ACCESS TO CREDIT AND ITS EFFECT ON THE ADOPTION OF AGRICULTURAL TECHNOLOGIES: THE CASE OF ZANZIBAR[1]

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Abstract

Access to credit is among key elements for improving agricultural production and poverty reduction. Credit can facilitate farm households to purchase the needed agricultural inputs and enhance their capacity to effect long-term investment in their farms. Despite this importance, the majority of farm households lacks access to formal credit. This study therefore was conducted in order to create knowledge of the factors that determine access of rural households to formal credit in Zanzibar and to establish the linkages between access to credit and the adoption of agricultural technology under the Zanzibar smallholder farming conditions.

Conceptually, access to credit can be influenced by institutional factors and household characteristics. Analyses of factors at the household level is therefore important to design strategic interventions aimed at deepening financial services through rural households in Zanzibar. In conducting this study, both primary and secondary data were collected. The data collection took place between May and June, 2006, covering the five districts of Unguja and Pemba islands. The districts involved in the study were North 'B', West and Central (for Unguja island) and Wete and Chake Chake (for Pemba island). In total 750 households were surveyed. Secondary data were collected from relevant institutions, including existing financial institutions. The analysis of data collected was done descriptively as well as econometrically using STATA 10.0 and SPSS 13.0 computer softwares.

The main findings of the study suggest that a number of socio-economic factors are important in influencing farm households' access to formal credit. These factors are: the number of accesses to credit, the possibility of keeping livestock, having a bank account, the value of productive assets owned, household income and the intensity of adoption of agricultural

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technologies. As regards factors determining farming technologies adoption, extension contacts intensity, household size, number of accesses to credit, and value of productive assets were found to significantly influence the adoption of agricultural technologies. However, with the exception of the number of accesses to credit, these variables were significant only for the non-credit constrained households and not for the credit constrained households. These results suggest the need for targeting credit interventions to farm households who are credit constrained for improving access to credit and the adoption of agricultural technologies.

1. INTRODUCTION

Most developing countries continue to rely on their agricultural sectors for economic growth, poverty reduction, and food security. In Zanzibar, agriculture contributed 30 percent to Gross Domestic Product in 2006 (GOZ, 2006). Although the sector contribution to the GDP exhibits a declining trend, agriculture still remains important to the majority of the Zanzibar population, particularly those living in rural areas. About 42 percent of the households in Zanzibar are directly engaged in agricultural activities for their income earning (GOZ, 2006). However, the majority of these farming households are categorized as smallholders with landholding of less than 1.2 ha (GOZ 2004).

Recognizing the importance of the agriculture sector to the Zanzibar economy and welfare of the majority of Zanzibar people, the Revolutionary Government of Zanzibar has placed a lot of emphasis on the role of credit and agricultural technology to increase agricultural productivity and household income. The adoption of agricultural technology is regarded as a key element for increasing productivity and production in the agricultural sector. However, to undertake productive investments in agricultural technology, smallholder farmers require sufficient access to financial capital. In Zanzibar, accessing subsidized credit to farm households has therefore been a long time policy option meant to financially empower farmers to purchase the needed technological inputs to increase productivity (GOZ, 2002). Specialized credit schemes were therefore established by government in collaboration with various donor agencies and non-governmental organizations to promote the adoption of specific agricultural technologies. The government also undertook reforms in the financial sector since 1991, by liberalizing the financial sector in order to increase the outreach of the formal financial services to the farming communities.

2. STATEMENT OF THE RESEARCH PROBLEM

The reforms and liberalization of the financial sector in Zanzibar were aimed at increasing the deepening of the formal financial services and addressing the need of the emerging private sector and household economy. This being the case, the outcomes of the reforms were expected to be an increased outreach of formal financial institutions and an enhanced access to formal financial services by the majority of people, both in urban and rural areas. Despite these efforts, the majority of smallholder farmers still lack access to formal credit. Smallholders' access to financial services is important for the adoption of improved farming technologies. So lack of access to credit constrains farmers to adopt recommended technological packages, which result into low productivity and production and hence low income of farm households. This poses a serious challenge to the effort to reduce poverty.

Recognizing the increasing marginalization of poor farming households with respect to access to formal credit and the constraints that smallholder farmers are facing in accessing the required capital for farming technologies adoption, various policy options are adopted and implemented with the aim of filling the financial gap created by the liberalization of the financial sector. The government has been taking deliberate efforts to encourage the existing commercial banks to open up micro-finance windows to serve the poor. This has been done by establishing credit guarantee schemes and by relaxing bank lending conditions. In addition, the government has been creating a favorable policy and legislative environment to encourage the establishment of Micro-finance Institutions (MFIs) and to mobilize members of communities to establish Savings and Credit Cooperatives (SACCOS).

Despite these efforts, commercial banks still confine their financial services to the low risk urban based customers and fail to realize the huge potentials by accumulating savings and lending to rural small borrowers. The MFIs, whose mission is to bridge the gaps between small clients and banking institutions, are found to be weak, fragmented and with limited scope and outreach. This continued overall inefficiency of the formal financial markets, which seem to have increased despite the financial reforms, make the fight against poverty reduction even more challenging. The existing inadequacy of the formal financial markets therefore continues to constrain rural development as potential households' savings remain untapped and profitable rural investments remain largely unfunded.

Although there are segments of evidence of poor performance of the formal financial markets with respect to accessing formal credit to the poor farming households, no study has been carried out to substantiate the argument. Moreover, no study has been carried out in Zanzibar so far, identifying the farm households' socio-economic factors that influence their credit access constraint condition in the formal credit markets. Also the inter-linkages that exist between access to formal credit and the adoption of agricultural technologies by smallholder farmers have not been explored. Understanding the extent farm households have accessed formal credit markets and factors, which influence them to be credit constrained, is therefore relevant and is an important step towards improving access to credit for the majority of the population. Similarly, understanding the inter-linkages between access to credit and technology adoption will shed light to the kinds of interventions that are needed for the credit access and non-credit access of constrained farmers to improve agricultural technology adoption. Thus this study is an attempt to fill the lack of knowledge and help policy makers and rural development planners in making informed decisions to improve rural development and achieve the country poverty reduction targets.

3. STUDY OBJECTIVES

The general objective of this study is therefore to establish to what extent smallholder farmers in Zanzibar have accessed credit from formal credit institutions and to assess its effect on the adoption of agricultural technologies. The study is guided by some key questions such as: (1) How many farm households in the sample have access to formal credit markets? (2) How many households are credit constrained? (3) What factors contribute to farming households becoming credit constrained in the formal credit markets? (4) Is there a linkage between access to credit and the adoption of agricultural technologies?

The specific objectives of the study are as follows:

- Assess the outreach of existing formal financial institutions.
- Examine the influence of household socio-economic characteristics in accessing formal credits.
- Assess the effect of access to formal credit on the adoption of agricultural technologies under smallholder farming conditions.
- Recommend on policy aspects regarding the approaches and strategies to improve access and the effectiveness of formal credit in smallholder agriculture in Zanzibar.

4. STUDY HYPOTHESES

- There is limited accessibility of formal credits in rural Zanzibar and smallholder farmers who are relatively poor tend to be marginalized.
- Socio-economic characteristics of smallholder farmers influence access to formal credit among smallholder farmers in Zanzibar.
- Access to formal credit affects positively the adoption of agricultural technologies among credit access constrained and not among the non-credit access constrained smallholder farmers.

5. CONCEPTUAL FRAMEWORK AND RESEARCH METHODOLOGY

5.1 Conceptual framework

The overall objective of this research work is to create knowledge on the factors that determine smallholder farmers' access to formal credit in Zanzibar on the one hand, and establish the inter-linkages between access to credit and the adoption of farming technologies on the other. Thus, the conceptual framework of this research centers on access of farm households to the formal credit system and the way they interlink with households farming technologies adoption levels. According to Dufhues and Buchenrieder (2005), households' decisions with respect to accessing credit are largely influenced by household socio-demographic characteristics, and by institutional factors.

The conditions, lending policies and operational procedures of the financial institutions represent the first category of factors that determine farm household access to formal credit. According to Dufhues, (2007) short term loans with many formal requirements are considered less attractive than long-term loans or more flexible short term loans like those provided in the informal sector. Hoff and Stiglitz, (1990) also note that high interest rates can crowd out poor more risk-averse households in favor of less poor more risk-taking households. High interest rates or high collateral requirements can make especially poor risk-averse households refrain from loan application (Sarap, 1990). The decision to apply for a loan is also constrained by the household's willingness to take a loan and the perceptions on the desirability of working with credit (Dufhues, 2007 and Mchujuko, 1991).

A second group of factors that influence access to formal credit can be referred to human capital (socio-demographic characteristics). These factors reflect the capacity of the household to meet formal credit institutions selection criteria, and constitute such factors as the personal characteristics of the household head (Dufhues, 2007, Mohamed, 2003, Temu *et al*., 2001 and Kashuliza, *et al*., 1998). The third category is the household characteristics determining the household's capacity to meet the collateral requirements. Basically, these are households' endowments such as owning registered land, houses, livestock and durable consumer goods (Ibrahim *et al*., 2007 and Nuryartono *et al*., 2005). Also social networks and engagement in non-farm activities are additional households' characteristics that can support households to meet the expectations of the financial institution on repayment capacity. The role of networks in relation to preferential access to credit has been extensively documented under the guise of the role patronage or political backup (Tibaijuka *et al*., 1989 and McKee, 1989).

In addition, access to information on available financial services, degree of access to extension services, market access intensity and the level of farming technology adoption are all key factors enhancing households' capacity to meet credit conditions to utilize it effectively (Temu, *et al*., 2001). In this study, it is conceptualized that some socio-economic factors influence farm households' credit constraint condition in formal credit markets. The study further conceptualizes that some socio-economic factors and household credit access attributes influence the intensity of agricultural technology adoption between credit constrained and non-credit constrained households.

5.2 Approaches to measure access to credit and credit constraints

Existing literature indicates the existence of three main approaches that can be used to determine household access to credit and credit constraints. These approaches are: (i) the indirect method which infers the presence of credit constraints from violations of the assumptions of the life cycle or permanent income hypothesis, (ii) detection of credit constraint by directly asking households and (iii) the use of the credit limit variable.

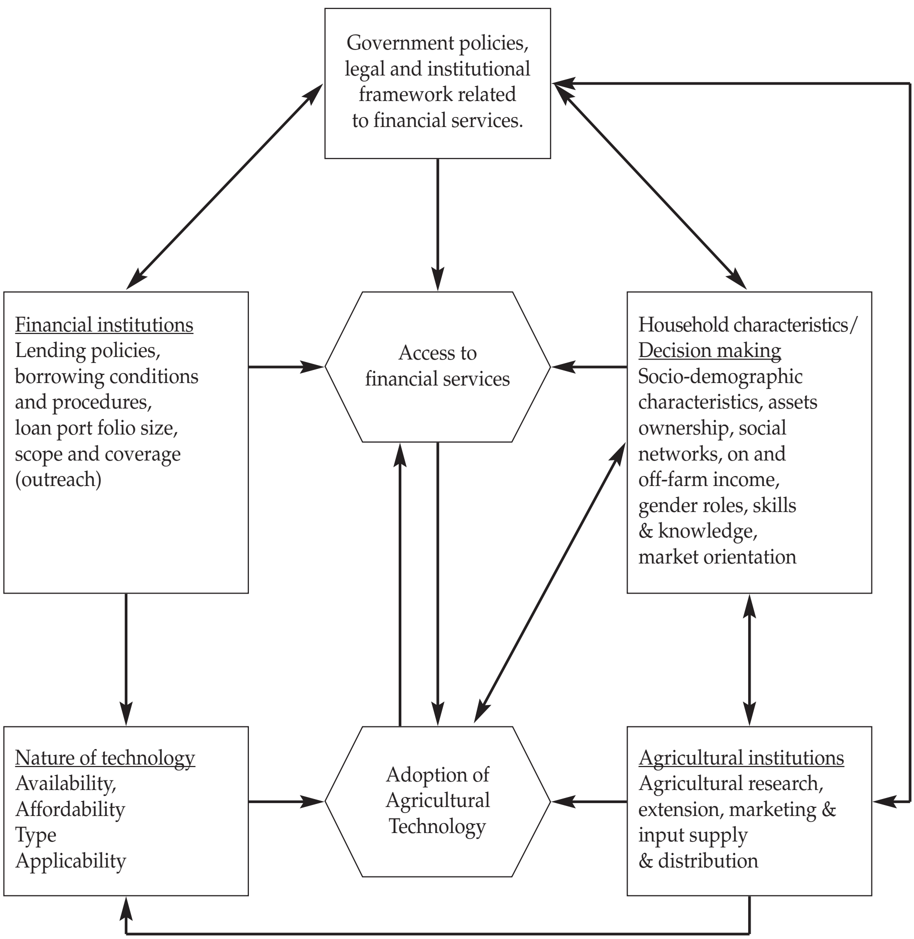
Empirical models testing for the presence of credit constraints based on life-cycle/permanent income or "consumption–smoothing" hypotheses use household consumption and income data to look for a significant dependence of consumption on transitory income. Empirical evidence of a significant dependence of consumption on transitory income is taken as an indication of a borrowing or liquidity constraint. The Life Cycle (LC)/Permanent Income Hypothesis (PIH) literature is extensive and is reviewed by Browning and Lusardi, (1996), Besley, (1995) and Deaton, (1992), among others. In general, the empirical evidence based on the Life Cycle/Permanent Income Hypothesis approach has been inconclusive.

The second method to detect the presence of credit constraints uses the information gained directly from household members on their participation and experiences in the credit market. In practice, households are classified as credit constrained, based on their responses to several qualitative questions regarding their loan applications and rejections during a given recall period. This classification is then used in reduced-form regression equations to analyze the determinants of the likelihood of a household being credit constrained and the effect of this likelihood on various household outcomes. The method was first applied by Jappelli, (1990) using data from a household survey in China. The method was subsequently used by Zeller, (1994), Schrieder and Heidhues, (1995) and Zeller, *et al*., (1996) with household survey data from Madagascar, Cameroon and Pakistan, respectively.

The third method to detect the presence of credit constraint uses the credit limit variable. According to Diagne and Zeller, (2001), the credit limit variable is an extension of the direct method. It refers to the extent of access to credit from a given source. It is measured by the *maximum* amount a household can borrow from that source. However, according to Diagne and Zeller (2001) the credit limit a borrower faces depends on the lender's and the borrower's characteristics and actions. It also depends on random events affecting the fortune of lenders and other potential borrowers who may compete for the same possible credit. Stiglitz and Weiss, (1981) also note that the concept of "credit limit" is based on the assumption that credit from any possible source is of limited supply i.e., lenders are constrained by factors beyond their control on the maximum amount they can possibly lend to any potential borrower. This maximum loanable fund is a function of available resources and is independent of the interest rate that can be charged and of the likelihood of default.

Of these three approaches, the most widely accepted and used measure of access to credit is the direct questioning of the households (Gilligan *et al.* 2005; Godquin and Sharma 2005). Jappelli, (1990) and Zeller, (1994) classify households as credit constrained if they report any rejected application of credit or report being granted less than the amount they initially asked for and were not able to get the corresponding amount through another credit application. They also classified households as being credit constrained if these households did not apply because they thought they would have been turned down. Gilligan (*et al*., 2005) and Feder (*et al*., 1990) resorted to the approach of directly asking borrowing households whether they would have liked more institutional credit at the going rates of interest. They also asked the non-borrowing households the reason for not borrowing. According to Feder (*et al*., 1990) borrowing households, which would have liked more institutional credit and non-borrowing households, which reported that they did not borrow because they could not obtain credit, were all credit constrained. Schrieder and Heidhues, (1997) also asked households whether, during the recall period, they had applied for a formal loan and if not, why they did not apply. Those households that applied for formal loan were also asked if they had received loan entirely as requested or not. From the responses to these questions, households were classified into credit constrained households and non-credit constrained households.

Figure 1. The conceptual framework of access to credit and the inter-linkages with farming technologies adoption



5.3 Research Methodology

5.3.1 Data needs and sources

Data for the study were obtained both from primary as well as from secondary sources. The secondary data were collected from various reports maintained by existing formal financial institutions such as commercial banks, micro-financial institutions and cooperatives, while the primary data were collected from a household survey of 750 farm households, carried out between May and June 2006.

The main data sets collected from the sample survey include:

- Demographic data i.e age, sex, education, marital status, main farm occupation, main off-farm activity and years of experience in farming of the head of the household and household size;
- Household resource ownership such as land, livestock, farm equipment;
- Household head's financial practices i.e. savings and credit access aspects, keeping financial records etc.;
- Levels of farming technologies adoption for various households;
- Access to extension services (extension contacts intensity).

5.3.2 Data collection instruments

A structured questionnaire was used as a tool to collect primary data from farm households. The questionnaire was designed to capture both qualitative and quantitative data from the respondents. The questionnaire was made up of six main sections, in which the first section was designed to collect background information on the demographic characteristics of the respondents. The second section was intended to obtain information on the type of farming activities that the households are engaged with and the use of available technological packages. Household information on assets ownership (land, livestock and productive equipment) was to be captured in section three of the questionnaire. The section four of the questionnaire was designed to obtain household information on access and use of financial services, while section five covers aspects related to household income and expenditures. The final section was designed to capture information on household access to extension services and degree of market integration.

The collection of information from the key stakeholders, mainly credit institutions, was done through the use of a checklist questionnaire. The data collected from these institutions include loan portfolio size, sector-wise allocation of loans and coverage. The questionnaires were also designed to collect information on institutions' lending conditions and procedures and organizations' opinion with regard to lending to smallholder farmers.

5.4 Sample size and sampling procedure

In sampling, five out of 10 districts were purposefully selected based on their agricultural potentials and presence of active credit operations. From each district, six *Shehias*[3] were randomly picked. In selecting respondents, a stratified random sampling technique was employed. With the assistance of *Shehia* leaders, lists of all units in the target population was first developed and later the population was stratified based on individual credit access status, gender and the level of farm technologies used. In order to be able to establish the existence of inter-linkages between farming technologies adoption and access to credit it was necessary to have a sample that contained a sufficient share of households who were credit constrained and those who were credit unconstrained. At the same time, the households had to be at different levels of farming technologies adoption. In addition, it was important to include in the sample a good number of women-headed-households in order to be able to assess the magnitude of gender disparity in terms of technology adoption and credit access. Therefore in drawing the sample for this study, special considerations were made to ensure fair representation of mentioned strata.

Credit schemes registers as well as knowledge and experience of extension agents and *Shehia* leaders were used in the stratification process. Selection of respondents from these strata was done randomly by picking every fourth name that appeared in the lists. The target was to interview at least ***20 respondents*** from each selected *Shehia.* The aim of creating unique sub-sets of the population was to ensure that each stratum was well represented in the study sample. The study approach used literature review, interviews and formal surveys. In the first phase, a literature research was done to acquire a basic understanding of existing relevant research reports and documents. This was followed by a number of interviews with key informants from various institutions. The second phase involved the formal survey of 750 randomly selected households in 30 *Shehias* of five districts of Unguja and Pemba. The survey was conducted from May to June 2006 and involved heads of farm households who were used as the units of the study.

5.5 Data processing and analysis

Data from the study were first coded and later entered into the Statistical Package for Social Sciences (SPSS) for Windows version 11.5, cleaned by run-

[3] Shehia is the smallest administrative unit of the government, which is the same as a village in the African context.

ning frequencies of individual variables and later analyzed. Clean data were also exported to other software packages such as Micro Soft Excel, LIMDEP for Windows (version 8) and Stata/SE for Windows (version 10) for further analysis.

A substantial part of the analysis was based on descriptive statistics such as frequencies, cross-tabulations, means and correlation coefficients of some critical variables. These statistics were used to profile respondents' characteristics, determine their financial practices with formal lenders as well as levels of adoption of improved farming technologies. To complement the descriptive analyses, some information was assessed qualitatively, based on sound judgment and economic rationale. The Statistical Package for Social Sciences (SPSS-PC) software was used to analyze most of the descriptive statistics, while STATA 10 statistical software was used to generate histograms and boxplots.

In order to determine socio-economic factors that influence farm household credit constraint condition in the formal credit markets, the probit regression model was employed. The probit model uses the normal Cummulative Distribution Function (CDF), which has been found to be very useful in analyzing dichotomous variables (Gujarati, 2004). In the probit regression model, the predicted probabilities for the dependent variable are never less than (or equal to) zero, or greater than (or equal to) one, regardless of the values of the independent variables.

This study was set to determine whether or not farm households are credit constrained in formal credit markets. A farm household head was considered to be non-credit constrained, if he/she is able to borrow from formal financial institutions, although for a number of reasons he/she may choose not to borrow. On the other side, a household head is considered to be credit constrained if HE/SHE is unable to borrow from formal financial institutions or cannot borrow as much as he/she wants. The dependent variable considered in the study therefore is binary in nature i.e. it can only have two possible values, one for the occurrence of an event, zero otherwise. In this case, the dependent (binary) variable is one for all household heads who are non-credit constrained and zero if otherwise. A mixture of continuous and categorical variables may therefore explain this dependent binary variable.

However, to overcome the problem of sample selectivity bias, the Heckman approach was employed. Heckman (1979) develops a simple two stages estimator to correct the bias that results from using nonrandomly selected samples to estimate behavioral relationships. This approach proposes the estimation of expected value of error and its inclusion as an extra explanatory variable in the regression (Wooldridge, 2002; Green, 2000;

Kennedy, 1998; Berndt, 1991). In other words, using a probit model, coefficients are first estimated by maximum likelihood and the estimates obtained for each observation are passed to the second equation to be used as an exogenous variable. This allows the parameters in the second equation to be estimated consistently by least square regression (Hoffmann and Kassouf, 2005). The theoretical exposition of the analytical model used in the analysis is given in annex 1.

From the foregoing discussion, the general form of the determinants of access to formal credit was specified as in equation 1 and the explanatory variables related to the model are summarized in Table 1.

$$C_a = \beta_0 + \beta_1 EDUC + \beta_2 GEND + \beta_3 LSTOC + \beta_4 LEAD + \beta_5 AGE + \beta_6 BANS + \beta_7 ACRE + \beta_8 FREC + \beta_9 NCRE + \beta_{10} VASS + \beta_{11} ICOM + \beta_{12} EXTI + B_{13} TECH + \beta_{14} HHS + \in_a \quad (1)$$

Where:

C_a = Whether household head has access to credit or not
β_i = Coefficients
$\in_a$ = Error term

Table 1. Variables specified in the analytical models

Variable name	Abbreviation	Specification	*A priori* sign	Variable category
Landholding size	ACRE	Number	Negative	Physical capital
Keeping livestock	LSTOC	Proxy	Positive	Physical capital
Value of productive assets	VASS	Tshs	Positive	Physical capital
Household cash income	ICOM	Tshs	Positive	Physical capital
Number of credit received	NCRE	Number	Positive	Physical capital
Bank savings	BANS	Proxy	Positive	
School years of hh head	EDUC	Number	Positive or negative	Human capital
Extension contacts intensity	EXTI	Index	Positive or negative	Human capital
Household size	HHS	Number	Negative	Human capital
Agric. Technology adoption intensity	TCH	Index	Positive or negative	Human capital
Keeping financial records	FREC	Proxy	Positive	Human capital
Age of household head	AGE	Years	Negative	Social capital
Sex of the respondent	GEND	Proxy	Negative	Social capital
Respondent leadership role	LEAD	Proxy	Positive	Social capital

In the analysis, the marginal concept was also used to predict the effect of a change in an explanatory variable on the probability of a favorable attitude toward access to formal credit. For continuous variables, derivatives of the probability function were evaluated at the mean values of the independent variables. The marginal probability was calculated by multiplying the coefficient estimate β_i by the standard probability density function $n(Xi,\beta_i)$ of the probit model evaluated at the mean values of the explanatory variables. For categorical explanatory variables with a value of zero or one, the marginal probability was calculated as the difference arising from $n(Xi,\beta_i)$ for $Xi = 0$ and $Xi = 1$ for the discrete variable (Mazuze, 2004 and Tambi *et al.*, 1999). The marginal probability was used to explain the likelihoods towards access to formal credit.

With the Heckman selection equation, the same exogenous variables as in the Probit model were specified (see Table 1). This is so in order to be able to ascertain socio-economic factors that influence household credit use intensity. Therefore, the dependent variable was the formal credit use intensity index which was developed from summing up selected indicators as attributes of households in accessing the formal credit. The selected indicators were given weight as scores and later summed and averaged to give intensity scores (see Annex 2).

The empirical model for the Heckman selection equation was therefore specified as follows:

$$C_I = \beta_0 + \beta_1 EDUC + \beta_2 GEND + \beta_3 LSTOC + \beta_4 LEAD + \beta_5 AGE + \beta_6 BANS + \beta_7 ACRE + \beta_8 FREC + \beta_9 NCRE + \beta_{10} VASS + \beta_{11} ICOM + \beta_{12} EXTI + B_{13} TECH + \beta_{14} HHS + \in_a \quad (2)$$

Where,

C_I = formal credit use intensity index
β_i = Coefficients
$\in_a$ = Error term

In the assessment of the impact of access to formal credit on the adoption of agricultural technologies, again using the direct elicitation approach, sampled households were categorized into credit constrained and non-credit constrained. An estimation of the impact of access to credit on the adoption of agricultural technologies between categories of household was done while accounting for selection bias. The impact of access to credit was estimated using a switching regression model.

The switching regression model accounts for the fact that each household has a non-zero probability of being credit constrained in each period, the probability varies depending on household characteristics, and only one realization of these probabilities is observed in each period. Consistent estimates parameters can be obtained by following a two-step Heckman procedure of estimating credit constraint equation as a Probit and estimating other two equations separately, while correcting for the selection bias by including the inverse Mills ratio from Probit as regressor in the two equations.

In this study, it was hypothesized that some socio-economic factors have significant effect on farm household access to formal credit; these socio-economic characteristics influence the adoption of agriculture technologies differently between households with access to formal credit and those without access to formal credit. The analysis in this study was carried out in two levels i.e. the first level was the determination of factors that influence farm household access to formal credit and the second level was the isolation of factors that influence adoption of farming technologies among credit access constrained and non-credit access constrained households. The detailed description of the steps followed is as given in annex 3.

The model specification for the reduced forms regression is as follows:

$$A_t = \beta_0 + \beta_1 EDUC + \beta_2 SGEND + \beta_3 EXTI + \beta_4 ACRE + \beta_5 NCRE + \beta_6 HHS + \beta_7 LSTOC + \beta_8 VASS + \beta_9 ICOM + \beta_{10} FCUI + \beta_{11} AGE + \in_t \ldots\ldots\ldots\ldots (3)$$

A_I = Agricultural technology adoption intensity
β_i = Coefficients
$\in_a$ = Error term

Independent variables specified in the model are presented in Table 2.

Some diagnostic tests were performed in order to examine the problems of autocorrelation, multicollinearity and heteroscedasticity. The use of the Durbin-Watson statistic test and the MLE method in most cases indicated the absence of these problems. The goodness-of-fit of the probit model was measured by the McFadden with likelihood ratio statistics as the basis of inference (Hawassi, 2006) with a chosen significance level of 10 percent probability level. Similarly the goodness-of-fit of the linear regression model was measured by adjusted R^2 (Maddala, 1988 and Gujarati, 1988) with a chosen significance level of 5 percent confidence level. Furthermore, inspection of the signs of the estimated parameters was made in order to confirm if they conform to the priori expectation. The inspections were also made on the values of the standard errors of the variables included in the model and to check whether the empirical model was correctly predicted. On the basis of these criteria, the empirical models used in this study were found to be appropriate in determining the main factors that significantly influence access

Table 2. Variables for the switching regression model on the adoption of agricultural technology[4]

Variable name	Abbreviation	Specification	*A priori* sign	Variable category
Keeping livestock	LSTOC	Proxy	Positive	Physical capital
Landholding size	ACRE	Number	Negative	Physical capital
Value of productive assets	VASS	Tshs	Positive	Physical capital
Household cash income	ICOM	Tshs	Positive	Physical capital
Number of credit received	NCRE	Number	Positive	Physical capital
School years of hh head	EDUC	Number	Positive	Human capital
Extension contacts intensity	EXTI	Index	Positive	Human capital
Household size	HHS	Number	Negative	Human capital
Farms household Credit use intensity	FCUI	Index	Positive or negative	Human capital
Age of household head	AGE	Years	Negative	Social capital
Sex of the respondent	GEND	Proxy	Negative	Social capital

to formal credit and technology adoption between the regimes of households (credit constrained and non-credit constrained).

Further analysis was done in order to measure the credit access and outreach. The proportion of farming households that had accessed credit in the formal credit markets were used as a measure of credit access, while the Principal Component Analysis (PCA), which is a multivariate technique, was used to measure poverty outreach (depth outreach). The PCA was used as an econometric instrument by the IFPRI in developing the poverty assessment tool in the late 1990s (Dufhues, 2007). The main objective of PCA is to reduce the dimension of observations so that different correlated variables are aggregated into fewer uncorrelated principal components, which can be seen as indices (Dufhues and Buchenrieder, 2005 and Fraser and Kazi, 2004). With this technique, most of the information contained in the data is represented in the new indices. Basically, this technique is viewed as "data reduction technique", since the set of original *m* variables is reduced to *n* principal components (PC), with $n \ll m$. This smaller number of components can then be used for interpretation purposes or further data analysis. The procedure car-

[4] The technology adoption intensity index was obtained by summing up and later averaging the weighted scores of adoption of desired farming technologies; three main farming lines enterprises were selected (see Annex 4).

ried out by the analysis is to calculate new uncorrelated principal components by linear combinations of the original, correlated variables. This is done by deriving (standardized) weights for each indicator. In algebraic terms this means that:

$$PC_1 = W_{11} \quad \nu_1 + w_{12} \quad \nu_2 + \ldots\ldots\ldots + w_{1m} \quad \nu_m$$
$$PC_2 = W_{21} \quad \nu_1 + w_{22} \quad \nu_2 + \ldots\ldots\ldots + w_{2m} \quad \nu_m$$
$$PC_m = W_{m1} \quad \nu_1 + w_{m2} \quad \nu_2 + \ldots\ldots\ldots + w_{mm} \quad \nu_m$$

Where w is the calculated weight and ν is the variable. Applied to poverty assessment, the PCA determines a subset of indicators that measures the relative poverty level of a household. In the end, a single indicator for each household is created, reflecting the household poverty status in relation to all other household of the sample (Fraser and Kazi, 2004). With the weights of the PC_i and the respective indicators, the poverty index is calculated for each household. Relative comparisons can be drawn by ordering the households according to their poverty index and sorting them into three groups of equal size. The lowest group incorporates the poorest households, while the middle group and the upper group embrace the poor and the less poor households. The advantage of PCA is that it creates a single indicator that is easy to use for analysis, while at the same time this single indicator is not limited to the monetary aspect addressed by household expenditures as the conventional method of (income) poverty.

The PCA technique allows to take the multiple dimensions of poverty into account and to integrate qualitative variables with quantitative ones. The indicators can be divided into three categories:

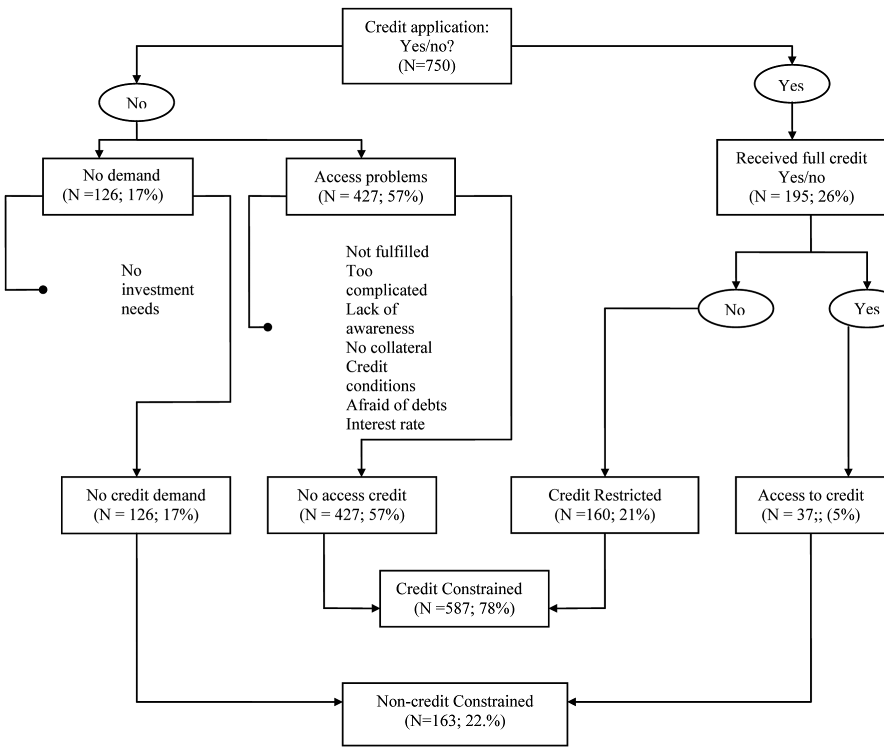
1. Means to achieve welfare, which includes indicators that reflect the earning capacities of a household. They are subdivided into human capital, social capital and ownership of assets.
2. Basic needs, which include indicators such as food consumption and shelter.
3. Other aspect of welfare which include indicators such as having leadership role, access to extension networks and market access.

6. RESULTS AND DISCUSSION

6.1 Credit constraints in formal credit markets

The number of households who were credit constrained in the formal credit markets among the whole sample of households were 587 (78%) and the remaining 163 (22%) were therefore non-credit constrained (see Figure 2). Of those households who were non-credit constrained, only 5% indicated to have obtained credit as they requested and the remaining 17% indicated to have no investment needs that needed credit support. Of those who were found credit constrained, 22% were quantity constrained and 56% had access problems caused by factors such as inability to satisfy credit requirements, lack of awareness on availability of credit, high interest rates and fear to be in debts.

Figure 2. Formal credit constraints in rural Zanzibar



6.2 Socio-economic characteristics of sampled households by access to credit

Table 3 shows that the average family size of the sampled households is 7 persons. This is the same for credit constrained and non-credit constrained households. The average age of sampled household heads is 48 years. Again, this is the same for credit constrained and non-credit constrained households. The average number of years of formal schooling for the whole sample is 6 years. Non-credit constrained households had on average two years more of formal schooling than the credit constrained households.

The average value of productive assets owned by the sampled households is Tshs 701 694 (US Dollar 540)[5]. The non-credit constrained households on average had productive assets valued three times more than that of credit constrained households. The average annual income of the sampled households is Tshs 1 048 192 (US Dollar 806), while the average annual income of non-credit constrained households is two times more than the average annual income of credit constrained households. The extension contacts intensity index (see Annex 5) is greater for the non-credit constrained households than for credit constrained households (0.5 versus 0.3). Likewise, the agricultural technology adoption intensity index of non-credit constrained households was greater than that of credit constrained households (0.5 versus 0.3).

Table 3. Socio-economic characteristics of sampled households by credit access status

	Credit constrained (N = 587)	Non-credit constrained (N = 163)	All sample (N = 750)
Age of head of household (years)	48	48	48
Family size	7	7	7
Formal education of the head of household (years)	6	8	6
Value of productive assets owned (Tshs)	494 853	1 446 576	701 694
Size of land owned (acres)	2.9	3.2	3.0
Household total annual income (Tshs)	802 660	1 93 409	1 048 192
Extension contacts intensity index	0.3	0.5	0.4
Agricultural technology adoption intensity index	0.3	0.5	0.3

Source: Own survey, 2006

5 US Dollar 1 = Tanzania Shilling (Tshs) 1,300.

6.3 Depth outreach of the formal financial sector

Outreach simply means the number of clients served. However, Meyer (2002) noted that outreach is a multidimensional concept and that, in order to measure outreach, we need to look into different dimensions. These dimensions include the number of persons served by financial institutions, the number of women served and the number of financial services provided. Similarly, Navajas *et al*. (2000) indicate that there are six aspects of measuring outreach: depth, worth of users, cost to users, breadth, length and scope. Depth outreach refers to the value society attaches to the net gain from the use of the micro credit by a given borrower (Navajas *et al*. 2000). This measure is used to identify poor clients. Therefore in order to establish the depth outreach of the formal financial sector in the study areas, the Composite Indicator of Multidimensional Poverty was developed to capture the non-income dimension of poverty in Zanzibar.

As mentioned in several studies on the limitations of income and expenditure as a measure of identification of the poor (Siddhisena and Jayathilaka, 2006), the study analyzed several other socio-economic dimensions including income in the identification of poor households using the sample data. The number of variables such as house status (type of wall, type of roofing material, floor type), income level, size of land owned, value of productive assets owned, owing livestock, leadership status, level of education and family size were initially used and significant factors were taken into account using the Principal Component based Factor Analysis.

The variables were weighted and rescaled with the Eigen (more than one) value and accordingly the poverty levels of sampled households were identified. The results of the Principal Component based Factor using SPSS are presented in Table 4 and Figure 5. Since the three Eigen values (greater than 1) explained 56% of the variability, three factors (F1 = Means to achieve the welfare; F2 = Basic needs; F3 = Other aspects of welfare) provide sufficient explanation of the eight variables listed (Table 5)[6]. The composite indicators were developed using the mean value of the three factors, multiplying them by the corresponding Eigen values.

[6] The variables included in the factors:

F1 = Ownership of productive assets, including land, household size, income, level of education, owning livestock

F2 = House status (Type of wall, Type of roofing material, Type of floor, Type of latrine

F3 = social status i.e leadership role.

Table 4. Eigen Values (24) and Factor Scores (25) of the Factor Analysis

Eigen Value	Percentage of Variance	Cumulative %
2.288	28.596	28.596
1.136	14.197	42.792
1.061	13.263	56.055
0.850	10.624	66.679
0.819	10.232	76.911
0.741	9.264	86.175
0.644	8.050	94.225
0.462	5.775	100.000

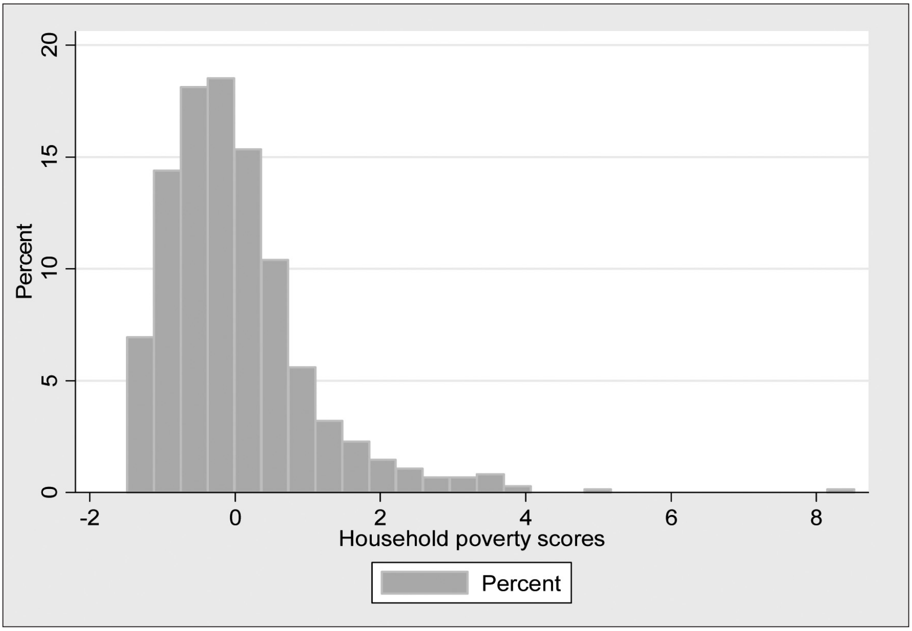
Table 5. Rotate Component Matrix

	Rotated Component Matrix[a]		
	1	2	3
ACREAGE	0.122	0.664	0.229
EDUC	0.481	0.039	0.522
FAMILY_S	-0.022	0.818	-0.017
ASSEE	0.775	0.213	-0.044
INCOME	0.754	-0.024	0.085
HOUSE_ST	0.611	-0.005	0.149
LEAD_S	0.003	-0.122	-0.834
LIVESTOC	-0.480	-0.396	0.290
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization A: Rotation converged in 5 interactions			

Note:
ACREAGE = Size of landholding (expressed in acres), EDUC = Level of education, FAMILY_S = Number of people in the household, ASSEE = Value of productive assets/farm equipment, INCOME = Average annual household income, HOUSE_ST = The status of the house (which is an aggregate of the Type of wall, Type of roofing materials, Type of floor and Type of latrine), LEAD_S = Household leadership role in the community), LIVESTOCK = Estimated market value of livestock owned by the household.

Source: Own survey, 2006

Figure 5. Poverty index distribution among sampled household heads



Based on these composite indicators for the sampled households, the variability of household poverty was measured and households were classified accordingly into three categories: *poorest, poor and less poor* (see Table 6).

As revealed from the classification 34% of the sampled households were categorized as poorest, while 24% were classified as poor and 42% as less poor. From Table 6 it is clear that better-off households are over-represented with respect to those who have accessed credit in the formal financial sector and that poor and poorest households are under-represented. As indicated in Table 6, only 10% of the households belonging to the poorest group have accessed credit in formal credit markets. The percentage of the poor household heads that had accessed formal credit is slightly higher than that of more poor households, while the proportion of less poor households who had accessed credit in formal credit markets is five times larger than that of poor household heads.

With these results, the poorest households in the sample are clearly under-proportionately served by the formal financial sector. This finding is also confirmed by Mohamed (2003), who indicated that the poorest have not ben-

Table 6. Outreach of formal credit markets by poverty groups

Credit access status	Poorest	Poor	Less poor	Total
Credit constrained households	41 (240)	27(157)	32(190)	100(587)
Non-credit constrained households	10(16)	15(24)	75 (123)	100(163)
Total	34(256)	24(181)	42(313)	100(750)

Source: Own survey, 2006

efited from the reforms of the financial sector, and continue to be marginalized by the formal financial sector. The report of Bank of Tanzania (2007), also confirms that the depth outreach of micro-financial institutions (MFIs) is shallow. It can therefore be concluded that despite ongoing financial reforms and the liberalization of the financial sector in Zanzibar, the breadth and depth of formal financial institutions is still low and the poorest households in rural areas are severely disadvantaged.

6.4 Determinants of formal credit constraint condition

The model for the estimation of the determinants of formal credit constraint condition in the formal credit markets included fourteen different explanatory variables (regressors). The Maximum Likelihood Method was used for estimating variable coefficients and marginal effects of regressors on the probability household being non-credit constrained in the formal credit markets. The results of the binomial probit model for the determinants of credit constraint condition are presented in Table 7. As can be seen from Table 7, the specified probit model fits very well the data as measured by McFadden (R^2). The high value of McFadden (74.7%) suggests a good predictive ability of the model implying that the variables included in the model explain about 74.7% of the variation in the dependent variable. Furthermore, the Chi-square statistic shows the model is highly significant at ($P \leq 0.01$), indicating that all variables included in the model are jointly different from zero. The model has also very high predictions (89.6%). All these confirm that there is a relationship between the dependent variable and explanatory variables included in the model.

The variables included in the model were Extension contacts intensity (EXTI), Landholding size (ACRE), Number of formal credit received (NCRE), Years of formal education of household head (EDUC), Age of the head of household (AGE), Household size (HHS), Sex of the respondent (GEND), Household head leadership status (LEAD), Keeping livestock

(LSTOC), Keeping financial records (FREC), Having bank account (BANS), Value of productive assets (VASS), Household head annual income (ICOM), and Agricultural technology adoption intensity (TECH).

With the exception of LEAD all variables included in the model possess the hypothesized direction of influence on the probability for farm household heads to have access to credit (being non-credit constrained) in the formal credit markets. Except for landholding size (ACRE), household size (HHS), sex of respondent (GEND) and household head leadership status (LEAD) all variables have a positive influence on the probability that farm households have an access to formal credit.

In this model, the coefficients of five out of fourteen explanatory variables are statistically significant at various levels of probability. The results show a positive and statistically significant coefficient for number of credit received by household heads (NCRE) at ($P \leq 0.01$), indicating that increased number of loans received by farm household increases the probability of household heads to access credit in the formal credit markets. The coefficient of the variable livestock keeping (LSTOC) being positive and statistically significant at ($P \leq 0.01$) suggests that keeping livestock increases the probability of a household head being non-credit constrained. Similar finding was obtained by Ellis and Mdoe (2002). In rural economy, keeping livestock, particularly cattle, is associated with a relative wealth of the household. Relatively wealthier households can afford to keep livestock (cattle) and this explains their high probability of being non-credit constrained.

The positive and statistically significant coefficient of having bank account (BANS) at ($P \leq 0.05$) implies that having a bank account increases the probability of a farm household being non-credit constrained. Having a bank account is regarded as an important factor for establishing contacts with bank officials and for getting information on credit. Bank savings may also be used as security for loans and therefore may increase bank account holders' chances of accessing formal credit.

The value of productive assets (VASS) had also a positive and statistically significant coefficient at ($P \leq 0.01$), implying that increasing the value of productive assets owned by households is likely to increase the probability of farm household head being non-credit constrained in the formal credit markets. Total income, as a proxy for welfare status, also confirms that increasing the household total income reduces the probability of a household being credit constrained. The variables total income was statistically significant at ($P \leq 0.01$). The interpretation of this finding is that a better household situation affects the decision of the lender to ration the loan or that the household has less demand for loan because of the households' own equity capital accumulated through past income earnings. The lender also considers the welfare status of a client or potential client before signing a contract to provide the loan.

The marginal effects, measured by marginal probabilities in Table 7, indicate the effect that an additional unit of a specified variable may have on the probability of household head being non-credit access constrained in the formal credit markets. However, the marginal probability computed for continuous variables is not comparable with those computed for dichotomous variables. As indicated in Table 7, the one unit increase in value of productive assets (VASS) increases the probability of household head becoming non-credit constrained by 0.0452 percent. Similarly, one unit increase in the level of household head income (ICOM) increases the probability of becoming non-credit constrained by 0.0895 percent.

The number of times that a household has received formal credit (NCRE) seems to have the greater influence in explaining the increase in the probability of accessing credit in the formal credit markets in the study areas. This is so because the one unit increase in the number of times that a household has accessed formal credit increases the farm household heads' probability of being non-credit constrained by 0.4895 percent.

In a situation of dichotomous variable, such as the case with keeping livestock and having a bank account, the results could be interpreted in the sense that the marginal probability of farm household towards accessing formal credit with respect to keeping livestock and having bank account are 0.1223 and 0.1263, respectively.

Further analysis of factors hypothesized to influence farm household access to credit in the formal credit markets were carried out using the OLS regression model. This was done specifically to see if these factors have similar effects on the intensity of formal credit use. Table 7 presents coefficients of determinants of farm households' intensity use of formal credit. The goodness of fit of the model is high as measured using adjusted coefficient of determination (Adjusted R^2). The coefficient of determination (R^2) for the credit use intensity equations, estimated using Heckman's procedure is 0.85, suggesting that the variables included in the model explain 85% of the variations in the dependent variable. The F-value is highly significant at ($P \leq 0.01$), indicating that the explanatory variables were statistically significant in explaining variation in the dependent variable.

As indicated in Table 7, seven coefficients out of fourteen were found to be significant at various probability levels. Except for household head leadership status (LEAD) all coefficients had the expected signs. The coefficient for the number of credit received was positive and statistically significant at ($P \leq 0.01$), indicating that the increase in the number of credit received increases the intensity of formal credit use by 0.14%. The coefficient for family size is negative and significant at (P≤0.1), meaning that the increase in the size of the household decreases the intensity of formal credit use by 0.002%.

Keeping livestock has a positive and significant coefficient at (P≤0.01) suggesting that keeping livestock increases farm household intensity of formal credit use by 0.03%. Livestock keeping has more economic incentives and is relatively less risky than crop farming under rain-fed conditions. Besides, there has been high concentration of credit for livestock activities and this explains why keeping livestock may induce increased use of formal credit. Similarly, having a bank account was also found statistically significant at (P≤0.01), indicating that having bank account increases the intensity of formal credit use by 0.29%. This finding is not surprising taking into account that having a bank account is taken by most lenders as one of the conditions for loan disbursement. Besides, having a bank account implies household integration into the formal financial system and this may remove households' barriers to access formal credit, which may be caused by lack of awareness, fear of formal organizations and lack of collateral. Bank savings can as well be used as security for receiving loans from formal credit markets. All these have the potential of increasing the intensity of formal credit use by households.

The value of productive assets was also found with positive and statistically significant coefficient at (P≤0.01), implying that increase in value of productive assets has the potential for increasing the intensity of the use of formal credit by 0.11%. Value of productive assets may be used by lenders as collateral or security for the loan. Households with greater value of productive assets therefore stand a better chance to get formal credit and hence their use of formal credit. Likewise, the household total income was found statistically significant at (P≤0.01), suggesting that an increase in household total income increases the intensity of formal credit use by 0.02%.

The intensity in the adoption of agricultural technologies in the household was also found to be statistically significant at (P≤0.1). The positive sign of its coefficient implies that increase in technology adoption intensity increases the use of formal credit by 0.03%. As already explained, applying improved technological packages, farmers need capital and in the absence of own funds, a household may resort to the use of credit. So in case of increased technological advancement, farmers may as well increase their intensity in the use of formal credit.

In the model, the coefficient of the inverse Mill's ratio variable (lambda), obtained from the probit equation, was also found to be statistically significant, which means that its inclusion in the model was necessary to avoid sample selection bias.

Table 7. Probit equation and credit use intensity equation using Heckman's procedure

	Participation equation (Probit)			Credit use intensity equation (Hekman procedure)	
Variables	Coefficient	Marginal effect	t-statistic	Coefficient	t-statistic
Constant	-10.767352	-2.312574	-5.343***	-0.399465	-6.314***
EXTI	0.061775	0.013268	0.144	0.009351	0.601
ACRE	-0.024266	-0.005217	-0.499	-0.001019	-0.575
NCRE	2.279272	0.489534	11.935***	0.144371	27.423***
EDUC	0.0016476	0.003539	0.612	0.001175	1.167
AGE	0.003348	0.000719	0.415	-0.000043	-0.154
HHS	-0.001848	0.000397	0.052	-0.002254	-1.796*
GEND	-0.169400	-0.038373	-0.611	-0.012627	-1.353
LEAD	-0.087454	-0.018783	-0.413	-0.009491	-1.183
LSTOC	0.569524	0.122321	2.553***	0.034190	4.133***
FREC	0.136496	0.027677	0.467	0.011385	0.993
BANS	0.496274	0.126329	2.063**	0.293693	28.615***
VASS	0.210517	0.045214	2.554***	0.114385	4.881***
ICOM	0.416914	0.089543	2.843***	0.018450	3.852***
TECH	0.161653	0.034719	0.575	0.031691	6.314*
Lambda	–	–	–	0.154740	17.715***
Log Likelihood Function		-99.39903		R-Squared	0.852591
Restricted Log Likelihood function		392.6341		Adj. R-Squared	0.84958
Pseudo R-Squared		0.74684		Durbin-Watson Stat.	1.89198
Chi Squared		586.4700		Model test F(15, 734)	283.02

Hosmer-Lemeshow Chi-squared	23.07320		Log-l	730.61
Degree of freedom	14		Restricted (b=0) log-l	12.6542
McFadden	0.74684			
Threshold Value for Predicting (Y=1)	0.5			
Households with access to credit	163			
Households with no access to credit	587			
Total sampled households	750			
Percentage of Right Prediction (%)	89.571			
Prediction failure (%)	10.429			

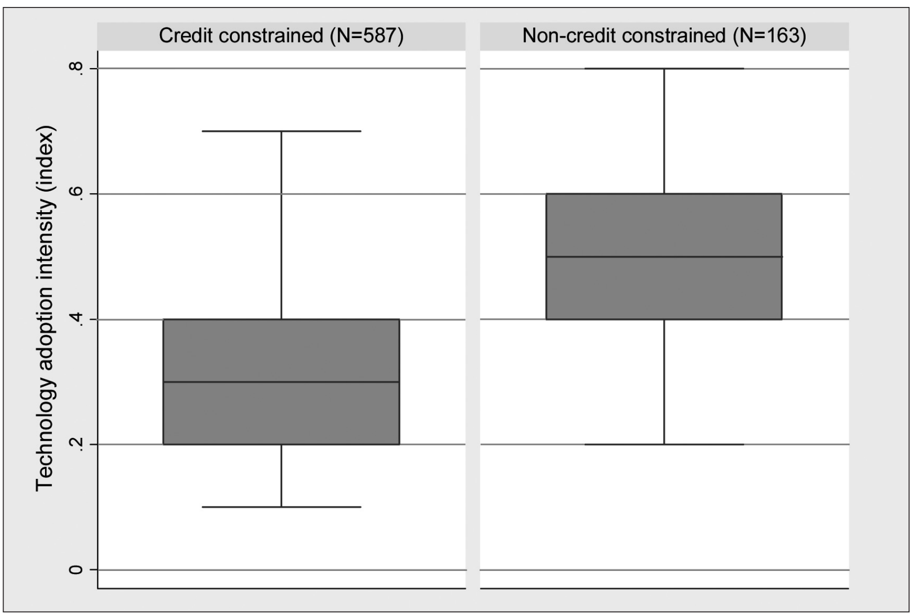
TECH	=	Intensity of adoption of agricultural technologies (index)
EXTI	=	Extension contacts intensity (index)
ACRE	=	Size of land owned by household (acres)
NCRE	=	Number of credit received by household head
EDUC	=	Level of formal education attained by household head
AGE	=	Age of the head of household (years)
HHS	=	Household size (number of people in the household)
GEND	=	Dummy variable for gender (1 = male, 0 = otherwise)
LEAD	=	Leadership of hh head (1= leader, 0 = otherwise)
LSTOC	=	Whether keeping livestock or no? (1 = Yes, 0 = otherwise)
FREC	=	Dummy for keeping financial records (1 = Keep records, 0 = otherwise)
BANS	=	Dummy variable for having bank account (1= have bank account, 0 = otherwise)
VASS	=	Total value of productive assets owned by household (Tshs)
ICOM	=	Average household annual income (Tshs)

Note: ***, ** and * Denotes significance at the 1%, 5% and 10% levels

6.5 Agricultural Technology Adoption – Credit constrained and non-credit constrained households

The results from cross tabulation analysis show the existence of a close relationship between agricultural technology adoption intensity and access to credit. Statistically, the relationship was found to be significant at (P≤0.01). These findings indicate that technology adoption may create demands for loans and this may influence the credit constraint condition of a household. This being the case, the hypothesis that state that there is no difference between credit constrained households and non-credit constrained households with regard to technology adoption intensity is rejected. Figure 6 illustrates the association between levels of agricultural technology adoption and access to credit.

Figure 6. The degree of household agricultural technology adoption intensity by credit access



The Reduced form coefficient estimates of second stage switching regression models for agricultural technology adoption are shown in Table 8. Despite the model's goodness of fit being low (low adjusted R^2) in both regimes (credit constrained and non-credit constrained), the F-value in both regimes is highly significant indicating that all variables included in the model are jointly different from zero. This is quiet acceptable for the kind of study of this nature (See Nuryartono *et al.*, 2005). In the estimation, the coefficient of lamda was found statistically significant in both regressions, suggesting that the sample did suffer from sample selection bias and that direct estimation of the model by OLS would have yielded biased estimates.

Extension contacts intensity did significantly influence the adoption of agricultural technologies for the non-credit constrained households, but it was not important for credit constrained households. The coefficient of extension contacts intensity for the non-credit constrained households was significant at 1% probability level and the sign of the coefficient was positive, implying that increasing extension contacts may influence technology adoption for non-credit constrained households. Extension contacts did not have significant effect on technology adoption for the credit constrained households. This indicates that for extension services to be effective in terms of enhancing agricultural technology adoption, farm households need to be non-credit constrained. The number of formal loans received by the household head significantly influenced the adoption of agricultural technologies for the credit constrained households. The positive coefficient of the variable number of credit accessed suggests that any additional loans that credit constrained households have received has a significant effect on the adoption of agricultural technologies. However, increasing the number of credit to non-credit constrained households may have an impact on agricultural technology adoption but not in the same way as it does with credit constrained households.

Household size was found to be statistically significant for the non-credit constrained households and not for the credit constrained households. The negative sign of the coefficient indicates that as household size increases, the agricultural technology adoption intensity for non-credit constrained decreases. There being no effect for the credit constrained households indicates that household size is not an important factor for technology adoption once the farm household is credit constrained. The value of productive assets and household income were also found to be important factors for technology adoption among non-credit constrained households. This implies that one unit increase in value of productive assets owned by household and one unit increase in income level of the household have the corresponding effect of increasing the intensity of technology adoption for the credit constrained households. From the results presented in Table 8, it can also be noted that the coefficient for lamda in all regression equations was significant. This suggests that the sample did suffer from sample selection bias and that direct estimation of the model by OLS would have yielded biased estimates.

Table 8. Estimated coefficient for agricultural technology adoption distinguished between credit constrained and non-credit constrained households

	Credit constrained		Non-credit constrained	
Variables	Coefficient	Std Error	Coefficient	Std Error
Constant	-0.479278	0.590587	-0.270771	0.203945
EXTI	0.025933	0.184575	0.146199	0.035793***
ACRE	-0.008833	0.022542	0.001224	0.003676
NCRE	3.270460	1.466647**	0.020307	0.0116594*
EDUC	0.000054	0.011365	0.000964	0.002407
AGE	0.0021154	0.003347	-0.00021	0.002407
HHS	-0.001326	0.015224	-0.007144	0.003216**
GEND	0.079750	0.117640	-0.005761	0.0235330
LSTOC	-0.006177	0.103256	-0.014084	0.017672
VASS	0.0179471	0.037841	0.036474	0.009984***
ICOM	0.056883	0.053074	0.019153	0.015572
FCUI	0.618740	0.458456	0.023223	0.050372
Lamda	-1.972086	0.828743**	-0.005755	0.018483
Adjusted R^2-	0.29784		0.39021	
F	21.71***		9.64***	
No. of observations	587		163	

EXTI	=	Extension contacts intensity (index)
ACRE	=	Size of land owned by household (acres)
NCRE	=	Number of credit received by household head
EDUC	=	Level of formal education attained by household head
AGE	=	Age of the head of the household (years)
HHS	=	Household size (number of people in the household)
GEND	=	Dummy variable for gender (1 = male, 0 = otherwise)
LSTOC	=	Whether keeping livestock or no? (1 = Yes, 0 = otherwise)
VASS	=	Total value of productive assets owned by household (Tshs)
ICOM	=	Average household annual income (Tshs)
FCUI	=	Farm household credit use intensity (index)

Note: ***, **, and * are significant at 1, 5, and 10 percent level respectively

7. SUMMARY, CONCLUSION AND RECOMMENDATIONS

7.1 Summary of the study

This study was carried out to establish the extent of access to credit among smallholder farmers in Zanzibar and determine factors that influence farm household credit constraint condition in formal credit markets. In addition, the study aimed at assessing the effect of access to credit on the adoption of agricultural technologies. The assumption was that farm households' access to credit is influenced by socio-economic factors and that increased access to credit positively affects the adoption of agricultural technologies among credit constrained households.

Both primary and secondary data were used in the study. The review of the existing literature provided much of the secondary information, while the primary data were obtained from interviews of key informants and the household survey. The checklist questions were used to interview key informants from banking institutions, relevant government departments, Savings and Credit Cooperatives (SACCOS) and Micro-finance NGOs. Data from the survey were collected from interviewing 750 households using structured questionnaires. A combination of sampling techniques was used and the primary data were collected in five districts (3 on Unguja and 2 on Pemba).

The study used both descriptive statistics and econometric models to analyze the data. The probit model and Hekman's selection equation were used to determine factors that influence sampled households credit constraint condition in the formal credit markets. In order to determine the impact of access to credit on the adoption of agricultural technology the Switching regression model (SRM) was employed while correcting for possible sample selection. With the switching regression model, the first step used the probit model to determine the relationship between farm household heads' credit constraint condition and a number of socio-economic and credit variables. The second stage followed was the estimation of farming technologies adoption function between credit constrained and non-credit constrained households using reduced forms equations.

The results from the study indicate that there is limited access of formal credit in the surveyed areas and that the majority of smallholder farmers are credit constrained in the formal credit markets. The study also revealed that a significant proportion of farm households in the areas covered by the survey had no credit demands in the formal credit markets. Socio-economic characteristics of the heads of households such as household size, having a bank account, value of productive assets owned by household, level of income of the head of the household, keeping livestock and the number of times a household has received formal credit, were found to be important determinants of farm household credit constraint condition in the formal credit markets. The results show that an increasing number of credit that a farm household receives from the formal credit markets increases their probability of being non-credit constrained. This could be due to the fact that many micro-financial institutions use a graduation mechanism in extending loans to small borrowers: they start with small loans and gradually increase the size of subsequent loans upon fulfilling the loan repayment obligations.

The household size was found to have a negative influence on farm household access to credit in the formal credit markets. These results were expected since the larger family size, despite having potential for labor supply, implies a high dependency ratio for the household. In African culture the head of the household has the responsibility of taking care of all members in the family. The high dependency ratio contributes to the degree of household poverty and hence limits household head to access formal credit. Also, the results indicate that increase in the value of productive assets owned and level of income increases the probability of farm households of becoming non-credit constrained in the formal credit markets. In addition, the results indicate that the probability of being non-credit constrained is higher for farm households who have a bank account. The positive sign of the coefficient of variable agricultural technology adoption intensity suggest the positive influence of agricultural technology adoption on credit access of smallholder farmers in the formal credit markets. The possible explanation for this finding is that an increase in technology adoption results in an increase in production and productivity and hence an increase in the farm's income. Increased income increases farm household socio-economic leverage which enhances their chances to access credit in the formal credit markets.

The results from the SRM show that the number of times a farm household has received formal credit influences technology adoption among credit constrained and non-credit constrained households. However, the effect is more for the credit constrained than for the non-credit constrained households. This suggests a need for targeting credit interventions. Increasing the number of credit would be more effective in influencing the adoption of agricultural technology when households are credit constrained. Extension contacts intensity has however a positive influence on agricultural technology adoption among non-credit constrained households and not for credit constrained households. These results imply that extending agricultural extension services to credit constrained households will have a minimum effect in terms of improving the adoption of agricultural technologies. Possibly this is a result of limited ability to apply the innovation due to lack of capital.

The household size was found to influence agricultural technology adoption negatively among non-credit constrained households and not among credit constrained households. These results imply that as household membership size of non-credit constrained household heads increases, the intensity of formal credit use decreases. The explanation for this is that household size is used as an indicator of the socio-economic status of the household. The bigger the household size, the lower socio-economic status of the household is. Households with lower socio-economic status are assumed to have less ability to adopt agricultural technologies. For credit constrained households, changes in household size do not matter when it comes to technology adoption. This is plausible finding due to the fact that farm households are credit constrained to be able to adopt agricultural technologies regardless of the size of household.

The value of productive assets was found to influence agricultural technology adoption positively among non-credit constrained households and not among credit constrained households. The value of productive assets owned reflects the relative wealth of household. The higher is the value of productive assets, the wealthier the household is and this has a significant effect on the adoption of agricultural technologies. However, the insignificant coefficient for the credit constrained household was expected. A possible explanation for this is that the value of productive assets owned could only influence technology adoption if a household is not credit constrained. Again, this finding suggests the importance of credit interventions for assets accumulation and for influencing technology adoption among smallholder farmers.

7.2 Policy implications and recommendations

7.2.1 Improving credit outreach and access

From the findings, we learn that outreach and access of formal credit in rural Zanzibar is low despite the financial sector reforms initiated since mid 1991. Therefore government needs to implement policy and legislative measures that will enhance increased outreach (breadth and depth) of formal credit institutions in the rural sector. These measures include the recommendations of the second generation of financial reforms i.e. introducing measures to reduce lending rates, promote the establishment of smallholder farmers special windows in banking institutions, develop rural financial facilities and services, establish strategic alliance between banks and MFIs and establish the credit guarantee fund for smallholder farmers.

In addressing socio-economic factors that constrain farm households to access formal credit, there is a need to devise a system ensuring the availability of repeated loans. Repeated loans are important to increase farm households' leverage to use formal credit. Keeping livestock was found to be an important factor for improving credit constraint condition of farm households. Therefore, mixed farming seems to be a viable option for improving farmers' access to credit. The majority of sampled households do not have a bank account. This poses significant challenges on savings mobilization in the rural sector, increasing availability of loanable funds and lowering farm household credit constraint condition in the formal credit. In order to address these challenges, lack of financial literacy and insufficient saving facilities need to be addressed.

Increased household income and value of productive assets are directly related to increased access to credit in the formal credit markets. Consequently there is a need to assist poor farm households in adopting measures that will ensure increased agricultural productivity and production to increase farm incomes. Farm households can also be encouraged to diversify their income sources within and away from agriculture so as to increase their income and improve access to credit in the formal credit markets. Increased income eventually leads to increased value of productive assets and therefore enhances access to credit in the formal credit markets.

7.3 Improving adoption of agricultural technologies

Facilitation of poor farm households to adopt improved agricultural technologies is therefore crucial. However, some farm households may be too poor to be able to adopt recommended technological packages. In this case, a special mechanism needs to be applied, providing grant (instead of credit) throughout the "transition zone" before being integrated into the formal financial sector.

From the results it is obvious that there is the need to target interventions aimed at improving the adoption of farming technologies. For example, for the effectiveness of extension services in enhancing technology adoption, there is a need to target extension interventions to households who are non-credit constrained. Otherwise, farmers may have knowledge but may fail to apply it due to lack of means to acquire and apply the technology. Repeated loans are important for both credit constrained and non-credit constrained households. However, the effect on technology adoption is more for the credit constrained households than the non-credit constrained households, suggesting that there is a need for targeted interventions for credit constrained households to help them adopt improved agricultural technologies.

The number of people in the household is a determining factor for the adoption of agricultural technology among non-credit constrained households. However, the negative sign of the coefficient implies an indirect relationship between technology adoption and household size i.e. increasing the number of people in the household decreases the intensity of the adoption of agricultural technologies. Bigger household size is assumed to have lower socio-economic status due to relatively higher dependency ratio and this has a negative effect on the adoption of agricultural technology. Greater awareness on the importance of family planning needs to be created and encouraged.

The positive and significant coefficient of the variable income for the non-credit constrained households indicates that increase in income is an important factor for technology adoption when farm households are not credit constrained. These results imply that there is a need to improve credit access constraint condition of farm households in order to facilitate the adoption of agricultural technologies. It is therefore recommended that comprehensive packages should be devised so that credit interventions are implemented hand in hand with other interventions aimed at enhancing the adoption of agricultural technologies. Implementing comprehensive packages will not only improve the effectiveness of extension services but will also enhance the effectiveness of credit and the development of technological innovations.

7.4 Suggestions for future research

This study has shed light into factors that influence credit access constraint condition of smallholder farmers and, at the same time, it has provided empirical evidence on the existence of the inter-linkages between access to credit and the adoption of agricultural technologies. Due to time limit the study was based on cross- sectional survey data to determine socio-economic factors that influence farm households' access to formal credit and establish the inter-linkages with adoption of agricultural technologies. In order to gather more reliable information, it is suggested that more research work on the topic be carried out using both cross-sectional and time series data to validate the findings that have been obtained.

References

Bank of Tanzania (BOT), 2007, "Microfinance Institutions Performance and Impact to Social-Economic Development: The Case of Zanzibar", Bank of Tanzania.

Berndt E.R., 1991, *The Practice of Econometrics. Classic and Contemporary*, Addison Wesley Publisher.

Besley T., 1995, Savings, "Credit and Insurance", in Behrman J. and T.N. Srinivasan (Eds.), *Handbook of Development Economics*, Vol. III, Amsterdam: North Holland.

Browing M. and Lusardi A., 1996, "Household Saving: Micro Theories and Micro facts", *Journal of Economic Literature*, 4, pp. 1797-1855.

Deaton A., 1992, "Households Savings in LDCs: Credit Markets, Insurance and Welfare", *Scandinavian Journal of Economics*, 94 (2), pp. 253-273.

Diagne A.M. and Zeller, 2001, "Access to Credit and its Impact on Welfare in Malawi", *IFPRI Research Report No. 116*, Washington DC.

Dufhues T., 2007, *Accessing Rural Finance: The Rural Financial Markets in Northern Vietnam*, Thesis for Award of PhD Degree at the University of Hohenheim. 145 pp.

Dufhues T. and G. Buchenrieder, 2005, "Outreach of Credit Institutes and Households' Access Constraints to Formal Credit in Northern Vietnam", Institute of Agricultural Economics and Social Sciences in the Tropics and Subtropics (Ed.), Research in Development Economics and Policy, *Discussion Paper* No. 01/2005.

Ellis F. and N. Mdoe, 2002, "Livelihoods and Rural Poverty in Tanzania", *Ladder Working Paper* No. 11.

Feder G, L.J. Lau, J.Y. Lin and X. Lou, 1990, "The Relationship Between Credit and Productivity in Chinese Agriculture: A Microeconomic Model of Disequilibrium", *American Journal of Agricultural Economics*, 72, pp. 1151-1157.

Fraser H.K. and V. Kazi, 2004, "Assessing the Relative Poverty of Clients and Non-Clients of Non-Bank Micro-Finance Institutions in Tanzania: The Case of Dar es Salaam and Coast Region", *Research on Poverty Alleviation*, Research Report No. 04.2.

Gilligan D.O., S. Harrower and A. Quisumbing, 2005, *How Accurate are Reports of Credit Constraints? Reconciling Theory with Respondents' Claims in Bukidnon*, Phillipines - IFPR, Washington.

Godquin M. and M. Sharma, 2005, *If only I could Borrow more! Production and Consumption Credit Constraints in the Phillipines*, IFPRI, Washington, DC.

GOZ, 2006, *Zanzibar Economic Status Report, 2006*, Zanzibar Government Printer, Zanzibar, Tanzania.

GOZ, 2002, *Agricultural Sector Review Report, 2002*. Zanzibar, Unpublished Report, Zanzibar, Tanzania.

GOZ, 2004, *Strategic Plan for Agriculture Sector Development in Zanzibar*, Unpublished Report, Zanzibar, Tanzania, pp. 40-68.

Greene W.H., 2000, *Econometric Analysis*, 4th Edition, Prentice Hall.

Gujarati D.N., 2004, *Basic Econometric*, Fourth Edition, The MacGraw-Hill. Inc., New York, London, Mexico City, New Delhi, Singapore, Tokyo.

Gujarati D.N, 1988, *Basic Econometrics*, Second Edition, The McGraw-Hill. Inc., New York, London, Mexico City, New Delhi, Singapore, Tokyo.

Hawassi F.G.H., 2006, *Analysis of Processing, Marketing and Demand for Processed Fruits and Vegetables in Tanzania*, Thesis Submitted for the Degree of Doctor of Philosophy of the University of Agriculture, Morogoro, Tanzania.

Heckman J., 1979, "Sample Selection Bias as a Specification Error", *Econometrica*, 47(1), pp. 153-161.

Hoff K. and J.E. Stiglitz, 1990, "Introduction, Imperfect Information and Rural Credit Markets. Puzzles and Policy Perspective", *The World Bank Economic Review*, 5(3), pp. 235-250.

Hoffmann R. and A.L. Kassouf, 2005, "Deriving Conditional and Unconditional Marginal Effects in Log Earnings Equations Estimated by Heckman's Procedure", *Applied Economics*, 37 (11), pp. 1303-1311.

Ibrahim G., K. Abbi and S. Torres, 2007, "Household-Level Credit Constraints in Urban Ethiopia", *Working Paper* No. 7/03, University of Leicester.

Jappelli T., 1990, "Who is Credit Constrained in the U.S Economy?", *Quarterly Journal of Economics*, 104, pp. 220-234.

Kashuliza A.K, J.P Hella, F.T. Magayane and Z.S.K. Mvena, 1998, "The Role of Informal and Semi- formal Finance in Poverty Alleviation in Tanzania: Results of a Field Study in Two Regions", Research on Poverty Alleviation, Research Report No. 98.1, pp. 35-47.

Kennedy P., 1998, *A Guide to Econometrics*, 4th Edition, Blackwell Publisher.

Maddala G.S., 1988, *Introduction to Econometrics*, Macmillan Publishing Company and Collier Macmillan Publishers, New York and London.

Mazuze F.N., 2004, *Analysis of Adoption and Production of Orange-Fleshed Sweet Potatoes: The Case Study of Gaza Province in Mozambique*, a Thesis Submitted to Michigan State University in Partial Fulfilment of the Requirements for the Degrees of Master of Science, Department of Agricultural Economics.

Mchujuko Y.A., 1991, *Arrangements for Agricultural Credit to Small farmers and Economic Development in Tanzania*, Unpublished MSc dissertation submitted to the University of Reading, England.

McKee K., 1989, "Micro-Level Strategies for Supporting Livelihoods, Employment, and Income Generation of Poor Women in the World: The Challenge of Significance", *World Development*, Vol. 17, No. 7, pp. 993-1006.

Meyer R.L., 2002, "Track Record of Financial Institutions in Assisting the Poor in Asia", *ADB Institute Research Paper*, No. 49, December 2002.

Mohamed K.S., 2003, "Access to Formal and Quasi- formal Credit by Smallholder Farmers and Artisanal Fishermen: A Case of Zanzibar", in Kikula I., J. Kipokola, I. Shivji, J. Semboja and B. Tarimo (Eds.), *Researching Poverty in Tanzania: problems,* *policies and perspectives*, Mkuki na Nyota Publishers, Dar es Salaam, Tanzania, pp. 111-148.

Navajas S., M. Schreiner, R.L. Meyer, C. Gonzalez-Vega and J. Rodriguez-Meza, 2000, "Micro Credit and the Poorest of the Poor: Theory and Evidence from Bolivia", *World Development*, Vol. 28, No. 2, pp. 333-346.

Nuryartono N., M. Zeller and S. Schwarze, 2005, "Credit Rationing of Farm Households and Agricultural Production: Empirical Evidence in the Rural Areas of Central Sulawesi, Indonesia", proceeding of Conference on International Agricultural Research for Development, October 11-13, Tropentag, Stuttgart-Hohenheim.

Sarap K., 1990, "Factors Affecting Small Farmers' Access to Institutional Credit in Rural Orissa, India", *Development and Change*, 21 (2), pp. 281-307.

Schrieder G. and F. Heidhues, 1997, "Access Constraints of Romanian Peasants in Relation to the Formal Financial Sector", *CERT Discussion Paper* No. 97/12, Edinburgh, UK: Heriot-Watt University, Centre for Economic Reform and Transformation (CERT).

Schrieder G. and H. Heidhues, 1995, "Reading the Poor Through Financial Innovations", *Quarterly Journal of International Agriculture*, 34 (2), pp. 132-148.

Siddhisena P. and R. Jayathilaka, 2006, "Identification of the Poor in Sri Lanka: Development of Composite Indicator and Regional Poverty Lines", Poverty Economic and Policy. *PMMA Working Paper*.

Stiglitz J. and A. Weiss, 1981, "Credit Rationing in Markets with Imperfect Information", *American Economic Review*, 71 (3), pp. 393-410.

Tambi N.E., W.A. Mukhebi, W.O. Maina and H.M. Solomon, 1999, "Probit Analysis of Livestock Producers' Demand for Private Veterinary Services in the High Potential Agricultural Areas of Kenya", *Agricultural Systems*, 59, pp. 163-176.

Temu A.E., M. Mwachanga and K. Kilima, 2001, "Agricultural Development Intervention and Smallholder Farmers Credit in Southern Tanzania: An Assessment of Beneficiaries", *African Review of Money, Finance and Banking*, pp. 119-140.

Tibaijuka A.L., M. Kisanga, J. Hamisi and M. Abubakar, 1989, "Strategies to Enhance Womens's Access and Effective Utilisation of Institutional Credit in Tanzania", Report on a survey on Women's Land Rights in Tanzania, Report to the Presidential Commission of Enquiry into Monetary and Banking Systems in Tanzania: Sub- committee on Women's Credit Facilities, Dar es Salaam.

Wooldridge J., 2002, *Econometric Analysis of Cross Section and Panel Data*, MIT.

Zeller M., 1994, "Determinants of Credit Rationing: A Study of Informal Lenders and Formal Credit Groups in Madagascar", *World Development*, 22 (12), pp. 1895-1907.

Zeller M.B., B. Sumiter and M. Sharma, 1996, "Credit for the Rural Poor: Country Case Bangladesh", final report submitted to Deutsche Gessellschaft für Technische Zusammerarbeit (GTZ), International Food Policy Research Institute, Washington, D.C.

Annex 1. Theoretical exposition of the use of Probit and Heckmans' procedures in determining farming households socio-economic factors that influence access to credit and the adoption of agricultural credit.

Consider the following equation, which causes sample selection.

$$C_i^* = \gamma' z_i + u_i \tag{1}$$

Where C_i^* is latent variable indicating whether a household is credit constrained or Not, and z_i is a vector of variables that affects C_i^*

The variable C_i^* is not observed, but we observe if the individual has accessed formal credit or not, in that way that:

$$C_i = 1 \quad \text{if} \quad C_i^* > 0$$

and

$$C_i = 0 \quad \text{if} \quad C_i^* \leq 0$$

Let the Y_i represent the natural logarithm of the formal credit use intensity by each individual, assuming that:

$$Y_i = \beta' x_i + \varepsilon_i \tag{2}$$

Where x_i is the vector of variables determining the credit use intensity.

Assuming that u_i and ε_i have a bivariate normal distribution with zero means, standard deviation σ_u and σ_ε and correlation ρ, and that C_i and z_i are observed for a random sample of individuals, but Y_i is observed only when $C_i = 1$, i.e, when the individual has access to formal credit, then

$$\begin{aligned} &E(Y_i \backslash C_i = 1) = E(Y_i \backslash C_i^* = >0) = E(Y_i \backslash u_i > - \gamma' z_i) \\ &= \boldsymbol{\beta' x_i} + E(\varepsilon_i \backslash u_i >- \boldsymbol{\gamma' z_i}) = \boldsymbol{\beta' x_i} + \rho \sigma_\varepsilon \lambda_i (\alpha_u) \end{aligned} \tag{3}$$

Where

$$\lambda_i(\alpha_u) = \varnothing(\alpha_u) / 1 - \Phi(\alpha_u) = \varnothing(-\alpha_u) / \Phi(-\alpha_u) = \varnothing(\gamma' z_i / \sigma_u) / \Phi(\gamma' z_i / \sigma_u \tag{4}$$

and $\varnothing$ and Φ are respectively, the normal density function and the normal distribution function. The function $\lambda_i(\alpha_u)$ is called the inverse of Mill's ratio.

Due to the correlation between x_i and $\lambda_i(\alpha_u$, a least squares regression of Y_i on x_i, omitting the term in $\lambda_i(\alpha_u$, would produce an inconsistent estimator of **β.** If the expected value of the error was known, it could be included in the regression as an extra explanatory variable, removing that part of the error correlated with the explanatory variables and avoiding inconsistency. The Heckman's procedure, in its first stage, consists of estimating the expected value of the error and, in its second stage, using it as an extra variable in the regression equation. In other words, using a probit model, parameters γ of the C_i equation are estimated by maximum likelihood. Having the estimates of γ, λ is obtained for each observation and used as an exogenous variable in the Y equation, allowing parameters β to be consistently estimated by least squares in the regression of Y_i on x and λ.

Annex 2. Indicators for formal credit use intensity (weighted)

Indicators	Total scores
Have you ever received formal credit (1 = Yes, 0 = No)	1
Source of credit (informal = 1, semi-formal = 2, formal = 3)	3
Form of credit (Kind = 1, cash = 2)	2
Number of times of getting formal credit (not more than twice = 1, more than twice = 2)	2
Average amount of credit received (less than Tshs 500,000 = 1, Tshs 500,000 – 1,000,000 = 2, Above Tshs 1,000,000 = 3)	3
Total Scores	11

Annex 3. Theoretical exposition of the determinants of farming households' access to credit using reduced forms regression equations

The probit regression was run to determine the socio-economic factors that influence farm households in the survey areas to access formal credit. In this case, the model was specified as follows:

$$C^* = \gamma' Z_i + \varepsilon_i \tag{1}$$

In equation (1), C* is dichotomous (1,0), indicating that whether observation i, is credit constrained or not; Z_i represent a vector of explaining variables such as household socio-demographic characteristics, households characteristics and institutional factors, γ is a vector of parameters; and ε_i is a random error term. Households are credit-constrained if the demand for credit exceeds the supply of credit, which means $C^*>0$. These responses were used to define a criterion function which is an observable: dichotomous variable I, where

$$\begin{aligned} &I = 1;\ iff\ I^* = \delta' Z_i + \varepsilon_i \geq 0 \\ &I = 0;\ iff\ I^* = \delta' Z_i + \varepsilon_i \leq 0 \end{aligned} \tag{2}$$

Where:
Z_i represents household socio-demographic characteristics, household characteristics and institutional factors that determine supply of credit
ε_i is a random error term with zero mean capturing stochastic factors affecting both the demand and supply of credit.

A probit maximum likelihood estimation is used to estimate the parameters δ in equation 2. It is assumed that var $(\varepsilon_i) = 1$ since δ is estimable only up to scale factor.

In order to determine factors that influence the adoption of farming technologies of the two groups of farmers, (i.e credit constrained and non-constrained households, the reduced form equations was used and the specification of the model was made as follows:

$$\begin{aligned} P_{ncc} &= \beta_{1i} X_{1i} + \varepsilon_{1i}\ ;\ \text{iff } I = 1 \\ P_{cc} &= \beta_{2i} X_{2i} + \varepsilon_{2i}\ ;\ \text{iff } I = 0 \end{aligned} \tag{3}$$

Where variables P_{cc} and P_{ncc} represent the degree of adoption of farming technologies for credit constrained and non-credit constrained households.

X_{1i} and X_{2i} are vectors of exogenous variables,
B_{1i} and β_{2i} are vectors of parameters, and
ε_{1i} and ε_{2i} random disturbance terms.

Maximizing the bivariate likelihood function for this model is feasible but time consuming (Maddala, 1994). Therefore Lee (1978), a two-stage estimation method is used to estimate the system in equation (2) and (3).

The conditional expected values of the error terms $\varepsilon_{1i,}$ andε_{2i} are:

$$E(\varepsilon_{1i} \mid \varepsilon_i = \delta' Z_i) = E(\sigma 1_\varepsilon \, \varepsilon_i \mid \varepsilon_i = \delta' Z_i) = \sigma 1_\varepsilon \quad \varnothing(\delta' Z_i)/\varphi(\delta' Z_i)$$
$$E(\varepsilon_{2i} \mid \varepsilon_i = \delta' Z_i) = E(\sigma 2_\varepsilon \, \varepsilon_i \mid \varepsilon_i = \delta' Z_i) = \sigma 2_\varepsilon \quad \varnothing(\delta' Z_i)/\ 1\text{-}\varphi(\delta' Z_i)$$

where $\varnothing$ and φ are the probability density function and the cumulative distribution function of the standard normal distribution respectively. The ratio $\varphi/\varnothing$ evaluated at $\delta' Z_i$ for each I is the Inverse Mills Ratio (IMR). For convenience,

$\lambda_{1i} = \varnothing(\delta' Z_i)/\ \varphi(\delta' Z_i)$ is defined for constrained

and

$\lambda_{1i} = \varnothing(\delta' Z_i)/\ [1\text{-}\varphi(\delta' Z_i)]$ for non-constrained (4)

These terms are included in the specification of equation (3):

$$P_{cc} = \beta_1{}' X_{1i} + \sigma_{1u} \lambda_{1i} + \varepsilon_{1i}\ ;\ \text{if } I = 1$$
$$P_{ncc} = \beta_2{}' X_{2i} + \sigma_{2u} \lambda_{2i} + \varepsilon_{2i}\ ;\ \text{if } I = 0 \qquad (5)$$

In order to be able to establish the household intensity of agricultural technologies adoption and the levels of adoption, three main farming activities that each surveyed household is engaged with were identified and the recommended technologies for each activity listed. The farming technology packages handbook from the Ministry of Agriculture, Livestock and Environment was used to identify available technologies for each farming enterprise. Based on these technological packages, the sampled households were assessed on their level of adoption and given scores. The scores were weighted and the weighted scores were summed up and averaged to determine the intensity of technology adoption.

Annex 4. Indicators for agricultural technology adoption intensity (weighted)

A. Crops	
Indicators	Total scores
Use of recommended varieties (Yes = 1, No = 0)	1
Use of correct plant spacing (Yes = 1, No = 0)	1
Planting in time (Yes = 1, No = 0)	1
Weeding (as recommended = 1, not as recommended = 0)	1
Use of inorganic fertilizer (Yes = 1, No = 0)	1
Use of organic manure (Yes = 1, N0 = 0)	1
Methods of applying fertilizers (recommended = 1, Not as recommended = 0)	1
Pests and diseases control (None = 0, traditional = 1, recommended biological/chemical = 2)	2
Keeping financial records (Yes = 1, No =0)	1
Irrigating crops (Yes = 1, No = 0)	1
Irrigation method used (Bucket = 1, sprinkler = 2, Furrow = 3)	3
Use of improved storage (modern = 1, traditional = 0)	1
Processing (modern = 1, traditional = 0)	1
Practicing mechanized farming (Yes = 1, No =0)	1
Method of mechanization (mechanical = 2, animal = 1)	2
Sub-total	19
B. Livestock	
Types of animal breeds (Improved breeds = 1, local breeds = 0)	1
Raring systems (Intensive = 2, semi-intensive = 1, extensive = 0)	2
Provision of shelter (modern = 2, traditional = 1, none = 0)	2
Feeding (as recommended = 2, partially = 1, not as recommended = 0)	2
Control of parasites and diseases (as recommended = 2, partially = 1, not as recommended = 0)	2
Use of Artificial Insemination (Yes = 1, No = 0)	1
Keeping financial records (Yes = 1, No =0)	1
Use of improved storage (modern = 1, traditional = 0)	1
Processing (modern = 1, traditional = 0)	1
Practicing mechanized farming (Yes = 1, No =0)	1
Method of mechanization (mechanical = 2, animal = 1)	2
Sub-total	16
Total Score (Crops + Livestock)	**35**

Source: Own survey

Annex 5. The procedure followed to obtain the extension contacts intensity of the sampled households

The extension contacts intensity was obtained by asking the respondents whether they have had any contacts with agricultural extension agents. For those who indicated to have the contacts were asked further to indicate the frequency of the contacts, source extension messages. They were further requested to indicate whether they read agriculture bulletin, newsletter or magazine and whether they listen to agricultural programmes aired through radio or Television. Respondents 'membership to Farmers' Research Groups (FRGs) was also explored. The responses from these questions were given scores which were weighted and summed and averaged to give final scores for each respondent. These scores were then used as intensity score for extension contacts of sampled households. The following Table shows indicators used to develop the scores.

Indicators	Total scores
Ever received advice on agriculture from extension services (Yes = 1, No = 0)	1
Source of the extension advice (government = 4, NGO = 3, trader = 2, fellow farmer = 1)	4
Frequency of extension contacts (very frequent = 4, frequent = 3, not frequent = 2, irregular = 1)	4
Reading agriculture bulletin, newsletter or magazine (Yes = 1, No = 0)	1
Listening to Radio/TV agricultural programmes (Yes = 1, No = 0)	1
Membership of Farmers Research Groups or any agriculture based initiative (Yes = 1, No = 0)	1
Total scores	**12**

Résumé

Cette étude a le but d'examiner les facteurs qui déterminent l'accès au crédit formel à Zanzibar et d'établir les liens entre l'accès au crédit et l'adoption de technologie au niveau rural pour les petites familles cultivatrices. L'accès au crédit peut être influencé par des facteurs institutionnels et par les caractéristique de l'unité familiale/productrice ; l'analyse des ces unités est donc importante pour une intensification des services financiers dans les zones rurales à Zanzibar. On a utilisé des donnés primaires et secondaires, entre Mai et Juin 2006 sur cinq districts des îles de Unguja et Pemba ; on a interviewé 750 unités tandis que les données secondaires ont été collectées dans les institutions concernées, y inclus les institutions financières. Les résultats suggèrent que plusieurs facteurs socio-économiques influencent l'accès des familles/unités productives au crédit formel : nombre de fois qu'on a au accès au crédit, la présence de bétail, d'un compte à la banque, la valeur des actifs productifs, le revenu de l'unité et l'intensité de la technologie. Cette dernière, à son tour, est influencée par l'intensité des contacts avec les structures d'appui, la taille de l'unité, le nombre de fois qu'on a eu accès au crédit, la valeur des actifs productifs se sont démontrés significatifs mais, à l'exception de l'intensité d'accès au crédit, ces variables sont significatives seulement pour les unités qui n'ont pas d'empêchements pour l'accès au crédit. Cela suggère une focalisation sur les unités qui ont un accès limité au crédit.