculated using two-outputs—crops and

livestock; (2) DEA-Malmquist index calculated including lower and upper bounds on the shadow prices; and (3) growth-accounting TFP index, where inputs are aggregated using fixed-input shares for all countries and periods. A brief comparison of the results is presented in Appendix 2B. These results are based on the data from 1971 to 2012, which are complete for all the relevant variables required for the different models.

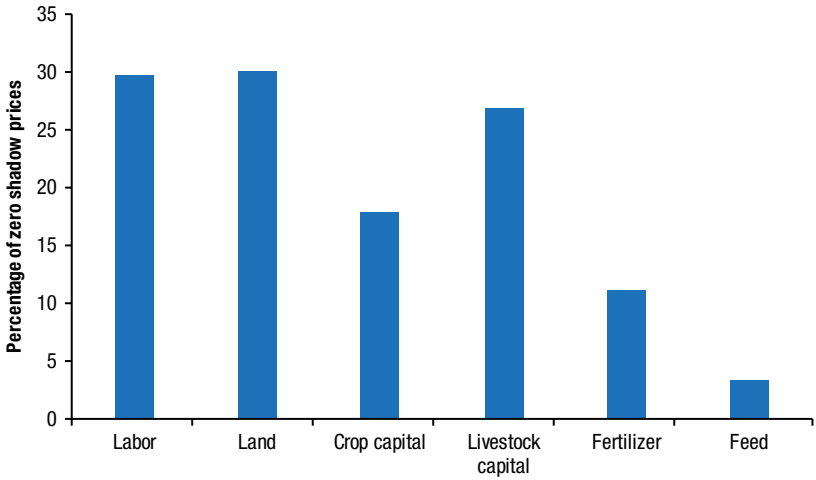
Appendix 2B: Comparative Analysis of Alternative Index-based Methods

This appendix compares the overall results produced by the four different methods described above: (1) our preferred method, referred to as the "DEA-Malmquist–1-output-index"; (2) the index calculated using two outputs, referred to as the "DEA-Malmquist–2-outputs-index"; (3) the index calculated including lower and upper bounds to shadow prices, referred to as the "DEA-Malmquist-bounds-index"; and (4) the index using the more conventional growth accounting method, referred to as "TFP-fixed-shares-index." These shares are average shadow shares for all countries obtained from the DEA, which are 0.10 for land, 0.20 for labor, 0.07 for fertilizer, 0.22 for feed, 0.22 for crop capital, and 0.18 for livestock capital. To rule out the possibility of zero shadow prices, upper and lower bounds are used by adding +1 and –1 standard deviation to the shares. Without the bounds, the incidence of zero input prices is shown in Figure 2B.1.

About 30 percent of countries on average per year show zero shadow prices for land and labor, and 27 percent show zero shadow prices for livestock capital. In contrast, the percentage of countries with zero crop capital and fertilizer shadow prices is much lower (18 and 11 percent, respectively), whereas only 3 percent of countries show zero shadow prices for feed. This suggests that zero shadow prices in our sample of countries are related to unusual combinations of inputs—for example, large values for labor relative to capital in crop production. With zero shadow price, input substitution is not defined and, continuing with the example, a reduction of labor will have no effect on productivity, given that its shadow price is zero, which means that labor in this case will not be considered for estimating efficiency.

Looking now at the respective results, Table 2B.1 shows the average TFP growth rates and their components for Africa as a whole, and Figure 2B.2 shows the growth paths over time. The results show that the more flexibility one allows in the calculation of the DEA-Malmquist index, the higher the estimated TFP growth (Table 2B.1) and the higher the TFP level in

FIGURE 2B.1 Percentage of zero shadow prices for different inputs, annual average (1971–2012)



Source: Authors' calculation and illustration based on DEA-Malmquist index method.

2012 compared with that in the initial 1971 period (Figure 2B.2). The DEA-Malmquist–2-outputs-index produces the highest TFP annual average growth rate of 1.8 percent in 1995–2012, compared with 1.3 percent resulting from the TFP-fixed-shares-index. On the other hand, TFP growth paths, as well as the improved performance that started in 1995, are similar for all indexes, although we find larger differences occurring during the first half of the analyzed periods, when the region experienced low or negative TFP growth. Although we did not carry out statistical tests on differences in the growth rates obtained with the different methods, many of the differences are small. We find high-correlation coefficients among the results (Figure 2B.3 and Figure 2B.4).

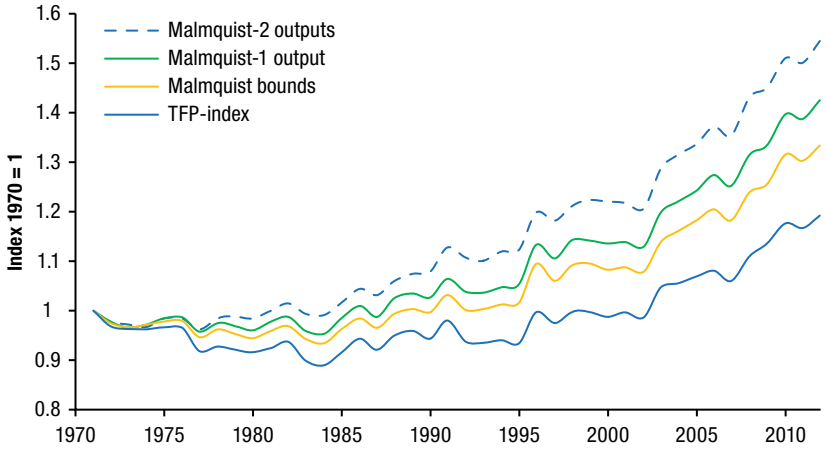
Differences in the methods are more enhanced for some countries. These are also reflected in Figures 2B.3 and 2B.4. Each point in the figures represents a country, and the coordinates of each point are the TFP growth rates of the TFP indexes being compared. Points on or close to the 45-degree line are those for which the method used has no or very little effect on TFP estimates. The parallel lines that bound the 45-degree line are calculated as the value of the growth rate in the 45-degree line minus (lower bound) or plus (upper bound) two standard deviations measured as the distance between the country points and the 45-degree line. The figures show that countries cluster along the 45-degree line with the highest variability for the DEA-Malmquist–2-outputs-index, as observed in the comparison of average

TABLE 2B.1 Annual average TFP growth rates for Africa using different TFP index methods, 1971–2012

	Malmquist index							
	1-output		2-outputs		Bounds		TFP fixed shares	
Index method	1971–1994	1995–2012	1971–1994	1995–2012	1971–1994	1995–2012	1971–1994	1995–2012
TFP	0.3	1.7	0.5	1.8	0.1	1.6	–0.2	1.3
Efficiency	–0.4	0.7	–0.4	0.5	–0.4	0.7	n.a.	n.a.
Technical Change	0.7	1.0	1.0	1.3	0.6	0.8	n.a.	n.a.

Source: Authors' calculations based on DEA-Malmquist and TFP index methods.
Note: n.a. = not applicable; TFP = total factor productivity.

FIGURE 2B.2 Average TFP indexes for Africa using different index methods, 1971–2012

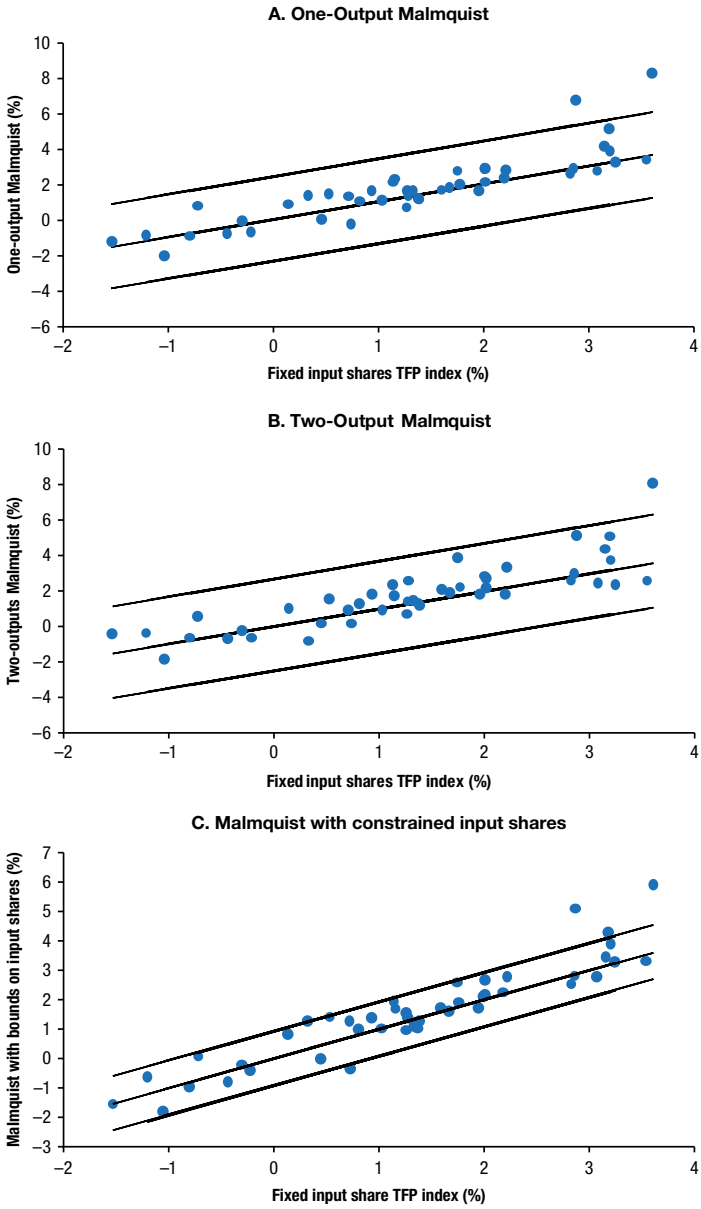


Source: Authors' calculation and illustration based on DEA-Malmquist and TFP index methods.
Note: TFP = total factor productivity.

indexes. Ranking country performance using the different methods will result in a similar order of countries. Note that with two exceptions, all countries are within the range of two standard deviations from the 45-degree line. Also note that the two exceptions are the countries with the highest TFP growth calculated using the DEA-Malmquist index.

For further analysis at the country level, Table 2B.2 shows the estimated annual average growth rate obtained with the different methods, as well as the absolute value of the difference between the DEA-Malmquist indexes and the TFP-fixed-share-index. Countries with the largest variation include

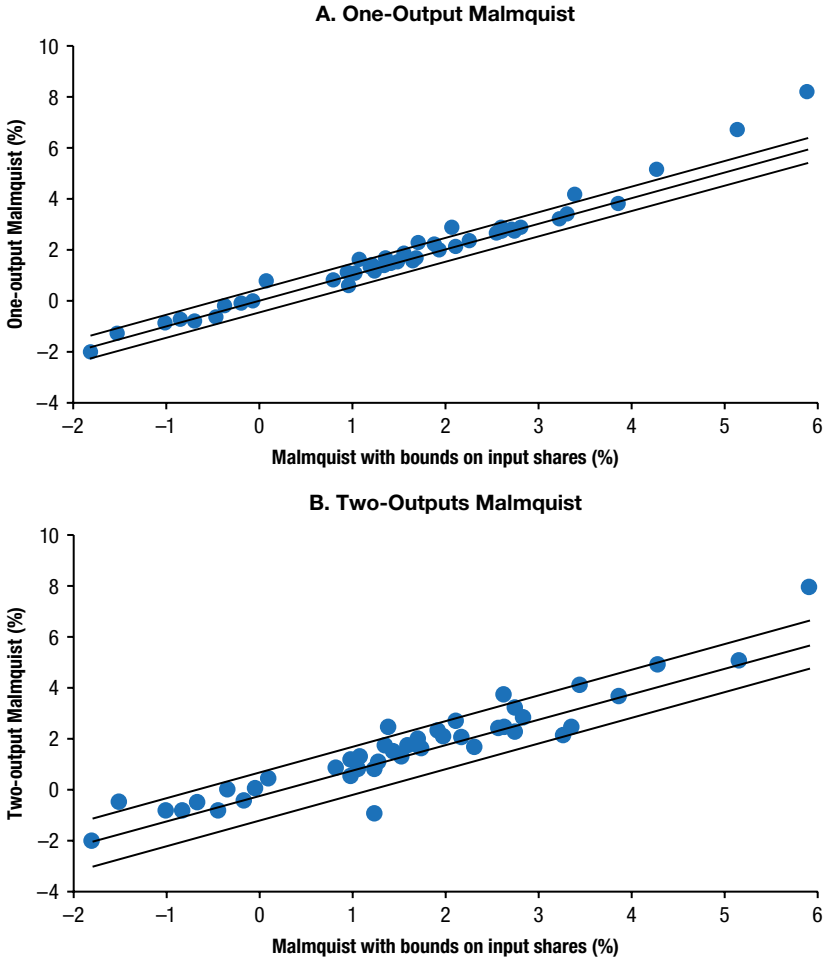
FIGURE 2B.3 Scatter plots of TFP growth rates from different index methods for Africa south of the Sahara (annual averages, 1995–2012)



Source: Authors' calculation and illustration based on DEA-Malmquist and TFP index methods.

Note: If methods deliver exactly the same total factor productivity (TFP) growth rate, points should be on the 45-degree line in the figure: distance to the line reflects differences in TFP estimates by the different methods. Upper and lower bounds are calculated as plus and minus two standard deviations, respectively.

FIGURE 2B.4 Scatter plots of TFP growth rates from different DEA-Malmquist index methods (annual averages, 1995–2012)



Source: Authors' calculation and illustration based on different DEA-Malmquist index methods.

Note: If methods deliver exactly the same total factor productivity (TFP) growth rate, points should be on the 45-degrree line in the figure: distance to the line reflects differences in TFP estimates by the different methods. Upper and lower bounds are calculated as plus and minus two standard deviations, respectively.

TABLE 2B.2 Annual average TFP growth rates for African countries using different TFP index methods, 1971–2012

	DEA-Malmquist index			TFP fixed-input shares[d]	Difference between DEA-Malmquist indexes and TFP fixed-input-shares index (absolute value)			
Countries	1 output[a]	2 outputs[b]	Bounds[c]		1 output[a]	2 outputs[b]	Bounds[c]	Average
Benin	8.2	8.1	5.9	3.6	4.6	4.5	2.3	3.8
Rwanda	6.7	5.2	5.1	2.9	3.8	2.3	2.2	2.8
Congo, Rep.	5.1	5.1	4.3	3.2	1.9	1.9	1.1	1.6
Sudan	2.7	3.9	2.6	1.7	1.0	2.2	0.8	1.3
Congo, Dem. Rep.	0.7	0.6	0.1	–0.7	1.5	1.3	0.8	1.2
Liberia	1.3	–0.8	1.2	0.3	1.0	1.1	0.9	1.0
Ghana	2.1	2.4	1.9	1.1	0.9	1.3	0.8	1.0
Mauritania	1.4	1.6	1.4	0.5	0.9	1.1	0.9	1.0
Madagascar	–0.3	0.2	–0.4	0.7	1.0	0.5	1.1	0.9
Burundi	–2.1	–1.8	–1.8	–1.0	1.0	0.8	0.8	0.9
Sierra Leone	4.1	4.4	3.4	3.1	0.9	1.3	0.3	0.8
Libya	2.2	1.8	1.7	1.1	1.1	0.6	0.6	0.8
Guinea	0.8	1.1	0.8	0.1	0.7	0.9	0.7	0.8
Kenya	2.8	3.4	2.7	2.2	0.6	1.2	0.5	0.7
Ethiopia	2.8	2.7	2.6	2.0	0.8	0.7	0.6	0.7
Gabon	1.6	1.9	1.4	0.9	0.7	1.0	0.4	0.7
Mozambique	3.8	3.8	3.8	3.2	0.6	0.6	0.7	0.6
Egypt	2.8	2.9	2.1	2.0	0.8	0.9	0.1	0.6
Gambia, The	–0.9	–0.3	–0.7	–1.2	0.3	0.9	0.5	0.6
Central Afr. Rep.	1.4	2.6	1.4	1.3	0.1	1.4	0.1	0.5
Swaziland	–1.3	–0.3	–1.5	–1.5	0.3	1.2	0.0	0.5
Tanzania	0.7	0.7	1.0	1.3	0.6	0.5	0.3	0.5
Burkina Faso	1.3	1.0	1.2	0.7	0.6	0.3	0.5	0.4
Angola	3.3	2.6	3.3	3.5	0.2	0.9	0.2	0.4
Zambia	2.7	2.5	2.7	3.1	0.4	0.6	0.3	0.4
Mali	0.0	0.2	–0.1	0.5	0.5	0.2	0.5	0.4
Zimbabwe	–0.7	–0.6	–0.5	–0.2	0.5	0.4	0.2	0.4
Namibia	–0.8	–0.6	–0.9	–0.4	0.4	0.2	0.4	0.3
Botswana	1.0	1.4	1.0	0.8	0.2	0.5	0.2	0.3
Algeria	3.2	2.4	3.2	3.2	0.0	0.8	0.0	0.3
Malawi	1.9	2.3	1.9	1.8	0.2	0.5	0.2	0.3
Senegal	1.6	1.5	1.5	1.3	0.3	0.2	0.2	0.2

(continued)

TABLE 2B.2 (continued)

Countries	DEA-Malmquist index			TFP fixed-input shares[d]	Difference between DEA-Malmquist indexes and TFP fixed-input-shares index (absolute value)			
	1 output[a]	2 outputs[b]	Bounds[c]		1 output[a]	2 outputs[b]	Bounds[c]	Average
Tunisia	1.6	1.9	1.7	2.0	0.4	0.1	0.3	0.2
Togo	1.6	1.5	1.1	1.3	0.2	0.2	0.3	0.2
Somalia	1.6	2.2	1.7	1.6	0.0	0.6	0.1	0.2
Cameroon	2.6	2.6	2.6	2.8	0.2	0.2	0.3	0.2
Morocco	1.1	1.3	1.0	1.4	0.2	0.1	0.3	0.2
Uganda	–1.0	–0.6	–1.0	–0.8	0.2	0.2	0.2	0.2
Guinea-Bissau	1.1	1.3	1.3	1.4	0.3	0.1	0.1	0.2
Niger	2.3	1.9	2.3	2.2	0.1	0.3	0.1	0.2
Côte d'Ivoire	1.8	1.9	1.6	1.7	0.1	0.3	0.1	0.2
Mauritius	–0.1	–0.2	–0.2	–0.3	0.2	0.1	0.1	0.1
South Africa	2.1	2.2	2.1	2.0	0.1	0.2	0.1	0.1
Nigeria	2.8	3.0	2.8	2.9	0.0	0.2	0.0	0.1
Chad	1.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0

Source: Authors' calculation based on different DEA-Malmquist and TFP index methods.

Notes: [a] Malmquist index with one output and six inputs; [b] two outputs (crop and livestock) and six inputs; [c] one output and six inputs, but upper and lower bounds (plus and minus one standard deviation from the mean, respectively) imposed to shadow prices; [d] fixed shares are average-input shadow shares from linear programming problems used to calculate distance functions. TFP = total factor productivity.

Benin and Rwanda. Republic of the Congo, Sudan, and Democratic Republic of the Congo also show relatively large differences. Comparing the results of Malmquist-DEA methods with those obtained from a Törnqvist-Theil index for 93 countries, Coelli and Prasada Rao (2001) concluded that the observed differences between estimates could result from poorly estimated shadow prices for some countries because of the dimensionality problem in DEA. Or, if shadow shares are well estimated, problems could arise from some countries differing significantly from the sample average, because of country-specific factors, such as land scarcity and labor abundance.

Appendix 2C: Country Groupings and Plots of Partial and Total Factor Productivity Levels

TABLE 2C.1 Countries by economic development classification and country's share in group's total agriculture value-added

		Low income	Middle income (MI) (69.5)
More favorable agricultural conditions	Mineral rich (LI–1) (4.4)	Central African Republic (9.5)	Algeria (8.6)
		Congo, Dem. Rep. (45.4)	Angola (2.4)
		Guinea (11.9)	Botswana (0.2)
		Liberia (4.7)	Cameroon (2.7)
		Sierra Leone (10.9)	Cape Verde (0.0)
		Zambia (17.6)	Congo, Rep. (0.2)
	Nonmineral rich (LI–2) (22.0)	Benin (4.3)	Côte d'Ivoire (2.8)
		Burkina Faso (6.0)	Djibouti (0.0)
		Ethiopia (31.4)	Egypt (19.4)
		Gambia, The (0.7)	Equatorial Guinea (0.2)
		Guinea-Bissau (0.7)	Gabon (–)
		Kenya (14.7)	Ghana (3.7)
		Madagascar (5.5)	Lesotho (0.1)
		Malawi (3.4)	Libya (–)
		Mozambique (5.4)	Mauritius (0.3)
		Tanzania (16.4)	Morocco (7.0)
		Togo (2.6)	Namibia (0.4)
		Uganda (8.8)	Nigeria (35.3)
		Zimbabwe (–)	São Tomé & Príncipe (0.0)
Less favorable agricultural conditions (LI–3) (4.1)		Burundi (6.5)	Senegal (1.1)
		Chad (11.1)	Seychelles (0.0)
		Comoros (–)	South Africa (4.3)
		Eritrea (–)	South Sudan (1.0)
		Mali (31.0)	Sudan (7.2)
		Mauritania (9.8)	Swaziland (0.2)
		Niger (21.0)	Tunisia (2.7)
		Rwanda (20.6)	
		Somalia (–)	

Source: Authors' calculations based on Diao et al. (2007) and World Bank (2012).

Notes: The figure in parentheses is the region's percentage share in Africa's total agriculture value-added, or the country's share in the region's total (2003–2010 annual average). Dashes mean data are not available. Data for South Sudan and Sudan are based on 2008–2010 values. LI–1 = low income, more favorable agriculture, and mineral rich; LI–2 = low income, more favorable agriculture, and non-mineral rich; LI–3 = low income and less favorable agriculture.

TABLE 2C.2 Countries by Regional Economic Community (REC) and country's share in REC's total agriculture value-added

CEN-SAD (66.8)	COMESA (37.4)	EAC (8.2)	ECCAS (7.9)
Benin (1.4)	Burundi (0.7)	Burundi (3.3)	Angola (21.4)
Burkina Faso (2.0)	Comoros (–)	Kenya (39.6)	Burundi (3.4)
Central African Rep. (0.6)	Congo, Dem. Rep. (5.3)	Rwanda (10.3)	Cameroon (24.2)
Chad (0.7)	Djibouti (0.0)	Tanzania (23.0)	Central African Rep. (5.3)
Comoros (–)	Egypt (36.1)	Uganda (23.8)	Chad (5.8)
Côte d'Ivoire (2.9)	Eritrea (–)		Congo, Dem. Rep. (25.4)
Djibouti (0.0)	Ethiopia (18.4)		Congo, Rep. (1.9)
Egypt (20.2)	Kenya (8.6)		Equatorial Guinea (1.7)
Gambia, The (0.2)	Libya (–)		Gabon (–)
Ghana (3.9)	Madagascar (3.3)		Rwanda (10.8)
Guinea (0.8)	Malawi (2.0)		São Tomé & Príncipe (0.1)
Guinea-Bissau (0.2)	Mauritius (0.5)		
Kenya (4.8)	Rwanda (2.3)		
Liberia (0.3)	Seychelles (0.0)		
Libya (–)	South Sudan (1.8)		
Mali (1.9)	Sudan (13.4)		
Mauritania (0.6)	Swaziland (0.3)		
Morocco (7.3)	Uganda (5.2)		
Niger (1.3)	Zambia (2.1)		
Nigeria (36.7)	Zimbabwe (–)		
São Tomé & Príncipe (0.0)			
Senegal (1.2)			
Sierra Leone (0.7)			
Somalia (–)			
South Sudan (–)			
Sudan (8.5)			
Togo (0.9)			
Tunisia (2.8)			

Source: Authors' calculations based on World Bank (2012).

Notes: CEN-SAD = Community of Sahel-Saharan States; COMESA = Common Market for Eastern and Southern Africa; EAC = East African Community; ECCAS = Economic Community of Central African States; ECOWAS = Economic Community of West African States; IGAD = Intergovernmental Authority for Development; SADC = Southern Africa Development Community; and UMA = Union du Maghreb Arabe. The figure in parentheses is the region's percentage share in Africa's total agriculture value-added, or the country's share in the region's total (2003–2010 annual average). The shares across the RECs do not add up to 100 percent, as the constituent countries are not mutually exclusive. Dashes mean data are not available. Data for South Sudan and Sudan are based on 2008–2010 values.

ECOWAS (36.4)	IGAD (17.8)	SADC (15.0)	UMA (13.2)
Benin (2.6)	Djibouti (0.1)	Angola (11.2)	Algeria (45.6)
Burkina Faso (3.6)	Eritrea (–)	Botswana (0.9)	Libya (–)
Cape Verde (0.1)	Ethiopia (38.8)	Congo, Dem. Rep. (13.3)	Mauritania (3.0)
Côte d'Ivoire (5.3)	Kenya (18.2)	Lesotho (0.4)	Morocco (37.1)
Gambia, The (0.4)	Somalia (–)	Madagascar (8.1)	Tunisia (14.3)
Ghana (7.1)	South Sudan (3.7)	Malawi (5.0)	
Guinea (1.4)	Sudan (28.2)	Mauritius (1.2)	
Guinea-Bissau (0.4)	Uganda (10.9)	Mozambique (8.0)	
Liberia (0.6)		Namibia (2.0)	
Mali (3.5)		Seychelles (0.1)	
Niger (2.4)		South Africa (20.0)	
Nigeria (67.4)		Swaziland (0.7)	
Senegal (2.2)		Tanzania (24.0)	
Sierra Leone (1.3)		Zambia (5.1)	
Togo (1.6)		Zimbabwe (–)	

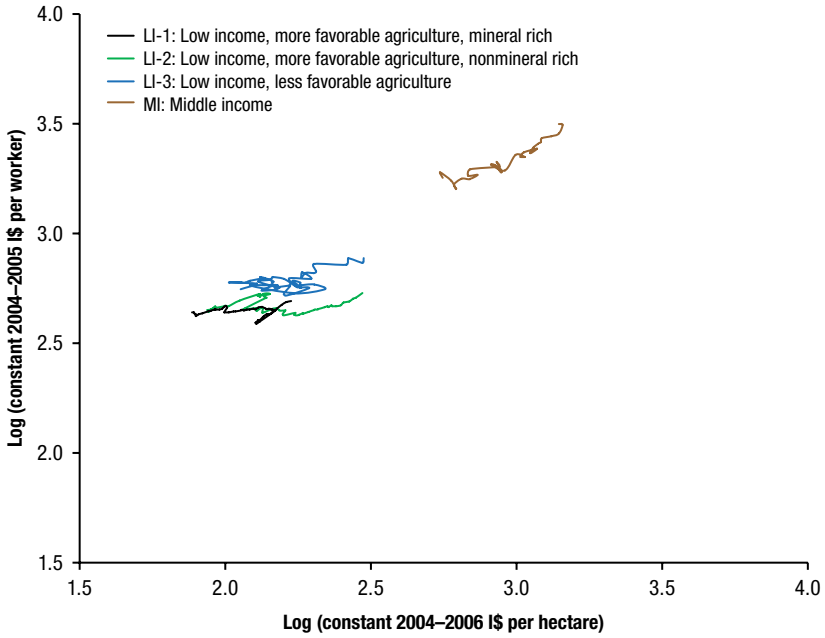
TABLE 2.C3 Countries by size and growth of agriculture sector

Size of agriculture sector		Growth of agriculture sector	
Large	Small	Fast-growing	Slow-growing
Egypt	Botswana	Angola	Burundi
Ethiopia	Gabon	Cameroon	Congo, Dem. Rep.
Kenya	Gambia, The	Malawi	Liberia
Morocco	Guinea-Bissau	Mozambique	Mauritius
Nigeria	Mauritius	Nigeria	Namibia
South Africa	Swaziland	Rwanda	Tunisia
Sudan		Sierra Leone	Zimbabwe
Tanzania		Zambia	

Source: Authors' calculations based on FAO (2014).

Notes: Large-agricultural economies have at least 3.0 percent of Africa's total agricultural output; small agricultural economies have less than 0.1 percent of Africa's total agricultural output; fast-growing agricultural economies surpass the CAADP agricultural growth rate target of 6.0 percent per year; and slow-growing agricultural economies have an agricultural growth rate of less than 1.0 percent per year.

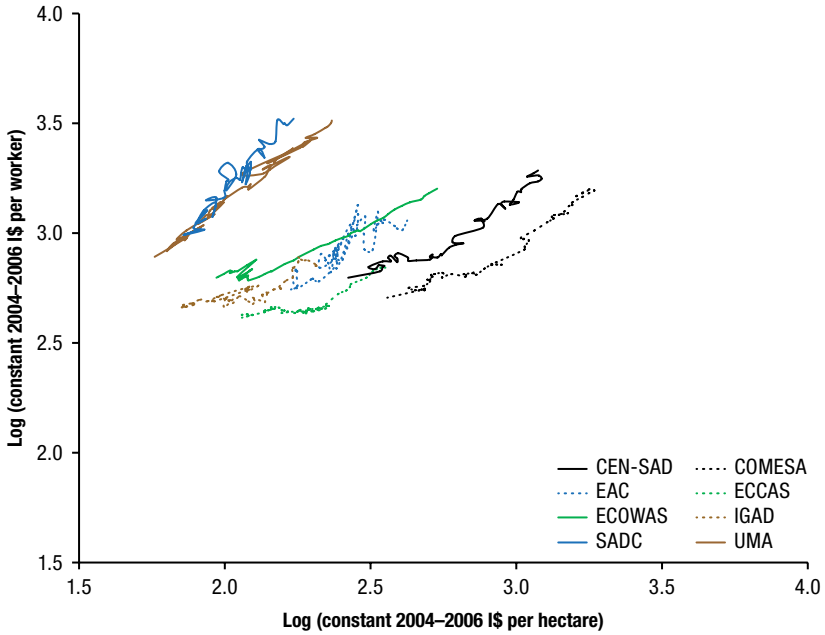
FIGURE 2C.1 Line plots of land and labor productivity by economic classification (1961–2012)



Source: Authors' calculation and representation based on FAO (2014).

Note: I$ = international dollar.

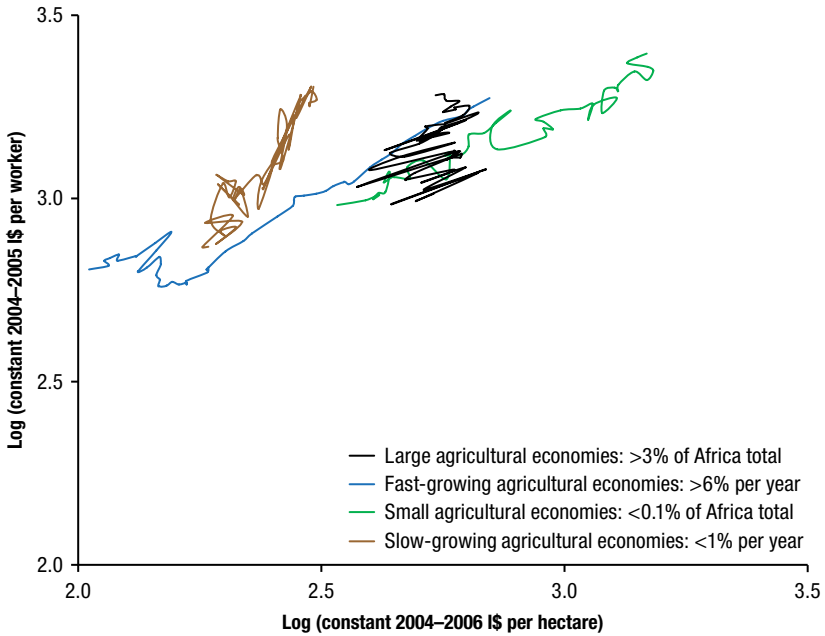
FIGURE 2C.2 Line plots of land and labor productivity by Regional Economic Community (1961–2012)



Source: Authors' calculation and representation based on FAO (2014).

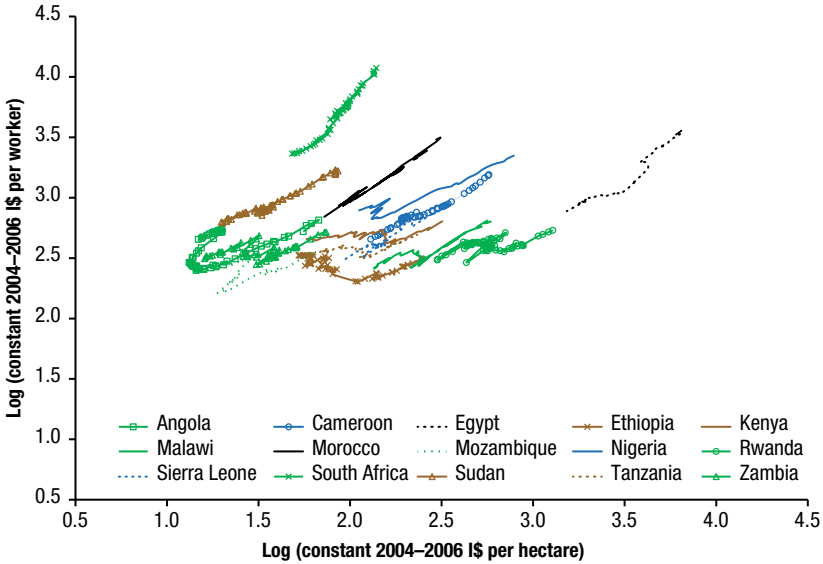
Notes: CEN-SAD = Community of Sahel-Saharan States; COMESA = Common Market for Eastern and Southern Africa; EAC = East African Community; ECCAS = Economic Community of Central African States; ECOWAS = Economic Community of West African States; IGAD = Intergovernmental Authority for Development; SADC = Southern Africa Development Community; and UMA = Union du Maghreb Arabe; I$ = international dollar.

FIGURE 2C.3A Line plots of land and labor productivity by size or rate of growth of agriculture sector (1961–2012)



Source: Authors' calculation and representation based on FAO (2014).
Note: I$ = international dollar.

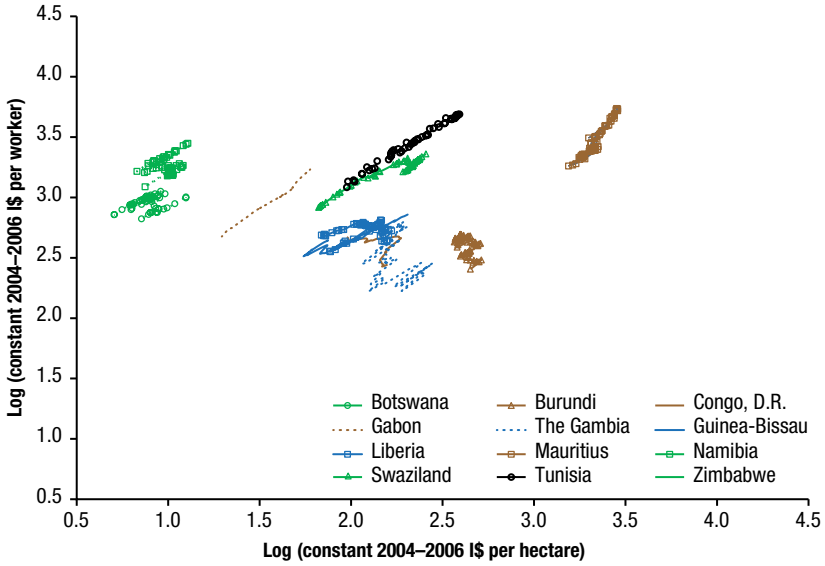
FIGURE 2.C3B Line plots of land and labor productivity for selected countries by size or rate of growth of agriculture sector (1961–2012)



Source: Authors' calculation and representation based on FAO (2014).

Notes: Countries with at least 3 percent of Africa's total agricultural output are large economies. Countries that surpass the CAADP agricultural growth rate target of 6 percent per year are fast-growing agricultural economies. I$ = international dollar.

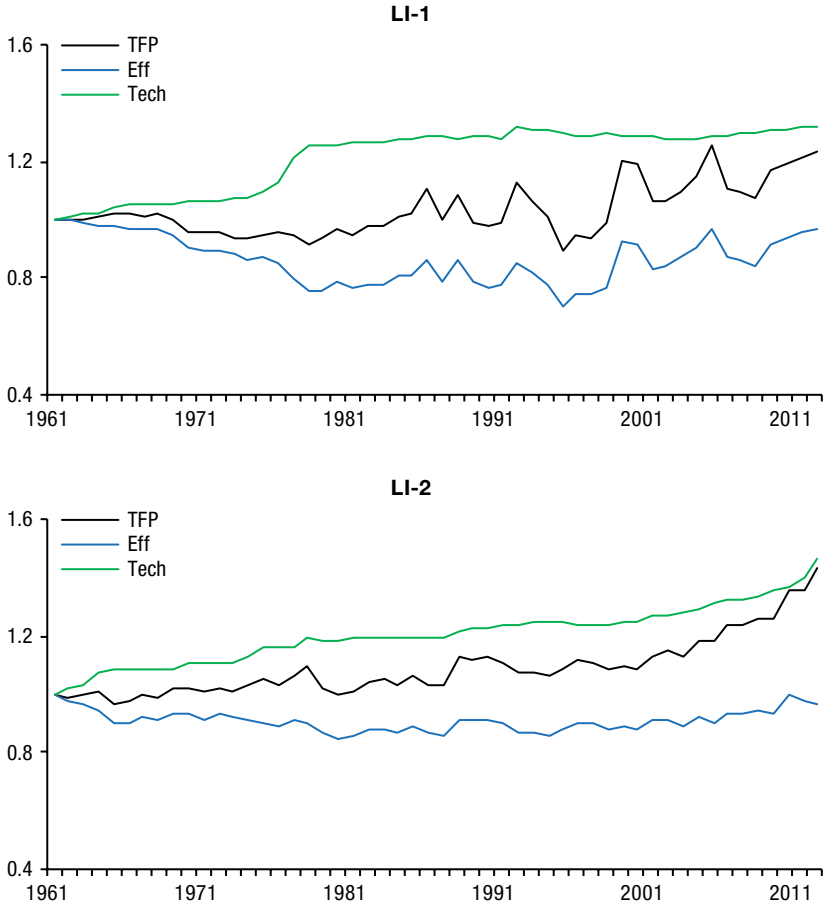
FIGURE 2C.3C Line plots of land and labor productivity for selected countries by size or rate of growth of agriculture sector (1961–2012)

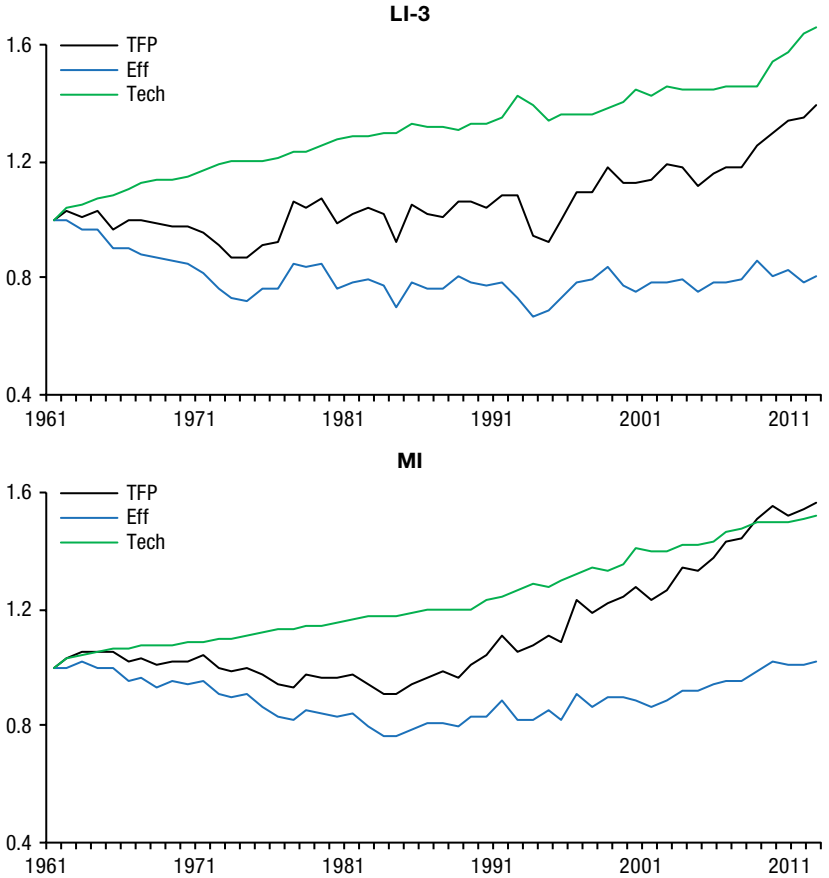


Source: Authors' calculation and representation based on FAO (2014).

Notes: Countries with less than 0.1 percent of Africa's total agricultural output are small agricultural economies. Countries with agricultural growth rates of less than 1.0 percent per year are slow-growing agricultural economies. I$ = international dollar.

FIGURE 2C.4 Levels of total factor productivity, efficiency, and technology by economic classification (1961–2012: indexed at 1961=1)

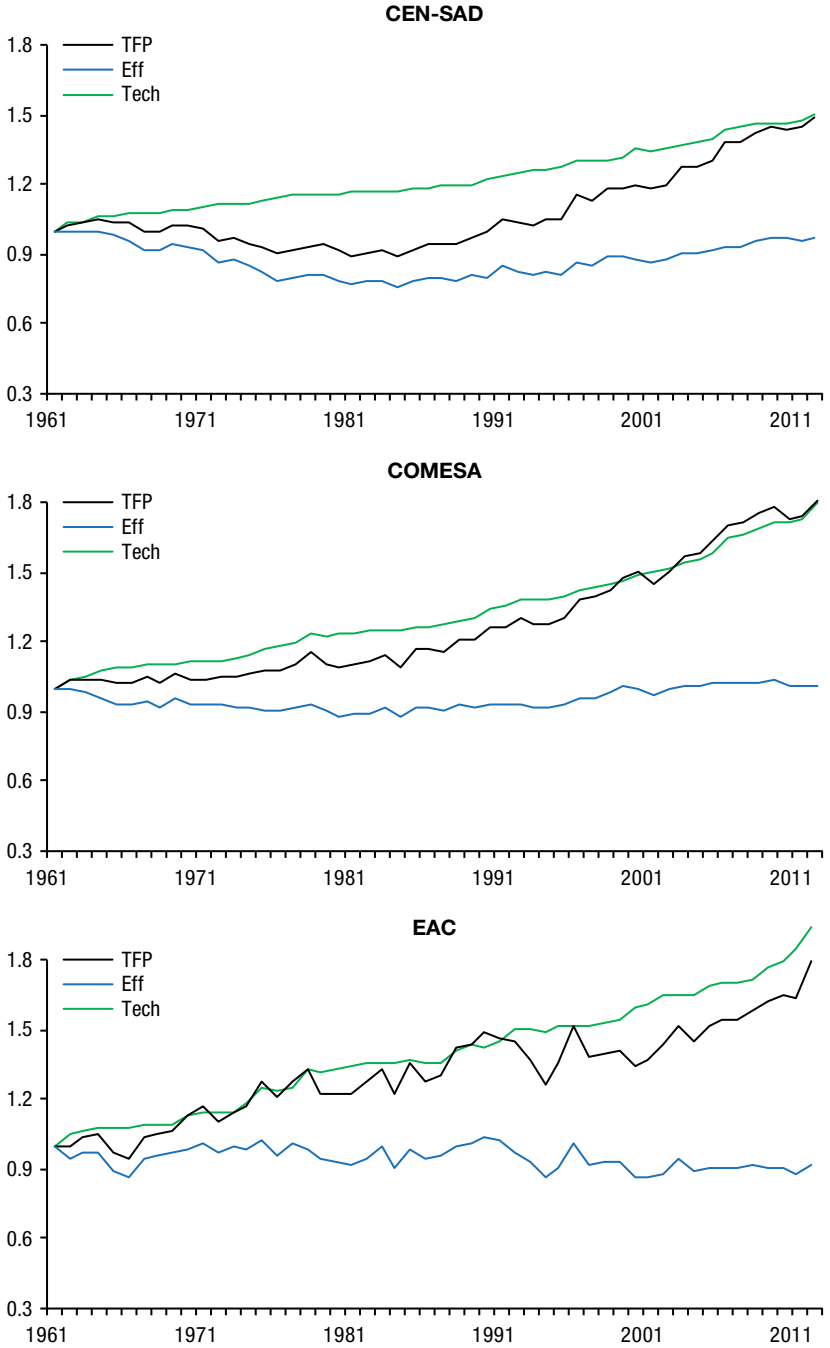


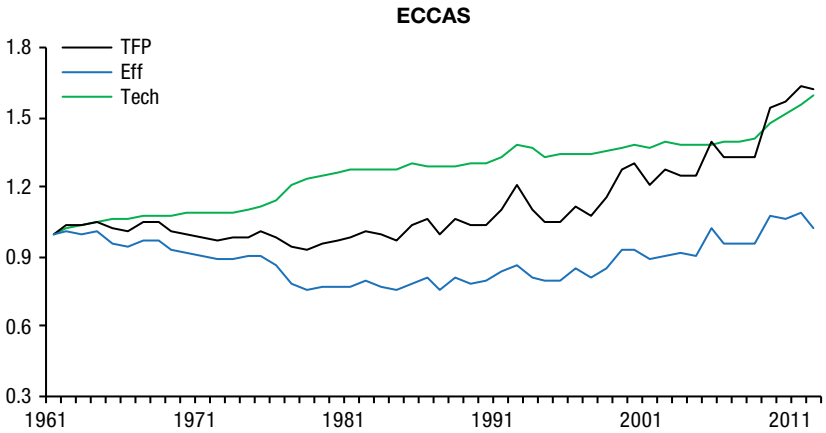


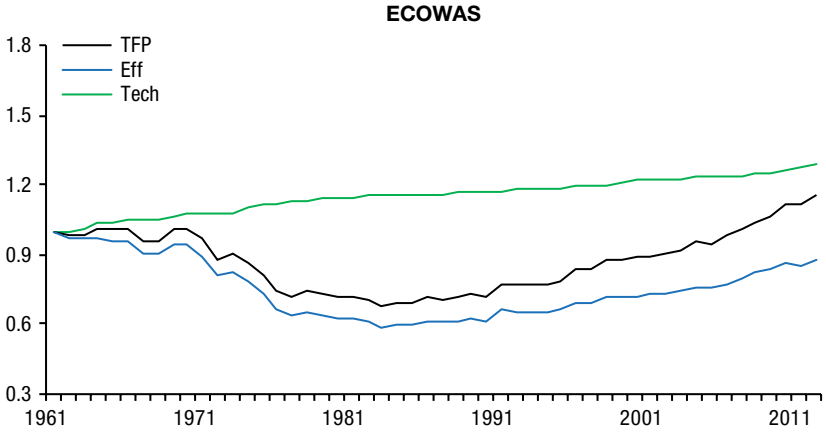
Source: Authors' calculation and illustration based on TFP model results.

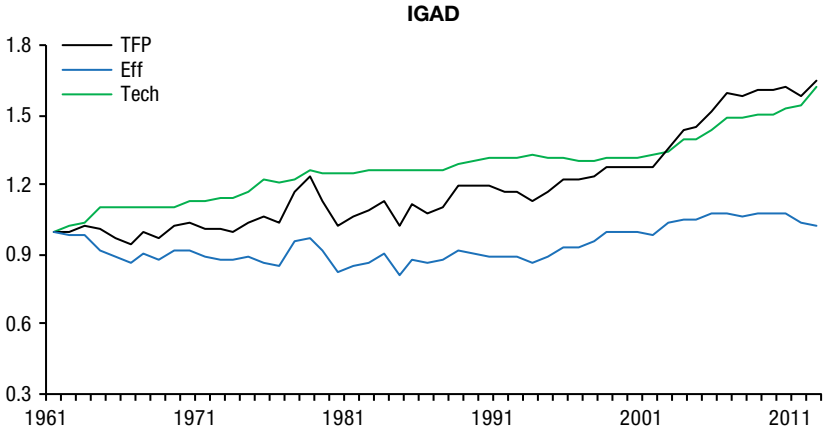
Notes: TFP = total factor productivity; Eff = efficiency; = Tech = technology. LI–1 = low income, more favorable agriculture, and mineral rich; LI–2 = low income, more favorable agriculture, and nonmineral rich; LI–3 = low income and less favorable agriculture; MI = middle income.

FIGURE 2C.5 Levels of total factor productivity, efficiency, and technology by Regional Economic Community (1961–2012: indexed at 1961=1)



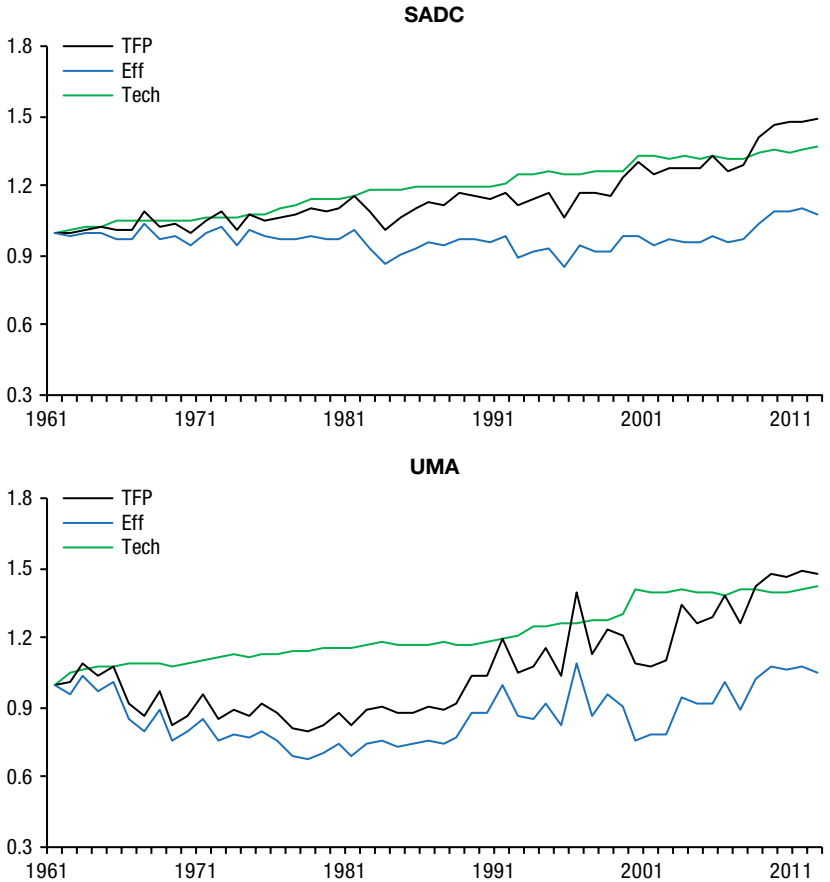

ECCAS
TFP
Eff
Tech
1.8
1.5
1.2
0.9
0.6
0.3
1961
1971
1981
1991
2001
2011


ECOWAS
TFP
Eff
Tech
1.8
1.5
1.2
0.9
0.6
0.3
1961
1971
1981
1991
2001
2011


IGAD
TFP
Eff
Tech
1.8
1.5
1.2
0.9
0.6
0.3
1961
1971
1981
1991
2001
2011

(continued)

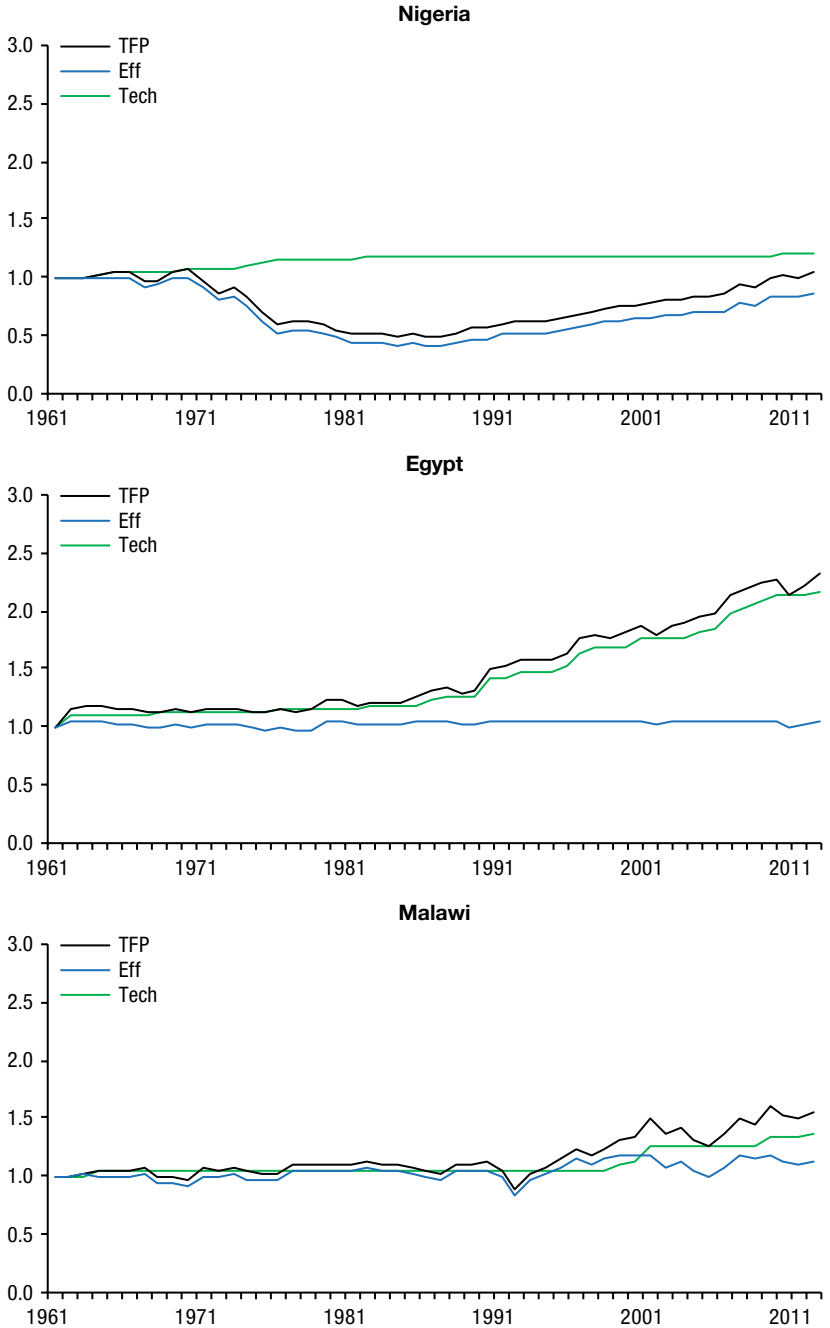
FIGURE 2C.5 (continued)



Source: Authors' calculation and illustration based on TFP model results.

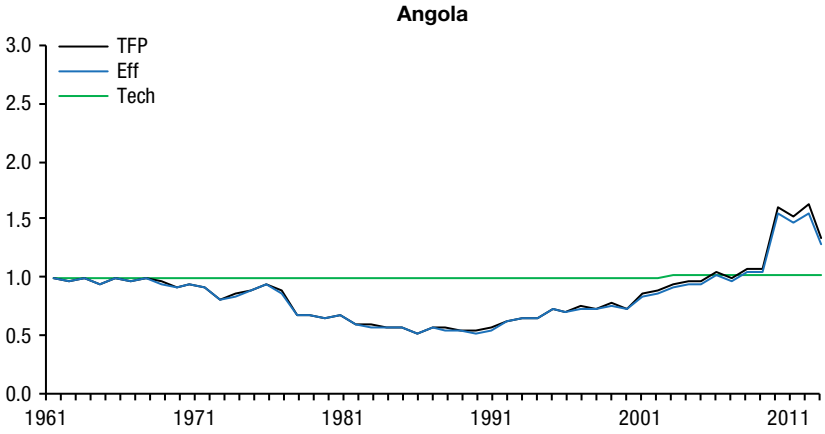
Notes: TFP = total factor productivity; Eff = efficiency; Tech = technology; CEN-SAD = Community of Sahel-Saharan States; COMESA = Common Market for Eastern and Southern Africa; EAC = East African Community; ECCAS = Economic Community of Central African States; ECOWAS = Economic Community of West African States; IGAD = Intergovernmental Authority for Development; SADC = Southern Africa Development Community; and UMA = Union du Maghreb Arabe.

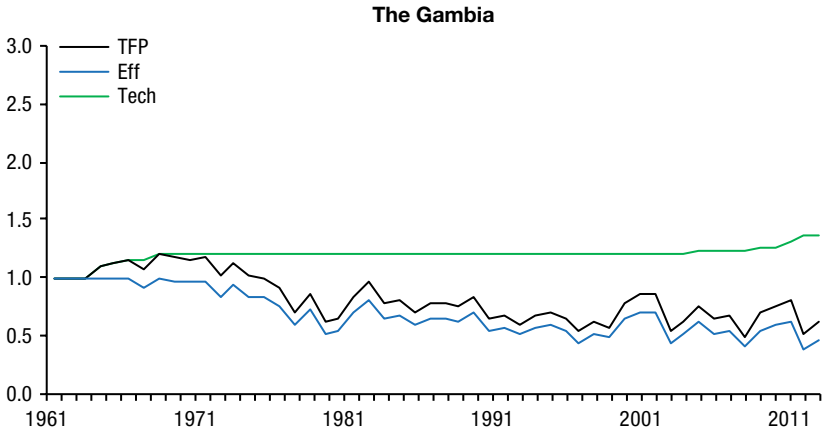
FIGURE 2C.6 Levels of total factor productivity, efficiency, and technology for selected countries (1961–2012: indexed at 1961=1)

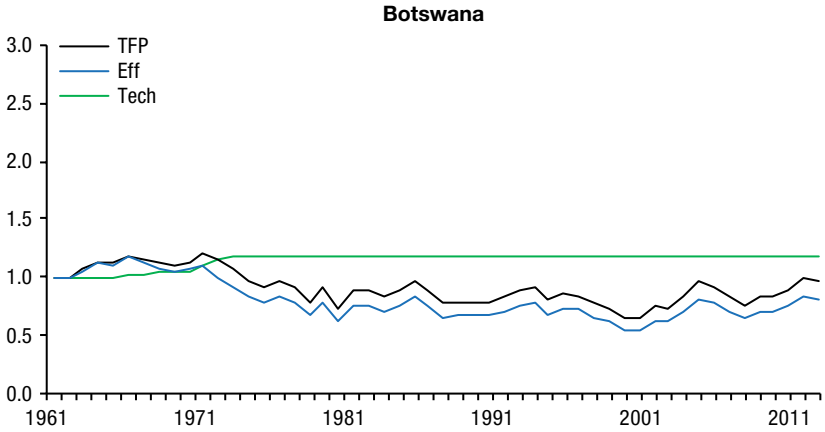


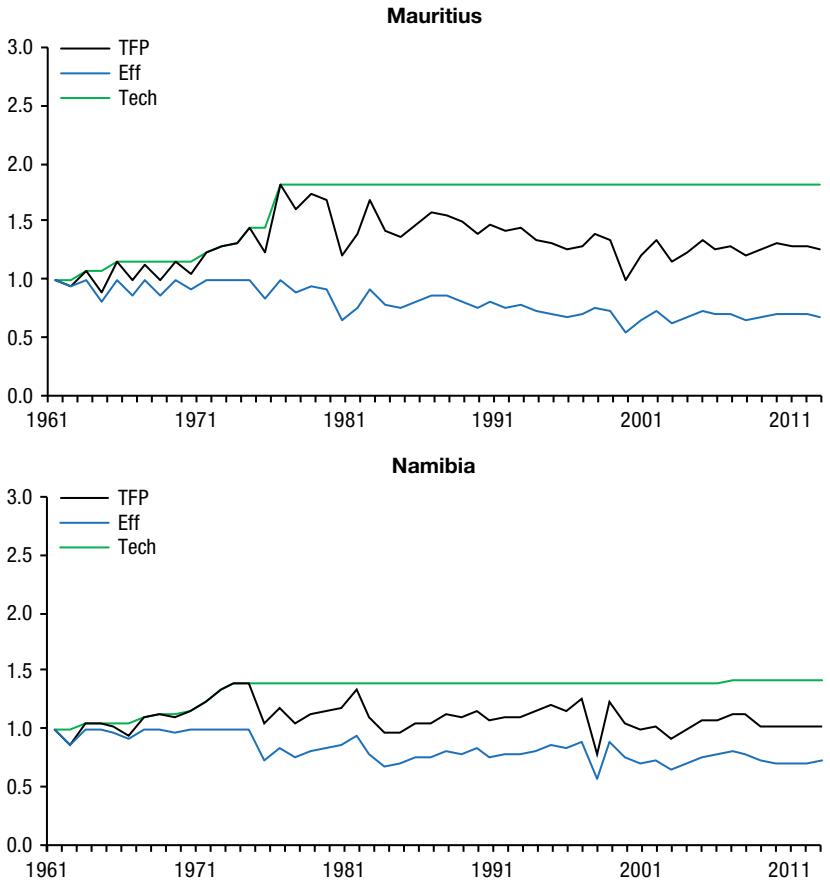
(continued)

FIGURE 2C.6 (continued)









Source: Authors' calculation and illustration based on TFP model results.

Notes: TFP = total factor productivity; Eff = efficiency; Tech = technology. The selected countries are the top two largest agricultural economies in terms of percentage share in Africa's total agricultural output—Egypt and Nigeria; the top two fastest-growing agricultural economies—Angola and Malawi; the bottom two smallest agricultural economies—The Gambia and Botswana; and the bottom two slowest-growing agricultural economies—Mauritius and Namibia.

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