Credit Constraint and Its Implication on Small Holder Farmers Technology Adoption in South Ethiopia: In Case of Gedeo Zone

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Abstract

The study is conducted using a primary data which is collected from 252 randomly selected households found in two woredas of gedeo zone with the objective of analyzing determinants of small holder farmers' demand for and access to credit and its implication on agricultural technology adoption and intensity of adoption. Probit and double hurdle models are employed to analyze the data. Being young, number of oxen and distance to credit market found to reduce the probability of being credit constrained. Age, number of oxen, family size and technology adoption found to increase credit demand while land size, tropical livestock unit and distance to credit market found with negative (unexpected) signs. In the double Hurdle model estimation while credit market participation, being literate, being young and livestock holdings found to determine the probability of technology adoption negatively. In the last estimation education, land size, and livestock holdings turned to affect intensity of adoption positively while number of oxen and distance to input market found to reduce expenditure farm technology.

Keywords: credit, technology adoption, intensity of adoption, probit and double hurdle model, gedeo zone, Ethiopia.

1. Introduction

Agriculture has historically been dominating the rural economy in Ethiopia. Not only this but it is the dominant sector in the Ethiopian economy where 83% of the population fully depends on and more than 43% of the GDP is generated (MoFED, 2012). This sector in turn is dominated by subsistence farming where more than 95% is a rain fed farming of which more than 90% owned by a smallholder (mostly less than half hectare) poor farmers. Despite this fact the sector is unable to feed the fast growing population and to reduce the dependence on food aid. It is characterized by small-scale subsistence farmers with average land holding of 0.5 hectare per household using backward farming system and low income. These small farmers produce 96% of the national agricultural output (Kahsay and Kugbei, 2004; Gebreselassie, 2006).

Tenaw & Islam (2009) and Anyiro & Oriaku (2011) argued that access to credit helps the rural poor economy in a variety of ways. Credit access can significantly increase the ability of households to meet their financial needs such as the purchase and use of improved agricultural inputs. Also, access to rural credit accelerates the rural households' willingness to adopt modern agricultural technologies that increase the income of the small farm holders and break the perpetuity of poverty cycle they are entangled with. Furthermore, access to credit allows rural households to smooth their consumption and economic activity in the case of adverse shocks. But, rural farmers cannot do this since access to credit is very limited for rural farm holders in almost all developing countries.

Formal institutions such as commercial banks and/or development banks cannot reach the rural poor smallholder farmers. This is mainly due to the lending terms and conditions of formal bank, rules and regulations that the rural poor cannot afford such as collateral requirements. (Nguyen, 2007). Similar problem is with microfinance institutions. Although these institutions are established to serve the poor they are not reaching the poorest of the poor; rather they are serving to the nonpoor. These institutions have no clear rules and criteria to target the poorest of the poor which is an indication that MFIs are drifting away from their original mission of reaching the poor (Ejigu, 2009). For example as the study by Ejigu (2009) shows, only 34% of the demand of the poor is reached by microfinance institutions in rural Ethiopia.

As discussed above, rural poor are constrained from accessing credit because of supply side issues and this will affect the input that farmers will use in their farmland. Besides, determinant of household demand to credit is another issue that needs to be investigated. Most existing studies and previous government policies tried to focus on constraints of access to credit which is the supply side; there are quite few studies that really analyze rural households' credit demand and supply contemporarily. So this paper will try to address factors that determine demand for and access to credit to small holder farmers simultaneously.

And also studies proved that one of the reasons for the failure or least performance of most African government credit schemes was their supply-leading approach or their non-adaptation to the demand for the service by the rural households (Mpuga, 2008). The purpose of this study is, therefore, to fill this gap by providing empirical evidence on factors that influence the rural households' access to credit as well as its

implication on technology adoption of those small holder farmers in southern part of Ethiopia. Precisely, this research will identify the gap (level of constraint) on access to credit and its determinants and thereby the implication of this constraint on the decision of farmers to adopt technology on their farm land.

2. Materials and Methods

2.1 Sample selection and data

The study area, Gedeo zone is found in the South Nations Nationalities and People Regional State (SNNPR) of Ethiopia. Livelihood in the zone is mainly dependent on agriculture and the zone is one of the major coffee and Enset producing zones of the region and the country. Administratively the zone is classified in to 7 districts (woredas).

The primary data used in this study is collected from 252 small holder farmers using structured questionnaire. To select the sample respondents, first two woredas, (dilla zuria and wenago) out of the six woredas were selected purposely. This is based on the fact that these two woredas produce cereals and maize intensively as compared to other woredas and farmers can use fertilizer and improved seeds for their cereal or maize production. Furthermore the agro ecologic character in these woredas is suitable to produce cereals. At the second stage 7 kebeles were selected again purposely from the two woredas with the help of agronomists from the respective woreda agriculture offices. At the final stage a total of 252 small holder farmers were selected randomly from the seven kebeles (36 from each kebele) to be interviewed as samples for the study.

3. Methods of Data Analysis

3.1 Farmers' demand for and access to credit

The general objective of this study is to determine possible factors that affect small holder farmers demand for and access to credit in Gedeo zone. However demand for and access to credit, are binary variables that take a value of one otherwise zero. Thus to analyze which variables and to what extent these factors will relate to the small householder's demand for and access to credit, the dependent variables have to take a value of one or zero based on whether a small householder uses credit or not. That is the regressand is a binary while the regressors can be either discreet or continuous (Gujarati, 2004).

In estimating the parameters that have discrete dependent variables the maximum likelihood (ML) estimation technique is a commonly used method. Accordingly the bi-variate probit model, one of the econometric models that use ML, is employed to estimate the parameters of demand for and access to credit in this study.

The model is set in such ways that take into account the multistage decision process of household credit demand. We first estimate separately the outcome of two decision processes: (i) the probability of having demand for credit (or credit market participation); and (ii) the probability of being credit constrained. We can introduce the equations for the two decision process which are based on the "latent" demand and supply functions:

 $LD = \hat{y}'X1 + \varepsilon D....(l) \qquad \qquad LS = \gamma'X2 + \varepsilon S...(2)$ (i) Credit market participation

An individual's decision to participate in the credit market depends on a set of explanatory variables, XI, and can be represented by the latent demand function LD in equation (1). LD is an unobservable or latent continuous random variable. XI is a vector of variables that determines whether a person would have demand for credit, and εD is a random error term.

We are only able to observe whether individuals have positive demand for credit through observable information from the survey questionnaire. We define another variable—d so that

hh have desire for credit if
$$L_D > 0 d = 1$$

hh don't have desire for credit if $L_D < 0 d = 0$.

Here, d is observable. We identify d = 1 if an individual has made an attempt to borrow or has been discouraged from borrowing and d = 0 if an individual has not attempted to borrow because he has no need. We exclude individuals who have not attempted to borrow because of other reasons and a probit model is estimated with d as a dependent variable. An individual is considered as discouraged if he indicates that the reason for not attempting to borrow is "too expensive," "believed would be refused because of my age, health or lack of partner" or "the procedure is so boring and other reasons."

(ii) Credit constraint

On the supply side, although an individual have demand for credit, he is subject to the lender's evaluation which indicated credit constraint. As expressed in equation 2, L_s is an unobservable continuous random variable and X2 is a vector of variables that affect the lender's decision to grant a credit or not. In this equation an

hh is not credit constrained if $L_s > 0$ or s=1

hh is credit constrained if $L_s < 0$ or s=0

Here, s is observable through the survey questionnaire. We define s = 0 if an individual has attempted to borrow but

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has been refused totally or partially, or has been discouraged. We identify s = l if an individual was able to obtain a loan which is equal to the amount he has requested. We estimate a probit model with *LS*, i.e. the probability of being constrained, as a dependent variable in cross sectional specification.

3.2 Farm technology adoption and its intensity

The other objective of this paper is to investigate the factors that determine the decision to adopt farm technology and the intensity of expenditure for the technology. To analyze this double-hurdle model is employed. The empirical model of farm investment expenditure decisions consists of two-stage decisions: (1) whether or not to spend the money on agricultural technologies such as fertilizer and improved seeds, (2) if the decision is to adopt, the next step is to decide on how much to spend for the adoption: intensity.

Cragg (1971) formulates the double-hurdle model by modifying the standard Tobit model. The double-hurdle model has a participation (Pi) equation:

Where P * is a latent variable that takes the value of 1 if the household adopt either fertilizer or improved seeds and zero otherwise, Y_i is a vector of household and village level characteristics that determine adoption decision and δ is a vector of parameters. The level of adoption (for improved seed and fertilizers) expenditure has the following equations:

$$Z = Z_i^* if Z_i^* > 0 and P_i^* > 0$$

$$Z = 0 otherwise$$

$$Z_i^* = \beta' X_i + V_i'$$
(4)

Where Zi is the observed value of the level of farm investment expenditure, X is a vector of the households' and village level characteristics and β is a vector of parameters. The amount of expenditure can be zero either when there is censoring at zero ($P_i^* \leq 0$) or if there is faulty reporting, or due to some random circumstance. Rewriting the above equation more elaborately can help us to show explicitly the processes involved in observing zero values (Jones, 1992):

$$p_{i} = p_{i}^{*} = \beta X_{i} + V_{i} > 0 \text{ if } \acute{O}Y_{i} + V_{i}' > 0 \text{ and } \beta' X_{1}^{i} + V_{i}' > 0$$

= 0 if $\acute{O}Y_{i} + V_{i}' > 0 \text{ and } \beta' X_{1}^{i} + V_{i}' \le 0$
= 0 if $\acute{O}Y_{i} + V_{i}' \le 0 \text{ and } \beta' X_{1}^{i} + V_{i}' > 0$

 $= 0 if \, \delta Y_i + V'_i \le 0 and \beta' X_1^i + V'_i \le 0$

The error terms, V'_i and V_i are distributed as follows:

$$V_i \sim N(0,1)$$
$$V'_i \sim N(0,\partial 2)$$

The double-hurdle model with independent error terms can be estimated by the following log-likelihood function (Moffatt, 2005):

$$LL = \sum_{0} \left[\ln \left[(1 - \Phi(\alpha Z)\phi\left(\frac{\beta Xi}{\sigma}\right) \right] + \sum_{+} \ln \left[\Phi(\alpha Z)\frac{1}{\sigma}\phi\left(\frac{\mathrm{Pi} - \beta Xi}{\sigma}\right) \right] \right]$$

4. Results and discussions

Table 1: Determinants of credit market participation and credit supply, probit estimation

| VARIABLES | SS Constraint Coefficient (robust standard error) | Marginal effect | Credit market participation coefficient (robust standard error) | Marginal effect |
|-------------------------------------|--|--------------------|---|--------------------|
| Sex of the HHHs (1=male, 0 female) | -0.335(0.390) | 105 | -0.373(0.333) | 148 |
| Education of HHH (1=literate, 0 | 0.282(0.324) | .075 | -0.189(0.245) | 075 |
| illitrate) | | | | |
| AgeHHH | -0.132 (0.060) ** | 038 | -0.087(0.052)* | 035 |
| Age ² | 0.002 (0.001) ** | .001 | 0.001(0.001)* | .001 |
| Landsize | -0.308(0.191) | 088 | -0.331(0.151)** | 131 |
| No of Oxen | 0.298(0.174)* | .085 | 0.440(0.159)*** | .174 |
| Family size | 0.001(0.065);2 | .001 | 0.102(0.053)* | .041 |
| Offarmincome | -0.241(0.234) | 068 | 0.136(0.196) | .054 |
| Distance to mkt by foot | 0.008(0.003)*** | .002 | 0.005(0.002)** | .002 |
| Tropical livestock unit | -0.146(0.096) | 042 | -0.194(0.085)** | 077 |
| Woreda Dummy(1=Dilla zuria, 0 other | 2.206(0.317)*** | 033 | 1.280(0.239)*** | .174 |
| wise) | | | | |
| Adoption of Fertilizer | -0.114(0.217) | .631 | 0.446(0.192)** | .478 |
| Constant | 1.119(1.292) | | 0.922(1.116) | |
| LR chi2(12) | 94.64 | | 54.76 | |
| Prob>chi2 | 0.000 | | 0.000 | |
| Pesdo R2 | 0.31 | | 0.158 | |
| Pseudo likelihood | -105.2393 | | -146.335 | |
| Observations | 252 | | 252 | |

Table 2: Determinants of technology adoption and intensity of adoption, DH estimation

| VARIABLES | Double Hurdle model | | | | |
|--------------------------------|----------------------------------|-----------------------------|------------------------|--|--|
| | decision to adopt new technology | intensity of adoption | intensity of adoption | | |
| | (coefficients robust standard | full sample | Actual non-zero values | | |
| | error) | (asymmetric standard error) | | | |
| credit constrained | -0.633(0.292)** | -1.872(81.59) | -30.05(217.0) | | |
| credit mkt participation | 0.743(0.252)*** | 102.4(67.72) | -155.0(152.4) | | |
| sex of hhh | 0.474(0.331) | 21.42 (93.73) | -24.21(311.3) | | |
| education of hhh | 0.849(0.248)*** | 210.4(67.57)*** | 225.8(167.6) | | |
| age of hhh | 0.104(0.0535)* | 10.88 (15.15) | 6.735 (41.29) | | |
| agehhh ² | -0.001(0.001)* | -0.108(0.163) | -0.082(0.464) | | |
| landsize | -0.1;25(0.156) | 128.3(43.80)*** | 242.7(89.50)*** | | |
| oxen | -0.416(0.169)** | -138.1(44.65)*** | -188.8(104.7)* | | |
| family size | -0.036(0.053) | 5.603(14.91) | -13.40(32.51) | | |
| offarmincome | 0.157(0.203) | 81.23(57.10) | 95.98(138.4) | | |
| Distance to mkt by foot | -0.004(0.002)* | -1.126(0.571)** | 0.811(1.304) | | |
| Tropical livestock unit | 0.447(0.096)*** | 131.2(22.63)*** | 180.5(51.56)*** | | |
| contact with development | -0.211(0.452) | 158.2(121.1) | 178.6(231.1) | | |
| agents | | | | | |
| dz | -0.650(0.279)** | -620.3(74.47)*** | -1,807(302.3)*** | | |
| Constant | -3.013(1.196)** | -279.7(335.0) | -18.29(922.0) | | |
| sigma | | 386.6(17.22)*** | 476.2(48.16)*** | | |
| Wald chi2(14) | 59.11 | 146.81 | 58.03 | | |
| Prob > chi2 | 0.000 | 0.000 | 0.000 | | |
| Log likelihood | -140.898 | -1858.844 | -1013.669 | | |
| Observations | 252 | 252 | 147 | | |
| Standard errors in parentheses | | | | | |
| *** p<0.01, ** p<0.05, * p<0.1 | | | | | |

The above tables show the results of probit and double hurdle model estimations. As can be seen from table 1 among the expected determinants of credit access age, number of oxen, distance to credit market and woreda dummies found positively correlated with the probability of being credit unconstrained. Age, number of oxen, family size and technology adoption found to increase households probability of credit market participation while land size, tropical livestock unit and distance to credit market found with negative signs. This might be due to tropical livestock unit and land size is an indicator of wealth in rural Ethiopia and wealthier households does not need to participate in credit market as they can use self-finance and distance by itself discourages rural households to participate in the credit market. In the model of technology adoption credit market participation, being literate, being young and livestock holdings found to determine the probability of technology adoption positively. As expected being credit constrained and far from input market affected

probability of technology adoption negatively. However, number of oxen found to relate with technology adoption negatively. This might be large number of oxen implies increased amount of manure which can be a substitute for fertilizer. While education, land size, and livestock holdings affect intensity of adoption positively number of oxen and distance to input market found to reduce expenditure on farm technology.

Conclusion

Using the household level data collected from 252 households, which are selected from two woredas this paper investigated Credit Constraint (both form demand and supply side) and Its Implication on Small Holder Farmers Technology Adoption in Gedeo Zone, South Ethiopia. Methodologically, Bivariate Probit Model and double hurdle model were used to determine access to and demand for credit and technology adoption and intensity of adoption, respectively.

After estimation being young, number of oxen and distance to credit market found to reduce the probability of being credit constrained. Age, number of oxen, family size and technology adoption found to increase credit demand while land size, tropical livestock unit and distance to credit market found with negative (unexpected) signs.

In the double Hurdle model estimation while credit market participation, being literate, being young and livestock holdings found to determine the probability of technology adoption positively having oxen, being credit constrained and far from input market affected probability of technology adoption negatively. In the last estimation education, land size, and livestock holdings turned to affect intensity of adoption positively while number of oxen and distance to input market found to reduce expenditure farm technology.

References

- Anyiro, C. O., & Oriaku, B. N. (2011). Access To And Investment Of Formal Micro Credit By Small Holder Farmers In Abia State, Nigeria. A Case Study Of Absu Micro Finance Bank, Uturu. Agricultural Economics, 6(2).
- Cragg J.G. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods, Econometrica, 39(5): 829-844.
- Ejigu, W. (2009). Performance analysis of a sample microfinance institutions of Ethiopia. Social science research network.
- Gujarati, D. (2004). *Basic Econometrics*, 4th ed. McGraw-Hill.Inc.
- Kahsay, M and Kugbei, S. (2004). Alternative Seed Supply Systems in Ethiopia. Area, 143-149.
- Mpuga, P. (2008). Constraints in Access to and Demand for Rural Credit : Evidence from Uganda. Most, 1-28
- Nguyen, C. H. (2007). Determinants of Credit Participation and Its Impact on Household Consumption : Evidence From Rural Vietnam *. *Management*, (May 2006), 18-21.
- Tenaw, S. Islam, K.M.Z.(2009). Rural financial services and effects of microfinance on agricultural productivity and on poverty. *University of Helsinki department of economics and management discussion papers no. 37.*