SP 2005-04
September 2005

Staff Paper

Department of Applied Economics and Management
Cornell University, Ithaca, New York 14853-7801 USA

Smallholders' Cost Efficiency in Mozambique: Implications for Improved Maize Seed Adoption

Helder Zavale, Edward Mabaya, and Ralph Christy

Smallholders' Cost Efficiency in Mozambique:

Implications for Improved Maize Seed Adoption

Helder Zavale, Edward Mabaya, Ralph Christy [1]

Abstract

The objectives of this paper are to estimate cost efficiency and investigate factors influencing the cost efficiency of maize-growing smallholders in Mozambique. The data used in this study came from a national random sample of 4,908 smallholder farmers conducted by the Ministry of Agriculture and Rural Development in 2002. Stochastic cost frontier and self-selection bias methods are used. The results indicate that twelve out of twenty factors are significantly found to be the determining factors influencing the cost efficiency. To enhance the cost efficiency of producing maize, policy makers should put more emphasis on improving rural infrastructures, providing better education, and providing access to credit.

INTRODUCTION

Agriculture is an important activity in Mozambique. Recognition of the crucial role of agriculture in the sustainable development of the country and the prevalence of high levels of poverty led the government of Mozambique (GOM) to set up policy strategies to promote agricultural and rural development. The goals of the government program for the agricultural sector and rural development include reduction of absolute poverty levels through actions in agriculture, health, education and rural development[2].

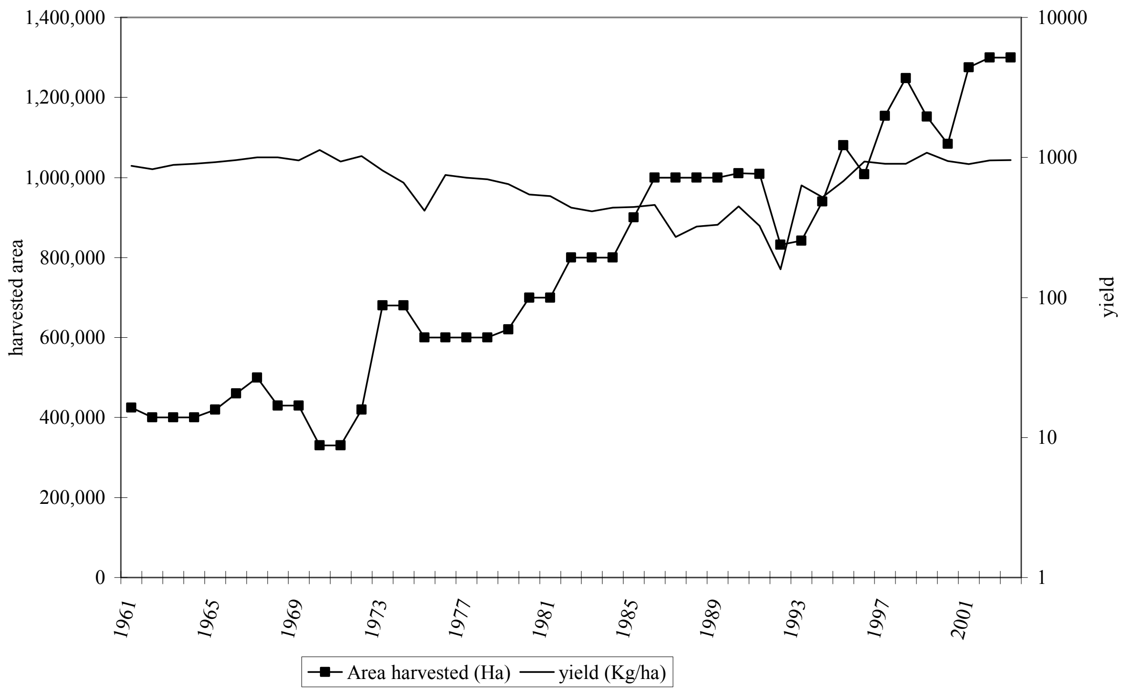
All policy and strategic documents followed by GOM recognize that gains in agricultural productivity should be sped up to guarantee the country's economic development in a sustainable way in general and to alleviate poverty in particular. Technological change is one of the major sources of economic growth. Therefore, given the role played by agriculture in the economic development process, there is a need to get agriculture moving. In

[1] Graduate Student, Research Associate, and Professor respectively in the Department of Applied Economics and Management at Cornell University, Ithaca, New York 14853. The corresponding author is Helder Zavale who can be reached by email at hz49@cornell.edu.

[2] The government policy strategies are based on (1) development of human capital, (2) rehabilitation of infrastructures, (3) creating a favorable environment for development of private sector, and (4) increasing agricultural productivity. The main government policy strategies are expressed in the Agrarian Policy and Strategy of Implementation (PAEI) approved in 1995.

Mozambique, due to the fact that the food and agriculture sector dominates the economy in terms of contribution to GDP, employment and incomes, agricultural growth will prove essential for improving the welfare of the vast majority of Mozambique's poor. In the process of development, agriculture can provide increased food supplies and higher rural incomes to enlarge markets for urban outputs, as well as to provide resources to expand urban output.

Despite the enormous potential of Mozambique's natural resource available for a healthy growth rate of the agricultural sector, the performance of the agricultural sector is relatively low. Though the poverty rate has declined from 69 percent in 1996 to 54 percent in 2002, many rural households depending on agriculture are still poor. Since the 1960s, the maize production in Mozambique has increased rapidly. As shown in figure 1, expansion in cultivated area is the main source of maize production growth. Achievements of production increase by bringing more land into cultivation will no longer work because fragile uncultivated land has increased. Unlike cultivated area, maize yield has decreased slightly since 1960, and average maize yield in Mozambique is lower that yield achieved in the Southern African in particular and in Sub Saharan Africa in general.



Source: FAOSTAT data, 2004

Figure 1 Production and yield of maize from 1961 to 2003 in Mozambique

Typical maize yields (generally intercropped) ranged between 400 and 800 Kg/hectare in Monapo, between 250 and 600 Kg/hectare in Ribaue, and between 200 and 400 Kg/hectare in Angoche, while CIMMYT quotes average maize yields of between 830 and 3,000 Kg/hectare among low input smallholders in the Southern Africa. On the other hand, the Mozambican population expanded from 12.1 million in 1980 to 18.1 million in 2001, and it is estimated to be 22.7 million in 2015. In face of current demographic trends, Mozambique has to improve its agricultural productivity urgently to alleviate its poverty incidence (Howard et al., 2001; Haggblade et al., 2004). Productivity can be increased through improved varieties and better management; however, productivity benefits will not be realized unless substantial improvements are made in seed production and distribution. Increases in productivity due to technological innovation could not be achieved if new technologies are not combined with appropriate and complementary enhancements in agricultural institutions and human capital. Also, it is largely recognized that agricultural output growth is not only influenced by technology enhancements but also by the efficiency with which available technologies are utilized.

Maize is one of the staple food and one of the most important crops produced in Mozambique. It occupies thirty-five percent of the total cultivated area and is grown by seventy-nine percent of the total number of holdings. Given the relative importance of maize in the subsistence agriculture in Mozambique, this paper has as its central objective to estimate the determinants of the cost efficiency of the smallholders using improved and traditional maize seed. Two techniques are employed in investigating the cost efficiency of smallholders: a stochastic cost frontier and a self-selection bias method.

This paper is organized in five sections. We first describe the data employed. After presenting the stochastic frontier cost function used to estimate cost inefficiency and cost-inefficiency function corrected for self-selection bias, we report the estimation results from this model. The final section focuses on the policy implications of the findings of this research.

DATA

The data used in this study was obtained from a national agricultural survey – widely known as *TIA (Trabalho de Inquerito Agricola)* – conducted by the Ministry of Agriculture and Rural Development (MADER) in the agricultural year 2001-2002. The survey collects a wide range of detailed information on various aspects of household economy, including income, expenditures, production, capital stock, land use, and demographic characteristics.

In Mozambique, there are three categories of farm holdings[3]: small, medium, and large. Data obtained from the Agricultural and Livestock Census presented in Table 1 shows that Mozambique has approximately 10,000 medium, 400 large holdings, and more than 3 million small holdings. The average cultivated area of these holdings is 1.26 hectares and about 84 percent of which is devoted to basic food crops (maize, rice, millet, cassava, sorghum, and pulses). The distribution of cultivated area is highly skewed. Maize, the main food crop, is grown predominantly by the smallholders. Horticultural and commercial cash crops make up approximately 10 percent of the small holdings' cultivated area.

Table 1 Farm holdings by size, 2000/2001

	Holding size			
	small	medium	large	Total
Number of farm holdings	3,054,106	10,180	429	3,064,715
Total cultivated area (ha)	3,736,577	67,726	62,064	3,866,368
Average cultivated area (ha)	1.22	6.65	144.67	1.26
Most common range of cultivated area (ha)	0.5 – 1.0	5.0 – 10.0	20.0 – 50.0	0.5 – 1.0
Percentage of cultivated area under basic food crops	84.4	74.2	14.8	84.7
Percentage of cultivated area under horticultural crops	5.2	8.7	2.5	5.2
Percentage of cultivated area under "cash crops"	4.3	4.7	82.8	5.6
Percentage of farm holding				
Use fertilizers	2.7	11.0	32.9	2.7
Use pesticides	4.5	10.3	36.1	4.5
Use animal traction	10.8	71.8	32.2	11.0
Use irrigation	3.9	16.9	35.4	3.7

Source: INE, Agricultural and Livestock Census, 1999/2000

Mozambique's agricultural sector is characterized by a large number of small holdings with primarily rain-fed subsistence production based on manual cultivation techniques and little use of purchased inputs. It can be seen from Table 1 that only 2.7, 3.7, and 4.5 percent of the total holdings use fertilizers, irrigation, and pesticides, respectively. Acquisition and use of purchased inputs can be facilitated by access to credit. The results of the Agricultural and Livestock Census 1999 – 2000 show that only 4 percent of the small and large holdings had access to credit, mostly from informal sources.

[3] Holding is defined as an economic entity of agricultural and livestock production under single management. Small holdings are those farms with less than 10 hectares of cultivated area, less than 10 heads of cattle, less than 50 goats, sheep, or pigs, and less than 5, 000 poultry. Medium holdings are those farms with between 10 and 50 hectares of cultivated area, between 10 and 100 heads of cattle, between 50 and 500 goats, sheep, or pigs, and between 5, 000 and 20, 000 poultry. Large holdings are any farms that have one or more component higher than the medium holding limit.

Table 2 Descriptive statistics of the explanatory variables of the adoption model

Variable	Definition	Mean	Standard Deviation
COST	Variable cost (US $)	590.03	678.34
PRLABOR	Wage rate of labor (US $ per hectare)	0.71	0.38
PRISEED	Price of maize seed (US $/Kg)	0.08	0.04
MAIZE	Maize production (Kg)	609.07	1,627.3
AREA	Cultivated area under maize (hectares)	0.94	1.51
HHSIZE	Household size	5.60	3.33
SEX	Gender of the household head (1 = male; otherwise = 0)	0.761	
AGE	Age of the household head (years)	43.88	14.89
EDUC	Highest formal schooling completed by household head (years)	2.80	4.02
JOB	Household head had off-farm employment = 1; otherwise = 0)	0.326	
DISTANCE	Distance to seat county (Km)	27.00	16.61
COTTON	Farm household grew cotton = 1; otherwise = 0	0.067	
TOBACCO	Farm household grew tobacco = 1; otherwise = 0	0.047	
FRAGMEN	Number of plots farming by household	2.55	1.39
EXTENS	Household had contact with extension service = 1; otherwise = 0	0.155	
FERTIL	Household used fertilizer = 1; otherwise = 0	0.053	
PESTIC	Household used pesticide = 1; otherwise = 0	0.071	
IRRIG	Household used irrigation = 1; otherwise = 0	0.155	
NORTH	Household located in northern macro agro-ecologic zone = 1; otherwise = 0	0.442	
CENTRAL	Household located in central macro agro-ecologic zone = 1; otherwise = 0	0.305	
ELECTRIC	Household had access to electricity = 1; otherwise = 0	0.080	
CREDIT	Household had access to credit = 1; otherwise = 0	0.117	
MARKET	Household had access to market = 1; otherwise = 0	0.269	
ROAD	Household had access to paved road = 1; otherwise = 0	0.192	

Table 2 summarizes the sample statistics of the explanatory variables of the stochastic cost frontier model. This table illustrates that the household size of a typical maize grower is on average 5.6 members. This household size is bigger than the Mozambique's average household size estimated to be 4.8 members. Regarding gender, only 24 percent of the sampled households are female-headed. The average age of the household head, 43.9, is slightly higher than the life expectancy, 42.0, of the population of Mozambique. With respect to formal education, the average household head's years of schooling is 2.8. The low level of literacy has implications for technological adoption and other interventions aimed at enhancing agricultural productivity. Table 2 shows that only about 16 of the sampled households received extension service from government or NGOs.

In Mozambique, agricultural inputs are not available to farmers or availability of these inputs is spatially limited due to lack of infrastructures, limited access to credit, low purchasing power, inappropriate agricultural input policies, and sometimes environmental constraints. The findings presented in Table 2 indicate that only 5, 7, and 16 percent of the surveyed households used fertilizer, pesticide, and irrigation respectively. One third of the households have off-farm employment and only about 7 and 5 percent grew cotton and tobacco respectively.

METHODS

Considerable literature has been devoted to the estimation of efficiency since the pioneering work of Farrell (1957). Drawing inspiration from Koopmans (1951) and Debreu (1951), Farrell showed how to define cost efficiency and how to decompose cost efficiency into its technical and allocative components. The large varieties of frontier models that have been renovated based on Farrell's ideas can be divided into two basic types, namely parametric and non-parametric. Parametric frontiers rely upon a specific functional form while non-parametric frontiers do not. Another important distinction is between deterministic and stochastic frontiers. The deterministic approach assumes that any deviation from the frontier is due to inefficiency, while the stochastic approach allows for "statistical noise". The stochastic approach accounts for factor beyond and within the control of firms such that only the latter causes inefficiency. The two basic methods of measuring efficiency: the classical approach and the frontier approach.

The classical approach is based on the ratio of output to a particular input – distance functions. The efficiency measures obtained from distance functions have the disadvantage of not being unit invariant. Dissatisfaction with the shortcomings of classical approach led economists to develop advanced econometric (stochastic production frontier) and linear programming (Data Envelopment Analysis – DEA) methods aimed at analyzing productivity and efficiency. While the former is a parametric technique, the latter utilizes a non-parametric approach. The efficiency measures obtained from these methods, stochastic production frontier and DEA, are unit invariant.

The DEA defines efficiency frontier based solely on the observed firm-level data without assuming any specific functional form. Firm-level efficiency is calculated by comparing each firm to the "best practice" defined by the frontier. The main limitation of the DEA is that any deviation from the frontier is interpreted as an indication of inefficiency. Erroneously, random disturbances that affect farm operation such as weather may be labeled as inefficiency. The deterministic DEA may lead to systematic overestimation of inefficiency (Nadolnyak et al., 2004).

The stochastic frontier approach, based on specific functional form and introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977), is motivated by the idea that deviations from the frontier may not be entirely attributed to inefficiency because random shocks outside the control of farmers can also affect output. This approach postulates that the error term is made up of two independent components. One error term is the usual two-sided statistical noise found in any relationship and the other is a one-sided disturbance representing inefficiency (Jondrow et al., 1982). Thus, it can be argued that stochastic frontier approach is more reliable than deterministic frontier approach due to the fact that the former accounts for statistical noise. Nonetheless, the stochastic frontier approach compounds the effects of misspecification of functional form with inefficiency, while DEA is nonparametric and less prone to this type of misspecification error.

From Farrell's framework, the frontier measure of efficiency implies that efficient firms are those operating on the production frontier. The amount by which a firm lies below its production frontier is regarded as the measure of inefficiency. A number of studies have used this approach (Battese and Coelli, 1995; Sharif and Dar, 1996; Wadud and White, 2000; Tzouvelekas et al., 2001). The unknown parameters of the stochastic frontier production function can be estimated using either the maximum-likelihood (ML) method or the corrected ordinary least-squares (COLS) method, suggested by Richmond (1974). The ML estimator is asymptotically more efficient than the COLS estimator, however (Coelli et al., 1998).

This study uses a cost-efficiency approach and combines the concepts of technical and allocative efficiency in the cost relationship. Assuming that cross-section data on the prices of inputs (w_i) employed, the quantities of outputs (y_i) produced, and the total expenditures are available for each of i farmers, the cost frontier can be expressed as:

$$C_i \geq VC(y_i, w_i; \beta)$$

Where C_i is the actual expenditure incurred by farmer i, $VC(y_i, w_i; \beta)$ is the cost frontier, and β is a vector of technology parameters to be estimated. Based on the specification of stochastic cost frontier, the difference between the actual and the frontier cost is capture in the disturbance term ε_i, which consists of two components, the two-sided random disturbance ν_i reflecting the effect of random factors such as weather and a one-sided nonnegative disturbance μ_i representing the cost inefficiency component. These two components of the disturbance term $\varepsilon_i = \nu_i + \mu_i$ are assumed to be independently distributed and $\nu_i \sim iidN(0, \sigma_\nu^2)$ and $\mu_i \sim iidN(0, \sigma_\mu^2)$. If the cost frontier is specified as being stochastic, the appropriate measure of cost efficiency becomes

$$CE_i = \frac{VC(y_i, w_i; \beta).\exp(v_i)}{C_i} = E(\exp\{-\mu_i\} \mid \varepsilon_i)$$

The measurement of the farm level inefficiency $e^{-\mu_i}$ requires first the estimation of the nonnegative disturbance μ_i, that is, decomposing ε_i into its two individual components (v_i and μ_i). For years, the failure of separating the error term of stochastic frontier models into its two components for each observation was criticized as a significant disadvantage of these models. However, the problem of decomposition was resolved by Jondrow et al. (1982) who suggested a decomposition method. In the case of normal distribution of v_i and half-normal distribution of μ_i, the conditional mean of μ given ε is shown to be:

$$E[\mu \mid \varepsilon] = \frac{\sigma_\mu \sigma_v}{\sigma}\left[\frac{f(\varepsilon\lambda/\sigma)}{1 - F(\varepsilon\lambda/\sigma)} - \frac{\varepsilon\lambda}{\sigma}\right]$$

Where $\lambda = \frac{\sigma_\mu}{\sigma_v}$, $\sigma^2 = \sigma_\mu^2 + \sigma_v^2$, and f and F are the standard normal density function and the standard cumulative distribution function, respectively.

The most commonly used functional forms for cost functions are Cobb-Douglas and Translog. To select the best functional form to describe the data, both Cobb-Douglas and Translog stochastic frontier cost functions were estimated. It is worth mentioning that the Cobb-Douglas function is the restricted form of the Translog function, in which the second-order terms in the Translog function are restricted to zero. The likelihood ratio test (LR) was used to select the best functional form and the estimate of the LR is strongly statistically different from zero at 1% level, meaning that Translog function provides better representation of the data. Consider the translog stochastic cost function based on the composed error model

$$\ln C = \beta_0 + \beta_Q \ln Q + \sum_{i=1}^{n} \beta_i \ln P_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln P_i \ln P_j + \sum_{i=1}^{n} \gamma_{Qi} \ln Q \ln P_i + v + \mu$$

Where, C represents household i's observed total variable cost, Q denotes the household's maize cropped area, P is the price of variable input used, $\varepsilon = v + \mu$ is the disturbance term consisting of two independent elements. The variable inputs used in the estimation of the cost function include price of maize seed ($PRISEED_i$) and wage rate of labor ($PRLABOR_i$). Since there is no record on family labor costs, the market wage for hired labor is approximated. Moreover, due to the fact that there is no record of the maize seed price, this price is assumed to be the same as for grain because Tripp (2001) contended that several studies in Africa have shown this to be the case if the grain is sold. In addition, due to the fact that the cost function is homogeneous of degree 1, the following restrictions were imposed prior to the estimation of the cost function,

$$\sum_i \beta_i = 1 \qquad \sum_i \gamma_{ij} = \sum_j \gamma_{ij} = \sum_i \gamma_{Qi} = 0$$

For a half normal distribution, the density functions for $\mu_i \geq 0$ and ν_i are respectively $f(\mu) = \frac{2}{\sqrt{2\pi}\sigma_\mu} \exp\left\{-\frac{\mu^2}{2\sigma_\mu^2}\right\}$ and $f(\nu) = \frac{2}{\sqrt{2\pi}\sigma_\nu} \exp\left\{-\frac{\nu^2}{2\sigma_\nu^2}\right\}$. The marginal density function of $\varepsilon = \nu + \mu$ is obtained by integrating the joint density function for μ and ε, which yields

$$f(\varepsilon) = \int_0^\infty f(\mu, \varepsilon) d\mu = \int_0^\infty \frac{2}{2\pi\sigma_\mu\sigma_\nu} \exp\left\{-\frac{\mu^2}{2\sigma_\mu^2} - \frac{(\varepsilon-\mu)^2}{2\sigma_\nu^2}\right\} d\mu$$

$$= \frac{2}{\sqrt{2\pi}\sigma}\left[1 - \Phi\left(\frac{-\varepsilon\lambda}{\sigma}\right)\right] \exp\left\{-\frac{\varepsilon^2}{2\sigma^2}\right\} = \frac{2}{\sigma}\phi\left(\frac{\varepsilon}{\sigma}\right)\Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)$$

Where $\lambda = \frac{\sigma_\mu}{\sigma_\nu}$, $\sigma^2 = \sigma_\mu^2 + \sigma_\nu^2$, and $\phi(.)$ and $\Phi(.)$ are the standard normal density function and the standard cumulative distribution function, respectively. The marginal density function is asymmetrically distributed with mean and variance of $E(\varepsilon) = E(\mu) = \sigma_\mu \sqrt{\frac{2}{\pi}}$ and $V(\varepsilon) = \frac{\pi - 2}{\pi}\sigma_\mu^2 + \sigma_\nu^2$, respectively. Using the marginal density function, the log likelihood function for a sample of n farmers is

$$\ln L = \text{constant} - n \ln \sigma + \sum_i \ln \Phi\left(\frac{\varepsilon_i \lambda}{\sigma}\right) - \frac{1}{2\sigma^2}\sum_i \varepsilon_i^2$$

The log likelihood function can be maximized with respect to the parameters to obtain maximum likelihood estimates of all parameters. The next step is to obtain estimates of the cost efficiency of each farmer. These estimates of the cost efficiency are obtained from the conditional distribution of μ_i given ε_i. Jondrow et al. (1982) showed that, in the the case of normal distribution of ν_i and half-normal distribution of μ_i, the conditional mean of μ_i given ε_i is

$$E(\mu_i \mid \varepsilon_i) = \frac{\sigma_\mu \sigma_\nu}{\sigma^2}\left[\frac{\phi(\varepsilon_i \lambda/\sigma)}{1-\Phi(-\varepsilon_i \lambda/\sigma)} + \frac{\varepsilon_i \lambda}{\sigma}\right]$$

Once point estimates of μ_i are obtained, a measure of the cost inefficiency of each farmer can be provided by $CE_i = E(\exp\{-\mu_i\} \mid \varepsilon_i) = \left[\frac{1-\Phi(\sigma_* - \mu_{*i}/\sigma_*)}{1-\Phi(-\mu_{*i}/\sigma_*)}\right]\exp\left\{-\mu_{*i} + \frac{1}{2}\sigma_*^2\right\}$.

A farmer may not reach the cost frontier because of various reasons. The cost inefficiency might arise due to socioeconomic, demographic, and environmental factors. In order to examine the effect of the potential determinants (z_{ji}) of cost inefficiency, the following equation was estimated

$$CE_i = \delta_0 + \sum_{j=1}^{n} \delta_j z_{ji} + \alpha_i Y_i + \tau_i$$

Where Y is the adoption variable (Y = 1 if improved maize seed adopted and 0 otherwise). Farmers' decision to adopt improved maize seed is dependent on the characteristics of farms and farmers; therefore, the adoption decision of a farmer is based on each farmer's self-selection instead of random assignment. Thus, any estimation technique failing to acknowledge and model this nonrandom selection may bias the estimates. The statistical problem is that the error term τ might be correlated with the adoption variables. Hence it is necessary to employ an estimation procedure that either eliminates this correlation or measures and includes the correlation in the regression. The technique used to take into account this endogeneity is sample selection bias model as a specification error motivated by Heckman (1978; 1979). This model has been extensively used by various authors. Using Maximum Likelihood (ML), a probit adoption function is estimated and used to correct the error term for potential self-selection bias. Vella and Verbeek (1999) suggest that instrumental variable approach can be alternatively used, but the former approach is at least as efficient as the latter. The farmer's decision on seed adoption depends on the criterion function,

$$Y_i^* = \gamma' Z_i + \mu_i$$

Where Y_i^* is an underlying index reflecting the difference between the utility of adopting and the utility of not adopting improved seed, γ is a vector of parameters to be estimated, Z_i is a vector of exogenous variables which explain adoption, and μ_i is the standard normally distributed error term. Given the farmer's assessment, when Y_i^* crosses the threshold value, 0, we observe the farmer using improved seed. In practice, Y_i^* is unobservable. Its observable counterpart is Y_i, which is defined by

$Y_i = 1 \quad \text{if } Y_i^* > 0$ (Household i used improved seed), and

$Y_i = 0 \quad \text{if otherwise}$

In the case of normal distribution function (Probit model), the model to estimate the probability of observing a farmer using improved seed can be stated as

$$P(Y_i = 1 | x) = \Phi(x'\beta) = \int_{-\infty}^{x'\beta} \frac{1}{\sqrt{2\pi}} \exp(-z^2/2)dz$$

Where, P is the probability that the ith household used improved seed, and 0 otherwise; x is the K by 1 vector of the explanatory variables; z is the standard normal variable, i.e., $Z \sim N(0, \sigma^2)$; and β is the K by 1 vector of the coefficients to be estimated.

To correct for self-selection bias, the cost-inefficiency function was estimated by the following regression

$$CE_i = \delta_0 + \sum_{j=1}^{n} \delta_j z_{ji} + \alpha_i Y_i + \rho\sigma_\tau\sigma_\mu\lambda_i + \tau_i$$

Where the terms ρ, σ_τ, and σ_μ represent the covariance of the adoption equation and the cost equation. It is assumed that τ and μ have a bivariate normal distribution with zero means and correlation ρ. These covariances can be broken down into the standard deviations, σ_τ and σ_μ, and the correlation ρ. However, given the structure of the model and the nature of the derived data, σ_μ can not be estimated so it is normalized to 1.0. The term λ_i is the Inverse Mill's Ratio, which is defined as,

$$\lambda = \frac{\phi(\gamma' Z_i)}{\Phi(\gamma' Z_i)}$$

Where ϕ and Φ are the probability density and cumulative distribution function of the standard distribution, respectively.

The cost-inefficiency function and the Probit model can be estimated by the Heckman's two-step estimator. Although this estimator is consistent, Nawata and Ii (2004) pointed out that it is not asymptotically efficient. Thus, the Maximum Likelihood (ML) estimator is employed to jointly estimate the cost-inefficiency function and Probit model. The above two-stage method, consisting of ML estimation of a stochastic cost frontier followed by the regression of the predicted cost inefficiency on the determinants of cost inefficiency, has been criticized. Although this estimation procedure has been recognized as a useful one, Coelli (1996) shows that the two-stage estimation procedure utilized for this exercise has been recognized as one which is inconsistent in its assumption regarding the independence and identity of the distribution of the inefficiency effects in the two estimation stages. Based on the work of Battese and Coelli (1995), Kumbhakar, Ghosh and McGuckin (1991), and Reifschneider and Stevenson (1991) noted this inconsistency and specified stochastic frontier models in which the inefficiency effects were defined to be explicit function of some household characteristics, and all parameters were estimated in a single-stage maximum likelihood procedure.

However, Liu and Zhuang (2000) argue that both approaches have a common drawback. Unless the efficiency variables are independent of the input variables, the production function estimates will be biased and inconsistent. In this study, the two-stage approach was used. In the first stage, using ML, the stochastic cost frontier was estimated. In the second stage, the cost-inefficiency function and the Probit model are jointly estimated using ML. Given that the cost inefficiency is censored between 0 and 1, OLS procedure may result in biased estimates usually toward zero. An appropriate approach, developed by Tobin 1958, for modeling censored dependent variable using ML is Tobit (Greene, 2003).

RESULTS

LIMDEP 8.0 software was used to derive estimates for the maximum likelihood function of the Translog stochastic frontier cost function and cost-inefficiency function. Estimates of both λ and σ are statistically different from zero, suggesting that one-side error component, related to farm specific inefficiency, dominates the random error term in the determination of $\varepsilon = \mu + \nu$ (Table 3). Thus, the deviation of observed variable cost from the frontier cost is due to both technical and allocative inefficiency. This deviation can be avoided without any lost in output.

Table 3 Maximum likelihood estimates of the frontier translog cost function

Variable	Coefficient	Standard Error	
Constant	6.605693	0.0613	***
Land	0.311460	0.0270	***
Land x land	0.046331	0.0038	***
Seed price	0.235211	0.0564	***
Labor price	0.764789	0.0564	***
Seed price x seed price	0.037591	0.0134	***
Seed price x labor price	-0.091540	0.0225	***
Seed price x land	0.015171	0.0113	
Labor price x labor price	0.053948	0.0114	***
Labor price x land	-0.015171	0.0113	
Variance			
λ	1.322580	0.0627	***
σ	0.591693	0.0137	***
Log likelihood	-2,267.95		
observations	3,603		

*** Statistically significant at the 1% level.

Due to the fact that technical and allocative efficiency have different causes, the decomposition of cost efficiency might be necessary to reveal which of the two components represents the main source of cost inefficiency. However, this requires availability of either input quantity or input cost share data. As expected, the estimates suggest that the relationship between the total variable cost and input prices (seed and labor) is positively significant. Also, the total variable cost of producing maize statistically increase in all the explanatory variable included in the model with the exception of the interactions between seed price and labor price, and labor price and cropped land. The interaction between labor price and cropped land is not statistically significant.

Fifteen of the twenty five parameter estimates of the Probit model were statistically significant. Household size; age; education; off-farm employment; location (southern, central, and northern agro-ecological zone); access to extension service, credit, seed stores, and electricity; use of pesticide, fertilizer, and irrigation; and farming of traditional cash crops (cotton and tobacco) are the determining factors influencing the probability of adopting improved maize seed in Mozambique (Table 4). For a detailed discussion of the factors influencing the likelihood of adopting improved maize seed, see Zavale (2005). This study focuses on the determinants of cost inefficiency of producing maize.

After correcting for self selection bias, the results presented in Table 4 show that twelve out of twenty explanatory variables are statistically related to cost inefficiency. Household size, gender, age of household head, years of schooling, distance, maize cropped area, fragmentation of land, use of pesticide, location of household in terms of macro agro ecological zone, access to electricity, and access to credit have a significant impact on cost inefficiency of the farm households surveyed.

The findings suggest that the larger the household size, the more cost efficient the household is. On average, a unit increase in household size drops off cost inefficiency by nearly 2 percent. A possible reason for this result might be that a larger household size guarantees availability of family labor for farm operations to be accomplished in time. Also, a large household size ensures availability of a broad variety of family workforce (children, adults, and elderly), which suggest that household heads can rationally assign farm operations to the right person. This finding is consistent with a previous study by Parikh, Ali, and Shah (1995).

Table 4 Estimates of the determinants of cost inefficiency corrected for self-selectivity

Probit function				Corrected cost-inefficiency function			
Variable	Coefficient			Variable	Coefficient		
Constant	0.231377	(0.2244)		Constant	0.856696	(0.0072)	***
Distance to seat county	-0.001402	(0.0015)		Distance to seat county	-0.000324	(0.0001)	***
Household size	0.019516	(0.0073)	***	Household size	-0.022046	(0.0004)	***
Gender	0.000495	(0.0573)		Gender	-0.030531	(0.0033)	***
Age of the household head	-0.014771	(0.0087)	*	Age of the household head	-0.000792	(0.0001)	***
Age of the household head squared	0.000057	(0.0001)		Years of schooling	-0.000604	(0.0003)	*
Years of schooling	0.011257	(0.0058)	**	Off-farm employment	0.003954	(0.0030)	
Off-farm employment	0.162429	(0.0493)	***	North	0.033153	(0.0036)	***
North	-0.678464	(0.0779)	***	Central	0.044983	(0.0040)	***
Central	-0.454732	(0.0698)	***	Extension service	0.003962	(0.0039)	
Extension service	-0.128939	(0.0677)	**	Use of fertilizer	-0.005208	(0.0074)	
Association membership	-0.030954	(0.1008)		Use of pesticide	-0.015640	(0.0066)	***
Access to price information	-0.025184	(0.0530)		Use of irrigation	-0.004281	(0.0039)	
Use of fertilizer	0.243128	(0.1168)	**	Electricity access	-0.011977	(0.0051)	***
Use of pesticide	0.188518	(0.1145)	*	Credit access	-0.012662	(0.0040)	***
Use of irrigation	0.139375	(0.0654)	**	Market access	-0.004471	(0.0035)	
Use of animal traction	0.014907	(0.0632)		Paved road access	-0.005123	(0.0036)	
Electricity access	0.343897	(0.0930)	***	Cotton farming	0.008785	(0.0070)	
Credit access	-0.266283	(0.0782)	***	Tobacco farming	0.004564	(0.0077)	
Market access	-0.035982	(0.0589)		Fragmentation of land	-0.003536	(0.0010)	***
Access to seed shop	0.102922	(0.0584)	*	Maize cropped area	0.018506	(0.0004)	***
Paved road access	-0.001531	(0.0605)		Sigma	0.080725	(0.0009)	***
Cotton farming	-0.211723	(0.1244)	*	Rho	-0.018131	(0.0226)	
Tobacco farming	-0.288330	(0.1234)	***				
Drought last 2 years	0.140419	(0.0931)					
Flood last 2 years	-0.092701	(0.0773)					
Log likelihood	1,869.79						
observations	3,603						

Standard error in parentheses

* Statistically significant at the 10% level; ** Statistically significant at the 5% level; and *** Statistically significant at the 1% level

With respect to gender, the negative and highly significant coefficient on gender variable does not support the hypothesis that female-headed households are less cost inefficient. The findings illustrate that male-headed households are 3.1 percent less cost inefficient than their counterpart. Another commonly hypothesized determinant of cost inefficiency is age of the household head. This variable was found to have a negative and significant impact on cost inefficiency, meaning that the older the household head is, the more cost efficient he or she is. This supports the idea of learning-by-doing because age can be interpreted as a proxy for experience.

As hypothesized by Schultz, education increases the ability to perceive, interpret, and respond to new events, enhancing farmers' managerial skills including efficient use of agricultural inputs. The negative and highly significant impact of education on cost inefficiency indicates that farmers with higher years of schooling are more cost efficient, supporting Schultz hypothesis. This result is similar to the findings of Kebebe (2001) and Binam et al (2004). Binam et al found substantial benefits of schooling for farmer efficiency in maize mono cropping system in Cameroon.

Further, the variable distance to county seat was found to be negatively associated with cost inefficiency. Surprisingly, the further the county seat is away from farm location, the less cost inefficient the maize-growing farm household is. This result is inconsistent with the findings of Binam et al (2004) that found technical inefficiency increases with the distance of the plot from the main access road, underscoring the importance of better infrastructure in agricultural development. In addition, in this study, cost inefficiency was found to decrease with access to paved road in the villages although this association is not statistically significant.

The link between efficiency and farm size measured as cropped area has been widely investigated using stochastic frontier methodology. The findings of this study do not support the notion of "efficiency economy of scale" that states that larger farms have efficiency advantage over smaller ones. The relationship between cost inefficiency and maize cropped area is positive and statistically significant, suggesting that smaller maize-growing farms are more cost efficient than their counterparts. The results concerning land fragmentation (number of plots that the maize-growing farm households own) suggest that land fragmentation has a negative and statistically significant effect on cost inefficiency. This does not support the prior expectation that a fragmented farm will cost more in terms of time wasted in moving from one plot to another. Although it is surprising, similar result has been reported by Kebede (2001). However, this finding is in contrast to findings of Wadud's study

(2003) that illustrate that farmers with less land fragmentation operate at higher level of technical efficiency.

As expected, the results of this study also suggest that maize-growing farm households using pesticides are more cost efficient than non-users. Although not statistically significant, use of fertilizer and irrigation are positively correlated to cost efficiency. In general, benefits of improved maize seed can not be realized unless other agricultural inputs such as fertilizer, pesticide, and water are available. The input sensitivity of high-yielding varieties may result in lower efficiency when either less than optimal level of other agricultural inputs (fertilizer, pesticides, and water) is applied or other agricultural inputs are not applied at all.

With regard to location of the maize-growing farm household, households located in the northern and central macro agro-ecological zones were found to be more cost inefficient than the ones located in the southern, suggesting that location, as found elsewhere, has an impact on farm efficiency. The location variable can be understood as an interaction amongst agro-ecological conditions, infrastructure, and agricultural policies. The differences in cost efficiency due to location can be attributed to distortions introduced by maize policies. Those policies are subsidizing the maize production in the southern and taxing it in the northern and central macro agro-ecological zones. In addition, the southern macro agro-ecological zone is generally characterized by better infrastructure conditions compared to the northern and central. It is obvious that badly developed infrastructure has negative impact on both technical and allocative efficiency. Access to electricity was found to enhance cost efficiency of the maize-growing farm households. The positive effect of credit availability on cost efficiency is not surprising. Similar results have been reported by Ali, Parikh, and Shah (1996); Kebede (2001); and Binam et al (2004). Credit availability shifts the cash constraints outward, enabling the farmers to timely purchase agricultural inputs that they can not provide from their own resources. The findings suggest that availability of credit can be used as an instrument for enhancing cost efficiency in the production of maize through the alleviation of cash constraints.

As shown in Table 4, the cost inefficiency of adopters and non-adopters of improved maize seed is not statistically different. The sign of the estimated coefficient of the variable associated with adoption of improved maize seed is negative. Although not statistically different, this suggests that adopters are more cost efficient than non-adopters.

Table 5 Summary statistics of the cost inefficiency indexes

	Cost inefficiency index
Mean	0.6977
Standard deviation	0.1140
Minimum	0.1268
Maximum	0.8962
Observations	3,603

Table 5 summarizes the cost inefficiency index. The average cost inefficiency was 0.70 percent, suggesting that on average 70 percent of the cost observed in the production of maize is due to inefficiency that can be avoided without any loss in total output from a given mix of production inputs. Hence, in the short run, there is a room for enhancing cost efficiency by 70 percent by adopting technology and management practices used by the best maize-growing farm households. Figure 2 illustrates the wide variation in levels of cost inefficiency across maize-growing farm households. The maximum and minimum cost inefficiency was 0.896 and 0.127 respectively.

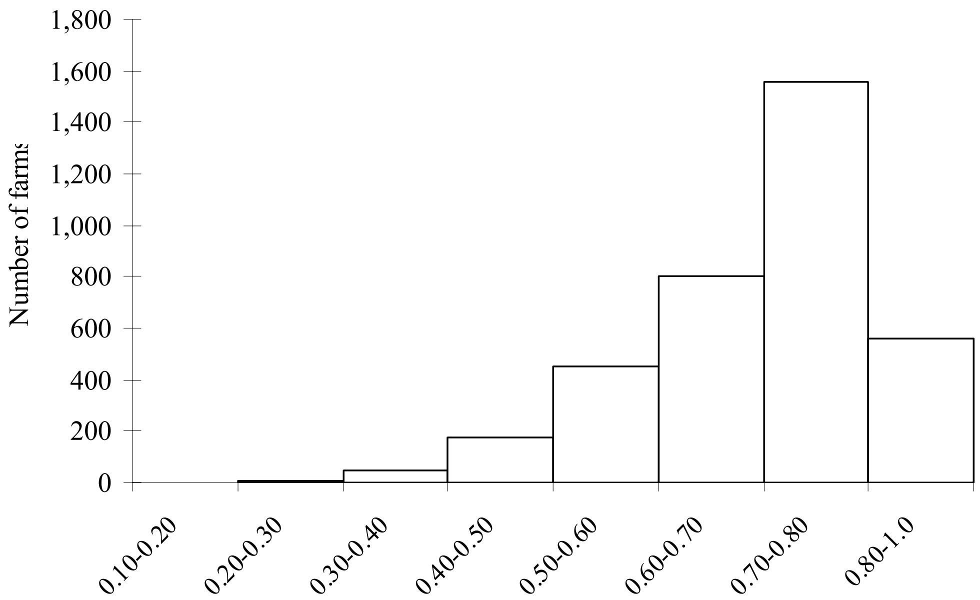


Figure 2 Frequency distribution of cost inefficiency index

IMPLICATIONS FOR PUBLIC POLICY

New agricultural technologies have the potential to increase productivity. However, increases in productivity due to technological innovation could not be achieved if new technologies are not combined with appropriate and complementary enhancements in agricultural institutions and human capital. Also, it is largely recognized that agricultural output growth is not only influenced by technology enhancements but also by the efficiency with which available technologies are utilized. This study estimates the cost function of producing maize in Mozambique by using stochastic frontier approach and investigates the determinants of cost efficiency taking into account the self-selectivity.

The results indicate that one-sided error component, that is related to farm specific inefficiency, dominates the random error term in the determination of $\varepsilon = \mu + \nu$, suggesting that the conventional cost function is not an adequate representation of the data. The findings illustrate that the deviation of observed variable cost from the frontier is due to both technical and allocative efficiency. The mean cost inefficiency is 70 percent. This result suggests that with the technology currently employed, in the short run, scope exists for fostering cost efficiency by 70 percent without any loss in total output from a given mix of production inputs. The results suggest that larger household size, male-headed households, older household head, better education, use of pesticides, and access to credit can bridge the gap between the efficient and inefficient maize-growing farm households. Furthermore, Geographic location (central and northern macro agro-ecological zones) is associated with lesser cost efficient maize-growing farm. Surprisingly, the further away from the county seat, the more land fragmented, and bigger maize cropped area, the less cost efficient the farm household is.

Measurements of cost efficiency reveal the potential that exists to enhance farmers' income by improving cost efficiency. Analysis of determinants of cost efficiency and adoption of improved maize seed indicates which characteristics of the farms, infrastructure, and natural resources should be targeted by policy makers to increase cost efficiency and adoption rates. The cost efficiency of maize-growing farm households and adoption rate of improved maize seed could considerably be improved by: i) improving rural infrastructures, ii) providing better access to education, iii) providing better access to credit, and iv) providing better extension services.

References

Aigner, Dennis;C. A. Knox Lovell; and Peter Schmidt. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6 (1):21-37.

Ali, Farman;Ashok Parikh; and Mir Kalan Shah. 1996. Measurement of economic efficiency using the behavioral and stochastic cost frontier approach. *Journal of Policy Modeling* 18 (3):271-87.

Battese, George E. and Tim J. Coelli. 1995. A Model for Technical Efficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics* 20 (2):325-32.

Binam, Joachim Nyemeck;Jean Tonye;Njankoua wandji; et al. 2004. Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. *Food Policy* 29 (5):531-45.

Coelli, Tim J.;D. S. Prasada Rao; and George E. Battese. 1998. *An introduction to efficiency and productivity analysis*. Boston: Kluwer Academic Publishers.

Farrell, M. J. 1957. The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society Series A* 120 (3):253-90.

Greene, William H. 2003. *Econometrics Analysis*. Fifth ed. Upper Saddle River, New Jersey: Prentice Hall.

Haggblade, Steven;Hazell; Peter;Ingrid Kristen; et al. 2004. African agriculture: past performance, future imperatives. In *Building on successes in African agriculture* Focus 12, edited by International Food Policy Research Institute (IFPRI) 2020 vision. Washington, DC: IFPRI 2020 vision.

Heckman, James J. 1978. Dummy endogenous variables in a simultaneous equations system. *Econometrica* 46 (6):931-60.

———. 1979. Sample selection bias as a specification error. *Econometrica* 47 (1):153-62.

Howard, Julie;Jan Low;Jose Jaime Jeje; et al. 2001. Constraints and Strategies for the Development of the Seed System in Mozambique. Research paper series 43E, Maputo, Mozambique: Ministry of Agriculture and Rural Development, Directorate of Economics.

Jondrow, James;C. A. Knox Lovell;Ivan S. Materov; et al. 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics* 19 (2-3):233-38.

Kebede, Tewodros Aragie. 2001. Farm household technical efficiency: A stochastic frontier analysis. A study of rice producers in Mardi watershed in the Western development region of Nepal. Masters thesis, Department of Economics and Social Sciences, Agricultural University of Norway.

Kumbhakar, Subal C.;Soumendra Ghosh; and J. Thomas McGuckin. 1991. A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in US Dairy Farms. *Journal of Business and Economic Statistics* 9 (3):279-86.

Kumbhakar, Subal C. and C. A. Knox Lovell. 2000. *Stochastic Frontier Analysis*. Cambridge: Cambridge University Press.

Liu, Zinan and Juzhong Zhuang. 2000. Determinants of technical efficiency in post-collective chinese agriculture: Evidence from farm-level data. *Journal of Comparative Economics* 28 (3):545-64.

Meeusen, Wim and Julien Van Den Broeck. 1977. Efficiency Estimation From Cobb-Douglas Production Functions With Composed Error. *International Economic Review* 18 (2):435-44.

Nadolnyak, Denis A.;Valentina M. Hartarska; and Stanley M. Fletcher. 2004. Estimating peanut production efficiency and assessing farm-level impacts of the 2002 farm act. Paper presented at the 2004 AAEA meetings, in Denver, Colorado.

Nawata, Kazumitsu and Masako Ii. 2004. Estimation of the labor participation and wage equation model of Japanese married women by the simultaneous maximum likelihood method. *Journal of the Japanese and International Economies* 18 (3):301-15.

Parikh, Ashok;Farman Ali; and Mir Kalan Shah. 1995. Measurement of economic efficiency in Pakistani agriculture. *American Journal of Agricultural Economics* 77 (3):675-85.

Reifschneider, David and Rodney Stevenson. 1991. Systematic Departures From The Frontier: A Framework For The Analysis Of Firm Inefficiency. *International Economic Review* 32 (3):715-23.

Richmond, J. 1974. Estimating The Efficiency Of Production. *International Economic Review* 15 (2):515-21.

Sharif, Najma R. and Atul A Dar. 1996. An Empirical Study of the Patterns and Sources of Technical Inefficiency in Traditional and HYV Rice Cultivation in Bangladesh. *Journal of Development Studies* 32 (4):612-29.

Tripp, Robert. 2001. *Seed provision and agricultural development: the institutions of rural change*. London: Overseas Development Institute.

Tzouvelekas, Vangelis;Christos J. Pantzios; and Christos Fotopoulos. 2001. Technical Efficiency of Alternative Farming Systems: the Case of Greek Organic and Conventional Olive-growing Farms. *Food Policy* 26 (6):549-69.

Vella, Francis and Marno Verbeek. 1999. Estimating and Interpreting Models With Endogenous Treatment Effects. *Journal of Business & Economic Statistics* 17 (4):473-78.

Wadud, Abdul. 2003. Technical, Allocative, and Economic Efficiency of Farms in Bangladesh: A Stochastic Frontier and DEA Approach. *The Journal of Developing Areas* 37 (1):109-26.

Wadud, Abdul and Ben White. 2000. Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods. *Applied Economics* 32 (13):1665-73.

Zavale, Helder. 2005. Analysis of the Mozambique's Maize Seed Industry: Factors Influencing the Adoption Rates of Improved Seed and Determinants of Smallholders' Cost Efficiency. Masters thesis, Department of Applied Economics and Management, Cornell University, Ithaca.

OTHER A.E.M. STAFF PAPERS

SP No	Title	Fee (if applicable)	Author(s)
2005-03	Adoption of Improved Maize Seed by Smallholder Farmers in Mozambique		Zavale, H., Mabaya, E. and R. Christy
2005-02	Farm Savings Accounts: Examining Income Variability, Eligibilitiy, and Benefits		Gloy, B., LaDue, E. and C. Cuykendall
2005-01	Market Opportunities for New Sauerkraut Products		Cuellar, S. and W. Uva
2004-01	Medicaid, County Property Levies, and Property Tax Levies on New York Farmland		Bills, N.
2003-04	A Brief Overview of Mozambique's Rural Development and the Role of US Assistance		Kyle, S.
2003-03	Political and Economic Prospects for Mozambique and Angola		Kyle, S.
2003-02	We're Rich!! Or Are We? Oil and Development in Sao Tome e Principe		Kyle, Steve
2003-01	Marketing New York Wine in New York City		Presler, T.
2002-04	Impacts of Trade Liberalization on the New York Horticultural Sector		G. B. White, N. L. Bills, and I. Schluep
2002-03	Insights Into the Economic Viability of a New CEA System Producing Hydroponic Lettuce		Ilaslan, G., G.B. White, and R.W. Langhans
2002-02	Health Care and Genesee County, New York: Economic Implications of Reduced Hospital Services		Bills, N. and D. Kay
2002-01	Questions Cooperative Directors Should Be Asking Management		Anderson, B. and B. Henehan

To order single copies of AEM publications, write to: Publications, Department of Applied Economics and Management, Warren Hall, Cornell University, Ithaca, NY 14853-7801. If a fee is indicated, please include a check or money order made payable to Cornell University for the amount of your purchase. Visit our web site: (*http:/aem.cornell.edu/research/sp.htm)* for a more complete list of recent papers.