Factors Influencing Adoption of Tissue Culture Banana in Western Kenya

Wanyama, J. Masinde

PhD student, Department of Agricultural Economics and Agribusiness Management
Egerton University, Kenya

Gideon, A. Obare

Department of Agricultural Economics and Agribusiness Management
Egerton University, Kenya

George Owuor

Department of Agricultural Economics and Agribusiness Management
Egerton University, Kenya

Lusike Wasilwa

Horticulture and Industrial Crops

Kenya Agricultural research Institute (KARI), Headquarters, Kenya

4th International Conference of AAAE

Diar Lemdina Hotel – Yasmine Hammamet, Tunisia

22 – 25 September 2013, in Tunisia

Prof. Tahar Akkari (Email: tahar.ak@gnet.tn)

Prof. Nick Vink (Email: nv@sun.ac.za)

Paper for presentation in an international workshop on FULL Contributed Papers for the 4th Conference of AAAE in Tunisia, *May 25 – 30, 2013, in Bonn, Germany*

Abstract

The objective of the study was to assess the factors influencing the likelihood of adoption and intensity of adoption of Tissue culture banana in four counties of West Kenya. The study utilized cross-section data to analyze the effect of farmers' demographic, socioeconomic and institutional setting, market access and physical attributes on the probability and intensity of TCB adoption. A double hurdle model was fitted on the data collected from randomly selected 330 farmers between July 2011 and November 2011. Secondary data were also used to complement the primary data. The study depicted relatively low adoption of TCB was 32% % of total sampled size. The results of the study provided empirical evidence of a significant influence on likelihood TCB adoption were availability of TCB planting material, proportion of banana income to the total farm income, per capita household expenditure and the location of the farmer in Kisii County, while those that significantly influenced the intensity of TCB adoption were. occupation of farmers, occupation of farmers, family size, labour source, farm acreage, farm fertility status, availability/access of TCB plantlets to farmers, distance to banana market, use of manure in planting bananas, agricultural extension services, average index technology attributes, bundumy was positive (sugarcane zone). Therefore, the results of the study suggest that the probability of adoption and intensity of use of TCB should be enhanced by taking cognizance of these variables in order to meet the priority needs of smallholder farmers who were target group and to alleviate the food shortage problem in the country in general and in the study area in particular. Opening up more TCB multiplication centres and widening the technology to other banana cultivars would enhance the impact of the technology.

Key words: Impact, Tissue culture banana intervention, propensity score matching, propensity score matching (PSM), productivity income, food security, Kenya.

1. Introduction

Increasing agricultural production is a priority option for reducing the ever increasing food insecurity and poverty not only in Kenya but also in other sub-Saharan Africa countries. It is estimated that about 80% of people live and work in rural areas, and nearly 90% of the population within rural areas is inherently linked to agriculture as a main livelihood strategy (ROK 2004a; ROK 2007). Therefore, agriculture is perceived as a vehicle for economic growth at both household and national levels. One of the challenges in agriculture is that farm sizes are progressively declining not only among the predominantly large-scale farming systems but also in the pre-dominantly smallholder zones of Kenya (McIntyre 2009). Farm lands are being converted to residential plots, roads and other non-farming activities (FAO. 1995). This challenge demands innovativeness among farmers and other actors in upgrading agricultural product value chains, targeting not only yield-increasing but also value-adding technologies.

Efforts have been spent on up-grading banana production through development and disseminating technologies. One such technology is the Tissue culture banana. This study, is not only concerned with the assessing the likelihood of TCB, but also with, the intensity of adoption. It is recognized that Agricultural technology (like TCB) adoption has multiple benefits to the target communities (Wambugu 2004). The technologies were perceived to raise farm productivity, and subsequently increase household incomes, enhance food security, increasing employment through rapid multiplication of TCB plantlets and distributing them to farmers (Nyang 2010). However, the question is 'what are the factors influencing the adoption of the TCB given that the technology has not been fully adopted among the target groups?' The technology has also been modified through use of suckers. As documented by a number of authors agricultural innovations that seemed promising have been met with partial success, as measured by empirical analyses on their rates of adoption (Feder et al. 1985). Limited access to credit, inadequate farm size, risk aversion, inconsistent supply of complementary inputs like TCB plantlets and household labor mobility has all been shown to inhibit farmer household investment in agricultural innovations.

Several authors have summarizes the critical household characteristics influencing technology adoption in the developing (Feder and Slade 1984; Adesina and Zinnah 1993;

Adesina and Baidu-Forson 1995; Baidu-Forson 1999; Rogers 2003; Doss 2006). These authors indicated that there are four primary classes: physical and natural characteristics - area of land under cultivation, acreage, pre-adoption income/wealth and access to water year around. Human assets include; quality and quantity of household labor, the age of household head and years of education of household head were proxies for the quality of labor and household size and the dependency ratio were proxies for quantity of labor. Social assets included farmer's membership in groups and the number of extension visits. Financial assets were; farmer access to formal or informal credit, capital assets and the quality and ownership status of the home (Nowak and Korsching 1983). This research sought to explicitly model the probability and intensity of TCB adoption in selected parts of west Kenya using these factors. The study utilized this literature in designing the survey instrument and modeling the likelihood and intensity of TCB adoption.

2. Methodology

The Study Area

The study was conducted in four counties of West Kenya. The counties consist of 16 districts. Trans Nzoia county is the main maize producing and exporting region in Kenya located at latitude 0°52´-1°18´S, and longitude 34°38´-35°23´E with human population is about 818,757 and a density of 741 persons per square kilometer. Bungoma county lies between latitude 0^0 25.3' and 0^0 53.2' North and longitude 34^0 21.4' and 35^0 04' East. The county population is estimated at 1,630,934million in 2009. The populations density is evenly distributed with an average population density of 482 persons per square km. It covers an area of 2,068 km2. West Pokot county lies between Latitudes 1^0 10' and 30^0 40'N and Longitudes 34^0 50'and 35^0 50'E with a total area of 9,100 km. square. The area is popularly known for its maize, wheat, tea, sugarcane, dairy and banana production. Some of the common food crops grown in the area are; cassava, finger millet, sorghum, ground nuts and vegetables.

2.1 Analytical techniques

Technology adoption is perceived to be a mental process through which decision maker goes through from first learning about an agricultural innovation to its final adoption/use (Feder and Slade 1984). Ultimately the individual becomes a user of an innovation/technology. Rogers, and Adesina & Zinnah (1993) present a conceptual model based for the farmers' adoption decisions. According to these authors, the decision is based on the assumption of utility maximization which remains unobserved. The decision whether to adopt a new technology is based on a comparison of marginal/additional net benefits/utility of new technology against the old one. Let us define the old and new technologies by the symbols 'o' and 'n'. The preference of the $i^{th.}$ farmer (y_i) for the technology adoption is given by the difference between the marginal net benefits of adopting 'n' technology against that of adopting 'o' technology which is unobserved. $y_i >$ 0 corresponds to the net benefit of the technology (NB_{net}) exceeding that of the 'o' technology while NB_o refers to the net benefits of the 'o' technology being smaller than that of the 'n' technology. We may write the following equation 1.

$$NB_{NetBen} = NB_n - NB_o \qquad \text{Equation 1}$$

In modeling the utility or satisfaction derived from the use/adoption of TCB, the economic values or benefits associated with non-TCB cultivars such as *bogoya*, *bokoboko* and with the TCB is considered. A typical smallholder-farming household seeks to maximize a multi-dimensional objective function, including food insecurity reduction, and increasing incomes. When there is a change in economic parameters associated to TCB technology use, the central question is related to how much benefits are received by the decision maker or household. Thus the change in benefits associated with this adoption was used as the basis for economic valuation process. When a farmer faces a change in a measurable attribute, for example higher benefits from TCB cultivars (Q), then Q changes from Q_0 to Q_1 (with $Q_1 > Q_0$). The indirect utility function U after the change becomes higher than the status quo. Now the status quo can be represented econometrically as follows (Equations 2 to 4):

$$U_{TCB} = U_{TCB}\,(Z_i, Y_i, T_i, \varepsilon_i) \qquad \text{Equation 2}$$

$$U_{Non\_TCB} = U_{NonTCB}(Z_i, Y_i, T_i, \varepsilon_i) \qquad \text{Equation 3}$$

$$U_{Net} = U_{TCB} - U_{Non\_TCB} > 0 \qquad \text{Equation 4}$$

Where, U_{Net}, refers to the farmer's net utility associated with adoption of TCB, U_{TCB} utility associated with adoption of TCB, U_{Non_TCB} utility associated with adoption of non-TCB, Z_j is a vector of the farmer's socio-economic variables, Y_i is bio-physical factors and T_i are TCB technology attributes, and ε_i is the stochastic error term representing other unobserved utility components not capture in the model. The farmers opted to adopt TCB technology *if and only (ioi) if* the following condition held (equation 5):

$$U_{Non\_TCB} = U_{TCB}(Z_i, Y_i, T_i, \varepsilon_i) > U_{NonTCB}(Z_i, Y_i, T_i, \varepsilon_i) \qquad \text{Equation 5}$$

Since the random components of the preferences are not known with certainty, it is only possible to make probabilistic statements about expected outcomes of TCB adoption. Thus, the decision by the farmer to adopt TCB is the probability that the farmer will be better off if this TCB variety is used. This is represented as follows (Equation 6):

$$\Pr ob(TCB) = \Pr ob[\mathrm{U}_{\mathrm{TCB}}(\mathrm{Z}_{\mathrm{i}}, \mathrm{Y}_{\mathrm{i}}, \mathrm{T}_{\mathrm{i}}, \varepsilon_{\mathrm{i}}] > \mathrm{U}_{\mathrm{NonTCB}}(\mathrm{Z}_{\mathrm{i}}, \mathrm{Y}_{\mathrm{i}}, \mathrm{T}_{\mathrm{i}}, \varepsilon_{\mathrm{i}})] \quad \forall_i \text{ i= 1, 2, 3 ….n Equation 6}$$

The underlying factors influencing the farmers to decision whether to maximize the utility by growing/adopting a technology and in this case it is Tissue culture banana (TCB) variety in relation to a non-TCB variety can be affected by diverse factors. The preference of the $i^{th.}$ farmer for the adoption (Y_i) to choose TCB or non-TCB can be influenced by a number of factors as given in the subsequent section can be modeled as shown in equation Equation 8.

$$U_{TCB}(Z_i, Y_i,) = f(Xi) + \varepsilon_i \qquad \text{Equation 8}$$

Empirical data analysis

The Double-hurdle model was used in this study to determine the factors that influence the decision to adopt and the extent of adoption of TCB in order to identify factors influencing the up-scaling of the technology. The underlying assumption in the DHM approach is that farmers make two decisions with regard to their decision to grow TCB. The first decision is whether they will grow TCB and the second decision is about the amount of land allocated, conditional on the first decision. The two decisions were, therefore, whether to grow TCB and how many plantlets of TCB to grow. The importance of treating the two decisions independently lies in the fact that factors that affect one's decision to adopt may be different from those that affect the decision on how much to adopt. This implies that households must cross two hurdles in order to adopt any given technology like TCB. Subsequently, the first hurdle needs to be crossed in order to be a potential adopter. Given that the farmers are potential TCB adopters, their current circumstances then dictate whether or not and the number of TCB stools to grow and this is the second hurdle. The DHM for the possibility that these two decisions are affected by a different set of variables. The advantage with this approach is that it allows us to understand characteristics of a class of households that would never adopt the TCB innovation. Thus, the probability of a household belonging to a particular group is subject to a set of household characteristics.

Recent applications of the double-hurdle model include Jones (1992) for Tobacco, Gould (1992) for Cheese consumption, Blisard and Blaycock (1993) for Butter, Gao *et al.* (1995) for rice, Jenson and Yen (1996) for food expenditures, Yen and Jones (1997) for cheese, Kimhi (1999) for Tobacco, Newman *et al*. for prepared meals, Mofatt (2005) on loan, Martínez-Espineira for wildlife evaluation and by Rao and Qaim (2011) on supermarket revolution in Kenya. For charitable donations, the double-hurdle model has been applied by Jones and Posnett (1991) and Yen *et al*. (1997). In addition Asfaw *et al.* (2010), follow the same analytical model to analyze the determinants of adoption and intensity of Chickpea technologies in Ethiopia.

However, if it is expected that zero observations are due partly to non-participation for non-economic reasons, then the 'TCB technology adoption' model should be used. Technology adoption models assume that zero observations are either corner solutions or farmers who did not practice the technology (in our case, households that never planted TCB technology). In the double-hurdle model, coefficients in each hurdle are allowed to differ, and a change in a variable that is in both hurdles can affect the probability of adoption differently to the way it affects area allocated to the TCB technology. The benchmark model below using the double-hurdle model framework specified by Cragg (1971) is given as:

Farmer i's adoption equation in growing of TCB can be expressed as;

$d_i^* = \mathbf{z_i}\,\boldsymbol{\alpha} + v_i$ with $d_i = 1$ for adoption or 0 otherwise Equation 9

Farmer i's adoption intensity equation can be expressed as;

$y_i^* = \mathbf{x_i}\,\boldsymbol{\beta} + u_i$ Equation 10

Where y_i^* represents the latent participation decision, and d_i^* is a latent variable describing participation. $\mathbf{z_i}$ and $\mathbf{x_i}$ are vectors of exogenous variables, and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are parameter vectors. Random errors u_i and v_i are normally distributed as N(0, 1) and N(0, σ^2), respectively. It also is assumed that u_i and v_i are independent.

In the standard tobit model, a latent variable y_{i2}^* is assumed to represent a household's utility associated with consumption of a good. It is assumed that observed technology adoption of technology equals desired adoption for positive values of y_{i2}^*, but equals zero if otherwise. In the double-hurdle model a second latent variable, y_{i1}^*, or hurdle, associated with the decision to adopt is added. Positive levels of adoption are only observed if both hurdles are positive. Formally, the model is as follows:

$y_{i1}^* = \alpha w_i' + v_i$ (Participation in TCB growing equation) Equation 11

$y_{i2}^* = \beta x_i' + u_i$ (Intensity of TCB adoption equation) Equation 12

$y_i = \beta x_i' + u_i$ if $y_{i1}^* > 0$ and $y_{i2}^* > 0$ Equation 13

$y_i = 0$ Otherwise

$v_i \sim N(0,1)$ and $u_i \sim N(0, \sigma^2)$ Equation 14 where y_{i1}^{*} is the latent variable describing the household's decision to adopt TCB, y_{i2}^{*} is the latent variable describing the level of adoption, y_i is actual level of TCB adoption, w_i is a vector of variables explaining whether a household adopts TCB, x_i is a vector of variables explaining how much land the household allocates to TCB, and v_i and u_i are the error terms.

The decision to adopt TCB and the extend of TCB adoption are influenced by variables $w_i^{'}$ and $x_i^{'}$ respectively, which are allowed to overlap. Adoption of agricultural technologies including TCB, is influenced by factors that can be broadly may be divided into three general categories: technology characteristics; characteristics of the farming environment into which the technology is introduced; farmer characteristics market characteristics, and agro-ecological conditions (Morris 1999; Doss 2003; Xu 2009; Rao and Qaim 2011). Against this background several factors were identified to influence TCB as shown in Table 1.

The model assumes that both participation and intensity equations are linear in their parameters. Consistent estimates of the Double-Hurdle model can be obtained by estimating (or maximizing) the likelihood equation given in equation 15 (Blundell and Meghir 1987). This means that for farmers to plant at least a TCB banana, they have to overcome two hurdles namely: to decide to plant TCB or not (i.e. to be a potential TCB household), and then to decide how many stools to plant. As shown in equations 11 and 12, the estimation of the double-hurdle model requires specification of the error structure. One commonly made assumption about the structure is that the errors ε and u are independently and normally distributed equation 14 (Reynold 1990; Moffatt 2005). They estimated the double-hurdle model by specifying a bivariate normal distribution for the error terms, allowing for dependence between the participation and intensity decisions; the results however suggested independence between the two decisions. Besides normality, the error term u_i has been assumed to be homoscedastic in most of these applications. If these assumptions are not met it will lead to inconsistent parameter results (Blundell and Meghir 1987; Yen and Jones 1997). Independence was assumed in Cragg's original model and subsequently by Atkinson *et al*. (1984), Blundell and Meghir (1987), Blisard and Blaycock (1993) and Newman *et al*. (Moffat). Jones (1992), Yen and

Jones (1997), Kimhi (1999) and Martínez-Espińeira all modelled dependence but failed to improve on the independent model. An exception to the trend is from Gould (1992), who found that assuming dependence significantly improved the model. After the above specification adjustments, the log-likelihood function (Blundell and Meghir 1987) is written as follows:

$$L(\alpha,\beta,h,\gamma)=\prod_{0}\left[1-\Phi(w_i^{'}\alpha)\Phi\left(\frac{x_i^{'}\beta}{\sigma_i}\right)\right]\prod_{1}\left[(1+\gamma^2 y_i^2)^{-1/2}\,\Phi(w_i^{'}\alpha)\sigma_i^{-1}\phi\left(\frac{I(y_i)-x_i^{'}\beta}{\sigma_i}\right)\right] \qquad \text{Equation 15}$$

In which '0' indicates summation over the zero observations in the sample, while ''+'' indicates summation over positive observation. The Φ and ϕ symbols are the probability density functions and cumulative distribution function for a standard normal random variable respectively. $x_i^{'}$ is a vector of farmer characteristics relevant in explaining the intensity of TCB planted such as gender, education level, age of head the household, marital status, dummy variables like farmer location indicating county of residence, and occupation. β is the corresponding vector of parameters to be estimated. is the observed level of consumption expenditure.

Computation of marginal effects of Variables

In limited dependent variable models (like DHM), the effects of explanatory variables must be evaluated at the mean of the dependent variables. For the standard (homoscedastic and truncated normal) Tobit model, McDonald and Moffitt (1980) suggest decomposition of the unconditional mean of the dependent variable into the probability (of a positive observation) and the conditional mean. The effects of explanatory variables on these components can then be assessed (Yen and Jen 1995).

The estimated coefficients in the double-hurdle model cannot be interpreted in the same way as in a linear regression model. To assess the impact of the regressors on the dependent variable y, it was necessary to analyse their marginal effects. This involved decomposing the unconditional mean into the effect on the probability of TCB adoption and the effect on the conditional level of number of TCB bananas weighted on arable land and differentiating these components with respect to each explanatory variable. The unconditional mean can be written as:

$$E[y \mid x_i] = P(y > 0)E(y_i \mid y_i > 0) \qquad \text{Equation 24}$$

In this double hurdle model the probability of adoption and the intensity of adoption conditional on participation are (Yen and Jones 1997):

$$P(y_i > 0) = \phi(w_i{}' \alpha)\phi\left({x_i \beta}/{\sigma} \right) \qquad \text{Equation 25}$$

$$E(y_i \mid y_i . > 0) = \phi\left({x_i \beta}/{\sigma} \right)^{-1} \int_0^{\infty} \left[{y_t}/{\sigma \sqrt{1+\theta^2 y_t{}^2}} \, \phi\left[{T(\theta y_t - x_i{}' \beta}/{\sigma_t} \right] \right] dt \qquad \text{Equation 26}$$

For the continuous explanatory variables, these marginal effects are used to calculate elasticities at the sample means. For the discrete or categorical variables, the marginal effects are used to calculate percentage changes in the dependent variable when the variable shifts from zero to one, *ceteris paribus*. The elasticities of the double-hurdle model are given by the derivation of the unconditional mean with respect to the explanatory variables. The unconditional mean of *y* consists of the probability of *y* being uncensored and the conditional mean of *y*. Average partial effect of x_k is;

$$\frac{\beta_k}{N} \sum_{j=1}^{N} F(x_i \beta) \qquad \text{Equation 27}$$

If x_k is continuous; If x_k is discrete, the average partial effect is the average of the discrete differences in the predicted probabilities. An average marginal effect is an estimate of a population-averaged marginal effect. The mean marginal effect for a population. The distribution of the covariates must be representative to consistently estimate the population-averaged marginal effect. Mean partial effects and marginal effects at the mean are different quantities and can produce different estimates. The standard errors for the two marginal effects are estimated following the bootstrap procedures with 100 replications as recommended by Burke (2009).

Test for multi-collinearity

Multi-collinearity (Linear dependencies) is among prominent econometric problems of cross sectional data. This property of econometric was tested among variables to ensure the consistency and unbiaseness of the Probit model estimates. Linear dependencies among regression variables constraints separating out the effects of each independent variable on the dependent variable. Each independent variable may be nearly redundant in the sense that it can be predicted well using the others. This is the problem of multicollinearity. This problem may dramatically impact the usefulness of a regression model and lead to inappropriate conclusions being drawn from incorrect parameter estimates and confidence intervals, particularly, small changes in the data values may lead to large changes in the estimates of the coefficients. The problem is more likely to arise the more independent variables that there are in the model. It is thus important to test for multicollinearity and remedy it prior to regression modeling.

To detect multicollinearity problem for continuous variables, Variance inflation factor (VIF) for each coefficient in a regression as a diagnostic statistic is used. Here, R represents a coefficient for determining the subsidiary or auxiliary regression of each independent continuous variable ***X***. As a rule of thumb, Gujarati (Moffat) stated that if the VIF value of a variable exceeds 10, which will happen if R^2 exceeds 0.90, then, that variable is said to be highly collinear. Therefore, for this study, VIF was used to detect multi-collinearity problem for continuous variables. On the other hand, for dummy variables contingency coefficient was used.

It is important to check multi-collinearity problem for continuous and dummy variables before running the model. As Gujarati, (Moffat) indicates, multi-collinearity refers to a situation where it becomes difficult to identify the separate effect of independent variables on the dependent variable because there exists strong relationship among them. In other words, multicollinearity is a situation where explanatory variables are highly correlated. There are two measures, which are often suggested to test the existence of multicollinearity. These are Variance Inflation Factor (VIF) for association among the continuous explanatory variables and Contingency Coefficients (CC) for dummy variables. Variance inflation factor (VIF) is used to check multicollinearity of continuous variables. As R_j^2 increase towards unity, that is, as the collinearity of Xj with the other regressors increase, VIF also increases and in the limit it can be infinite. The larger the value of VIF, the more troublesome or collinear is the variable Xj. As a rule of thumb, if the VIF greater than 10, which will happen if Rj^2 is greater than 0.90, that variable is said to be highly collinear (Gujarati, 2003). Multicollinearity of continuous variables can also be checked using Tolerance. Tolerance is unity if Xj is not correlated with the other explanatory variable, whereas it is zero if it is perfectly correlated with other explanatory variables. The popular measure of multi-collinearity is defined as

$$VIF = \left[1 - R_j^{\ 2}\right]^{-1} \qquad \text{Equation 29}$$

Where, Rj^2 is the coefficient of determination in the Auxiliary regression

Contingency coefficient is used to check multi-collinearity of discrete variables. It measures the relationship between the two variables (raw and column variables) of a cross tabulation. The value ranges between 0-1, with 0 indicating no association between the two variables and value close to 1 indicating a high degree of association between variables. The decision criterion (CC < 0.75) is that variables with the contingency coefficient are computed as follows;

$$CC = \sqrt{\left[\chi^2 \big/ \left(N + \chi^2\right)\right]} \qquad \text{Equation 30}$$

Where, CC is contingency coefficient, χ 2 is chi-square test and N is total sample size. Statistical package for Social Science (SPSS) 12 was used to compute both VIF and CC.

Conversely, test for heteroscedasticity had undertaken for this study in the second hurdle. There are a number of test statistics for the detecting heteroscedasticity; According to Guiarati (2003) there is no ground to say that one test statistics of hetroscedasticity is better than the others. Therefore, due to its simplicity, Kroenker-Bessett (KB) test of heteroscedasticity was used for this study. Similar to other test statistics of heteroscedasticity, KB test is based on the squared residuals $\acute{u}^2$ However, instead of being regressed on one or more regressors, the squared residuals are regressed on the squared estimated values of the regressand.

2.2 Definition of Variables and Working Hypothesis

From the theoretical and conceptual model above, several hypotheses can be derived that merit empirical examination. These hypotheses can be divided between factors that affect adoption and those that affect the degree of TCB adoption. For Logit estimation, a household was regarded as an adopter of TCB if and only if he/she was found to have planted at least one TCB cultivar using original TCB plantlets. Those who used TCB suckers from TCB plantlets were treated as non-adopters. In this study the dependent variable in this model was a binary choice variable which was 1 if a household planted TCB and 0 if otherwise. For the second hurdle (truncated Tobit model), TCB adoption became continuous and the dependent variable was the number of TCB stools weighted on the arable land per household. It is recognized that there is no firm economic theory that dictates the choice of which explanatory variables to include in the double-hurdle model to explain technology adoption behaviour of farmers. However, the adoption of agricultural technologies is influenced by a number of interrelated factors within the decision making environment in which farmers/households operate. For instance, Feder *et al.* and Adesina (1995) identified lack of credit, limited access to information, aversion to risk, inadequate farm size, insufficient human capital, tenure arrangements, absence of adequate farm equipment, chaotic supply of complimentary inputs and inappropriate transportation infrastructure as key constraints to rapid adoption of innovations in less developed countries. However, not all factors are equally important in different areas and for farmers with different socio-economic situations. The household characteristics deemed to influence TCB adoption in this study include household heads characteristics (age, gender and education) and household size.

Dependant variable

The dependent variable for the DHM analysis was dichotomous in nature in the first hurdle representing farmer's adoption of TCB and in the second hurdle the level of adoption which in this case was the number of TCB stools planted weighted on the arable land under each household. This was to distinguish or discriminate between those who had adopted TCB and those who had not in the study area. The dependent variable took a value of “1” for adopters and “0” for non-adopters of TCB while in the second hurdle it was the number of TCB planted by each household.

Explanatory variables of the study

Review of literatures on factors influencing farmers’ access to technologies and the author's knowledge of the adoption studies area were used to establish working hypotheses of this study. It is recognized that, the observed adoption choice of an agricultural technology like TCB was hypothesized to be the end result of socio-economic characteristics of farmers and a complex set of inter-technology preference comparisons made by farmers (Adesina and Baidu-Forson 1995). Several hypotheses were derived on the decision factors that affected the probability and intensity of adoption of improved maize varieties (Table 2). In this study, the following hypotheses are used as a priori expectations. Among number of factors, which have been related to farmers’ access to TCB, in this study, the following demographic, socio-economic, communication and institutional factors were hypothesized to explain the dependent variable.

Working hypotheses

Age of the farm household head-This was a continuous variable, defined as the farm household heads’ age at the time of interview measured in years. Farmer's age may negatively influence both the decision to adopt and extent of adoption of improved maize varieties. It was hypothesized that older farmers are more risk averse and less likely to be flexible than younger farmer counterparts and thus have a lesser likelihood of adopting new technologies like TCB.

Sex of Household head-Gender consideration in technology development and dissemination is critical. This variable was a dummy variable that assumed a value of “1” if the head of the household was male and “0” female. From earlier studies, there were two major factors which restricted women’s access to new technologies more than men.

These were related to women’s lack of control over production resources and social capital (eg land, attending meetings for new knowledge). With this background including the existing gender differences; male headed households have mobility, participate in different meetings and had more exposure to information related to TCB; therefore it was hypothesized that male headed households had more access to use TCB than men.

Education level-Education augments one's ability to receive, decode and understand information relevant to making innovative decisions (Wozniak 1984). Thus, it is hypothesized that farmers with more education are more likely to be adopters than farmers with less education. It was assumed that educated people were able to read and write. The three levels of education were 0=none, 1=primary, 2=secondary and 3=post secondary. Of the three variables only two entered the model to avoid the dummy variable trap. Farmers with higher education were assumed to read and write and were expected to have more exposure to the external information and therefore accumulate new knowledge on agricultural innovations like TCB. For example the educated people had the ability to analyze costs and benefits of new innovations. The more educated the household head was the more likely he will use adopt a new technologies like TCB.

Family labor-Family size, a proxy to labor availability, may influence the adoption of new technologies positively as its availability reduces the labor constraints faced in banana production. The family size referred to the total number of family members/persons of the household who could work on the farm. This was measured in measured in man equivalent. The larger the number of family labor, the more the labor force available for agricultural production purpose. In addition, the more the family labor force available, the lower was the demand for hired labor. This meant that no or low cost for hired labor for households with large family sizes. If demand for hired labor decreased due to availability of family labor the need for TCB decreased. Therefore, family labor was hypothesized to have negative impact on access to TCB.

Hired labour-Hired labor use, may influence the adoption of new technologies positively as its availability reduces the labor constraints faced in banana production. Adoption of TCB was hypothesized to demand additional labour in planting, weeding and harvesting including packaging for sale.

Marriage status of HoH- Marriage was hypothesized to influence the adoption of TCB positively or negatively.

Fertility-(Tolerance to poor soil): Fertility conditions are hypothesized to be positively related to the probability and use intensity of TCB varieties. If farmers perceived that improved TCBs have larger bunch and finger and are as good as and palatable as the local varieties, rate and intensity of adoption are expected to be higher.

Off-farm income-The availability of off-farm income can affect the probability of adoption positively since it can increase the farmer's financial capacity to pay for improved inputs like buying TCB plantlets, fertilizer, manure and hiring labour.

Plantlet price-Since improved banana planting material, TCB are more expensive relative to banana suckers, cost of planting material was hypothesized to negatively influence the adoption of TCB technology. The price of TCB plantlets was perceived to enhance the likelihood and extend of adoption of TCB. The lower the price the higher the adoption and vise versa.

TCB plantlet availability- in order to make use of technologies, farmers should be able to get planting material either in the formal or informal distribution systems. Thus, seed availability is hypothesized to positively influence the adoption of TCB technology.

Extension contact-Agricultural extension may also enhance the efficiency of making adoption decisions. Based on the innovation-diffusion literature (Adesina and Forson 1995), it was hypothesized that extension visit is positively related to adoption by exposing farmers to new information and technical skills. In this study, this referred to the number of extension contacts with the respondent in a year. Farmers who had frequent contacts with extension agents were expected to have more information on TCB and therefore they would influence farm household’s demand for new technologies like TCB.

Participation of households in TCB production-This was a dummy variable which took a value “1” and “0” for TCB participants and 0=otherwise (control group). If a household participated in TCB project, then it is expected to have good knowledge on the benefits of TCB. Therefore, it was expected that, this variable positively influenced farmers to expand the area under TCB.

Membership in farmer groups-This is a dummy variable which took a value “1” for membership and “0” otherwise. Some of the households were members of merry-go-round group which could provide multipurpose services. Therefore, it was hypothesized that farmers who are members of groups had more access to new technologies like TCB.

Experience in banana farming-This refers to the number of years the household head had been involved in banana farming. A farmer having more experience in banana farming had higher tendency towards using the new technologies and vice versa. Hence, this variable was assumed to have positive influence on the dependent variables.

Experience in farming-This referred to the number of years the household head had been involved in farming. A farmer who had more experience in farming had higher tendency towards using the TCB technology and vice versa. Hence, this variable was assumed to have positive influence on the dependent variables.

Farm size in hectare-This is the total land size owned by the household head. It was a continuous variable. The larger the farm sizes the more the likelihood of allocating more land and accompanying resources to TCB. The main hypothesis was that the farmer who cultivates larger size of land can utilize more capital and will demand for TCB and therefore he/she will be more accessed to TCB.

Total livestock ownership-This referred to the total number of animals possessed by the household measured in tropical livestock unit (TLU). Livestock is considered as another asset which could be liquidated as security against emergency. In addition livestock manure could be used add nutrient to the banana fields. As the total number of animals in the household increases, the household would be less likely to go for new technology. This could be attributed to increase wealth and income base of farm households which makes more money available in the households that minimizes demand for innovation. Hence this variable was assumed to have negative influence on the dependent variable.

Attitudes towards TCB index-The other factor, which was perceived to influence the household’s access to TCB, was their attitude on TCB pests and diseases tolerance. Many farmers, as can be expected, had perception of TCB being tolerant to pests and diseases. This is because TCB was assumed to be clean without any infections with no pest and insect damage. It was measured based on the farmer’s positive or negative perception.

This was rated on scale of 1-5. Therefore, it was expected that farmers who rated TCB as tolerant were likely to adopt TCB.

Price of banana fruits-Price in the banana fruits in the market may also have a direct impact on the adoption behavior of farmers. If farmers perceive that there will be attractive price for the banana fruits, the probability of adoption and proportion of banana area under the TCB cultivars would increase.

An index on TCB characteristics-(Tolerance): If farmers perceive that a certain banana variety has better diseases, pests, and lodging tolerance, Better yield potential (finger size, bunch size) and storability, early maturity there will be higher probability for adoption of such banana varieties. This was a summation of all the attributes of TCB and since they were 8 attributes the maximum score was 56.

Farmers access to credit (CREDIT)-smallholder farmers are expected to form a group (that can serve as collateral) to take credit from different credit sources. But farmers perceived that credit was difficult to access credit from these sources. It is a dummy variable which takes a value "1" for those who received credit and "0" otherwise. Therefore, it was expected that farmers who are unable to get credit were not able to use formal credit.

Farmers perception of TCB (FPPERF)-farmers were expected to have good knowledge on benefits of TCB. Therefore, it was expected that farmers who had positive information on TCB rated it high

Physical distance of farmers from TCB sources (DINST)-Farmers near the TCB plantlet materials had the advantage of reducing cost of transportation and were likely to acquire it cheaply than those who lived more distant locations. Therefore, location advantage was expected to increase access to use TCB.

Distant to markets-Access to good infrastructure can form a backbone for rural household commercialization. Farmers will grow perishable crops for markets only when they are assured that they can market them easily. "Distance to fertilizer shop" in the last cropping season was used to proxy access to market. Distance to the nearest road is used as a proxy for the cost of taking the produce to the market. The hypothesis is that good infrastructure has a positive impact on the decision to engage in commercial horticulture production or a shift from subsistence TCB to a more commercial TCB orientation.

Off-farm employment-Rain-fed agriculture is highly seasonal, carries some inherent risk, and is characterized by lumpy cash flows. In the absence of well-developed markets coupled with lack of formal farm insurance, farmers will tend to self-insure. One form of self-insurance is engaging in off farm employment. In poor countries where agriculture marketing is in the initial stages of development, other sources of income like salaries and transfer payments are very significant. However, the way they affect agricultural commercialization is very ambiguous. The extra income could be used as an important source of income when it comes to investment in farm enterprises. In other cases where the investment is labor intensive with close management required then they will be negatively correlated with commercial crops. Then non-farm income could play an important role in enterprises choices and investments decisions.

Proportion of banana revenue to total farm income-Proportion of income from banana was hypothesized to influence farmer's adoption of TCB. This is because of the high yielding attributes of TCB.

Table 1: Description of Variables Explored used in TCB impact assessment

	Type	
Dependent		
PARTCP	Dummy	1=TCB growing; TCB; 0=otherwise
No of TCB stools	continuous	Number of TCB stools
Independent		
TREAT	Dummy	Dummy farm type 1=Treated; 0=otherwise
LnINTENSITY	Continuous	Log of Number of stools per arable land in ha.
LNBANAREA	Continuous	Log of banana area in ha
Q1RESEX	Dummy	Head of household sex 1=female
LnHHAGE^2	Continuous	Log of Age of head of household in year squared
Q1HHEDUC	Dummy	Head of household education level
OCC_OFF	Dummy	Occupation of HHH –off-farm income
OCC_PTY	Dummy	Occupation of HHH-farming
Q1HHHMAR	Dummy	Marital status of HHH 1=married
Q1FAML	Continuous	Family size
PEROD	Continuous	Period grown banana in years
LnPERIODV2	Continuous	Log of Period grown banana in years
LnHECT	Continuous	Log of farm size in ha.
LnQ2AR_HA	Continuous	Log of arable land in ha.
owtitle	Dummy	Land tenure 1=own with title;0=otherwise
Q2FERT	Continuous	Fertility level of the farm
Q2LABHR	Dummy	HH hired casual labour

Q2LABFAM	Dummy	HH only uses family labour
Q8TCAVL	Dummy	Availability of TCB plantlets
LnQ9DIST2	Continuous	Distance to TCB plant source
LnQ10BPRC_A	Continuous	Price of banana plantlets
CREDIT	Dummy	Used credit access to buy TCB
MANUREDM	Dummy	Used manure to plant
FERTBDUM	Dummy	Used inorganic fertilizer to plant
LnBANPROP	Continuous	Log of Proportion of banana revenue to total farm revenue
AVEINDEX	Continuous	TCB banana attributes index
overinde	Continuous	Overall perception index of banana benefits
lnPCDy	Continuous	Per capita consumption expenditure in KES
trandumm	Dummy	Trans Nzoia county dummy
bundumy	Dummy	Bungoma county dummy
kisidumy	Dummy	Kisii county dummy
wpokdumy	Dummy	West Pokot county dummy
dismeext	Dummy	Dissemination pathway to government extension dummy
dismefam	Dummy	Dissemination pathway Farmer-to-farmer extension dummy
dismemas	Dummy	Dissemination pathway Mass media dummy
dismeres	Dummy	Dissemination pathway research dummy

A summary description of the explanatory variables used in the model is presented in

Table 2: Descriptive Statistics

Variable	Definition	N	Min.	Max.	Mean	S D
TREAT	Dummy farm type 1=Treated; 0=otherwise	330	0.00	1.00	0.2000	.40061
LnINTENSITY	Log of Number of stools per arable land in ha.	330	0.00	6.85	0.7259	1.60944
LNBANAREA	Log of banana area in ha	330	-5.298	1.386	-.40935	1.118685
Q1RESEX	Head of household sex 1=female	330	0.00	1.00	0.4091	.49241
LnHHAGE^2	Log of Age of head of household in year squared	330	6.27	9.00	7.8092	.53805
Q1HHEDUC	Head of household education level	330	0.00	3.00	1.6121	.84399
OCC_OFF	Occupation of HHH –off-farm income	329	0.00	1.00	0.1489	.35657
OCC_PTY	Occupation of HHH-farming	329	0.00	1.00	0.0851	.27946
Q1HHHMAR	Marital status of HHH 1=married	330	0.00	1.00	0.8455	.36202
Q1FAML	Family size	330	2.00	17.00	7.0484	2.58867
PEROD	Period grown banana in years	230	1.00	50.00	14.2663	11.15003
LnPERIODV2	Log of Period grown banana in years	330	1.00	50.00	12.6375	10.02324

Variable	Definition	N	Min.	Max.	Mean	S D
LnHECT	Log of farm size in ha.	330	-2.54	6.56	.1365	1.47341
LnQ2AR_HA	Log of arable land in ha.	330	-4.62	6.56	-.0537	1.43057
owtitle	Land tenure 1=own with title;0=otherwise	330	0.00	1.00	.5455	0.49869
Q2FERT	Fertility level of the farm	328	1.00	3.00	2.1341	0.54210
Q2LABHR	HH hired casual labour	330	0.00	1.00	.7182	0.45057
Q2LABFAM	HH only uses family labour	330	0.00	1.00	.8727	0.33378
Q8TCAVL	Availability of TCB plantlets	330	0.00	1.00	.1909	0.39361
LnQ9DIST2	Distance to TCB plant source	330	-3.91	6.40	.8387	1.57268
LnQ10BPRC_A	Price of banana plantlets	330	0.00	5.52	1.9473	2.15675
CREDIT	Used credit access to buy TCB	118	0.00	1.00	0.1525	0.36108
MANUREDM	Used manure to plant	329	0.00	1.00	0.8845	0.32011
FERTBDUM	Used inorganic fert to plant	329	0.00	1.00	0.1550	0.36247
LnBANPROP	Log of Proportion of banana revenue to total farm revenue	330	-3.40	4.61	2.5061	1.99910
AVEINDEX	TCB banana attributes index	330	0.0	152.5	24.119	16.3335
overinde	Overall perception index of banana benefits	330	0.0	29	14.30	9.231
lnPCDy	Per capita consumption expenditure in KES	330	4.343	14.944	9.146	1.648
trandumm	Trans Nzoia county dummy	330	0	1	0.49	0.501
bundumy	Bungoma county dummy	330	0	1	0.13	0.340
kisidumy	Kissi county dummy	330	0	1	0.15	0.362
wpokdumy	West Pokot county dummy	330	0	1	0.22	0.416
dismeext	Access to government extension dummy	330	0	1	0.49	0.501
dismefam	Farmer-to-farmer extension dummy	330	0	1	.09	.288
dismemas	Mass media dummy	330	0	1	.14	.350
dismeres	Research dummy	330	0	1	.02	.144

3 Results and discussions

3.1 General socio-economic characteristics of respondents

Shown in Table 3, are the general socio-economic characteristics of the respondents. The average household size was for TCB practicing farmers was 6.9 while those non-practicing one was 7.2 with an over all mean of 7.0 members. The age of those farmers who were not practicing TCB was 51.2 years while those were not was 51.6 years with an overall mean age of 51.4. The distance to the banana selling markets was 38km for those who planted TCB while for those who did not was 14.3 km. The pooled mean for market distance was 37.1. The period of planting bananas for TCB adopters was 33 years while those for non-adopters was 12.9 years with an average pooled mean of 23 years. The average number of years in planting TCB bananas was about seven years. The number of years in farming was 22 years for non-TCB adopters while those who had adopted TCB was 20 years. The overall mean period in years for respondents was 20 years. The average number of livestock for TCB adopters was 7.5 while that for non-adopters was 4.4. The average farm size was about 10.6 acres for TCB adopters while that for non adopters was 6.7 acres with an overall mean of about 8.8. On the other hand the average arable land for adopters was 8.7 acres while that of non-adopters was 5.2 with an overall mean of 7.1 acres. The main occupation for adopters was 73.1 (farming), and 17.2% (off-farm) while for non-adopters was 72.2% (farming) and 12.7% (off-farm). The proportion of male headed respondents for adopters was 45% while for non adopters was 37%. Across all the groups majority of farmers had attained at least primary level of education. Most of the respondents 52% for adopters and 61% for non adopters) had land title deeds. Most of the farmers perceived fertility level of farmers to be at least from medium to high (89% for adopters and 98% for non adopters). The proportion of household using family labour was about 84% for both groups and those using hired labour was higher in TCB practicing farmers (79%) compared to those who were not planting TCB (66%).

Table 4: Descriptive statistics sampled farmers and farm characteristics by participating and non-participating groups.

	Participating in TCB n-65		Non-participating in TCB n=149		Full sample n=330	
	Mean	SD	Mean	SD	Mean	SD
Family size	6.892	2.36204	7.205	2.83356	7.0368	2.5910
Age of HoH-years	51.2209	13.2580	51.604	13.4330	51.3988	13.3202
Distance source -km	38.3208	93.81560	14.2857	20.04756	37.1104	916527
Period planted bananas-years	32.6456	194.2597	12.9388	10.82553	23.0373	139.2844
Period planted TCB-years	6.5138	5.22180				
Period in farming-years	20.2669	14.04456	21.5798	12.34634	20.8521	13.3062
Livestock ownership (TLU)	7.4583	16.02322	4.3956	3.86689	6.0578	12.1607
Farm size in ha	10.6901	65.54834	6.6656	40.81992	8.8104	55.3439
Arable area_ha	8.6554	58.95581	5.2659	33.56793	7.0521	48.5842
Number of banana stools	126.663	458.5245	35.4595	51.99652	84.1348	340.1497
Number of TCB banana stools	131.269	586.859	…	…	54.0123	375.7650

TCB performance index		26.949	18.2190	20.750	13.2626	24.0980	16.401
Main occupation HoH %	Farming		73.6		72.7		73.1
	Petty trade		5.2		12.7		8.6
	Off- farm		17.2		12.7		1.5
Gender of HoH %	male		45.2		37.2		82.5
	female		16.0		19.3		17.5
Education HoH %	None		3.4		6.7		4.9
	Primary		44.6		50.7		47.4
	Secondary		26.9		30.7		28.6
	Post secondary		25.1		12.0		19.1
Land tenure %	1=with title		52.1		61.3		56.1
	0=without		47.9		38.7		37.1
Fertility %	low dummy		10.4		7.3		9.0
	medium dummy		67.6		70		68.7
	High dummy		22.0		27.7		22.3
Labour source %	family		83.9		83.5		83.7
	hired		78.6		65.5		73.8
TCB plantlet availability %			44.9		12.5		43.2
Proportion Banana revenue-farm		54.223	41.73887	42.936	43.587		

3.2 Awareness and Adoption TCB Technological components

Farmers' awareness of new technologies is an essential step toward their adoption (Dimara and Skuras, 2003). Overall most farmers were aware of TCB technology through several information sources These sources included resrach institutions, Extension agents both government and NGO), radio programmes, and fellow farmers (either neighbours or early adopters). Other common information sources include Field days, and ASK shows.

Table 5 shows the adoption levels of technological packages of bananas. Out of 330 farmers interviewed 66 (31%) of them used TCB plantlets and 89% used TCB suckers to plant bananas while those who used normal suckers were 68%. Besides, 45.3% of the respondents indicated that they could TCB planting materials were easily available despite the distance and transportation costs. The sources of cash to buy TCB plantlets was 16.1%, 37.5% and 46.4% for credit, own savings and farm sales respectively, The proportion of farmers with banana spacing ranging from 9 to 16 square meters was 32.7% while 637.3% were outside this range. The average mean banana spacing was 10 square meters. The proportion of farmers using basal and top-dress inorganic fertilizers was 15.7% and 8.3% respectively. About 29.2% of respondents were practicing earthing up banana stools. The majority (60.1% were propping bananas while 39.1% were not. About 44.1 of the farmers practiced disease control in their banana orchards.

Table 6: Levels of adoption of banana technological components

Technological component	%response n=330
Planting material-use of TCB plantlets (yes=1)	31.7
Planting materials-use of Suckers (yes=1)	68.3
Availability of planting material (yes=1)	45.3
Sources of cash for purchase of plant materials-credit (yes=1)	16.1
Sources of cash for purchase of plant materials-own savings	37.5
Sources of cash for purchase of plant materials-farm sales	46.4
% farmers with Spacing 9-16M^2 (yes=3_4 by 3_4M^2)	32.7
Mean banana spacing meters square	10.1
% farmers using manure (yes=1)	88.3
% farmers using Inorganic basal fertilizer (yes=1)	15.7
% farmers using Inorganic top-dress fertilizer (yes=1)	8.3
% practicing earthing-up	29.2
Pruning of bananas –number of plants per stool	6.3
% response Earthling up of bananas (yes=1)	29.2
Propping of bananas (yes=1)	60.1
Pest control (yes=1)	33.9
% response with disease control (yes=1)	44.1

3.3 DHM Model Results

Prior to running the DH model multicollieraity test was used. Table 6 presents the VIF test result for collinearity of variables used in the two hurdles with respect to the two dependent variables. The result reveals that there was no significant collinearity between the specified explanatory variables and the dependent variables in the two hurdles. The VIF indicators showed that there was no serious multocollineraity since none of the variable was above 10. The result implies that the estimates of the two models to an appreciable extent are consistent and probably unbiased. The results for dummy variable using correlation analysis also showed that there was low multicollinearity.

Table 6: Variance inflation factors (VIF) of the continuous explanatory variables Multi-collinearity test result for continuous variables (n=330)

	Collinearity Statistics	
Variable	Tolerance	VIF
q1hhage	45.99	0.021744
q1hhage2	45.70	0.021882
q2ar_ha	23.01	0.043465
hect	22.95	0.043573
aveindex	1.17	0.851311
overinde	1.17	0.854231
banprop	1.14	0.878695
q1faml	1.08	0.929894
perod	1.03	0.966823
q9dist	1.02	0.966823
_cons		

Source: survey data, 2011.

Table 7 presents results of the Cragg -Tobit alternative model of household participation in TCB. Tiers 1 and 2 are maximum likelihood coefficients of the determinants of probability of engagement in TCB and the intensity of TCB use respectively.

Analysis of the Probit Model Results (*First hurdle)*

The logit model proposed for the first stage of the double hurdle to predict farmer's likelihood of adopting TCB Banana technology. Out of the 20 variables in the model, five were significant at $p<0.10$ levels. The analysis showed that the variables that significantly influenced the probability of TCB adoption were; availability of TCB planting material (q8tcavl), proportion of banana income to the total farm income (lnbanprop), per capita household expenditure (Lnpcdy), and the location of the farmer in Kisii County (Kisidumy).

Accessibility of TCB plantlets to farmers was hypothesized to positively influence TCB adoption. The planting material was to be availed to farmers either through formal or informal distribution systems.. The study findings revealed that this variable positively, and significantly ($p\leq0.01$) influenced farmers to plant TCB. Meaning that enhanced accessibility of TCB banana plantlets increases the likelihood of farmers adopting TCB technology. This is in line with the upgrading strategies by ISAAA and KARI partnership activities of promoting TCB (Manyangarirwa 2006).

Results from this study, also showed that the variable farmer's who are location in Kisii County was positive and significant ($p \leq 0.10$). This implied that farmers' location in the Kisii County were more likely to participate in TCB technology production than those located in other areas. This is consistent with the fact that that these region (Kisii county) and its environment have a favourable banana production zone and also it is one the main banana growing regions in Kenya with relatively small-scale farms compared to west Pokot, Bungoma and Trans Nzoia counties. Farmers in Kisii region sell a lot of bananas in other regions of Kenya like Nairobi and Kisumu. This trade orientation significantly contributes to farm revenue and probably the likelihood in TCB participation.

The proportion of income received from bananas (lnbanprop) was perceived to significantly influence adoption of TCB. From the results the variable was positive and significant ($p \leq 0.10$) implying that income from bananas encouraged farmers to grow to adopt new innovations like planting TCB.

Per capita household expenditure (Lnpcdy) was positive and significant ($p \leq 0.10$). This indicated that the higher the per capita household expenditure the higher the likelihood of farmers adopting TCB technology. This could be attributed to the fact that income from TCB technology could be used in meeting household expenditure.

Contrary to expectations hypothesized to influence the likelihood of TCB adoption but were not significantly different from zero and negatively influenced the likelihood of TCB adoption were: use of family labour (q2labfam), hiring of labour (q2labhr), marital status (q1hhhmar), food security (q33fdsht), family size (q1faml), Bundumy, TCB plantlet price (lnq10bprc_a), and farm size (Lnhect), Those variables that were not significantly different from zero and positive were: age of HHH (lnhhage2), sex of HHH (q1hhsex), education level of HHH (q1hheduc), off-farm occupation of HHH (occ_off,) use of manure (manuredm) and inorganic fertilizer use (Fertbdum). This suggests that all these variables did not change the likelihood of TCB adoption as compared to non-adopters. Surprisingly, the plantlets price which ranged from KES 70 to KES 180 per plantlet was negative and non-significant. The statistical insignificance of these variables leads one to conclude that probably price is not an issue in TCB adoption and the problem could be distribution and access of the planting materials.

Implications of the Logit Model

The Logit model, as utilized in this first state, provides fairly accurate predications of the type of farmer most likely to adopt a TCB technology in the Kenya. Marginal effect estimates suggest that the variables most impactful on the probability of adoption include farm size, crop mix and livestock sales as a percent of total sales. Age also is important, with younger farmers more likely to adopt. While education was not statistically significant at the 0.10 level, its relatively high t-value suggests further studies more focused on education are warranted. The same may also be said of the tenancy percentage another variable insignificant in this probit, but with a moderately high t–value.

The Second Stage Model (Second hurdle)

This second stage model explored TCB intensification among farmers (Table 16). Because this analysis considers only TCB adopters, this model is conditional on the first stage model. This second stage model uses truncated Tobit regression method. The number of TCB stools weighted on acreage under arable land per farmer was used in this second as dependent variable. The farmers were asked the number of stools planted and the area under arable land. The number was weighted on the arable land planted because in a number of farmers the bananas did not have specific plots but were inter-planted among other crops or planted on single rows with varying intra- and inter-plant stools. Subsequently, in this second model the farmers were pruned from 330 to 66 the TCB adopters only. The adopters were those farmers who planted TCB bananas using TCB plantlets. Those who used TCB suckers were considered non-adopters. The variables involved in this intensity adoption model were: TCB banana plantlet price (lnq10bprc_a), age of the household head (lnq1hhage), off-farm as main occupation of the HHH (occ_off), farming as the main occupation of HHH (ocup_far), family size (q1faml), total farm area (lnhect), perceived fertility level of the banana plots (q2fert), use of hired labour (q2labhr), use of family labour (q8tcavl), distance to banana product markets (lnq9dist2), use of manure (manuredm), use of inorganic fertilizer (fertbdum), proportion of income from bananas (lnbanprop), government extension (dismeext), farmer-to-farmer extension (dismefam), average index on TCB banana crop (aveindex), overall index on the benefits/advantages of TCB) (overinde), a dummy location of farmer in Trans Nzoia county (trandumm), a dummy location of farmer in in Bungoma county (bundumy) and a dummy location of farmer in in Kisii county (kisidumy). Out of the 20 variables considered in this model 11 were significant ($p \leq 0.10$).

Eleven factors (occ_off, Ocup_far, q1faml, Lnhect, q2fert, q8tcavl, lnq9dist2, Manuredm, Dismeext, Aveindex, Bundumy) were found to significantly influence the TCB adoption intensity. The variable off-farm as main occupation of farmers (cook-off), was positive and significant ($p \leq 0.01$). Probably this implied that those farmers who engaged in off-farm occupation were likely to intensify TCB production by expanding banana acreage using the superior TCB plantlets for enhanced production. This is in line with the working hypothesis as these farmers are likely to have additional income which enhanced their purchasing power to buy TCB plantlets. This is also in line with economic theory that more income means higher purchasing power for consumers.

The variable farming as main occupation of farmers (ocup_far), was positive and significant ($p \leq 0.05$) implying that those farmers who were fully engaged in farming as the main occupation for intensifying TCB banana production. Given that banana production is increasing being commercialized in Kenya, the productivity enhancing TCB technology is likely to be adopted by farmers who are inclined to farm income generation activities.

The variable use of family members as main labour source on the farm (q1faml), was positive and significant, ($p \leq 0.01$). This implied that the higher the family sizes the higher the TCB intensification. This is because the variable was a proxy for not only consumer units but also a source of farm labour. The higher the family size the higher the demand for TCB banana for food and also probably supply for labour to work in TCB production. Availability of labour is crucial in enhanced investment in TCB intensification and subsequently commercialization.

The variable farm acreage (lnhect), was negative and significant ($p \leq 0.01$). The higher the farm size the lower the TCB technology intensification compared to large farm sizes. Farmers with smaller farm sizes were likely to intensify TCB technology which is a source food and surplus for sell to meet household financial obligations. This in line with project objectives in alleviating food security among the smallhoder farmers in the region (Mbogoh 2003; Wambugu 2004).

The variable farm fertility level (q2fert), was negative and significant, ($p \leq 0.05$). This implied that the lower the perceived fertility level the lower the TCB intensification and vice versa. Since bananas generally require relatively high fertility levels, if the farms are relatively low in fertility levels then expansion of TCB is likely to be low because of the poor productivity. This could also be attributed to low production of TCB technology under low fertility regimes. Reversing this trend requires optimal application of organic and inorganic fertilizers.

The variable availability of TCB plantlets to farmers (q8tcavl) was positive and significant, ($p \leq 0.05$). Enhanced access of farmers to TCB technology increased the intensification of TCB. This is in line with the hypothesis because the demand for TCB is progressively increasing against the low supply. The demand for some varieties like Grand Naine outstripped supply in main supply centres. In some situations the farmers book in advance.

The variable distance to banana market (lnq9dist2), was negative and significant, ($p \leq 0.10$). The more the distances to the product market the less likelihood of TCB intensification. The longer the distance the more the transaction costs and the less the profit that accrue to the farmer. This could act as a disincentive to expand the TCB technology. This demanded the opening up of more banana markets and value addition technologies including packaging to increase farmers' profit margins.

The variable, use of manure in planting bananas (manuredm), was positive and significant, ($p \leq 0.01$). This implies that farmers who applied manure were likely to intensify TCB banana technology. This could be attributed to the fact that manure was easily available and also not expensive among farmers in the study region. This contributes to the enhanced use of manure among farmers who were expanding TCB technology.

The variable contact with agricultural extension services (dismeext) was positive and significant, ($p \leq 0.05$). Contacts with Government extension agents enhanced the intensification of the TCB technology. This is true given that government extension agents are represented up to sub-locational. They also play a lead role in promoting the TCB technology in partnership with other agents along the banana value chain.

The variable average index technology attributes (aveindex) was negative and significant, ($p \leq 0.05$). This index measured the technological attributes of TCB technology. The likert scale rating ranged from 1 to 4 (1=very poor; 2=Poor; 3=Good; 4=Excellent). The technological attributes considered were; disease-tolerant, pest–tolerant, yield potential, sweetness, cookability, lodging, suckering ability, finger size, finger length, bunch size, feed for livestock, drought- tolerant, maturity period, ripening and storability. The index was computed by summing up the farmers' scores against each of the attributes.

The variable bundumy was positive and significant ($p \leq 0.05$). This implied that being a farmer in Bungoma enhanced the TCB technology intensification. This could be attributed to low levels of banana acreage in the region against the competing crops like sugarcane.

Table 7: Parameter estimates of the generalized double hurdle model of TCB adoption in Kenya

	Coef.	Std. Err.	Z	P>z	[95% Conf.	Interval]
Tier1: Dummy 1=TCB: Probability of Adoption: Dependent variable=Whether a farmer adopted TCB technology						
lnq10bprc_a	-0.02323	0.048779	-0.48	0.634	-.1188318	0.072377
lnhhage2	0.101033	0.192421	0.53	0.600	-.2761054	0.478172
q1hhsex	0.37717	0.300848	1.25	0.210	-.2124821	0.966821
q1hheduc	0.16086	0.125279	1.28	0.199	-.0846825	0.406402
occ_off	0.039117	0.283012	0.14	0.890	-.5155773	0.593811
q1hhhmar	-0.16682	0.302628	-0.55	0.581	-.759955	0.426324
q1faml	-0.06077	0.039893	-1.52	0.128	-.1389607	0.017419
Lnhect	-0.00495	0.079818	-0.06	0.951	-.1613878	0.151494
q2labhr	-0.26542	0.215541	-1.23	0.218	-.6878724	0.157032
q8tcavl	1.18791	0.232832	5.1	0.000	.7315675	1.644252
q2labfam	-0.27031	0.359839	-0.75	0.453	-.975584	0.434957
Manuredm	0.514059	0.356644	1.44	0.149	-.1849496	1.213067
Fertbdum	0.220637	0.307009	0.72	0.472	-.3810893	0.822363
q33fdsht	-0.11371	0.188868	-0.6	0.547	-.4838866	0.256461
Lnbanprop	0.08457	0.047421	1.78	0.075	-.1775148	0.008373
Lnpcdy	0.097231	0.058851	1.65	0.099	-.018115	0.212577
Dismeext	0.057228	0.192973	0.3	0.767	-.3209934	0.435449
Trandumm	0.216047	0.241316	0.9	0.371	-.2569232	0.689018

	Coef.	Std. Err.	Z	P>z	[95% Conf.	Interval]
Bundumy	-0.03249	0.387989	-0.08	0.933	-.7929351	0.727954
Kisidumy	-0.87727	0.5274	-1.66	0.096	-1.91095	0.15642
_cons	-2.72428	1.835827	-1.48	0.138	-6.322432	0.873878
Tier2: Dependent variable = Number of TCB banana stools weighted on arable land						
lnq10bprc_a	0.034636	0.086416	0.4	0.689	-.1347364	0.204009
lnq1hhage	-0.18951	0.702693	-0.27	0.787	-1.566764	1.187741
occ_off	2.233473	0.730983	3.06	0.002	.8007728	3.666173
Ocup_far	1.624593	0.659046	2.47	0.014	.3328865	2.9163
q1faml	0.179473	0.068559	2.62	0.009	.0450995	0.313846
Lnhect	-0.31439	0.115074	-2.73	0.006	-.5399301	-0.08885
q2fert	-0.51528	0.256112	-2.01	0.044	-1.017253	-0.01331
q2labhr	-0.08671	0.384654	-0.23	0.822	-.8406157	0.667201
q8tcavl	0.717411	0.317617	2.26	0.024	.094893	1.339929
lnq9dist2	-0.183	0.09853	-1.86	0.063	-.3761149	0.010117
Manuredm	2.14072	0.814319	2.63	0.009	.5446831	3.736756
Fertbdum	0.651159	0.593836	1.1	0.273	-.512738	1.815057
Lnbanprop	0.016989	0.093745	0.18	0.856	-.1667474	0.200725
Dismeext	1.018347	0.327077	3.11	0.002	.3772877	1.659407
Dismefam	0.783393	0.522338	1.5	0.134	-.240371	1.807157
Aveindex	-0.01627	0.008072	-2.02	0.044	-.0320939	-0.00045
Overinde	0.004084	0.0181	0.23	0.822	-.0313917	0.039559
Trandumm	0.2483	0.444372	0.56	0.576	-.6226522	1.119252
Bundumy	1.533865	0.771191	1.99	0.047	.0223594	3.045371
Kisidumy	-1.04704	1.65511	-0.63	0.527	-4.290995	2.196918
_cons	0.045445	2.743833	0.02	0.987	-5.332368	5.423258
sigma _cons	1.065935	0.098234	10.85	0.000	.8734004	1.258469
Number of obs					330	
Wald chi2(20)					58.76	
Prob > chi2 =					0.0000	
Log likelihood					-222.332	
No of iterations					7	

Note: *, **, *** indicates that the corresponding coefficients are significant at the 10%, 5% and 1% level respectively; p-values in parentheses; p-values obtained via bootstrapping at 100 repetitions in hurdle 1 to account for first stage estimation; coefficients in hurdle one along with coefficients and p-values in hurdle two obtained using *margins* command in Stata 11

.

Impact of selected explanation variable on TCB adoption - The Marginal effects

Based on the assumption of conditional independence, we ran the DHM parameters and the un-conditional marginal effects (partial effects) using the Cragg command in STATA version 11 as proposed by Burke (2009a). The marginal effects were computed through bootstrapping. It is recognized that the marginal effects are used to calculate percentage changes in the dependent variable when the exogenous variable shifts from zero to one for categorical variables and elasticities at the sample means for continuous variables. The APE incorporates the partial effect of both hurdles, which allows making unconditional inferences about the factors affecting the intensity of TCB adoption.

According to Green the average partial effect parameter measures the change in the expected outcome due to a small change in the program level. Similarly, the average partial effect on the treated (APET) measures the change in the expected outcome of the program participants due to a small change in the program level. In this impact evaluation were interested in APE and APET. These parameters are not directly estimated, and standard errors of the estimated parameters are not calculated by standard statistical software. Subsequently, the coefficients of program variable can have misleading economic meaning. The standard error of the estimates can be calculated using the Delta method (Greene 2003) or they can be estimated using the bootstrap method. In this study we used the later (Burke 2009a).

There are two situations of APE, the conditional and the unconditional. The conditional average partial effects (CAPE), indicates the effect of each independent variable on a household's TCB intensity (level of adoption), but only for the subsample comprising households that reported the outcome changes. The unconditional average partial effects (UAPE) shows the expected overall effect of each independent variable on household's probability of adoption and intensity of TCB adoption ie taking into consideration both the probability of participating in TCB and the intensity of TCB bananas adoption per household. The marginal effects are of particular importance for policy interpretation as it provides information on overall effect of each variable on the contribution of probability and intensity of TCB adoption and subsequently its contribution to benefits.

In this study the marginal effects generated after running the DHM were average partial effect of each variable unconditional averaged across the sample observation on the expected value of TCB adoption. The marginal effects estimates reported in Table 8 were useful to quantify the impact of the significant explanatory variables on the probability of TCB adoption. Test of significance for these average partial effects was done using the bootstrap method in Stata 11 with 100 replications.

The marginal effects are used to calculate percentage changes in the dependent variable when the exogenous variable shifts from zero to one for categorical variables and elasticities at the sample means for continuous variables. The marginal effects denote the size and direction of the impact of the explanatory variables on the TCB adoption levels. The elasticities of the double-hurdle model, which were evaluated at the respective means of the independent variables. This indicates the effect of a change in one of the explanatory variables on the unconditional mean of the dependent variable.

The unconditional marginal effect of a one percentage point increase in the availability of TCB would increase the adoption of TCB by about 107% A similar relationship holds for increased importance of use o manure which would increase the TCB adoption by 8%. This implies that use of manure would enhance the adoption of TCB and this could be due to probably the manure effect on banana production..

Eliminating of heteroscedacity

The sample can be replicated many times, using bootstrapping technique. In bootstrapping, you need to draw a large number of samples out of your sample, where each sample. The original sample is treated as if it was the population and then repeatedly draw the sub-sample from it. This process can be done with replacement and some observations may appear more than once in the new sub-samples. From the sub-sample drawn one can now compute the statistic of interest (mean, variance SE, regression coefficient). The distribution of the estimated results will enable you compute the confidence intervals boundaries for the computed statistic. According to percentile method 95% of CI is formed by the value above which there are 2.5% of the estimated results and the vale below which there are 2.5%. In STATA 11 this was run using bootstrapping command (Burke 2009a). The number of samples to be drawn can be specified for example it can be 50 or 100.

Table 8: Un-conditional average partial (marginal) effects of TCB adoption after double hurdle estimation in Kenya, 2012

Variable	Mean	Std. Dev.	Min	Max	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf Interval]	
lnq10bprc_a	-0.012	0.009	-0.045	0.017	-0.012	0.040	-0.290	0.771	-0.091	0.067
occ_off	0.457	0.443	0.000	1.731	0.457	0.373	1.220	0.221	-0.275	1.188
q1faml	-0.014	0.021	-0.087	0.110	-0.014	0.034	-0.400	0.688	-0.080	0.053
lnhect	-0.063	0.047	-0.198	0.000	-0.063	0.044	-1.450	0.147	-0.149	0.022
q2labhr	-0.226	0.169	-0.666	-0.001	-0.226	0.167	-1.360	0.175	-0.552	0.101
q8tcavl	**1.073**	**0.812**	**0.002**	**3.143**	**1.073**	**0.236**	**4.550**	**0.000**	**0.611**	**1.535**
manuredm	**0.813**	**0.675**	**0.001**	**2.366**	**0.813**	**0.382**	**2.130**	**0.033**	**0.065**	**1.561**
fertbdum	0.298	0.241	0.001	0.868	0.298	0.273	1.090	0.274	-0.236	0.832
lnbanprop	-0.063	0.047	-0.198	0.000	-0.063	0.044	-1.450	0.147	-0.149	0.022
dismeext	0.237	0.238	0.000	0.914	0.239	0.195	1.230	0.220	-0.143	0.622
trandumm	0.218	0.167	0.000	0.636	0.218	0.251	0.870	0.386	-0.274	0.709
bundumy	0.022	0.034	-0.013	0.171	0.267	0.380	0.700	0.483	-0.478	1.012
kisidumy	**-0.891**	**0.687**	**-2.605**	**-0.002**	**-0.891**	**0.536**	**-1.660**	**0.096**	**-1.940**	**-1.940**
mean	0.1422									
_cons										
Censored observations										
Log likelihood										
Wald chi2(24)										

*Note: ***, **, and * significant at 1%, 5%, and 10% respectively, Standard errors are in parentheses*

(a) "Unconditional" implies results are not conditioned on being an adopter or adoption intensity (all probabilities are conditional on explanatory variables). ie. *Uncond'* refers to the unconditional effect on the level of adoption, i.e. the total effect.
(b) Standard errors of estimated elasticities and discrete effects are computed using the bootstrapping method
(c) Additional issues are:

- Probability elasticity is used for continuous variables and interpreted as the percentage change in TCB participation probability in response to the percentage change in the continuous variable.
- Probability marginal effect is reported for discrete variables and denotes absolute change in TCB participation probability in response to one level increase for the multilevel discrete variable (eg household size) or 0/1 change for the dummy variable.

- The inverse mills ratio (IMR) is the probability density function divided by the cumulative density function (productivity density function [pdf] / Continuous density function [cdf]).

4 Summary and Conclusions

The general objective of the study was to assess adoption and intensity of adoption of inorganic fertilizer in selected counties of West Kenya. As part of the food security programme through agricultural development, the Kenyan government launched the TCB program. In principle, proper use of a TCB can result in clean banana orchard free of disease and pests if all agronomic management practices are adhered to. The program was expected to result in enhanced food security and income generation through changes in the production and productivity of banana production. In spite of intensive efforts to expand the use TCB technologies the production is still low with significant portions being imported. There has been a growing mixed reactions by researchers, extension personnel and policy makers about the effectiveness of TCB adoption to alleviate the food scarcity and income generation in the country. The purpose of this study was to understand the factors influencing likelihood of TCB adoption and intensity of TCB adoption. The TCB innovation has been in existence for well over a decade and continues to expand in farmers in the country. However, a more interesting question might be in the face of adoption, *what factors influence TCB adoption and are the factors influencing likelihood of adoption the same factors influencing the intensity of adoption*? This study aimed at examining data from respondents who had adopted TCB and to analyze the effect of demographic, economic characteristics and biophysical factors on the farmer's adoption process. A survey was conducted in 2011 where a random sample of 330 farmers were selected From a sample frame established in randomly selected villages in sub-locations, cross-sectional data were collected to analyse the effect of farmers socioeconomic and institutional setting and physical attributes on the probability and intensity of TCB. The study used data obtained from a survey of farmers in four counties of west Kenya in 2011. The research question was that what were determinants of TCB adoption?. In order to conduct this, a double hurdle model was adapted. The first stage is adoption of TCB technology and the second stage of the model is a measure intensity of adoption. Prior to running the DHM and also to better understand the effect of various individual characteristics on TCB adoption descriptive statistics were generated. There were 20 variables used in the logit model, four of which were significant at the 10% level. The significant variables were availability of TCB planting material (q8tcavl), proportion of banana income to the total farm income (lnbanprop), per capita household expenditure (Lnpcdy), and the location of the farmer in Kisii County (Kisidumy). The variables have been found to be significant in many previous studies in adoption and adoption theory suggests these variables are important in terms of targeting technologies.

The second stage model considered only TCB adopters, and the model is conditional on the first stage model. This second stage model uses Tobit model. The number of TCB weighted on arable land was used as the dependent variable. Findings from the second stage regression model estimating the intensity of TCB adoption, the study identifies 11 variables that significantly (p>0.10) influences TCB adoption intensity. They included while those that significantly influenced the intensity of TCB adoption were. occupation of farmers, occupation of farmers, family size, labour source, farm acreage, farm fertility status, availability/access of TCB plantlets to farmers, distance to banana market, use of manure in planting bananas, agricultural extension services, average index technology attributes, bundumy was positive (sugarcane zone).

Therefore, the results of the study suggest that the probability of adoption and intensity of use of TCB should be enhanced by taking congninceof these variables in order to meet the priority needs of smallholder farmers who were target group and to alleviate the food shortage problem in the country in general and in the study area in particular. Opening up more TCB multiplication centres and widening the technology to other banana cultivars woul enhance the impact of the technology.

References

Adesina, A. A. and J. Baidu-Forson (1995). "Farmers' perception and adoption of new a agricultural technology: Evidence from analysis in Burkina Faso and Guinea, west Africa." Agricultural economics **13**(1995): 1-9.

Adesina, A. A. and M. M. Zinnah (1993). "Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone " Agricultural Economics **9**(1993): 297-311.

Amemiya, T., 1985. (1985). Advanced Econometrics. T.J. Press, Pad stow Ltd: Great Britian.

Ayieko, M. W., Tschirley, D.L., Mathenge, M.W., 2004. (2004). Fresh fruit and vegetable consumption patterns and supply chain systems in urban Kenya: implications for policy investment priorities. Working Paper 16. Tegemeo Insititute of Agricultural Policy and Development, Nairobi.

Baidu-Forson, J. (1999). " Factors influencing adoption of land-enhancing technology in the Sahel: lessons from a case study in Niger. ." Agricultural Economics **20**: 231-239.

Berhanu, G. and S. M. Swinton (2003). Investment in soil conservation in northern Ethiopia: The role of land tenure security and public programme, Agricultural Economics, 29. p. 69-84.

Blundell, R. W. and C. Meghir (1987). " A Bivariate Alternatives to the Univariate Tobit Model." Journal of Econometrics **33** (January/February): 179-200.

Burke, W. J. (2009a). Triple hurdle model of smallholder production and market participation in Kenya's dairy sector. Michigan, Michigan State University. **Master of Science in Agricultural Economics** 1-83.

Crowley, F., Eakins, J., Jordan, D., (2012). "Participation, Expenditure and Regressivity in the Irish Lottery: Evidence from Irish Household Budget Survey 2004/2005." The Economic and Social Review **43**(2): 199–225.

Doss, C. R. (2003). "Understanding Farm Level Technology Adoption: Lessons Learned from CIMMYT's Micro Surveys in Eastern Africa. CIMMYT Economics Working Paper 03-07. Mexico, D.F.: CIMMYT."

Doss, C. R. (2006). "Analyzing technology adoption using microstudies: limitations, challenges, and opportunities for improvement." Agricultural Economics **34** (2006): 207-219.

FAO. (1995). Planning for sustainable use of land resources. Towards new approach. Rome, Italy**:** pp 1-60.

Feder, G. and R. Slade (1984). "The acquisition of information and the adoption of new technology. ." American Journal of Agricultural Economics. **66,** (1984): 312–320.

Gaforth, C. (1993.). Extension Technique for Pest Management; In Decision Tools for Pest Management, A.B. . London, UK, International Walling land U.K.

Gebremedhin, B. and S. Swinton (2003). "Investment in Soil Conservation in Ethiopia: The Role of Land Tenure Security and Public Programs." Agricultural Economics **29** (1): 69-84 (http://dx.doi.org/10.1016/S0169-5150(03)00022-7).

Greene, W. H. (2003). Econometric Analysis, New Yolk University, . New Yolk University, Upper Saddle River, New Jersey USA.

Humphreys, B. R. (2010). Dealing With Zeros in Economic Data. Accessible at www.ualberta.ca/~bhumphre/class/zeros_v1.pdf**:** pp 1-27.

Int. J. Eco. Res., 151-165 (2011). "Determinants of food consumption expenditure in Ethiopia " Int. J. Eco. Res., **2**(5): 151-165.

Kanampiu, F. K., Kabambeb, V., Massawec, C., Jasid, L., Friesena, D., Ransoma,J. K., Gresself, J., (2003). "Multi-site, multi-season field tests demonstrate that herbicide seed-coatingherbicide-resistance maize controls Striga spp. and increases yields in several African countries." Crop protection **Vol. 22**(2003): 697-709.

Legese, G., Jaleta, M., Langyintuo, A., Mwangi, W., La Rovere, R., (2010). Characterization of Maize Producing Households in Adami Tulu - Jido Kombolcha and Adama Districts in Ethiopia. Country Report – Ethiopia. Nairobi: CIMMYT. Country Report – Ethiopia. Nairobi: CIMMYT.**:** pp 1-51.

Manyangarirwa, W., Turnbull, M., McCutcheon, G.S., Smith, J.P., (2006). "Gene pyramiding as a Bt resistance management strategy: How sustainable is this strategy?" African Journal of Biotechnology Vol. 5 (10), pp. 781-785, 16 May 2006 **Vl 5**(10): 781-785.

Martínez, E., R., (2004a). A Box-Cox double-hurdle model of wildlife valuation: the citizen’s perspective.**:** 1-34.

Mbogoh, S. G., Wambugu, F. M., Wakhusama, S., (2003). Socio-economic impact of biotechnology Applications: some lessons from the pilot tissue culture (tc) banana production promotion project in Kenya, 1997-2002. Proceedings of the 25th International Conference of Agricultural Economists (IAAE), Durban, South Africa, Document Transformation Technologies.

McIntyre, B. D., Herren, H. R., Wakhungu, J., Watson, R. T., (2009). Agriculture at a Crossroads. Sub-Saharan Africa (SSA) Report. Volume V. H. R. H. Beverly D. McIntyre, Judi Wakhungu, Robert T. Watson. Island Press, International Assessment of Agricultural Knowledge, Science and Technology for Development.

Moffat, P. G. (2003). Hurdle Models for Loan Default. School of Economic and Social Studies. University of East Anglia. United Kingdom.

Moffat, P. G. (2005). " Hurdle models of loan default." Journal of the Operational Research Society **56**(9): 1063-1071.

Moffatt, P. G. (2005). " Hurdle models of loan default." Journal of the Operational Research Society **56**(9): 1063-1071.

Morris, M. L., Tripp,R., Dankyi, A.A., (1999). "Adoption and Impacts of Improved Maize Production
Technology: A Case Study of the Ghana Grains Development Project. Economics Program Paper 99-01. Mexico, D.F.: CIMMYT."

Nguthi, F. N. (2007). Adoption of agricultural innovations by smallholder farmers in the context of HIV/AIDS: The case of tissue-cultured banana in Kenya. Hoogleraar Sociologie van Consumenten en Huishoudens. Wageningen, Wageningen Universiteit. PhD: pp 1-226.

Nkonya, E., Schroder, T., Norman, D., (1997). " Factors affecting adoption of improved maize seed and fertiliser in northern Tanzania. ." J. Agric. Econ. **48,**(1997): 1–12.

Nowak, P. J. and P. J. Korsching (1983). Social and institutional factors affecting the adoption and maintenance of agricultural BMPs. In: Schaller, F. & Bauley, H. Agricultural Management and Water Quality, 1st ed. Ames, Iowa: Iowa University Press, pp. 349-373.

Nyang, M. N., Webo, C., Roothaert, R. L., (2010). The Power of Farmers Organisations in Smallholder Agriculture in East Africa Working Papers. A review of 5 project initiatives of the Maendeleo Agricultural Technology Fund. FARM-Africa Working Paper. London, UK, FARM-Africa**:** pp 1-44.

Rao, E. J. O. and M. Qaim (2011). The supermarket revolution and impacts on agricultural labor markets: Empirical evidence from Kenya, RTG 1666 GlobalFood · Heinrich Düker Weg 12 · 37073 Göttingen Germany www.uni-goettingen.de/globalfood**:** pp 1-29.

Reynold, A. (1990). "Analysing fresh vegetable consumption from Household data." Southern Journal of Agricultural economics **22**(1990): 31-38.

Rogers, E. M. (2003). Diffusion of innovations. New York, Free Press. 477pp.

ROK (2004a). Strategy for revitalizing agriculture 2004-20014. . Nairobi, Kenya., Ministries of Agriculture, Livestock and Fisheries Development, and Cooperative Development and Marketing.

ROK (2007). Kenya Vision 2030. The popular version. Nairobi, Kenya., Government ministry**:** pp. 1-32.

Wambugu, F. (2004). Food, Nutrition and Economic Empowerment: The Case for Scaling up the Tissue Culture Banana Project to the Rest of Africa,. Paper presented at the NEPAD/IGAD regional conference "Agricultural Successes in the Greater Horn of Africa". Nairobi, Kenya, NEPAD/IGAD. **2004:** pp 1-8.

Xu, Z., Burkea, W. J., Jaynea, T. S., Govereh, J., (2009). "Do input subsidy programs "crowd in" or "crowd out" commercial market development? Modeling fertilizer demand in a two-channel marketing system." Agricultural Economics **40** (2009): 79–94.

Yen, S. and A. Jones (1997). "Household consumption of cheese: An inverse hyperbolic sine double hurdle model with dependent errors." American Journal of Agricultural Economics **79**(1997): 246-251.

Yen, S. T., Dellenbarger, L. E., Schupp, A. R., (1995). "Determinants of Participation and Consumption: The Case of Crawfish in South Louisiana." J. Agr, and Appkd &OH. **27**(l): 253-262.

Yen, S. T. and H. H. Jen (1995). Determinants of Household Expenditures on Alcohol, Center for Agricultural and Rural Development Iowa State University.

Young, S. R. and W. W. Wilson (1996). "Credit allocation decision of wheat exporting countries." Canadian journal of Agricultural economics **44**(1): 53-65.