Determinants of fertilizer use on maize in Eastern Ethiopia: A weighted endogenous sampling analysis of the extent and intensity of adoption

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Abstract

Factors influencing the extent and intensity of fertilizer adoption on maize production in Ethiopia were analyzed. A Weighted Endogenous Sampling Maximum Likelihood estimator was used in the specification of a Probit and Tobit fertilizer adoption models. The results have important implications for the formulation of policies and programs targeted to promotion of fertilizer use in small-scale maize production. Those include improved road infrastructure, consideration of weather related crop failure insurance programs, development of drought tolerant cultivars and targeting particular farmer groups.

1. Introduction

Agriculture contributes about 52% of the GDP and 85% of the population is dependent directly or indirectly on agriculture in Ethiopia. While agriculture is growing at 1.6% per annum, the population of the country is growing at 3% and is expected to double by year 2020 (Befekadu and Brehanu, 2000). This indicates the need to increase productivity of agriculture to keep pace with population to ensure adequate supply of food in the future. As a result, the government has embarked on a massive agricultural extension program since 1994/95 to promote the use of improved crop production technologies, a key component of which is chemical fertilizers. However, adoption and intensity of fertilizer application, especially on maize grown by smallholders remained very low despite government efforts to promote its use. Di-Ammonium phosphate (DAP) and urea are the two most important fertilizers that are widely promoted by the extension program. Consumption of the said two fertilizers has dropped significantly between 1995 and 1997 showing a slight increase of only 3% in 1999.

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Maize is one of the major cereals grown in Ethiopia and is the main staple food in many parts of the country. Maize production has slightly increased over the past decade with area expansion being the main source of growth compared to negligible yield gains. Fertilizer has been a major component of improved maize production technologies being promoted by the extension package. It is therefore of critical importance for agricultural research and policy design to better understand the reasons behind the persistence of low fertiliser adoption by farmers in the country. This study makes an attempt to analyse determinants of fertiliser use by small-scale maize producers in Ethiopia.

The analytical framework and empirical models of technology adoption are discussed in section 2. The empirical model and sampling procedures are specified in section 3. Section 4 presents and discusses findings and conclusions and policy implications are drawn in the last section.

2. Analytical framework and empirical models of technology adoption

Limited dependant variables models have been widely used in technology adoption studies. The said models are based on the assumption that, in adopting new agricultural technologies, the decision maker (farmer) is assumed to maximize expected utility (expected profit) from using a new technology subject to some constraints (Feder *et al*, 1985). In the case of categorical dependent variables (binomial or multinomial) qualitative choice models of adoption such as the logit and Probit are usually specified. These models are commonly used to analyse situations where the choice problem is whether or not (0-1 value range) to adopt a new technology. The Probit specification has advantages over logit models in small samples. The present study therefore employed a Probit model to examine determinants of farmers' decision to adopt or not adopt fertilisers on maize. The Probit model specification used in this study is given by

$$AF = F(\alpha + \beta x_i) = F(z_i) \tag{1}$$

Where, AF is the discrete adoption choice variable, F is the cumulative probability distribution function, β is the vector of parameters, x is the vector of explanatory variables and z is the Z-score of βx area under the normal curve.

The expected value of the discrete dependent variable in the Probit model conditional on the explanatory variables is given by

$$E[y/x] = 0[1 - F(\beta' x)] + [F(\beta' x)] = F(\beta') \tag{2}$$

The marginal effect of each explanatory variable on the probability of adoption is:

$$\frac{\partial E[y/x]}{\partial x} = \phi(\beta' x)\beta \tag{3}$$

Where $\phi(.)$ is the standard normal density function.

While the Probit model is adequate for analysing adoption decisions that occur over a discrete range such as yes or no, it does not handle the case of adoption choices that have a continuous value range that is truncated from below. This is the typical case for fertiliser adoption decisions where some farmers apply positive levels of fertiliser while others have zero applications (non-adopters). Intensity of use is a very important aspect of technology adoption because it is not only the choice to use but also how much to apply that often more important. The Tobit model of Tobin (1958) is used to handle truncated distribution dependent choice variables such as level of fertiliser use. This study used the Tobit model specification to analyse determinants of the variation in intensity of fertilizer use by maize farmers as given by

$$\begin{aligned} AD &= x\beta(z) + \sigma f(z) + \varepsilon \\ &AD^*, \text{ if } \quad AD^* > AD_0 \\ &0, \quad \text{if} \quad AD^* < AD_0 \end{aligned} \tag{4}$$

Where AD is the adoption intensity (level of application), AD_0 is the critical value adoption intensity, x, β and $F(z)$ are as defined in (1). σ is the standard error term, $f(x)$ the value of the derivative of the normal curve at a given point (density function).

McDonald and Moffit (1980) showed that the marginal effect of an explanatory variable on the expected value of the censored (truncated distribution) dependent variable is given by

$$\frac{\partial E(AD)}{\partial x_i} = F(z)\beta_i \tag{5}$$

On the other hand, the change in the probability of adoption as the explanatory variable x_i changes is given by:

$$\frac{\partial F(z)}{\partial x_i} = \frac{f(z)\beta_i}{\sigma} \tag{6}$$

And the change in the intensity of adoption among adopters as an explanatory variable changes is given by:

$$\frac{\partial\left(AD^{*}\right)}{\partial x_{i}}=\beta_{i}\left[1-\frac{zf\left(z\right)}{F\left(z\right)}-\frac{f\left(z\right)^{2}}{F\left(z\right)^{2}}\right] \tag{7}$$

Adoption of agricultural technologies is influenced by a number of interrelated components within the decision environment in which farmers operate. For instance, Feder *et al* (1985) identified lack of credit, limited access to information, aversion to risk, inadequate farm size, insufficient human capital, tenure arrangements, absence of adequate farm equipment, chaotic supply of complementary inputs and inappropriate transportation infrastructure as key constraints to rapid adoption of innovations in less developed countries. However, not all factors are equally important in different areas and for farmers with different socio-economic situations.

Socio-economic conditions of farmers are the most cited factors influencing technology adoption. The variables most commonly included in this category are age, education, household size, landholding size, livestock ownership and other factors that indicate the wealth status of farmers. Farmers with bigger land holding size are assumed to have the ability to purchase improved technologies and the capacity to bear risk if the technology fails (Feder *et al*, 1985). This was confirmed in the case of fertilizer by Nkonya *et al* (1997) in Tanzania, Hassan *et al* (1998a) in Kenya and Yohannes *et al* (1990) in Ethiopia whereas; farm size did not matter in Nepal (Shakaya and Flinn, 1985).

The role of education in technology adoption has been extensively discussed in the literature. Education enhances the allocative ability of decision makers by enabling them to think critically and use information sources efficiently. Producers with more education should be aware of more sources of information, and more efficient in evaluating and interpreting information about innovations than those with less education (Wozniak 1984). Education was found to positively affect adoption of improved maize varieties in West shoa, Ethiopia (Alene *et al*, 2000), Tanzania (Nkonya *et al*, 1997) and Nepal (Shakaya and Flinn, 1985).

Some new technologies are relatively labour saving and others are labour using. For those labour-using technologies, like improved varieties of seeds and fertilizer labour availability plays significant role in adoption. Green and Ng'ong'ola (1993) found regular labour to be an important factor that positively influences adoption of fertilizers in Malawi.

On the other hand, age of the household head is an important factor affecting adoption of agricultural technologies. The convention approach to adoption study considers age to be negatively related to adoption based on the assumption that with age farmers become more conservative and less acceptable of new ideas. On the other hand, it is also argued that with age farmers gain more experience and acquaintance with new technologies and hence are expected to have higher ability to use new technologies more efficiently. Some studies found age to be an important determinant of adoption (Hassan *et al*, 1998b) while others didn't (Voh, 1982; Nkonya *et al*, 1997; Chilot *et al*, 1998).

The effect of family size on adoption can be ambiguous. It can hinder the adoption of technologies in areas where farmers are very poor and the financial resources are used for other family commitments with little left for purchase of farm inputs (Voh, 1982; Shakya and Flinn, 1985). On the other hand, it can also be an incentive for adoption of new technologies as more agricultural output is required to meet the family food consumption needs (Yonannes *et al*, 1989) or as more family labour is required for adoption of labour intensive technologies (Hassan *et al*, 1998a).

In addition, adoption of new agricultural technologies depends on a number of institutional factors. The introduction of new technologies creates demand for information useful in making decisions (Wozniak, 1984). Agricultural extension organizations supply useful information about new agricultural technologies. Access to such sources of information can be crucial in adoption of improved varieties (Nkonya *et al*, 1997; Hassan *et al*, 1998b; Chilot *et al*, 1998). Furthermore, risk associated with the adoption of agricultural technologies is another important factor in adoption decisions (Parikh and Bernard, 1988; Yohannes *et al*, 1990; Shiyani *et al*, 2002; Hassan *et al*, 1998).

The studies reviewed above show inconsistent results about the determinants of adoption of new technologies by farmers. In addition, none of the above studies addressed how adoption of fertilizer is affected by farmers' perceptions about the expected rainfall conditions, the perception of farmers about the current prices of fertilizers and the topographic conditions of maize farm plots.

3. Specification of the empirical model

In light of the results of previous empirical research, this study considered a number of explanatory variables in modelling the fertiliser adoption behaviour of maize farmers in Ethiopia. Socio-economic factors such as age of the head of the household head, family size, literacy, land holding size and wealth status of the farmer were considered important determinants of adoption. The age of the household head (Age) is measured in years, total land holding size (Land) is measured in Quindi[2] and literacy (Litd) takes a value of one if the farmer is literate and zero otherwise. Household size (Housz) is measured by the number of people living in the household. Income from T'chat[3] (T'chatd) and off farm income (Offincd) were included to reflect the financial ability of the farmer to buy external inputs, both take the value of one if the farmer earns income from the respective activities and zero otherwise. Furthermore, to analyse the effect of the expected profitability of fertilizer adoption, farmers' perception about the current price of fertilizer (Fertpd) was included. This takes value of one if the farmer feels the price is too high and zero otherwise. The topographical nature of land (Slopd), which takes the value of one if the plot is flat and zero otherwise was included. Furthermore, to see the effect of risk associated with the use of fertilizer, farmers' perception about the expected rainfall condition during the production year (Raind) was included. This is measured as one if the farmer perceived the rainfall is good and zero otherwise. Distance of the home of the farmer (Mktd) from the nearby market and the residence of the extension worker (Extd) both measured in minutes of walking distance were selected to capture the impact of institutional constraints on fertilizer adoption in the area.

The above explanatory variables were used to estimate the Probit and Tobit models of fertiliser adoption as specified below

$$\begin{aligned} AF = {} & \beta_0 + \beta_1 Age + \beta_2 Land + \beta_3 Litd + \beta_4 Raind + \beta_5 T'chatd + \beta_6 Offincd + \\ & \beta_7 slopd + \beta_8 Housz + \beta_9 Fertpd + \beta_{10} Mktd + \beta_{11} Extd \end{aligned} \tag{8}$$

Where AF takes the value of one for adopters or zero for non-adopters in the case of the Probit model and is the level of fertiliser used in kg per quindi of land in the Tobit model**.**

4. Study area and sampling procedure

The study was conducted in Dadar district, located in the Eastern Hararghe zone of the Oromiya regional state of Ethiopia. Being part of the Ethiopian highlands, the area receives an average annual rainfall of more than 900 mm. Maize and sorghum are the major cereals grown in the area. Maize is the main staple food crop in the district. Being one of the major maize producing

[2] *Quindi is a local measure of land holding. One hectare is equivalent to eight quindis.*
[3] *T'chat is a perennial shrub grown widely by farmers in East Hararghe. The leaves of the shrub are chewed by humans for stimulation purposes.*

districts in the zone, the area has been included in the government's agricultural extension package since 1996/97. Purposive sampling of a total of 100 farm households was surveyed. Accordingly, 50% the surveyed farmers were from those who have chosen to join the extension package and the remaining 50% were from farmers chosen not to participate in the extension package. In studies involving limited dependent variable models, sometimes the observed sample of the dependent variable is deliberately skewed in favour of one outcome or the other. In estimating models for such studies, the bias in the sample could easily be transmitted to parameter estimates. Manski and Lerman (1997) proposed a Weighted Endogenous Sampling Maximum Likelihood (WESML) method of correcting for this bias. Their estimator requires that the true population proportion w_1 and w_2 and sample proportions p_1 and p_2 be known. Then the estimator is obtained by maximizing the weighted likelihood given by

$$Log\ L = \sum_{i}^{n} w_i \log F\left(q_i \beta' x_i\right) \tag{9}$$

Where, $w_i = y_i\left(\frac{w_1}{p_1}\right) + \left(1 - y_i\right)\left(\frac{w_2}{p_2}\right)$

The second step involves the correction of the appropriate covariance matrix of the estimator. White's (1982a) robust 'sandwich' estimator for the asymptotic covariance matrix of the quasi-maximum likelihood estimator is given by

$$Est.asy.\mathrm{var}\left(\hat{\beta}\right) = \left[\hat{H}\right]^{-1} \hat{\beta} \left[\hat{H}\right]^{-1} \tag{10}$$

Where, H is the Hessian matrix of the parameters. However, the shortcomings of WESML and choice based sampling estimator are the very large standard error of the parameters that are obtained at the end (Greene, 2000).

The sample size indicated above is used in this study by making modifications following the above procedure. Secondary sources from the district level office of agriculture show that about 25% of the farmers in the area use fertilizer in maize production. So the weighting variable for the estimation of the model is given by

$$w_i = y_1\left(\frac{0.25}{0.5}\right) + (1 - y_1)\left(\frac{0.75}{0.5}\right) \tag{11}$$

Where, y_1 is the value of the dependent variable, which takes values of one and zero in the Probit model. Where as in the Tobit model, y_1 is censored at zero for non-adopters and takes continuous values greater than zero for adopters. The correction for the asymptotic covariance matrix of the Probit model is made following the procedure in the second step above. The Tobit model was estimated by using the weighting variable only, as there is no procedure developed so far for the correction of the covariance of the estimated parameters.

5. Results and discussion

5.1 Probit model results

The explanatory variables of the Probit model reported in Table 1 had the expected sign. Age was negatively and significantly related to adoption of fertilizer suggesting that old farmers are more conservative with respect to fertilizer use than young farmers in the study area. Farmers' expectation of a good rainfall season was positively and significantly associated with fertilizer adoption. Farmers' perception that the current fertilizer price is high was negatively and significantly related to adoption. The removal of fertilizer subsidy in the country since 1997 has increased the actual price of fertilizer by more than 20%.

Table 1: Estimated results of probit model of adoption of fertilizer

Variable	Coefficient	Standard error	P-value	Marginal effect
Constant	-0.380	0.890	0.670	-0.0820
Age	-0.037*	0.016	0.019	-0.0079
Land	0.069	0.075	0.350	0.0150
Litd	0.400	0.390	0.270	0.0920
Raind	0.964*	0.390	0.013	0.2100
T'chatd	0.320	0.410	0.430	0.0690
Offincd	0.210	0.390	0.600	0.0440
Slopd	-0.690	0.460	0.140	-0.1500
Housz	0.110	0.082	0.180	0.0240
Fertpd	-2.080**	0.700	0.003	-0.4500
Mktd	-0.007	0.006	0.890	-0.0002
Extd	-0.008	0.013	0.550	-0.0017

Restricted log likelihood -67.74464 ; Chi-Square 63.66396 ; ** Significant at 1% ; * Significant at 5%

The marginal effect values of the Probit model in Table 1 show the change in the probability of adoption of fertilizer for each additional unit increase in independent variables. Farmers with the perception of good rainfall conditions had 21% higher probability of adoption than farmers who perceived a bad season. Farmers who thought that the price of fertilizer was high had 45% less probability of adoption. The probability of adoption decreases by 0.79% for every year of age. The probability of adopting fertilizer by farmers cultivating medium to steep maize plots was 15% higher than for farmers cultivating flat maize plots.

5.2 Tobit model results

The results of the Tobit model reported in Table 2 show that all the variables have the expected sign. The marginal effects show that for each additional year of age, the use of fertilizer declines by 0.87kg/ha for the entire sample and by 1.6kg/ha for adopters. Positive expectation about the rainfall condition increased the use of fertilizer by 22.07kg/ha and 41.92kg/ha for the entire sample and among adopters, respectively. The perception of high price reduced the use of fertilizer by 46.2kg/ha and 87.79kg/ha for the entire sample and for adopters, respectively. Farmers planting maize on flat land tend to use about 29 kg of fertilizer less than those planting on slopes. This can be attributed to the fact that farmers cultivating flat land experience less leaching of fertilizer compared to steep slopes land.

Table 2: The Tobit model of fertilizer adoption in Dadar district

Variable	Coefficient	Standard error	P-value	Total change $\frac{\partial E(AD)}{\partial x_i}$	Change in probability $\frac{\partial F(z)}{\partial x_i}$	Change among adopters $\frac{\partial(AD)}{\partial x_i}$
Constant	28.86	107.79	0.789			
Age	-5.18*	2.29	0.024	-0.87	-0.014	-1.600
Land	9.28	8.27	0.262	1.56	0.026	2.970
Litd	51.08	47.52	0.282	8.61	0.142	16.350
Raind	130.99**	48.04	0.006	22.07	0.364	41.920
T'chatd	31.06	49.45	0.529	5.23	0.086	9.940
Offincd	21.94	49.44	0.657	3.69	0.061	7.020
Slopd	-91.18	59.36	0.125	-15.36	-0.254	-29.180
Housz	14.31	9.77	0.143	2.41	0.039	4.580
Fertpd	-274.35**	93.97	0.004	-46.23	-0.763	-87.790
Mktd	-0.019	0.59	0.975	-0.03	-0.00005	-0.006
Extd	-0.930	1.68	0.579	0.16	-0.0025	-0.290

Log likelihood function -186.95; σ = 141.71; ** Significant at 1%; * Significant at 5%; z = -0.976;
Censored observations = 50 ; Uncensored observations = 50; $F(z)$=0.76 ; $f(z)$=0.394

6. Conclusions and policy implications

Fertilizer is considered the most important input for the achievement of increased agricultural productivity and food security status of farm households in Ethiopia. However, fertilizer adoption remains very low, especially among small-scale farmers in the country. The results of this study showed that the age of the farmer, farmers' expectations of rainfall conditions and farmers' perception of the price of fertilizer significantly affect the use and intensity of adoption of fertilizer in the study area.

In situations where the expected rainfall (weather) condition is bad, farmers are unwilling to use fertilizer. This is because farmers are not insured against losses as a result of bad weather and forced to pay the cost of fertilizer they received on credit. Due to the fact that crop loss insurance schemes are non-existent in countries like Ethiopia, agricultural research has to focus on the development of moisture stress tolerant and early maturing varieties. In addition, the expansion of small-scale irrigation projects in rural areas can help overcome the adverse effects of rainfall shortage experienced by most parts of the country. On the other hand, depending on the expected rainfall condition during a particular year fertilizer demand may be high or low. Thus, agricultural extension and suppliers of agricultural inputs (public or private) should adjust the price and the services they provide accordingly.

Increased fertilizer prices and the concomitant decrease in output prices have been the most important factors associated with use of new agricultural technologies in Ethiopia recently. Part of the increase in fertilizer prices to farmers is the increased transportation cost for the movement of fertilizer from the central market. Due to poor road conditions, running costs for transport operators is very high. The development of rural roads reduces the transaction cost associated with acquisition of farm inputs and sale of farm products. This enables farmers to buy farm inputs at lower prices and sell their produce at competitive prices. More effort in expanding roads in rural areas is therefore needed.

References

Alene AD, Poonyth D & Hassan RM (2000). Determinants of the adoption and intensity of use of improved maize varieties in the central highlands of Ethiopia: A Tobit analysis. *Agrekon* 39(4):633-643.

Befekadu D & Brehanu N (2000). *Annual report on the Ethiopian economy*. The Ethiopian Economic Association. Volume 1.

Chilot Y, Shapiro BI & Mulat D (1998). Factors influencing adoption of new wheat technologies in Walmara and Addis Alem areas of Ethiopia. *Ethiopian Journal of Agricultural Economics* 1(1):63-84.

Feder G, Just RE & Zilberman D (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change* 33(2):255-298.

Green DAG & Ng'ong'ola DH (1993). Factors affecting fertilizer adoption in less developed countries: An application of Multivariate Logistic analysis in Malawi. *Journal of Agricultural Economics* 1:99-109.

Greene WH (2000). Econometric Analysis. 4th Edition. Prentice Hall Inc, New York.

Hassan RM, Onyango R & Rutto JK (1998a). *Determinants of fertilizer use and the gap between farmers' maize yield and potential yields in Kenya.* In: Hassan RM (ed), Maize technology development and transfer: A GIS approach to research planning in Kenya. CAB International, London.

Hassan RM, Onyango R & Rutto JK (1998b). *Adoption patterns and performance of improved maize in Kenya.* In: Hassan RM (ed), Maize technology development and transfer: A GIS approach to research planning in Kenya. CAB International, London.

Hassan RM, Onyango R & Rutto JK (1998). *Relevance of maize research in Kenya to maize production problems perceived by farmers.* In: Hassan RM (ed), Maize technology development and transfer: A GIS approach to research planning in Kenya. CAB International, London.

Manski CF & Lerman SR (1997). The estimation of choice probabilities from choice based samples. *Econometrica* 45:1977-1988.

Mcdonald JF & Moffit RA (1980). The use of Tobit analysis. *Review of Economics and Statistics* 62:318-320.

Nkonya E, Schroeder T & Norman D (1997). Factors affecting adoption of improved maize seed and fertilizer in Northern Tanzania. *Journal of Agricultural Economics* 48(1):1-12.

Parikh A & Bernard A (1988). Impact of risk on HYV adoption in Bangladesh. *Agricultural Economics* 2:167-178.

Shakya PB & Flinn JC (1985). Adoption of modern varieties and fertilizer use on rice in the Eastern Tarai of Nepal. *Journal of Agricultural Economics* 36:409-419.

Shiyani RL, Joshi PK, Asokan M & Bantilan MCS (2002). Adoption of improved chickpea varieties: KRIBHCO experience in tribal region of Gujarat, India. *Agricultural Economics* 27:33-39.

Tobin J (1958). Estimation of relationships for limited dependent variables. *Econometrica* 26:24-36.

Yohannes K, Gunjal K & Garth C (1990). Adoption of new technologies in Ethiopian agriculture: The case of Tegulet-Bulga district, Shoa province. *Agricultural Economics* 4(1):27-43.

Voh J (1982). A study of factors associated with the adoption of recommended farm practices in Nigerian Village. *Agricultural Adminstration and Extension* 9:17-27.

White H (1982). Maximum likelihood estimation of misspecified models. *Econometrica* 50:1-26.

Wozniak GD (1984). The adoption of interrelated innovations: A human capital approach. *Review of Economics and Statistic*s 66:70-79.