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Agricultural Productivity and Public Expenditures in Sub-Saharan Africa

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ABSTRACT

National governments, especially in sub-Saharan Africa, have limited budgets and are forced to make difficult funding decisions regarding the provision of social services and the support of agricultural programs. These provisions can play a critical role in rural incomes and agricultural production but due to data constraints, the effects of different types of social services on agricultural productivity in this region have not been analyzed in detail. This research provides indication that certain types of social services can influence agricultural production efficiency using the currently available data and multiple empirical methods. Specifically, it estimates the role of social services in the efficiency of input use for agricultural production, using both Stochastic Frontier Analysis and a Structural Equation Model. Ultimately, our conclusions are substantially limited by data constraints, but provide some indication that certain types of social services can influence agricultural production efficiency for a select set of African countries.

Keywords: cross-country analysis, stochastic frontier, efficiency analysis, sub-Saharan Africa, public expenditures

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1. INTRODUCTION

Public resource allocation in a number of social service sectors is often required due to market failures and low levels of development (Mogues, et al. 2011). Unfortunately, while these conditions apply to agriculture in sub-Saharan Africa, a relatively small amount of public funds is spent on agriculture, with education receiving a priority and health to a lesser extent (Mogues, et al. 2011). The effect of government provisions, in general, on agricultural productivity is not clear from previous studies (Reinikka and Svensson 2002). Given the uniqueness of African agriculture and the diversity of government structures within the continent, this analysis is focused only on the lesser developed countries of sub-Saharan Africa. This research analyzes the available agricultural production and social indicators data for this region, exploiting multiple analytical options with the limited data that does exist and taking advantage of a newly-compiled dataset on annual precipitation for agricultural land.

The first research to analyze cross-country agricultural production, Bhattacharjee (1955) relied upon the United Nations Food and Agricultural Organization (FAO) data from the 22 countries for which data was available. However, this study and many other cross-country analyses of productivity are not able to include many African countries given the lack of data available for this region over time. The research that has been done (and the relevant results) is summarized very briefly below. A more thorough review of agricultural productivity research specifically for sub-Saharan Africa can be seen in Block (2010).

In general, research on productivity growth across countries is often done using production functions, relying upon a range of factors that could influence differences in productivity. Factors such as fertilizer, labor, land, and mechanization (mainly calculated through the use of tractors or animals) remain crucial inputs for agricultural production, but the role of each is not uniform across regions. O'Gorman and Pandey (2010) note that in the developing world, inequality in agricultural labor productivity has become more pronounced over the past 40 years (partially attributed to improved seed varieties), and the role of particular inputs and climatic conditions can vary greatly between regions. This is to be expected as farmers in countries of sub-Saharan Africa, for example, are not as well-equipped as farmers in other regions to respond to (or control for) instability in factors of production such as rainfall or market prices in inputs or outputs. Biophysical conditions such as soil quality and precipitation can also have indirect impacts to production due to their influence on historical agricultural production systems and infrastructure, although these impacts are not always straightforward. For example, while some studies show that in Africa, land quality is an important consideration in agricultural production (Wiebe 2003), others show that it does not play such a large role (Thirtle, et al 2003). Considering these results, we try multiple methods of controlling for climatic conditions in our cross-country analysis, something that is often ignored in agricultural production efficiency analysis due to the lack of data available.

Any factor that influences the agricultural sector can greatly impact the economy of rural areas. For example, Thirtle, et al (2003) found that a 1 percent increase in yields could reduce the number of people living under US$1 per day by more than 6 million (of which 95 percent were in Africa and Asia). Agricultural production in sub-Saharan Africa is constrained by a range of factors that extend beyond the traditional agricultural inputs or climatic factors. For example, when compared to other regions, the public sector in sub-Saharan Africa provides less overall infrastructure than other areas, creating a challenge for economic development and poverty reduction there (UN HABITAT 2011). Lack of infrastructure such as transportation and communications can greatly reduce access to markets, substantially limiting income and economic opportunities, both on- and off-farm. Even in places where markets are accessible, a lack of financial services such as credit or savings programs can limit the ability to acquire yield-enhancing inputs or diversify production. In addition to physical inputs, agricultural productivity can also be impacted through a lack of adequate infrastructure such as health services or educational services which can lead to a reduction in the ability to work and reduce other job opportunities (via access, education, and health status).

Changes in the broader economic structure will likely be needed for agricultural reform and advanced inputs to result in changes to agricultural productivity in many African countries (Morgan and Solarz 1994). While there have been a number of programs implemented to increase public investments in developing countries, these programs have often not had the desired effect on poverty (Anderson, de Renzio, and Levy 2006). This can be due to corruption, insufficiency of funds, improper targeting, or a number of other reasons. Despite this, there have been indications that positive changes are possible. When implemented properly, policy changes that enhance availability and quality of infrastructure services for the poor can have a significant effect on health, education, and incomes of rural populations (Calderón and Servén 2004). This research strives to identify social services expenditures that have the greatest impact on agricultural productivity, given the importance of agricultural production for rural livelihoods.

2. SOCIAL EXPENDITURES AND PRODUCTIVITY

It should be noted that cross-country studies on the impact of infrastructure development often focus on gross domestic product (GDP) growth or social indicators such as the human development index (HDI) or infant mortality rate (IMR) rather than agricultural production measures. Using social indicators, for example, has demonstrated that pro-poor expenditures (such as public health spending) can have an impact on welfare, especially in areas with low levels of development (Gomanee, et al. 2003). Unfortunately, many of the studies on particular types of public expenditures and impacts look at particular expenditure categories in isolation (Mogues, et al. 2011). However, for a few countries (India, China, Uganda, and Thailand), a range of expenditures have been analyzed and the productivity effects were particularly high for agricultural research, followed by road infrastructure in Uganda and India (Mogues, et al. 2011). Still, in many cases, and especially in sub-Saharan Africa, the effects of particular government expenditures on productivity remain unclear.

Data Constraints

The biggest constraint hindering this understanding of the impact of expenditures on productivity is a lack of sufficient data. While public spending data could be considered the most direct measurement of public expenditures in particular types of social services, it has been shown to be an imprecise measure for use in evaluating the effect of infrastructure on poverty in cross-country analysis (UN HABITAT 2011). For example, in Latin America, it was found rural subsidies did not benefit agricultural GDP, but social services and public goods in rural areas did have positive and significant impacts (Allcott, Lederman, and Lopez 2006). Similar conclusions have been documented in Indonesia, in which public spending on agriculture and irrigation positively impacted agricultural growth while public spending on fertilizer subsidies, in particular, negatively impacted agricultural growth (Armas, et al. 2010). Of course, the extent of data that exists for the different regions varies and particular conclusions for sub-Saharan Africa are more limited in the literature than for other regions. Because of this, the studies on this topic remain limited despite the fact that the relationship between health conditions and productivity seems more consistent than those between health conditions and income (McNamara, et al. 2010).

Theoretical Background

As mentioned, while previous studies found that economic growth is not as responsive to agricultural spending as it is to spending on social services such as education, transportation, and communication, results are mixed and the link between agricultural growth and rural incomes appears to be strong (Mogues, et al. 2011). One study of note used stochastic frontier analysis to estimate the relationship between agricultural efficiency and health measures in Ethiopia and found a positive relationship (Ulimwengu 2009). Another interesting attempt to measure the impacts of particular social components on agricultural productivity and efficiency, Fulginiti, et al. (2004), uses FAO data from 41 countries for the period 1960 to 1999 to analyze the productivity differences among countries of sub-Saharan Africa.

Regardless of the output variable measured, there are some constraints to production and development that cannot be ignored in cross-country analyses. Especially in Africa, it is important to consider the initial institutional and economic environment when analyzing cross-country data given the various political and economic histories throughout the continent. Government expenditures on education and health services in particular (depending on the composition), can have a significant effect on poverty, but these impacts can be greatly reduced through corruption or inequality (Mosley, et al. 2004). In fact, it is estimated that many of the studies that show mixed results between aggregate education and health spending and social indicators are partially due to this inefficiency (Gupta, et al. 2002). This is particularly crucial to consider in sub-Saharan Africa as inefficiently-used public spending greatly impacts the development outcomes in most countries of this region.

Further complicating the understanding of the impact of such programs on poverty in developing countries is a lack of a data on the changes in infrastructure in Africa over the last 30 years (Estache, et al. 2005). Using the data that does exist has also not led to a clear picture of the effects of particular services, as MacNamara, et al. (2010) documents for health services' mixed results on labor productivity in Africa. However, it is unclear if these mixed results are in fact, due to the lack of a causal link or due to improper targeting, insufficient funds, or incomplete or inadequate analysis. For example, these results are often from studies that evaluate only a limited number of African countries (such as those with sufficient data available). Ignoring those countries with missing data lead to biased analysis as one would assume that the data is not missing at random and that countries with missing data vary in other ways from those with sufficient data (such as different levels of conflict, corruption and accountability). To try to alleviate these gaps, some studies have taken five-year averages for their analysis to try to draw broader conclusions (for example, Estache, et al 2005). As this research is faced with many of the same data constraints as previous studies, we implement a variety of empirical approaches to try to answer this question.

While social services and related constraints are likely to have broad-reaching impacts, this analysis focuses on the impacts of various factors on agricultural output and efficiency in agricultural input use. In countries of sub-Saharan Africa, where the majority of the population lives in rural areas, this is likely a rational simplification in order to evaluate the impacts of infrastructure on opportunities and growth. To analyze this impact, we use a panel of secondary data from the World Development Indicators (WDI), the Food and Agricultural Organization (FAO) and other sources, discussed in more detail in the following sections. Furthermore, in analyzing the impact of these social expenditures, one would expect that the channels through which infrastructure or public expenditures affect agricultural productivity is not directly but through impacts on the effectiveness of productive inputs, including labor.

Efficiency Analysis

Unlike typical production functions, efficiency analysis allows a relaxation of the assumption that all countries are producing in a technically efficient manner and allows evaluation of the impact of infrastructure on agricultural output and efficiency of input use (Kumbhakar and Lovell 2000). Allowing a range of efficiencies in agricultural production would seem to be especially important in developing countries. In general, technical efficiency was defined by Farrell (1957) as the ability of a (firm) to produce the largest possible output using the given inputs. Producers will fall below this optimum level of production due to inefficiency. For example, when people are healthier, they are likely to have a higher quality of labor inputs; when infrastructure is available, farmers are likely to be able to get higher quality seeds and fertilizer; land inputs may also become more efficient due to soil conservation or water capture techniques.

Stochastic production frontiers, as proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) have been implemented in many different settings. Efficiency in production is generally estimated using both parametric (such stochastic frontier analysis (SFA)) and nonparametric approaches (such as Data Envelopment Analysis (DEA)). There are strengths and weaknesses to each approach. For instance, non-parametric approaches do not assume a specific functional form, but are less robust when there is measurement error (Saradifis 2000) and do not allow for unobserved variables (Biesebroeck 2007), so are likely not a good choice for our dataset. Other longitudinal productivity studies have also found that SFA performs better than DEA and by the use of flexible functional forms (such as translog), some of the limitations that it imposes can be overcome (Headey, et al. 2010). Therefore, we estimate a stochastic frontier model, including both an inefficiency term and a stochastic error term. For a panel dataset, the model is defined as shown in Equation 1 (Battese and Coelli 1995):

$$Y_{it} = f(x_{it};\beta)\exp(V_{it} - U_{it}) \tag{1}$$

In the model as used here, Y_{it} represents the net production for the ith country in the tth year of observation and $f(x_{it}\beta)$ is the function of production inputs for each country's agricultural production along with the parameters to be estimated with Vit representing the stochastic error and U_{it} a non-negative random variable representing technical inefficiency. The explanatory variables of technical efficiency(U_{it}) can be represented by Equation 2 in which W_{it} is a random variable that depends upon the distribution assumptions and $z_{it}\delta$ is a set of explanatory variables for inefficiency and their coefficients (Battese and Coelli 1995).

$$U_{it} = z_{it}\delta + W_{it} \tag{2}$$

These functions can be estimated using maximum likelihood methods with distributional assumptions on the inefficiency term as half-normal, truncated normal, or gamma distributions. While the ranking of technical efficiencies has been shown to not be greatly affected by the selection of the inefficiency distribution (Chakraborty, Biswas, and Lewis 2001), the determinants of technical efficiency can be sensitive to these distributional assumptions (Jaforullah and Devlin 2009). In our case, we estimate $U_{it} \sim (\mu it, \sigma it)$, assuming a truncated-normal distribution of the inefficiency term (truncated below zero), as is done in many preceding studies. It should also be noted that time-invariant models underestimate efficiency by confusing it with heterogeneity and stress the importance of not assuming homogeneity between firms (Abdulai and Tietje 2007). For these reasons (time and firm heterogeneity), this analysis does not pool the data and allows the panel structure to remain intact, with time controls for changes in technical efficiency and productive structure, as done in Battese and Coelli (1995).

State Variable Approach

While studies focused on agricultural productivity have often used stochastic frontier analysis (SFA) to estimate the relationship between agricultural efficiency and health measures (Ulimwengu 2009) or farmer education (Phillips and Marble 1986), efficiency analysis is not the only way that this question can be approached. For example, Fan et al. (2000a and 2000b) used a simultaneous structural equation framework to describe the impact of government spending on growth and poverty in India. They found that in addition to other factors such as population growth and annual rainfall conditions, the combined effects of public expenditures on agricultural productivity and incomes ultimately reduce rural poverty. This framework was later modified by adding variables such as urban growth, institutions, and policies (Fan et al. 2002).

Fan et al.'s framework (2000) has the merit of detailing the multiple channels through which government expenditures can affect agricultural productivity and accounting for endogeneity and possible interactions between variables. However, while empirically appealing, this framework is limited in being able to identify underlining economic behavior. Other studies have explicitly modeled the relationship between agricultural productivity and health. For example, Pitt and Rosenzweig (1986) incorporated a health variable into the utility specification. Benin et. al. (2009) estimated the role of public expenditures in Ghana using a system of equations where expenditures are used as a determinant of agricultural productivity growth.

Frontier approaches, as discussed previously, have both strengths and weaknesses. In particular, they assume the possible production frontier is the same across farms, which can ignore important differences between production possibilities and technological options (Mundlak 1988). Mundlak et al. (2008) proposed that the wide variation in the estimation results of agricultural production functions may be partially due to the exclusion of state variables representing the political, economic, or physical environment. Other production analyses have taken this into account as well (Yesuf, et al. 2008; Kalaitzandonakes and Dunn 1995). For our analysis, we attempt to adopt the framework developed by Mundlak et al. (1997) using data recently made available by IFPRI (Malaiyandi 2010).

Under Mundlak et al.'s (1997) framework, each producer chooses a technology subject to its constraints under the prevailing socio-economic environment. From his framework, *X* represents the vector of inputs where $F_j(X)$ is the associated production function for the jth technique, and F_j is concave and twice differentiable, T represents the available technology for all possible techniques with $T = \{F_j(X); j = 1, \ldots, J\}$. The set of inputs *(X)* comprises constrained *(k)* and unconstrained *(v)* inputs, *X= (v, k)* where the assumption is made that constrained inputs have no alternative cost. It is assumed that once the technology is chosen, profit is maximized by selecting the optimal level of inputs *(X)* to be assigned to technique *(j)* (Mundlak et al. 1997).

For the detailed empirical framework, see Mundlak et al. (1997) and for an application for one country, see Allen, et al (forthcoming). As pointed out by Mundlak, et al. (1997), the aggregate production function is defined conditional on state variables (s). In this case, we assume *states* of social services can be represented by annual expenditures in particular sectors. It follows that changes in *(s)* will then imply changes in x^* as well as in *F(x*,s)*. The authors assume the following functional form for an aggregate function *F(x,s)*:

$$F(x, s) \approx \ln y = \Gamma(s) + \beta(s, x) \ln x + u \tag{3}$$

where y is the value added per worker, $\beta(s, x)$ and $\Gamma(s)$ are state-dependent slope and intercept of the function respectively and u is a stochastic term (Mundlak et al. 1997). Variation in the state variables will affect both $\beta(s, x)$ and $\Gamma(s)$ directly as well as indirectly through their effect on inputs *X* and it is possible that state variables are correlated. Using this structure allows evaluation of the elasticity of average input productivity with respect to a given state variable (s_i), removing it from the productivity residual and possibly leading to less biased estimates.

For this specification, a two-stage, generalized mixed linear model (see Verbeke and Molenberghs 2000) is used to estimate equation (4). The first stage summarizes a vector of country-specific regression coefficients and the second stage links these estimates to exogenous covariates through multivariate regression techniques. More explicitly, Y_i is the n_i −dimensional vector of repeated measurements of production for the country *(i)*:

$$Y_i = X_i\beta_i + \varepsilon_i \tag{4}$$

where X_i is a $(n_i * q)$ matrix of exogenous variables, β_i to represent the q-dimensional vector of regression coefficients, and ε_i as the residual components. This uses the normal assumptions for ε_i in that it is independently distributed normal with zero mean, zero and covariance matrix $\sigma^2 I_{n_i}$,where I_{n_i} is a ni-dimensional identity matrix) (Verbeke and Molenberghs 2000).

In the second stage, the following is used to capture country heterogeneity:

$$\beta_i = Z_i\gamma + b_i \tag{5}$$

Equations (4) and (5) are combined to yield the generalized mixed effects model (which mixes both the fixed-effect (γ) and the random, country-specific effect (b_i):

$$Y_i = K_i\gamma + X_i b_i + \varepsilon_i \tag{6}$$

where $K_i = X_i Z_i$ is a $(n_i * p)$matrix of exogenous covariates. Following Laird and Ware (1982), a linear mixed effects model satisfies the following conditions: $b_i \sim N(0,D)$, $\varepsilon_i \sim N(0, \sum_i)$, and $b_1, \ldots. b_N, \varepsilon_1, \ldots \varepsilon_N$ are independent. The empirical implementation process and the data used follows.

3. DATA AND SUMMARY STATISTICS

For both models, we rely upon the same agricultural dataset for inputs and outputs. As mentioned, the dependent variable for our models is the net value of production for all agricultural crops in thousands of international dollars[1] from FAO (FAO 2011). The data used as inputs for agricultural production are the commonly used agricultural inputs including the following collected from FAO for the period 1961 to 2010: labor (thousands of people employed in agriculture); land (thousands of hectares of land in agricultural crop production); livestock (head of cattle or other livestock); fertilizer (total fertilizer consumption in tons); and tractors (tractors in use in the country). The percentage of irrigated crop land was used as well and was calculated using data from the Food and Agricultural Organization (FAO 2011). To control for country-specific heterogeneity, we include the percent of land in agriculture and alternatively, the agro-ecological zone as shifter variables in the translog spsecification. Unlike many estimations of production, we also include the amount of precipitation (millimeters per year) that falls on agricultural land. This data was obtained using climate data from the University of East Anglia and adjusted for agricultural land using data from IFPRI's Harvest Choice project (You et al 2009; Williams and Breneman 2009).

The variables included to account for inefficiency were informed by the existing literature in an effort to account for differences between countries that could influence the ability to efficiently use agricultural inputs. We make the assumption that overall health and survival to an advanced adult age could be a sufficient indicator of ability to work in agriculture and therefore, we use annual life expectancy rates to account for the quality of labor (WDI 2010). As done by Fulginiti, et al. 2004, to account for political stability and institutional strength, we include a variable for the number of years since independence from the Central Intelligence Agency (CIA) World Factbook (2009). The rates of immunization for diphtheria, pertussis (whooping cough), and tetanus (in combination and referred to DPT) (percentage of children aged 12-23 months old) was used as a proxy for health provisions (WDI 2011).

Other variables were compiled from the World Development Indicators as well, such as the pupil-teacher ratio for primary and secondary schools, the net enrollment rate in primary schools, literacy rates, health and education spending as a percentage of GDP, domestic credit to the private sector as a percentage of GDP, net overseas development assistance, prevalence of malaria, TB, and HIV, and the rural population with access to water and sanitation. Other variables tested in the modeling included the world governance indicators of Kaufmann et al. (2009) and the freedom indicators from Freedom House (2011). All variables considered are summarized in Table A.1 in the Appendix. Many of the variables were not sufficiently observed to draw conclusions and were not included in the final model. They are listed only as background for model specification.

Multiple imputation has been used in developing country analysis as a result of the ability of some newer programs to tackle the potential issues that arise, and can be preferred to listwise deletion (removing observations that contain any missing values) (Daniels and von der Ruhr 2003; You and Sanjeev 2005; Daniels and von der Ruhr 2003; and Tavits 2008).

Using the "mi" package of R (Gelman et al. 2011) we estimated missing years using all education variables available including public spending on education, net enrollment rate in primary schools, literacy rates, and the pupil-teacher ratio in primary schools. Unfortunatley, it appeared the model was possibly no longer appropriate given the high value of gamma in our model. Taking this a step further, we also took advantage of the recently available dataset that relies upon multiple imputation (CANA datset) (Castellacci and Natera. 2011), including the teacher/pupil ratio and other variables such as roads. As shown in the appendix (Table A.3), it is not clear that this data is appropriate for our purposes given how drastically it changes other estimation results, such as the influence of land and irrigation, from all the

[1] International dollars are hypothetical units of currency that are held at constant purchasing power parity (PPP) for the US dollar in 2004.

other models that were attempted and the large change in the log-likelihood estimation under the same degrees of freedom.

Given our lack of data on education outcomes, we move to the state variable approach for a select set of countries for which this data is available. For this approach, we used data available through IFPRI from 1980 to 2006 for a select set of countries (Botswana, Burkina Faso, Cameroon, Cote d'Ivoire, Ethiopia, Ghana, Kenya, Malawi, Mali, Nigeria, Togo, Uganda, Zambia, and Zimbabwe) (Malaiyandi 2010). For these countries and range of years used in our analysis (1980-2002), the public expenditures per capita are shown in Table 3.1.

Table 3.1—Per capita expenditures in public services, 1980-2002

Per capita Expenditures in International Dollars					
Sector	**Obs**	**Mean**	**Std Dev**	**Min**	**Max**
Education	309	82462	134343	321	887766
Health	309	26363	33754	150	272229
Agriculture	309	27421	37197	537	209698
Transportation	309	27928	38764	25	208253
Social Services	309	18389	34082	26	240838

Source: SPEED Data, International 2000.

4. EMPIRICAL RESULTS

In this section, we present the results of both the full model relying upon the SFA as well as the results using a sub-sample with the latent variable approach, both specified in more detail in the following sections.

Public Expenditures and Efficiency in Production

Using the data described above, we estimate the following, normalized by their means:

$$\ln(Y_{it}) = \beta_0 + \beta_1 \ln(Labor_{it}) + \beta_2 \ln(Fertilizer_{it}) + \beta_3 \ln(Tractors_{it}) + \beta_4 \ln(Land_{it}) + \beta_5 \ln(Livestock_{it}) + \beta_6 \ln(precipitation_{it}) + \beta_7 \ln(irrigation_{it}) + \beta_8 \ln(\%agland_{it}) + \beta_9 (time) + V_{it} + U_{it} \quad (7)$$

in which inefficiency is estimated by the following base equation

$$U_{it} = \delta_0 + \delta_1 (LifeExpect_{it}) + \delta_2 (immunization_{it}) + \delta_3 (Independ_{it}) + \delta_4 (time) + W_{it} \quad (8)$$

This seems to make sense in that the *X* variables should represent inputs into production while the Z variables represent observed heterogeneity that is not related to the production structure (Greene 2005). While data is available for a longer time frame, the models in equations 7 and 8 are estimated for the period of 1980 to 2002 given missingness before 1980 in some of the variables and the lack of information on fertilizer usage after 2002. A total of 39 sub-Saharan African countries are included partially due to incomplete information, but also because our estimates for the frontier are better with similar production units. Because of this, South Africa and Mauritius were excluded given their higher level of development than other countries in sub-Saharan Africa. Nigeria's production was also seen to be much higher than all other countries (by a factor of 10). As a result, it was dropped from analysis to avoid biasing the frontier. Not all variables are observed in all years and some countries are measured in more years than others leading to many dropped observations. For example, Eritrea and Ethiopia were not observed before 1993 and Liberia and Sierra Leone had many missing years, so all models were run with and without these countries for comparison purposes. The results were similar despite their exclusion so they were left in the model.

In addition, in order to estimate a stochastic frontier model, we have to make assumptions regarding the functional form. We start by modeling a Transcendental Logarithmic (Translog) stochastic frontier function, a more flexible functional form than Cobb-Douglas to allow cross-elasticities and non-linear effects in the variable inputs. The Cobb-Douglas estimations do not fit as well as the Translog estimates in that there are skewed residuals, the inefficiency component is not significant, and the Likelihood Ratio test show that the cross-terms are significant at the 0.05 level. Therefore, we estimate the Translog model as:

$$\ln Y_t = \alpha_0 + \sum \beta_i (\ln X_{it}) + \frac{1}{2} \sum_i \sum_j \beta_{ij} (\ln X_{it} \ln X_{jt}) + V_{it} - U_{it} \quad (9)$$

The efficiency effects model as specified in Equation 9 is estimated with the econometric package *frontier* for R (Coelli and Henningsen 2011; R Core Development Team 2011). Here, *Y* represents the net agricultural crop production, as mentioned previously, and the *X* variables represent the agricultural inputs, also discussed above. The percentage of land in agriculture is used as a control variable for relative importance of agriculture in the country and therefore, only included as a shifter variable.

In general, many observations are dropped due to missing values in one of the variables to be estimated, especially if we extend our model back to 1961. However, the models with this data do not seem to fit the data very well in that gamma is unbelievably small and the efficiency levels do not seem realistic in some cases (as high as 99 percent efficient). We also estimated the production frontier with other variables as well, such as the pupil-teacher ratio, health and education spending, incidences of malaria and HIV, access to water and sanitation, and political risk (see discussion of variable sources above), but given missing values, we are limited on the conclusions that can be drawn. This lack of a substantial panel of data is a common problem in estimating the impacts of infrastructure and other social services on productivity in Africa (Block 2010). Listwise deletion (as is often done when missing values are encountered) can make it difficult to draw conclusions across the sample. Of bigger concern is the fact that dropping all observations with a missing predictor leads to biased and inefficient results (Honaker and King 2010).

In an effort to expand this analysis, we estimated the frontiers using five-year averages to be able to include variables such as educational expenditures or outcomes. Other SFA analyses have found that country means over intervals were "better behaved" than yearly data (Greene 2005). Unfortunately, the models with five year averages did not seem to fit in our case in that gamma was equal to 1.00, which is clearly not appropriate. One set of results are included in the Appendix (Table A.4). Averages of other variables (such as access to drinking water, sanitation, health spending, governance indicators and freedom indices rather than years of independence, and so forth) were attempted but none of these variables proved to be a significant determinant of inefficiency. Given the results of these models, we can assume that our model is best specified using annual data (as shown in Table 4.1) rather than 5 year averages, likely due to the short panel that is available for our variables.

Table 4.1—Translog specification, 1980-2002

logProd (mean diff)	Estimate	StdError		Estimate	StdError
constant	0.232***	0.051			
labor	0.560***	0.044	tract*tract	0.015	0.018
fert	0.182***	0.015	tract*land	0.193***	0.016
tract	0.123***	0.023	tract*livestock	-0.216***	0.019
land	0.088**	0.033	tract*precip	0.058*	0.023
livestock	-0.035	0.028	tract*irrigation	0.010	0.008
precip	0.317***	0.054	land*land	-0.252***	0.051
irrig	-0.002	0.023	land*livestock	0.349***	0.034
labor*labor	0.102	0.058	land*precip	0.109*	0.045
labor*fert	-0.008	0.011	land*irrigation	-0.011	0.018
labor*tract	-0.004	0.017	livestock*live	-0.255***	0.040
labor*land	-0.325***	0.030	live*precip	-0.580***	0.054
labor*livestock	0.173***	0.035	live*irrigation	0.069***	0.016
labor*precip	0.446***	0.058	precip*precip	-0.739***	0.107
labor*irrigation	-0.188***	0.018	precip*irrig	0.069**	0.023
fert*fert	0.019***	0.004	irrigation*irrig	0.012	0.011
fert*tract	0.004	0.005	% ag land	0.067***	0.018
fert*land	0.031***	0.008	time	0.010***	0.002
fert*livestock	-0.026**	0.009			
fert*precip	0.030	0.017			
fert*irrigation	0.036***	0.005			
Inefficiency	Estimate	StdError			
Z_lifeexpectancy	-0.057***	0.005			
Z_immunizations	0.011***	0.002	LogLik	-9.501	
Z_time	0.005	0.007	cross sections	39	
Z_independence	0.000***	0.000	time periods	23	
sigmaSq	0.197***	0.015	obs	755	
gamma	0.972***	0.012	mean eff	0.719	

Source: Author's estimations.

The results in Table 4.1 show most inputs are significant and nonlinear except for land and precipitation. It makes sense that precipitation has a quadratic relationship with production in that production can decline after too much rainfall is received if the ability to store this excess is limited. The results (also consistent across specifications) show that irrigation is not significant, which is not surprising in sub-Saharan Africa, where irrigation levels are very low. The percent of land that is in agriculture is also a significant control variable for intra-country differentials in production strategies.

From the results, it appears that inefficiency could be a significant contributor to cross-country differentials in yearly productivity and input productivity. It also seems (consistent across model specifications) that life expectancy is significantly and negatively associated with inefficiency, showing that increases in health likely increase efficiency in agricultural production. Immunization rates seem to have the opposite effect but given that this is national data, it could be that these are not good representation of rural health outcomes. There are cross-country differences that are likely captured by the independence variable, which is significant across specifications.

Average efficiency estimates by country are included in Table 4.2. However, while some of these countries fit our expectations in terms of productivity when compared with others, some countries seem to not fit very well. To look at how these change between model specifications, the comparisons of mean efficiencies by country for the models presented in Tables 4.1 and A.2 to A.4 can be seen in Figure A.1 in the Appendix.

Table 4.2—Efficiency estimations from Table 4.1

Country	Efficiency	Country	Efficiency
Benin	0.929	Kenya	0.789
IvoryCoast	0.916	Maurtania	0.755
Cameroon	0.889	Central Af Rep	0.726
Sudan	0.875	Lesotho	0.699
Namibia	0.873	Senegal	0.671
Chad	0.868	Tanzania	0.654
Gabon	0.864	Burkina Faso	0.647
Mali	0.856	Sierra Leone	0.640
Togo	0.841	Mozambique	0.602
Madagascar	0.839	Guinea	0.573
Somalia	0.838	Liberia	0.536
Ghana	0.836	Rwanda	0.534
Uganda	0.833	Gambia	0.525
Cape Verde	0.831	Burundi	0.517
Botswana	0.830	Malawi	0.470
Swaziland	0.825	Ethiopia	0.402
Congo	0.817	Eritrea	0.360
Zimbabwe	0.801	Angola	0.348
Niger	0.796	Zambia	0.295

Source: Authors' estimations.

Public Expenditures as Latent Variable

As mentioned in the previous specification, we assume aggregate production is a function of the commonly-used inputs including labor, land, animal power, tractors, fertilizer, and irrigation as well as constraints in the natural environment (such as precipitation). Following from Mundlak (1988), we assume that production technologies are heterogeneous across countries and that input decisions are jointly made with production choices, depending on state variables (such as social services or support). As these state variables affect production both directly and indirectly (through the impact on other inputs), they should be considered endogenous (Mundlak 1988).

Empirically, state variables for health, education, agriculture, transportation, and other public services are estimated as a function of government expenditures on health while controlling for country fixed effects *(k)*. These state variables (estimated) are used to estimate marginal productivities of inputs *(β_{il})* using the following production function (in this case for health *(h)*, but follow for all of the state variables we consider (education, social services, transportation, and agriculture):

$$y_i = \beta_0 + \textstyle\sum_l \beta_{il} x_{il} + \beta_{kl} p_{kl} + \varepsilon_i \tag{10}$$

$$\beta_{il} = \gamma_{0l} + \gamma_{1l} h_k + u_{il} \tag{11}$$

where y: output; x: agricultural inputs (described in the previous section); p: precipitation over the agricultural year and ε, u: iid error terms.

Structural Model for Health Expenditures and Outcomes

Unfortunately, production functions often force the use of imperfect indicators of health or education since actual outcomes are unobservable (Baldacci et al. 2003). They argue that using proxies for unobservable social outcomes does not efficiently estimate the impacts of expenditures and suggest estimating a latent variable as well as associated covariances to explain the relationship between public expenditures and this unobservable variable (Baldacci et al 2003). They find that estimates of government spending elasticities are higher under this approach than under traditional specifications (Baldacci et al. 2003). Therefore, for the health indicators (the only indicators for which we have a sufficient panel of data to implement this approach, as mentioned earlier), following Baldacci, we estimate a general covariance structure model:

$$s = \Lambda\xi + \delta \tag{12}$$

In this case, Λ is the matrix of covariances between the latent (unobserved) variable ξ and the observed social variables (s). In the case of two observable variables (s and w), assuming ξ and η are uncorrelated with the error terms, equation 14 can be written as:

$$s_j = \Lambda_x\xi + \delta \text{ and } w_j = \Lambda_y\eta + \varepsilon \tag{13}$$

We then specify a structural equation model (for details see Fox 2002; Hox and Bechger 1998; Maccallum and Austin 2000; and StataCorp 2011) specified as:

$$\eta = \beta\eta + \Gamma\xi + \zeta \tag{14}$$

The variables β are the regression coefficients on the endogenous latent variables (η) and Γ represents the coefficients measuring the effects on the exogenous latent variables (ξ) with ζ specified as random disturbances. The results of this are shown in Table 4.3.

From Table 4.3, it is apparent that health expenditures per capita are a significant determinant of health, as it is measured here (by immunizations and life expectancy). This significance could be used to support the use of expenditures to capture social variables in production estimations in our case, so we move forward with the state variable models.

Table 4.3—Latent variable estimation for health

Variables	Coefficients
Health Outcome	
Health Expenditures/capita	2.331***
Education Indicators	
Life Expectancy	1
Immunizations	5.591***
Variances	
Health	0.945
Life Expectancy	26.20***
Immunizations	340.85***
Log Likelihood	-3000.5
N	336
*p<0.10, **p<0.05,***p<0.001	

Source: Authors' estimations.

State Variables and Production

Using both the results from the structural model presented in Table 4.3 and the two-stage approach, we condition the agricultural output(y_i) for country (i) on state variables (s) that may not be properly captured through input quantities (x) alone. As mentioned above, variations in the state variables (across districts) are expected to affect not only β but also the inputs (x) directly (Mundlak et al. 2008). The results of these latent variable approaches are shown in Table 4.4 and compared to the model without latent variable consideration.

Table 4.4 shows the significance of precipitation for production, even after controlling for country fixed effects. In models that use the structural system or direct mixed estimation, the inclusion of social outcomes induces a shift in the size and significance of input elasticities, especially for the labor variable. This is particularly true when health expenditures are considered, but also holds for education. In addition, Table 4.4 shows that many of the interactions terms between the state variables and agricultural inputs are significant.

Table 4.4—Production estimation with government expenditures considered

lprod	no state	health	educ	trans	social	agric	educ & health	agri & trans	educ & trans	social & health	Baldacci
lland	0.45	0.522	0.49	0.469	0.626	0.439	0.48	0.409	0.471	0.626	0.58
	(1.45)	(1.64)	(1.44)	(1.49)	(1.66)	(1.44)	(1.44)	(1.33)	(1.40)	(1.69)	(1.86)
llabor	0.630**	0.502*	0.536**	0.558*	0.666***	0.519*	0.510*	0.507*	0.526*	0.626***	0.646**
	(3.16)	(2.51)	(2.68)	(2.57)	(4.12)	(2.44)	(2.49)	(2.10)	(2.33)	(3.82)	(3.06)
lanim	0.455*	0.504*	0.437	0.465*	0.276	0.583**	0.476*	0.574*	0.423	0.292	0.43
	(2.07)	(2.37)	(1.94)	(2.05)	(1.18)	(2.66)	(2.13)	(2.51)	(1.81)	(1.28)	(1.92)
lprec	0.146***	0.145***	0.142***	0.157***	0.139***	0.144***	0.140***	0.148***	0.147***	0.134***	0.142***
	(4.41)	(4.29)	(4.19)	(4.62)	(4.22)	(4.18)	(4.11)	(4.34)	(4.34)	(4.08)	(4.28)
lhlth		-21.95*					-13.7			-16.76	(0.11)
		(-2.24)					(-1.15)			(-1.67)	(-1.68)
lland*hlth		2.475**					2.295*			2.205*	0.01
		(2.74)					(2.21)			(2.44)	1.22
llabor*hlth		0.690*					0.586			0.793**	0.00
		(2.38)					(1.82)			(2.68)	(0.42)
lanim*hlth		-0.501					-0.907			-0.738	-0.001
		(-0.77)					(-1.28)			(-1.17)	(0.07)
ledex			-12.86*				-6.897		-13.89*		
			(-2.09)				(-0.93)		(-2.20)		
lland*edex			0.855				0.185		0.99		
			(1.22)				(0.23)		(1.38)		
llabor*edex			0.42				0.325		0.446		
			(1.53)				(0.98)		(1.59)		
lanim*edex			0.123				0.214		0.09		
			(0.21)				(0.33)		-0.16		
ltrans				-6.258				-9.647	(2.55)		
				(-1.04)				(-1.56)	(-0.41)		
lland*trans				-0.977				-1.880*	(1.20)		
				(-1.35)				(-2.45)	(-1.64)		

Table 4.4—Continued

lprod	no state	health	educ	trans	social	agric	educ & health	agri & trans	educ & trans	social & health	Baldacci
llabor*trans				-0.796*				-0.978*	-0.981*		
				(-2.01)				(-2.39)	(-2.46)		
lanim*trans				1.536*				2.490**	1.509*		
				(2.11)				(3.17)	-2.05		
lsocial					-37.32***					-31.95**	
					(-3.52)					(-2.85)	
lland*social					-6.184**					-7.715**	
					(-2.74)					(-3.26)	
llabor*social					-2.726**					-3.364**	
					(-3.05)					(-3.27)	
lanim*social					8.208***					9.215***	
					(4.04)					-4.26	
lagex						8.984		11.02			
						(1.40)		(1.70)			
lland*agex						1.557		2.601**			
						(1.80)		(2.79)			
llabor*agex						1.153*		1.336**			
						(2.35)		(2.65)			
lanim*agex						-2.310**		-3.272***			
						(-2.61)		(-3.47)			
constant	-3.370*	-3.708*	-2.695	-3.156*	-2.743	-4.106**	-2.932	-3.592*	-2.263	-2.623	-4.275*
	(-2.35)	(-2.54)	(-1.76)	(-2.11)	(-1.83)	(-2.75)	(-1.88)	(-2.34)	(-1.44)	(-1.73)	(-2.55)
CountryFE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	373	360	360	360	360	360	360	360	360	360	373
aic	-532.9	-504.8	-501.3	-501.8	-528.2	-504.8					
bic	-485.8	-442.6	-439.1	-439.6	-466	-442.6					
*	p<0.05,	**	p<0.01,	***	p<0.001						

Source: Fulginiti and Perrin (1993).

To further interpret the significance of the results in Table 4.4, we use metrics developed by Fulginiti and Perrin (1993), relying upon the elasticity of production with respect to states variables and evaluated as $\frac{\partial y}{\partial z} = \frac{\partial y}{\partial \beta}\frac{\partial \beta}{\partial z} = \sum_l \gamma_{ls} x_l + b_s$ where both y and z are in log form. Using the estimates presented in Table 4.4 and following from Fulginiti and Perrin (1993), we estimate the elasticity of productivity for particular inputs with respect to our state variables and present only the significant results in Table 4.5.

Table 4.5—Marginal productivity of significant inputs by specification

Input	no state	health	educ	transport	social	agri	health/ Baldacci
land	0.22	2.30	1.08	-1.14	-5.52	1.75	0.32
labor	0.46	1.03	0.85	-0.36	-2.16	1.76	0.43
animal	0.75	0.24	0.83	2.45	8.55	-1.47	0.70

Source: Fulginiti and Perrin (1993).

From Table 4.5, it is clear that the estimates of marginal productivity change significantly based on the variables that are considered in the model. While public expenditures appear to have quite a few outliers in the estimations, consideration of the health and education expenditures (both with and without the structural equation approach) changes the estimates of marginal input productivities.

5. CONCLUSIONS AND RECOMMENDATIONS

This research has strived to further the discussion regarding the impacts of infrastructure on agricultural production rather than economic development in general, which is particularly important in rural economies. Our attempts to use the data available have provided more in-depth understanding of the data constraints that limit analysis of the determinants of production efficiency in sub-Saharan Africa.

However, using multiple empirical approaches has provided evidence that country-specific heterogeneity is a significant consideration for agricultural production in sub-Saharan Africa and that in addition to considering this heterogeneity in production estimates, consideration of climate-related variables should not be ignored. Despite limited data availability, the results also provide some evidence that public service expenditures (especially on health and education) can influence input productivity and efficiency in agriculture. Overall, the results call for better data on public service expenditures so that the relationships between labor, health, and government provisions can be better understood.

APPENDIX: SUPPLEMENTARY TABLES AND FIGURE

Table A.1—Summary statistics

Variable	Units	Obs	Mean	Std. Dev	Min	Max
Characteristics of the Variables						
countries	countries	43				
year	year	49			1961	2010
production	crop value (2004/06)(1000 Int$)	1977	1.04E+06	2.21E+06	5.76E+03	2.58E+07
labor	people in agri (1000s)	1914	3070	3895	35	2.88E+04
fertilizer	tons consumed	1742	1.90E+04	4.25E+04	0	4.61E+05
tractors	agri tractors used	1923	2835	4971	1	6.73E+04
land	crop production area (1000 ha)	2000	3615	5532	40	40500
livestock	oxen equivalents	1105	3.80E+06	6.23E+06	0.00	4.27E+07
Inefficiency variables						
life expectancy	life expect at birth	2064	48.8	6.9	26.4	71.0
independence	years since independence	1978	97.6	307.1	17	2000
percland_agri	% of land in agriculture	1942	45.7	19.5	7.6	91.2
% irrigated	% of ag land irrigated	1849	3.630	6.270	0.005	32.250
precip	mm year on ag land	1849	106	300.8	0.1	1946
landquality	land quality index (crop land)	1760	87.7	21.7	38	128
immun	% of children with DPT immun	1037	56.9	25.4	1	99
education expen	% of GDP spend on educ	369	4.3	4.2	0.4	49.5
Variables collected and considered for inefficiency						
credit	% of GDP (domestic credit)	940	14.8	12.5	1	180
free	freedom (1=most free)	829	3.5	2.0	1	7
TB	TB incid per 100,000 people	756	288.5	168.5	42.0	1198
hivPrev	% hiv prevalance (15-49 yrs)	710	5.1	6.6	0.1	28.9
incid_mal	% of pop with malaria	580	0.11	0.11	0.00	0.94
pupil/Teach Prim	pupil-teach ratio, primary	552	45.2	12.3	19.3	91.1
net enrollment rate	% enrollment, primary	471	63.7	20.4	8.2	99.6
radio	% HH with radio	450	50.2	15.8	0	91.9
pupil/Teach Secon	pupil-teach ratio, secon	441	25.0	7.9	10.7	64.8
wgi	world governance indicator	420	-0.7	0.6	-2.5	0.8
infant mort rate	mortality per 1,000 live births	418	106.9	36.6	24	252
pavedroads	% total roads paved	406	20.1	16.2	0.8	78
Cars_passenger	cars per 1,000 people	378	9.0	9.9	0.13	47
malaria mortality	annual mortality per 100,000	352	24.2	47.4	0	610
pubhealth	% of health exp paid by public	221	52.9	18.1	17.9	100
healthexp	% of GDP spen on health	211	2.4	1.5	0.2	9.6
physicians	# physicians/1000 people	250	0.1	0.1	0.0	0.572
schooling	average years of school	180	4.2	2.0	0.8	9.6
ruralSanitation	% rural with improved sanit	158	21.5	15.6	0	62
ruralWater	% rural with improved water	157	48.9	18.0	4	91
literacy	adult literacy (%)	122	53.4	22.1	8.7	93
women	% of women in nonag jobs	108	26.4	11.5	3.8	51.6

Source: Author's estimations.

Table A.2—With school data (not imputed)

logProd (mean diff)	Estimate	StdError		Estimate	StdError
constant	0.110	0.092			
labor	0.475***	0.081	tract*tract	0.000	0.044
fert	0.246***	0.036	tract*land	0.239***	0.031
tract	0.160***	0.039	tract*livestock	-0.256***	0.036
land	0.070	0.053	tract*precip	0.103**	0.034
livestock	-0.019	0.050	tract*irrigation	0.005	0.019
precip	0.107	0.107	land*land	-0.192	0.100
irrig	-0.034	0.045	land*livestock	0.303***	0.063
labor*labor	0.116	0.105	land*precip	0.081	0.095
labor*fert	-0.009	0.030	land*irrigation	0.016	0.035
labor*tract	-0.003	0.033	livestock*live	-0.073	0.097
labor*land	-0.4178***	0.059	live*precip	-0.310**	0.108
labor*livestock	0.196*	0.078	live*irrigation	0.036	0.032
labor*precip	0.263*	0.131	precip*precip	-0.783**	0.268
labor*irrigation	-0.250***	0.035	precip*irrig	0.147*	0.066
fert*fert	0.027*	0.011	irrigation*irrig	0.031	0.023
fert*tract	0.017	0.013	% ag land	0.122***	0.032
fert*land	0.036	0.023	time	0.014***	0.004
fert*livestock	-0.047*	0.021			
fert*precip	-0.020	0.034			
fert*irrigation	0.062***	0.017			

Inefficiency	Estimate	StdError		
Z_lifeexpect	-0.063***	0.009		
Z_immun	0.014***	0.004		
Z_time	-0.002	0.011	LogLik	3.323
Z_independence	0.001**	0.000	cross sections	39
Z_pupilteach	0.003	0.002	time periods	12
sigmaSq	0.1715***	0.025	obs	262
gamma	0.999***	0.003	mean eff	0.682

Source: Author's estimations.

Table A.3—Using CANA dataset for education

logProd (mean diff)	Estimate	StdError		Estimate	StdError
constant	0.216***	0.065			
labor	0.514***	0.046	tract*tract	-0.037	0.023
fert	0.160***	0.021	tract*land	0.265***	0.038
tract	0.105**	0.033	tract*livestock	-0.231***	0.028
land	0.044	0.042	tract*precip	0.024	0.032
livestock	-0.057	0.045	tract*irrigation	0.102***	0.014
precip	0.029	0.073	land*land	-0.293***	0.072
irrig	0.213***	0.030	land*livestock	0.101*	0.041
labor*labor	0.300***	0.071	land*precip	0.133	0.068
labor*fert	-0.019	0.014	land*irrigation	0.141***	0.029
labor*tract	0.015	0.022	livestock*live	0.095	0.061
labor*land	-0.330***	0.032	live*precip	-0.570***	0.077
labor*livestock	0.034	0.049	live*irrigation	-0.075	0.039
labor*precip	0.292	0.080	precip*precip	-0.853***	0.144
labor*irrigation	0.230***	0.021	precip*irrig	0.109***	0.027
fert*fert	0.014**	0.005	irrigation*irrig	0.125***	0.020
fert*tract	0.007	0.008	% ag land	0.099***	0.019
fert*land	0.039**	0.014	time	0.018***	0.003
fert*livestock	-0.023	0.014			
fert*precip	0.058	0.030			
fert*irrigation	0.041***	0.007			

Inefficiency	Estimate	StdError		
Z_lifeexpeca	-0.035***	0.006		
Z_immuna	0.005***	0.001		
Z_pupteach	-0.008***	0.001	LogLik	47.820
Z_timea	0.005	0.005	cross sections	33
Z_independence	0.000***	0.000	time periods	23
sigmaSq	0.078***	0.013	obs	639
gamma	0.901***	0.071	mean eff	0.680

Source: Author’s estimations.

Table A.4—Five year averages

logProd (mean diff)	Estimate	StdError		Estimate	StdError
constant	-0.255	0.349			
labor	0.346**	0.129	tract*tract	0.002	0.040
fert	0.119*	0.057	tract*land	0.315***	0.026
tract	0.285***	0.036	tract*livestock	-0.243***	0.051
land	0.104	0.107	tract*precip	0.136*	0.054
livestock	-0.073	0.075	tract*irrigation	-0.010	0.017
precip	0.179	0.151	land*land	-0.353***	0.090
irrig	-0.141*	0.057	land*livestock	0.280***	0.055
labor*labor	-0.553***	0.088	land*precip	-0.141	0.127
labor*fert	-0.022	0.029	land*irrigation	0.022	0.037
labor*tract	-0.039	0.037	livestock*live	-0.352***	0.031
labor*land	-0.081	0.047	live*precip	-0.433*	0.197
labor*livestock	0.467***	0.053	live*irrigation	0.084**	0.030
labor*precip	0.813***	0.121	precip*precip	-1.109***	0.236
labor*irrigation	-0.335***	0.024	precip*irrig	0.147**	0.047
fert*fert	-0.022*	0.010	irrigation*irrig	0.071***	0.013
fert*tract	0.038***	0.011	% ag land	0.235**	0.076
fert*land	-0.090***	0.025	time	0.088***	0.009
fert*livestock	0.030	0.022			
fert*precip	-0.111**	0.039			
fert*irrigation	0.015	0.010			

Inefficiency	Estimate	StdError		
Z_immun	0.014***	0.003	LogLik	-28.515
Z_teach	-0.028***	0.004	cross sections	37
sigmaSq	0.484***	0.045	time periods	6
gamma	1.000***	0.000	obs	187
			mean eff	0.708

Source: Author's estimations.

Table A.5—Time as an input and controlling for AEZ

logProd (mean diff)	Estimate	StdError		Estimate	StdError
constant	0.30***	0.037			
labor	0.538***	0.049	tract*tract	0.049**	0.018
fert	0.206***	0.016	tract*land	0.186***	0.017
tract	0.114***	0.025	tract*livestock	-0.243***	0.019
land	0.120***	0.034	tract*precip	0.021	0.023
livestock	-0.040	0.031	tract*irrigation	-0.006	0.008
precipitation	0.326***	0.054	tract*time	0.007***	0.001
irrigation	-0.037	0.022	land*land	-0.197***	0.055
time	0.0121***	0.003	land*livestock	0.362***	0.034
labor*labor	0.197**	0.063	land*precip	0.231***	0.050
labor*fert	-0.011	0.011	land*irrigation	0.023	0.018
labor*tract	-0.013	0.017	land*time	-0.009***	0.002
labor*land	-0.370***	0.030	livestock*livestock	-0.238***	0.044
labor*livestock	0.148***	0.038	live*precip	-0.662***	0.061
labor*precip	0.450***	0.063	live*irrigation	0.073***	0.016
labor*irrigation	-0.217***	0.017	live*time	0.005*	0.002
labor*time	-0.002	0.003	precip*precip	-0.814***	0.118
fert*fert	0.024***	0.004	precip*irrig	0.089***	0.022
fert*tract	-0.002	0.005	precip*time	0.008	0.004
fert*land	0.034***	0.008	irrigation*irrig	0.009	0.012
fert*livestock	-0.023*	0.009	irrigation*time	-0.003*	0.001
fert*precip	0.033*	0.017	time*time	0.000	0.001
fert*irrigation	0.038***	0.005	AEZ	0.063***	0.018
fert*time	0.001	0.001			

Inefficiency	Estimate	StdError		
Z_lifeexpectancy	-0.060***	0.006		
Z_immunizations	0.012****	0.001	LogLik	18.209
Z_time	-0.005	0.007	cross sections	39
Z_independence	0.000***	0.000	time periods	23
sigmaSq	0.178***	0.014	obs	755
gamma	0.969***	0.015	mean eff	0.723

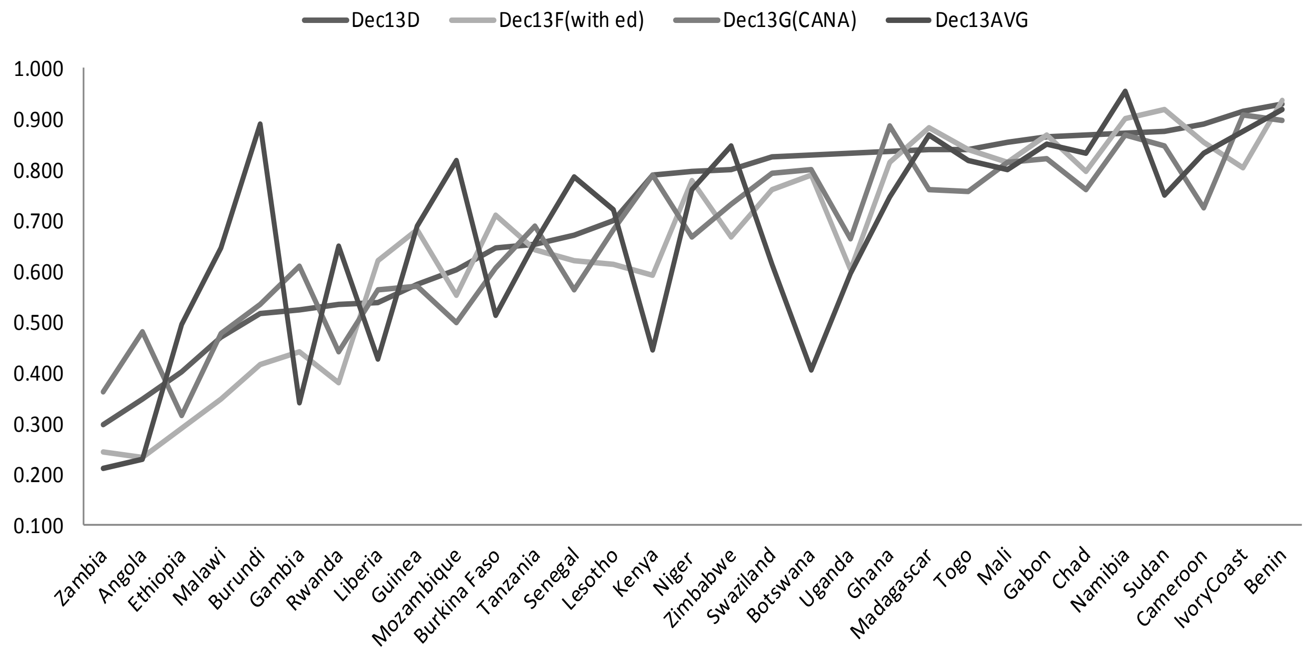
Source: Author's estimations.

Table A.6—Efficiency estimates from Table A.5

Country	Average	Country	Average
Angola	0.354	Maurtania	0.823
Botswana	0.807	Mozambique	0.588
Burundi	0.517	Namibia	0.885
Cameroon	0.883	Niger	0.779
Cape Verde	0.850	GuineaBissau	0.691
Central Af Rep	0.739	Eritrea	0.418
Chad	0.888	Zimbabwe	0.798
Congo	0.853	Rwanda	0.486
Benin	0.927	Senegal	0.692
Gabon	0.854	Sierra Leone	0.788
Gambia	0.518	Somalia	0.847
Ghana	0.843	Sudan	0.866
Guinea	0.628	Swaziland	0.797
IvoryCoast	0.900	Tanzania	0.699
Kenya	0.780	Togo	0.855
Lesotho	0.663	Uganda	0.781
Liberia	0.545	Burkina Faso	0.658
Madagascar	0.846	Ethiopia	0.386
Malawi	0.473	Zambia	0.299
Mali	0.867		

Source: Author's estimations.

Figure A.1—Average efficiencies by model, 1980–2002



Source: Authors' creation.

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