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DP/120/2010

THE KENYA INSTITUTE FOR PUBLIC POLICY RESEARCH AND ANALYSIS (KIPPRA)

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Kenya Institute for Public Policy
Research and Analysis

KIPPRA Discussion Paper No. 120
2010

The KENYA INSTITUTE for PUBLIC POLICY RESEARCH and ANALYSIS

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Published 2010

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ISBN 9966 777 73 3

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This paper is produced under the KIPPRA Young Professionals (YPs) programme. The programme targets young scholars from the public and private sector, who undertake an intensive one-year course on public policy research and analysis, and during which they write a research paper on a selected public policy issue, with supervision from senior researchers at the Institute.

KIPPRA acknowledges generous support from the Government of Kenya (GoK), European Union (EU), the African Capacity Building Foundation (ACBF), and Think Tank Inititative of IDRC.

Abstract

This study provides empirical evidence of technology adoption and the effects of production risk on it among smallholder farmers, using cross-sectional data collected from semi-arid districts in Kenya (Machakos and Taita Taveta). Several approaches are used: probit approach to estimate the effects of farm and household level variables on adoption of terracing as a soil and water management technology, and instrumental variable Two Stage Least Squares method to estimate productivity, and moment-based approach to capture variability risk (variance/second moment of maize yield) and downside risk (skewness/third moment of maize yield). Variability risk is also used together with farm and household level variables to determine the impact of production risk on technology adoption decisions.

The results show that household size; and institutional factors such as social capital, security of land tenure and the slope of land are important in increasing the probability of adoption of terracing technology. Expected yield as shown by the first moment has a positive effect on adoption of fertilizer. Variability of yield has a positive effect on manure use, and a negative effect on fertilizer application. High probability of crop failure (downside risk) increases the possibility of terracing and manure application by farmers, and reduces the possibility of fertilizer application. Other important factors that influence technology adoption decisions are region and distance from household to the farm. Productivity is found to be positively influenced by fertilizer adoption, manure and labour application, and soil and water management, while land size is found to negatively influence productivity.

These results have important policy implications, such as technology adoption which ought to be encouraged because it increases productivity. However, these technologies are associated with risks against which farmers should be cushioned, if they are to embrace them. Also, institutional, household, farm-level and regional factors are important in technology adoption, and any policy aimed at enhancing technology uptake must carefully consider them. Since regions respond differently to different technologies, it may be important to develop region-specific policies rather than rely on toolbox approach.

Abbreviations and Acronyms

CIMMYT	International Maize and Wheat Improvement Centre
GDP	Gross Domestic Product
IFPRI	International Food Policy Research Institute
SSA	Sub-Saharan Africa
SWC	Soil and Water Conservation

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1. Introduction

In Sub-Saharan Africa (SSA), over 70 per cent of the poor live in rural areas. The rural poor are very dependent on their natural resource base, particularly their soil and its productive capacity. The main physical asset of poor farmers is land. Its contribution to farmer's income is far more important than physical capital. Yet, land degradation in the form of soil erosion and nutrient depletion poses a threat to food security and sustainability of agricultural production particularly in less favoured dryland areas. In Kenya, the magnitude of soil erosion losses to the economy has been estimated as equivalent to US$ 390 million annually or 3.8 per cent of GDP (Cohen, Brown and Shepherd, 2006). In response, the government and development partners have devoted substantial resources to improve environmental conditions and increase agricultural productivity.

The use of modern farm technology (such as soil and water conservation technologies, and fertilizer) that would enable farmers to increase farm productivity while conserving the soil capital has been emphasized as a possible solution (World Bank, 2008; and Ministry of Agriculture, 2004). However, adoption of modern technology has been limited in most of Sub-Saharan Africa. This is the case in Kenya where small scale agriculture is characterized by little use of external inputs, soil erosion and high nutrient depletion. The government has initiated extension worker programmes to promote the adoption of improved technology. Despite these concerted efforts by the government and development partners, the adoption rate of improved farm technology is disappointingly low.

Many questions about the determinants of farm technology adoption remain unclear. Previous research has been devoted on individual and plot characteristics (Feder, Just and Zilberman, 1985). Other recent studies have explored the role of social factors on technology adoption (Foster and Rosenzweig, 1995; and Nyangena, 2008). A key element missing from the research is lack of empirical analysis on the role of risk in technological uptake and production effects among low income farmers. Production risk is an important element in agricultural production decisions, particularly in the uptake of farm technology. If poor people are risk averse, they will be reluctant to invest in the uptake of modern technology because it involves taking risks, and they will remain poor in the absence of mechanisms to minimize the downside effects (Antle, 1983; and Dercon, 2004). For risk averse individuals, an increase in variance with enormous downside risk may make the individual worse off. Only economically secure farmers that are in possession of sufficient defense against downside risk will undertake profitable capital investments and innovations, while the majority of the poor remain under risk-induced poverty trap (Eswaran and Kotwal, 1990; Rosenzweig and Binswanger, 1993; Mosley and Verschoor, 2005; Dercon and Christiansen, 2007; and Yesuf and Bluffstone, 2009).

Despite the significant role that risk exposure plays in production decisions, empirical literature looking into the role of production on farm investment decisions in low income rain-fed agriculture is scanty. Notable exceptions are the works of Koundouri *et al.* (2006), Groom *et al.* (2008), and Kassie *et al.* (2008). With the exception of Kassie *et al.* (2008), others used cross sectional data and econometric approaches that left the unobserved heterogeneities uncontrolled for. If correlated to some of the observed factors that would potentially create inconsistency and bias in the parameter estimates, it leads to wrong policy conclusions. In this study, plot level data that mimics the major features of panel data, and a pseudo fixed effect econometric approach to control for unobserved heterogeneities, are used. This study employs a two-stage instrumental variable estimation approach to address the potential endogeneity problems. It will extend the literature on farm technology adoption in low income countries by bringing the issue of risk exposure using more robust and alterative estimation procedures.

The paper is organized as follows: a brief empirical literature review is done in Section 2. Section 3 discusses the conceptual framework used to analyze the farmers' adoption decisions in the presence of production risk. The section also has the econometric specification. The descriptive statistics of the data are discussed in Section 4. While the empirical results and discussion are presented in Section 5, a summary of the findings and policy conclusions are discussed in Section 6.

2. Overview of the Existing Literature

Modern inputs such as fertilizer and Soil and Water Conservation (SWC) adoption are important for enhancing agricultural productivity. Manure application could also be a crucial supplement or even a substitute to fertilizer especially among the resource poor small holders. In SSA, adoption levels are low. Feder, Just and Zilberman (1985) conducted a comprehensive survey to summarize factors influencing adoption of farm technologies and agricultural innovations. Among other factors, whether to adopt a technology or not depends on the profitability of the technology, farmer education/learning and other observed and unobserved differences among farmers and across farming systems (Suri, 2005).

In Kenya, studies by the International Maize and Wheat Improvement Centre (CIMMYT) and other similar research institutions have examined the factors that condition productivity of maize and factors that condition adoption of farm technologies among maize growers. These studies show that farmer characteristics such as age, gender, level of education and wealth, and institutional factors such as access to capital and labour markets, land tenure security and social capital are important factors in farm technology adoption decisions (Mwangi, Lynam and Hassan, 1998; Doss, 2003; Foster and Rosenzweig, 1995; Jackson and Watts, 2002; and Nyangena, 2008).

Missing from literature in Kenya and other SSA countries, is the link between risk exposure and technology adoption decisions. When farmers are poor and depend merely on natural rain for their farming, and in the mean time cannot foresee a safety net where they can fall back to incase of a bad outcome, they would be hesitant to engage in an investment activity that involves some probability of downside risk even if such activities promise higher returns (Just and Pope, 1979; and Rosenzweig and Binswanger, 1993). Under such circumstances, the farmers households opt to stick to low-risk technologies despite low returns, a move that perpetuates the vicious circle of poverty (Dercon and Christiansen, 2007; and Yesuf and Bluffstone, 2009).

Using a dynamic model and observed data from the Philippines, Shively (1997 and 2001) showed how investment in soil conservation affects consumption risk and how these risks influence incentives for soil conservation of small farmers in low income countries. His results showed that the risk of consumption shortfall generates inefficient patterns of soil conservation adoption on small farms. Observed adoption patterns reflect risk characteristics of the soil conservation method, differences in farm size, and risk exposure among farmers. Similarly, using panel data and historical rainfall distributions as proxy for counterfactual consumption risk, Dercon and Christiansen (2007) showed how low consumption outcomes during harvest failure discourage the application of fertilizer by small farmers in Ethiopia.

Despite a growing trend of literature on the impact of consumption risk on farm technology adoption, the role of production risk is less documented. Understanding the link between production risk exposure and technology adoption is vital to scaling up existing successful farm technologies across poor farm households and reducing food insecurity and rural poverty in many countries. This study is an effort to understand this linkage using detailed plot level information and proper econometric tools in arid areas of Kenya.

3. Conceptual Framework

This study applies the mean-variance approach suggested by Just and Pope (1979) and applied by Antle (1983) to explore the role of higher moments of the distribution.

An expected utility framework to represent investment and production decisions made under uncertainty and market imperfections is used. Following Koundouri *et al.* (2006), the assumption is that farmers are risk averse and utilize a vector of conventional inputs X, together with soil and water conservation to produce a single output q. The household incurs production risk because crop yield is affected by uncertain climatic conditions. This risk is captured by a random variable ε, whose distribution $G(.)$ is exogenous to the household's actions. Let *(p)* and *(r)* be the corresponding vector of output and input prices respectively, farmers are assumed to be price takers in both markets.

Soil and water conservation is assumed to be an important input in farm production process. Adoption of SWC is used in combination with other inputs such as manure and fertilizer, and is captured through incorporation of the function $H(\alpha)x_{swc}$. The production function $q=f[H(\alpha)x_{swc},X]$ is assumed to be well behaved, continuous and twice differentiable.

Allowing for risk aversion, the household's problem is to maximize the expected utility of gross income as follows:

$$\underset{x_{swc},X}{Max}\ E[U(\varpi)] = \max_{x_{swc},X} \int E(U\{[pf(\varepsilon, h(\alpha)x_{swc}, X) - r(x) - r(x_{swc})]\}dG(\varepsilon) \quad \text{............(1)}$$

U(.) is the von Neumann-Morgenstern function. Given that *(p)* and *(r)* are non-random, the first order condition for SWC input choice is given by the following:

$$E(r_f U') = \left[p \frac{\partial f(\varepsilon, h(\alpha)x_{swc}, X)}{\partial x_{swc}} U' \right] \quad \text{..(2a)}$$

$$\frac{r_{swc}}{p} = E\left[\frac{df(\varepsilon, x_{swc}, X}{\partial x_{swc}} \right] + \frac{\mathrm{cov}(U'; \partial f(\varepsilon, x_{swc}, X)/\partial x_{swc})}{E[U']} \quad \text{..................(2b)}$$

where U' is the change in utility of income following a change in income $\left[\frac{\partial U(\varpi)}{\partial \varpi} \right]$.

A similar procedure could be used to derive the First Order Necessary Condition (FONC) for other variables. For the risk neutral households, the first term in the right hand side of (2b) will disappear and adoption of farm technology will depend on the traditional marginal conditions. For the risk averse households, this term is different from zero. The second term on the right hand side in (2b) is different from zero and measures deviations from the risk neutrality situation. The term is proportional and should be opposite in sign to the marginal risk premium with respect to the SWC input. Whether households adopt the SWC technology (A=1) or not (A=0) will be determined by production risk in addition to adoption costs and other factors. These include farm specific attributes such as plot size, slope and soil type. This decision is modeled as a binary choice, where a household can choose to adopt or not a particular SWC technology. A household will only adopt SWC technology if the expected utility with adoption $E[U(\varpi^1)]$ is greater than the expected utility without adoption $E[U(\varpi^0)$. That is:

$$E[U(\varpi^1)]-E[U(\varpi^0) > 0 \quad \text{...}(3)$$

3.1 Empirical Methodology

This section presents the empirical methodology to examine the determinants of technology adoption and value of productivity. Risk averse decision makers have an incentive to reduce their risk exposure. Farm households in low income economies are typically risk averse (Dercon, 2004). They experience a loss in welfare when there is variability (as measured by variance) in their production or consumption pattern.

The econometric estimation of production risk impact on SWC technology adoption is conducted in two steps. First, we compute the first three sample moments of return distribution of each household, namely the mean, the variance and the skewness coefficients. In the second phase, the estimated moments are then included alongside other explanatory variables in the adoption model.

In the first stage, maize production per unit area was regressed on observed plot, household and institutional characteristics to get the estimates of the mean effect. The model has the following functional form:

$$y=f(x_{swc},X,\beta)+\varepsilon \quad \text{...}(4)$$

where y is the maize production per unit of land obtained by the household; is the random variable capturing unobserved features and production εshocks such as drought, rainfall and floods etc); and β is a vector of parameters to be estimated.

The j^{th} central moment of value of maize production about its mean is given as:

$\varepsilon_j = e\{[Y(.)-\mu]^j\}$ for j = 2....m..(5)

where μ denotes the mean value of maize production or the first moment of value of maize production per unit area. The estimated errors from the mean regression $\varepsilon - f(x_{swc}, X, \hat{\beta})$ are estimates of the first moment of value of maize production distribution. The estimated errors or residuals are then squared and regressed on the same set of explanatory variables as in equation 6:

$$\varepsilon^2 = f_2(x_{swc}, X, \hat{\beta}_2) + v \quad \text{...(6)}$$

The least squares estimates of $\hat{\beta}_2$ are consistent and asymptotically normal (Antle, 1983). The predicted values of ε^2 are also consistent estimates of the second central moment (variance of maize production) of maize production distribution. This approach has been used in the literature (Antle 1983; Kim and Chavas 2003; and Koundouri *et al.*, 2006).

Consistent estimates can only be obtained when unobserved heterogeneity that may be correlated with observed explanatory variables are controlled. This can be achieved by exploiting the panel data characteristic. Two options are available, using household specific fixed effects or random effect. In our case, fixed effect is undesirable because some households have only a single plot and would be dropped in the analysis. Random effect, on the other hand, is only consistent when unobserved heterogeneity is uncorrelated with the explanatory variables. This implies that we cannot use purely fixed effect or purely random effect models. Instead, a blend of the two, pseudo fixed effect model (Mundlak, 1978), which includes the mean values of plot variant explanatory variables, is used. Mundlak's approach is based on the assumption that unobserved effects are linearly correlated with explanatory variables:

$\mu h = \alpha + \mathrm{e}h,\ \mathrm{e}h \sim iid(0, \sigma_e^2)$

where α is the corresponding vector of coefficients, *x* is the mean of plot-variant explanatory variables within each household, and e is a random error term, which is uncorrelated with *x*'s. Mean distance of plots from household, mean plot slope, mean soil type and mean plot size are strong determinants of technology adoption. If observed explanatory variables are uncorrelated with the random effects, the vector α will collapse to zero.

4. Methodology and Data Sources

This study is based on primary data collected by the International Food Policy Research Institute (IFPRI) from Machakos and Taita Taveta districts of Kenya in 2003. A sample of 321 households was visited and a detailed questionnaire used to collect the requisite data. Of the 321 households surveyed, 43 per cent are from Machakos District while 57 per cent are from Taita Taveta District. The main variables used in the study are summarized in Table 4.1. The variables are categorized into three: household characteristics, farm characteristics and institutional factors.

4.1 Household Characteristics

Household characteristics include age, sex and education of the household head, household size and the district of location, whether Machakos or Taita Taveta. Age of the household head has a bearing on his/her approach to technology; that is whether the head will be open or conservative. Age also influences one's exposure to new technologies. For technologies that require physical labour input, the farmer's age is important. Thus, age can either increase or decrease the probability of technology adoption. Average age of household heads in Machakos is 49 years, while that of Taita Taveta is 53 years, both of which fall within the same age bracket.

The gender of the household's head is important in technology adoption. It influences the level of access to improved technology. In Africa, women have lower access to information regarding new technologies. The impact of this is on men, different from that of women. For instance, women are likely to bear heavier burden when harvest is poor or when water is scarce. As a result, women may be more concerned about SWC than men. It is also important to note that men control more resources and are likely to take up technologies that require more financial input than their female counterparts. Therefore, the direction that the household head takes on technology adoption could vary with the nature of the technology and gender. In Machakos District, 91 per cent of households are male headed, while in Taita Taveta, 77 per cent of households are male headed.

Education level of the household head influences decision making. A well educated farmer can access and assimilate information faster and better. Further, education opens more avenues for generation of

Table 4.1: Summary statistics

	Machakos		Taita Taveta		Districts combined	
Variable	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Household characteristics						
Age of household head	49	14	53	13	51	14
Male headed households	0.91		0.77		0.83	
Education of household head	7	4	6	4	6	4
District of location	0.43		0.57		1	
Household size	6	3	6	3	6	3
Farm characteristics						
Farm size (ha)	3.5	6.7	3.2	4.6	3.3	5.6
Maize yield per ha (kg)	200	300	167	249	181	300
Manure input per ha (kg)	759.6	1775	170.8	213.9	602	1544
Fertilizer input per ha (kg)	20.3	23	0	0	20.3	23
Labour input per ha (days)	50	60.2	80.8	214.3	67.5	166.8
Terrace length per ha (mts)	325.5	392.9	162.8	396.2	233.2	402.5
Proportion of terraced plots	0.85		0.5		0.65	
Proportion of plots manured	0.6		0.17		0.35	
Proportion of plots using fertilizer	0.33		0		0.14	
Flat plots	0.21		0.26		0.24	
Lower slope plots	0.4		0.34		0.37	
Mid slope plots	0.28		0.35		0.32	
Upper slope plots	0.11		0.05		0.07	
Sandy plots	0.23		0.1		0.16	
Sandy loam plots	0.44		0.64		0.55	
Loamy silt plots	0.25		0.16		0.2	
Clay soil plots	0.08		0.1		0.09	
Distance from household	262.6	609	1137.3	1942.2	758.9	1576.5
Institutional factors						
Access to extension services	0.24		0.44		0.33	
Cost to nearest market (minutes)	108	19	89	39	97	33
Membership in organizations	0.81		0.48		0.62	
Tenure security	0.23		0.13		0.17	

non-farm income, which could be employed in technology adoption. The years of schooling by the household head are considered with an assumption that most household decisions are made by the head. Education of the household head increases the likelihood of adoption of improved technologies. While the average level of education is primary school for the two districts, secondary level of education and beyond constitute 33 per cent of the sample in Machakos District and only 20 per cent in Taita Taveta.

Households derive farm labour from the household population. As a result, household size influences whether a household will adopt a given technology or not. Larger households are more likely to adopt intensive technologies. However, for technologies that require heavy financial outlay, large households may be disadvantaged because their resources are over-stretched by the basic household needs. For our sample, average household size is similar across the two districts.

Location of the household may influence adoption of farm technology through access to information and market. Households that have access to prime markets for agricultural products are motivated to use land more intensively and sustainably. They are able to adopt technologies partly because they aim at maximizing output and earn sufficient revenue to invest in technology adoption. Farmers in Machakos are hypothesized to be better adopters because of their proximity to Nairobi, a market for high value crops. Our sample is made up of 43 per cent and 57 per cent of households from Machakos and Taita Taveta districts, respectively.

4.2 Farm Characteristics

Farm size dictates the level of inputs. Small farms have a greater likelihood of adopting technologies because they are more intensively managed. Large farms can afford to use land unsustainably because, although their output per hectare may be low, the total output is still high. Holders of such large plots have the luxury of switching to other portions of the plot, once others are degenerated. Therefore, sustainable land management may not be an urgent requirement. For our sample, there is no marked difference in the average land holding size.

Fertility enhancement is important in determining the maize yield per plot. Our sample reveals that 60 per cent of plots in Machakos use manure, while only 17 per cent in Taita Taveta use manure. Intensity of manure application varies markedly in the two districts; an average farmer in Machakos applies more than four times the quantity applied by his counterpart in Taita Taveta. Thirty three per cent of farmers in Machakos apply fertilizer, while no farmer in Taita Taveta uses fertilizer. Perhaps this explains why average maize yield is slightly higher in Machakos than in Taita Taveta. A further explanation could be the extent of terracing in the two districts; 85 per cent of plots in Machakos and 50 per cent in Taita Taveta are terraced. Even terrace intensity varies greatly across the two districts; terracing is twice as intensive in Machakos as in Taita Taveta.

Maize cultivation in Taita Taveta District is more labour intensive than in Machakos, taking about 81 man days on average as opposed to 50 man days in Machakos. This may have a bearing on uptake of technologies that require more labour. The cost of this labour, whether hired or domestic, may also impede uptake of technologies that require substantial financial investment. Perhaps this explains why fertilizer application has not been taken up by Taita Taveta households.

Slope of land plays a major role in determining the use to which the land in question may be put and how the land should be managed. For instance, the upper slope may have thin soils unsuitable for cultivation, while the plain, despite its deep soils, could be so poorly drained making it less attractive for agriculture. Technologies such as terracing would also be necessary in undulating land than on plains. In both districts, 60 per cent of plots fall within plains and lower slope, while approximately 40 per cent fall within mid and upper slope. In each district, however, mid slope and lower slope host a larger proportion of the farms, 68 per cent and 69 per cent for Machakos and Taita Taveta, respectively. Machakos district has 11 per cent of the sampled plots on the upper slope, while Taita Taveta has only 5 per cent.

Soil type on a plot influences the level to which different technologies may be adopted. For instance, sandy soils are porous and more likely to discourage terracing. In Machakos, 67 per cent of plots have soils of sandy nature, while Taita Taveta has 74 per cent of plots with the same. Loamy and clay soils occupy 33 per cent and 26 per cent of plots in Machakos and Taita Taveta, respectively.

How far a plot lies from the household determines the level of a household's investment in such a plot. Long distance may discourage application of heavy inputs such as manure because it is not easy to monitor. Therefore, a household may not apply expensive inputs such as fertilizer because the investment may go to waste. The average distance of plots from households is 263 metres in Machakos District, and 1,137 metres in Taita Taveta District. Thus, plots in Machakos District stand a better chance of being better managed.

4.3 Institutional Factors

Access to government extension services is important as a source of information on new technologies, especially if farmers are receptive and willing to implement the information obtained. This effectively bridges the gap created by low education among farmers. Of the households interviewed, 24 per cent in Machakos District and 44 per cent in Taita Taveta District confirmed having access to extension services.

Distance to the nearest market affects the ease and cost of obtaining farm inputs as well as the cost of marketing the farm products. The average trekking time to the nearest market centre is 108 minutes in Machakos District and 89 minutes in Taita Taveta District. This indicates that there is no marked difference between the two districts.

Social capital refers to attributes of people and organizations that influence their responses to economic opportunities. Such opportunities could be arising from technologies. A household enjoys social capital when it interacts with other households and participates in group activities. In this study, social capital is measured by examining the number of social organizations that a household actively participates in. From such organizations, the household could benefit from farmer-farmer extension, collective action, financial and equipment support and easy access to government services. We hypothesize that a household richer in social capital is more likely to adopt technologies. From the sampled households, 81 per cent in Machakos District and 48 per cent in Taita Taveta District engage in social organizations.

Security of tenure, to a large extent, influences long term investment in land. Technologies such as terracing or application of manure may not yield immediate results. Therefore, a farmer is more likely to adopt them only when security of land tenure is guaranteed. In Machakos District, 23 per cent and 13 per cent of those sampled expressed certainty of security of their land tenure.

5. Results

5.1 Technology Adoption

Farmers have various technologies for simultaneously producing crops and conserving soil and water. We estimate a probit for terracing adoption with slope, gender, soil type, security of tenure, and district dummies. The results are presented in Table 5.1. The log likelihood ratio statistics {Chi-Square (16)} for the specification implies that the model fits the data and that the variables are jointly significant at 1 per cent.

Table 5.1: Probit estimates for adoption of terracing

Variable	**Marginal effect**
Household characteristics	
Household size	0.49***(5.21)
Education of household head	0.01(1.44)
Age of household head	0.002(1.14)
Male head of household	-0.13**(-2.28)
Taita Taveta District	-0.34***(-6.39)
Farm characteristics	
Plot size	0.0004 (0.1)
Low slope	0.1*(1.65)
Medium slope	0.19***(2.93)
High slope	0.09 (1.01)
Sandy loam	0.09 (1.24)
Loamy silt	0.05 (0.69)
Clay	0.18*(1.82)
Distance of plot from household	0.000 (0.1)
Institutional factors	
Social capital	0.06**(2.00)
Distance to nearest market	0.001 (0.82)
Secure tenure	0.15**(2.25)
Number of observations	481
Wald Chi^2 (16)	89.28***
Obs. predicted	0.65
Pred. probability	0.7

Z-values in parentheses.

***, **,* significant at 1%, 5% and 10%, respectively.

Household size has a positive and significant influence on terracing adoption, other things being equal. An increase in household size by one member increases the predicted probability of terracing adoption by about 0.49. This could be because a larger household has sufficient labour required for terracing, which is normally labour-intensive. Where hired, labour is scarce or expensive. Adoption of labour-intensive technologies is less attractive for those with limited family labour. This is normally the case with small holders who basically rely on household labour for almost all farm activities.

Male headed households have a 0.13 lower probability of adopting terracing than female headed households. This indicates that women are better environmental stewards perhaps because they are more heavily impacted by environmental degradation. For instance, water scarcity has a heavier bearing on women and the girls who are duty bound to guarantee domestic water supply. It is therefore not surprising that women headed households are more proactive in SWC.

Households in Taita Taveta District, compared to those in Machakos District, have a lower predicted probability of uptake of terracing technology by 0.34. Proximity of Machakos to Nairobi, which is a market centre for high value crops, is a possible explanation for this. Also, Machakos is better endowed with social capital than Taita Taveta. This could translate into better access to cheap labour, equipment and finances required for terracing. This finding of higher social capital is corroborated in a study that compared the levels of social capital in Machakos, Kiambu and Meru (Nyangena, 2008).

Further, among the surveyed farmers, Machakos District has a higher proportion of secondary school education and higher graduates. Therefore, they have better access to information on technologies and are better suited to assimilate the information compared to their counterparts in Taita Taveta. Security of tenure is yet another possible explanation to this difference because the summary statistics indicate that a larger proportion of farmers in Machakos believe they have a secure land tenure, as this would encourage long term investment in land. The statistics further reveal that maize cultivation in Taita Taveta is more labour-intensive, and this could imply that households in the district are constrained in terms of labour to be employed in terracing, a labour-intensive technology.

A household that participates in more social organizations has a higher chance of implementing terracing. A rise in membership by one social organization increases the possibility of adopting terracing by the household by 0.06, if other factors remain the same. A possible explanation to this is that social groups provide fora for farmer to farmer extension services, filling the knowledge gap arising from low education. Further, such groups are sources of cheap labour as the members can assist each other in constructing terraces, or they may be a source of soft loans to the members, either in terms of money or equipment needed for terrace construction.

Perceived security of land tenure, in relation to perceived lack of the same, increases the predicted probability of a farmer adopting terracing by 0.15, other variables remaining the same. This is because terracing is expensive, yet the returns are not immediate. A farmer would only be motivated to undertake investment in terracing if convinced that land possession and use will remain in his hands for a long time because, only then, will he be able to recoup the investment. Security of tenure, if backed by documents, could improve access to credit, input markets, product markets and technical information. This finding is consistent with Parthasarathy and Prasad (1978) who found that tenants had a lower tendency to adopt technology than the land owners.

The effect of slope of land on terracing is greatest at the medium slope where, compared to the plain, the predicted probability of terracing increases by 0.19. This is perhaps because the effect of surface run-off is greatest at mid slope due to the steep gradient and accumulated water from the upper slope. Mid slopes are also areas of more intense agricultural activities, because the soils are better drained and deep enough to support crops. Thus, farmers would invest more in protecting soils at the mid slopes than anywhere else. It is important to note that plain land itself is a terrace and therefore the farmers are not expected to terrace plots on the plains. It is understandable that the probability of terracing increases with the rise in slope.

In reference to sandy soils, all the other soil types increase the possibility of a farmer embracing terracing as a method of soil and water management. However, only clay has a significant influence. Clay increases the predicted probability of a farmer terracing his plot by 0.18. This is probably because sand is porous and if the objective of terracing is to increase water retention, then it would be more meaningful to terrace a plot with clay soils than with sandy soils. Moreover, terraces on clay soils would be more stable and long lasting, and this would be a sufficient motivation for the farmer to give preferences to plots with clay soils while terracing.

5.2 Determinants of Productivity

The hypothesis is that productivity is positively correlated with level of inputs in accordance with economic theory. The impact of sustainable soil and water management, among other factors, on productivity is tested. Tables 5.2 and 5.3 show the results, and Chow's Test (F-Statistics) confirms the goodness of the model and the stability of coefficients to changes in specifications.

Our interest is to show that fertilizer input is influenced by distance, a proxy for fertilizer cost, which has been identified as our instrumental variable to tackle endogeneity in fertilizer variable in our productivity function. Indeed, the results indicate that a longer distance from the farm to the source of the fertilizer reduces the uptake of fertilizer. This is consistent with the theory of demand of inverse relationship between

Table 5.2: Determinants of fertilizer use (First stage regression)

Variable	**Parameter estimate**
Household characteristics	
Sex of household head	-0.082 (-0.94)
Farm characteristics	
Log manure intensity (kg)	-0.009 (-0.27)
Log labour intensity (man-days)	-0.028 (-1.10)
Log terrace intensity (metres)	0.013 (0.72)
Log acreage (hectares)	-0.100***(-2.55)
Manure x terrace	0.020***(3.15)
Institutional factors	
Log distance to nearest market	12.015***(4.36)
Log distance to nearest market squared	-1.333***(-4.34)
Constant	-26.556 (-4.34)
Number of observations	488
F-Statistic	(8, 479)=13.1***

t-values in parentheses. ***, significant at 1%

Table 5.3: Regression estimates for output per hectare (productivity)

Variable	Parameter estimate	Parameter estimate	Parameter estimate
	OLS	**IV-2SLS**	**Control function**
Household characteristics			
Male headed households	0.271 (1.44)	0.327**(1.72)	0.327**(1.76)
Farm characteristics			
Log fertilizer intensity (kg)	0.170**(2.38)	0.950**(1.95)	0.950**(2.01)
Log manure intensity (kg)	0.175***(3.05)	0.165**(2.29)	0.165**(2.83)
Log labour intensity (man days)	0.387***(5.73)	0.414***(7.8)	0.414***(6.35)
Log terrace intensity (metres)	0.103***(2.68)	0.082**(2.06)	0.082**(2.09)
Log acreage (hectares)	-0.283***(3.04)	-0.216**(-2.32)	-0.216**(-2.12)
Manure x terrace	-0.023**(-2.00)	-0.037**(-2.28)	-0.037***(-2.57)
Residuals	-	-	-0.811*(-1.67)
Constant	2.302 (7.61)	2.089 (7.38)	2.089 (6.66)
Number of observations	488	488	488
F statistic	(7,480)=16.26***	(7,480)=17.27***	(8,479)=14.94***

t values in parentheses

***, **,*, significant at 1%, 5% and 10%, respectively.

quantity demanded and price for all normal goods. As indicated earlier, the distance in our context implies price. F-statistic of 13.1 is an indication of a correct choice of the instrument and that the instrument is strong (Staiger and Stock, 1997; and Bound *et al.*, 1995).

From the control function, we are able to tell that the OLS model is plagued with endogeneity problem. This is shown by the statistical significance of the coefficient of the residuals according to Durbin Watson-Wu Haussmann test. This then provides the motivation to transit from the OLS model to the IV-2SLS. The results will be based on the outcomes of the Two-Stage Least Squares Model.

Fertilizer application is a positive and significant determinant of productivity. A one per cent increase in the quantity of fertilizer applied per hectare of land leads to 0.95 per cent increase in maize yield, if other factors are equal. Like fertilizer, manure input is also positively and significantly correlated with productivity, although the magnitude of effect is greater in fertilizer. A one per cent increase in manure input, other variables remaining unchanged, leads to 0.165 per cent increase in productivity. Other inputs with positive impacts are labour and terracing. A 1 per cent rise in labour input per hectare of land leads to 0.414 per cent increase in maize output per hectare as long as the other variables are not altered. When intensity of terracing is increased by one per cent, maize output per hectare increases by 0.082 per cent. Thus, from the inputs with positive outcomes from our sample, fertilizer ranks the highest followed by terracing, manure and labour in retrospect.

These results illustrate that technology adoption, holding all other factors constant, is positively correlated with productivity and it is consistent with the findings of Lopez (1998) and Ahuja (1998). The fact that labour input has a positive impact on productivity further conforms to the findings of Ahuja (1998). Since most households in the study region draw labour from the household population, this finding points to the fact that larger households are more productive because they have more labour to employ on the farm. We must appreciate the fact that high household population is essential for implementing other labour-intensive methods of conservation such as terracing and, as much as it reduces the per capita landholding, it is likely to boost output per unit of land given appropriate inputs. An important implication of this finding is that sustainable soil and water management technologies increase yields.

Total land owned by a farmer has significant but negative impact on output of maize per hectare, implying that farmers with large pieces of land have a lower productivity. An increase of land acreage by one per cent reduces productivity by 0.216. From the previous findings on adoption of conservation technology, plot size is negatively correlated with terracing. This partly explains why land size negatively impacts on productivity. Poorly managed land may yield high total output, but there will be low output per unit area of land. This confirms the stylized fact that smaller farms are better managed and used more intensively, leading to higher productivity.

Maize output per hectare of land by male headed households is 32.7 per cent higher than that of female headed households. Perhaps this is due to the fact that males control more of the resources used in agricultural production. Alternatively, they have more time to supervise farm activities unlike their female counterparts who have also to direct a lot of their time to domestic chores, especially in the African social setting.

One unexpected result is realized. That is, interaction of manure and terracing, leading to negative but significant impact on productivity. A one per cent increase in this interaction, holding other variables constant, leads to 3.7 per cent fall in productivity. This could be due to adverse effects of over application of manure on intensively terraced land, which may alter the soil PH, increase water logging or provide favourable breeding ground for harmful soil organisms. Another possibility is that when land is initially properly manured, introduction of terraces reduces the area of land that is actually under crop cultivation. Thus, while productivity may have gone up, failure to record the exact area of land under crop cultivation may give the wrong impression.

5.3 Risk and Technology Adoption

The moments-based approach is used on the productivity function in the previous section to generate risks associated with maize production across all the plots. We generate the first three moments—mean, variance and skewness—and apply them to test whether small scale farmers in our study area are risk averse or not before examining their impacts on adoption of various production technologies. Table 5.4 presents the estimated risk parameters.

The results show that farmers are risk averse particularly in adoption of terracing and use of manure. The constant term is significant in terracing and fertilizer use, and insignificant in manure use. This implies that manure input is efficiently utilized. As for terracing and

Table 5.4: Estimates of risk on technology adoption

Terracing	**Fertilizer use**	**Manure use**	**Risk parameter**
	Estimate	**Estimate**	**Estimate**
Variance	0.178	-0.08	0.09
Skewness	-0.002	0.003	-0.0001
Constant	0.807	0.493	0.353

fertilizer use, inefficiency exists. These conclusions are also manifested in the summary statistics, which show gross under application of fertilizer. The coefficients of variance are positive and significant for terracing and manure use, indicating that farmers are willing to forego part of their expected yield to avoid the risks associated with terracing and application of manure. Farmers exhibit an Arrow-Pratt type of risk aversion. The coefficients of the third moment (skewness) of the two technologies are negative and significant, showing that farmers are also averse to downside risk. The results are exactly the reverse for fertilizer application by the farmers in our sample. In Table 5.5, the results of terrace, manure and fertilizer use are adopted.

The likelihood of adoption of the three technologies using a modified probit model is estimated. The motivation is to display the derivatives of the explanatory variables, which approximate the change in the probability of adoption at the variables' mean. The results indicate that there is a correlation between the observed explanatory variables and the unobserved effects. Therefore, ignoring this correlation could lead to a bias in estimation of the impact of production risk on technology adoption.

The first moment has a highly significant effect on adoption of fertilizer. The higher the expected yield, the higher the probability of using fertilizer. The farmer behaves rationally and considers the chance of making profits. This explains why the farmer is more willing to apply fertilizer, which is a high cost input, when expected yields are high because, only then, will the farmer recover costs and make profits. From our earlier findings on productivity, the effect of fertilizer on yield is greater than that of manure. Perhaps the farmers understand this and when they expect higher yields, they would rather use fertilizer to maximize output.

The variance of yield has a positive effect on manure application and a negative effect on fertilizer adoption. This indicates that higher yield variability discourages farmers from use of higher cost inputs such as fertilizer and instead encourages the use of low cost inputs such as manure. This means that farmers are risk averse and would be hesitant to invest heavily in high risk ventures. The farmer would rather have a lower output than invest heavily in pursuit of higher but uncertain output.

A higher probability of crop failure (downside risk), as measured by the skewness of yield, increases the chance of a farmer terracing the

Table 5.5: Determinant of terrace, manure and fertilizer adoption

	Terrace adoption	**Manure use**	**Fertilizer adoption**
Explanatory variable	**Marginal effect**	**Marginal effect**	**Marginal effect**
Risk measures			
Predicted mean yield of maize	-0.011 (-0.11)	-0.13 (-1.27)	0.146***(3.31)
Predicted variance of yield	0.027 (1.27)	0.05**(2.37)	-0.053***(-5.90)
Predicted skewness of yield	-0.0004** (-2.09)	-0.001** (-2.83)	0.001***(12.28)
Household characteristics			
Household size	0.034***(4.65)	0.002 (0.30)	-0.005 (-1.47)
Age of household head (years)	-0.0001 (-0.71)	0.0002 (0.15)	-0.0006 (-0.94)
Education of household head (yrs)	0.009*(1.66)	0.009*(1.66)	0.002 (0.98)
Sex of household head (male)	-0.157***(-2.88)	-0.035 (-0.64)	-0.018 (-0.80)
Social capital	0.04*(1.94)	0.015 (0.74)	0.009 (0.99)
Farm characteristics			
Plot size	0.003 (0.29)	0.01 (1.14)	0.004 (0.92)
Distance of plot from household	-0.00003 (-1.51)	-0.0001** (-2.75)	-0.000 (-0.25)
Low slope	0.02 (0.29)	0.045 (0.65)	0.011 (0.37)
Medium slope	0.008 (0.07)	0.103 (0.92)	0.022 (0.46)
High slope	-0.14 (-0.81)	-0.011 (-0.06)	0.022 (0.29)
Location-Taita Taveta	-0.36***(-7.11)	-0.39***(-7.87)	-0.137***(-6.42)
Sandy loam	-0.005 (-0.07)	0.082 (1.11)	0.034 (1.09)
Loamy silt	-0.145 (-1.15)	0.142 (1.13)	0.02 (0.37)
Clay	-0.09 (-0.57)	0.104 (0.65)	0.032 (0.47)
Others	-0.046 (-0.13)	0.56(1.6)	0.077 (0.51)
Average plot size	0.004 (0.45)	-0.0004 (-0.04)	0.002 (0.59)
Average plot distance from household	0.0001**(2.27)	0.00005* (1.75)	0.000 (0.85)
Average plot slope	0.095 (1.57)	0.035 (0.58)	0.01 (0.38)
Average soil type	0.11*(1.78)	-0.055 (-0.92)	0.0001 (0.00)
Institutional factors			
Distance to nearest market (minutes)	0.0003 (0.43)	0.0002 (0.29)	-0.0004 (-1.57)
Secure land tenure	0.124**(2.29)	-0.081 (-1.52)	-0.038*(-1.66)
No. of observations	496	496	496
Wald Chi^2	(24)=180.82***	(24)=192.18***	(24)=1503***

Z-Values in parentheses

***, **, *, significant at 1%, 5% and 10%, respectively.

plot or applying manure. At the same time, a low probability of crop failure increases the possibility of a farmer applying fertilizer on the plot. Farmers thus use fertilizer to increase output, and use terracing and manure as ways of stabilizing output or curbing crop failure. Alternatively, farmers terrace and apply manure on plots that are already extensively degraded (and no longer promise any yields) as a means of rehabilitating them. On the contrary, fertilizer is applied on plots with better prospects of yields as a mechanism for increasing gains.

Besides production risk variables, plot level variables such as distance of plot from household and district of plot location; household characteristics such as household size, education and sex of household head; and household social networks, and institutional factors such as security of land tenure have statistically significant effects on farmers' decision to adopt or not to adopt a given technology.

Household size is positively correlated with terracing. That is, a marginal increase in household membership increases the probability of the household adopting terracing as a means of SWC. This is not surprising because terracing is labour-intensive and would favour households with abundant labour supply. Therefore, where households rely on family labour like in our area of study, a large household becomes an obvious positive predictor of terracing.

Education of the household head increases the probability of farm technology adoption. This is because the household head, the main decision maker in a household, is more capable of accessing and assimilating information regarding the various technologies, their advantages and the dangers of not adopting them if better educated. Education also opens up other avenues for earning income. Thus, an educated household head is more likely to have more resources that can be invested in technology adoption.

Female household heads have a higher chance of adopting SWC technology compared to their male counterparts. Perhaps this is because smallholder agriculture is dominated by women, and any failure of crops would impact on them more heavily. An alternative explanation is that women are more active in participating in social groups. In our sample, for instance, 54 per cent of social organization meetings were attended by women in Machakos District, while men attended only about 41 per cent. In Taita Taveta District, 73 per cent of such meetings were attended by women, while only a paltry 24 per cent were attended by men. Through such organizations, women are able to mobilize labour, tools/equipment and financial resources for terracing. It is also through such organizations that government and farmer-to-farmer extension services are delivered. This argument is reinforced by the significant positive influence that social capital has on the probability of terrace adoption.

Distance from household to the plot reduces the probability of manure use. This is because manure is normally accumulated in the backyard and since it is heavy and bulky, farmers would be less willing to apply it when the farm is too far from the household. Moreover, where the farmer relies on hired labour, it becomes expensive to apply manure on farms far from the homestead. Equally important is the management challenges of farms that lie far from the household. Such farms are easy culprits of crop theft and invasion by animals. As a result, a household may not find it prudent to invest heavily in such plots. It is also possible that distant plots have been acquired or opened up for cultivation lately and, therefore, they are less exhausted, hence the lower need for manure use.

Farmers in Taita Taveta, compared to their counterparts in Machakos, are less likely to adopt terracing, manure and fertilizer application. Farming in Machakos is more profitable, being closer to Nairobi which provides ready market for high value crops. This motivates farmers in Machakos to use land sustainably through terracing and manure application and to enhance output through fertilizer use. Profitability of farming in Machakos also implies that the farmers have relatively more resources to invest in farm technology. Other reasons that give Machakos an edge over Taita Taveta in farm technology adoption include better participation in social organizations, secure land tenure and less labour intensive agriculture. Again, it must be appreciated that terracing in Machakos dates back to the colonial periods and therefore the technology has been in the area for a longer period, making it to diffuse to a wider cross section of the farmers.

Secure land tenure increases the probability of adoption for terracing. Terracing being an expensive technology in the short run and one whose returns are not immediate would only be undertaken by the farmer if assured of land ownership. Farmers who have no secure land tenure would prefer short term investments in land. It is thus not surprising that the probability of fertilizer adoption decreases with secure land tenure because the farmer's focus shifts to longer time horizons rather than short term gains.

6. Summary and Recommendations

6.1 Summary

This study examined three important areas: adoption of sustainable soil and water management using probit model; agricultural productivity in Taita Taveta and Machakos with the aim of capturing production risks, the predicted variance and skewness of maize yield; and the role of production risks in technology adoptions, terracing, manure application and fertilizer application. A cross sectional plot level data was used.

Empirical analysis revealed that farm characteristics, farmer (household) characteristics and production risks are important in technology adoption decisions. Variability of maize output reduces the probability of adopting fertilizer use and increases the probability of manure use. This implies that farmers are risk averse but also keen on maximizing their profits by adopting technologies that promise high returns with low risks. With high risks, they opt for cheaper technologies even if such technologies do not guarantee high returns.

Predicted mean yield increases the probability of fertilizer application by farmers. The underlying rationale is that farmers are profit motivated, only ready to invest in high cost inputs when they expect higher returns, capable of repaying the costs and earning profits.

Higher probability of crop failure (downside risk) encourages farmers to apply terracing and manure, while low probability of crop failure increases the possibility of fertilizer use. This indicates that use of fertilizer is meant to enhance output, while terracing and manure input are meant to maintain the level of yield or to restore severely degraded soils that no longer promise good yields. Thus, farmers view terracing and manure application as mechanisms for reducing downside risks.

Other factors that are important in technology adoption include farm location, distance of plot from household and tenure security as perceived by farmers. Social capital is also important but only in influencing terrace adoption.

For productivity, fertilizer has the greatest impact followed by labour, manure then terracing. Large plots reduce productivity, implying that smaller plots are better managed, more intensively utilized and more productive. Male headed households are also more productive perhaps because men control more resources that translate into better agricultural inputs and supervision, or because they are fairly better at risk taking in relation to technology adoption.

6.2 Policy Recommendations

These findings have various policy implications:

a. When making agricultural/land management policies, it is important to consider the role of risks. For instance, while considering to promote use of fertilizer by farmers, policies must be put in place to ensure minimal fluctuations in agricultural returns and maintain high returns. This is possible with introduction of safety nets that could prevent negative fluctuation. Generally, all technologies have a degree of risks associated with them and because farmers are risk averse, economic instruments to hedge against exposure to risks are necessary to motivate farmers to easily and quickly adopt the desired technologies. Formal crop insurance is one of the options that the government could consider. Alternatively, the government could set up an incentive scheme (e.g. subsidies) for the adopters to cushion them against risks.

b. Women farmers appear more risk averse as explained by their low productivity. Apparently, they are more hesitant to adopt technologies that would guarantee higher output per unit of land. As a result, government policies targeting improved agricultural production should, foremost, target women farmers and cushion them against risks associated with technology adoption.

c. Technologies are adopted at different rates in different regions. Policies should thus be customized to different conditions in different areas. Toolbox approach to policy should be discouraged. Regional, farm-level and household-level factors should all be fused in the policies if they are to succeed.

d. Security of tenure is essential for adoption of terracing as a sustainable soil and water management technology. This makes it necessary for the government to not only issue land titles, but also make citizens to have faith in the sanctity of such titles. This will stimulate long term investment in land and help farmers break the poverty trap.

e. Optimal landholding size should be determined and implemented because beyond an economically viable maximum, productivity falls.

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ISBN 9966 777 73 3