OSIPP Discussion Paper : DP-2010-E-001

Estimating Agroforestry's Effect on Productivity in Kenya: An Application of a Treatment Effects Model

March 11, 2010

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【Keywords】 soil conservation technology; sustainability and agricultural productivity; self-selected participation; treatment effects model
【JEL Codes】 O13, H43, Q57

【Abstract】
This study investigates the effects of adopting agroforestry and other soil conservation technologies (SCTs) on agricultural productivity in Kenya, using plot-level data on agricultural production. Using a treatment effects model, it is found that adopting agroforestry methods, as well as manure, chemical fertilizer, and terracing/trenching, increases total factor productivity (TFP) and land productivity. The TFP gain is estimated to be 40.7 percent from agroforestry.
The average treatment effect for the adopters, however, turns slightly negative due to the negative self-selection effect, possibly because the agroforestry adopters tend to perceive adverse conditions on their land, which motivates them to adopt SCTs. In this sense, agroforestry and the other SCTs are preventive actions predominantly taken by farmers facing adverse conditions. The analysis demonstrates that both the simple mean comparison and the least squares estimation, due to their failure to reflect those complexities, could obscure the real benefits of SCTs.

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Acknowledgement: I am grateful for financial support from the Japan Society for the Promotion of Science, Grant-in-Aid for Scientific Research (C), 2007-2009.

1. *Introduction*

In Africa, sustainable use of agricultural land is becoming increasingly important for maintaining capacity for the food supply and livelihood of the agricultural sector. The increased food demand due to the rapidly growing population has increased the importance of improving productivity of land; however, degradation of existing cultivated land due to soil erosion and decline in soil fertility has constrained the sustainable use of existing cultivated land which frequently leads to land abandonment and conversion of natural forests into agricultural land. Recently, many studies in social science as well as conservation science have demonstrated the agroforestry's effect of soil conservation. Benefits of agroforestry are manifold, for example, mitigation of soil erosion, preservation of soil moisture, replenishment of soil fertility by providing organic fertilizers and alleviation of crop failure risks (Young, 1989; Okoji and Moses, 1998; Mathuva *et al*., 1998). The advantage of agroforestry is that it relies mainly on locally available natural resources, and thus is suitable to local agro-systems.

Studies to assess the economic benefits of agroforestry are rather scarce, although the extent to which this technology should be promoted critically depends on the size and nature of the benefits. The diverse and complex effects of agroforestry and its long wait period before realization of the effects seem to make it difficult to quantify the effects. In addition, the self-selective nature of adoption of agroforestry complicates econometric estimation.

This study analyzes the effect of the adoption of agroforestry on agricultural productivity in Kenya, using plot-level data obtained from the International Food Policy Research Institute (IFPRI) in two districts in western Kenya in 2001. We measure the impacts of adoption by estimating in terms of the total factor productivity (TFP) of major crops because sustained high TFP ensures stable long-run economic development in the agricultural sector. A positive effect of agroforestry on TFP would imply that more output can be produced for a given amount of inputs, or that land and other inputs can be conserved for given output levels. Empirical studies on soil conservation technologies (SCTs) have focused on their effect on income or agricultural revenue. However, since those unnormalized outcome variables are correlated with land size or the amount of other inputs, the estimated effect of adoption is likely to be biased if adoption is not independent of input size. Land productivity is a normalized outcome variable that is often used in the literature of agricultural intensification (Lee *et al*., 2006), but this partial productivity measure fails to reflect substitution with other inputs, like labor and capital; thus, an increase in land productivity does not guarantee an increase in agricultural revenue. If a positive effect on TFP alone is found, the existence of other benefits of agroforestry makes it even more profitable.

Furthermore, we take the self-selective nature of adoption into account in our empirical method by employing a treatment effects model that is widely used in the literature of program participation (for example, Pitt and Khandker, 1998). A least squares estimation that ignores self-selection is expected to yield biased estimates of the impact, as is common in program participation studies of development projects. For example, an adopter of agroforestry may have earned higher agricultural income even without adoption, if there are common determinants of his ability to earn higher income and likelihood of adoption. We also examine the effect of the adoption of several SCTs such as the application of manure and chemical fertilizer, trenching, terracing, and ridging.

This paper is organized as follows. Section 2 reviews the situation of Kenya and Africa regarding agricultural productivity and the circumstances of the adoption of agroforestry and other SCTs. Section 3 presents the empirical methodologies. Section 4 describes the data and study sites used for this study. Section 5 discusses the empirical results, and Section 6 concludes.

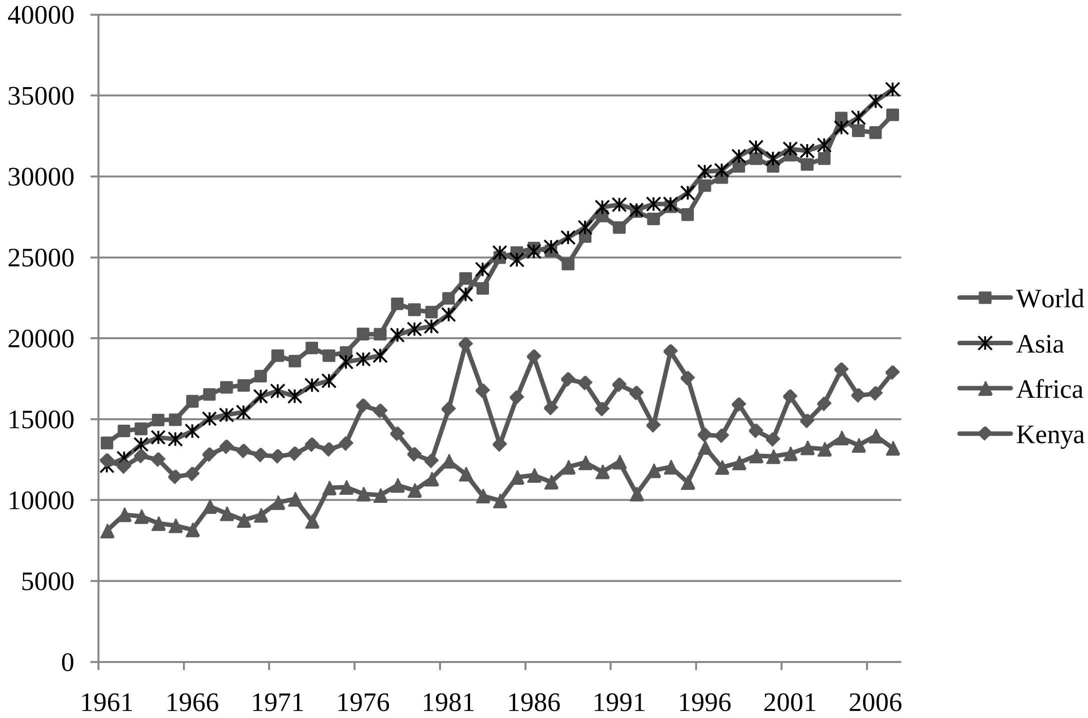
2. Agricultural productivity and soil conservation technologies in Kenya

The growth of agricultural productivity in Africa has been remarkably low in the past decades. As Figure 1 shows, the growth rate of agricultural productivity in Africa in terms of the yield of cereals in hectogram per hectare in 1960–2007 was 63 percent, whereas the average growth rat for the world during that period was 150 percent. In 1960 Kenya's productivity was about 50 percent above Africa's average, and was almost equal to Asia's average, but in 2007 Africa's productivity was only half that of Asia. This fact demonstrates the poor performance of Kenya's agriculture and calls for further investigation of the factors that constrain growth in agricultural productivity.

In Kenya, soil quality is known to be relatively good among African countries. The region generally has fertile Alfisols, and aggressive soil conservation measures have not been widely employed. Fallows are commonly practiced to maintain soil fertility in Kenya, but they have become untenable as the fallow period became shorter due rapid population growth (Amadalo *et al*., 2003). Kenyan farmers have gradually come to perceive the severity of soil erosion and resulting productivity decline (Amadalo *et al*., 2003). In these circumstances, SCTs have drawn significant attention from farmers and government in the country.

The function of agroforestry in conserving soil seems to make it a promising alternative to the traditional fallow technique. With the help of the agroforestry extension program by the Kenya Forest Department and dissemination by international non-governmental organizations, agroforestry has been implemented in several regions in Kenya (Scherr, 1995). Agroforestry contributes to soil conservation in several ways. Pattanayak and Mercer (2002) report that intercropped trees (contour hedgerows) successfully mitigate soil erosion by forming natural terraces in a sloping land and replenish soil fertility with prunings from the trees. Many scientific studies point out agroforestry's role of maintaining or improving soil fertility by preserving soil organic matter and physical properties of soil (for example, Okoji and Moses, 1998).

Figure 1: Yield of cereals (hectogram per hectare (Hg/Ha))



Source: Author's calculation based on FAOSTAT of the Food and Agricultural Organization.

Despite various advantages of agroforestry, agroforestry-based development projects in the 1980s and 1990s were frequently unsuccessful due to inadequate attention to socioeconomic issues affecting its adoption and continuation (Mercer and Pattanayak, 2003). It is generally found in the empirical literature that adverse conditions of the land, such as slope, tend to promote adoption (e.g., Obunde *et al*., 2004; Place *et al*., 2005; Otsuki and Ogo, 2009). It is also generally found that only relatively richer farmers tend to adopt agroforestry (Marenya and Barrett, 2007; Otsuki and Ogo, 2009). That may be because they can bear the setup and running costs of agroforestry and because they can bear the time cost of waiting for the effects to be observed due to their relatively lower time preference. It is also generally supported that formal education and access to information on appropriate agricultural technologies promote adoption (Caviglia-Harris, 2003). Obunde *et al*. (2004) and Otsuki and Ogo (2009) found that having formal land titles promotes the adoption of agroforestry in Kenya.

The dominance of the economic benefit and cost of agroforestry is not self-evident, due both to its multifaceted effects and to the potential of hindering efficient production. It is possible that the space needed for planting trees and the inflexibility of the choice and plantation patterns of crops may reduce productivity per unit of land. It is also possible that the increased labor requirement for maintenance may reduce productivity in the total factor measure. Agricultural experiments in Kenya also demonstrated a drawback of the intercropping of tree species that compete with crops for water (Mathuva *et al*., 1998). Place *et al*. (2005) found that the average productivity of the agroforestry adopters in terms of per hectare yield of maize (*Zea mays*) is more than two times that of the non-adopters in western Kenya although the self-selection problem is not taken into account.[1] Pattanayak and Mercer (2002) found that the land user's perception of soil quality tends to be higher for those who adopt agroforestry.

A farmer that adopts one type of SCT may be also active in adopting other SCTs. Agroforestry is frequently combined with other SCTs like chemical fertilizer and terracing. Some techniques are more complementary, rather than substitutive. Table 1 presents a tabulation of the incidence of agroforestry and other SCTs in both counts and probability. Most of the technologies are adopted jointly with agroforestry. The conditional probability of the adoption of manure and chemical fertilizers, is much higher for agroforestry adopters than for non-adopters. Organic fertilizers generated from intercropped trees or fallow plants do not contain sufficient phosphorus, and therefore, it is effective to combine agroforestry with chemical fertilizers (Amadalo *et al*., 2003). The conditional probability for agroforestry adopters to also adopt trenching, terracing and ridging is lower than that of non-adopters.

[1] Two types of agroforestry technologies are examined in Place et al. (2005) – (1) improved fallow that tree species are planted in the fallow period and (2) biomass transfer that organic nutrients from tree species are brought to crops as fertilizer.

Table 1: Combination patterns between agroforestry and other soil conservation technologies by the number of sample observations

		Manure			Chemical fertilizer			Trenching/Terracing			Ridging		
		No	Yes	Total	No	Yes	Total	No	Yes	Total	No	Yes	Total
Agro forestry	No	56	5	61	56	5	61	70	49	119	64	55	119
		(32.4%)	(2.9%)	(35.3%)	(32.4%)	(2.9%)	(35.3%)	(23.7%)	(16.6%)	(40.2%)	(21.7%)	(18.6%)	(40.3%)
	Yes	61	51	112	61	51	112	110	67	177	154	22	176
		(35.3%)	(29.5%)	(64. 7 %)	(35.3%)	(29.5%)	(64.7%)	(37.2%)	(22.6%)	(59.8%)	(52.2%)	(7.5%)	(59.7%)
	Total	117	56	173	117	56	173	180	116	296	218	77	295
		(67.6%)	(32.4%)	(100%)	(67.6 %)	(32.4%)	(100%)	(60.8%)	(39.2%)	(100%)	(73.9%)	(26.1%)	(100%)

Source: Author's estimation based on the IFPRI plot-level data for Suba and Laikipia.
Note: The counts are based on non-missing observations in each category of conservation technology.
Inside the parentheses are fractions in percentage.

3. Empirical methodologies

3.1 Literature on treatment effects models

Our objective is to statistically examine the effect of the adoption of agroforestry on the agricultural productivity in the studied area of Kenya. Since the adoption of SCT is self-selective, both a simple comparison of the means of the outcomes between adopters and non-adopters and a least squares estimation with an adoption dummy variable are inappropriate. Both approaches assume that adoption is random event, and so the outcomes would be comparable. However, unobserved factors such as the management and production skills of the farmers can increase both the likelihood of adoption and productivity. In this sense, the adoption and non-adoption outcomes for the same person should be compared in order for the effect of adoption to be evaluated. Since the counterfactual (the outcome for the case which is not chosen) is not actually observable, the above approaches fail to make a proper comparison, resulting in an inconsistent estimate of the treatment effect.

The treatment effects model that is widely used in the program evaluation literature (e.g., Pitt and Khandker, 1998) allows us to compare the real outcome with the counterfactual, thus incorporating the self-selective nature of agroforestry. Pattanayak and Mercer (2002) estimated the effect of agroforestry on perceived soil quality using a treatment effects model where the selection bias is corrected by including the inverse Mill's ratio as a regressor following Heckman (1978). Caviglia-Harris (2003) also used the two-stage sample selection model to estimate the agroforestry's deterrent effect on deforestation in the Brazilian Amazon. Kassie *et al*. (2008) estimated the effect of the adoption of stone bunds as a kind of SCT on the value of crop outputs using matching method introduced first by Rosenbaum and Rubin (1983).

There are several studies that apply the treatment effects model to evaluate the effect of SCTs other than agroforestry. Warning and Key (2002) evaluated the effect of participation in contract-farming program in Senegal, using a two-step estimation of the equations for participation (the first stage) and for determining the impact of participation (the second stage). Here, the inverse Mill's ratio estimated from the first stage probit model is included in the right hand side of the second stage model in order to correct for the sample selection bias caused by the self-selection of participation. Bolwig *et al*. (2009) examined the effect of participation in the organic farming contract on agricultural revenue in Uganda using a similar sample selection model but with maximum likelihood estimation rather than the two-stage method.

3.2 Treatment effects model

A standard treatment effects model is as follows:

$$Y_i = X_i'\beta + \delta I_i + v_i , \qquad (1)$$

where Y_i, $i = 1, 2, ..., N$ is a dependent variable that represents an outcome, X_i a vector of exogenous variables, β a vector of coefficient parameters for X_i, I_i adoption status which is a binary treatment variable, δ a coefficient estimator for I_i

that is interpreted as a treatment effect, and ν_i an error term that follows normal distribution with mean zero and variance σ_ν^2. The adoption of individuals based on a set of determinants Z_i is specified as:

$$I_i^* = Z_i'\gamma + \upsilon_i\,, \tag{2}$$

where I_i^* is a latent variable, γ a vector of coefficient parameters, and υ_i an error term. The latent variable is unobservable, and its relationship with I_i is specified by:

$$I_i = 1 \text{ if } I_i^* > 0, \text{ otherwise } I_i = 0\,. \tag{3}$$

If unobserved factors in (2) are correlated with ν_i, then the correlation coefficient between υ_i and ν_i (denoted as ρ) is non-zero, and thus the OLS estimator is inconsistent (Greene, 2008). Following Greene (2008), the expected outcome for participants assuming normal distribution for *I* becomes

$$E[Y_i \mid I_i = 1, X_i, Z_i] = X_i'\beta + \delta + E[\nu_i \mid I_i = 1, X_i, Z_i]$$

$$= X_i'\beta + \delta + \rho\sigma_\nu[\phi(Z_i'\gamma) / \Phi(Z_i'\gamma)]\,, \tag{4}$$

where $\rho\sigma_\nu$ equals the covariance between ν_i and υ_i, $\phi(Z_i'\gamma)$ the marginal probability density of standard normal at $Z_i'\gamma$, and $\Phi(Z_i'\gamma)$ the cumulative probability of standard normal at $Z_i'\gamma$. The third term includes the inverse Mill's ratio to control for a possible sample selection bias, $\lambda_i \equiv \phi(Z_i'\gamma) / \Phi(Z_i'\gamma)$, and $\beta_\lambda \equiv \rho\sigma_\nu$ will be the coefficient parameter for λ_i. The expected outcome for non-participants becomes

$$E[Y_i \mid I_i = 0, X_i, Z_i] = X_i'\beta + \rho\sigma_\nu\left[-\phi(Z_i'\gamma)/1 - \Phi(Z_i'\gamma)\right]. \tag{5}$$

The inverse Mill's ratio for (5) is $\lambda_i \equiv -\phi(Z_i'\gamma)/1 - \Phi(Z_i'\gamma)$. The difference in the expected outcome between participants and non-participants then becomes

$$E[Y_i \mid I_i = 1, X_i, Z_i] - E[Y_i \mid I_i = 0, X_i, Z_i] = \delta + \text{selection term}\,. \tag{6}$$

The positive (negative) sign of the selection term implies that the OLS overestimates (underestimates) δ, and the sign of the selection term depends on that of ρ. A maximum-likelihood estimation is proposed by Maddala (1983) and Greene (2008), as it produces consistent estimators. Maddala (1983) also proposed a two-step estimation that also produces consistent estimators. It estimates (3) by a probit estimation in the first stage and then estimates (1) by including the predicted value of selectivity correction as an additional regressor. While many studies that evaluate the effect of SCTs use the two-stage estimation for the analytical tractability, we use the maximum-likelihood estimation. We chose that method because it estimates the adoption equation and productivity equation jointly and because it allows us to test the significance of the cross-equation correlation ρ. If we cannot achieve convergence in the maximum-likelihood estimation, we use the two-stage estimation.

3.3 Productivity estimation

We focus on total factor productivity (TFP) in measuring a measure of individual farmer's performance in agricultural production as well as land productivity whereas most studies focus on land productivity such as per acre yield in the impact analysis of soil conservation. Our analysis mainly focuses on TFP because an increase in TFP unambiguously leads to an increase in on-farm income from the crops of interest given the input factor and product prices being unchanged. In contract, an increase in land productivity does not ensure an increase in on-farm income because the amount of labor and other inputs may change simultaneously. If a SCT requires a substantial amount of additional labor and other inputs, on-farm income may decline on net.

In the standard definition, TFP is defined as $TFP_i = y_i / F(X_i)$, where $F(\cdot)$ is a production function, y_i the actual output, and X_i a vector of inputs. In our analysis, the output is measured in terms of the total value of maize and beans produced. Maize is the preferred staple and main crop and is often planted jointly with beans (Amadalo *et al*., 2003). As inputs, we include labor (L) and land (H), as they are the major inputs in the agricultural system in Kenya.[2] We construct labor from the total number of

[2] It is ideal to include a measure of capital stock as an input in the production function estimation, but it is difficult to construct such a variable from the dataset since not many farmers in the sample use

man-days for production activities, including land preparation, plantation, weeding, and harvesting. We use area under cultivation for the land variable.

We use a stochastic frontier model because it has the advantage of isolating random noise from the productivity component (see Kumbhakar and Lovell, 2000, for example). The stochastic frontier model for the Cobb-Doublas production function is specified as follows:

$$\ln y_i = \alpha_0 + \alpha_L \ln L_i + \alpha_H \ln H_i + \varepsilon_i - u_i, \qquad (6)$$

where α's are intercept and coefficient parameters, and ε_i is an error term that represents a random noise which is associated with with a zero mean and a constant standard error and represents a random component of output associated with random events such as weather. The term u_i is the inefficiency component that will be converted to technical efficiency scores under a simple transformation (see Kumbhakar and Lovell, 2000, for example). The technical efficiency is interpreted as TFP in the cross-section framework in a single time period. This model is estimated using a maximum-likelihood method assuming half-normal distribution on the inefficiency term.

4. *The study area and data*

Our empirical analysis relies on a survey dataset of household attributes, agricultural production, environmental conservation measures, and other factors that affect agricultural production in Kenya in 2001. The dataset is titled "The Land Tenure, Agricultural Productivity and the Environment: Suba and Laikipia Districts, Kenya, 2001" and is publicly available from the IFPRI. The details of the survey project and key findings are reported in Obunde *et al*. (2004).

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machinery or other capital goods. Also manure and chemical fertilizer are often considered as inputs, but we deal with them as soil conservation technologies for the comparison with agroforestry.

Two districts in Kenya were selected for the survey project. Suba is a district located at Kenya's western border with Tanzania, where the land is largely characterized as hilly with thorny bushes. Laikipia is a district located slightly west of the center of Kenya, in an area dominated by an elevated plateau covered by volcanic ash (Obunde *et al*., 2004). Since a major part of the areas of those districts are highland, their climate is mild, despite its equatorial location. In addition, these areas receive moderate rainfall, and therefore, the climate is favorable for crop production. However, the land in the two districts is generally hilly; as approximately 75 percent of the plots in the sample reported that the land is sloping, thus making soil conservation important. Approximately a quarter of the sample area experiences erosion of surface soil.

According to the Obunde *et al*. (2004), four sub-locations were chosen from a cluster of 10 sub-locations in each of the two districts, with attention to (1) the similarity of both clusters in terms of agro-ecological conditions and (2) the wide variety of land tenure systems. In each sub-location, 40 respondents were randomly selected. The empirical analysis in this study uses the observations from 245 plots that are held by 209 farmers after eliminating observations with missing values. The number of plots is greater than that of farmers because some farmers hold multiple plots.

Table 2 shows the list of variables used in our empirical analysis. The variables are grouped into SCTs, plot-specific attributes, and farmer-specific attributes. The variables of SCTs reflect the status of the adoption of those technologies. For example, the agroforestry variable, which is a binary variable, takes value one when agroforestry is adopted and zero otherwise.[3] The plot-specific and farmer-specific attributes are used as explanatory variables either in the first-stage adoption regression or the second-stage productivity regression.

The factors that seem to affect both adoption and productivity, such as soil fertility, slope, land title, farm size, access to credit and years of education, enter into both the

[3] Improved fallow may be considered as agroforestry, because fast growing tree species are sometimes planted in the fallow period, but it is not distinguished. As long as crops are produced, it is considered that the land is not left fallow. So we rule out the possibility of improved fallow from our data.

adoption and productivity equations. The adoption equation also includes the perceived severity of environmental degradation, income, the number of owned cattle, the dummy of residence of more than 10 years, and the district dummy. Those variables are thought to affect the adoption decision more significantly than productivity, and they are also useful for identification. Distance to input and output market is included only in the productivity equation because market access presumably affects the costs of input acquisition and sales of outputs directly.

Table 2: The variables used for the empirical analysis

Soil conservation technologies	
Agroforestry	Dummy of adoption of SCTs; 1 = adopted, 0 = not adopted
Manure	
Chemical fertilizer	
Trench/Terrace	
Ridges	
Plot- specific attributes	
Soil fertility	Fertility of soil; 1 = poor, 2 = fair, 3 = good, 4 = very good
Slope	Gradient of land; 1 = flat, 2 = gently sloping, 3 = steep
Degradation	Perceived environmental degradation; 5 = none, 4 = negligible, 3 = moderate, 2 = serious, 1 = very serious
Land title	Holding formal land title; 1 = yes, 0 = no
Farm size	Total area of land in hectare
Distance to the input market	Distance to the input market in kilometer
Distance to the output market	Distance to the product market in kilometer
District dummy	Dummy of district; 1 = Suba, 0 = Laikipia
Farmer- specific attributes	
Log income	Log of total income
Credit	Application to loans; 1 = applying, 2 = not applying
Cattle head	The number of cattle head owned
Family size	The number of family members
Sex of head	The sex of the household head
Year of education	The number of years of formal education
Residence more than 10 years	Dummy of residency for more than 10 years

5. *Empirical results*

5.1 Total factor productivity

The coefficients of the production function, i.e., α_L and α_H in Equation (6), are estimated to be 0.366 and 1.084, respectively, using a maximum-likelihood method. They are significant at the 1 percent level as well as the intercept.[4] Technical efficiency scores are calculated for each sample once the inefficiency term u_i is adjusted such that technical efficiency scores will not take values beyond the range [0, 1].[5] The descriptive statistics for the technical efficiency measure are the mean being 0.458, the standard error 0.206, the minimum 0.009, and the maximum 0.851.

5.2 The effect of adoption of agroforestry and other soil conservation technologies

Our econometric model to examine the impact of the adoption of agroforestry on productivity, which we denote as the productivity equation, is specified by setting a productivity index as Y_i, exogenous factors to influence Y_i as X_i, and the adoption dummy of agroforestry as I_i in Equation (1). The adoption equation is specified by setting the exogenous determinants of the adoption of agroforestry as Z_i in Equation (2). For the productivity equation, we also consider alternative SCTs, namely, manure application, chemical fertilizer application, trenching and/or terracing, and ridging. A total of 153 to 245 observations are used, depending on data availability.

Table 3 presents the results of both the productivity and the adoption equations where the technical efficiency scores are used as the productivity measure. The table shows the coefficient estimate and the standard error of each variable and the inverse Mill's ratio λ. The table also shows the estimate of the coefficient parameter ρ for the productivity and the adoption equations, and the chi-squared statistics for the Wald test

[4] We do not assume constant returns to scale (CRS) in the underlying production technology which is often done in this kind of analysis because this assumption is sometimes too restrictive and unrealistic. We obtain a very similar result for the estimated coefficients and the TFP scores, however, when we assume the CRS.
[5] The exponential transformation should be made to the estimated inefficiency because the variables in Equation (6) are in the logarithm.

for model predictability. The *p*-values for the Wald test suggest joint significance of the coefficient parameters at the significance of more than one percent in all the five models, implying good model predictability.

The results of the adoption equation indicate that slope, income, and land titles are important for the adoption of agroforestry, confirming the results in the previous studies. Significant coefficient parameters are largely different across the treatment types, but it can be generally said that adverse conditions of the land tend to push farmers to adopt SCTs. Using a survey from farmers in Zambia, Ajayi (2007) showed that the potential to adopt soil conservation technologies is higher for farmers who are more concerned about the condition of their such as soil fertility. Having the land title seems to stimulate the adoption of agroforestry, fertilizer and ridges, confirming the previous studies (e.g., Place *et al*., 2005).

The results of the productivity equation indicate that adoption increases TFP while only ridging decreases TFP.[6] Agroforestry adopters as well as adopters of manure, fertilizer, and trenching/terracing, on average, enjoy higher productivity and therefore higher on-farm income. Combining this with the first stage finding that farmers with sloping land tend to adopt agroforestry, mitigation of possible productivity loss due to soil erosion seems to be the motivation behind adoption of agroforestry. The negative coefficient estimate for ridges may result from their typical use only to make space for crop roots to spread out and to promote drainage of water. Ridges are supposed to enhance outputs, but the labor needed to create and maintain ridges and the land space needed for ridges may result in a lower TFP.

[6] Given the fact that those technologies are often jointly adopted, it is perhaps more appropriate to estimate their effects jointly in the productivity regression. In this study, however, we focus on the model with a single treatment because it is a common approach in the literature and because models with multiple treatments involve further methodological complexities.

Table 3: Regression results on productivity (dependent variable=total factor productivity)

	Model1	Model2	Model3	Model4	Model5
Soil conservation technology	Agroforestry	Manure	Fertilizer	Trench/terrace	Ridges
Productivity equation					
Soil conservation technology	0.148 ** [b]	0.275 ***	0.223 ***	0.361 ***	−0.165 **
	(0.070) [a]	(0.039)	(0.047)	(0.033)	(0.084)
Soil fertility	0.000	0.076 ***	0.034	−0.003	−0.020
	(0.024)	(0.029)	(0.028)	(0.030)	(0.022)
Slope	0.012	0.070 ***	0.037	−0.010	−0.006
	(0.024)	(0.026)	(0.023)	(0.029)	(0.028)
Land title	0.143 ***	0.150 ***	0.113 ***	0.256 ***	0.178 ***
	(0.034)	(0.031)	(0.034)	(0.034)	(0.026)
Farm size	−0.006 **	−0.012 ***	−0.009 ***	−0.010 ***	−0.006 **
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Credit	0.031	−0.047	−0.019	−0.012	−0.001
	(0.054)	(0.061)	(0.05)	(0.086)	(0.065)
Years of education	0.008 ***	0.007 **	0.004	0.004	0.009 ***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
Distance to input market	0.000	−0.001	−0.001	0.002 **	0.000
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
Distance to output market	0.012 *	0.008	0.01	0.012 *	0.012 *
	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)
λ	−0.101 **	−0.142 ***	−0.115 ***	−0.217 ***	0.116 **
	(0.043)	(0.011)	(0.035)	(0.018)	(0.048)
Adoption equation					
Soil fertility	0.118	−0.560 **	0.449	0.090	−0.803 ***
	(0.219)	(0.253)	(0.352)	(0.155)	(0.259)
Slope	0.480 ***	−0.172	0.367	0.393 **	−0.742 ***
	(0.175)	(0.213)	(0.326)	(0.153)	(0.204)
Environmental degradation	−0.174 *	0.132	−0.207	−0.087	0.093
	(0.096)	(0.141)	(0.251)	(0.060)	(0.097)
Land title	1.007 ***	0.074	0.677 *	−0.691 ***	0.643 **
	(0.339)	(0.291)	(0.388)	(0.196)	(0.285)
Farm size	−0.017	−0.030	0.036	0.010	0.016
	(0.030)	(0.035)	(0.059)	(0.020)	(0.022)
Log income	0.305 **	0.240 *	0.392 *	0.028	0.118
	(0.121)	(0.132)	(0.222)	(0.062)	(0.113)
Credit	−0.577	0.274	−0.825	0.148	−6.917
	(0.368)	(0.473)	(0.761)	(0.370)	(0.000)
Cattle	0.034	0.260 ***	0.195	0.063 ***	0.005
	(0.030)	(0.073)	(0.149)	(0.015)	(0.036)
Family size	−0.047	−0.053	−0.193 ***	−0.011	0.000
	(0.042)	(0.040)	(0.074)	(0.020)	(0.055)
Sex of household head	−0.159	−0.027	0.187	0.143	−0.103
	(0.236)	(0.278)	(0.477)	(0.130)	(0.255)
Years of formal education	−0.030	−0.013	0.064	0.005	0.038
	(0.025)	(0.036)	(0.047)	(0.020)	(0.029)
Residence more than 10 years	0.561	1.614 **	0.287	−0.191	−0.277
	(0.351)	(0.680)	(0.984)	(0.152)	(0.313)
District dummy	1.476 ***	4.186 ***	10.765 ***	0.844 ***	−2.009 ***
	(0.271)	(1.281)	(2.779)	(0.157)	(0.386)
Estimation method	ML	ML	Two-step	ML	ML
ρ (P-value)	−0.545 (0.040) **	−0.816(0) ***	−0.691	−0.914 (0) ***	0.619 (0.039) ***
Model χ^2 (P-value)	155.4 (0) ***	155.3 (0) ***	91.0 (0) ***	258.1 (0) ***	138.2 (0) ***
N	245	153	154	245	244

Source: Author's estimation based on the IFPRI plot-level data for Suba and Laikipia.

Note: [a] Inside parentheses are robust standard errors. [b] The symbols "*," "**" and "***" mean a 10, 5, and 1 percent significance levels, respectively. A command "treatreg" of Stata version 11 is used for the estimation.

The difference of TFP between adopters and non-adopters is given by the coefficient estimate for the adoption dummy, and is greatest for trenching/terracing, indicating the effectiveness of this type of SCT. Combining the results of the adoption regression that trenching and terracing are likely used by farmers who have land on a hillside, adopters are not only successful in preventing soil erosion, but also in increasing productivity. A simulation using the predicted values demonstrates that TFP would increase by 116.2 percent as a result of adoption compared to the predicted values under a non-adoption scenario. The same logic seems to hold for agroforestry, manure, and fertilizer. The simulated TFP increase for those technologies is estimated to be 40.7, 71.9 and 56.6 percent, respectively.

Soil fertility and slope have a positive impact on TFP in Model 2, but their effect is not significant in the other models. With the full application of SCTs, low soil fertility and slope may no longer have a devastating effect. Having land title is found to increase TFP in all models. This result is consistent with findings of previous studies that having secure land title promotes a farmer's investment in land improvement (e.g., Feder and Onchan, 1985). Land size has a negative effect, possibly because a small-scale operation is more efficient in traditional agricultural production, which does not rely heavily on machinery. This result is consistent with Obunde *et al*. (2004) that used the same dataset, and they claim that this results from the intensification of production with decreases in land size. This negative correlation between land size and productivity is reported in various studies. Formal education has a positive effect in three models, confirming the fact that formal education contributes to acquisition of skills and knowledge in improved agricultural production.

The chi-squared test for the significance of the cross-equation correlation coefficient ρ indicates independence of the two equations, and the results suggest that independence is rejected at the 1 or 5 percent levels of significance. This implies that the sample selection bias is present in terms of adoption of SCTs. The negative selection bias implies a negative correlation between the unobserved determinants of adoption and those of productivity. This result deviates from our original expectation that a more active adopter of SCTs is likely to have higher returns to the adoption of SCTs. A possible explanation is that the farmers who encounter unobserved adverse factors of their land tend to adopt SCTs. There seem to be other adverse factors than low soil fertility and sloping, such as limited access to irrigation and susceptibility to soil erosion. These negative factors may have dominated the positive factors such as production and management skills.

In addition, using the same estimation method as for TFP, we examine the impact of SCTs on land and labor productivity. The outcome variable is replaced by the value of output per hectare as a land productivity index, or the value of output per worker as a labor productivity index. Those indices are normalized by the maximum value of productivity in the sample. The results are presented in Table 4. The results of land productivity are quite comparable with those of TFP, confirming that those SCTs mainly increase land productivity. The impact of SCTs on labor productivity is significantly negative in the case of agroforestry, while most of other measures are insignificant. Agroforestry might be a technique that requires more labor than its alternatives, resulting in the negative correlation with labor productivity. When the fact that its effect on TFP is positive is considered, it can be said that its effect of increasing land productivity outweighs its effect of lowering labor productivity. This result also emphasizes the necessity to consider labor opportunity cost. If the opportunity cost is sufficiently low, as is likely in low-income countries, techniques to increase land productivity are justified (Lee *et al*., 2006).

Table 4: Regression results on land and labor productivity

Dependent variable = land productivity					
Treatment type	Agroforestry	Manure	Fertilizer	Trench/terrace	Ridges
Treatment	0.250 ***[b]	0.280 ***	0.335 ***	0.327 ***	−0.243 ***
	(0.029)[a]	(0.049)	(0.046)	(0.033)	(0.058)
(The rest of the regression result is suppressed)					
Dependent variable = labor productivity					
Treatment	−0.040 ***	0.008	−0.013	−0.037	0.052 *
	(0.016)	(0.013)	(0.025)	(0.040)	(0.031)
(The rest of the regression result is suppressed)					

Source: Author's estimation based on the IFPRI plot-level data for Suba and Laikipia.
Note: [a] Inside parenthesis are robust standard errors. [b] The symbols "*," "**" and "***" mean a 10, 5, and 1 percent significance levels, respectively.

For comparison, we demonstrate the difference between the treatment effects model and a simple comparison of the means and a least squares estimation with a focus on TFP. A simple comparison of the means of TFP between adopters and non-adopters of agroforestry indicates that the TFP of the adopters is higher than that of the non-adopters as was found in Place *et al*. (2005). The mean TFP of the adopters is 0.495, and that of the non-adopters is 0.395. The difference is 0.100 and 25 percent higher than the non-adopters' average, but smaller than the estimates from the treatment effects model. In addition, the ordinary least squares estimation for agroforestry is found to yield a downwardly biased estimator for the treatment effect (0.013) due to ignoring the selectivity correction. Thus, the use of those alternative methods could generally lead to erroneous estimates for the effect of SCTs.

Those results generally suggest that most the SCTs of interest can contribute to sustainable land use by maintaining or improving productivity of crops. This sustainability implication is not fully confirmed, however, since the productivity is measured at a particular time period in our analysis. The temporal change of productivity is not investigated. Still, it is fair to presume that the adopters of SCTs are likely to maintain high productivity in a long term because most SCTs, particularly agroforestry, involve sunk cost and wait period which can be only compensated by a long-term stream of benefits.

A common caveat associated with the use of a cross-section dataset need attention, however. Some of the regressors in the productivity equation may be endogenous, and thus are simultaneously determined with the productivity. The endogeneity of the adoption decision is most likely, but has been dealt with by the stage-wise estimation. Among the rest, land titles are likely to be a source of endogeneity. If one tends to acquire private land titles for highly productive land, an upward bias on the coefficient is expected.

5.3 Average treatment effect on adopters

The average treatment effect (ATE) on adopters of SCTs can be investigated by taking the difference between the conditional mean outcomes of the adoption ($I=1$) and the counterfactual ($I=0$). The treatment effects model allows us to estimate the outcome under both scenarios ("adopt" and "do not adopt") for each sample. As Table 5 shows, the conditional mean of the case of adoption is 0.486, which is lower than that of non-adopters (0.539), and the difference is statistically significant although small. This result is accounted for by the negativity of the selection term in Equation (6) that outweighs the positive effect of soil conservation δ. The negative selection term follows the negative cross-equation correlation ρ. According to the standard interpretation of the average treatment effect (ATE), a particular farmer who adopts agroforestry would have had lower productivity, had he not adopted agroforestry. This does not imply that adoption actually makes a farmer worse off than in the case of non-adoption, but implies that farmers with potentially low productivity tend to adopt SCTs. Adopters are aware of their land's proneness to soil erosion due to greater disadvantages than those of average producers, driving them to adopt countervailing measures. In other words, without soil conservation efforts, they would suffer from poor productivity.

We obtain negative ATEs for chemical fertilizer and trenching/terracing, and positive ATEs for manure and drainage as shown in the table. The same explanation applies to the SCTs with negative ATE. For manure, the ATE is still positive after discounting the positive selection effect. For drainage, the adoption effect (δ) is negative, but the positive selection effect outweighs the adoption effect, resulting in a positive average treatment effect.

Table 5: The mean predicted total factor productivity of adopting farmers

	I=1 (adoption)	*I*=0 (counterfactual)	Difference	t-value	P-value
Agroforestry	0.486	0.539	−0.053	−18.46	0.000
Manure	0.552	0.529	0.023	2.58	0.013
Fertilizer	0.590	0.619	−0.029	−2.77	0.000
Trench/terrace	0.451	0.453	−0.002	−0.84	0.403
Ridges	0.419	0.378	0.042	5.76	0.000

Source: Author's estimation based on the IFPRI plot-level data for Suba and Laikipia.

6. Conclusions

Soil conservation technologies (SCTs) will be a key factor to ensure sustainable food production and to alleviate the pressure for deforestation to expand cultivated land. This study investigates the effect of adopting agroforestry and other SCTs on agricultural productivity in Kenya, using plot-level data on agricultural production in two selected districts in Kenya in 2001. A treatment effects model is used to accommodate the self-selective nature of technology adoption, and it is found that the adoption of agroforestry, as well as manure, chemical fertilizer, and terracing/trenching, significantly increase both land and total factor productivity (TFP). The TFP gain is estimated to be 40.7 percent on average for agroforestry, demonstrating a considerable contribution of agroforestry to the sustainability of agricultural production. The TFP gain mainly stems from the soil conservation effect of agroforestry, and its other benefits such as the harvest of tree crops would make it even more attractive. Agroforestry may be labor-intensive technique, thus lowering labor productivity, but it remains profitable if the labor opportunity cost is low, as is likely in low-income

African countries. Thus, the dissemination programs to support adoption of agroforestry and other SCTs are expected to have significant economic impacts on the agricultural sector in Kenya.

The average treatment effect for the adopters, however, turns slightly negative due to the negative self-selection effect, possibly because the adopters of agroforestry tend to perceive adverse conditions of their land, which drives them to adopt SCTs. In this sense, agroforestry and the other SCTs can be better characterized as preventive actions predominantly taken by farmers facing adverse conditions. This makes it difficult for the evaluators to observe the benefits of the SCTs as they often rely on the simple mean comparison and the least squares estimation which could obscure the real benefits of SCTs due to their failure to reflect those complexities. The dissemination programs should consequently aim to demonstrate appropriate economic benefits of the adoption. Such programs also would benefit farmers who do not necessarily face adverse conditions in production.

References

Ajayi, O. C. 2007. User Acceptability of Sustainable Soil Fertility Technologies: Lessons from Farmer's Knowledge, Attitude and Practice in Southern Africa. Journal of Sustainable Agriculture 30(3): 21-40.

Amadalo, B., Jama, B., Niang, A., Noordin., Nyasimi, M., Place, F., Franzel, S., & Beniest, J. 2003. Improved Fallows for Western Kenya: An Extension Guideline. Nairobi: World Agroforestry Center.

Bolwig, S., Gibbon, P., & Jones, S. 2009. The economics of smallholder organic contract farming in Tropical Africa. *World Development* 37(6): 1094－1104.

Caviglia-Harris., & Jill, L. 2003. Sustainable agricultural practices in Rondônia, Brazil: do local farmer organizations affect adoption rates? *Economic Development and Cultural Change* 52: 23–49.

Feder, G., & Onchan, T. 1987. Land ownership and farm investment in Thailand. *American Journal of Agricultural Economics* 69(1): 311–320.

Greene, W. H. 2008. *Econometric Analysis*. 6th Edition. New Jersey: Prentice–Hall, Upper Saddle River.

Heckman, J. J. 1978. Dummy endogenous variables in a simultaneous equation system. *Econometrica* 46(6): 931–959.

Kassie, M., Pender, J., Yesuf, M., Kohlin, G., Bluffstone, R., & Mulugeta, E. 2008. Estimating returns to soil conservation adoption in the Northern Ethiopian highlands. *Agricultural Economics* 38: 213–232.

Kumbhakar, S. C., & Lovell, C. A. K. 2000. *Stochastic Frontier Analysis.* New York: Cambridge University Press.

Lee, D. R., Barrett, C. B., & McPeak, J. G. 2006. Policy, technology, and management strategies for achieving sustainable agricultural intensification. *Agricultural Economics* 34: 123–127.

Maddala, G. S. 1983. Limited-Dependent and Qualitative Variables in Econometrics. New York: Cambridge University Press.

Marenya, P. P., & Barrett, C. B. 2007. Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in Western Kenya. *Food Policy* 32(4): 515–536.

Mathuva, M. N., Rao, M. R., Smithson, P. C., & Coe, R. 1998. Improving Maize (*Zea mays*) yields in semiarid highlands of Kenya: agroforestry or inorganic fertilizers? *Field Crops Research* 55(1-2): 57–72.

Mercer, D. E., & Pattanayak, S. K. 2003. Agroforestry adoption by smallholders. In *Forests in a Market Economy*, Sills EO and Abt KL (eds). The Netherlands: Kluwer Academic Publishers: 283–299.

Obunde, P. O., Mbogo, C. M., Oluoch-Kosura, W., & Kamoni, A. W. 2004. Effects of land tenure on agricultural productivity, and the environment: a case study of Suba and Laikipia districts. *IFPRI Eastern Africa Food Policy Network* Report **7**. Washington, D.C.: International Food Policy Research Institute.

Okoji, M. A., & Moses, J. 1998. Adoption of Agroforestry for Soil Conservation in Akwa Ibom State, Nigeria. *Journal of Sustainable Agriculture* 13(1): 5 – 13.

Otsuki, T., & Ogo, T. 2009. Determinants of adoption of agroforestry in Kenya. Osaka University. mimeographed.

Pattanayak, S. K., & Mercer, D. E. 2002. Indexing soil conservation: farmer perceptions of agroforestry Benefits. *Journal of Sustainable Forestry* 15(2): 63–85.

Pitt, M. M., & Khandker, S. R. 1998. The impact of group-based credit programs on poor households in Bangladesh: does the gender of participants matter? *Journal of Political Economy* 106(5): 958–996.

Place, F., Adato, M., Hebinck, P., & Omosa, M. 2005. The impact of agroforestry-based soil fertility replenishment practices on the poor in Western Kenya. *IFPRI Research Report* 142. Washington, D.C.: International Food Policy Research Institute.

Rosenbaum, P. R., & Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1): 41–55.

Scherr, S. J. 1995. Economic factors in farmer adoption of agroforestry: patterns observed in Western Kenya. *World Development* 23(5): 787–804.

Warning, M., & Key, N. 2002. The social performance and distributional consequences of contract farming: an equilibrium analysis of the *Arachide de Bouche* program in Senegal. *World Development* 30(2): 255–263.

Young, A. 1989. *Agroforestry for Soil Conservation*. Walingford and Nairobi: CAB International and International Council for Research in Agroforestry.