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Executive Summary

Empirical studies on agricultural technology adoption generally divide a population into adopters and non-adopters, and analyze the reasons for adoption or non-adoption at a point in time. In reality, technology adoption is not a one-off static decision rather it involves a dynamic process in which information gathering, learning and experience play pivotal roles particularly in the early stage of adoption. A conceptual framework for adoption pathway is suggested in which farmers move from learning to adoption to continuous or discontinuous use over time. The characteristics of both the user and the technology are considered important in explaining adoption behavior and the pathway for adoption. The resultant pathway has further implication for the time frame and the volume of potential impact of a new technology.

The framework was applied to understand the adoption pathway for vertisol management technology and related factors in three on-farm research sites in highland Ethiopia. The principal component of the technology package is an animal drawn drainage equipment called broadbed maker (BBM) which is used to solve the problem of waterlogging of vertisols in order to grow improved wheat varieties. Analysis of a sample of 585 households from the three sites confirmed that a simple classification of farmers as adopters and non-adopters was inadequate to understand the adoption process. Rather a multistage decision process in which farmers moved from learning to adoption to continuous or discontinuous use was more appropriate. The sets of factors that significantly influenced decisions to acquire knowledge about BBM, to adopt and then to use it continuously or discontinuously were different. The sets of significant factors influencing BBM adoption also differed depending on whether adoption was defined as a binary variable (adoption vs non-adoption) or as a truncated continuous variable with non-adopters having zero value and adopters having different positive values. The lag between learning and adoption, and the possibility of discontinuation and readoption imply that a longer period will require for majority of the farmers to use the technology than if adoption was a one off decision leading to continuous use.

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Introduction

In the literature on technology adoption, a distinction is made between diffusion and adoption. Diffusion is considered to begin at a point in time when an innovation is ready for use, and the main focus of diffusion is to explain how the innovation or technology is made available to the potential users. The earliest users of the technology may be called innovators and the diffusion process involves the spread of the innovation to the rest of the population. On the other hand, adoption studies consider the behavior of individuals in relation to the use of the technology, particularly the reasons for adoption at a point in time, or the reasons for time of adoption for individual users, are of primary interest. Relative to adoption, diffusion may be viewed as a dynamic process over time. Inter-farm or inter-sectoral diffusion curve may be derived by aggregating the frequency distribution of adopters arranged on a time scale (Stoneman, 1983; Feder et al., 1985; Thirtle and Ruttan, 1987).

Empirical studies on agricultural technology adoption generally divide a population into adopters and non-adopters (potential adopters), and analyze the reasons for adoption or non-adoption at a point in time principally in terms of socio-economic characteristics of the adopters and non-adopters (Thirtle and Ruttan, 1987; Feder and Umali, 1993). Based on evidence in consumer demand theory that demand for a product is significantly affected by the consumer's perceptions of the product's attributes (e.g. Jones, 1989; Lin and Milon, 1993), some recent adoption studies have included farmers' subjective assessment of technology attributes as explanatory variables (Nowak, 1993, Adesina and Zinnah, 1993; Adesina and Baidu-Forson, 1995).

In this paper, the deficiencies of these static approaches to analyze and predict the potential for adoption of a new technology, particularly at the early stage of diffusion, are discussed. Then an alternative approach is suggested in which information gathering, learning and experience play pivotal roles. At a given point in time, the decision to adopt, reject or defer decision is postulated to be influenced by the belief derived from the knowledge and perception about the technology at that point in time. The prior belief of a point in time may be later modified on the basis of new knowledge and/or observed performance, and a new decision about adoption may be taken. The characteristics of both the user and the technology are considered important in explaining adoption behavior and the pathway for adoption. The resultant pathway for adoption has implications for the time frame and the volume of potential impact of a new technology. The approach is then tested with vertisol technology adoption in Ethiopia.

Adoption Pathways: A Conceptual Framework

The conventional adoption pathway for a new technology may be depicted by the logistic frequency distribution and its corresponding logistic curve shown in Figures 1a and 1b respectively (Davies, 1979; Sahal, 1981; Stoneman, 1983; Mahajan et al., 1990). If N is the fixed population of potential adopters of a new technology, then the number of new adopters in period t may be expressed as

$$\frac{dn_t}{dt} = \beta \frac{n_t}{N}(N - n_t) \qquad (1)$$

where parameter β measures the speed of diffusion. For constant β, the absolute increase in adopters at any point in time, $\frac{dn_t}{dt}$, depends on the product of the proportion that has already adopted, n_t/N, and the number of remaining potential adopters, $N-n_t$. Equation 1 may be solved for the frequency distribution of adoption over time as:

$$n_t = N(1+e^{-\alpha-\beta_t})^{-1} \qquad (2)$$

where α is the constant of integration, that positions the distribution curve on the time axis. Equation 2 is the cumulative density function of the logistic frequency distribution and for constant β, it gives a bell-shaped frequency distribution for numbers adopting over time (Figure 1a). Equation 2 also gives sigmoid (S-shaped) logistic curve (Figure 1b), which is symmetric around the inflection point occurring at time $-(\alpha/\beta)$ corresponding to 50% adoption, and approaches zero and N asymptotically, as t tends to minus and plus infinity respectively. However, any unimodal frequency distribution will have a sigmoid cumulative density function but may or may not be symmetric depending on, for example, whether the population is homogenous or heterogeneous, and how quickly the new technology is modified or become obsolete and replaced by newer technology (Sharif and Kabir, 1976; Mahajan et al., 1990; Davies, 1979; Sahal, 1981; Chatterjee and Eliashberg, 1989).

In the model described above, at a point in time a population is divided into two groups, adopters and potential adopters. Rogers (1983) identified five stages in a typical technology adoption-decision process and categorized adopters, according to time of adoption, as innovators, early adopters, early majority, late majority and laggards (Figure 1a). Innovators are described as respectable local opinion leaders; the early majorities are deliberate and willing followers, while late adopters often needed peer pressure or influence to adopt. The laggards are skeptical about the new, so cling to the past and adopt at the tail end.

Models of this nature implicitly assume that the entire population eventually adopts the innovation and that, once adopted, the innovation is never rejected (Thirtle and Ruttan, 1987). In some models a population is divided into adopters, rejecters, disapprovers, and the remainder who are as yet uncommitted (Sharif and Kabir, 1976). However, the implicit assumption here is that once rejected or disapproved, the technology is never adopted again. In reality, neither 'never rejected' nor 'for ever rejected' is a realistic assumption for most agricultural technology adoption process, particularly at the early stage of adoption.

Most agricultural innovations evolve as they diffuse. An innovation may be changed or modified by a user in the process of its adoption and diffusion. Therefore, potential adopters may play an important role in the process of technology generation by being involved in the generation process rather than being merely passive recipients of an

innovation once it has been generated (Rogers, 1983). Incorporation of farmers as participants and their perceptions and preferences as important elements in the technology generation process are considered essential for generation of appropriate technology (Ashby et al., 1989; Asfaw Negassa et al., 1991).

When farmers are not involved in the technology generation process, awareness and knowledge about a new technology precedes any adoption decision. Several authors have emphasized the importance of information gathering and updating information through learning-by-doing in the adoption process. There may be a lag between the time when farmers first hear about an innovation and the time they adopt it (Kislev and Shchori-Bachrach, 1973; Lindner et al., 1979; Stoneman, 1981; Rogers, 1983; Bhattacharya et al., 1986; Oren and Schwartz, 1988; Tsur et. al., 1990; Feder and Umali, 1993; Fisher et al., 1996). However, empirical verification of the linkage between learning and adoption and what factors influence such linkage is rare. Saha et al. (1994) have developed and tested a model in which producers' knowledge about a new technology (Phase I) determine the decision to adopt (Phase II) which in turn determine the intensity of adoption (Phase III).

Learning about and adoption of a technology may actually involve more complex processes (Figure 2). Any adoption decision is preceded by a period of awareness and learning. Initially only limited amount of information may be available or only a limited amount of available information may be digested. The information includes knowledge about how the technology functions and where and how to get access to it. The optimal level of information is reached when information acquired over a period of time reaches a threshold level at which a decision on adoption can be made. Following Saha et al. (1994), a producer's optimal information level may be considered as the outcome of an underlying utility maximization problem:

$$i^* \equiv i\,(S) \qquad (3)$$

where i^* denotes the optimum level of information and S is a vector of related producer characteristics. A producer is considered to <u>know</u> about the new technology if

$$i^*\,(S) > i^o \qquad (4)$$

where i^o is the threshold level of information at which a decision about adoption can be made.

On the basis of knowledge at a point in time, a perception or belief about the technology is developed and a decision to adopt or reject or defer decision may be taken. The subsequent decisions may follow two pathways (Figure 2). In the first pathway, a decision to adopt is followed by a decision about the intensity or extent of adoption (in practice, these two decisions may be initially taken simultaneously). New knowledge and experience is gathered from learning-by-doing as well as observing other adopters, and a decision is made to increase intensity and/or modify

the technology,[1] or to discontinue the use of the technology. After acquiring more knowledge, a decision to re-adopt or defer adoption is taken and the process continues until a more stable decision is taken.

In the second pathway, the initial perception or belief is modified on the basis of new knowledge and/or observed performance of adopters, and a new decision about adoption is taken. A decision to adopt takes the farmer along pathway 1 (Figure 2). A decision to reject or defer decision will keep the farmer within the second pathway whereby a new decision is taken after acquiring more knowledge.

Thus, the "innovation assessment lag", defined as the time required between initial awareness and actual use of a technology, may vary depending on the farmer's access to knowledge, ability to decode that knowledge and formulate decision (Lindner et al., 1979; Fisher et al., 1996). The lag is very short for innovators and very long for laggards.

The possibilities of permanent discontinuation or temporary discontinuation and re-adoption imply that a distinction need to be made between "the number of new adopters" (Equation 1) and "the number of net new adopters" in period t; the latter being defined as

$$\frac{dn_{nt}}{dt} = \beta \frac{n_{nt}}{N}(N - n_{nt}) \qquad (5)$$

where $n_{nt} = n_t - n_{ot} + n_{rt}$ is net new adopter in period t, n_t is the number of new adopters in period t, n_{ot} is the number dropped out in period t and n_{rt} is the number re-adopted in period t. It is obvious that the frequency distribution of net new adopters, n_{nt}, over time is likely to give a bell-shaped curve only if $n_{ot} = n_{rt}$. If $n_{ot} > n_{rt}$, i.e. number of drop-outs is greater than the number of re-adopters, the density function may not be bell-shaped but the shape of the logistic curve may be bell-shaped rather than S-shaped, i.e. as t tends to infinity, n_{nt} tends to zero.

Equations 1 and 5 have completely different implications about the time frame and volume of potential impact of a new technology. They also have important practical implication for farmers and extension agencies. Compared to equation 1, the situation under equation 5 implies a much longer period will elapse before a majority of the potential adopters will adopt and use the technology in a sustained manner. It is therefore necessary to understand the possible pathways for adoption of a new technology and the associated factors, and take corrective measures, e.g. take more positive steps for diffusion of information for increasing awareness, remove supply constraints, to facilitate rapid adoption.

The adoption pathway described above is tested with vertisol technology in Ethiopia.

[1] Technical progress consists of infrequent major innovations coupled with a steady accretions of innumerable minor improvements and modifications done by users, particularly innovators and early adopters (Rosenberg, 1982).

Vertisol Technology Development and Testing in Ethiopia

Vertisols (heavy black clay soils) cover some 43 million hectares comprising 19% of total land area in sub-Saharan Africa. Nearly 30% of the vertisol area is located in Ethiopia alone, particularly in the highland region (Mohamed Saleem, 1995). Vertisols are productive soils but difficult to manage due to their poor internal drainage and resultant flooding and waterlogging during the wet season. Consequently, vertisols in Ethiopia are currently underutilized, and largely used for dry season grazing. The cultivated vertisols give low yields, and are exposed to soil erosion because the fields are ploughed before the main rains and, sown towards the end of the rainy season to avoid waterlogging. While vertisols remain underutilized, population pressure has pushed crop production and livestock grazing to steep slopes causing serious devegetation and soil erosion. Therefore in food deficit Ethiopia, removing constraints to crop production in vertisol areas is of very high importance (Tekalign Mamo et al., 1993).

In some parts of Ethiopia, particularly around Debre Berhan, farmers practice soil burning to minimise waterlogging problem. Small mounds are created with surface soil, dung and left over straw are put inside the mounds to burn the soil, then the burnt mounds are leveled again. In another area around Inewari, farmers construct hand-made broadbed and furrows, principally using women and child labor, to facilitate drainage. Both soil burning and hand-made broadbed making are labor intensive operations, and they are not technically very efficient, so these traditional techniques do not enable full use of the potential of vertisols (Tekalign Mamo et al., 1993).

Animal traction is extensively used for tillage in Ethiopia but the traditional plough, called *Maresha*, pulled by a pair of oxen cannot invert or shape the soil so that land tilled with *Maresha* remain covered with water during heavy rains. In order to facilitate drainage, the Ethiopian Joint Vertisol Project (JVP)[2] developed a broadbed maker (BBM) by joining two *Mareshas* with a crossbar about 1.5 meter long, then attaching a metal wing on the outside of each *Maresha* and link the two wings with a looping metal chain from behind. When operated by a pair of oxen, the two *Mareshas* of the BBM create two furrows on two sides of a 1.5 meter bed, the chain levels the soil on the bed and covers seeds when sown or planted on the bed. At the time of heavy rain, the furrows allow excess water from the bed to be expelled to a sub-field or main drain at the end of the plot. This drainage technique allows early sowing and longer growing period. The JVP has developed a suitable agronomic package (crop varieties, planting dates, and fertilizer regime) to complement the BBM (Mohamed Saleem, 1995).

After on-station trials, the BBM package was tested on-farm at five vertisol sites in the Ethiopian highlands during 1986-89 in collaboration with a small number of farmers selected in collaboration with the local Peasant Associations, which had a

[2] A consortium in which Ethiopian Institute of Agricultural Research, Alemaya University of Agriculture, Ministry of Agriculture, and International Livestock Research Institute (ex-International Livestock Center for Africa) and International Crops Research Institute for the Semi-Arid Tropics are partners.

dominating role in rural Ethiopia at that time. The field sites are Hidi, Ginchi, Inewari, Dogollo and Dejen, located at altitudes ranging from 1850 to 2600 meters above sea level and receiving from 850-1200 mm annual rainfall. These initial tests provided opportunities to verify the technical and economic performance of the BBM package and related problems. The results led to modification of some components of the package.

In 1990, the new Ethiopian Government deregulated the Peasant Associations and Cooperatives and gave individual farmers more secured usufruct to land which gave them a better position to take decisions about choice of technology. So during 1990-95, on-farm research was continued in three of the five sites (Inewari, Ginchi and Hidi) with a particular focus on the adoption behavior of the participants in on-farm research. The JVP through the local extension office of the Ministry of Agriculture (MOA) provided training to prospective participants on the BBM package including handling, dismantling and reassembling of the BBM. Additionally in 1993, experienced and well performing farmers in Inewari were recruited to recruit new farmers and train them with the objective of encouraging farmer-to-farmer diffusion. Participants were extended improved seeds and fertilizers on credit to be repaid after harvest of the crop, and the services of BBM were provided free of charge. One set of BBM served 6-8 farmers. The credit was provided out of a revolving fund granted by Oxfam America. A committee managed the fund with representatives from JVP, the MOA and the Peasant Associations. In 1995, the management of the revolving fund was handed over to the Peasant Associations with local MOA staff having a supervisory role.

In 1995, a survey was conducted in the research villages to test if farmers were willing to buy and own the old BBM sets, consisting of two wings and a chain (farmers already had *Mareshas*), rather than getting free service from the project, and the price they were willing to pay. Willingness to buy and own would indicate farmers' confidence in the technology and interest in its continued use. One hundred ninety farmers expressed interest to buy 81 BBMs available for sale, and the average price they offered was Birr 21.34±1.12 (US$1 = Birr 6.20). The average was 32 Birr when farmers offering less than 10 Birr were excluded. A new set cost about Birr 150 when they were manufactured 8 years earlier. Therefore the sale price was fixed at Birr 30 and the sets were sold for cash through a lottery among interested buyers present on a pre-arranged day in each location. New BBM owners used it themselves, lent to relatives and neighbors and in some cases rented out at a fee. This was also an indication that farmers with traction animal could earn extra income by renting out BBM services to those without traction animal or with inadequate traction animal.

Since 1992, the government has gradually introduced market liberalization policies and a drive for achieving food self-sufficiency. Consequently a congenial environment has emerged for diffusion and adoption of improved technologies. Responding to this opportunity, the MOA and several NGOs including Sasakawa Global 2000 have started diffusion of the BBM package alongside other improved technologies. A private manufacturer of BBM, who was formerly an ILRI technician involved in the design and testing of BBM, is also active in the diffusion effort

through selling BBM sets as well as imparting training to local blacksmiths in the fabrication of the equipment. Exact number of BBMs adopted so far and the area covered is not known but anecdotal evidence suggest that after a slow start, over 15000 BBMs have been distributed by various agencies.

The Need for Understanding Adoption Pathways for BBM and Related Factors

During on-farm research, information on the BBM package was made accessible to all the farmers in the research village yet it was observed that some farmers participated in the research process for different duration either continuously or discontinuously, some did not yet participate, some even did not know how the technology functioned. For example, a total of 495 farmers in two sites (Inewari and Hidi) participated in on-farm research and adaptability tests at one time or another during 1989-1995 (Table 1). However, the maximum number of actual participants in a given year was 268 and by 1995 the number of actual participants decreased to 124 because of discontinuation by a larger number than readopters. When the number of cumulative adopters were plotted against time, the curve (Figure 3) resemble the left half of the usual S-shaped logistic curve (see equation 2 and figure 1b). If this pattern continues over a longer period, the farmers in the two research sites would perhaps show a similar adoption pattern depicted by Figure 1b. When the number of net adopters were plotted against time, a more or less bell shaped logistic curve appeared with a tendency for adoption to cease long before all potential adopters have adopted the technology (Figure 3). Such a shape was the result of more adopters dropping out than new adopters coming in over time (see equation 5).

The time period for the on-farm research for which the data are presented here is rather short to judge whether some or all of the drop-outs can be categorized as 'rejecters' (c.f. Sharif and Kabir, 1976), or some or all of them will readopt the technology at some future date. The latter is most likely to happen, in which case the shape of the curve showing cumulative net adopters will rise upwards again.

The exact distribution of net adopters in the two research sites over the short research period and the resulting curve may or may not be typical of any new agricultural technology but the phenomena that led to such distribution are real for any technology. Therefore, there was a need to undertake systematic analysis of factors that contributed to differences in the rate of acquisition of knowledge and differences in the pattern and duration of use of the BBM technology. The findings from this analysis will be useful for understanding the probable adoption pathways for BBM package and its implication for impact in the wider community. This will also help in designing any countrywide ex-post impact assessment of the BBM package.

Data Source and Analytical Framework

In the three research sites, there were 1553 households in 10 Peasant Associations (5 in Inewari, 2 in Hidi and 3 in Ginchi). Out of these, 598 (28%) households participated in on-farm research and tests during 1989-95, so they could be considered as adopters. During on-farm research, some basic socio-economic profile of adopters

was recorded and usable records were available for 474 adopters. No records were kept for non-adopters.

During late 1995 and early 1996, a survey was conducted among 474 adopters to verify some information recorded earlier and for additional information. In addition, out of 1553 non-adopters, a stratified sample of 120 households was selected for interview but by the end of the survey 111 could be interviewed; others were either not accessible or refused to collaborate. The distributions of total and sample households are shown in Table 2.

In figure 4, two sets of classification of the sample households are shown. Panel A shows that about half of the non-adopters did not yet acquire sufficient knowledge about BBM while the other half had acquired knowledge but did not yet decide to adopt[3]. Among adopters, about two thirds used the technology discontinuously and one third continuously. Panel B shows that 91% of the sample farmers knew about BBM of which 89% adopted, and the use pattern was the same as that in Panel A. It was argued earlier that acquisition of knowledge and information precedes any decision to adopt (Figure 2). Therefore Panel A cannot be considered to correctly depict the sequence of learning and adoption. Panel B shows a more appropriate sequence: farmers move from learning to adoption to continuous or discontinuous use. Logit analysis will be applied to test whether the pathway depicted in Panel B is more appropriate than that in Panel A to identify factors that play important role at each stage of the adoption pathway.

In figure 4, one set of classification divides farmers as adopters or non-adopters and the Logit analysis will identify factors influencing those characteristics. It is also of interest to know which factors influenced the duration of use of BBM once it was adopted, duration being a proxy for intensity of adoption. The variables affecting the decision of whether or not to adopt may not be the same as those affecting the duration of its use. Also a given variable may increase the probability of adoption of a technology but reduce the probability or have no effect on duration of use, and vice versa (Goetz, 1995). So Tobit regression will be used to simultaneously identify the factors influencing adoption and duration of use. These models are described in the following two sections.

Factors Affecting BBM Knowledge, Adoption and Use Patterns: Logistic Regression Analysis

When the dependent variable is binary and can take only two values, use of ordinary multiple regression techniques and discriminant analysis are not suitable because a number of essential assumptions of such models are not satisfied and the predicted values cannot be interpreted as probabilities. An alternative is to use logistic

[3] It was argued earlier that a producer is considered to *know* about a new technology if his/her acquired information reaches a threshold level. In the present case, the threshold level of information was not directly observable, so a farmer was considered to have knowledge about BBM if he/she heard about the BBM and its functions and/or saw it functioning. Here acquisition of information was the key, acquisition of operational skill for the BBM was not yet an issue.

regression model, which requires far fewer assumptions but directly estimates the probability of an event occurring or not occurring. In logistic regression, maximum-likelihood method is used to estimate parameters (Norusis, 1993).

A multivariate logistic regression model is usually written in terms of the log of odds, which is called logit, as:

$$Log\left[\frac{Prob\ (event)}{Prob\ (no\ event)}\right]=\beta_o+\beta_1X_1+\ldots+\beta_KX_K \qquad (6)$$

where β_s are estimated coefficients and X_s are independent variables. The logistic coefficient is interpreted as the change in the log odds associated with one unit change in the independent variable. The coefficients do not measure marginal effects of independent variables but only show if any variable has significant influence on the dependent variable. The significance of the estimated coefficients may be shown in terms of Wald Statistics, t ratios, correlation coefficients or E (β), i.e expected value of β. Among these, E (β) gives a more direct interpretation of β and it is derived by rewriting equation 6 in terms of odds rather than log odds as follows:

$$\frac{Prob(event)}{Prob(no\,event)}=e^{\beta_o+\beta_1 x_1+\cdots+\beta_k x_k} \qquad (7)$$

Now, e raised to the power β_i is the factor by which the odds change when the ith independent variable increases by one unit. If β_i is positive, E (β_i) > 1 which means that the odds are increased. If β_i is negative, E(β_i)< 1 which means that the odds are decreased. If β_i = 0, E (β_i) = 1 which leaves the odds unchanged (Norusis, 1993).

Several logistic regression equations were estimated to identify factors influencing farmers' probability of acquisition of BBM knowledge, probability of adoption of BBM and probability of continuous use of BBM on the basis of classification Panels A and B in Figure 4. The SPSS Logistic Regression Procedure (Norusis, 1993) was used to estimate parameters. Variables considered in these models are shown in Table 3. The direction of influence of the independent variables on the three dependent variables could not be determined *a priori*.

A summary of the best-fit models based on percent correct prediction is shown in Table 4. Comparison of results for classification Panels A and B show that the predictive power of the equations are significantly higher for the sequential classification in Panel B than in Panel A. For example, when the adoption status is defined for the entire sample (Panel A, equation 1) characteristics of 81% of the cases can be correctly predicted. When adoption status is defined for only those who have knowledge about BBM (Panel B, equation 2) 92% cases can be predicted correctly. Similarly, when BBM knowledge is defined only for non-adopters (Panel A, equation 2) 78% cases can be predicted correctly compared to 91% when BBM knowledge is defined for the entire sample (Panel B, equation 1).

Taking Panel B as a better classification method to depict adoption pathway, estimated coefficients and related statistics for three best fit equations fitted to Panel B are shown in Table 5. The models correctly predicted 91% cases in terms of BBM knowledge, 92% cases in terms of BBM adoption and 78% cases in terms BBM use pattern. The slightly less predictive power of the model describing use pattern indicates that some factors other than those included in the model contributed to differences in use pattern. One factor that contributed to discontinuous use in case of some farmers, but could not be included in the model, was irregular rainfall pattern. In some years, too heavy rainfall early in the crop season made soil on some plots so wet and heavy that it made BBM use impossible.

In general, compared to Inewari, a farmer located in Hidi or Ginchi was less likely to have acquired BBM knowledge. Among those who had BBM knowledge, a farmer located in Hidi was many times more likely to have adopted BBM while a farmer in Ginchi was significantly less likely to have adopted BBM. Among adopters, a farmer located in Hidi or Ginchi was significantly less likely to have used the package continuously. The discontinuous use was more pronounced in Ginchi.

These differences might be because farmers in Inewari use handmade broadbeds, so they probably were generally more eager to learn about a better substitute and use it. Also the farmer-to-farmer training program practiced in Inewari in 1993 gave Inewari farmers a better opportunity to learn compared to the other two locations. Inewari and Hidi farmers also had more regular access to credit compared to those in Ginchi. Some of the other factors, or their interactions, which might have influenced differences in BBM knowledge, adoption and use pattern among the three sites are size of land ownership, extent of vertisol and waterlogging problem, animal ownership and education. Average cropland per farm was 1.45 ha in Inewari, 1.75 ha in Hidi and 2.95 ha in Ginchi. Vertisols constituted 49% of cropland in Inewari, 51% in Hidi and 91% in Ginchi. However, only 19% of cropland in Inewari and 17% in Hidi faced major waterlogging problem compared to 42% in Ginchi. Farmers in Inewari owned 1.66 work animals per farm compared to 2.21 in Hidi and 2.17 in Ginchi. Fifty nine percent of the household heads in Inewari and 61% in Ginchi had primary or higher level education compared to 38% in Hidi.

Among other factors, education, area of cropland, area of cropland under vertisol, number of work animals, family size and distance from market had significant influence on whether a farmer has acquired BBM knowledge or not. Household heads with better education (primary level or over) were less likely to know about BBM than those with no formal education. Households with larger cropland area and area under vertisol and larger number of work animals were more likely to have acquired BBM knowledge. Among these, area under vertisol had the most dramatic effect on the odds of a farmer being knowledgeable about BBM: with one unit increase in the area under vertisol, the odds of a farmer knowing about BBM increased 4.5 times. Since BBM is specifically meant to address the problem of vertisol, high degree of influence of this variable on farmers' willingness to learn about BBM would be normally expected. The positive effect of number of work animals on acquisition of BBM knowledge might be explained by the fact that a pair of animals was required to pull

the BBM, so farmers with two or more animals were perhaps more interested to know about the BBM than those having none or only one animal.

Larger family size decreased the odds of learning about BBM to some extent perhaps because larger family labor supply decreased the need for alternative technology. Greater distance from market also decreased the odds of learning about BBM perhaps because the transaction costs of acquiring knowledge increased with distance and also information to distant parts of the research areas might have trickled down slowly.

Among those having knowledge about BBM, location, education, BBM training, cropland area, area with major waterlogging problem, distance to market and work animal ownership had significant influence on whether BBM has been adopted or not. The odds of adoption decreased as the level of education increased while skill training in BBM increased the odds of adoption several times. Some adopters actually did not initially acquire the skill to operate the BBM, they hired somebody else to operate it. A typical example would be a farmer without BBM operational skill and another farmer with skill joining together with their *mareshas* to make the BBM.

Farmers with larger cropland area and larger area with major waterlogging problem were more likely to have adopted BBM. Although area under vertisol significantly increased the odds of a farmer acquiring knowledge about BBM, it had no influence on adoption. Instead area with major waterlogging problem significantly increased the odds of adoption. In the sample sites, 60% of the cropland was under vertisol, nearly 50% of cropland had some waterlogging problem but only 23% of cropland suffered from heavy waterlogging problem that would benefit from BBM type technology.

Greater distance to market decreased the odds of adoption perhaps because distance adds to costs of a new technology and reduces potential net benefits. Ownership of larger number of work animals also decreased the odds of adoption, a characteristic rather difficult to explain except that work animal ownership and cropland are highly correlated and cropland has a strong positive influence on adoption.

Among those who adopted BBM package, area under vertisol, area with major waterlogging problem, perception about problem with BBM technology and access to credit had significant influence on whether BBM was used continuously or discontinuously. Higher level of education increased the odds of continuous use but BBM training had no influence on use patter. Both area under vertisol and area with major waterlogging problem increased the odds of using BBM continuously, which would be expected. The odds of continuous use was higher for farmers who perceived that the BBM had some problems or disadvantages compared to those who did not perceive such problem. This was an apparently unexpected result but could be explained by the fact that those who used continuously and for a longer period also were more likely to have experienced or detected problems of the BBM. The most important problem reported by farmers was about the heaviness of the BBM unit. The other problem mentioned by a few was the unsuitability of the BBM for too wet soil.

Credit for BBM package was not a relevant variable in the equation explaining BBM knowledge because credit was accessible to those who knew about the BBM and had decided to adopt. Also credit could not be used as a variable in the equation explaining adoption as all adopters had access to credit at least once. However, Longer duration of access to credit for BBM package significantly increased the odds of continuous use among adopters.

Expected extra yield from BBM use had no significant influence on BBM use pattern although higher extra yield would be normally expected to induce continuous use. A possible reason is that both within and between sites, there was wide variation in expected extra yield. The extent of higher yield expected from improved wheat compared to the traditional crop (local wheat or teff) the BBM package would replace was 418±13 kg for the three sites (441±19 kg for Inewari, 365±20 kg for Hidi and 441±30 kg for Ginchi).

Factors Affecting Adoption and Duration of BBM Use:Tobit Regression Analysis

In the logistic regression model 2 (Table 5), adoption was considered a binary dependent variable, and factors influencing the probability of adoption were identified. In order to simultaneously identify the factors influencing adoption and the duration of use of BBM, adoption was defined as a truncated continuous variable in which non-adopters had zero period of use and adopters had varying periods of use. Then tobit regression of the following form was used:

$$Y_i = \beta' X_i + u_i \qquad (8)$$

where Y is a continuous truncated variable, X is a set of independent variables, β is a vector of parameters including a constant to be estimated, u is an error term, and both Y and u have normal distributions, actually truncated normal distributions. The parameters are estimated by maximum log-likelihood iteration. The parameters do not measure marginal effects of independent variables, they only show if any regressor has significant influence on the regressand (for general properties of the tobit model see Tobin, 1958; McDonald and Moffit, 1980; Kinsey, 1984).

Two estimators were used in empirical estimation of equation 8 by employing the tobit procedure of LIMDEP software (Anon., 1995). First, a full tobit model was used in which the entire sample of adopters and non-adopters were considered. In this case an estimated coefficient show the joint effect of a regressor on both the probability of the dependent variable being non-zero, i.e probability of adoption of BBM, and the duration of use of BBM. Second, a truncated model was used in which only farms with non-zero adoption were considered. In this case, an estimated coefficient show the effect of a regressor on the probability of longer duration of use of BBM. The sample with non-zero adoption is a truncated part of a larger sample, hence truncated tobit rather than OLS estimator is appropriate to estimate coefficients (Goetz, 1995).

The definition of the independent variables used in both the models are described in Table 3. The estimated coefficients of the full tobit model indicate that compared to farmers in Inewari and Hidi, those in Ginchi had a significantly higher probability of

adoption and longer period of use of BBM (Table 6). Among the three sites, sample farmers in Ginchi had the highest proportion of land under vertisol (91% compared to 49% in Inewari and 51% in Hidi) and the highest proportion of land with major waterlogging problem (42% compared to 19% in Inewari and 17% in Hidi). BBM training, area of cropland, number of work animals, and duration of access to credit had significant positive influence and family size had a significant negative influence on the probability of adoption and duration of use of BBM. All the positive effects are plausible; the negative effect of family size may also be plausible if larger labor supply from larger families reduce the need for BBM type technology for drainage.

The estimated coefficients of the truncated model indicate that farmers in Ginchi had a higher probability of using BBM for longer periods. With the exception of area of cropland, all the factors that significantly influenced the probability of adoption and duration of use also influenced in the same manner the probability of longer period of use. Of all the variables, access to credit had the most significant influence on both the probability of adoption and the duration of use of BBM. Surprisingly, area under vertisol and area with major waterlogging problem had no significant influence on the probability of adoption and duration of use of BBM.

Summary and Conclusions

Empirical studies on agricultural technology adoption generally divide a population into adopters and non-adopters, and analyze the reasons for adoption or non-adoption at a point in time. In reality, technology adoption is not a one-off static decision rather it involves a dynamic process in which information gathering, learning and experience play pivotal roles particularly in the early stage of adoption. A conceptual framework for adoption pathway is suggested in which the decision to adopt, reject or defer decision at a point in time is postulated to be influenced by the knowledge and perception acquired at that point in time. A new decision about adoption may be taken later after acquiring more knowledge and/or by observing performance of those who had already adopted. The characteristics of both the user and the technology are considered important in explaining adoption behavior and the pathway for adoption. The resultant pathway has further implication for the time frame and the volume of potential impact of a new technology.

This conceptual framework was applied to understand the adoption pathway for vertisol management technology and related factors in three on-farm research sites in highland Ethiopia. The principal component of the technology package is an animal drawn drainage equipment called broadbed maker (BBM) which is used to solve the problem of waterlogging of vertisols to grow improved wheat varieties. During on-farm research over a period of eight years, farmers in the research villages were observed to respond differently to the technology package: some adopted and continued to use it, others adopted at different times and discontinued but readopted later, some knew about the technology but did not yet adopt while some farmers did not yet show interest to learn about the technology.

Analysis of a sample of households from the three research villages confirmed that a simple classification of farmers as adopters and non-adopters was inadequate to understand the adoption process. Rather a multistage decision process in which farmers move from learning to adoption to continuous or discontinuous use was more appropriate. Application of logistic regressions to binary dependent variables BBM knowledge (yes vs no), BBM adoption (yes vs no), and BBM use pattern (continuous vs discontinuous) showed that the set of significant factors influencing these dependent variables were different. For example, higher level of education significantly decreased the odds of learning and adopting BBM but significanly increased the odds of continuous use once adopted. BBM training significantly increased the odds of adoption but had no influence on use pattern. Cropland per farm increased the odds of acquiring BBM knowledge and adoption but had no significant influence on the use pattern. Cropland under vertisol significantly increased the odds of acquiring BBM knowledge and use pattern but had slight negative influence on BBM adoption. Area under major waterlogging problem had no influence on BBM knowledge but significantly increased the odds of adoption and continuous use. Distance of the household from the nearest market had decreased the odds of acquiring knowledge and adoption but had no influence on use pattern. Number of work animals owned significantly increased the odds of acquiring knowledge and also increased the odds of continuous use but significantly decreased the odds of adoption. Access to credit significantly increased the odds of adoption and continuous use but was not relevant for BBM knowledge.

In order to simultaneously identify factors that influenced adoption and the duration of use of BBM, adoption was defined as a truncated continuous variable with non-adopters taking zero value and adopters taking different positive values, then tobit regression was applied. Also a truncated tobit model was applied to only the adopters with different duration of adoption. The results show that the set of factors significantly influencing the probability of adoption and duration of use are different than that significantly influencing adoption as a binary variable. In the tobit model, only area under cropland, work animal ownership, BBM training and access to credit had significant positive influence and family size had significant negative influence on the probability of adoption and longer period of use of BBM. In the truncated model, the factors that had significant influence and the directions of their influence were the same as those in the tobit model, except area of cropland, which had no significant influence.

These results indicate that technology adoption is not a one-off static decision rather it is a dynamic process involving acquisition of knowledge, learning, adoption and then using it continuously or discontinuously. The set of factors that play important roles in the adoption decision process may be different at different stages of the process. The lag between learning and adoption, and the possibility of discontinuation and readoption imply that a longer period will require for majority of the farmers to use the technology than if adoption was a one off decision leading to continuous use.

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Table 1: Utilization of BBM technology package in Inewari and Hidi on-farm research sites[a]

Year	New adopters	Cumulative adopters	Discontinued	Readopters	Net new Adopters[b]	Cumulative net adopters
1989	19	19	-	-	19	19
1990	35	54	-	-	35	54
1991	68	122	35	-	33	87
1992	195	317	27	13	181	268
1993	136	453	139	3	0	268
1994	36	489	199	18	-145	123
1995	6	495	40	35	1	124
Total	495		440	69		

a: The records for Ginchi were not available in a suitable form for integration with the other two sites.
b: Net new adopters in year t = New adopters in year t - Discontinued in year t + Readopters in year t.

Source: On-farm research participant records

Table 2: Number of total and sample households by adoption status in the three research sites

	Inewari	Hidi	Ginchi	All sites
	N (%)	N (%)	N (%)	N (%)
Total households	1252 (100)	333 (100)	566 (100)	2151 (100)
Adopters	342 (27)	153 (46)	103 (18)	598 (28)
Non-adopters	910 (73)	180 (54)	463 (82)	1553 (72)
Total sample	276 (100)	176 (100)	133 (100)	585 (100)
Adopters	225 (82)	146 (83)	103 (77)	474 (81)
Non-adopters	51 (18)	30 (17)	30 (23)	111 (19)

Source: Field survey

Table 3: Description of variables used in logistic regression models

Variable name	**Nature**	**Description/code**
BBM knowledge	Binary	Have = 1, Don't have = 0
BBM Adoption	Binary	Adopter = 1, Non-adopter = 0
BBM use pattern	Binary	Continuous = 1, Discontinuous = 0
Location	Categorical	Inewari = 1, Hidi = 2, Ginchi = 3
Education	Dummy	Primary or more = 1, No formal literacy = 0
BBMTraining	Dummy	Attended a BBM skill training session run by JVP or by a contact farmer, or attended a field day where BBM operation was demonstrated = 1, Not attended = 0
Age	Continuous	Age of household head (years)
Cropland	Continuous	Area under crop (hectare)
Vertisol	Continuous	Cropland under vertisol (ha)
Waterlogged	Continuous	Cropland with major waterlogging problem (ha)
Familysize	Continuous	Number of persons in family
Distance	Continuous	Distance of household from nearest market (km)
Workanimal	Continuous	Number of work animals owned
BBMProblem	Dummy	Experienced problem with BBM: Yes = 1, No = 0
Extrayield	Continuous	Expected extra yield (kg/ha) from crop produced with BBM compared to one replaced by BBM
Credit	Continuous	Number of years received credit for BBM package

Table 4: Per cent correct prediction from different best-fit logistic regression equations

Sample category and size	Dependent Variable	% correct prediction
Panel A		
Eq1: All (585)	BBM Adoption status (Adopter=1 Non-adopter=0)	80.8
Eq2: Non-adopters (111)	BBM knowledge (Have=1 Don't have=0)	78.4
Eq3: Adopters (474)	BBM use pattern (Continuous=1 Discontinuous=0)	78.0
Panel B		
Eq1: All sample (585)	BBM knowledge (Have=1 Don't have=0)	90.9
Eq2: Have BBM knowledge (531)	BBM Adoption status (Adopter=1 Non-adopter=0)	92.2
Eq3: Adopters (474)	BBM use pattern (Continuous=1 Discontinuous=0)	78.0

Table 5: Estimated coefficients of Logistic regressions on BBM knowledge, adoption and use pattern

Variables	Dependent variables		
	BBM knowledge	BBM adoption	BBM use pattern
	β (Exp(β))	β (Exp(β))	β (Exp(β))
Location			
Inewari	0.0	0.0	0.0
Hidi	-0.468 (0.626)	4.027 (55.82)	-0.599 (0.550)
Ginchi	-2.114 (0.121)	-1.117 (0.327)	-3.465 (0.031)
Education	-0.345 (0.708)	-1.226 (0.294)	0.411 (1.508)
BBMtraining	-	3.128 (22.83)	-0.027 (0.973)
Age	-0.021 (0.979)	0.006 (1.005)	0.010 (1.010)
Cropland	0.219 (1.245)	0.440 (1.551)	-0.057 (0.945)
Vertisol	1.514 (4.543)	-0.042 (0.894)	0.226 (1.253)
Waterlogged	0.004 (1.004)	0.775 (2.170)	0.258 (1.295)
Familysize	-0.135 (0.874)	0.123 (1.134)	0.006 (1.009)
Distance	-0.136 (0.873)	-0.300 (0.741)	0.025 (1.030)
Workanimal	0.479 (1.615)	-0.392 (0.676)	0.122 (1.130)
BBMproblem	-	-	0.437 (1.545)
Extrayield	-	-	0.006 (1.001)
Credit	-	-	0.892 (2.440)
Constant	2.612	3.022	-5.058
-2 Log Likelihood	303.320	189.783	423.609
Goodness of fit	535.667	393.364	443.554
% correct prediction	90.85	92.19	77.99

Codes for dependent variables: BBM Knowledge: yes=1 no=0; BBM adoption: yes=1 no=0; BBM use pattern: continuous=1 discontinuous=0

Table 6: Maximum likelihood estimates for factors affecting adoption and the duration of use of BBM in three research sites

Independent variable	Estimator	
	Tobit	Truncated
Constant	-0.413 (-2.678)	-1.369 (-5.822)
Location		
Inewari	0.000	0.000
Hidi	-0.116 (-0.867)	-1.145 (-0.744)
Ginchi	0.377 (3.185)*	0.584 (3.345)*
Age	0.001 (0.257)	0.002 (0.526)
Cropland	0.127 (2.013)*	0.132 (1.434)
Vertisol	-0.061 (-1.002)	-0.080 (-0.881)
Waterlogged	0.035 (0.832)	-0.015 (0.255)
Familysize	-0.030 (-2.437)*	-0.039 (-2.087)*
Distance	0.030 (1.980)	0.031 (1.419)
Workanimal	0.066 (2.461)*	0.106 (2.632)*
BBMTraining	0.085 (2.775)*	0.104 (2.332)*
Education	0.016 (0.039)	0.019 (0.251)
BBMproblem	0.034 (0.500)	0.063 (0.594)
Extrayield	-0.001 (-1.876)	-0.001 (-0.569)
Credit	0.943 (40.144)*	1.119 (32.813)*
Log likelihood function	-347.749	-360.072

Figures in the parenthesis are t-ratios. *indicate significant at less than 5% level.

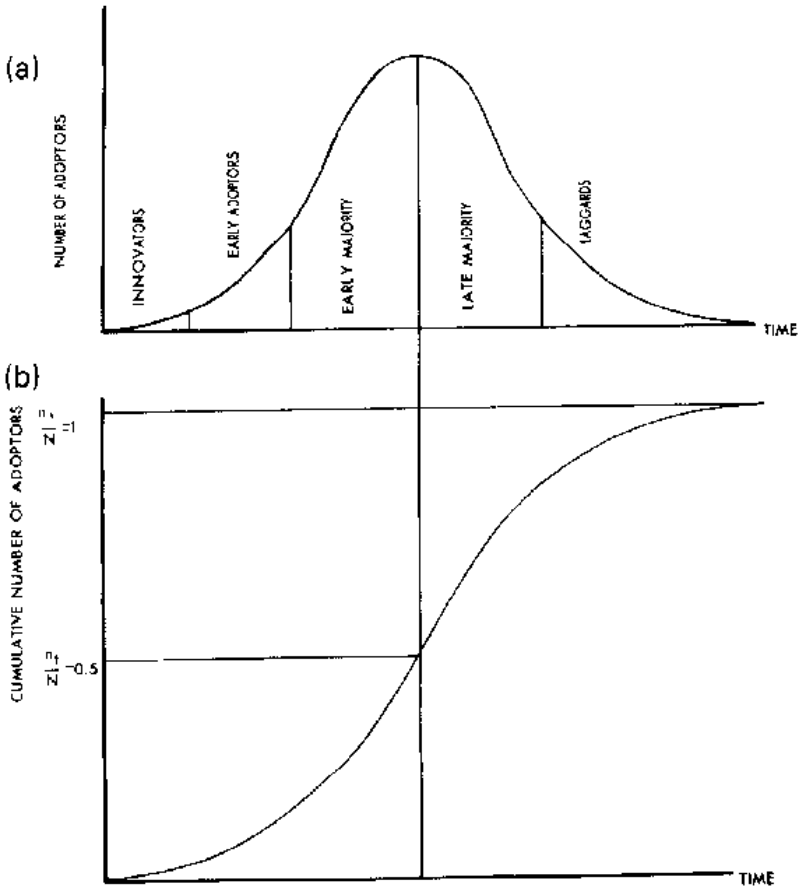
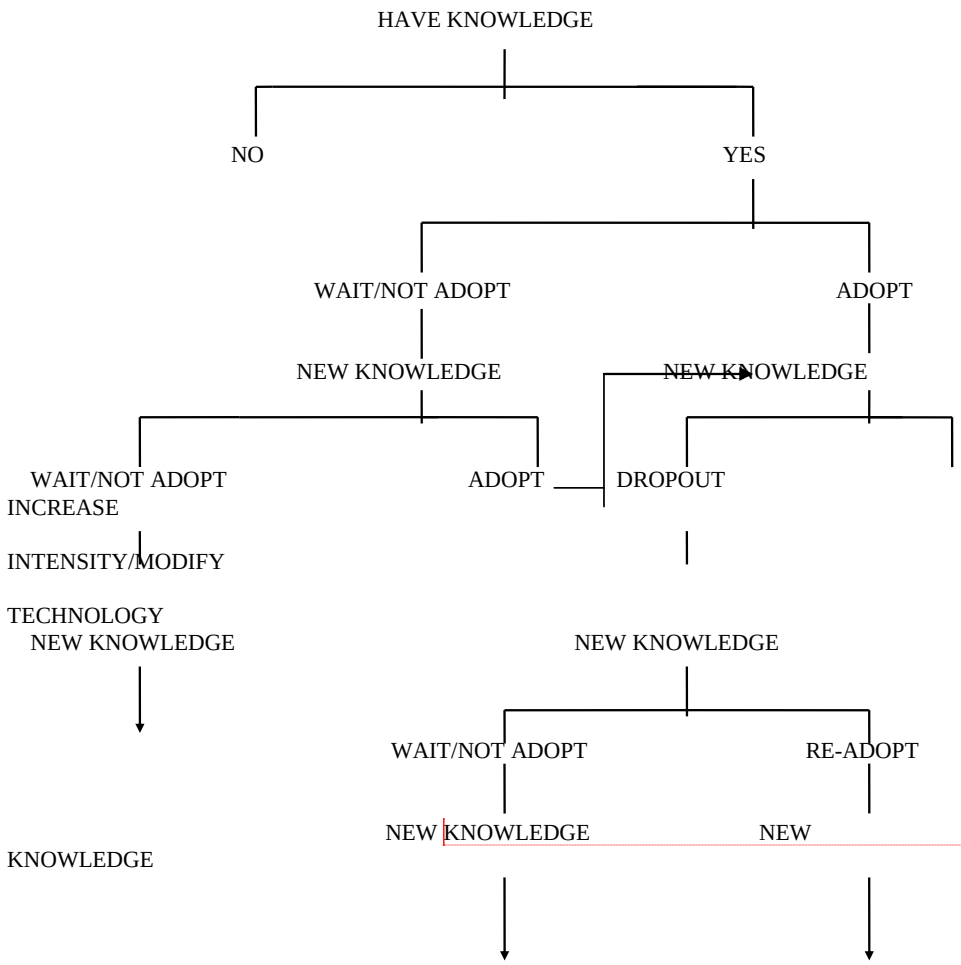


Figure 1: (a) Adopter categorisation (b) The logistic curve

Figure 2 : Learning and adoption pathways for a new technology



Comment [PU1]:

Source: Jabbar et al, 1996

Fig.3 Chikungunya cases and deaths of IB-M during epidemic period 1989-95

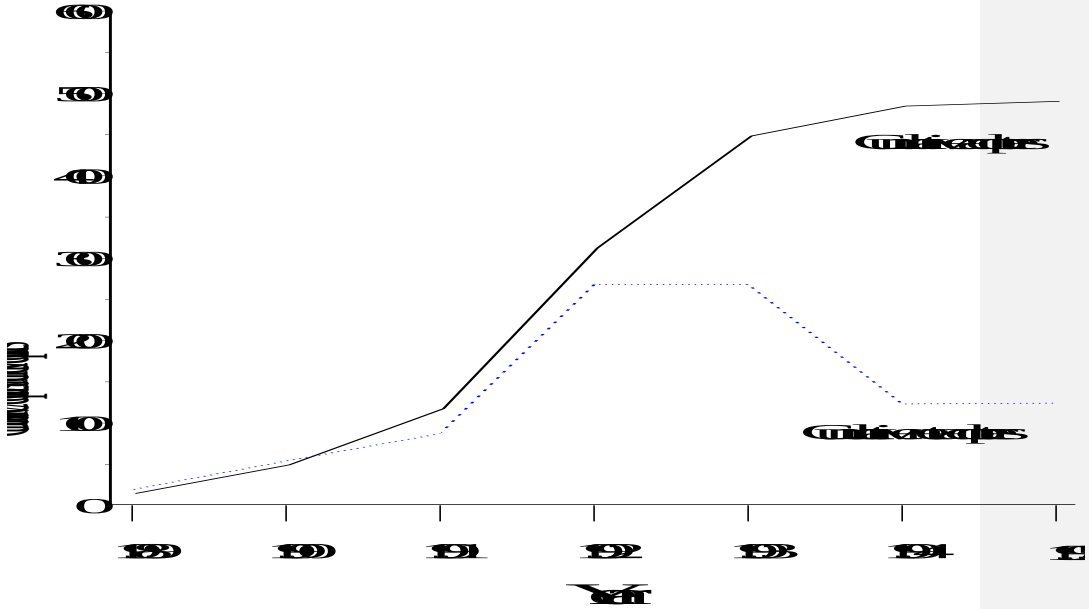


Figure 4: **Distribution of sample households according to BBM knowledge, adoption and use pattern in three research sites**