DOES ADOPTION OF IMPROVED MAIZE VARIETIES REDUCE POVERTY? EVIDENCE FROM KENYA

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Poster paper prepared for presentation at the International Association of Agricultural Economists Conference, Gold Coast, Australia, August 12-18, 2006

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1. INTRODUCTION

1.1 The current poverty situation in Kenya

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

Low agricultural productivity and poor marketing of farm produce are some of the causes of rural poverty. Low productivity is attributed to the use of traditional farming methods, poor soil fertility, unpredictable weather, high costs of inputs, poor quality of seed and lack of credit facilities. These multiple setbacks have led to food shortages, underdevelopment of farms, low farm incomes, and poor nutritional status, especially among children, increasing further the population's vulnerability to poverty in the future.

1.2. Technology as a package of innovations

Productivity-improving farm technology is a bundle of innovations rather than a single technical or managerial intervention. Thus, for example, adoption of high yielding maize varieties will lead to significant increases in maize production if farmers also adopt new ways of planting, weeding, or if they apply new types of fertilizers. It is this package nature of technology that makes its welfare, efficiency and distributional effects difficult to evaluate. In particular, the poverty reduction effects of maize technology adoption are difficult to measure for a number of reasons, including the following:

- The macro level effects may not always be simple aggregates of the micro level effects of adoption, because of social externalities of technology adoption.
- Large maize farmers might adopt the technology, with small and poor farmers not adopting, with the consequence that aggregate growth effects of adoption would be large, but at the micro level, output growth would not be observed among many small farmers. In this case, the distributional effects of technology adoption may worsen poverty if they lead to substantial increases in prices of commodities commonly consumed by the poor.
- Small maize farmers may be adopting improved maize seed but not as part of a full technological package as required so that the effect of the technology on productivity would be small or absent.

1.3. Links between farm technologies, productivity and poverty

Productivity-improving agricultural technologies reduce poverty by increasing rural agricultural incomes, reducing food prices, facilitating the growth of non-farm sectors, and by stimulating the transition from a low productivity subsistence agriculture to a high productivity agro-industrial economy. The potential for poverty reduction through the above transmission mechanisms depends on the extent to which agricultural productivity can be increased. Agricultural innovation can have both direct and indirect effects on poverty. Direct effects of technological innovation on poverty reduction are those productivity benefits enjoyed by the farmers who actually adopt the innovation. The benefits typically manifest themselves in form of higher farm profits. The indirect effects are productivity-induced benefits passed on to others by the innovating farmers. These may comprise lower food prices, higher non-farm employment levels or increases in consumption for all farmers. Which of these effects is dominant depends largely on the speed with which farmers adopt new technologies and on whether or not the affected households are net food buyers or sellers.

1.4. Pro-poorness of technology adoption

Adoption of a technology is pro-poor if it benefits the poor relatively more than the non-poor (Kakwani, 2005). Clearly, such a technology must be affordable by the poor. Moreover, its benefit must be substantial relative to its cost (including the adoption risks it involves). Although the benefits and determinants of adopting new farm technologies are stressed in the literature, the impact of these technologies on poverty reduction is often overlooked.

1.5. Overview of previous studies

In her Kenyan study, Suri (2005) has provided a succinct overview of the determinants of maize technology adoption, starting with the seminal work of Griliches (1957) in USA. Understanding the determinants of maize technology adoption is the first step in the design of policies that facilitate farmers' adoption of these technologies. Suri shows that technology profitability, farmer learning, as well as observed and <u>unobserved</u> differences among farmers and across farming systems are major determinants of adoption. Learning through social networks (Jackson and Watts, 2002) may also be an important determinant of technology adoption. The CIMMYT studies in Kenya and other East African countries (Mwangi et al., 1998; and Doss, 2003) examine the adoption decision processes for maize and fertilizer technologies, and show that farmer characteristics such as age, gender and wealth are key to the decision to adopt. Suri (2005) makes a new contribution to this literature by demonstrating that aggregate adoption rates may remain low or stagnant despite high average returns to new maize technologies, either because marginal returns to adoption are low, or because the farmers with comparative advantage in adoption have already done so. However, absent from this literature is an assessment of the effect of diffusion of new maize varieties on poverty reduction. This paper marks a beginning of a research agenda to fill this gap.

2. MODELS

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

2.1. Discrete-discrete choice model

Bivariate probit is the appropriate model for assessing whether a farm household will adopt a high-yielding maize variety, and whether conditional on adoption, the household's risk of falling into poverty is reduced. Let **S** denote characteristics of the farmer and **Z** the attributes of the technology and let **k** be the new technology and **l** the existing technology. The probability of adopting a new maize technology can be expressed as

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

where U_k and U_l are perceived net benefits associated with the adoption of technologies k and l respectively, and e is a stochastic disturbance term. From equation (1), a binary probit model of technology choice can be formulated from the assumption that the disturbance term is normally distributed (Maddala, 1983).

Equation (1) can be used to predict the probability that household i will adopt maize technology k given its characteristics (**S**) and the attributes of the technology (**Z**). It can also be used to assess the effect of technology adoption on poverty reduction. Specifically, the predicted probability from equation (1) can be used as a regressor in the poverty status equation to examine whether or not poverty and adoption are negatively correlated. The poverty status of a household can be computed using the following expression (Mwabu et al., 2000).

$P_{\alpha}=1/N\bullet\Sigma_q((Z-Y_i)/Z)^{\alpha}$……………………………………………………(2)

where,

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

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

Z = overall poverty line;

N = total number of households;

q = the total number of poor households;

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

Note that if $\alpha=0$, the poverty measure, P_0, becomes the *headcount index*, which indicates the percentage of households below the poverty line. For $\alpha=1$, P_1 is the *average poverty gap*, or the average income shortfall of all households calculated as a proportion of the poverty line; and for $\alpha=2$, P_2 is the *severity index*, which is the weighted sum of poverty gaps.

Once the poverty status of the household is determined using equation (2), a probit model of the probability of being poor can be estimated along the lines of equation (1). However, care should be taken to identify the two models. Since poverty status (equation 2) is income-based, identification in this case is achieved by omitting income from the probit model of the poverty status (equation (3)). Note therefore that this is fortuitous exclusion restriction.

Pr (Y_i <**y**) = f(X, Φ) ………………………………..(3)

where,

Pr (.) is the probability that a household has an income lower than the poverty line. Y_i is income (expenditure) of household i and **y** is the poverty line. X is a vector of determinants of poverty, a subset of S in equation (1). The term Φ is the predicted probability of adoption, derived from equation (1), the coefficient of which shows the effect of technology adoption on poverty status. Due to space limitation, the empirical analysis focuses on the effect of technology adoption on headcount ratio.

2.2. The discrete-continuous choice model

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

$W_i = f(X, \Phi)$ ………………………………..(3)

where

W_i is the poverty depth or severity of household i.

The effects of technology adoption (proxied by Φ) on poverty depth or severity can differ from its effect on the poverty status. If Φ is negatively correlated with W_i it implies that households that adopt new technologies, despite being poor, suffer less from poverty than the non-adopters.

The effects of Φ on poverty depth and poverty severity can also differ. For example, Φ can be positively correlated with poverty depth, but negatively associated with poverty severity. Briefly, technology adoption can increase the *headcount* ratio by worsening income distribution; increase the poverty *depth*, also by worsening income distribution; and reduce poverty *severity* by improving incomes of the poorest of the poor, irrespective of what happens to income distribution. This cascade of effects of technology adoption reveals the complex nature of processes that reduce poverty.

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

$\mathbf{q_i} = f(\underline{S}, \Phi)$ ………………………………..(4)

where,

$\mathbf{q_i}$ is maize output of farmer i.

In equation (4), the vector $\underline{S}$ includes farm inputs and socioeconomic characteristics of the farmer, as well as the community level factors that affect production such as the social infrastructure. Equation (4) helps determine whether technology adoption is associated with increased maize production. If Φ has no effect on maize production, then technology adoption cannot reduce poverty. In the case where adoption has an effect on productivity, equation (4) helps assess the relative importance of technology in increasing maize yields compared with other farm inputs. This evaluation is key to determining whether or not resources should be spent to increase technology diffusion. If equation (4) shows a zero effect of Φ on maize production, it suggests that even if farmers are poor they may be efficient (Schultz, 1964) so that only a *new* maize technology or additional farm resources would improve their condition.

3. DATA

The field study was done in 2001 in Laikipia and Suba districts, in Rift Valley and Nyanza provinces, respectively. Both districts have diverse topographical features, climatic conditions and cultural settings. Laikipia receives relatively more and more reliable rain than Suba, and so it is more suitable for rainfed agriculture. A total of 320 households were randomly sampled for interviews (Obunde et al., 2004). The data were collected on a wide range of variables, including household characteristics, land productivity; farming systems, land tenure, access to markets, parcels of land owned, farm size, and acreage under maize, adoption of new maize seeds and other crop varieties and use of farm inputs such as fertilizers and pesticides.

4. RESULTS

We present descriptive statistics on backgrounds of households before turning to results concerning adoption of improved maize and its effects on yields and poverty.

4.1 **Livelihoods of households**

4.1.1 Main occupations of household heads

The main occupation in the two districts is farming, accounting for 73.7% of livelihood activities in Laikipia and 90.1% in Suba. The remaining activities comprise petty trade and wage employment.

4.1.2 Household incomes

The daily per capita income for the two districts is about a dollar each, that is, USD 1.30 for Laikipia and USD 1.08 for Suba (USD 1.20 for both). The income levels shown are representative of economic status of households in most districts in the country considering that 60% of households live below the poverty line of less than $US1.00 per day (i.e., Kenya Shillings 76.00 in 2005).

4.1.3 Prices of agricultural produce

The average price of maize per bag of 100kg in Suba is Ksh 593 (US $ 7.70) compared with Ksh 477 (US $6.30) in Laikipia, a difference of more than Ksh 100 (US $1.30).

Thus, although the government mandated maize price per bag is Ksh. 400 (US $5.25) in both districts, the actual prices are quite different. Beans are three times as expensive as maize. This price differential is a major problem for households because the staple food in the districts is a mixture of maize and beans. In Laikipia, the mean price per bag of beans at the time of the survey was Ksh 1620 (US $ 21.30) while in Suba it was Ksh 1773 (US $ 23.33).

4.1.4 Crop acreage

The area covered by sole maize crop in any of the three parcels of land owned by a household in Laikipia is a mere 1%, while the rest is under beans (0.2%) and mixed cropping (98.7%). In Suba, maize monocrop covers a much higher proportion of land, (28.9%), compared with beans alone (7.2%) and mixed cropping (63.9.2%). In both districts, out of 506.8 hectares utilized for crop cultivation, only 77.2 hectares or 15.2% is used for growing maize without any inter-cropping. This finding has implications for the type of maize technologies developed for farmers. In particular, in developing improved maize technologies, consideration should be given to the fact that the maize will be grown as an inter-crop rather than as a pure stand.

4.2 Maize technologies and maize yields

4.2.1 Hybrid maize adoption

Maize is widely grown in both Laikipia and Suba districts. Out of a total of 310 households interviewed, 94% grew maize. Hybrid maize is the most common type of maize grown in Laikipia, grown by 59% of households, whereas in Suba, hybrid maize is grown by 6% of the households.

The most common hybrid maize grown in Laikipia is H614, which is grown by 30.7% of households, followed by H625, H626, H627 which are grown by 26% of households. In Suba, the hybrid varieties adopted by a few households are PH1-Pannar (2%), H513 and

H511 (1.5%), and H512 (0.6%). The maize varieties grown in Laikipia are suited to areas with adequate annual rainfall, whereas those varieties grown in drier Suba district are not suited to low rainfall.

4.2.2 Maize yields

Laikipia has higher maize yields than Suba district, with 13 bags for hybrid maize, and 7 bags for local maize per acre. In Suba productivity per acre was 4 bags for hybrid maize and 2 bags for local maize. In both cases, hybrid maize has higher yields than traditional maize.

4.2.3 Usage of modern farm inputs

Modern farming methods are more widely used in Laikipia than in Suba district.
In Laikipia, 62.5% of households use a tractor for land preparation; 42.5% use manure; and 39.4% use fertilizers and certified seed. In Suba, the ox-plough is used to prepare the land, and only about 16% of households use fertilizers or certified seed.

4.3 Conditional probabilities of maize adoption

These are predicted probabilities of maize adoption given some characteristics of farmers and the environment in which they operate. Table 1 shows that the price of maize, education level, and distance to roads are the main determinants of hybrid maize adoption by farmers. In particular, an increase in the price of maize encourages adoption of high yielding varieties because holding other things constant, such a change raises profitability of maize. Education is positively associated with probability of adoption, indicating that literate farmers are more likely to use new maize varieties. As expected, there is a strong negative relationship between maize technology adoption and the distance away from an all weather road. Gender is not a major determinant of hybrid maize adoption: being a male has a statistically insignificant negative effect on adoption.

4.4 Technology adoption and maize yields

Table 2 depicts a positive association between improved maize adoption and maize yield per acre. Adopters of new maize varieties have higher maize yields than non-adopters. While this is an intuitively appealing finding, there is need to point out that the farmers that are obtaining high maize yields are also the ones most able to experiment with new varieties of maize. In contrast, low productivity farmers do not have such ability and may not innovate. Thus, because of this endogeneity issue, the regression results in Table 2 should be interpreted with caution.

4.5 Maize technologies and poverty reduction

Tables 3a and 3b show estimation results for a bivariate model of maize technology adoption and poverty reduction. The results reported in Table 3a mimic earlier findings (Table 1) where distance to an all weather road reduces adoption probability while education increases it. The results in Table 3b indicate that the probability of adopting improved maize varieties is negatively associated with poverty. That is, improved maize adoption reduces poverty. On the other hand, an increase in maize price increases poverty.

The complex effects of maize price on poverty should be noted. An increase in maize price encourages technology adoption (Table 1), raising the yields and incomes of maize growers (Table 2). Thus, an increase in maize prices reduces poverty among maize sellers, but increases poverty among maize buyers. The overall effect of an increase in maize price on poverty status of a household depends on whether the household is a net buyer or seller of maize. The result here suggests that most households in the study areas are net maize buyers. Note that we have imperfectly dealt with identification problem in the bivariate probit model (Tables 3a-b) by omitting income from the poverty status equation.

5. CONCLUSION

The results reported in this paper have several policy implications. To start with, only 34.7% of the land owned in the two districts is already cultivated, which suggests that there is potential to increase maize production by expanding maize acreage.

Next, adoption of hybrid maize is associated with poverty reduction. There is thus a need to find mechanisms for extending high yielding varieties of maize to districts with high poverty rates. To this end, provision of social infrastructure, especially access roads to market centers, and extension of agricultural education to farmers would increase the spread of improved maize varieties.

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Table 1: A Probit Model of Determinants of Maize Technology Adoption (Dependent Variable is Probability of Adopting Hybrid Maize)

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

Table 2: Hybrid Maize and Maize Yields (Dependent Variable is Bags of Maize per Acre)

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

Table 3a: A Bivariate Model of Maize Adoption and Poverty Reduction (First Equation: Dependent Variable is Adoption of Improved Maize Varieties)

Variable	Estimated Coefficient	*t*-statistic
Constant	-1.4462	-4.51
Distance to all weather road (kms)	-0.2372	-4.32
Years of Schooling	0.34266	2.37
Sex (1 = Male)	0.04055	0.18
Per Capita Household Income (Ksh)	0.0000086	1.78
Log Likelihood	-230.398	
Wald Chi-Square	121.17 (p = .000)	
Number of Observations	277	

Table 3b: A Bivariate Model of Maize Adoption and Poverty Reduction (Second Equation: Dependent Variable is Probability of Being Poor)

Variable	Estimated Coefficient	*t*-statistic
Constant	1.83030	5.89
Price of Maize (Ksh)	0.00320	4.22
Years of Schooling	-0.01599	-0.11
Probability of Adopting Hybrid Maize	-4.99237	-5.98
Number of Observations	277	