Sub-Saharan Africa: Methods for Examining Institutions and Agricultural Productivity

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Abstract

This study estimates nonparametric non-stochastic Malmquist indices and a stochastic Fourier production frontier to examine agricultural productivity and its interactions with socio-political institutions in 41 sub-Saharan African countries during 1961-1999. We have learned from this study that on average, agricultural productivity in SSA was negative during the 1960's and 1970's, but has been positive during the last two decades. Institutions offer a significant explanation of at least some of the differential performance across countries.

Introduction

The 53 countries and 612 million people of Sub-Saharan Africa (SSA) constitute the poorest region in the world, with per capita incomes of about $500 per year. Agriculture contributes about 35% of the regional GNP, employs more than two-thirds of the total labor force and contributes about 40% of foreign exchange as well as staple food supplies. The productivity of agriculture is therefore clearly an important key to improved living conditions within this vast area. While our understanding of SSA agricultural productivity is not very complete, the rate of improvement seems to be the lowest of any comparable region in the world. Although the rate of increase in agricultural output has been about 2.3% over the past two decades, a number of productivity studies have indicated that productivity itself has decreased. Contradicting this is a recent FAO study that showed 0.5% productivity gains in the region during the 1970's and 1980's. The central theme of this research is to obtain a reliable measure of

SSA agricultural productivity growth and to evaluate possible reasons for differences across countries, with special attention to institutional explanations. Three approaches are used to address these two issues: 1) non-parametric non-stochastic contemporaneous and cumulative Malmquist indexes, and 2) a parametric stochastic frontier translog-Fourierproduction function.

Related Studies

Productivity change is commonly measured with a Tornquist-Theil index, the share-weighted rate of output change minus the share-weighted rate of input change. Because of a lack of information on land and labor payments and because of market distortions, this approach is not feasible in Africa because the shares of inputs are not identifiable. Alternatively, productivity change can be estimated by estimating changes in aggregate parametric or non-parametric agricultural production functions. To implement this concept, we make use of a panel of countries, under the assumption that they share a common technology with country-to-country differences accounted for by dummy variables or unique country variables such as land quality. These approaches have been applied to SSA agriculture in the past decade, with results we relate below.

Block (1994) estimated a parametric system of annual production functions for 39 SSA countries, with TFP growth computed from the change in intercepts of two consecutive production functions. He reported average annual TFP changes between –0.5% and 1.6%. Thirtle, Hardley, and Townsend (1995) estimated an average annual TFP growth rate of 0.838% for 22 SSA countries during 1971-1986, using an input-based non-parametric Malmquist approach. They found that some of the variation in technical change was explained by investments in infrastructure, research and development, and secondary education. Lusigi and Thirtle (1997) estimated that the average rate of TFP growth in 47 African countries was 1.27% per year for the period 1961-1991, again using input-based non-parametric Malmquist indexes. They also estimated parametric frontier models and found that land quality and R&D contributed to output growth. In an update of this analysis, Suhariyanto, Lusigi, and Thirtle (2001) changed the form of input variables from input per unit of land to level of input, which changed the estimated average productivity rate from 1.27% to –0.86% per year.

In the 2000 annual report of Food and Agricultural Organization of the United Nations (FAO), agricultural growth rates for 89 developing countries were calculated as a Tornqvist-Theil index, using input cost shares from studies in Brazil and India. This study estimated the average productivity growth rate to be 0.49% per year for 1961-1996. Eleven of the fourteen countries with negative TFP growth rates were SSA countries. Yu, Fulginiti, and Perrin (2001) used a nonparametric Malmquist approach to examine agricultural productivity in 37 SSA countries from 1961 to 1998, and found an average productivity decline of -1.1% per year.

SSA countries have also been included in some studies of a more global scope. Fulginiti and Perrin's (1997) study of eighteen LDC's during 1980-1995 reported productivity decline in more than half of them, including the three SSA countries in that sample. Arnade (1998) examined 70 countries during 1961-1993 and found productivity declines in 5 out of 6 SSA countries. Rao and Coelli (1998) studied the agricultural productivity of 97 countries over 1980-95, and found that 9 of 22 SSA countries exhibited negative TFP growth.

In addition to these studies there have been a number of single-factor agricultural productivity studies and some scattered studies of individual countries. The weight of evidence from the studies we have examined indicates that a substantial number of SSA countries have experienced declines in agricultural productivity during the past four decades.

Alternative Models

Productivity is defined as output per unit of input. Productivity growth aims at capturing output growth not accounted for by growth in inputs. In this context two questions immediately arise. First, what are the components of productivity growth? Second, what potential institutional and socio-political factors have affected agricultural productivity performance in SSA in the last four decades? Here we describe the models we use to address these questions.

The non-stochastic, non-parametric Malmquist index.

The nonparametric method to measure productivity change utilizes mathematical programming to define the production technology frontier and to determine the distance of each observation in the sample to that frontier. An index of the annual change in productivity of each country is calculated from these results. This method allows economists to decompose a country's productivity growth into three components, namely, efficiency change (catching up to technology), technical change, and scale change (if technology exhibits non-constant returns to scale). The contemporaneous Malmquist constructs the technology frontier from observations during a single year , and constructs a country's productivity index and its components using this frontier and a reference frontier technology constructed from observations during a reference period, usually an adjacent year. The cumulative Malmquist approach constructs the technology frontier at each point in time using the observations made from the starting point up to and including that point in time . The successive reference production sets constructed in this way are nested within each other. The idea is that "what was possible in the past remains always possible in the future". This amounts to allowing only for outward shift of the frontier over time. The procedure for constructing cumulative Malmquist index is outlined below. Contemporaneous Malmquist index is analogous to it, but instead the reference technology is defined using information only from a single period.

The cumulative technology at time r is defined as

(1) $T^{(1,r)}_{cumulative}$ = { $(x^s, y^s): x^s$ can produce y^s , s = 1,…, r}

The contemporaneous technology at time t is defined in a similar manner, but with $s = r$, rather than $s = 1,\ldots,r$.

The output distance function for an observation at time t relative to the technology at time r is defined as

(2) $D^r_{cumulative}(x^t, y^t) = \inf\{\theta : (x^t, y^t/\theta) \in T^{(1,r)}_{cumulative}\}$

Denote with k = 1,…, K the cross-sections, and with n = 1,…, N the inputs $x_n^{k,t}$ at each time period t = 1, …, T. These inputs are used to produce m = 1,…, M outputs $y_m^{k,t}$. Each observation of inputs and outputs is strictly positive. Using t and s to denote time, for each country k' =1,…, K, the distance function value for country k' at time t with respect to the cumulative technology at time r is:

$$(3)\quad [D^{r}_{cumulative}(x^{k',t}, y^{k',t})]^{-1} = \max \theta^{k'}$$

$$\text{subject to} \qquad \theta^{k'} y^{t}_{k',m} \leq \sum_{s=1}^{r}\sum_{k=1}^{K} z^{s}_{k} y^{s}_{k,m} \qquad m = 1,\ldots, M$$

$$\sum_{s=1}^{r}\sum_{k=1}^{K} z^{s}_{k} x^{s}_{k,n} \leq x^{t}_{k',n} \qquad n = 1,\ldots, N$$

$$z^{s}_{k} \geq 0 \qquad k = 1,\ldots,K \text{ and } s = 1,\ldots, r$$

The output-based Malmquist productivity change index between two consecutive period *t* and *t+1* is defined as

$$(4)\quad M^{t}_{cumulative} = \left(\frac{D^{t+1}_{cumulative}(x^{t+1}, y^{t+1})}{D^{t}_{cumulative}(x^{t}, y^{t})}\right)\left[\left(\frac{D^{t}_{cumulative}(x^{t+1}, y^{t+1})}{D^{t+1}_{cumulative}(x^{t+1}, y^{t+1})}\right)\left(\frac{D^{t}_{cumulative}(x^{t}, y^{t})}{D^{t+1}_{cumulative}(x^{t}, y^{t})}\right)\right]^{1/2}$$

where the ratio outside of brackets captures the change in technical efficiency, and the term in the square brackets is a measure of technical change between the two periods.

While we use Equation (7) to provide an answer to the first issue of interest, namely the measurement of productivity growth, we relate these results to variables indicating quality of inputs and socio-political institutions. These variables might help understand the evolution of productivity change as well as the differential performance of countries in the panel. This is done by a simple regression of the Malmquist productivity index on a set of proxies for these concepts.

Parametric Stochastic Frontier Production Function

Essentially different from the indexes described above, a stochastic frontier model provides statistical inference for parameters, as well as estimates of technical efficiency, technical change and other production function parameters. Technical inefficiencies are captured by a one-sided error term. Variables that might potentially explain the differential performance across countries are included in the analysis. We rewrite the standard neoclassical production function the following way, re-labeling it a production frontier :

(5) $$Y_{it} = f(x_{it}, t; \beta)\exp(-u_{it})$$

where Y_{it} is output of the *i*-th country in time period *t*, x_{it} is an *nx1* vector of inputs for the *i*-th country in time period *t*, β is a vector of unknown parameters and u_{it} is a non-negative random variable associated with technical inefficiency across production units. In our case, it accounts for heterogeneity across countries that can cause departures from maximum potential output.

We use this production function to break down the growth rate of aggregate output into contribution from the growth of inputs versus productivity change:

(6) $$\dot{TFP}_{it} = \dot{Y}_{it} - \sum_{n} \varepsilon_{itn} \dot{x}_{itn}$$

where a dot over a variable indicates its rate of change, and ε_{itn} is the production elasticity of input *n*, for country *i* in year *t*, $\varepsilon_n = \dfrac{\partial \ln f(x,t,\beta)}{\partial \ln x_n}$. TFP growth using the production function in equation (1) and dropping subscripts for simplicity, can be decomposed as:

(7) $$\dot{TFP} = TC + EC$$

where a shift of the production frontier representing technical change is

$$TC = \frac{\partial \ln f(x,t;\beta)}{\partial t},$$

and technical inefficiency change is represented by the evolution of *u* through time.

EC can be interpreted as the rate at which a country moves toward or away from the production frontier, which itself may be shifting through time due to innovations.

The technical efficiency change component requires a little more explanation given that it will also be the basis for information that will lead us to answer the second of our questions, the identification of institutional and political factors that underlie differential productivity growth performance across countries in SSA. Technical inefficiency across the production units involved is captured in the production frontier of equation (5) by the non-negative random variable u. The ratio of observed output for the i-th country relative to its potential output defined by the production frontier, given the levels of inputs, is used to define the technical efficiency of the i-th country in period t,

$$(8)\quad TE_{it} = \frac{y_{it}}{f(x_{it};\beta)} = \exp(-u_{it})\,.$$

This measure of technical efficiency takes on values zero to one, with a value of one indicating full technical efficiency. It can also be thought of as indicating the size of the output of the i-th country at time t relative to the output produced by a fully efficient country using the same input vector. The ratio of *TE's* between two periods gives an alternative way of calculating *EC*.

Given that the *TE* term indicates discrepancies in the productivity performance across countries, the frontier methodology lends itself to the inclusion of potential determinants of country heterogeneity which we refer to as 'efficiency changing variables'. We specify a frontier model where the technical inefficiency effects are defined to be an explicit function of country-specific institutional and socio-political factors that we hypothesize have influenced the differential performance of these countries. We then specify the technical inefficency effect u_{it} of the i-th country in the t-th period as a truncated $N(\mu_{it}, \sigma^2)$ distribution, where

$$\mu_{it} = h_{it}\delta,$$

in which h_{it} is a (1xp) vector of variables that influence the efficiency of the country, such as institutional and socio-political conditions, and δ is (px1)vector of unknown scalar parameters to be estimated.

Data and Estimation

FAO data on output and conventional agricultural inputs (land, labor, fertilizer, tractors and animals) are reasonably complete for 41 SSA countries for 1961-1999, and are available at the FAOSTAT website. These data have been used in nearly every previous study of agricultural productivity in SSA countries.

Agricultural output is expressed as the quantity of agricultural production in millions of 1989-1991 "international dollars". Agricultural land is measured as the sum of arable land and permanent crops, in 1,000 hectares. Agricultural labor is measured as the number of persons who are economically actively engaged in agriculture, in thousands. The livestock variable is a weighted average of the number of animals on farms in 1,000's. The farm machinery variable we use is simply the number of agricultural tractors. Fertilizer is quantity of fertilizer plant nutrient consumed (N plus P_2O_5 plus K_2O), in metric tons.

Our approach is to consider productivity to constitute changes in output, so measured, for given levels of this set of traditional inputs. Some measurable factors that we hypothesize may impact this productivity include the quality of labor and land, and institutional and political factors such as war that affect the ability or incentive of producers to extract output from a given bundle of traditional inputs. These variables we call efficiency-changing variables. Two types of efficiency changing variables are considered in this analysis, those that allow for *qualitative* input differences and those that will capture differences in the *institutional and socio-political* environment across countries.

In the first set we include:

a) Labor quality - adult illiteracy rate, taken from World Development Indicators (World Bank).

b) Land quality – percentage of irrigated land are used as proxies for land quality, calculated as the ratio of irrigation land over total agricultural land (FAOSTAT).

In the second set we include the following:

a) Colonial heritage because of its persistent influence in political, economic, cultural, military, financial and religious structure. We utilize dummy variables for former British, French, and Portugal colonies (versus Belgian, Dutch and Italian as reference).

b) Independence, *i.e.* years after independence. These data were collected from Encyclopedia Britannica.

c) Armed conflict. Because war could clearly affect productivity, we constructed three dummy variables to indicate intervention in agricultural production by armed conflicts and wars. The value of WAR1 is 1 when a minor conflict took place, WAR2 is 1 when an intermediate conflict occurred, and a WAR3 equals to 1 indicating a war in the country. The data set was created based on data from Gleditsch et. al.

d) Political rights and civil liberties. We constructed two dummy variables to represent the Freedom House index of political rights and civil liberties, with countries categorized as free or partly free (contrasted with not free), from 1972 to 1999.

The nonparametric, non-stochastic Malmquist index of equation (4) is calculated solving the linear programming problems of equation (3) using DEAP 2.1 by Coelli. The simple regression model used to associate these productivity estimates with variables representing input quality and institutions is

$$\begin{aligned} (9) \quad & PRODUCTIVITYGROWTH = \alpha_0 + \alpha_1 IRRIGATE + \alpha_2 ILL + \alpha_3 INDEP + \alpha_4 UK \\ & + \alpha_5 FRANCE + \alpha_6 PORTUGAL + \alpha_7 DROUGHT + \alpha_8 WAR1 + \alpha_9 WAR2 \\ & + \alpha_{10} WAR3 + \alpha_{11} ETHIOPIA + \alpha_{12} FREE + \alpha_{13} PARTFREE + \varepsilon \end{aligned}$$

A fixed effects model with errors corrected for heteroskedasticity and autocorrelation was implemented.

The stochastic frontier of equation (5) is approximated with a Fourier flexible form, a linear combination of trigonometric and polynomial terms that have the capability of representing exactly any well-behaved multivariate function and its derivatives. The Fourier flexible functional form has been used to approximate dual cost structures but it has not been used to approximate a primal production frontier. This paper does so. Assuming symmetry, the production frontier to estimate for SSA agriculture is:

$$(10) \qquad \ln Y = u_0 + \sum_{i=1}^{5} b_i^{'} x_i + \frac{1}{2} x' C x + b_t T + b_{tt} T^2 + [m_T \cos(z_T) + n_T \sin(z_T)]$$

$$
\begin{aligned}
&+\sum_{i=1}^{5}\sum_{j>i}^{5}[m_{ij}\cos(z_i - z_j) + n_{ij}\sin(z_i - z_j)] \\
&+\sum_{i=1}^{5}\sum_{j>i}^{5}[m_{ij1}\cos(z_i - z_j - z_T) + n_{ij1}\sin(z_i - z_j - z_T)] \\
&+\sum_{i=1}^{5}\sum_{j>i}^{5}[m_{ij2}\cos(z_i - z_j + z_T) + n_{ij2}\sin(z_i - z_j + z_T)] \\
&- u + v
\end{aligned}
$$

where Y is the agricultural output while *x* is the vector of inputs (land, labor, livestock, machinery, and fertilizer); t is the time trend used as a proxy for technical change; the *z*'s are scaled values of *lnx*'s and *t*. *u* is the one sided error assumed truncated at zero of $N(\mu,\ \sigma_U^2)$ as introduced before that captures heterogeneity across countries and is the basis for differences in technical efficiency. In order to allow for measurement error and other random factors the production frontier is augmented by adding a random error *v*, an iid $N(0,\ \sigma_v^2)$ that is independent of *u*. This is a parametric *stochastic* production frontier.

As stated before, the technical inefficiency term is a function of input quality proxies and institutional and socio-political variables. Due to data availability, two efficiency models are introduced that accommodate different sampling periods: model 1 excludes political freedom and ranges from 1961 to 1999, and model 2 includes every variable but starts at 1972. In model 2, estimated with data from 1961 to 1999, the technical inefficiency is specified as

$$
\begin{aligned}
&\mu_{it} = \delta_0 + \delta_1 IRRIGATE + \delta_2 ILL + \delta_3 INDEP + \delta_4 UK \\
(11)\qquad &+\delta_5 FRANCE + \delta_6 PORTUGAL + \delta_7 DROUGHT + \delta_8 WAR1 + \delta_9 WAR2 \\
&+\delta_{10} WAR11 + \delta_{11} ETHIOPIA + \delta_{12} FREE + \delta_{13} PARTFREE + \varepsilon
\end{aligned}
$$

where δ is a 1x13 vector of parameters to be estimated.

FRONTIER 4.1 by Coelli (1996) is used for estimating equations (10) and (11), using the maximum-likelihood (ML) method. It allows simultaneous estimation of the parameters of the stochastic frontier and the model for the technical inefficiency effects.

Several hypothesis tests on production structure and technical inefficiency parameters implied that the appropriate model for this study appears to be the translog Fourier flexible form with technical inefficiency. Two implications follow rejection of the various functional form hypotheses. First, the agricultural production function clearly does not have the Cobb-Douglas or translog form. The Fourier series terms are significant additions to the model, indicating that the translog model might be misleading. Second, since the full Fourier flexible form produces estimates of the production function with the least amount of approximation error, estimates of the technical change from this model may well be the most accurate as well.

However, as the specification of production technology grows more complicated, there is a rapid increase in the number of data points at which monotonicity is violated. This result is in accord with a similar conclusion by Fleissig, Kastens, and Terrell. One estimation objective is to find a functional form that approximates the production function as closely as possible, while another is to estimate a form that is consistent with monotonicity over as much of the data space as possible. In other words, we have to sacrifice some approximation accuracy to reduce monotonicity violations. We used no formal method of weighting these two objectives, but after examining a range of Fourier terms suggested by the literature, we selected a translog augmented only by $\cos(z_T)$ and $\sin(z_T)$ as our final model.

Productivity rates

The results of the analyses are summarized in Table 1. The three models concur that on average, there were no productivity gains in SSA agriculture during the 1960's and 1970's, bet there have been productivity improvements since then. Within this general concurrence, there is a considerable disparity among the models as to the point estimates of the average rate.

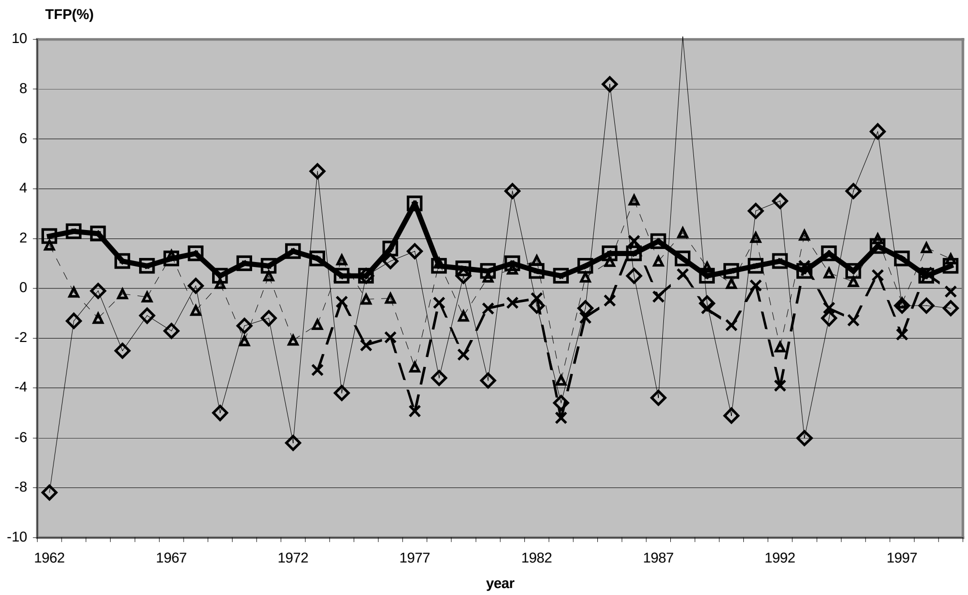
Table 1. Country average productivity rates, by model and decade

	Non-parametric Malmquist		Parametric Stochastic Frontier	
	contemporaneous	cumulative	w/o freedom	with freedom
1962-70	-3.1	-0.8	0.2	N/A
1971-80	-1.5	-0.2	-0.1	0.1
1981-90	0.6	1.5	0.2	0.1
1991-99	1.5	1.9	0.3	0.2
1962-99	-0.6	0.6	0.2	0.1

Averaging over the whole period, the cumulative Malmquist model estimates higher rates of productivity gain than the contemporaneous model, by about one full percentage point. The stochastic frontier models with and without freedom provide estimates that are very close to one another, but closer to zero than the two Malmquist estimates, especially during the 1990 when the Malmquist procedure gives productivity estimates that are close to levels achieved in the US.

As is evident from Figure 1, the contemporaneous Malmquist averages have the most year-to-year volatility, while those from the stochastic frontier model are the most stable. These differences can be explained by the nature of the models. The non-parametric Malmquist indexes implicitly use relative marginal products at the frontier to weight inputs together (parametric Malmquists explicitly have this property, though it is not clearly established in this non-parametric case.) The contemporaneous frontiers are clearly more volatile than the cumulative frontiers, and thus one would expect more

Figure 1. Average productivity rates by year



volatility in the weighting of the inputs, and thus in the productivity index itself. The stochastic frontier approach provides even more stable estimates of the frontier, ascribing more of the year-to year variability to random errors rather than changes in technology.

This average performance across countries masks substantial differences across countries, which we do not report here.

Institutions and Productivity Change

After measuring productivity we are interested in relating the patterns of productivity growth to a series of variables that could help understand its evolution and the differences in performance across countries. Two sets of variables are identified: a) those that will account for input quality differences, and b) those that indicate different socio-political circumstances through time and in each country.

Although ideally in the first set we would like to have variables that would adjust all inputs for their quality, data availability restricts us to three: land quality, illiteracy, and droughts. We expect that higher quality of land would induce higher productivity while droughts and a more illiterate population would be consistent with lower rates of productivity growth.

The second set of variables, also referred in this paper as institutional variables, is chosen to potentially capture the socio-political climate. The variables chosen, given data availability, are: previous colonial history, years since independence, violence and armed conflicts and degree of civil and political freedoms[1]. We expect that war and violence will depress productivity growth while we have no priors for the other variables.

Two very different approaches, as explained above, where used to associate these variables with productivity performance. The first approach consists of a simple linear regression of Malmquist productivity change indexes on this set of variables, as indicated in equation (9). The second approach using the stochastic frontier model is very different in nature. As it is explained in equations (10) and (11), these variables are incorporated into the estimation of the frontier function. They are included as potential explanations for the one-sided error term and are estimated simultaneously with the rest of the parameters of the production function.

[1] Results that include the proxies for political and civil freedoms are from a regression for a shorter period of time given data availability. Also included was a dummy equal to 1.0 for Ethiopia for the years after secession of Eritrea in 1992, because the combined country data do not quite match the previous series for Ethiopia alone.

Results from the first approach are presented in Table 2. Parameter estimates are from the regression of the Malmquist productivity indexes, contemporaneous and cumulative, on the quality and institutional variables as indicated in equation (9). The only variables that seem to be strongly associated with the evolution of productivity growth are years since independence and colonial history. The estimates indicate that former British and Portuguese colonies have outperformed former Belgium, Italian and Dutch colonies. Former Portuguese colonies have the best performance while former French colonies' performance is no different than that of the comparison group. It is also notable that the longer the country has been independent the higher has been the rate of productivity growth. It is surprising to find that indicators of input quality and variables indicating violence and armed conflict are insignificant.[2]

Results from the second approach are in Table 3. These are estimates of the parameters of the efficiency-changing variables associated with the one-sided error term u, specified as the *δ's* in equation (11). These estimates indicate that the more irrigated land the higher is agricultural productivity growth while droughts depresses it. In terms of the institutional variables, we see that former British and Portuguese colonies have poorer performance than the control group and that former French colonies do not significantly differ in their performance from the control group. The estimates for the parameters of the indexes of political and civil freedoms indicate that the freer the country the higher the rate of productivity growth. We note that the stochastic estimate of agricultural productivity growth does not seem to be affected by how long the country

[2] The results do not change much when the proxy for political and civil freedoms is included and the regression spans a shorter period. For this period, the drought variable turns out significant in affecting productivity negatively.

has been independent or by the presence of armed conflict and violence. The last result, in particular, is surprising.

It is probably not appropriate to make inferences from a comparison across such different methods, nevertheless some comments are provided. The proxies used for labor quality and the ones for violence and armed conflict seem not to be capturing their impact on productivity growth. It is conceptually difficult to believe that better human capital does not have any effect on productivity. We then think that a better proxy for human capital needs to be constructed and incorporated. It is also important to note that a casual look at the output series shows stagnation and decreases during periods of violence that seem not to be captured in this analysis. During these periods, however, the data also show a drop in the use of inputs, which would explain some of the reduction in output. Even so, we would expect that violence and war would decrease resources devoted to innovations, and thereby reduce the rate of productivity gains. Possibly a variable that reflects the cumulative effects of persistent violence on the stock of knowledge would be more appropriate. We conclude that a better proxy is needed to capture such an effect.

It is also important to note that the first approach establishes an association between these variables and an index of productivity growth, which include two components, technical change and efficiency change. The second approach uses the quality and institutional variables and associates them only with the one sided error term representing efficiency change or differential performance across countries. The technical change component is not included.

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Table 2. Accounting for contemporaneous and cumulative productivity change in 41 SSA countries.

	Productivity change – Contemporaneous Malmquist				Productivity Change –Cummulative Malmquist			
	model 1 1961-1999		model 2 1972-1999		model 1 1961-1999		model 2 1972-1999	
	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value
Constant	-1.997	0.178	-0.315	0.872	2.346	0.041	3.158	0.038
Input quality								
Irrigation	0.010	0.913	-0.002	0.985	-0.056	0.540	-0.161	0.184
Drought	-1.077	0.078	-1.833	0.013	-0.477	0.394	-1.041	0.120
Illiteracy	-0.018	0.150	-0.019	0.222	0.003	0.810	0.002	0.892
Institutional environment								
Independence	0.035	0.005	0.027	0.075	0.031	0.006	0.018	0.184
UK	3.325	0.003	2.368	0.103	2.314	0.003	1.993	0.059
France	2.583	0.019	1.749	0.206	0.683	0.351	0.737	0.434
Portugal	4.005	0.004	3.787	0.030	3.159	0.004	3.512	0.009
Minor conflicts	0.703	0.484	2.624	0.050	-0.107	0.905	1.917	0.106
Intermediate conflicts	-2.095	0.124	-2.541	0.193	-1.616	0.180	-1.483	0.361
War	0.624	0.472	0.515	0.617	-0.171	0.838	0.090	0.928
Free	-	-	1.171	0.332	-	-	0.502	0.668
Partly free	-	-	0.060	0.929	-	-	0.339	0.567
Ethiopia	4.324	0.132	3.166	0.330	5.757	0.068	5.002	0.121

Table 3. Parameter estimates for efficiency changing variables from stochastic translog-Fourier frontier model.

	model 1		model 2	
parameter	estimate	t-ratio	estimate	t-ratio
Intercept	0.27	1.84	-0.27	-0.91
Input quality				
Irrigation	-0.22	-24.48	-0.229	-23.73
Drought	0.15	3.26	0.12	2.36
Illiteracy	0.0005	0.63	-0.0005	-0.46
Institutional environment				
Independence	-0.002	-1.39	-0.001	-0.79
UK	0.23	2.19	0.72	3.01
France	-0.22	-2.13	0.16	0.69
Portugal	0.75	6.29	1.25	5.58
Minor conflicts	-0.11	-1.30	0.04	0.46
Intermediate conflicts	-0.19	-1.96	-0.03	-0.25
War	-0.05	-0.73	0.13	1.39
Free	-	-	-0.40	-5.43
Partly free	-	-	-0.26	-4.04
Ethiopia	-0.99	-1.52	-2.75	-1.94