

Full Length Research Paper

Speed of Improved Maize Seed Adoption by Smallholders Farmers in Southwestern Ethiopia: Analysis Using the Count Data Models

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Accepted 6th April, 2015

The use of improved maize seed is being promoted in Ethiopia as one of the agricultural extension packages to support smallholder agricultural production. Despite the important role adoption of improved maize seed plays in maize productivity, very few studies have been conducted to analyze the factors influencing their speed of adoption rate. This study analyses the determinants of speed of latest improved maize seed adoption rate using data from a cross-sectional smallholder maize producer in Southwestern Ethiopia. Poisson and Negative binomial models of the count regression model, the latter found to best fit the data, are used for the analysis. The results show that age of the household, extension service, proximity to development center, livestock holding, cooperative membership, use of mobile-cell phone, played an important role in the speed of adoption of improved maize seed among smallholder producers'.

Keywords: Speed of improved maize seed adoption, count data models, Ethiopia

INTRODUCTION

Maize is one of the major five staple cereal crops. High productivity and efficacy in its production is critical to improve food security, achieve or maintain agricultural growth and reduce the level of poverty in Ethiopia. Recognizing its potential, the governmental and non-governmental organizations, and researchers have been undertaking various activities to boost the productivity and production for long. Despite such efforts considerable numbers of farming households still remain food insecure in the country. Previous studies such as Arega (2003), Arega and Rashid (2005), Jon (2007), Anderson and Kay (2010), Legesse et al. (2011), and Mosisa et al. (2011) explained that both raising production levels and reducing its variability are essential to raise maize productivity. Among others, these could be achieved through adoption of improved agricultural technologies among smallholder maize producer farmers.

Although there have been good attempts to improve the productivity of maize through the utilization of improved production technologies over the past years in the country. However, some recent studies such as Paarlberg et al. (2006), ECEA (2009) and Yu and Nin-Pratt (2014) attest that the current utilization of better production technologies on the part of maize producing farmers is not to the required levels. This may be due to demographic, socio-economic, marking, farm attributes, institutional and agronomic factors.

Even though a lot of studies have been conducted on technology adoption and the factors influencing adoption behavior among maize producing farmers in Ethiopia (Shiferaw and Tesfaye, 2006; Jon, 2007; Yu et al., 2011; Hailu, 2008; Yu and Nin-Pratt, 2014). Most of them measures, the decision to adopt as a binary one (i.e. Adopt and not adopt), intensity of adoption by the extent to which cultivated areas covered by the technology. Virtually no studies analyzed the various factors affecting speed of the latest technology adoption rate among maize producing farmers. In analyzing the speed of technology adoption, count data models are employed in which the number of years and month it took a farmer to adopt the newly released improve maize seed i.e. PHB30G19 (*Shone*) once disseminated to farmers. Thus, research in this area is vital for understanding the problems related to improved production technology dissemination, which are useful to improve maize productivity and enhancing food security in the country.

The objective of this study is to identify the determinants of speed of latest improved maize seed adoption rate by smallholder farmers in Southwestern Ethiopia using cross-sectional data collected from 385 farm households in three districts of the Jimma zone of southwestern Ethiopia.

In the following section, we describe the research methodology, including a study area, sampling techniques and the data, analytical method and describe the variables used in the model. The section then

presents and discusses the main results of the study, and concludes and policy implication is provided in the last section.

METHODOLOGY

Study area

The study was carried out in Jimma zone of Oromia regional state in Ethiopia. Jimma zone is located southwestern parts of Addis Ababa and it is one of the major maize growing areas of Ethiopia. Based on the 2008 census report of CSA the zone has a total population of 2,495,795 of whom 1,255,130 are men and 1,240,665 women. Jimma zone bordered with east Wollega zone in the north, with east shawa zone and southwest Shawa zone in the northeast, with SNNPR administration in the southeast and south part, and with Illubabor zone in the west. Jimma zone divided into 17 *woredas* and it lies between latitudes 7°15' N and 8°45' S, and longitudes 36° 00' E and 37°40' E. (BoFED, 2008). Jimma zone generally lies with the altitude ranges between 900 and 3334 meters above sea level. More than half of the zone (52%) lies between 1500 and 2000 meters above sea level. Areas between 1500 and 2000 meters above sea level are found in the all areas of *Limmu-Seka*, *Menna*, east *Kersa*, northern area of *Dedo*, *Omonada*, eastern and southern *Gera*, *Seka-Chekorsa* and *Sokoru* and eastern *Gomma*. On the other hand, the majority of the remaining *woredas* has an intermediate plateau topography that highly ideal for farming, which lies within altitude 2000-2500m (Socio-Economic Profile Report, 2009).

Sampling techniques and the data

In order to select a sample of farm households, multi-stage sampling techniques was employed. The three-stages that involve the selection of (1) *woredas* (districts), (2) *kebeles* (lowest administrative unit) and (3) Smallholder farmers are as follows: The three-stages that involve the selection of (1) *woredas* (*district*), (2) *kebeles* (lower administrative unit) and (3) smallholder farmers are as follows: In the first stage, three *woreda*, namely *Omonada*, *Seka-Chekorsa* and *Kersa* were randomly selected from 12 maize growing *woredas* of Jimma zone of southwestern Ethiopia. In the second stage, the study included 15 percent of total maize growing *Kebeles* within each of the three selected *woredas* using simple random sampling method. Based on these criteria, four *kebeles* from *Omonada* and two *kebeles* from *Seka-Chekorsa* and three *kebeles* from *Kersa woreda* were selected randomly that give rise to a total of nine *Kebeles*. In the third stage, the study selected 385 smallholder farmers randomly from lists of

names of maize farmers in the *kebeles* using a computer-generated random number table. The data set contains detailed information on households' demographic and socioeconomic characteristics, farm specific attributes, marketing, and institutional characteristics.

Analytical methods

Previous literature on the speed of technology adoption typically employs count data econometric models such as the Poisson or negative binomial models. Count data econometric models are used to study problems where the dependent variable takes on only non-negative values. The dependent variable in the current study is a non-negative integer variable. It is taken to be the number of years and months it took to adopt the latest maize technology after dissemination in the study areas by a farmer j , $j = 1, 2, \dots, n$, where n is the sample maize producing farmers. The technology considered to be PHB30G19 (*Shone*) improved maize seed disseminated in the study area before six years (i.e. in 2009 G.C.). The dependent variable was influenced by a vector of independent variables (X_i). These variables explained the difference in time of adopting improved maize technology among maize-dominated smallholder farmers.

Following Cameron and Trivedi (1998, 2009), let Y_j be the realization of the random variable Y_j , where Y_j is the number of years and months it took farmer j to adopt PHB30G19 (*Shone*) improved maize seed in study areas. The distribution of Y_j is dependent on a set of observed exogenous variables X_j and unobserved variables U_j . Let E be the expectation operator and be a vector of k parameters to be estimated so that the mean of the count data model is given by:

$$E(Y_j / x_j, u_j) = \lambda_j(x_j, \beta, U_j) = \lambda_j \tag{1}$$

In most applications, the log-linear specification of the mean of the count data models λ on the explanatory variables is used and assuming this relationship, equation (1) becomes:

$$\log \lambda_j = x_j \beta + u_j = \sum_{k=1}^k x_{jk} \beta_k + U_j \tag{2}$$

Where e^{u_j} , $j = 1, 2, 3, \dots, n$ are assumed to be independent and identically distributed (i.i.d) with $E(e^{u_j}) = 1$, and $\text{var}(e^{u_j}) = \eta^2$. In this specification, when the x_j has a constant term, the assumption of unit mean value for $E(e^{u_j})$ does not lead to loss of generality. The model assumes independence of u_j from X_j to obtain:

$$E(Y_j / X_j) = E_{\mu} E(Y_j / x_j, u_j) = e^{x_j \beta} = \mu_j \tag{3}$$

$$\text{and } \text{var}(Y_j / x_j) = \mu_j + \eta^2 \mu_j^2 \tag{4}$$

Thus, the choice of the count data model to use is governed by the assumption made about the distribution of U_j (Cameron and Trivedi, 1998, 2009).

A. Poisson regression model

The starting point in count data models is the specification of the Poisson regression model. Following Cameron and Trivedi (1998, 2009), Poisson model was employed for the estimation of the speed of adopting latest improved maize seed (PHB30G19) by maize-dominated smallholder farmers in the Jimma zone of Southwestern Ethiopia. The fundamental specification of the Poisson model is that the discrete random variate Y_i , conditional on X_i and U_i , is distributed as a Poisson (λ_j) variate such that:

$$\text{Prob}(Y_j = y_j / x_j, U_j) = \frac{e^{-\lambda_j} \lambda_j^{y_j}}{y_j!} \tag{5}$$

$Y_j = 0, 1, 2, \dots, m$

The most common formulation for λ_j being the log-linear model.

$$\ln \lambda_j = \beta X_j \tag{6}$$

In principle, the Poisson model is simply a non-linear regression model. However, it is far easier to estimate the parameters with maximum likelihood technique. For an independent sample of n observations, the log-likelihood function for the Poisson is:

$$\text{Ln } L = \sum_{j=1}^n \{ -\lambda_j + y_j \beta X_j - \text{Ln}(y_j!) \} \tag{7}$$

and the vector score or the likelihood equations given by the first order necessary condition are

$$\frac{\partial \text{Ln } L}{\partial \beta} = \sum_{j=1}^n x_j (y_j - \lambda_j) = 0 \tag{8}$$

The maximum likelihood estimate (MLE) of being a solution to the following moment equations:

$$\sum_{j=0}^N X_j y_j = \sum_{j=1}^N X_j e^{x_j \beta} \tag{9}$$

From equation (9), Hessian or the second order derivative matrix becomes:

$$\frac{\partial^2 \text{Ln } L}{\partial \beta \partial \beta'} = \sum \lambda_j x_j x_j' \tag{10}$$

Under regularity conditions, the Hessian is negative definite for all X. The log-likelihood function equation is strictly concave and the MLE is unique (Cameron and Trivedi, 1998, 2009).

B. Negative Binomial Regression Model

Poisson model makes the strong assumption that the mean and variance in the Poisson distribution is equal (i.e., equi-dispersion), which is presented by $E(Y_j / X_j) = Var(Y_j / X_j)$. This restriction of the equality of the mean and variance in the Poisson distribution is often not realistic as it has been found that the conditional variance tends to exceed the mean, that is, $E(Y_j/X_j) < Var(Y_j/X_j)$. This results in an over-dispersion problem, (i.e. the degree to which the variance differs from the mean) and hence the Poisson model breaks down and cannot be used to explain farmer adoption behavior (Cameron and Trivedi, 1998, 2009).

A more generalized model to account for the over-dispersion problem is based on the negative binomial probability distribution expressed as:

$$f(y / \mu, \alpha) = \frac{\Gamma(y + \alpha^{-1})}{\Gamma(y + 1)\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}} \left(\frac{\mu}{\alpha^{-1} + \mu}\right)^y \tag{11}$$

Where $\mu = e^{x^B}$ $y = 0, 1, 2, \dots$ and $\alpha \geq 0$ characterizes the degree of over-dispersion. That is, in the case of the negative binomial model, the variance is not equal to the mean. That is with $v(y / x_i) = \mu + \alpha\mu^2$. Once the negative binomial model is estimated, the presence of significant over-dispersion is given by the significance of the alpha coefficient. If the estimated alpha coefficient is significantly greater than zero, then over-dispersion is present and the estimated negative binomial model is preferable to the Poisson model. If the estimated alpha coefficient is zero, then the conditional mean is equal to the conditional variance and the negative binomial model reduces to the Poisson model (Grogger and Carson, 1998; Cameron and Trivedi, 1998, 2009).

In response to the problem of over-dispersion in the estimation of Poisson model, Cameron and Trivedi (1998, 2009) have proposed a regression-based test for over-dispersion, which tests for the significance of the parameter as compared with the Poisson model. The technique tests the following hypotheses.

$$H_0 : Var[Y_j] = E[Y_j] \tag{12}$$

$$H_1 : Var[Y_j] = E[Y_j] + \alpha g(E[Y_j]) \tag{13}$$

H_0 fits the basic Poisson assumption since it says that the variance is equal to the mean, while H_1 postulates that in the case of over-dispersion, the variance is not equal to the mean or is greater than the mean by some function of the mean, $g(E[Y_j])$. The hypothesis test for over-dispersion is performed by regression.

$$z_j = \frac{(y_j - \lambda_j)^2 - y_j}{\lambda_j \sqrt{2}} \text{ or } w_j = \frac{g(\lambda_j)}{\sqrt{2\lambda_j}} \tag{14}$$

Where λ_j is the predicted value of Y_j from the Poisson regression and $g(\lambda_j)$ is the assumed probability density function (pdf) of U_j (Cameron and Trivedi, 1998; 2009).

This test makes several assumptions, but the most important one is that under either H_0 or H_1 consistent estimates of $E[y_j] = \lambda_j$ are obtained from the Poisson regression model (Cameron and Trivedi, 1998, 2009). Cameron and Trivedi further showed that the test for over-dispersion, which they called T_{op} , can easily be performed by testing the significance of the single coefficient in the Linear Ordinary Least Squares (OLS) regression of Z_j on W_j . They proposed the following assumption on $g(\lambda_j)$ when performing the test for over-dispersion.

$$g(\lambda_j) = \lambda_j \text{ and } g(\lambda_j^2) \tag{15}$$

When the regressions are conducted, the chi-square statistic is used to test whether the coefficients of the regression are significantly different from zero. If the coefficient is significantly different from zero, it implies that there is evidence of over-dispersion in the data and the basic Poisson specification is rejected. Thus, depending on the response of the data to the model, if the basic Poisson model is rejected then a compound Poisson (or negative binomial) model was the alternative model because it allows for over-dispersion (Cameron and Trivedi, 1998, 2009). As such, a basic Poisson regression model and a negative binomial (compound poisson) models were fitted to cross-sectional data of smallholder's farmers to determine what factors affect the speed of PHB30G19 or *shone* maize technology adoption among maize producing farmers in Jimma zone of Southwestern Ethiopia. Summary statistics of the variables used in the negative binomial regression model provided in Table 1.

Table1: Variables definition and descriptive statistics and their expected hypothesis

Description of variables	Measurement	Mean (S.D)	Expected sign
Dependent variable			
Number of years and month it took a farmer to adopt PHB30G19 or <i>shone</i> improved seed.	Number	1.88 (1.92)	
Independent variable			
Demographic characteristics			
Age of household head	Years	45.35 (8.85)	+
Female heads	Dummy	11.4 (0.32)	-
Socioeconomic characteristics			
Formal Education	Years	2.78 (1.66)	+
Livestock holding	TLU	4.71 (2.52)	+
Off and/ non-farm income in log	Birr	3.82 (4.28)	+
Farm attributes			
Maize farming experience	Years	22.67 (9.21)	+
Institutional service			
Frequency of extension contact	Number	3.32 (3.3)	+
Distance to development center	Walking hour	0.86 (0.79)	-
Cooperative membership	Dummy	45.97 (0.50)	+
Use of cash credit	Dummy	16.36 (0.37)	+
Market access			
Use of mobile cell phone	Dummy	71.14 (0.45)	+
Distance to near market center	Walking hour	2.31 (1.42)	-

Source: Computed from survey data

EMPIRICAL RESULTS

Both Poisson and the negative binomial regression models were estimated to analyze the speed of latest improved maize seed adoption (i.e. PHB30G19 or *Shone* maize seed) in the study areas. The estimated Poisson model was tested for over-dispersion since the model has been criticized because of its implicit assumption that the variance of the dependent variable equals its mean. The test result indicated a chi-square (624.2) with p-value (0.000), implying that there is over-dispersion problem in the data. Thus, the Poisson model was rejected, and therefore a negative binomial model was chosen since it allows for overdispersion (Cameron and Trivedi, 2009).

The negative binomial model is fitted into the survey data for 2013/14 growing seasons. Table 2 summarizes the parameter estimates of the model. Before going directly to the results, however, the variables included in the model were tested for the problems of multi-collinearity and heteroscedasticity. The Variance Inflation Factor (VIF) for multi-collinearity was estimated and it is found to be low (a maximum of VIF of 1.59). This shows that there is no problem of multi-collinearity in the data. However, Breusch-Pagan test for heteroscedasticity indicated a large chi-square (16.32), implying there is heteroscedasticity problem in the each model. Hence, we used robust standard errors to avoid the problem in the final model. Moreover, the likelihood ratio test of the model indicated the overall goodness of fit of the model

and it was statistically significant at one percent level of significance.

The results of the model indicate that frequency of extension contacts, use of mobile cell-phone, distance from farmer residence to development center, membership of farmer cooperatives, age of household head and livestock holding are significantly affected the speed of maize seed adoption at less than 5 percent significant levels.

Age of household head has statistically significant positive effect on the speed of technology adoption at five percent level of significance.. This implies that older farmers are more likely to adopt the newly released improved maize seed likes PHB30G19 (*Shone*) than a young farmers in the study areas. Adoption literature largely show that the impact of age of a farmer on technology adoption cannot be pre-determined because older farmers are sometimes considered to be risk-averse and thus less willing to try new technologies compared to young farmers. The other stand of literature considers that older farmers have more experience due to the previous knowledge gained, resources and authority that would allow them more possibilities for trying new technologies than younger and inexperienced farmers. Thus, the result of this study contributes to this ongoing debate.

As hypothesized, the parameter estimate for use of mobile cell phone with the household head has the right sign (positive) and significant at one percent level of significance. This result implies that those farmers who

Table 2: Maximum likelihood parameter estimates of the negative binomial regression model

Variables	Coefficient	Std. Error	t-ratio
Age of household head	0.012**	0.006	1.92
Female heads	-0.181	0.194	-0.93
Formal education	0.038	0.034	1.13
Livestock holding	0.421***	0.146	2.88
Use of credit	0.074	0.136	0.54
Cooperative membership	0.227**	0.106	2.14
Frequency of extension contact	3.752***	0.999	3.76
Distance to development center	-0.489***	0.106	-4.62
Distance to near market center	-0.056	0.044	-1.29
Livestock holding	0.011**	0.006	2.01
Experience of maize farming	-0.003	0.006	-0.50
Off and/ non-farm income	-0.016	0.011	-1.53
Constant	-3.803***	1.054	-3.61
Dispersion		Mean	
Log likelihood		-627.58	
LR χ^2 (12), Pr > χ^2		168.48***	

***, ** and * indicate the level of significance at 1, 5 and 10 percent, respectively.

Source: Model result

use mobile cell phone are more likely to adopt the newly released improved maize seed like PHB30G19 (*Shone*) than those who do not have mobile cell phone. Farmers who own mobile cell phone has better information access and hence are more likely to be informed about the newly released improved maize seed than those who do not own.

Result on farmers' membership of cooperatives, which is a proxy for measuring the role of social organization in the adoption process, is statistically significant at five percent level of significance, and has the expected sign (positive). This implies that farmers who are a member of farmer cooperatives are more likely to adopt the newly released improved maize seed like PHB30G19 (*Shone*) than those who are not members. This shows participation in farmer cooperatives increases the speed of a farmer to adopt newly released maize technology. This is because membership to farmer cooperatives has advantage of hearing information on the availabilities of the newly incoming improved production technologies. Farmer cooperatives also provided credit of the new improved technology for its members. In most cases, newly released production technologies were disbursed through farmer cooperatives. This might have increased the probability of having access to newly released technology by member farmers.

As postulated, the result on extension contacts is statistically significant at one percent level of significance, and has the expected sign (positive) implying extension contact was influential in the farmer's adoption behavior contributing to increased speed of adoption of the latest improved maize seed like PHB30G19 (*Shone*). The higher the number of

extension contacts, the better the farmer aware on the newly released improved maize seed. This might have increased the probability of having access to newly released maize technology like PHB30G19 (*Shone*) in the area.

Distance from development center was statistically significant at one percent level of significance, and has the expected sign (negative) indicating that farmers far away from development centers are less likely to adopt the newly released maize seed technology (like PHB30G19 maize seed) than those who are closer to development centers. The possible explanation for this is that farmers far away from development centers might face greater transaction and transport costs, and lack information on availabilities of the latest released technology provided by extension system.

As hypothesized, the parameter estimate for livestock holding has the right sign (positive) and significant at five percent level of significance. In this study, the size of livestock holding is a wealth indicator variable that shows the household's ability to acquire improved production technologies for maize production. A wealthier farmer may be the first to try newly released maize seed, especially if it is newly released improved maize seed like PHB30G19 (*Shone*). Thus, possession of large livestock size has positively affected the speed of improved maize seed adoption in the study area.

CONCLUSION AND POLICY IMPLICATION

Utilization of improved production technologies such as improved seed has been promoted by the extension

system in Ethiopia, as a way of supporting smallholder agricultural production. Despite the important role that the adoption of the improved production technologies plays in enhancing overall productivity, very few studies have been conducted to analyze the factors influencing speed of improved production technology adoption rate among maize producing farmers. In this study, thus, the determinants of speed of improved maize seed adoption rate are examined using a cross-sectional data of 385 smallholder farms in Southwestern Ethiopia.

The empirical results show that the important role of farming experience (age of the farmer is used as its proxy variable) in affecting the speed of latest improved maize seed adoption rate since older farmers had more experience, resource and authority that would allow more possibilities for trying new technologies than younger and inexperienced farmers. This implies that the regional government should arrange experience sharing program in each districts that would help for knowledge sharing among farmers.

The importance of wealth (livestock holding size is used as its proxy variable) in affecting the speed of latest improved maize seed adoption rate highlights the need to improve the existing livestock production system through upgrading the provision of animal health service, nutrition and providing adequate technical support (introduction and dissemination of improved animal breeds) so as to achieve a sustained improvement in maize productivity in the area.

The speed of latest improved maize seed adoption rate was highly influenced by the use of extension service (frequency of contacts). As a result, policies and strategies should therefore place more emphasis on strengthening the existing agricultural extension service provision through recruitment, incentive, training and upgrading the educational level of extension workers, and providing non-overlapping and congruent responsibilities of extension worker in the area.

Membership of farmer cooperatives (social organization) also appears to positively influence the speed of improved maize seed adoption rate. It is thus important that strengthening the existing farmer cooperatives will reinforce farmer-to-farmer knowledge sharing. This could be done through providing training to farmers, incentives, and facilitating the required facilities by the regional government such as office and store.

Finally, use of mobile cell-phone by the head of the household (via facilitating information acquisition) and proximity to development center (via facilitating information dissemination, and reducing the transaction and transport costs) were considered vital to the speed of latest improved maize seed adoption, policies and strategies that strengthen the existing rural telecommunication service and establishment of nearby development center in each *kebeles* need to give due attention in this regards.

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