Does Adoption of Improved Maize Varieties Reduce Poverty? Evidence from Laikipia and Suba Districts in Kenya

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Abstract

Adoption of technologies that increase farm yields is a prerequisite for poverty alleviation in agrarian societies. However, the link between adoption of improved varieties and poverty reduction is not well understood or documented. This relationship is explored with an example of improved maize seed adoption in Laikipia and Suba—two rural districts in Kenya. We show that adopters of improved maize seed have higher yields per acre and that poverty is negatively correlated with technology adoption. Policies for increasing diffusion of these technologies include improving access roads to market centres to enhance maize profitability, and increasing awareness among farmers about improved maize varieties.

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All remaining errors are our own.*

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1. Introduction

1.1 The current poverty situation

Poverty in Kenya has worsened consistently over the past two decades despite the anti-poverty measures designed by the government and international development agencies to deal with the problem. Currently, 60 per cent of the Kenyan population is estimated to be below the poverty line, with the majority of the poor residing in rural areas where agriculture is the main source of livelihood. Lack of progress in poverty reduction is partly due to inadequate implementation of previous anti-poverty measures which, to a certain extent, paid insufficient attention to the development of agriculture, the backbone of the Kenyan economy. In particular, transfer of new technologies to farmers may have suffered due to under-financing of the national agricultural extension system (Bindlish and Evenson, 1997; Bindlish *et al*., 1993).

Low agricultural productivity and poor marketing of farm produce are some of the major causes of rural poverty. Low productivity is attributed to traditional farming methods, poor soil fertility, unpredictable weather patterns, high costs of inputs, poor quality of seeds, and lack of credit facilities. These adverse conditions have led to food shortages, under-development of farms, low farm incomes, and poor nutritional status, especially among children.

Poverty estimates in the last decade provide a fairly good account of the welfare trend in the country. Studies based on the 1994 Welfare Monitoring Survey - WMS (Republic of Kenya, 1998; and Mwabu *et al*., 2000) show that the total number of the poor in 1994 ranged from 39 per cent to 44 per cent of the total population. The 1997 WMS shows that the poor constitute 52.3 per cent of the population. By the year 2000, it was estimated that 59.6 per cent of the rural population lived below the poverty line, with a majority of the poor residing in rural areas. The increase in poverty in the country is evident from the growing numbers of people without adequate food and nutrition.

Substantial regional differences exist in poverty incidence (Republic of Kenya, 1998). In the 1990s, over 50 per cent of the rural population was poor compared with 30 per cent of the urban population. Rural poverty is marked by its connection to low labour productivity in agriculture and landlessness. Further, poverty in the rural areas tends to be attributed to insufficient non-farm employment and low rates of technology adoption.

Rural people adopt diverse livelihood strategies to deal with poverty. These strategies are aimed at increasing incomes, reducing vulnerability, and ensuring food security. These welfare indicators are mainly determined by the asset position of households. Since household assets are heterogeneous, households pursue different livelihood strategies. As most of the rural households are agricultural-oriented, increasing agricultural productivity is a key strategy in the fight against rural poverty. To that end, increases in food and farm outputs can, in general, be achieved by:

- Enhancing productivity of land already owned, rented, or worked on by the rural people;
- Introducing improved technologies, including better seeds, tillage methods, crop rotation systems, and drought resistant crops; and
- Improving management of pests and soils.

With maize being the dominant food crop in Kenya, as well as the primary source of calories for most households, transfer of improved maize technology to farmers should reduce poverty. This would be possible if the technology were to increase maize yields of the farmers adopting it without adversely affecting production in other household activities. This is an important consideration in both the short- and long-run.

If in the short-run, adopting high yielding maize were to withdraw household labour from growing vegetables and raising basic livestock, the nutrient intake of subsistence farmers would be compromised, with deleterious effects on health. In this case, diversified subsistence farmers would suffer a reduction in outputs from farm and off-farm activities, whereas for pure subsistence farmers, the adverse effect on health would reduce only farm production.

In the long-run, adoption of high yielding maize could reduce future household income, if it were to withdraw children from school to work on farms, thus reducing their level of schooling. Adoption of high-yielding maize must therefore meet a stringent condition if it is to reduce poverty in both the short and long run. The condition is that the net effect of the new technology on production of all household goods and services, including human capital, must be positive. In other words, adoption of high-yielding maize would still reduce poverty, even if it were to reduce non-maize activities, provided that the loss incurred in these other activities is compensated for by the productivity gains from the adoption.

1.2 Technology as a package of innovations

It is worth noting that productivity-improving farm technology is a bundle of innovations rather than a single technical or managerial intervention. Thus, for example, adopting high yielding maize varieties will lead to significant increases in maize production if farmers also adopt new ways of planting, weeding, or if they apply new types of fertilizer. It is this package nature of technology that makes its welfare, efficiency and distributional effects difficult to evaluate. In particular, the poverty reduction effects of technology adoption may be observed at the macro level but fail to be observed at the micro level (and vice-versa) for several reasons:

- The macro level effects are not simple aggregates of the micro effects. There may be social externalities in technology adoption that make aggregate level effects larger or smaller than a simple aggregate of the effects at the local level.
- Large farmers might adopt the technology, while small and poor farmers may not. Aggregate growth effects of technology adoption would therefore be large but at the micro level, and growth would not be observed among many small farmers. In this case, the distributional effects of technology adoption would favour large farmers, and actually worsen poverty, if the effects were to lead to substantial increases in prices of commodities commonly consumed by the poor.
- Small farmers may be adopting technology but not in a full package as required, hence the effect of the technology on productivity is small or absent. For example, farmers may be adopting new seeds but may not be planting them in recommended quantities or may not be using fertilizers or weeding as required. In this case, technology adoption may not be associated with poverty reduction or with increases in farm productivity.

Despite important early research on farm technological innovations as packages (Byerlee and Hesse de Polanco, 1986), little work has been done in this area in African agriculture, a situation that needs to be addressed. If an agricultural technology consists of perfectly complementary components, the entire package of the components must be adopted for the technology to improve farm yields. In such a setting, the goal of extension workers should be to help farmers adopt all the components of the technology at the same time. However, if the components are imperfect substitutes in enhancing farm productivity, farmers would adopt them in a sequence, depending on each component's profitability, riskiness, divisibility, complexity and availability (Byerlee and Hesse de Polanco, 1986). For example, a farming technology consisting of new seed varieties, herbicides, and fertilizer could be adopted over time in this order, or in some other sequence. Since the components of the technology are imperfect substitutes, that is, their interaction is productivity-enhancing, they will all be adopted over time. Eventually, rational adoption decisions of farmers will display a portfolio of farm technologies, rather than a choice of one technology over other technologies, as in a given point in time. This portfolio nature of technology adoption has received little attention in the literature.

1.3 Links between agricultural technologies, productivity and poverty

Productivity-improving agricultural technologies reduce poverty through four channels:

- By increasing rural agricultural incomes;
- By reducing food prices for both urban and rural poor;
- By facilitating the growth of non-farm sectors, thus creating high wage employment; and
- By stimulating the transition from low productivity subsistence agriculture to a high productivity agro-industrial or manufacturing economy.

The potential for poverty reduction through the above transmission mechanisms depends on the extent to which agricultural productivity can be increased. Agricultural innovation can have both direct and indirect effects on poverty. Direct effects of technological innovation on poverty reduction are those productivity benefits enjoyed by the farmers who actually adopt the innovation. The benefits typically manifest themselves in form of higher profits. The indirect effects are productivity-induced benefits passed on to others by the innovating farmers. These benefits may comprise lower food prices, higher non-farm employment levels or increases in production and consumption. Which of these effects dominate depends largely on the speed with which farmers adopt new technologies and on whether or not the affected households are net food buyers or sellers.

1.4 Pro-poorness of technology adoption

More generally, adoption of high-yielding maize is pro-poor if it benefits the poor relatively more than the non-poor. Clearly, such a technology must be affordable by the poor. Moreover, its overall benefits must be substantial relative to its cost (including the risks it involves) for it to be worth adopting. Although the benefits of adopting new farm technologies are stressed in the literature (Bindlish and Evenson, 1997), the cost of their adoption is often overlooked.

2. Models

We use discrete-discrete and discrete-continuous choice models to evaluate the effects of adoption of high-yielding maize varieties on household poverty in Laikipia and Suba districts in Kenya.

2.1 Discrete-discrete choice model

Model specifications

Bivariate probit is one of models that can be used to assess whether a household will adopt a high-yielding maize variety, and whether conditional on adoption, the household would be better-off. Let ***S*** denote characteristics of the farmer, ***Z*** the attributes of the technology, ***k*** the new technology and ***l*** the existing technology. The probability of adopting a new maize growing technology can be expressed as:

$$\Pr(\boldsymbol{k}) = \Pr\,\{U_k(\boldsymbol{S},\boldsymbol{Z}_k) + e_k > U_l(\boldsymbol{S},\boldsymbol{Z}_l) + e_l\} \text{ ....}(1)$$

Where $U_k(\boldsymbol{S},\boldsymbol{Z}_k)$ and $U_l(\boldsymbol{S},\boldsymbol{Z}_l)$ are the net benefits associated with the adoption of technologies k and l, respectively, and e is a stochastic disturbance term.

From equation (1), a binary probit model of technology choice can be formulated from the assumption that the disturbance term is normally distributed. A common alternative assumption is that the error term is logistically distributed, in which case a binary logit model would be the appropriate formulation (Maddala, 1983; Mwabu *et al.*, 2006). However, because of the advantages of probit over logit (Maddala, 1983), we assume that the disturbance term in equation (1) is normally distributed and thus use the probit model.

Equation (1) can be used to predict the probability that household i will adopt technology k given its characteristics (***S***) and the attributes of the technology (***Z***). This prediction role is an important function of the model because the model can be used to shift households from low-yield to high yield technologies by modifying some elements of ***S*** and ***Z*** using public policy (Doss, 2003).

Equation (1) can be extended in several directions. First, instead of estimating a probit model of technology adoption, a tobit model can be estimated to study the intensity of the adoption (Maddala, 1983). For example, farmers can be categorized into two groups: those planting zero acres or zero kilograms of improved maize seed and those planting at least one acre or at least one kilogram of improved maize seed. In this case, tobit estimation would yield predicted probability of adoption, as well as the predicted intensity of adoption in terms of acreage planted or the kilograms of maize seed planted. Poverty status can then be conditioned on adoption and the intensity of adoption (see below).

A second possible extension of equation (1) could involve estimation of a multinomial logit model of technology adoption. In this case, improved maize cultivation is viewed as the adoption of a package of farming technologies. For example, a farmer may decide: (a) not to plant improved maize varieties; (b) to plant improved varieties and at the same time to use fertilizer; (c) to do (a) and (b) and also to undertake the recommended intensity of weeding; and so on. A multinomial approach to the modeling of technology adoption in this case would yield, for each farmer, predicted probabilities of adopting various bundles of technologies, such as the null package (a) above, and a two-element package (b) above, among others. This information can be used to examine the technology package with the greatest impact on poverty reduction. However, because of data limitation, this approach will not be explored in this paper.

A third extension of equation (1) would involve examining the effect of predicted intensity of adoption on the poverty status of adopters. In this case, estimation would be conducted on a selected sample of adopting farmers. Consequently, a need arises to correct the estimated parameters for the sample selection bias using the heckit method (Wooldridge, 2002). The heckit model may be estimated in two steps or in one step using maximum likelihood method (Wooldridge, 2002). The coefficient on the inverse of the Mills ratio is the parameter that corrects the effect of adoption on poverty for any bias arising from estimation based on a selected, rather than a random sample (Maddala, 1983; Wooldridge, 2002). It should be noted that in this case, the technology adoption variable is continuous rather than discrete. Moreover, the poverty status of non-adopters is missing (by construction) from the poverty estimation sample because the interest is on poverty status of farmers who have been exposed to the improved maize technology.

Finally, as noted earlier, the sequential discrete adoption decisions of various technologies over time could be modeled as a portfolio of technologies held by farmers over a specified time period. This sort of analysis would reveal the optimal sequence in which the various components of a technology should be adopted. For example, in the dry areas of Mexico, the optimal sequencing of a three-component farming technology (new seed varieties, fertilizer and herbicides) was found to start with varieties, followed by fertilizer and herbicides, whereas in the wet areas, the seed varieties were adopted first, followed by application of herbicides and fertilizer (Byerlee and Hesse de Polanco, 1986).

Endogeneity of technology adoption

There is the question on how to determine whether technology adoption is associated with poverty reduction. This is a difficult problem because even if the probability of technology adoption is negatively correlated with the probability of being poor, no causal interpretation may be given to that relationship; that is, it may be difficult to tell whether any observed poverty reduction is due to technology adoption. This is because maize technology adoption is *endogenous* to poverty reduction. If , for example, improved maize seeds happen to be adopted by high-income households, the adoption of these seeds will be negatively correlated with poverty because the poor (the low-income households) cannot afford the new seeds. Obviously, in this case, adoption of improved maize seed cannot be said to reduce poverty as it is the non-poor who are adopting.

In order to give a causal interpretation to the negative relationship between poverty and adoption of improved maize technology, the adoption must be endogenized; instruments for maize technology adoption must be available. These are variables that can be used to predict adoption and intensity of improved maize varieties without affecting the poverty status of households. Examples of such variables include distances from household farms to sources of improved maize seeds, the prices of the seeds, and the sizes of packages in which they are sold. The same variables that pertain to complementary inputs such as fertilizer would be valid instruments. The sign and significance of the coefficient on predicted probability of adoption and predicted intensity of adoption (based on these instruments) in a poverty status model can now be used to determine whether or not cultivation of improved maize varieties reduces poverty. In particular, a negative and statistically significant coefficient would suggest that adoption of improved maize varieties reduces poverty.

Measuring poverty

The poverty status of a household can be computed using the following expression (Mwabu *et al.*, 2000).

$$P_{\alpha}=1/N \cdot \sum_{q}((Z-Y_{i})/Z)^{\alpha} \qquad (2)$$

Where,

P_{α}= a measure of food or overall poverty;

Y_i = total (or food) expenditure of household i per adult equivalent (i =1...N);

Z = overall (or food) poverty line;

N = total number of households;

q = the total number of poor households;

α = FGT parameter, which may be interpreted as a measure of poverty aversion, for $\alpha \geq 0$.

Note that if α=0, the poverty measure, P_0, becomes the *headcount index*, which indicates the percentage of households below the poverty line; that is, the number of poor households expressed as a proportion of the population. For α=1, P_1 is the *average poverty gap*, or the average income shortfall of all households calculated as a proportion of the poverty line; and for α=2, P_2 is the *severity index*, which is the population mean of the weighted sum of poverty gaps, with weights being defined as the squared proportionate poverty gaps.

Once the poverty status of the household is determined using equation (2), a probit model of the probability of being poor can be estimated along the lines of equation (1). However, as already noted, care should be taken to identify the two models, that is, to find valid instruments for poverty adoption. The instruments are commonly known as exclusion restrictions because although they are included in the adoption equation, they are excluded from the poverty status equation of the form:

$$\Pr(Y_i < \boldsymbol{y}) = f(X, \ddot{O}) \quad \ldots\ldots \quad (3)$$

Where,

$\Pr(Y_i < \boldsymbol{y})$ is the probability that a household has an income, Y_i, lower than the poverty line, $\boldsymbol{y}$**;**

X is a vector of determinants of poverty, which excludes the instruments for maize technology adoption;

$\ddot{O}$ is a predicted probability of adopting improved maize seed. Notice that the variable $\ddot{O}$ can be replaced by intensity of technology adoption as desired.

2.2 The discrete-continuous choice model

From equation (2), it can be seen that at the household level, the *poverty gap* and *poverty gap squared* are continuous measures of the poverty status, with the former showing the poverty depth and the latter the poverty severity. Thus, the dependent variable in equation (3) is now continuous rather than discrete as in equation (1). Equation (3) may be re-written as

$$W_i = f(X, \ddot{O}) \quad \ldots\ldots \quad (3)$$

Where

W_i is the poverty depth or severity of household i.

The effects of technology adoption on poverty depth or severity can differ substantially from its effect on the poverty status. If $\ddot{O}$ is negatively correlated with W_i it implies that households that adopt new technologies, despite being poor, suffer less from poverty than the non-adopters. In particular, the incomes of the adopters are closer to the poverty line and the poverty they experience is less severe than that of the non-adopters.

It is worth observing that the effects of $\ddot{O}$ on poverty depth and poverty severity can differ significantly. For example, $\ddot{O}$ can be positively correlated with poverty depth, but negatively associated with poverty severity. In other words, technology adoption can increase inequality among the poor while at the same time reduce poverty severity. Technology adoption would reduce poverty depth if it were to increase the incomes of a few households closer to the poverty line while substantially reducing the incomes of the poorest households thereby increasing the mean poverty gap. However, if technology adoption increases the incomes of the poorest of the poor as well as the incomes of the households closer to the poverty line, the mean poverty gap squared would fall, thereby bearing a negative relationship with technology adoption. As before, $\ddot{O}$ can be replaced with intensity of technology adoption as desired.

Thus, technology adoption can have the following interesting effects on poverty:

- It can increase the *headcount* ratio (by worsening income distribution);
- It can increase the poverty *depth* (also by worsening income distribution); and
- It can reduce poverty *severity* (by improving incomes of the poorest of the poor, irrespective of what happens to income distribution).

The above cascade of effects of technology adoption reveals the intricate nature of antipoverty policies. In particular, some antipoverty measures may reduce the headcount ratio, but others may increase it while reducing the poverty depth. Further, there are policies that could increase the headcount ratio as well as the poverty depth, while reducing poverty severity.

Adoption of new maize growing technology affects poverty by changing household income. It is relevant, therefore, to examine the effect of adoption on household production. Equation (4) depicts a farm production function in which technology adoption is hypothesized to affect output.

$$\boldsymbol{q}_{\mathbf{i}} = f(\underline{S}, \ddot{O}) \qquad 4)$$

where

q_i is maize production of farmer i, say, per season.

In equation (4), the vector $\underline{S}$ includes farm inputs and socioeconomic characteristics of the farmer, as well as the community level factors that affect production, such as social infrastructure. Equation (4) helps determine whether technology adoption is associated with increased maize production. If $\ddot{O}$ has no effect on maize production, then technology adoption cannot reduce poverty. In the case where adoption has an effect on productivity, equation (4) helps assess the relative importance of technology in increasing maize yields relative to other farm inputs. This assessment is key to determining whether or not resource allocation at the farm level is efficient.

If equation (4) applies only to poor farmers, a zero effect of $\ddot{O}$ (or technology intensity) on maize production would suggest that the farmers are poor but efficient (Schultz, 1964). In that case, an increase in maize production and poverty reduction can be achieved only by giving farmers more resources or another maize cultivation technology. Because of data limitations, only a few of the models discussed above are estimated. In particular, focus is on bivariate model of poverty reduction and technology adoption without addressing the endogeneity of adoption. Thus, the estimated coefficient on technology adoption in the poverty equation should not be given a causal interpretation. Equation (4) can also be used to investigate the effects of adoption on wage rates and market labour supply. Since some of the adopting households would not be participants in the labour market, Heckman procedure would be required to correct for sample selection bias (Wooldridge, 2002).

3. Study Site and Data

3.1 The study sites

The field study was done in Laikipia and Suba districts located in Rift Valley and Nyanza provinces, respectively (Obunde, *et al.*, 2004). Both districts have diverse topographical features, climatic conditions and cultural settings. At the time of the survey, the population of Laikipia was 362,177, more than double that of Suba, which was 170,326. Laikipia had 78,175 households, more than double those of Suba, 33,987. However, the average household size in Suba (4.6) was slightly larger than that of Laikipia (4).

Agriculture is the main activity in the two districts and contributes 75 per cent of household income in Laikipia and 51 per cent in Suba. Nearly 79 per cent and 97 per cent of farmers in Laikipia and Suba districts, respectively, practice food crop farming, suggesting that subsistence farming is dominant in Suba (Republic of Kenya, 2002a,b). Livelihood in the two districts is dependent more on crop farming than on livestock keeping. In Laikipia, 108,853 people work in crop sub-sectors, compared with 27,462 people with livestock tending as their main activity. A similar activity pattern is found in Suba (see below).

Laikipia

Laikipia is one of the districts in the Rift Valley that borders Samburu to the north, Isiolo to the northeastern, Meru Central to the south, Nyandarua and Nakuru to the southwest, and Koibatek and Baringo to the west. It covers an area of 9,693 km^2 and lies between altitude 0^0 18" and 0^0 51" north and between longitude 36^0 11" and 37^0 24" east.

The district is sub-divided into 7 divisions, namely: Central (2,392 km^2), Lamuria (1,261 km^2), Mukogodo (1,103 km^2), Rumuruti (2,786 km^2), Nyahururu (167 km^2), Ol Moran (1,227 km^2) and Ng'arua (757 km^2). It is further divided into 34 locations and 65 sub-locations. The arable land in the district is 1,984 km^2 while the non-arable is 7,107 km^2. The altitude of the district varies between 1,000m above the sea level at Kipsing plains and 2,600m around Marmanet forest. The district consists mainly of a plateau bounded by the Great Rift Valley to the west, and by the Aberdare ranges and Mount Kenya to the south.

River Ewaso Nyiro and its many tributaries, which have their catchments in the Aberdares and Mount Kenya, serve the district. The flow of rivers from the south to the north indicates that the district has a downward slope to the north. The district experiences relief rainfall that varies between 400mm and 750mm. However, the distribution of rainfall varies from one part of the district to another. North Marmanet receives over 900mm, while the drier parts of Mukogodo and Rumuruti divisions receive slightly over 400mm annually. The long rains occur from March to May and the short ones in October and November. The annual temperatures range between 16^0 c and 26^0c, with June and February being the coolest and hottest months, respectively.

Suba

Suba is one of the 12 districts in Nyanza Province. Located in the southwestern part of Kenya along Lake Victoria, it borders Bondo to the north across Lake Victoria, Homa Bay to the east, Migori to the south and Lake Victoria to the west. The district covers an area of 1,056 km^2 exclusive of water surface. Out of these, 530 km^2 is arable land, while the rest is unsuitable for crop growing. The land under water covers an area of 119 km^2.

Suba is made up of 5 divisions, namely: Mbita (211 km^2), Lambwe (139 km^2), Central (307.6 km^2), Gwassi (332.9 km^2) and Mfangano (65.1 km^2). The divisions are further split into 20 locations and 51 sub-locations. The district altitude varies from 1,125m to 2,275m above the sea level. The district has an island equatorial type of climate that is modified by the effect of altitude and its closeness to Lake Victoria.

The annual rainfall ranges from 700mm to 1,200mm with 60 per cent reliability. Gwassi Division receives the highest rainfall in the district while parts of Mbita and Central Division, particularly along the lakeshore, receive the least. The district experiences high temperatures throughout the year, which range from 17.1^0c to 34.8^0c. The hot months are between December and March, with February being the hottest. Due to its coolness and breezes from the lake, Gwassi is more suitable than other areas of the district for food and cash crop cultivation such as cotton and sunflower.

3.2 Data and survey design

The data were collected from Suba and Laikipia districts as part of the International Food Policy Research Institute (IFPRI) Eastern Africa Food Policy Network Studies (Obunde *et al.*, 2004). A total of 320 households were sampled for interviews from the two districts. The data were collected on a wide range of household and farm items, as well as technological variables, including the following:

- Household characteristics (sex, age, level of education, occupation, household income, and size of household);

- Land productivity (crop yields);
- Farming environment (cropping patterns, vegetation cover, soil conservation methods and degree of land degradation);
- Land tenure (type and user's right to sell land, heir to the land, renting out of the land);
- Access to credit (source of credit and whether land title was used as collateral);
- Parcels of land owned, farm size, and number of acres under maize;
- Adoption of seeds of improved maize as well as other crop varieties;
- Use of farm inputs (fertilizer, pesticides, manure and seeds);
- Land investments (trees planted, fencing, ridges, water management structures, drainage, access roads, tree-stump removal, terracing, drilling of bore holes);
- Proportion of land cultivated; and
- Functioning of inputs and produce markets.

However, no information was collected on distances to sources of improved maize seeds or on costs of the seeds.

The quantitative data were collected using a detailed pre-tested questionnaire. A combination of direct observation and informal interviews were also conducted to fill any gaps left by the survey and to verify the information collected. The survey was undertaken in 4 sub-locations per district. These were randomly selected from a cluster of 10 sub-locations in each district. Each of the clusters had almost the same agro-ecological conditions. Stratification was undertaken to ensure that various types of tenure security were captured in the final sample.

In Suba District, the survey was carried out in Gwassi Division, from which the four selected sub-locations were: Magunga and Samba in Gwassi Central Location; Tonga in Gwassi West Location; and Kibwer in Gwassi East Location. In Laikipia, the selected sub-locations in Ng'arua Division were: Dimcom in Sipili Location; Mwenje and Mithiga in Kinamba Location; and Kiambogo in Gituamba Location.

Within each sub-location, eight clusters were formed, out of which four were randomly selected. This clustering ensured that every part of the sub-location was given an equal chance of being included in the sample. In each of the selected clusters, a list of the household heads was compiled. A total of 40 respondents were then randomly selected from the aggregate list of farm families in each sub-location.

In the context of this study, the unit of observation was defined as any family unit that had a parcel of land to cultivate. In polygamous families, the term ‘household’ was construed to mean a family of each of the wives that had been allocated parcels of land by the husband. This is in line with the customary tenure system where each of the wives is normally allocated parcels of land by the husband to cultivate. The same applied to sons who had been allocated parcels by their fathers to cultivate even though they still resided in their father’s homestead.

4. Results

We present descriptive information about socioeconomic backgrounds of households before turning to results relating to adoption of hybrid maize and the associated activities such as weeding and usage of fertilizer.

4.1 Occupations of households and livelihood strategies

4.1.1 Main occupations of household heads

The main occupation for the heads of households in the two districts is farming, accounting for 73.7 per cent of livelihood activities in Laikipia and 90.1 per cent in Suba. The remaining activities comprise petty trade and wage employment (Table 1).

Table 1: Main occupation of household head by district

Occupation	Laikipia	Suba	Both
None		1 (0.70)	1 (0.34)
Farming	109 (73.65)	128 (90.14)	237 (81.72)
Teaching	10 (6.76)	3 (2.11)	13 (4.48)
Artisan/blacksmith	3 (2.03)	3 (2.11)	6 (2.07)
Civil servant	4 (2.70)	1 (0.70)	5 (1.72)
Trader/shopkeeper	3 (2.03)	1 (0.70)	4 (4 (1.38)
Agricultural labourer			
Non-agricultural labourer			
Student			
House worker			
Retired	12 (8.11)	2 (1.41)	14 (4.83)
Unemployed			
Military/police			
Petty trade	2 (1.35)		2 (0.69)
Other paid employment	5 (3.38)	2 (1.41)	7 (2.41)
Other		1 (0.70)	1 (0.34)
Total Sample	148 (100.0)	142 (100.0)	290 (100)

Note: Sample proportions (%) in parentheses.

Source: Survey data, 2004

4.1.2 Household incomes

Table 2 shows mean annual incomes for Laikipia and Suba districts in Ksh and US$. The income levels shown are generally representative of economic status of households in most districts in the country, considering that 60 per cent of households live below the poverty line of less than US$1 a day. As Table 2 shows, the daily per capita income for the two districts is about a dollar each. Even when combined, the daily mean per capita income for the two districts amounts to about a dollar. Although Laikipia has a higher per capita income, this income is not significantly different from the mean income for Suba. The per capita income for the two districts is just slightly higher than US$1 a day (a monthly income of less than Ksh3000 = US$39.47).

Table 2: Estimated per capita income in Kenya shillings by district

District	Total household income		Per capital income		Daily income	No. of households
	Ksh	US$	Ksh	US$	US$	
Laikipia	5,524,000	72,684.21	36,104.60	475.06	1.30	153
Suba	4,111,000	54,092.11	29,575.50	389.15	1.08	139
Both	9,635,000	126,776.3	32,996.60	434.17	1.20	292

Note: Kshs. 76= US$ 1

Source: Survey data, 2004

As shown on Table 3, most households lie within the 1st quartile of income distribution in Laikipia and within the 2nd quartile in Suba, suggesting that the distribution of income is worse in Laikipia than in Suba, though the difference is small. However, the opposite is observed for the highest quartile, where the lowest income is in Suba. The total income for both districts shows that most households lie within the 2nd or middle quartiles.

4.1.3 Non-cropping activities on the main plot

Apart from pure farming, households in the study sites participate in other activities such as planting, weeding, and spraying crops. The survey results show a variety of non-cropping activities on the household's main plot (parcel number 1). Although the value of these activities is not quantified, it is likely

Table 3: Household mean per capita income by quartiles in Laikipia and Suba in Kenya shillings and US$

District	1st Quartile (Lowest)		2nd Quartile		3rd Quartile		4th Quartile (Highest)	
	Ksh	**US$**	**Ksh**	**US$**	**Ksh**	**US**	**Ksh**	**US$**
Laikipia	5,830 (53)	76.71	15,000 (31)	197.37	30,000 (31)	394.74	100,526 (38)	1,322.71
Suba	5,976 (42)	78.63	15,000 (48)	197.37	30,000 (28)	394.74	109,524 (21)	1,441.11
Both	5,895 (95)	77.57	15,000 (79)	197.37	30,000 (59)	394.74	103,729 (59)	1,364.86

Note: Percentages of households in parentheses.

Source: Survey data, 2004

to be considerable, as the activities contribute to improving farm productivity and the surrounding environment (Table 4).

Table 4: Non-cropping activities on the main farm by district

Non-cropping activity	Laikipia		Suba		All	
	No.	**%**	**No.**	**%**	**No.**	**%**
Trench digging/terracing	55	50.9	53	49.1	108	100
Drainage development	28	56.0	22	44.0	50	100
Agro forestry	141	68.1	66	31.9	207	100
Tending tree crops	119	75.8	38	24.2	157	100
Bore hole digging	83	96.5	3	3.5	86	100
Irrigation works	18	94.7	1	5.3	19	100
Stump removal	132	75.4	46	4.6	178	100
Ridge removal	10	15.9	53	84.1	63	100

Source: Survey data, 2004

4.1.4 Prices of agricultural produce

The average price of maize per bag in Suba is Ksh 593 compared with Ksh 477 in Laikipia, a difference of more than Ksh 100. Although the minimum price is Ksh 400 in both districts, the actual prices vary. Beans are about three times more expensive than maize. This price differential is a major problem for households because the staple food in the district is a mixture of maize and beans. In Laikipia, the mean price per bag of beans at the time of the survey was Ksh 1,620 while in Suba it was Ksh 1,773. Prices of main food items are much higher in the poorer district (Suba).

4.1.5 Key farm activities

In Laikipia, 52.8 per cent of households practice maize farming compared with Suba's 47.2 per cent. Beans farming is practised by 63.2 per cent of households in Laikipia and 36.8 per cent in Suba. The number and the proportion of households who keep livestock are shown in Table 5. It is evident from the Table that poultry keeping is practised by most households. Indeed, households without poultry can be considered poor. Both districts keep different breeds of cattle, with Laikipia keeping mainly the crossbreed and Suba the indigenous breed. Sheep rearing is dominant in Laikipia, but goats do well in the two districts.

Table 5: Crop and livestock activities by district

Farm activity	Laikipia		Suba		Total	
	Number	%	Number	%	Number	%
Maize growing	153	52.8	137	47.2	290	100
Beans farming	151	63.2	88	36.8	239	100
Keeping crossbreed cattle	89	97.8	2	2.2	91	100
Rearing indigenous cattle	9	9.5	86	90.5	95	100
Keeping sheep	61	67.8	29	32.2	90	100
Keeping goats	50	45.5	60	44.5	110	100
Keeping donkey	18	41.9	25	58.1	43	100
Keeping poultry	118	48	128	52	246	100

Source: Survey data, 2004

4.1.6 Availability of credit

In Laikipia, all the 14 people who applied for education loan were successful, but in Suba, 5 out of 7 applicants were successful. The credit applied ranged from Ksh3,600 to Ksh300,000, with a mean of Ksh 52,171.40. Farmers in the two districts do not generally seek credit to improve their farms as much as they seek it to pay for the education of their children

4.1.7 Size of crop acreage cultivated

The area covered by maize alone in any three parcels of land owned by a household in Laikipia is a mere 1 per cent, while the rest is covered by beans (0.2 per cent) and mixed cropping (98.7 per cent). In Suba, on the other hand, maize alone covers a much higher proportion of land (28.9 per cent), beans (7.2 per cent) and mixed cropping (63.9 per cent). In both districts,

Table 6: Area under maize and beans by district (ha)

Crop	Plot 1	Plot 2	Plot 3	All plots	%
Laikipia					
Maize	2.4	0	0	2.4	1.0
Beans	0.4	0	0	0.4	0.2
Mixed	204.9	19.5	0.6	244.4	98.8
Total	207.7	19.5	0.6	247.8	100.0
Suba					
Maize	42.1	27.8	4.9	74.8	28.9
Beans	11.6	6.2	0.8	18.6	7.2
Mixed	97.4	61.8	6.4	165.6	63.9
Total	151.1	95.8	12.1	259.0	100.0

Source: Survey data, 2004

out of 506.8 hectares utilized for crop cultivation, only 77.2 hectares or 15.2 per cent was used for growing maize without any inter-cropping (Table 6).

4.2 Maize technologies and maize acreage

4.2.1 Hybrid maize adoption by characteristics of farmers

Maize is widely grown in both Laikipia and Suba districts. However, not all households grow it. Out of a total of 310 households interviewed, 94 per cent grow maize. Hybrid maize is the most common type of maize grown in Laikipia, accounting for 59 per cent of total maize grown. In Suba district, the opposite was found, with 94 per cent of households saying they grew local maize.

The most common hybrid maize grown in Laikipia is H614, which is grown by 30.7 per cent of households, followed by H625, H626, and H627, which are grown by 26 per cent of households. In Suba, the hybrid varieties adopted by a few households are PH1-Pannar (2 per cent), H513 and H511 (1.5 per cent), and H512 (0.6 per cent). As can be seen from Table 8, more than 50 per cent of the farmers in Laikipia had adopted improved maize technologies compared with less than 10 per cent in Suba.

In both Laikipia and Suba, 68 per cent of the farmers who had adopted hybrid maize were male and about 32 per cent were female. In Laikipia, 70 per cent of males had adopted hybrid maize compared with 30 per cent of females. In Suba, the situation is different, where more females (62.5%) than males (37.5%) had adopted hybrid maize.

Table 7: Maize varieties grown by district

Maize variety	Laikipia		Suba	
	No.	%	No.	%
Local	62	40.5	130	94.2
PH1 Pannar	3	2.0	3	2.2
H513, H511	1	0.7	2	1.5
H614	47	30.7	2	1.5
H625, H626, H627	40	26.1	-	-
H512	-	-	1	0.6
Total	153	100.00	138	100.00

Source: Survey data, 2004

The mean farm size allocated for maize in Laikipia was 6.3 hectares compared with 3.4 hectares in Suba. Most farmers use land parcel number 1 (the main plot), in both districts, for maize growing.

4.2.2 Maize yields by district

Laikipia has higher maize yields than Suba district, with 13 bags for hybrid maize, and 7 bags for local maize per acre. In Suba, productivity per acre is 4 bags for hybrid maize and 2 bags for local maize (Table 8).

4.2.3 Usage of modern farm inputs

In Laikipia, 62.5 per cent of households use a tractor for land preparation; 42.5 per cent use manure; and 39.4 per cent use fertilizer and certified seeds. However, in Suba, use of ox-plough is the dominant farming technique practiced by 80.7 per cent of the households. Only about 16 per cent of

Table 8: Hybrid maize yields per acre (in 90 bags) by district

District	Hybrid yield per acre				
	Obs	Min	Mean	Max	Std
Laikipia	91	2.50	13.04	23	4.84
Suba	7	0.67	4.18	10	3.46
	Local maize yield per acre				
Laikipia	62	2.0	7.34	20.0	3.89
Suba	128	0.1	2.44	9.8	1.89

Source: Survey data, 2004

Table 9: Farming technologies in usage within the district

Do you use thefollowing:	Laikipia			Suba		
	Yes	No	Total	Yes	No	Total
Fertilizer?	63 (39.38)	97 (60.63)	160 (100)	24 (16.00)	126 (84.00)	150 (100)
Pesticides?	31 (19.38)	129 (80.63)	160 (100)	3 (2.00)	147 (98.00)	150 (100)
Ox-plough?	2 (1.25)	158 (98.75)	160 (100)	121 (80.67)	121 (80.67)	150 (100)
Manure?	68 (42.50)	92 (57.50)	160 (100)	3 (2.00)	147 (98)	150 (100)
Certified seeds?	63 (39.38)	97 (60.63)	160 (100)	24 (16.00)	126 (84)	150 (100)
Tractor?	100 (62.50)	60 (37.50)	160 (100)	1 (0.67)	149 (99.33)	150 (100)

Note: Sample proportions (%) in parentheses.

Source: Survey data, 2004

households use fertilizer or certified seeds (Table 9). Modern farming methods are more widely used in Laikipia than in Suba District.

4.3 Factors influencing adoption of maize technologies

4.3.1 Gender

Most of the land users who had adopted hybrid maize were male, accounting for 68 per cent of adopters. Among 302 heads of households, 10 per cent were absent husbands, who accounted for 3.1 per cent of the sample.

4.3.2 Formal education of the land user

Most of the land users (56.3%) had attained primary school level of education, 13 per cent secondary school level while less than 1 per cent had attained university education. Most adopters (49.5%) had primary level of schooling, 18 per cent secondary level, and less than 1 per cent had university education.

The majority of the land users with no education were females in both districts (Table 10). However, male household heads with at least primary education were the majority in the two districts.

4.3.3 Non-formal education

In Laikipia, 22.4 per cent of males had received informal education compared with 17.1 per cent of females (Table 11). In Suba, 18.6 per cent of males and 19.3 per cent of females had received non-formal education. In Laikipia,

Table 11: Formal education by sex of land user by district

Education level	Laikipia		Suba	
	Male	Female	Male	Female
None	23 (21.5)	25 (60.9)	6 (10.5)	19 (22.1)
Primary	55 (51.4)	14 (34.2)	41 (71.9)	51 (59.3)
Secondary	15 (14.0)	1 (2.4)	8 (14.0)	11 (12.8)
College	12 (11.2)	1 (2.4)	2 (3.5)	5 (5.8)
University	2 (1.9)	-	-	-
Total	107 (100.0)	41 (100.0)	57 (100.0)	86 (100.0)

Note: Percentages of households in brackets.

Source: Survey data, 2004

Table 12: Informal education by sex of land user

Non-formal education	Laikipia		Suba	
	Male	Female	Male	Female
None	83 (77.6)	34 (82.9)	46 (80.7)	70 (81.4)
Adult education	3 (2.8)	5 (12.2)	1 (1.8)	1 (1.2)
Farm train	7 (6.5)	1 (2.4)	8 (14.0)	10 (11.6)
Artisan	14 (13.8)	1 (2.4)	2 (3.5)	5 (5.8)
Total	107 (100.0)	41 (100.0)	57 (100.0)	86 (100.0)

Note: Percentages of households in brackets.

Source: Survey data, 2004

farmers with non-formal education had undergone an artisan training (13.8% of males) and adult education (12.2% of females). In Suba, those with informal education had also received farm training (14% of males and 11.6% of females).

4.3.4 Farm sizes

In Laikipia, households own larger farms than in Suba, with mean farm sizes being 3.1 and 2.5 hectares. However, farm sizes vary considerably across villages in the two districts. The majority of the landowners possess between 1 and 3 hectares of land in Laikipia (49.7%) and Suba (59%). Few households possess less than 0.5 hectares of land in either district (Table 12).

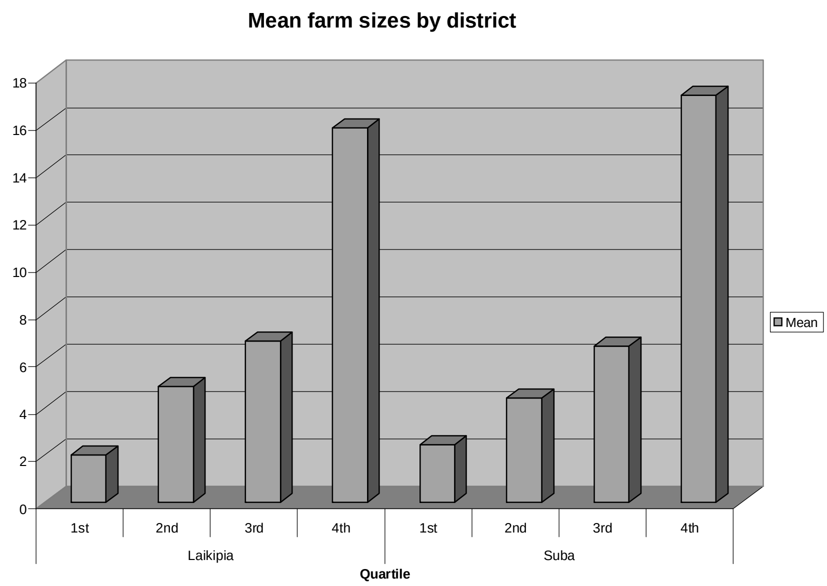
Table 12: Distribution of farm sizes in hectares by district

Farm size (ha)	Laikipia	Suba
Below 0.5	13 (8.3)	4 (2.8)
0.5 to 1	15 (9.6)	27 (18.8)
Between 1 and 3	378 (49.7)	85 (59.0)
Between 3 and 5	29 (18.5)	15 (10.4)
Over 5	22 (14.0)	13 (9.0)
All	157 (100.0)	144 (100.0)

Source: Survey data, 2004

A significant number of households fall in the bottom quartile of land distribution, indicating that land ownership in the districts is highly unequal (Figure 1).

Figure 1: Mean farm sizes by district



4.3.5 Household size

The mean household size in the two districts is 7 persons, but this varies considerably by district (Table 13).

Table 13: Household size by district

District	All households					Hybrid maize adopters			
	Min	Max	Mean	Median	No.	Min	Max	Mean	No.
Laikipia	2	19	8.2	8.0	157	2	19	8.0	90
Suba	1	16	6.3	6.0	142	4	16	7.4	8
All	1	19	7.3	7.0	299	2	19	7.9	98

Source: Survey data, 2004

Table 14: Gradient of land by hybrid maize adoption

Gradient	No. of observations	%	No. of observations	%
	Laikipia		Suba	
Flat	19	20.88	2	28.57
Gently sloping < 15d	49	53.85	4	57.14
Steep slope	91	25.27	1	14.29
Total	91	100.0	7	100.0

Source: Survey data, 2004

4.3.6 Land gradient

Land in the two districts is gently sloping, less than 15 degrees. Many households mentioned land gradient as an important factor in hybrid maize adoption (Table 14).

4.3.7 Livestock ownership

Besides crop cultivation, the farmers in the two districts keep livestock, but livestock ownership varies considerably by village.

Table 15: Number of livestock owned by district

Type	Laikipia	Suba	Both
Crossbreed cattle	273	7	280
Indigenous cattle	28	552	580
Sheep	411	143	554
Goats	242	334	576
Donkeys	31	60	91
Poultry	1,963	1,531	3,494

Source: Survey data, 2004

Laikipia owns the highest number of crossbreed cattle, sheep and poultry. Suba owns the highest number of indigenous cattle, goats and donkeys (Table 15).

4.3.8 Other factors

Other determinants of maize technology adoption include interaction of gender with schooling and with household and environmental characteristics; uncertainties associated with technology; and the cost of accessing and using technology.

4.4 Conditional probabilities of maize adoption

In this section we show how some of the factors described in section 4.3 above affect probabilities of adopting new maize technologies. Conditional adoption probabilities are predictions of technology adoption given some characteristics of farmers and the environment in which they operate. They differ from sample (unconditional) adoption technologies in that they are attributable to a specified set of factors, unlike sample probabilities for which hypothesized causal factors are unidentified.

4.4.1 Effects of household characteristics on technology adoption

Table 16 shows that price of maize, education, and distances to passable roads are the main determinants of hybrid maize adoption by farmers. In particular, an increase in price of maize encourages adoption of hybrid maize because, holding other things constant, such an increase raises profitability of maize. Education is positively associated with probability of adoption, indicating that literate farmers are more likely to use new maize innovations. As expected, there is a strong negative relationship between maize technology adoption and the distance from an all-weather road. Gender is not a major determinant of hybrid maize adoption. However, being male has a statistically insignificant negative effect on adoption.

4.4.2 Effects of technology on maize yields

Table 18 depicts a positive association between hybrid maize adoption and maize yields per acre. The result indicates that adopters of new maize varieties have higher maize yields than non-adopters. While this is an intuitively appealing finding, there is need to point out that farmers that are experiencing high maize yields are also the ones most *able* to experiment with new varieties of maize. In contrast, low productivity farmers do not

Table 16: A Probit Model of determinants of maize technology Adoption

Variable	Marginal Effects	z-statistic
Price of Maize	0.0004716	3.56
Years of Schooling	0.1551645	3.97
Distance to Shopping Center (kms)	-0.175136	-1.15
Sex (1 = Male)	-0.006199	-0.08
Distance to all weather road (kms)	-0.008980	-5.06
Log Likelihood	-137.287	
Pseudo R-squared	0.253	
Number of Observations	286	

Note: Dependent variable is probability of adopting hybrid maize

Source: Survey data, 2004

have such ability and may not innovate. Thus, the results in Table 17 cannot be unambiguously interpreted as suggesting that new maize technology is the source of high maize yields in the study districts. The inherent feedback effects in the maize production function disallow such an interpretation. Because of data limitation, Instrumental Variable (IV) estimation methods could not be used to deal with this problem. The coefficient on the district dummy indicates that maize yields are higher in Laikipia than in Suba District.

4.4.3 Effects of agricultural technology on poverty reduction

Tables 18a and 18b show estimation results for a bivariate model of maize technology adoption and poverty reduction. The results reported in Table 18a mimic the findings in Table 16, where distance to all-weather roads reduces adoption probability while education increases it. The results in Table 19b indicate that the *probability of adopting* new maize technology is negatively associated with poverty. That is, hybrid maize adoption reduces poverty. On the other hand, an increase in maize price increases poverty. However, the complex effects of maize price on poverty should be noted. An increase in maize price encourages technology adoption (Table 16), raising the yields and incomes of maize growers (Table 17). Thus, increases in maize prices reduce poverty among maize sellers, but increase poverty among maize buyers. The overall effect of an increase in maize price on poverty status of a household depends on whether the household is a net buyer or seller of maize.

Table 17: The effect of technology on maize yields controlling for other covariates

Variable	Estimated Coefficient	*t*-statistic
Constant	0.36379	0.49
Probability of adopting hybrid maize	5.85237	3.53
Years of schooling	0.70658	1.87
District (1 = Laikipia)	6.0074	8.23
Sex (1 = Male)	-0.67271	-1.14
F-statistic (4, 271)	88.32 (p =.000)	
Adj R-squared	0.559	
Number of Observations	276	

Note: Dependent variable is bags of maize per acre

Source: Survey data, 2004

Table 18a: Bivariate Model of technology adoption and poverty reduction

Variable	Estimated coefficient	*t*-statistic
Constant	-1.4462	-4.51
Distance to all-weather road (km)	-0.2372	-4.32
Years of schooling	0.34266	2.37
Sex (1 = Male)	0.04055	0.18
Per capita household income (Ksh)	0.0000086	1.78
Log Likelihood	-230.398	
Wald Chi-Square	121.17 (p = .000)	
Number of observations	277	

Note: First Equation: Dependent variable is maize technology adoption

Source: Survey data, 2004

Table 18b: Bivariate Model of technology adoption and poverty reduction

Variable	Estimated Coefficient	*t*-statistic
Constant	1.83030	5.89
Price of maize (Ksh)	0.00320	4.22
Years of schooling	-0.01599	-0.11
Probability of adopting hybrid maize	-4.99237	-5.98
Number of observations	277	

Note: Second Equation: Dependent variable is poverty status (probability of being poor)

Source: Survey data, 2004

5. Conclusion

The analysis undertaken in the paper has several policy implications. We have shown that only 34.7 per cent of the land owned in the two districts is cultivated, which suggests that there is potential to increase maize production in the districts by increasing the acreage under maize. Few farmers in the study districts are applying for loans, perhaps because credit institutions are inaccessible. There is need for the government to avail credit to farmers to finance the cost of technology adoption.

Although adoption of hybrid maize is widespread in Laikipia District, few farmers in Suba grow hybrid maize. The study has demonstrated that adoption of hybrid maize is associated with high maize yields and poverty reduction. There is need therefore to find mechanisms for extending high yielding varieties of maize to Suba District, which is one of the poorest districts in the country. Specifically, provision of social infrastructure and extension of education facilities would facilitate the spread of new maize varieties in Suba and other districts.

References

Bindlish, V. and R. E. Evenson (1997), "The Impact of T & V Extension in Africa: The Experience of Kenya and Burkina Faso", *World Bank Research Observer*, 12(2):183-201.

Bindlish, V., R. E. Evenson and M. Gbetibouo (1993), *Evaluation of T & V-Based Extension in Burkina Faso*, World Bank Technical Paper 226, Washington DC.

Byerlee, Derek and Edith Hesse de Polanco (1986), "Farmers' Stepwise Adoption of Technological Packages: Evidence from the Mexican Altiplano," *American Journal of Agricultural Economics*, 68(3): 519-527.

Doss, C. R. (2003), "Understanding Farm Level Technology Adoption: Lessons Learned from CIMMYT's Micro Surveys in Eastern Africa," CIMMYT Economics Working Paper No. 03-07, Mexico, D.F.: CIMMYT.

KIPPRA (2005), "Agricultural Technologies in Kenya", A Research Proposal, mimeo.

Maddala, G. S. (1983): *Limited-Dependent and Qualitative Variables in Econometrics*, Cambridge: Cambridge University Press.

Mwabu, G., T. Kiriti, G. Ndenge, J. Kirimi, J. Mariara, R. Gesami, W. Masai, P. Kimuyu, M. Chemengich and F. Munene (2000), "Poverty Profiles and Determinants in Kenya," University of Nairobi, mimeo.

Mwabu, G., W. Mwangi and H. Nyangito (2006), "Does Adoption of Improved Maize Varieties Reduce Poverty? Evidence from Kenya". Poster paper presented at the IAAE Conference at Gold Coast, Queensland, Australia, 12-18 August.

Obunde, P. O., C. M. Mbogo, W. O. Kosura and A. W. Kamoni (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 No. 7, Kampala, Uganda.

Republic of Kenya (1998), Poverty Profile Reports, Ministry of Planning and National Development, Nairobi.

Republic of Kenya (2002a), "Laikipia District Development Plan, 2002-2008: Effective Management for Sustainable Economic Growth and Poverty Reduction," Ministry of Planning and National Development, Nairobi.

Republic of Kenya (2002b), "Suba District Development Plan, 2002-2008: Effective Management for Sustainable Economic Growth and Poverty Reduction," Ministry of Planning and National Development, Nairobi.

Schultz, T. W. (1964), *Transforming Traditional Agriculture*, New Haven: Yale University Press.

Wooldridge, Jeffrey M. (2002), *Econometric Analysis of Cross-section and Panel Data*, Cambridge MA: MIT Press.

Related KIPPRA Publications

Kimenyi M. S. (2002), Agriculture, economic growth and poverty reduction, KIPPRA OP No. 3.

Nyangito H. and Ndirangu L. (2002), Impact of institutional and regulatory framework on the food crops subsector in Kenya: 1990-1999, KIPPRA DP No. 18.

Odhiambo W. and Nyangito H. (2003), Measuring agricultural productivity in Kenya: A review of approaches, KIPPRA DP No. 26.

Odhiambo W., Nyangito H. O. and Nzuma J. (2004), Sources and determinants of agricultural productivity in Kenya, KIPPRA DP No. 34.

Omiti, J, et al. (2006), Participatory prioritization of issues in smallholder agricultural commercialization in Kenya, KIPPRA DP No. 64.

Waiyaki, N et al. (2006), Determinants of seed maize pricing in Kenya, KIPPRA DP No. 61.