Production risk and farm technology adoption in the rain-fed semi-arid lands of Kenya

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Abstract

This study provides empirical evidence on the effects of production risk on smallholder farmers' adoption of farm technology, using plot-level data collected from two semi-arid districts in Kenya, Machakos and Taita Taveta. Using Mundlak's approach (1978), the study found that factors such as yield variability and the risk of crop failures indeed affect technology adoption decisions in low-income, rainfed agriculture. However, the direction and magnitude of effects depend on the farm technology under consideration. The results explain why poor farm households in rainfed and risky production environments are reluctant to adopt new farm technologies that could improve production: it is because the technologies involve enormous downside risks. This result underscores the fact that productivity gain is a necessary, but not sufficient, condition to attract farmers to adopt new technologies and agricultural innovations.

Keywords: farm productivity; production risk; farm technology adoption; Kenya

JEL classification: D81 ; Q12 ; Q18

Grâce à des données au niveau de la parcelle, réunies dans deux districts semi-arides du Kenya, le Machakos et le Taita Taveta, cette étude apporte une preuve empirique des effets du risque de production concernant l'adoption d'une technologie agricole par les petits fermiers. Au moyen de l'approche de Mundlak (1978), l'étude a révélé que pour la culture sèche, à petits revenus, des facteurs comme la variabilité des récoltes et le risque de pertes de récoltes affectent en effet les décisions d'adopter une technologie. Pourtant, la direction et la magnitude des effets dépendent de la technologie agricole à l'étude. Les résultats expliquent pourquoi les petits fermiers des zones de culture sèche et de production à risque sont réticents à l'idée d'adopter de nouvelles technologies agricoles qui pourraient améliorer la

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production : parce que les technologies impliquent d'énormes risques baissiers. Ce résultat souligne le fait que le gain de productivité est une condition nécessaire mais pas suffisante pour motiver les fermiers à adopter de nouvelles technologies et innovations agricoles.

Mots-clés : *productivité agricole ; risque de production ; adoption de la technologie agricole ; Kenya*

Catégories JEL : *D81 ; Q12 ; Q18*

1. Introduction

In sub-Saharan Africa, more than 70% of the poor live in rural areas. The rural poor are heavily dependent on their natural resource base, particularly soil and its productive capacity. The main physical asset of poor farmers is land, and its contribution to their income is far more important than physical capital. Land degradation in the form of soil erosion and nutrient depletion pose a threat to food security and the sustainability of agricultural production, particularly in the less favored 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% of gross domestic product (Cohen et al., 2006). In response, government and development partners have devoted substantial resources to improving environmental conditions and increasing agricultural productivity. In particular, they have emphasized as a possible solution the use of modern farm technology – such as soil and water conservation technologies and fertilizer – that would enable farmers to increase their productivity while conserving the soil capital (MoA, 2004; World Bank, 2008). However, adoption of modern technology has been limited in most of sub-Saharan Africa. This is particularly the case in Kenya, where small-scale agriculture remains characterized by little use of external inputs, soil erosion and high nutrient depletion. The government has initiated extension worker programs to promote the adoption of improved technology. However, despite the concerted efforts by government and development partners, the adoption rate of improved farm technology remains disappointingly low.

Many questions about the determinants of farm technology adoption remain unanswered. Earlier research was devoted to individual and plot characteristics (see Feder et al., 1985, for a detailed survey). More recent studies have explored the role of social factors in technology adoption (Foster & Rosenzweig, 1995; Nyangena, 2008). A key element missing from the research is empirical analysis of the role of risk in investing in technology 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 modern technology; thus, they will remain poor unless ways are found to minimize the downside effects (Antle, 1983; Dercon, 2004). For risk-averse individuals, an increase in variance with enormous downside risk may make the individual worse off. Only economically secure farmers who have sufficient defense against downside risk will undertake profitable capital investments and innovations, while most of the poor remain caught in a risk-induced poverty trap (Eswaran & Kotwal, 1990; Rosenzweig & Binswanger, 1993; Mosley & Verschoor, 2005; Dercon & Christiaensen, 2007; Yesuf & Bluffstone, 2009).

Despite the significant role that risk exposure plays in production decisions, there is scant empirical literature on the role of production risk in farm investment decisions in low income rainfed agriculture. Notable exceptions are the works of Hassan and Hallam (1990), Fufa and Hassan (2003), Koundouri et al. (2006), Groom et al. (2008) and Kassie et al. (2008). With the exception of Kassie et al. (2008), they used cross-sectional data and econometric approaches that left the unobserved heterogeneities uncontrolled for. If correlated to some of the observed factors that could potentially create inconsistency and bias in the parameter estimates, this could lead to the wrong policy conclusions. In this study we used plot-level data that mimic the major features of panel data. We also used a pseudo-fixed effect econometric approach to control for unobserved heterogeneities. Unlike the above studies, we also used a two-stage instrumental variable estimation approach to address the potential endogeneity problems involved in our estimation. Our study extends the literature on farm technology adoption in low-income countries by bringing out the issue of risk exposure through alternative and more robust estimation procedures.

The data used in this study were collected by the International Food Policy Research Institute (IFPRI) in 2003 from 321 maize-growing households in two districts, Taita Taveta and Machakos, which are in an arid region of Kenya. The data were collected at plot level and thus are rich with details of households and plots. Manure, chemical fertilizer and terracing are the major farm technologies adopted in our study sites and hence are the only ones considered in our study.

Our choice of maize is premised on the fact that this is a key food crop in Kenya, constituting 3% of Kenya's overall GDP, 12% of agricultural GDP and 21% of the total value of primary agricultural commodities (GoK, 1998). Maize cultivation occupies about 1.4 million hectares of land in the country, with 25% of large-scale farmers and 75% of small-scale farmers engaged in its production. The productivity of maize has been on a downward trend since the 1970s, a period that was preceded by a fairly successful maize green revolution. Pingali (2001) estimates per capita maize production at 79 kg and consumption at 103 kg, implying that the country is increasingly importing maize.

The rest of the paper is organized as follows. Section 1 offers a brief overview of the literature, Section 2 discusses the conceptual framework used to analyze the farmers' adoption decisions in the presence of production risk, Section 3 presents the econometric specifications, Section 4 describes and discusses the data, Section 5 presents and discusses the empirical results, and Section 6 concludes by summarizing the findings and offering policy recommendations.

2. The literature on poverty, risk exposure and farm technology adoption

To increase agricultural productivity, modern inputs such as soil and water conservation technologies and fertilizer are important. Manure application can also be a crucial supplement to or even substitute for fertilizer, especially among the resource-poor smallholders. In sub-Saharan Africa, adoption levels remain low. Feder et al. (1985) conducted a comprehensive survey to summarize factors in adopting farm technologies and agricultural innovations. Among other factors, whether to adopt a technology or not depends on the profitability of the technology, farmer education and other observed and unobserved differences among farmers and across farming systems (Suri, 2009).

In Kenya, studies by the International Maize and Wheat Improvement Center (CIMMYT) and other similar research institutions examined the factors that affect the productivity of maize and the adoption of farm technologies among maize growers. These studies showed that farmer characteristics such as age, gender, levels of education and wealth, and institutional factors (such as access to capital and labor markets, land tenure security and social capital) are important in farm technology adoption decisions (see Foster & Rosenzweig, 1995; Mwangi et al., 1998; Jackson & Watts, 2002; Doss, 2003; Nyangena, 2008). Missing from the literature, in the Kenyan and other cases in sub-Saharan Africa, is the link between risk exposure and technology adoption decisions. When farmers are poor, they depend solely on rain for their farming and cannot create a safety net to fall back on during times of drought and other setbacks. As a result, they are hesitant to engage in any investment that involves some possibility of downside risk, even if it promises higher returns (Just & Pope, 1979; Rosenzweig & Binswanger, 1993). Under such circumstances, farmer households opt to stick to low-risk technologies despite the low returns – a decision that perpetuates the vicious circle of poverty (Dercon & Christiaensen, 2007; Yesuf & Bluffstone, 2009).

Using a dynamic model and observed data from the Philippines, Shively (1997, 2001) showed how investments in soil conservation may affect small farmers' production and threaten their food security – a consumption risk that may be a disincentive to adopt soil conservation technologies in low-income countries. His results showed that on small farms the risk of consumption shortfall generates inefficient patterns of soil conservation adoption. The observed adoption patterns reflected the risk characteristics of the soil conservation method, and the differences in farm size and risk exposure among farmers. Similarly, using panel data and historical rainfall patterns as a proxy for counterfactual consumption risk, Dercon and Christiaensen (2007) showed how low-consumption outcomes during harvest failure discourage the application of fertilizer by small farmers in Ethiopia.

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

2. Conceptual framework

This section describes the conceptual framework used to explain farm households' input use and production investment. This study applies a flexible moment-based approach, as first suggested by Antle (1983, 1987).

Following Koundouri et al. (2006), we assume that farmers are risk averse and use a vector of conventional inputs, X, and other soil conserving and conditioning inputs, such as soil and water conservation, fertilizers and manure, represented by vector S 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 vectors of output and input prices, respectively; farmers are assumed to be price takers in both markets. The prices are assumed to be nonrandom and hence climatic variables are the only source of uncertainty. The production function is given by:

$$q = f[S, X / H] \,, \tag{1}$$

where q is output, S and X are soil conserving and conditioning, and standard inputs that are conditioned by plot and household endowments, (H).[1] This function 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:

$$\underset{S,X}{Max} \quad E[U(\varpi)] = \max_{X,S} \int E\{[pf(\varepsilon, S, X) - r(X) - r(S)]\} dG(\varepsilon) \tag{2}$$

$U(.)$ is the von Neumann-Morgenstern function. The first-order condition for the soil conserving and conditioning input choice is given by the following:

$$E(r^s\ U') = \left[p \frac{\partial f(\varepsilon, S, X)}{\partial S} U' \right] \text{, and} \tag{3a}$$

$$\frac{r^s}{p} = E\left[\frac{\partial f(\varepsilon, S, X)}{\partial S} \right] + \frac{\operatorname{cov}(U', \partial f(\varepsilon, S, X) / \partial S)}{E[U']} \,, \tag{3b}$$

where U' is the change in utility of income following a change in income, $\left[\frac{\partial U(\varpi)}{\partial \varpi} \right]$, ϖ is the farm income and r^s is the price of the soil conserving and conditioning input. A similar procedure could be followed to derive the first-order necessary conditions for the standard input X. For the risk-neutral households, the second term in the right-hand side of equation (3b) 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 equation (3b) 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 soil conserving and conditioning input.

In the absence of risk and market imperfections, the optimal solution for the soil conserving and conditioning input would depend mainly on the input and output vectors and plot characteristics. However, in the presence of risk aversion and market imperfection, the

[1] Hereafter, H is suppressed for simplicity.

optimal solution would also depend on the shape of functions $U(.)$, $f\ (.)$ and $G(.)$, and household endowments.

Solving equations (3a) and (3b) is empirically difficult. In addition to the choice of technology specification, the distribution of ε needs to be known and the agent's preferences need to be specified. For this reason, Antle (1983, 1987) proposed a flexible estimation approach that has the advantage of requiring only cross-sectional information on prices and input quantities, plus other observables, such as plot and household characteristics and endowments. According to this approach and without loss of generality, maximizing the expected utility of farm income with respect to any input is equivalent to maximizing a function of moments of the distribution of ε, those moments having themselves X and S as arguments (see Antle 1983, 1987). In our study, we computed the first three moments of our stochastic production function and included them as our covariates in analyzing the adoption decisions for each soil conserving and conditioning input. Our empirical approach is discussed in the next section.

3. Empirical methodology

This section presents the empirical methodology used in this study to compute moments of production function and analyze the major determinants of farm technology adoption in Kenya. The econometric estimation of production risk impact on soil conserving and conditioning technology adoption is conducted in two steps. First, we compute the first three sample moments (namely, mean, variance and skewness) of each household from the production function, then the estimated moments are included alongside other explanatory variables in a pseudo-fixed effect probit model to determine whether production risk has any impact on farm technology adoption.

Using plot-level data from Kenya, maize production per unit area was regressed on farm inputs, including soil conserving and conditioning inputs, observed plot, and household and institutional characteristics to get the estimates of the mean effect. The model takes the following form:

$$Y = f(S, X, \beta / H) + \varepsilon \ , \qquad (4)$$

where Y is the maize production per unit of land obtained by the household; S and X are production inputs/technologies as described above, ε is the random variable capturing unobserved natural shocks (mainly climate-related) and other unobservables, β is a vector of parameters to be estimated and H and plot are household endowments.

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

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

where μ denotes the mean value of maize production. The estimated residuals from the mean regression are estimates of the first moment of value of maize production distribution. The estimated residuals ε are then squared and regressed on the same set of explanatory variables as in equation (6):

$$\varepsilon^2 = f_2(S, X, \hat{\beta}_2 / H) + v \tag{6}$$

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 (see Antle, 1983; Kim & Chavas, 2003; Koundouri et al., 2006).

Consistent estimates can only be obtained when unobserved heterogeneity that may be correlated with observed explanatory variables is controlled for. We achieve this by exploiting the panel data characteristics of our data. Two options are available: 1) using household-specific fixed effects or 2) using random effect. In our case, fixed effect is undesirable because some households have only a single plot and would be dropped in the analysis. Furthermore, some of our variables of interest (such as institutional variables) are measured at the household level. The use of fixed effect would mean excluding those variables from the analysis. Random effect, on the other hand, would leave the household heterogeneities uncontrolled for. This implies that we cannot use purely fixed effect or purely random effect models. Instead, we blend the two. A pseudo-fixed effect model (Mundlak, 1978) runs a random effect model, but mimics the basic features of a fixed effect model by including the mean values of plot-variant explanatory variables in our regression, so that most of the household heterogeneities would be controlled for indirectly. Mundlak's approach is based on the assumption that unobserved effects are linearly correlated with explanatory variables, as specified below:

$$\mu_h = \alpha \bar{x} + e_h,\ e_h \sim \text{iid}(0, \sigma^2_\varepsilon), \tag{7}$$

where α is corresponding vector of coefficients, $\bar{x}$ is the mean of plot-variant explanatory variables within each household and e is a random error term which is uncorrelated with $\bar{x}$. The fact that α is significant implies that household heterogeneity is an issue and should be properly taken care of, using a fixed or pseudo-fixed effect approach. Following Mundlak's approach, we included mean distance of plots from homesteads, mean plot slope, mean soil type and mean plot size in our regression to account for some of the household heterogeneities in a random effect model. The use of the pseudo-fixed effect approach would also help us to address the problem of endogeneity bias, if it is caused by household heterogeneities. But, if the causes are plot (time) varying factors, we still need to address the problem of endogeneities with other alternative approaches. In our estimation, we tested and found that fertilizer use is an endogenous variable in our production model. We thus used a two-stage instrumental variable (IV) approach and a control function approach to address the problem of endogeneity in our estimation. These are discussed in more detail in the results section below.

4. The data

This study was based on primary data collected by IFPRI from the Machakos and Taita Taveta districts in Kenya in 2003. A random sample of 321 households (43% from Machakos and 57% from Taita Taveta) was visited and a detailed questionnaire used to collect the requisite data. The basic descriptive statistics of the variables used in the paper are summarized in Table 1.

Table 1: Basic descriptive statistics

Variable	Machakos		Taita Taveta		Districts combined	
	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 where plot is located	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
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
Labor input per ha (days)	50	60.2	80.8	214.3	67.5	166.8
Terrace length per ha (meters)	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 fertilized	0.33		0		0.14	
Flat plots	0.21		0.26		0.24	

Gentle slope	0.4		0.34		0.37	
Medium slope	0.28		0.35		0.32	
Steep slope	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 homestead (meters)	262.6	609	1137.3	1942.2	758.9	1576.5
Institutional factors						
Access to extension services	0.24		0.44		0.33	
Time to nearest market (minutes walking)	108	19	89	39	97	33
Membership in organizations	0.81		0.48		0.62	
Tenure security	0.23		0.13		0.17	

The average land holding is slightly more than three hectares in both districts. In our sample, 55% of the plots are sandy loam, 20% are loamy silt and the remaining 25% are sandy clay. Furthermore, in both districts 60% of the plots are on flat land or gentle slopes, and approximately 40% are on medium to steep slopes. The average distance of plots from homesteads is 759 meters. In terms of use of soil conserving and conditioning inputs, about 65%, 35% and 14% of plots are terraced, spread with manure, and fertilized, respectively, although the intensity of use of these technologies varies by district.

In terms of basic household characteristics, 83% of the households are male-headed, the average age of the household heads is 51 years, and the household heads have on average six years of education.

In terms of access to basic infrastructure and institutions, 33% of households reportedly have access to agricultural extension services and 62% are members of one or more civil or local organizations and networks (a proxy for social capital). The average distance to the nearest market is about 97 walking minutes. In terms of tenure security, only 17% of the sampled households feel secure in their land tenure, while 83% feel they have no form of tenure security.

5. Results and discussion

In this section, we present and discuss the regression results. We first present the results from our production model, together with our estimates of the three moments (mean, variance and skewness). We then present and discuss the pseudo-probit model results for each of the technologies, where production risk factors are included as right-hand side variables.

5.1 The production model results

Although crop output is not the direct focus of our study, it is important to highlight a few results about it because it is the source of our risk variables. Fertilizer is an endogenous variable and would bias our results if not addressed. As a result, we employ an instrumental variable two stage least squares (IV 2SLS) approach to tackle the problem. Other variables, such as labor and manure, are treated as purely exogenous because the households depend on their own manure, which takes a long time to accumulate, and household population for labor. The F-statistic of 20.45 is an indication of strong instruments and the over-identification test results of 0.009 Sargan score and Basmann chi-square with p-value of 0.92 indicate that the instruments are valid (see Bound et al., 1995; Staiger & Stock, 1997).

The results are consistent with the theory and findings of other studies. They indicate that technologies are output increasing. Labor turns out to be the input with the greatest impact on output, followed by manure and then terracing. The impact of fertilizer, although insignificant, has the right sign, which indeed has economic significance. The statistical insignificance of fertilizer input could be largely because most of the farm households apply insufficient quantities, as shown by the summary statistics.

Table 2: Regression estimates of the production function (output per hectare as the dependent variable)

Variable	Parameter estimate IV-2SLS
Household characteristics	
Male-headed households	-0.150 (0.284)
Farm characteristics	
Log fertilizer intensity (kg)	0.275 (0.321)
Log manure intensity (kg)	0.170*** (0.066)
Log labor intensity (man days)	0.438*** (0.05)
Log terrace intensity (meters)	0.101*** (0.036)
Manure and terrace	-0.022 (0.014)
Constant	2.265 (0.284)
Sargan (score) $chi^2(1)$= 0.0093 (p = 0.923)	
Basmann $chi^2(1)$= 0.0091 (p = 0.924)	
No. of observations	494
F-statistic	(2, 486) = 20.447***

5.2 The adoption model results

In this section, we generate the first three moments of the production function in the previous section and use them as additional covariates to examine their impacts on the farm technology adoption decision. We used a pseudo-fixed effect probit model to examine these relationships. As discussed in Section 5.1, above, the pseudo-fixed effect model helps us to control for unobserved heterogeneities and address the problem of selection and endogeneity. The fact that the mean values of plot varying explanatory variables are significant indicates the superiority of our pseudo-fixed effect estimates over a simple random effect probit model that leaves the unobserved heterogeneities uncontrolled for. Table 3 presents the results of our pseudo-fixed effect adoption model.

Table 3: Determinant of terrace, manure and fertilizer adoption

Explanatory variable	Terrace adoption	Manure		Fertilizer	
		Adoption	Intensity	Adoption	Intensity
Risk measures					
Predicted mean yield of maize	0.037 (0.039)	0.102** (0.36)	-0.273(0.59)	0.173***(0.02)	0.615***(0.037)
Predicted variance of yield	-0.038 (0.039)	-0.165***(0.036)	-2.18***(0.577)	-0.015(0.02)	-0.065*(0.038)
Predicted skewness of yield	0.005*** (0.002)	-0.0001 (0.002)	0.045**(0.022)	-0.01***(0.0009)	-0.033***(0.002)
Household characteristics					
Household size	0.034*** (0.007)	-0.002 (0.006)	-0.004(0.034)	-0.001(0.004)	0.021***(0.007)
Age of household head (years)	0.001 (0.002)	-0.001 (0.001)	-0.007(0.008)	-0.00003(0.0008)	0.002(0.002)
Education of household head (years)	0.010* (0.005)	0.002(0.005)	0.025(0.025)	0.004 (0.003)	0.008(0.005)
Sex of household head (male)	-0.163**(0.058)	0.116** (0.053)	0.785***(0.287)	0.14*** (0.03)	0.518***(0.056)
Social capital	0.045**(0.022)	0.022 (0.96)	0.124(0.108)	0.008(0.012)	0.011(0.022)
Farm characteristics					
Plot size	0.001 (0.009)	0.013(1.31)	0.038(0.043)	0.002(0.005)	-0.006(0.009)
Distance of plot from homestead	-0.00003 (0.00002)	-0.00005** (0.00002)	-0.0003**(0.0001)	0.000(0.000)	0.00003*(0.00002)
Gentle slope	0.007 (0.069)	0.025 (0.063)	0.065(0.328)	0.002 (0.035)	-0.056(0.066)
Medium slope	-0.024(0.11)	0.091(0.101)	0.494(0.529)	-0.01 (0.057)	-0.117(0.107)
Steep slope	-0.178 (0.171)	0.011 (0.57)	0.205(0.817)	-0.005(0.088)	
Location, Taita Taveta	-0.350***(0.05)	-0.198***(0.046)	-1.322***(0.241)	-0.109***(0.026)	0.034(0.049)
Loamy soil	-0.146 *(0.085)	0.080 (0.078)	0.234(0.409)	-0.019 (0.044)	-0.006(0.082)
Clay soil	-0.09 (0.128)	0.157 (0.117)	0.42(0.616)	-0.045 (0.066)	-0.138(0.123)
Average plot size	0.006 (0.01)	0.002 (0.009)	-0.017(0.047)	0.002 (0.005)	-0.004(0.009)
Average plot distance from homestead	0.0001**(0.00003)	0.00004* (0.00002)	0.0002(0.0001)	0.000 (0.000)	0.000(0.000)
Average plot slope	0.118** (0.059)	0.023 (0.054)	0.096(0.283)	0.025 (0.031)	0.054(0.057)
Average soil type	0.137*(0.074)	-0.127* (0.068)	-0.247(0.358)	0.035 (0.038)	0.089(0.072)
Institutional factors					
Distance to nearest market (minutes walking)	0.0002 (0.0006)	0.0002 (0.0006)	-0.001(0.003)	0.008(012)	-0.00001(0.0006)
Secure land tenure	0.125**(0.053)	-0.074(0.049)	-0.237(0.256)	-0.025(0.028)	0.028(0.052)

Number of extension visits	-0.016 (0.017)	-0.046**(0.016)	-0.274***(0.082)	0.016 *(0.009)	0.045***(0.017)
No. of observations	483	483	480	483	483
Wald chi^2	(23)=211.38***	(23)=356.14***	(23)=455.48***	(23)=949.86***	(23)=2523.28***

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

The first moment has a highly significant positive effect on fertilizer adoption and manure application. This implies that farm households are driven by profit/output maximization and would be motivated to apply yield increasing methodologies whenever they are guaranteed higher returns. The same positive effect is also reflected in the intensity of fertilizer application.

Yield variability, as reflected by the second moment, has a negative impact on manure application, intensity of manure application, and fertilizer application. This indicates that farmers are discouraged from applying manure and applying manure plus fertilizer in sufficient quantities when yields are less certain. They would rather accept a low output than invest heavily in pursuit of a higher, but uncertain, output. As much as farmers are driven by profit/output maximization, they are also risk averse and will minimize investment in risky ventures.

A higher possibility of crop failure (downside risk), as measured by skewness of yield, increases the probability that farmers will adopt terracing and reduces the probability that they will adopt fertilizer. At the same time, this probability increases the intensity of manure use and reduces the intensity of fertilizer application. Farm households possibly view terracing and more intensive application of manure as measures for rehabilitating plots that are heavily degraded and no longer promise any yields. Fertilizer, a yield enhancing input, is only attractive to the farmer when the possibility of crop failure is low – the farmers are motivated to adopt fertilizer technology and apply fertilizer in sufficient quantities when yields are more guaranteed. Alternatively, the farm households could view manure and terracing as risk-reducing and fertilizer as risk-increasing.

Besides production risk variables, plot-level variables (such as distance of plot from homestead and district where the plot is located), household characteristics (such as household size, education, sex of household head and household social networks), and institutional factors (such as security of land tenure and number of visits by government extension officers) have statistically significant effects on farmers' decisions to adopt or not adopt a given technology.

Household size is positively correlated with terracing. That is, a marginal increase in household membership increases the probability that the household will adopt terracing as a means of conserving and conditioning soil. This is not surprising, since terracing is labor-intensive and would favor larger households. Therefore, when households rely on family labor, as in the districts we studied, a large household becomes an obvious positive predictor of terracing. Intensity of fertilizer application is also positively influenced by household size and, again, this is possibly due to the high labor input requirement associated with it.

Education of the household head increases the probability of a farm household adopting terracing. This is because a better educated household head, the primary decision maker, is more capable of accessing and assimilating information about the various technologies, their advantages, and the dangers of not adopting them.

Female household heads have a higher probability of adopting soil conserving and conditioning technology than their male counterparts. This is perhaps because smallholder agriculture is dominated by women, and any crop failure would affect them more heavily. On the other hand, female-headed households have a lower probability of adopting manure and fertilizer. This is probably because men control more resources and therefore male-headed households have a better chance of purchasing fertilizer. Further, accumulating manure requires keeping livestock, an activity most commonly associated with men. A more intensive application of fertilizer and manure is also associated with male-headed households.

Social capital has a positive effect on the probability of terrace adoption. Social capital and networks help farmers to mobilize the necessary labor, equipment and skills for terrace construction. Quality networks may also be essential for mobilizing financial resources and agricultural extension services that can translate into better agricultural practices.

Distance from the homestead to the plot reduces the probability and intensity of manure use. Because manure is normally accumulated in the backyard and is heavy and bulky, farmers may be less willing to apply it if the plot is farther from the homestead. Moreover, where the farmer relies on hired labor, it becomes more expensive to apply manure on plots far from the homestead. Equally important are the management challenges of farms that lie far from the homestead. Such farms are more vulnerable to 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 may have been more recently acquired or opened up for cultivation (and therefore the soil is less exhausted), hence the reduced need for manure. Conversely, distance from homestead to plot is directly related to intensity of fertilizer application. This could indicate that farm households tend to substitute fertilizer for manure as homestead-to-plot distance increases.

Farmers in Taita Taveta are less likely than their counterparts in Machakos to adopt terracing, manure and fertilizer application. Farming in Machakos is more profitable because it lies closer to Nairobi and ready markets for high-value crops. This motivates farmers in Machakos to use land more sustainably through terracing and manure application and to increase output through fertilizer use. The profitability of farming in Machakos also means that the farmers have more resources to invest in farm technology. Other factors that give Machakos an edge over Taita Taveta in farm technology adoption are better participation in social organizations, more secure land tenure and less labor-intensive agriculture. Again, it must be appreciated that terracing in Machakos dates back to the colonial periods. The technology has been in the area for a longer period and its use known to a wider cross-section of farmers. Intensity of manure application is also lower in Taita Taveta than in Machakos.

Secure land tenure increases the probability of adoption of terracing. Terracing is an expensive technology in the short run and its returns are not immediate, meaning it would only be undertaken by a farmer who was assured of the land ownership. Farmers who have no secure land tenure 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 a longer time horizon rather than short-term gains. In such circumstances, the farmer may be concerned with the negative effects of fertilizer to the soil in the long run.

The number of visits by government agricultural extension officers negatively influences the probability of manure application but increases the probability of fertilizer use. This implies that extension services in the country focus on modern farm inputs and put hardly any emphasis on traditional farm inputs, such as manure, despite their advantages. Consequently, farmers who have more contact with extension officers reduce their use of traditional inputs in favor of modern inputs.

6. Summary and policy recommendations

This study examined the role of production risk in the adoption of soil conserving and conditioning inputs in two semi-arid districts of Kenya, Taita Taveta and Machakos. Antle's method of moments was used to generate the three moments of production of maize. These three moments were later used as covariates in the pseudo-fixed effect probit model to examine their effects on adoption decision.

Empirical analysis revealed that production risk factors (both yield variance and downside risk) are important determinants of farm technology adoption decisions in rural Kenya. Variability of maize output reduces the probability of manure use and intensity of fertilizer application. The predicted mean yield increases the probability of fertilizer and manure application by farmers. The intensity of fertilizer use is also positively influenced by the predicted mean yield. A higher probability of crop failure (downside risk) encourages farmers to undertake terracing and apply manure more intensively, but lowers the probability and intensity of fertilizer use. This indicates that use of fertilizer is meant to increase output, while manure input and terracing are used to maintain the level of yield or to restore severely degraded soils that no longer promise good yields. Thus, farmers view manure application and terracing as means to reduce downside risk.

Other factors that are important in technology adoption are farm location, distance of plot from homestead, education of household head, number of visits by agricultural extension officers and tenure security as perceived by farmers. Social capital, gender of the household head and household size are also important.

These findings have various policy implications. When formulating agricultural or land management policies, it is important to consider the role of risks. Generally, all technologies have a degree of risk associated with them. When farmers are risk averse, economic instruments to hedge against exposure to risks are necessary to motivate them to adopt the desired technologies quickly and easily. For instance, when considering promoting the use of fertilizer and manure, policies must be put in place to hedge against the potential production risk associated with the introduction of the technology. Given the missing insurance market, this is perhaps possible through the introduction of safety nets to guard against such downside risk.

The impact of production risk on technology adoption varies by technology type. Policies, therefore, should be customized to different technologies in different environments. A toolbox, one-size-fits-all, approach to policy should be discouraged. Regional, farm-level and household-level factors should all be fused into the policies, if such policies are to succeed.

Security of tenure is essential if policies are to succeed in promoting greater adoption of terracing as a sustainable soil and water management technology. This makes it necessary for the government not only to issue land titles but also to convince citizens of the sanctity of such titles. This will stimulate long-term investment in land and help farmers avoid the poverty trap. Social capital and networks also need to be encouraged to scale up successful adoption of soil and water conservation technologies in areas where access to information and labor scarcity are key constraints.

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