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Technical efficiency and productivity potential of cocoa farmers in West African countries.

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The Sustainable Tree Crops Program (STCP) is a joint public-private research for development partnership that aims to promote the sustainable development of the small holder tree crop sector in West and Central Africa. Research is focused on the introduction of production, marketing, institutional and policy innovations to achieve growth in rural income among tree crops farmers in an environmentally and socially responsible manner. For details on the program, please consult the STCP website <http://www.treecrops.org/>.

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Abstract
This paper uses survey data to examine the technical efficiency and productivity potential of cocoa farmers, in West and Central Africa. Separate stochastic frontier models are estimated for farmers in Cameroon, Ghana, Nigeria and Côte d'Ivoire along with a stochastic metaproduction frontier to obtain alternative estimates for the technical efficiencies of farmers in the different countries. The mean productivity potential of cocoa farmers is also estimated, by using a decomposition result applied to both the national and the metaproduction frontiers. The determinants of technical efficiency are assessed in order to identify the reasons for differences across countries.

Key words: Cocoa farmers, efficiency, metaproduction frontier, productivity potential, Technological gap.

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Introduction

In the course of the last 40 years industrial tree crops, notably cocoa, coffee, oil palm and rubber, have largely dominated the export agriculture in West and Central Africa.
Perennial tree crop systems in Africa are important for national macroeconomic balances and rural livelihoods. Among the perennial tree crops, cocoa, used in chocolate industries is of particular importance in the humid forest agro-ecology of West and Central Africa.
West and Central Africa currently produce about 70% of the total global supply. During the last three production years, Côte d'Ivoire and Ghana alone produced about 43% and 16% of world output, respectively, and about 62% and 22% of total African cocoa production. Other key producers are Indonesia, with about 14% of global production, followed by Nigeria, Cameroon, and Brazil, each producing about 5% of world output. Recent global and African-specific production trends are shown in tables 1.

Table 1. World cocoa production (1000s of metric tonnes and percent share of world production)

Country/region	2001/02		2002/03		2003/04		2004/05 (forecast)	
	Tonnes	Share	Tonnes	Share	Tonnes	Share	Tonnes	Share
Côte d'Ivoire	1,218	43%	1,367	43%	1,500	44%	1,275	41%
Ghana	371	13%	498	16%	605	18%	530	17%
Nigeria	170	6%	170	5%	165	5%	170	5%
Cameroon	131	5%	155	5%	150	4%	150	5%
Other Africa	31	1%	37	1%	38	1%	39	1%
Total Africa	**1,920**	**68%**	**2,227**	**70%**	**2,458**	**72%**	**2,164**	**70%**
Indonesia	453	16%	430	14%	420	12%	415	13%
Malaysia	15	1%	24	1%	25	1%	26	1%
Other Asia	61	2%	64	2%	65	2%	67	2%
Total Asia/Oceania	**528**	**19%**	**518**	**16%**	**510**	**15%**	**508**	**16%**
Brazil	124	4%	163	5%	163	5%	164	5%
Ecuador	83	3%	87	3%	100	3%	93	3%
Other America	163	6%	167	5%	165	5%	170	5%
Total Americas	**370**	**13%**	**416**	**13%**	**428**	**13%**	**427**	**14%**
World total	**2,819**	**100%**	**3,161**	**100%**	**3,396**	**100%**	**3,099**	**100%**

Source: Tiaji et al. (2005)

In general, world cocoa production is expected to gradually increase in the medium term. The Food and Agriculture Organization (FAO) has projected a 2.2% annually growth rate during the present decade, compare to a growth rate of about 1.7% per year in the 1990s, and expects production to reach 3.7 million tonnes by 2010. Opinions are mixed over the extent to which Africa will contribute to this expected growth.

In most of West and Central African countries, growth in the sub-sector was achieved by increasing the area cultivated rather than by improving yield. That means that cocoa production has been among the most significant factors associated with the near disappearance of the West African Guinea Rainforest. The process typically entails tree felling, slashing and burning, followed by the simultaneous planting of food crops and cocoa together. The food crops provide temporary shade for the young seedlings during the first two or three years, after four years the cocoa shrubs begin to produce, reaching their mature and until about 18 years after planting production increases annually. The yields begin gradually to decline due to exhaustion of soil nutrients, erosion and increasing occurrence of

pests and plant diseases. Some 20 to 30 years after planting, the farmer is confronted with a major investment decision: either he reinvests in uprooting, replanting, soil improvement and future pest abatement or he migrates to a fresh area. In sparsely populated regions it is simpler to shift the agricultural frontier than it is to replant old cocoa. For small farmers the replanting option is often more expensive in terms of capital requirements, crop risks and labour and commercial inputs, such as herbicides, pesticides and fertilisers. Cocoa farms are increasingly encroaching on the West African Guinea Rainforest ecosystem, which has been identified as a global biodiversity hotspot with over 1,900 endemic species.

Reversing the negative environmental effects of low productivity systems will require greater investment by both the public and private sector to improve productivity, which is dependent on technical change and efficiency gains. The intensification of agricultural production in Africa through increased input use and the introduction of high-yielding varieties is a complex process. A relevant question for agricultural policy makers is to what extent can the cocoa sector be made more efficient, by achieving more output with the current input level and technology system. In other words what is the scope for increasing cocoa productivity by improving the technical competency of farmers using currently existing technology?

We propose in this paper to estimate the technical efficiency of cocoa farmers using baseline survey data collected in 2001/2002 by the Sustainable Tree Crops Program (STCP). The technical efficiency of cocoa farmers is estimated by using different stochastic production frontiers and meta-frontier production function methods.
Contrary to most studies on efficiency, which focused on specific countries, the present study covers the principal cocoa-producing countries in the region. Furthermore, the use of stochastic frontier meta-production function is a methodological improvement. Despite the wide number of empirical studies on technical efficiency, and the proliferation of methodological frontier studies, no empirical study using stochastic frontier metaproduction function has been applied for West African cocoa.

The paper proceeds as follows: in the subsequent section, the analytical framework of the metafrontier approach is described. Section 2 presents the empirical model and the design of the data used. In section 3, the results are presented and discussed and the last section draws conclusions and implications for policy.

1 The metafrontier approach

A number of authors such as Aigner, Lovell, and Schmidt (1977), and Meeusen and Van der Broeck (1977) developed the “stochastic composed error frontier methodology”. The main principle of the model is to specify the error term as the sum of two parts, one normal and the other from the one-sided or half normal distribution.
The specification of the stochastic production frontier model, allows for a non-negative random component in the error term to generate a measure of technical inefficiency or the ratio of actual to expected maximum output, given input levels and the existing technology. Apart from allowing for the measure or assessment of technical inefficiency, stochastic frontier models also acknowledge the fact that random shocks outside the control of producers such as weather conditions among others could cause variations in maximum output. The variation in output could also occur as a result of farms operating at various levels of inefficiency due to poor incentives, mismanagement, inappropriate input levels or imperfect competition (Kumbakar and Lovell, 2000).

While the technical efficiency of producers measured with respect to a given frontier is comparable, this is not normally the case among producers that operate under different technologies. Such problems arise when comparisons of producers from different countries are involved. The metaproduction function concept is based on the hypothesis that all producers in different countries have potential access to the same technology. However, each producer may choose to operate on a different part of it depending on circumstances such as natural endowments, relative prices of, and availability of inputs, and the economic environment (Lau and Youtopoulos, 1989).

The metaproduction function concept was first introduced by Hayami (1969) and Hayami and Ruttan (1970, 1971). As stated by Hayami and Ruttan (1971, p. 82): "The metaproduction function can be regarded as the envelope of commonly conceived neoclassical production functions." In their discussion of agricultural productivity across various countries, Ruttan et al. (1978, p. 46) state: "We now define the metaproduction function as the envelope of the production points of the most efficient countries." The concept of a metaproduction function is theoretically attractive because it is based on the simple hypothesis that all producers in different regions (countries, regions, etc.) have potential access to the same technology. Following the seminal work of Hayami and Ruttan (1970), Mundlak and Hellinghausen (1982) and Lau and Yotopoulos (1989) employed the approach to compare agricultural productivity across countries. Some econometric advantages of applying the metaproduction function are discussed by Lau and Yotopoulos (1989), but the lack of comparable data and the presence of inherent differences across regions are the major limitations of the approach. Boskin and Lau (1992) used a new framework for the analysis of productivity and technical progress, based on direct econometric estimation of the aggregate metaproduction function.

The concept of a *stochastic frontier* metaproduction function used in this paper is similar to that of the standard metaproduction function approach, proposed by Hayami (1969) and Hayami and Ruttan (1971). The principal difference between these two metaproduction function models is that the error term in the former model comprises a symmetric random error and a non-negative technical inefficiency term, as in the stochastic frontier production function model, originally proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977).

A stochastic frontier metaproduction function model was adopted by Gunaratne and Leung (2001) and Sharma and Leung (2000) in studies of the efficiency of aquaculture farms in several countries. Sharma and Leung (2000) used the Battese and Coelli (1995) stochastic frontier metaproduction model to estimate technical inefficiency among South Asian carp producers.

Recent extensions and modification of the stochastic frontier metaproduction function approach found in Battese and Rao (2002) and Battese et al. (2004) are briefly reviewed.
Let us consider that the whole sample of producers is composed of K subsets (K>1) representing K countries and farms in each country operate under a country specific technology, T^k (k=1, 2,……,K).

Since all the K's technology can be considered as a subset of an "over-arching technology" referred to as the meta-technology, which is represented by T^*, the metatechnology can be stated as the "absolute best" technology produced by the state of knowledge. This leading technology is accessible if neither endowment nor policy constraints are facing producers.

Battese et al. (2004) showed how technical efficiency scores for farms across countries can be estimated using a stochastic frontier metaproduction function model, and used a decomposition result to present an analysis of regional productivity potential and efficiency levels.

Suppose that the inputs and outputs for farms in a given cocoa sector are such that stochastic frontier production function models are defined for different countries within the cocoa sector. Suppose that for the *j*-th country, there are sample data on N_j farms that produce cocoa from the various inputs and the stochastic frontier model for this country is defined by

$$Y_{ij} = f(x_{ij}, \beta_j)e^{V_{ij} - U_{ij}},\ i = 1, 2, \ldots\ldots, N_j, \qquad (1)$$

where the $V_{ij}s$ are assumed to be identically and independently distributed as $N(0, \sigma_v^2)$-random variables, independent of the $U_{ij}s$, which are defined by the truncation (at zero) of the $N(\mu_{ij}, \sigma^2)$-distributions, where the μ_{ij}s are defined by some appropriate inefficiency model, for example, one of the Battese and Coelli (1992, 1995) models. For simplicity, the subscript, j, is omitted so the model for the *j-th* country is given by:

$$Y_i = f(x_i, \beta)e^{V_i - U_i} \equiv e^{x_i\beta + V_i - U_i}. \qquad (2)$$

This expression assumes that the exponent of the frontier production function is linear in the parameter vector, β, so that x_i is a vector of functions (e.g., logarithms) of the outputs for the *ith* farm.
The metafrontier production function model for farms in all countries of the cocoa sector is expressed by:

$$Y_i = f(x_i, \beta^*)e^{V_i^* - U_i^*} \equiv e^{x_i\beta^* + V_i^* - U_i^*},\quad i = 1, 2, \ldots\ldots, N, \qquad (3)$$

Where β^* denotes the vector of parameters for the metafrontier function such that

$$x_i\beta^* \geq x_i\beta. \qquad (4)$$

(4) states that the metafrontier dominates all the country's frontiers. That is the meta-technology describes the unconstrained best practice according to the state of knowledge.
The metafrontier production function is thus defined as a deterministic parametric function (of specified functional form) such that its values are no smaller than the deterministic components of the stochastic frontier production functions of the different groups involved, for all groups and time periods. The metafrontier is assumed to be a smooth function and not a segmented envelope of the stochastic frontier functions for the different groups. A graph of the metafrontier function is presented in figure 1.

Three stochastic frontier models are indicated in Figure 1. The observed values are indicated by numbers that correspond to the particular regional frontiers, whereas their corresponding (unobservable) stochastic frontier outputs are indicated by the numbers in circles above them. The value of the curves corresponding to the circled numbers can be considered as means of the potential stochastic frontier outputs for the given levels of the inputs. The metafrontier function has values that are no less than the deterministic functions associated with the

stochastic frontier models for the different groups involved. Some stochastic frontiers, and even their corresponding stochastic frontier outputs, may exceed values of the metafrontier, as indicated in Figure 1 (Battese et *al*, 2004).

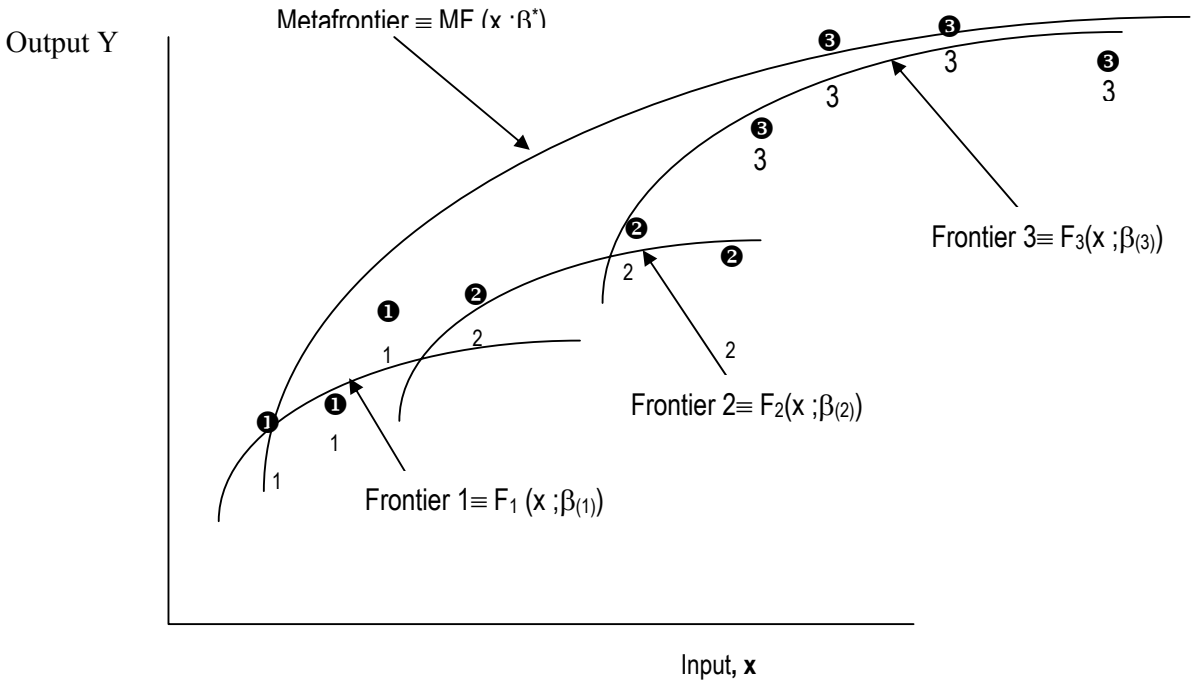

Figure 1: Metafrontier function model according to Battese et al. (2004)

The metafrontier model of equations (3) and (4) is related to the concept of the metaproduction function that was defined by Hayami and Ruttan (1971). However, in our model, the metafrontier function is a production function of specified functional form that does not fall below the deterministic functions for the stochastic frontier models of the group involved. Battese and Rao (2002) give a more extensive literature review and proposed a stochastic metafrontier model that assumes a different data-generation mechanism for the metafrontier than for the different group frontiers. The model in this paper assumes that data-generation models are only defined for the frontier models for the farms in the different groups.

The observed output for any unit can be consequently defined by the stochastic frontier for the *jth* group (equation 2) and using the metafrontier function (3), such that:

$$Y_i = e^{-U_i} \times \frac{e^{x_i\beta}}{e^{x_i\beta^*}} \times e^{x_i\beta^* + V_i} \qquad (5)$$

where the first term of the right-hand side of equation (5) is the technical efficiency relative to the stochastic frontier for the *jth* group,

$$TE_i = \frac{Y_i}{e^{x_i\beta + V_i}} = e^{-U_i} \qquad (6)$$

The second term on the right-hand side of equation (5) is the technology gap (TGR) for the observation for the sample farm involved,

$$TGR_i = \frac{e^{x_i\beta}}{e^{x_i\beta^*}} \qquad (7)$$

This measures the ratio of the output for the frontier production function for the *jth* group relative to the potential output that is defined by the metafrontier function, given the observed inputs. The technology gap ratio ranges from zero to one because of equation (4).

The technical efficiency of the *ith* farm, relative to the metafrontier, denoted by TE_i^*, is defined in an analogous way to equation (6). It is the ratio of the observed output relative to the last term on the right-hand side of equation (5), which is the metafrontier output, adjusted for the corresponding random error, i.e.,

$$TE_i^* = \frac{Y_i}{e^{x_i\beta^* + V_i}} \qquad (8)$$

Equations (5)-(8) imply that an alternative expression for technical efficiency relative to the metafrontier is given by

$$TE_i^* = TE_i \times TGR_i \qquad (9)$$

Equation (9) implies that the technical efficiency ratio of the *ith* producer relative to the metafrontier is the product of the technical efficiency relative to the stochastic frontier for the given group and the TGR. In other words, the technical efficiency scores for producers that don't use the same technology can be corrected (to make them comparable) using the distance between the regional frontier and the leading metafrontier. For example, if TE=0.9 then the technical efficiency measure indicates that the observed output is 90 per cent of the potential output, using the same input vector. If TGR is 0.6 that is, given the input vector, the potential output vector for country j technology is 60 per cent of that represented by the metatechnology. Then, using (9), the technical efficiency with respect to the metatechnology is 0.54. Note that this precludes the technical efficiency with respect to the meta-technology from being greater than the technical efficiency measure relative to the regional frontier.

The parameters and measures associated with the metafrontier model of equations (2)-(4) can be estimated as follows:

Step 1. Obtain the maximum-likelihood estimates, $\hat{\beta}$ for the $\beta-$parameters of the stochastic frontier for the *jth* group, using, for example, the FRONTIER program (Coelli, 1996).

Step 2. obtain estimates, $\hat{\beta}^*$, for the β^*-parameters of the metafrontier function such that the estimated function best envelopes the deterministic components of the estimated stochastic frontiers for the different groups. To identify the best envelope, it is necessary to specify a criterion that can be used in judging the best. Two criteria are often considered, one based on the sum of absolute deviations and the other based on the sum of squares of deviations of the metafrontier values from those of the group frontiers.

Step 3. Estimates for the technical efficiencies of farms relative to the metafrontier function can be predicted by

$$T\hat{E}_i^* = T\hat{E}_i \times TG\hat{R}_i \qquad (10)$$

where $T\hat{E}_i$ is the predictor for the technical efficiency relative to the given group frontier, as proposed in Battese and Coelli (1992), which is programmed to be calculated in FRONTIER; and $TG\hat{R}_i = e^{x_i\hat{\beta}} / e^{x_i\hat{\beta}^*}$ is the estimate for the TGR for the *ith* farm in the *jth* group relative to the cocoa sector potential, obtained by using the estimates for the parameters involved.

1.1 Minimum Sum of Absolute Deviations

Given the estimates for the parameters of group stochastic frontiers, $\hat{\beta}_{(j)}, j= 1,2,...R$, obtained by Step (1) above, the $\hat{\beta}^* -$ parameters can be estimated by solving the optimization problem below:

$$\begin{aligned} &\min L \equiv \sum_{i=1}^{N} (\ln f(x_i, \beta^*) - \ln f(x_i, \hat{\beta}_{(j)}) \\ &s.t \quad \ln f(x_i, \beta^*) \geq \ln f(x_i, \hat{\beta}_{(j)}) \end{aligned} \tag{11}$$

There are several interesting features to the application of this criterion. First, the deviations used here are essentially logarithms of $f(x_i, \beta^*) / f(x_i, \hat{\beta}_{(j)})$, which represent the radial distance between the metafrontier and the *jth* group frontier, evaluated at the observed input vector for a farm in the *jth* country. Thus, the use of equation (11) implies that the resulting metafrontier minimizes the sum of logarithm radial distances between the metafrontier and the group frontiers[†]. Second, since the optimization is subject to the inequality restriction, all the deviations involved are positive and, therefore, the absolute deviations are simply equal to the deviations. Third, if $f(x_i, \beta^*)$ in equation (3) is assumed to be log-linear in the parameters (as it is in this paper), the optimization problem in (11) simplifies to the following linear programming (LP) problem:

$$\begin{aligned} &\min L \equiv \sum_{i=1}^{N} (x_i \beta^* - x_i \hat{\beta}_{(j)}) \\ &s.t. \quad x_i \beta^* \geq x_i \hat{\beta}_{(j).} \end{aligned} \tag{12}$$

The solution to the above problem is equivalently obtained by minimizing the objective function, $L^* = \bar{x}\beta^*$, subject to the linear restriction of equation (11), where $\bar{x}$, is the row vector of means of the elements of the $x_i -$ vectors for all observations in the data set. This follows because the estimates of the stochastic frontiers for the different groups, $\hat{\beta}_{(j)}$, $j = 1,2,....R$, are assumed to be fixed for the linear programming problem.

1.2. Minimum Sum of Squares of Deviations

Minimization of the objective function in (11) assigns the same weight for all the radial distances for all the farmers in the sample. An alternative approach is to estimate the parameters of the metafrontier function by minimizing the sum of squares of the deviations of the values on the metafrontier function from the group-specific stochastic frontiers at the observed inputs levels. This method assigns higher weights to the deviations associated with farmers that have larger technology gap ratios. This leads to the following optimization problem:

[†] The radial distance is used in defining the input and output distance functions that from the basis for all productivity comparisons (see Coelli et al., 1998, Chapter 3).

$$\min L^{**} \equiv \sum_{i=1}^{N} (x_i\beta^* - x_i\hat{\beta}_{(j)})^2$$
$$s.t. \quad x_i\beta^* \geq x_i\hat{\beta}_{(j)} \tag{13}$$

This approach is similar to the use of the least-square criterion. The optimization problem in (13), identical to constrained least-squares estimation, is a quadratic programming (QP) problem that minimizes the Euclidean distances of the values on the metafrontier from those on the estimated stochastic frontier functions.

2. Empirical application

2.1 Empirical model

The functional form chosen for the stochastic frontier function for all the countries is the translog form. The translog functional form for the *ith* unit in the in a particular country is defined by:

$$\ln Y_i = \beta_0 + \sum_{m=1}^{4} \beta_m x_{m_i} + \sum_{m=1}^{4}\sum_{k\geq m}^{4} \beta_{mk} x_{mi} x_{ki} + v_i - u_i \tag{14}$$

Indices i *and* m respectively represent the input m used by unit i.

$\ln Y_i$ denotes the natural logarithm of the total quantity of cocoa produced measured in kilograms,

m = 1, denotes the total productive cocoa area in hectares

= 2, denotes the cost of pesticide (fungicides and insecticides) used in cocoa production measured in USD

= 3, denotes the amount of labour, which includes both family, exchange, and hired labour in man-days

= 4, denotes the average age of cocoa farm measured in years

$v_i s$ are assumed to be independently and identically distributed $N(0,\sigma_v^2)$ two sided random errors, independently of the $u_i s$.

2.1.1 Determinants of technical efficiency

Battese and Coelli (1995) suggest that the technical inefficiency effects, u_i in (14) could be replaced by a linear function of explanatory variables reflecting farmer/country-specific characteristics. This approach gives the opportunity of accounting for resource quality differences across farmers/countries along with socio-political and institutional differences that might affect behaviour.

The technical inefficiency effects $u_i s$ are non-negative random variables, and assumed to be independently distributed as truncations at zero of the normal distribution. Specifically,

$$u_i = \delta_0 + \sum_{j=1}^{m} \delta_j z_i^j + \omega_i \tag{15}$$

where $z_i^j{}'s$ are farmer explanatory variables associated with technical inefficiencies;

j = 1, the producers' level of education (number of completed years of schooling for the farmer)

= 2, the age of the farmer (in years)
= 3, Distance of the plot from the main access road (in kilometres)
= 4, a dummy variable representing the gender of the farmer (1= male; 0= female)
= 5, a dummy variable to measure if the farmer belongs to a farmer organization or association. Value is 1 if yes, and 0 otherwise
= 6, extension contact (dummy variable to measure the influence of agricultural extension on efficiency. Value is 1 if the farmer has had contact with an agricultural extension officer in the past year, 0 otherwise)
= 7, access to cash credit (dummy variable to measure the influence of credit constraints on efficiency. Value is 1 if the farmer received credit in the past year, 0 otherwise)
= 8, is the level of shade in the cocoa farm. Value is 0 for the no shade farm, 1 for the low shade farm, 2 for the medium shade cocoa farm and, 3 for the heavy shade cocoa farm.
δ_0 and δ_j are parameters to be estimated and ω is a random variable with zero mean and finite variance σ_ω^2 defined by the truncation of the normal distribution such that $\omega_i \geq (\delta_0 + \sum_j \delta_j z_i^j)$. This implies that the means, $\mu_i = \delta_0 + \sum_j \delta_j z_i^j$ of the u_i are different for different units.

Two routes are possible in investigating the determinants of technical efficiency variation among farmers in the sample. The two stage approach is the most intuitive and involves the estimation of the technical efficiency effects from both models by regressing these on a set of unit farmers' specific characteristics. This, though widely used, implies that the inefficiency effects which are assumed to be independently and identically distributed in the estimation of stochastic frontier are a function of farmers' specific effects in the second stage, thus violating the assumption that the efficiency effects are identically distributed (Battese and Coelli, 1995). The inefficiency effects would only be identically distributed if the coefficients of the farmer specific factors are simultaneously equal to zero (Coelli, 1995). It is possible to overcome this problem by using a single stage maximum likelihood approach (Battese and Coelli, 995). The technical inefficiency effects are specified to be a function of a vector of farmer specific variables and a random error as in (14) and a single stage maximum likelihood estimation technique is used to estimate the parameters of the production frontier and of the technical inefficiency variables simultaneously.

2.2 Data

The present study will be based on data collected by the International Institute of Tropical Agriculture (IITA) in 2002 in Côte d'Ivoire, Ghana, Nigeria and Cameroon.
A baseline survey of major cocoa growing regions of West and Central Africa was conducted to provide baseline parameter estimates of production systems in the sub-region. In all of the countries indicated, villages and clusters of households were randomly selected and household heads interviewed using structured questionnaires. In Nigeria, 1083 households were visited in 35 villages and towns of Ondo State, which accounts for 40 to 50 percent of annual production in Nigeria. In Cameroon, 1003 households in 83 villages in the Southwest, Center and South Provinces were visited with production from these sites accounting for over 80 percent of national production. In Ghana, the surveys were conducted with 1000 households from 85 villages in the Brong Ahafo, Ashanti, Eastern and Western regions which together account for approximately 90% of national production. In Côte d'Ivoire, a list of farmers obtained from a national census of cocoa and coffee producers conducted in 1998 allowed the opportunity of selecting households using a random number procedure. A total of

1372 households from 20 sub-division and 134 villages, hamlets and cocoa "camps" across the cocoa belt of Côte d'Ivoire were interviewed.

Table 2: Number of villages and farmers surveyed.

	Villages	Farmers
Côte d'Ivoire	134	1372
Ghana	85	1000
Nigeria	35	1083
Cameroon	83	1003
Total	337	4458

The main objective of this survey was to understand the general constraints and opportunities of cocoa based systems in the humid forest zone of West and Central Africa, with a view towards increasing the productivity of agricultural land and labor employed by asset-poor households, and thus contributing to alleviation of rural poverty.

Conducted in close consultation with research collaborators in Cameroon, Côte d'Ivoire, Ghana, and Nigeria, data were collected with a questionnaire that was made of six parts:

1 - Agricultural systems and rural livelihoods (demographics, other enterprise, farm size, capital inventory)

2 - Rural service provision (input markets, credit markets, market and production information, rural organization)

3 - Tree stocks by age, replanting, uprooting and new planting

4 - Agronomic practices and output by plot

5 - Labour practices

6 - Post harvest practices and cocoa marketing

After discarding a few incomplete records, the final sample retained for the analysis is based on 3,746 farmers. A basic summary of the observations on the variables for the different countries is presented in table 3.

Table 3: Summary statistics for data on farmers in the West and Central Africa cocoa sector[a]

	CAMEROON N = 824	GHANA N = 861	NIGERIA N = 1041	RCI N = 1020	POOLED N = 3746	Prob.
Quantity of cocoa produced (kg)	1453.77 (2050.081)	917.177 (1117.17)	1770.030 (2520.04)	1583.275 (2164.27)	1453.587 (2091.97)	<0.000
Area (ha)	5.87 (7.329)	2.534 (2.656)	4.725 (4.235)	4.472 (6.628)	4.405 (5.63)	<0.000
Labor (adult-equivalent)	4.40 (4.702)	2.113 (2.55)	3.014 (2.22)	3.735 (3.641)	3.308 (3.4)	<0.000
Cost of pesticides ($USD)	189.19 (479.450)	16.874 (34.066)	155.330 (175.51)	40.274 (105.78)	99.626 (259.89)	<0.000
Average age of cocoa farms (years)	30.24 (17.387)	16.121 (10.69)	24.557 (11.204)	19.788 (11.88)	22.570 (13.84)	<0.000
Age of the farmer (years)	50.30 (14.913)	46.786 (14.57)	55.633 (15.33)	49.778 (13.33)	50.831 (14.89)	<0.000
Gender of the farmer (%)	98% (15%)	89% (31%)	89% (31%)	96% (19.4%)	93% (25.7%)	<0.000
Membership in farmer organization (%)	38% (48.5%)	11% (30.8%)	24% (42.8%)	35% (47.8%)	27% (44.5%)	<0.000

Number of extension contacts	1.31 (2.545)	0.652 (1.93)	0.421 (1.376)	0.587 (1.88)	0.715 (1.97)	<0.000
Access to credit (%)	28% (44.8%)	18% (38.6%)	53% (50%)	12% (32%)	28% (45.1%)	<0.000
Level of shade (0 to 3)	1.71 (0.755)	1.033 (0.81)	1.433 (0.627)	1.136 (0.93)	1.322 (0.83)	<0.000
Educational level of the farmer (years)	6.59 (3.824)	8.248 (4.29)	1.586 (2.025)	0.552 (0.73)	3.702 (4.26)	<0.000
Distance to paved road (km)	17.73 (19.733)	9.863 (20.10)	2.853 (4.143)	15.246 (17.94)	11.312 (16.97)	<0.000

[a] Values in parenthesis are the standard deviations.

These statistics indicate that there are considerable differences among cocoa farmers in different countries so far as the means of the outputs and inputs are concerned.

3 Estimation and results

The single-stage maximum likelihood procedure of the FRONTIER 4.1 program (Coelli, 1996) was used to estimate the parameters of the stochastic frontiers and efficiency determinants for each country and for pooled data. Results are presented in table 4.

Table 4: The maximum-likelihood estimates of the translog stochastic frontiers with the preferred inefficiency models for cocoa farmers in different countries in West and Central Africa, together with estimates of parameters of the metafrontier production function.

Variable	Coefficient	Cameroon	Ghana	Nigeria	Côte d'Ivoire	Pooled	Meta (LP)
Constant	β_0	6.715 (11.321)[b]	4.941 (-10.822)	5.96 (7.406)	5.293 (13.718)	4.951 (25.482)	5.727
Area	β_1	0.645 (3.692)	0.728 (5.053)	0.652 (3.135)	0.767 (4.406)	0.931 (12.020)	0.689
Labour	β_2	0.310 (4.12)	-0.025 (-0.142)	0.026 (0.115)	0.509 (2.662)	0.181 (2.113)	0.252
Pesticides	β_3	-0.366 (-5.842)	-0.075 (-1.846)	-0.585 (-6.112)	-0.235 (-5.464)	-0.062 (-1.760)	0.0001
Trage	β_4	-0.277 (-1.223)	0.955 (3.577)	0.254 (0.685)	0.759 (3.021)	0.91 (7.763)	0.387
Area^2	β_{11}	0.002 (0.072)	0.055 (1.957)	-0.007 (-0.268)	-0.092 (-3.036)	0.009 (0.604)	0.0017
Labour^2	β_{22}	0.046 (1.644)	-0.001 (-0.030)	-0.017 (-0.612)	-0.003 (-0.094)	0.036 (2.717)	0.0109
Pesticide^2	β_{33}	0.031 -12.258	0.013 (4.529)	0.066 (17.065)	0.023 (6.301)	0.046 (13.307)	0.0424
Trage^2	β_{44}	-0.003 (-0.097)	-0.11 (-2.281)	-0.02 (-0.347)	-0.155 (-3.345)	-0.156 (-7.807)	-0.04
Area*Labour	β_{12}	-0.111 (-2.157)	0.026 (0.619)	0.008 (0.175)	0.086 (1.552)	0.031 (1.238)	0.009
Area*Pesticide	β_{13}	0.002 (0.234)	-0.006 (-1.014)	-0.03 (-1.641)	-0.014 (-1.891)	-0.061 (-6.843)	-0.0018
Area*Trage	β_{14}	-0.085 (-2.014)	-0.028 (-0.534)	-0.059 (-1.196)	0.019 (0.302)	-0.115 (-4.354)	-0.0012
Labour*Pesticide	β_{23}	-0.013 (-1.140)	-0.002 (-0.364)	0.018 (0.955)	-0.009 (-1.260)	-0.007 (-0.756)	-0.0003
Labour*Trage	β_{24}	0.025 (0.47)	0.018 (0.292)	0.01 (0.161)	-0.094 (-1.518)	-0.018 (-0.607)	0.0163
Pesticide*Trage	β_{34}	0.03 (2.228)	-0.017 (-2.049)	0.003 (0.105)	0.022 (2.617)	0.015 (1.408)	0.0131

Variance parameters

$\sigma^2 = (\sigma_u^2 + \sigma_v^2)$		1.054	0.703	1.631	1.277	0.937
		(3.122)	(6.169)	(3.20)	(3.134)	(9.437)
$\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$		0.712	0.753	0.802	0.785	0.624
		(7.209)	(7.758)	(12.673)	(13.3)	(13.967)
Log Likelihood		-866.31	-930.66	-1042.41	-1138.48	-4312.33
Inefficiency effects						
Constant	δ_0	-2.148	0.826	-1.798	-2.125	-0.313
		(-1.327)	(1.160)	(-0.966)	(-0.882)	(-0.515)
Fage	δ_1	0.698	0.074	0.263	0.36	0.173
		(1.785)	(0.489)	(0.817)	(1.019)	(1.310)
Gender	δ_2	-1.095	-0.256	-0.608	-0.588	-0.34
		(-2.133)	(-1.945)	(-2.166)	(-1.724)	(-3.038)
Ruralorg	δ_3	-0.021	-0.243	-0.321	-0.305	-0. 912
		(-7.00)	(-1.460)	(-2.488)	(-1.620)	(-5.33)
Extension	δ_4	-0.162	0.233	-0.23	-0.129	-0.009
		(-1.839)	(1.411)	(-2.104)	(-1.201)	(-0.500)
Credit	δ_5	-0.88	-0.283	-0.84	1.411	-0.272
		(-2.211)	(-1.625)	(-2.609)	(1.463)	(-10.259)
Level of Shade	δ_6	0.306	0.073	-0.027	-0.223	0.197
		(2.095)	(0.987)	(-0.213)	(-1.805)	(4.266)
Education	δ_7	0.24	-0.074	-0.336	0.106	0.013
		(1.543)	(-1.571)	(-2.516)	(1.010)	(0.543)
Distance	δ_8	0.047	-0.009	-0.274	-0.065	-0.06
		(0.875)	(-0.153)	(-2.071)	(-12.286)	(-4.076)

[b] Variables in parenthesis are asymptotic t-ratios

Two sets of specification tests were performed. In the first, the null hypothesis that there are no technical efficiency effects in the models is tested using a likelihood ratio (LR) test of the one sided error. The null hypothesis is strongly rejected as the LR test statistics 55.82, 42.80, 52.68, 51.98 and 135.99 for Cameroon, Ghana, Nigeria, Côte d'Ivoire and pooled stochastic frontier respectively which are all greater than the (mixed) Chi-square value of 3.84.

As indicated above, Table 4 presents estimates of the parameters of the stochastic frontiers for all the nations separately and also using pooled data. Note that if the stochastic frontiers across nations do not differ, then it is possible to just use the pooled stochastic frontier. Therefore a LR test was performed in order to see if all the national stochastic frontiers share the same technology. The generalized likelihood-ratio (LR) test statistic for the null hypothesis that the national frontiers are identical for all cocoa farmers in West and Central Africa was calculated after estimating the stochastic frontier by pooling the data from all the four countries. The value of the LR statistic was 668.940[‡], which is highly significant. This result strongly suggests that the four national stochastic frontiers for cocoa farmers in West and Central Africa are not the same.

Based on this, the parameters of the metafrontier are estimated by solving the LP problem. The LP problem in (12) was solved using Lingo software. The LP was preferred in this paper because in their recent paper, Battese et al., (2004) found an insignificant difference between

[‡] The LR Statistic is defined by $\lambda = -2[\ln(L(H_0))/\ln(L(H_1))] = -2[\ln(L(H_0)) - \ln(L(H_1))]$. where $\ln(L(H_0))$ is the value of the loglikelihood function for the stochastic frontier estimated by pooling the data for all countries and $\ln(L(H_1)) = \sum_{i=1}^{4} LLF_i$ is the sum of the values of the loglikelihood functions for the four national production frontiers. The degrees of freedom for the Chi-square distribution involved are 78, the difference between the number of parameters estimated under H_1 and H_0.

the LP and the quadratic programming (QP) estimates for the parameters of the metafrontier function, but there are significant differences between the metafrontier coefficients and their corresponding coefficients of the stochastic frontier for the pooled data.
The direct estimates of the first set of the coefficients of (14) do not bear any economic meaning (Kalirajan and Tse, 1989). The output elasticities with respect to cocoa area, labor, insecticide expenses, fungicide expenses and the age of the cocoa farms are estimated at the mean inputs values for the different national stochastic frontiers. The estimates are presented in table 5[§]. A comparison of the elasticities for particular inputs in table 5 needs to be done with caution because the mean input levels are not the same for the different regions. However, differences in inputs production elasticities between the four countries imply that production structure and technology are different.

Table 5: Output elasticities obtained from the national stochastic frontiers for cocoa farmers in West and Central Africa (figures in parenthesis are standard errors of estimates)[**].

	Cameroon	Ghana	Nigeria	Côte d'Ivoire	Pooled
Farm size	0.276[c]	0.662	0.196	0.728	0.448
	(0.025)	(0.146)	(0.077)	(0.214)	(0.095)
Labour	0.148	0.024	0.214	0.288	0.172
	(0.072)	(0.058)	(0.0595)	(0.0486)	(0.0661)
Pesticide	0.022	-0.045	0.005	-0.072	0.047
	(0.012)	(0.030)	(0.056)	(0.065)	(0.0501)
Tree age	-0,078	0.563	0.153	0.366	0.358
	(0.11)	(0.243)	(0.409)	(0.078)	(0.0736)

[c] Calculated at the sample mean;

As table 6 shows, the greatest share of productivity is due to the labour and farm size in Cameroon, farm size, and tree age in Ghana, farm size, labour and tree age in Nigeria and in Côte d'Ivoire. Whereas in West and Central Africa countries, the greatest share of productivity is generally due to the farm size, labour and the age of the cocoa farm.

3.1 Explaining technical efficiency

Another empirical result of interest is the nature of the efficiency change, as reflected in the estimates of δ from equation (15). The parameter estimates of the inefficiency effects

[§] As mentioned by Anderson and Thursby (1986), elasticity estimators in translog models are non-linear transformations of the parameter estimators, consequently, precise estimates of the parameters of the translog function neither imply nor guarantee precise estimates of elasticities.

[**] Output elasticities have been computed as follow: $\varepsilon_i = f_i \times \frac{x_i}{y}$ where,

$f_i = \frac{\partial f(.)}{\partial x_i} = \frac{y}{x_i} \times \left(\beta_i + \sum_j \beta_{ij} \times \ln(x_j) \right)$ and the Standard errors were calculated in the following way (see for example, Kalirajan and Tse, 1989):

$$Var(\varepsilon_i) = Var(\beta) + \sum (\ln x_j)^2 Var(\beta_{ij}) + 2\sum \ln x_j \operatorname{cov}(\beta_i, \beta_{ij}) + 2\sum \ln x_k \ln x_j \operatorname{cov}(\beta_{ij}, \beta_{ik})$$

stochastic production frontier model employed to identify the factors influencing farmers' levels of technical inefficiency are listed in the lower panel of table 4. The results show that variables gender of the farmer, number of contacts with the extension agents, access to credit, and shade index have a significant impact on technical inefficiency among cocoa farmers.
All the significant coefficients on the efficiency variables for Nigeria, Cameroon, Ghana and Côte d'Ivoire have the right sign except the coefficients of the shade index in Côte d'Ivoire.
The variables gender and credit seem to have greatest effects on improving technical efficiency in Cameroon, Nigeria, and in West and Central African countries as a whole. Their effect on technical efficiency in Côte d'Ivoire and Ghana is also significant.

The level of shade adversely affects technical efficiency in Cameroon and the pooled equation, with similar qualitative effect (although not significant) in Nigeria and Ghana.
The role of credit cannot be overemphasized in the agricultural productivity of the poor rural farmers in West and Central Africa. Farmers who received production credit across the region were more technically efficient. Their ability to purchase and apply inputs on credit when needed, and not just when they had adequate cash savings on hand, allow for more timely operation and optimal input applications. The positive and significant impact of credit on technical efficiency implies that overcoming credit constraints is likely to enhance the productive efficiency of cocoa farmers in West and Central Africa. Credit market failures have been underlined in the literature as an explanation for poverty traps and the non-profit maximizing behavior of smallholders (Dercon 2003, Udry 1996). Our analysis suggests that access to credit can significantly increase the ability of poor households with little or no savings to acquire agricultural inputs. Easing potential capital constraints reduces the opportunity costs of capital-intensive assets relative to family labour and permits the substitution of capital-intensive labour-saving assets such as improved cocoa hybrid-fertilizer technologies. The development of viable rural credit institutions is viewed by many economists as a necessary condition for increasing land and labor productivity, a crucial factor in encouraging development, in particular in many African countries (Delgado, 1995; Zeller et al., 1997a; 1997b).

Across the region the frequency of reported extension contact had a positive impact on technical efficiency in Cameroon and Ghana ($p<0.10$) while in the pooled regression and in the other countries there was no significant effect. The limited impact of agricultural extension programs on cocoa productivity is similar to results reported in past analyses of the productivity of agriculture in developing countries (Feder et al., 2004). Although agricultural extension programs are key policy instruments for government seeking to improve the productivity of agriculture, many observers have documented the poor performance of extension and informal education systems, due to bureaucratic inefficiency, deficient program design, and inherent weaknesses of publicly operated, staff-intensive, information delivery systems. One design deficiency highlighted by researchers and practitioners is the tendency to transmit knowledge in a "top-down" manner. Often, the information conveyed is presented as a technological package comprising recommended practices. For knowledge intensive agricultural technologies, advocacy for participatory, discovery learning approaches to extend science-based knowledge and practices has grown in recent years (Braun et al., 2002). Pilot extension programs based on a farmer field school approach have been developed for cocoa farmers in Côte d'Ivoire, Ghana, Nigeria and Cameroon by the Sustainable Tree Crops Programs with yield gains ranging from 15 to 30% for the average participant.

3.2 Technical Efficiencies and Technology Gap Ratios (TGR)

The values of the TGR, together with the technical efficiencies obtained from the national stochastic frontiers (TE) and the metafrontier (TE*) were computed for all farmers in the different countries. Summary statistics for these measures are presented in table 6. The TGR values can be interpreted as the mean technological gap between the meta-frontier and the national efficiency frontier for a given vector of inputs. These results imply that the mean producer in Cameroon, if he or she were technically efficient, (i.e. on the national efficiency frontier and producing an output of 2.2 tons), could still increase output by 30% or approximately 1 ton if he or she were to adopt the most efficient meta-technology for the region. The TGR gap for the mean producer was much smaller in Ghana, Nigeria and Côte d'Ivoire respectively, ranging from 0.1 to 0.27 t (4 to 12%) indicating that the extant technologies in these countries is near the possibilities' frontier of the meta-technology.

Table 6: Summary statistics for the TGRs and the technical efficiencies obtained from the national stochastic frontiers and the metafrontier production function for West and Central Africa cocoa farmers(**)

	Cameroon	Ghana	Nigeria	Côte d'Ivoire	Prob.
	0.70	0.88	0.96	0.92	
TGR	(0.08)	(0.014)	(0.015)	(0.16)	< 0.001
	0.65	0.44	0.74	0.58	
National TE	(0.16)	(0 .19)	(0.12)	(0.17)	< 0.001
	0.45	0.39	0.71	0.53	
Metafrontier TE*	(0.12)	(0.16)	(0.12)	(0.16)	< 0.001

(**) figures in parenthesis are standard deviations

In the near and medium term, the TE efficiency gap is the most likely indicator of the potential gains to government extension programs and the development of rural credit institutions. In the longer term the TE*-TE gap can be reduced by investments in new technology innovations already existing within the region. Given the relative size of the TGR gaps, such a strategy would probably only make sense in Cameroon. If the TE efficiency gaps were completely closed, the additional output per mean producer would range from 0.6 to 1.2 t per cocoa farmer as mean yields increase from 36 to 127%. According to the model results, the smallest yield gain would occur in Nigeria while Ghana would see the largest overall gain (127%). On the basis of this analysis, the expected returns from increased investment in extension, improved infrastructure and credit institutions should be highest in are expected to be highest in Cote d'Ivoire and Ghana where the average efficiency gaps were 260 and 460 kg per ha, respectively (average yields were 350 and 360 kg per ha). The findings suggest that achieving significant growth in the cocoa sector in Nigeria will require new innovations in the way cocoa is produced. In relative terms, Nigeria should invest more of its public sector resources into the research and development of new innovations.

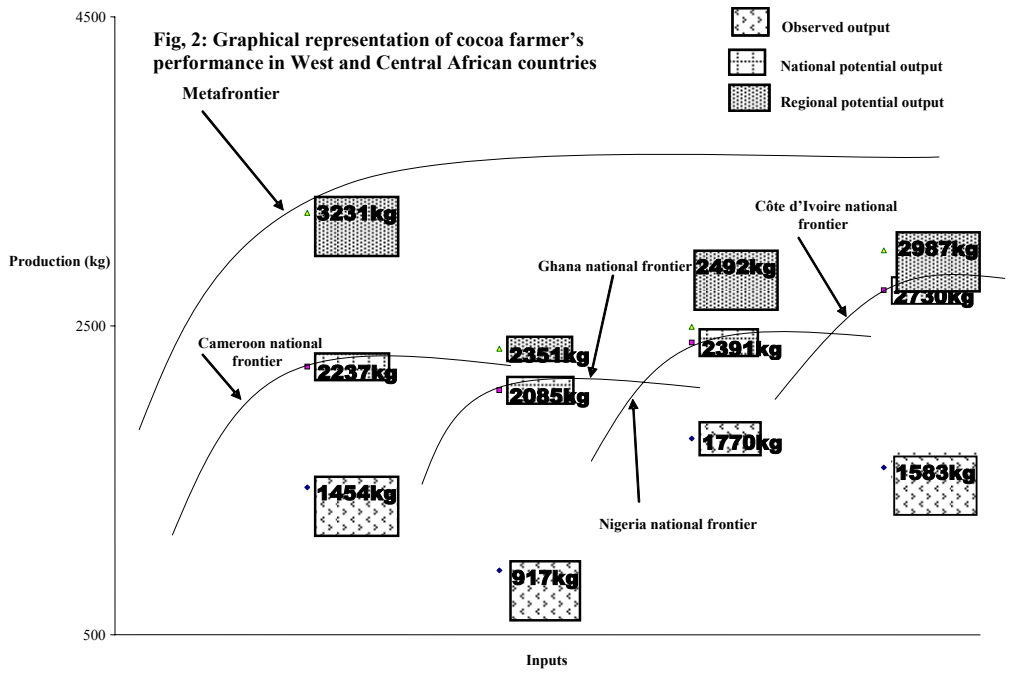

Figure 2 illustrates results presented above. In the same graphic are presented national frontier curves of the four countries and the metafrontier curve. The inefficiency levels are indicated by the distance between the production point and the frontier curve, while the technology gap ratios are represented by the distance between the regional and the metafrontier curve.

Conclusion

With the main objective of evaluating technical efficiency scores for farmers across countries, the technical efficiencies of cocoa farmers in West and Central Africa are estimated using a. In addition, we have estimated regional productivity potential and efficiency levels using a stochastic frontier approach and decomposition result involving both the regional stochastic frontiers and the metafrontier.

The data used in this study support the view that the mean productivity potential and technical efficiency ratios give additional explanation compared to the analysis based only on individual national stochastic production frontiers. The productivity potential ratio plays an important part in explaining the ability of cocoa farmers in one country to compete with other farmers from different countries at the regional level. This ratio provides estimate of the technology gap between the country and the region as the whole.

Elsewhere, the effects of some salient determinants of technical efficiency are assessed in order to identify factors associated with technical efficiency. The Battese-Coelli approach was used to estimate the efficiency effects of a set of farmers/farms characteristics, with the production frontier specified as translog flexible form.

We found that the gender of the farmer, the number of contacts with the extension agents, the access to credit and the amount of canopy shade in the farm all had significant effects on the agricultural performance of cocoa farmers in the West and Central African countries.

In terms of strategies and policies, our findings suggest that rural credit and extension policies warrant attention, particularly in Ghana and Cote d'Ivoire where the TE gaps were greatest.

Results from the baseline surveys reveal that most farmers across the cocoa belt of West Africa have very limited access to production credit with the exception of cocoa farmers in Ondo and Osun State in Nigeria and in the SouthWest Province of Cameroon. In these two regions over 60 percent of farmers had purchased fungicides and insecticides using production loans provided by market intermediaries. The development of these private sector credit institutions is one of the important innovations to have accompanied market liberalization in the 1980s and 1990s in these two regions. The study recommends more in-depth appraisal of these institutions and the legal and regulatory framework which has permitted their evolution with a view towards replicating such institutions in other parts of West Africa. Linking credit to marketing services provided by farmer cooperatives should also be explored as part of this effort.

Investments in extension and farmer training are critical to closing the efficiency gaps that this study has revealed. Training in knowledge intensive subjects such as Integrated Pest Management and Integrated Soil Fertility Management require new innovative approaches and tools. Farmers also need training in the proper establishment and cultural practices associated with the high yielding hybrid cocoa. The rapid spread of mobile phone systems and "Service Message System (SMS)" text messaging offers a potential new route for reaching farmers with new information. The Internet is another tool that should not be ignored for communicating with farmers. Associated with hybrid cultivation training is a need for greater accessibility to hybrid seed of certified quality. Currently most farmers do not use hybrid planting material because of its limited availability. In addition to the sector-specific recommendations above, public investment in physical rural infrastructure is crucial for improving farmers' efficiency and revenue in West Africa. Better roads and improved communications result in more timely field operations and reduced transaction costs in acquiring inputs and rural credit. These types of public investments will generate broad based benefits across sectors.

The challenge now facing government ministries, donor agencies and the private sector is to scale up and deliver the needed innovations to the cocoa growing communities of West and Central Africa.

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References

Aigner, Denis.J., Lovell, C. K., & Schmidt, Peter. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics* 6 (1), 21-37.

Anderson, Richard G. and Thursby, Jerry G., (1986). Confidence intervals for elasticity estimates in translog models. *The Review of Economic and Statistics* 68 (4), 647-656

Anti-Slavery International. (2004). The cocoa industry in West Africa: A story of exploitation.

Battese, George.E., & Coelli, Tim. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20 (2), 325-332.

Battese, George.E., & Coelli, Tim.J. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. *Journal of Productivity Analysis* 3 (1), 153-169.

Battese, George.E., & Rao, D.S.Prasado. (2002). Technology gap, efficiency, and a stochastic Metafrontier function. *International Journal of Business and Economics*, 1 (2), 87-93.

Battese, George.E., Rao, D.S.Prasado., & O'Donnell, Christopher.J. (2004). A Metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis* 21 (1), 91-103.

Boskin, Michael.J., & Lau, Lawrence.J. (1992). Capital, technology and economic growth. In *Technology and the Wealth of Nations*, N. Rosenberg, R. Landau, et D.C. Mowery, eds., Stanford: Stanford University Press.

Braun, Ann. R, Thiele, Graham., and Fernandez, Maria., 2002. Farmer field schools and local agricultural research committee: complementary platforms for integrated decision-making in sustainable agriculture. *ODI, Agricultural Research and Extension*, Network Paper 105.

Coelli, Tim.J. (1996). A guide to FRONTIER Version 4.1: A computer Program for Frontier Production Function Estimation. *CEPA Working Paper 96/07*. School of Economics, University of New England, Armidale.

Coelli, Tim.J. 1995. Recent Development in Frontier Modelling and Efficiency measurement. *Australian Journal of Agricultural Economics* 39 (3), 219-245.

Delgado, Christopher, L., 1995. *Africa's changing agricultural development strategies: Past and present paradigms as a guide to the future*. 2020 Vision Food, Agriculture, and the Environment Discussion Paper 3. Washington, D.C.: International Food Policy Research Institute.

Dercon, Stefan. (2003). "Poverty traps and development: The equity-efficiency debate revisited." Paper prepared for the Conference on Growth, Inequality, and Poverty,

organized by the Agence Francaise de developpement and the European Development Research Network (EUDN), September 2003.

Gunaratne, Lokugam.Hewa.P, & Leung, PingSun. (2001). Asian black tiger shrimp industry: A productivity analysis. *In Economics and Management of Shrimp and Carp Farming in Asia: A collection of Research Papers Based on the ADB/NACA Farm Performance Survey,*

Hayami, Yujiro. (1969). Sources of agricultural productivity gap among selected countries. *American Journal of Agricultural Economics* 51 (3), 564-575.

Hayami, Yujiro., & Ruttan, Vernon.W. (1970). Agricultural productivity differences among countries. *American Economic Review*, 60 (5), 895-911.

Hayami, Yujiro., & Ruttan, Vernon.W. 1971. *Agricultural Development: International perspective.* Baltimore: John Hopkins University Press.

Kalirajan, Kaliappa.P. & Tse, Yiu Kuen., (1989). Technical efficiency measures for the Malaysian food manufacturing industry. *The Developing Economies* 27 (2): 174-184.

Lau, Lawrence.J., & Yotopoulos, Pan.A. (1989). The Metaproduction function approach to technological change in World agriculture. *Journal of Development Economics* 31 (2), 241-269.

Leung, PingSun.S., & Khem.R. Sharma, eds., Bangkok: Network of Aquaculture Centers in Asia-Pacific (NACA).

Meeusen, Wim., & Van Den Broeck, Julien (1977). Efficiency Estimation From Cobb-Douglas Production Function with Composed Error. *International Economic Review* 18 (3), 435-444.

Mundlak, Yair., & Hellinghausen, Rene. (1982). The inter-county agricultural production function: Another view. *American Journal of Agricultural Economics* 64 (4), 664-672.

Ruttan, Vernon.W., Binswanger, Hans.P., Hayami, Yujiro., Wade, William.W., & Weber, Aadolph. (1978). Factor productivity and growth: A historical interpretation. *In Induced Innovation: Technology, Institution, and Developments*, Binswanger, H.P., et V.W. Ruttan, eds., Baltimore: John Hopkins University Press.

Sharma, Khem.R., and Leung, PingSun. (2000). Technical efficiency of carp pond culture in South Asia: An application of stochastic Metaproduction frontier function model. *Aquaculture Economics and Management* 4 (3&4), 169-189.

Tiaji, Salaam-.Blyther., Hanrahan, Charles., & Nicolas, Cook. (2005). Child Labor in West African Cocoa Production: Issues and U.S. Policy. CRS Report for Congress. Congressional Research Service.

Udry, Christopher. (1996). "Efficiency and Market Structure: Testing for Profit Maximization in African Agriculture" mimeograph. Yale University.

Available at http://www.econ.yale.edu/~cru2//pdf/separate.pdf . Accessed October 15, 2007.

Zeller, Manfred., Diagne, Aliou., & Mataya, Charles., 1997a. Market access by smallholder farmers in Malawi: Implications for technology adoption, agricultural productivity, and crop income. *Agricultural Economics* 19(1&2): 219-229.

Zeller, Manfred., Schrieder, Gerturd., von Braun, Joachim., & Heidhues, Franz., 1997b. *Rural finance for food security for the poor: Implications for research and policy*. Food Policy review 4. Washington, D.C.: International Food Policy Research Institute.