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Determinants of Agricultural Technology Adoption in Mozambique

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DETERMINANTS OF AGRICULTURAL TECHNOLOGY ADOPTION IN MOZAMBIQUE

Abstract

Analysis of improved agricultural technology adoption in Mozambique using farm household data collected in the cropping season 2001/02 and 2004/05 indicates that households with access to credit and extension advisory services as well as members of agricultural associations are more likely to adopt new agricultural technologies. Households with higher levels of education are also more likely to adopt. Finally, results suggest that out grower scheme by providing credit to farms can help stimulate agricultural technology adoption.

***Keywords**: technology adoption, agriculture, probit model, Mozambique*

***JEL Classification System**: C12; C13*

1. Introduction

Agriculture in Mozambique is subsistence-oriented. To reach the objectives of food security and nutrition for all as well as to reduce poverty, there is a need to progressively transform the agricultural sector away from subsistence-oriented household-level production towards an integrated economy fueled by agricultural productivity growth. In almost all areas of the globe where the agricultural transformation process has been documented, agricultural productivity growth has been driven by improved farm technologies, including improved seeds, fertilizer, and water control (Johnston and Kilby, 1975; Mellor, 1976; Gabre-Madhin and Johnston, 2002).

In Mozambique, improved agricultural technology has been stressed in key planning documents as an important means for achieving reductions in hunger and poverty (PARPA II (2006), PROAGRI II, IIAM investment plan (2006), Estratégia da Revolução Verde (2007)). In fact, current public policy explicitly calls for a green revolution in Mozambique. Nevertheless, despite the efforts of the Ministry of Agriculture over the past dozen years, the adoption of new agricultural technologies remains low. For example, less than 7% of agricultural households that plant maize, a staple crop, use improved cultivars of maize. Adoption of improved cultivars of the other major food crops is even lower. Less than 5% of the smallholder farmers use fertilizer and pesticide in any given year.

While the finding of low levels of technology adoption is well accepted, few studies attempt to explain the slow rate of adoption of modern agricultural technology in Mozambique. Bandiera and Rasul (2006; Langyintuo and Mekuria (2005) and Zavale et al., (2005) are among the few researchers who have looked at adoption of improved technologies in Mozambique. We seek to help fill this gap. We use a rich data set generated by the Ministry of Agriculture (MinAg) to analyze the key determinants of agricultural technology adoption in Mozambique. The paper is organized as follows: Section 2 reviews the relevant literature. Section 3 describes agricultural technology in Mozambique. Section 4 presents the methodology used. The data and description of the variables used in the analysis are presented in section 5. Results and discussion are found in section 6. Section 7 concludes.

2. Literature Review

The literature on agricultural technology adoption is vast and somewhat difficult to summarize compactly. Traditionally, economic analysis of agricultural technology adoption (or lack thereof) has focused on imperfect information, risk, uncertainty, institutional constraints, human capital, input availability, and infrastructure as potential explanations for adoption decisions (Feder et al. 1985;

Foster and Rosenzweig 1996; and Kohli and Singh 1997). A more recent strand of literature focuses on social networks and learning. In the following, prominent analyses of agricultural adoption, from both traditional and social network perspectives, are presented. The literature is then synthesized into three paradigms of technology adoption.

In studying agricultural technology adoption, analysis of the adoption of high yielding varieties (HYV) in India has been particularly influential. Kohli and Singh (1997) found that inputs played a large role in the rapid adoption of HYVs in the Punjab. They claimed that the effort made by the Punjab government to make the technological innovations and their complementary inputs more easily and cheaply available allowed the technology to diffuse faster than in the rest of India.

Butzer et al (2002) used a choice of technique framework to characterize the decision to adopt HYVs in India. They found that since HYVs require higher levels of fertilizer and irrigation to realize their yield potential, their introduction corresponded with a large jump in the demand for fertilizer and irrigated land. McGuirk and Mundlak (1991) also use a choice of technique framework in a study of the transformation of Punjab agriculture during the Green Revolution and find that the short period of transition from the use of traditional varieties to the adoption of HYVs was largely determined by the availability of irrigation facilities and fertilizer. This result partially stems from the fact that, as mentioned before, to fully utilize the yield potential of HYVs, it is necessary to apply considerably larger doses of fertilizer and water per unit of land.

More recently, an influential body of literature on technology adoption has focused on the effect of social learning on adoption decisions. The basic motivation behind this literature is the idea that a farmer in a village observes the behavior of neighboring farmers, including their experimentation with new technology. Once a year's harvest is realized, the farmer then updates his priors concerning the technology which may increase his probability of adopting the new technology in the subsequent year.

Bandiera and Rasul (2002) looked at social networks and technology adoption in Northern Mozambique and found that the probability of adoption is higher amongst farmers who reported discussing agriculture with others. Besley and Case (1993) use a model of learning where the profitability of adoption is uncertain and exogenous. Looking at a village in India, they found that once farmers discover the true profitability of adopting the new technology, they are more likely to adopt. Alternatively, Foster and Rosenzweig (1995) and Conley and Udry (2002) use a target-input model of new technology which assumes that the best use of inputs is what is unknown and stochastic. Applying this model to high yielding varieties (HYV) adoption in India, Foster and Rosenzweig (1995) found that initially farmers may not adopt a new technology because of imperfect knowledge about management of the new technology; however, adoption eventually occurs due to own experience and neighbors' experience. Similarly, Conley and Udry (2002), looking at pineapple cultivation in Ghana, analyze whether an individual farmer's fertilizer use responds to changes in information about the fertilizer productivity of his neighbor. They found that a farmer increases (decreases) his fertilizer use when a neighbor experienced higher than expected profits using more (less) fertilizer than he did, indicating the importance of social learning.

Overall, to explain adoption behavior and determinants of technology adoption, three paradigms are commonly used. The paradigms are: the innovation-diffusion model, the adoption perception and the economic constraints models. The underlying assumption of the innovation-diffusion model is that the technology is technically and culturally appropriate but the problem of adoption is one of asymmetric information and very high search cost (Feder and Slade, 1984; Shampine, 1998; Smale et al., 1994). The second paradigm, the adopters' perception paradigm, on the other hand, suggests that the perceived attributes of the technology condition adoption behavior of farmers. This means that, even with full farm household information, farmers may subjectively evaluate the technology differently than scientists (Kivlin and Fliegel, 1967; Ashby et al., 1989; Ashby and Sperling, 1992). Thus, understanding farmers' perceptions of a given technology is crucial in the generation and diffusion of new technologies and farm household information dissemination.

The economic constraint model contends that input fixity in the short run, such as access to credit, land, labor or other critical inputs limits production flexibility and conditions technology adoption decisions (Aikens et al., 1975; Smale et al., 1994; Shampine, 1998). Recent studies have shown that using the three paradigms in modeling technology adoption improves the explanatory power of the model relative to a single paradigm (Adesina and Zinnah, 1993; Morris et al., 1999, Gemeda et al., 2001).

3. Agricultural Technologies in Mozambique

A large number of promising technologies are already available in Mozambique. These include improved maize open pollinated varieties (OPV), hybrid seeds and chemical packages, improved on farm storage techniques, methods of small scale irrigation such as treadle pumps and others. Unfortunately, while available in principle, farmers' contact with new technology is distinctly limited in practice. This translates to low rates of technology adoption. Tables 1 and 2 illustrate the low rates of technology adoption among rural farm households as well as some other household characteristics.

Table 1: Rural household technology and characteristics (in percent unless noted).

	Cropping season	
Percentage Technology	2001/02	2004/05
Fertilizer use	3.7	3.5
Pesticide use	6.7	5.1
Animal traction use	11.2	8.6
Hired permanent labor	2.2	1.6
Hired seasonal labor	15.5	18.0
Grow cotton	7.2	5.6
Grow tobacco	3.8	2.6
Access to extension	13.7	15.7
Membership in Ag. Association	3.9	6.8
Distance0 (<11)	40	40
Distance1 (11-20 km)	16	16
Distance2 21-40 km)	18	18
Distance3 (>40 km)	21	21
Farmsize1 (<0.75 ha)	21	20
Farmsize2 (0.75-1.75 ha)	37	35
Farmsize3 (1.75-5.0 ha)	33	36
Farmsize4 (>5 ha)	9	9
Easy access to land in the village (1=yes)	75	73
Household head male	77.0	73.0
Household head age (years)	44	46
Household head education (years of schooling)	2.8	2.0

Sources: TIA 2002 and TIA 2005.

Table 2: Percentage of smallholders using improved seeds in 2004/05 by province.

Province	Maize	Rice	Peanut small	Peanut large	Beans	Cowpeas
Niassa	6	3	2	0	2	3
Cabo Delgado	2	0	1	2	0	0
Nampula	6	4	2	3	11	4
Zambezia	5	4	3	8	7	3
Tete	11	8	6	3	4	3
Manica	15	0	6	8	15	5
Sofala	5	2	3	4	9	3
Inhambane	5	9	12	7	30	7
Gaza	4	6	10	5	7	4
Maputo prov	13	7	50	12	26	10
Total	7	3	4	6	8	5

Source. TIA 2005

In light of the low technology levels indicated by Tables 1 and 2, it is not surprising that practice of irrigation is also highly circumscribed even though rainfall variability explains most of the swings in total production. Crop irrigation is primarily confined to peri-urban production with vegetables, sugarcane and irrigated rice in a few limited areas. Only 4% of the smallholder farmers reported the use of irrigation in 2005 and 7.5% in 2002. FAO estimates irrigation potential for 3.3 million hectares in Mozambique (FAO, 2002), with only 40,000 hectares currently irrigated, and not all of that functional. Pouring water on fields is still the most common method of irrigation reported by farmers using irrigation. In 2002, 76 percent of those using irrigation used manual irrigation followed by gravity with 18%. Use of pumps is negligible.

Farmers contact with new technologies depends mostly on the presence of non governmental organizations (NGOs), donor supported projects, or outgrower schemes (primarily cotton and tobacco). Outgrower schemes have been relatively successful. In the cropping season 2001-2002, 56% of cotton growers surveyed declared use of pesticide, while only 3.8% of non cotton growers used pesticide. Fertilizer users were concentrated amongst tobacco growers with more than 36% declaring use of fertilizer in their fields, particularly those with tobacco. Only 3.5% non-tobacco growers used fertilizers.

In addition, rural households have the potential to benefit from public research and extension. Arguably, research and extension should be the fundamental core of government activity to support agricultural development. Instead, these activities are repeatedly described as under-funded (Coughlin, 2006; Eicher, 2004; Gemo, et al., 2005). Some orders of magnitude are instructive. The Ministry of Education and Culture employed nearly 70,000 teachers in 2004 with the number of teachers growing continuously since 1992. The Ministry of Agriculture, on the other hand, employed 708 extension agents in 2004 with the number of extension agents essentially constant since 1999 (MADER, 2004). Since 2004, the number of public extension agents has declined to about 600. The result is that only one-third of rural districts are being served by the public extension services (Gemo, 2006). Extension activities by NGOs supplement the public extension services; nevertheless, as shown in Table 1, only about 15% of rural households benefit from contact with an extension agent, public or otherwise.

An important policy debates center on the best ways to encourage adoption of improved technologies. While efforts to encourage technology adoption have not achieved broad scale national impact (Arndt, Jones, and Tarp 2007), reasonably significant resources have been dedicated to areas such as research and extension, delivery of credit, and formation of agricultural associations. If one or more of these efforts could be shown to have yielded positive returns in terms of technology adoption, these demonstrated impacts would buttress the argument for enhanced commitment to that mode of encouraging agricultural technology adoption. We turn now to the approach for examining technology and its determinants.

4. Methodology

We employ two snapshots of farmers' technology adoption decisions for two cropping seasons (2001-02 and 2004-05). As will be detailed in the next section, the data contain a significant panel element permitting analysis of changes in technology adoption by household. Three separate analyses are undertaken: the determinants of agricultural technology adoption in each season using the cross section element of the data and comparison of changes in adoption decisions between the two cropping seasons using the panel element of the data. The methodologies employed are described in the next two subsections.

Cross Sectional Analysis

For a snapshot of technology adoption, using the two cross-sectional data sets, it is assumed that the gain to farmer i of using the new technology is parameterized as $\gamma x_i + u_i$, where x_i is a vector of farm and farmer characteristics and u_i is an independently and identically distributed farm specific *ex ante* shock. It is often assumed that these shocks are normally or logistically distributed, and the model is then run as a probit, logit or multinomial logit.

Probit and Logit models are based on normal and logistic cumulative distribution functions, respectively. Both models are quite similar, the main difference being that the logistic distribution has slightly fatter tails. Here the probit model is used.

In the probit model, the households are assumed to make decisions based upon an objective of utility maximization. For a given decision, separate models are developed for each decision. The underlying utility function depends on household specific attributes X (e.g. age of household head, sex of the household head, education, membership to an agricultural association, access to credit, etc) and a disturbance term having a zero mean:

$$U_{i1}(X) = \beta_1 X_i + \varepsilon_{i1} \quad \text{for adoption} \tag{1}$$

and $U_{i0}(X) = \beta_0 X_i + \varepsilon_{i0}$ for non-adoption. (2)

As utility is random, the *i*th household will select the alternative "adoption" if and only if $U_{i1} > U_{i0}$. Thus, for the household *i*, the probability of adoption is given by:

$$P(1) = P(U_{i1} > U_{i0}) \tag{3}$$

$$P(1) = P(\beta_1 X_1 + \varepsilon_{i1} > \beta_0 X_i + \varepsilon_{i0}) \tag{4}$$

$$P(1) = P(\varepsilon_{i0} - \varepsilon_{i1} < \beta_1 X_i - \beta_0 X_i) \tag{5}$$

$$P(1) = P(\varepsilon_i < \beta X_i) \tag{6}$$

$$P(1) = \Phi(\beta X_i) \tag{7}$$

where Φ is the cumulative distribution function of the standard normal distribution. The parameters β are estimated by maximum likelihood x' is a vector of exogenous variables which explains adoption. In the case of normal distribution function, the model to estimate the probability of observing a farmer using a new technology can be stated as:

$$P(Y_i = 1 \mid x) = \Phi(x'\beta) = \int_{-\infty}^{x'\beta} \frac{1}{\sqrt{2\pi}} \exp\left(-z^2/2\right) dz \tag{8}$$

where P is the probability that the i[th] household used the new technology, and 0 otherwise. The probit model is generated by a simple latent model of the form shown below in equation

$$Y^{*} = x'\beta + \varepsilon \tag{9}$$

where $\varepsilon \mid x$ is a normally distributed error term.

Several dependent variables are analysed. The dependent variables are whether or not the farm household used improved seed, fertilizer, pesticide, animal traction or mechanization. Explanatory variables are gender of the farm household head (head gender), age farm household head (head age), level of formal education of farm household head (schooling), distance to center (distance), access to credit, membership to an agricultural association, land accessibility and whether the household grows cotton and or tobacco. The agro-ecological zone where the household is located is also added to control for the possibility that more favourable zones might be more likely to adopt some new technologies. More detail on dependent and independent variables will be provided in the next section.

An important limitation of the cross sectional analysis is an inability to control for unobserved heterogeneity across households. For example, while the data sets permit control for education levels of household heads, considerable heterogeneity in farm management skills likely exists even after controlling for this factor. Unobserved heterogeneity can lead to faulty conclusions. For example, if more adept farmers are more likely to join an association, then a positive and significant coefficient on membership in an association could reflect the self-selection of adept farmers into associations rather than any benefits of being in an association per se. The panel dimension of the data set employed here allows for much more rigorous control of unobserved heterogeneity. We turn to the methods employed to exploit the panel dimension in the next subsection.

Changes in Aggregate Technology Score between 2002 and 2005

The analysis of changes in technology adoption by households uses the panel dimension of the rural income surveys for the cropping season 2001/02 and 2004/05. Analysis of change in aggregate technology score between 2002 and 2005 starts from a linear regression model of the form:

$$y_{it} = \beta' x_{it} + \theta_i + u_t + u_{it} \tag{10}$$

where the index i refers to households and t indicates the time period which corresponds to the two data sets available for 2001-02 and 2004-05. The quantity u_t is a time effect that applies to all households in time t. The parameter θ_i is a fixed effect for observation i. This fixed effect includes unobserved factors such as the intrinsic aptitude of the household for agricultural production. In the case of two periods, the fixed effects are removed by taking differences as shown below:

$$y_{i2} - y_{i1} = (u_2 - u_1) + \beta'(x_{i2} - x_{i1}) + u_{i2} - u_{i1} \ . \tag{11}$$

Variables that do not vary over time, such as household fixed effects, are dropped out of the model. Equation (11) is consistently and efficiently estimated using OLS.

The dependent variable in the panel dimension is the difference in a technology score developed specifically for this analysis. The score is calculated in a very simple and straightforward manner. For each household in the panel, the agricultural technology score is the number of agricultural technologies used by the household in each cropping season. When a given technology is used by a household, it counts as one (1) and zero (0) otherwise. The list of agricultural technologies considered include: improved seeds use, fertilizer use, pesticide use and animal traction use for each household and each year. As a result, for each household in each year, the maximum score is four and the minimum score is zero.

Descriptive statistics for the first differences of the dependent and explanatory variables are presented in Table 3. The change in the technology is modelled as a function of changes in access to extension, changes in membership to an association, changes in access to agricultural credit, and changes in labour availability. Initial levels of key variables in 2001-02 are also included as independent variables. These variables include: education, hired labor (permanent or seasonal), extension visit, membership to an association, and credit access.

Table 3 Descriptive Statistics on Changes between 2002 and 2005

Variable Obs	Obs	Mean	Std. Dev.	Min	Max
Technology change	3908	1.15	0.72	-2	4
Labour difference	4482	0.24	2.20	-13	19
Perm labour difference	3908	-0.02	0.31	-1	1
Temp labour difference	3908	0.15	0.55	-1	1
Extension difference	3908	-0.17	0.60	-1	1
Association differences	3908	0.04	0.33	-1	1
Credit difference	3908	-0.09	0.38	-1	1
Drought difference	3908	0.10	0.41	-1	1

Source: Calculated by authors from TIA 2002 and TIA 2005

The explanatory variables in differences presented in Table 3 permit analysis that incorporates a great deal of control for unobserved heterogeneity across households. Continuing the discussion on membership in an association, if those households that were not members of an association in 2002 but became a member by 2005 also report a greater than average tendency to adopt new technology (controlling for other factors), then it is more likely that membership in an association influenced the decision to adopt. As such, the analysis in differences using the panel approach provides an important check on the cross-section results.

5. Data and Description of Variables

The data used in this analysis come from detailed rural household surveys of about 4,908 rural households in 80 districts in 2002 (TIA02), and 6,149 households interviewed in 94 districts in 2005 (TIA05). A panel data set was built covering 4104 households that were included in both surveys. The rate of attrition (households that moved away or dissolved between TIA02 and TIA05) was 16%. The "Trabalho de Inquérito Agrícola" known as TIA surveys are designed to be representative of rural zones at provincial and national levels. The TIA surveys include detailed field production information and rich demographic and infrastructure information for each household and community. In addition, production data for each field is obtained including size of field, production estimates, labour input associated with each type of planting activity, fertilizer application and seed usage. The demographic information for each household includes the age, gender and education level of each household member; how far a household is from a bus stop, a usable road, a telephone booth, mobile phone service, and extension service; non-farming income by household member; whether a household received credit; how much land a household owns; and land tenure. Information on producer prices, communication services, pests and diseases were also obtained from the community survey.

It is potentially important to point out that rainfall quantity was higher in the first cropping season when compared to the cropping season 2004/05. The cropping season 2004/05 had a higher number of days without rain in almost every province with the exception of Gaza when compared to the cropping season captured by TIA

2001/02. These differences in the quantity and distribution of rainfall are particularly felt in maize production which is sensitive to drought especially in the flowering and tasseling stages. Drought has implications for some technology adoption decisions. In particular, farmers intending to use fertilizer as side dressing or apply pesticides may have opted not to do so due to unfavorable climate outcomes. Other decisions, such as use of improved seed and animal traction, are typically made prior to the realization of climate. Hence, drought should not impact those decisions.

The explanatory variables for the regressions were identified in the proceeding section. The choice of explanatory variables is explained in more detail here.

The gender of the household head is a dummy variable that takes the value of 1 if the head of the household is male, and 0 if female. It has been argued by some authors that women are generally discriminated against in terms of access to external inputs and information (Dey, 1981). This hypothesis implies that males are more likely to adopt improved technology than females.

The age of household head is incorporated as it is believed that with age, farmers accumulate more personal capital and, thus, show a greater likelihood of investing in innovations (Nkamleu et al., 1998). However, it may also be that younger household heads are more flexible and hence likely to adopt new technologies. The expected sign of the coefficient on age is indeterminate.

Membership to an agricultural association is included because it has been shown that farmers within a group learn from each other how to grow and market new crop varieties. As discussed, the evidence suggests that network effects are important for individual decisions, and that, in the particular context of agricultural innovations, farmers share information and learn from each other (Foster and Rosenzweig 1995;

Conley and Udry 2000). The expected sign on the coefficient on membership in an agricultural association is positive.

Farmers contacts with extension agents was measured as a binary variable: 1 if the farmer has been in contact with any extension, 0 otherwise. Contact with extension agents is expected to have a positive effect on adoption based upon the innovation-diffusion theory. Such contacts, by exposing farmers to availability of information can be expected to stimulate adoption (Polson and Spencer, 1991; Voh, 1982; Kebede et al., 1990). A positive relationship is hypothesized between extension visits and the probability of adoption of a new technology.

More educated farmers are typically assumed to be better able to process information and search for appropriate technologies to alleviate their production constraints. The belief is that education gives farmers the ability to perceive, interpret and respond to new information much faster than their counterparts without education. In Mozambique, the majority of farmers are illiterate and average number of years of schooling of the household head is correspondingly low (see Table 1). The expected sign on the coefficient on education is positive.

Distance to market is assumed to play an important role in technology adoption. The hypothesis here is that, the further away a village or a household is from input and output markets, the smaller is the likelihood that they will adopt new technology. Input and output markets are also known to influence the adoption of improved agricultural technologies. The coefficient on the distance of the village to the nearest major input or output markets is expected to be negative.

Constrained access to credit figures prominently among the often cited reasons why technology fails to diffuse (Feder, Just and Zilberman, 1985). Differential access to credit or capital is often cited as a factor in differential rates of technology adoption. This seems to be particularly true in indivisible or lumpy technologies such as machinery. At the same time, a number of studies have found that lack of credit does significantly limit adoption of high yielding varieties (HYV). The lack of sufficient accumulated savings by smallholder farmers may prevent them from having the necessary capital for investing in new technologies. Also, capital market failure exists in Mozambique. The expected sign on the coefficient on credit is positive.

The size of the family farm is a factor that is often argued as important in affecting adoption decisions. It is frequently argued that farmers with larger farms are more likely to adopt an improved technology (especially modern varieties) compared with those with small farmers as they can afford to devote part of their fields (some times the less productive parts) to try out the improved technology. It is also known in the literature that lumpy technologies, such as mechanized equipment or animal traction, require economies of size to ensure profitability. There is often a minimum threshold farm size for adoption. But, in general, there are no observed consistent patterns of farm size acting as a constraint to agricultural technology adoption (Just and Zilberman, 1983). The expected sign on the coefficient on farm size is indeterminate.

Perceptions of land scarcity at both the household and community levels are indicated by a variable labeled "easy access to land" in the village, which takes on a value of 1 if the household perceptions are that it is easy to obtain land and zero (0) otherwise. It is expected that the easier the land accessibility the less likely is to farmer adopt a new agricultural technology. The expected sign on the coefficient on easy access to land is negative.

Outgrower schemes, where a processor is granted monopsony purchase rights in an access zone, have strongly influenced technology choices in those zones.

Monopsony rights are conferred in order to relax markets failures in the area of input markets (seeds, fertilizer and pesticides), provision of technical advice, and output markets. For example, Tete province has the highest fertilizer use of all provinces due to the expansion of tobacco outgrower schemes which provide fertilizer on credit. Pesticide use is associated with cotton growing. Nampula, Sofala and Cabo Delgado are the provinces with the most cotton producers. Cotton outgrower schemes, which distribute cotton seed and pesticide, particularly insecticides against leafhoppers and bollworms, are responsible for the apparent high level of pesticide use in these provinces. Farmers that grow cotton or tobacco are expected to use more fertilizer and pesticides due to these outgrower schemes.

6. Results and Discussion

Agricultural Technology Adoption in 2001/2002 and 2004/05- Cross Section Analysis

A series of probit models were estimated for adoption of improved seeds; fertilizer use, pesticide use and use of mechanization in the previous cropping season. The estimated marginal effects are presented in Table 4 and Table 5 for 2002 and 2005 respectively. A large number of results are generated. The discussion here focuses on the most salient sets of results. The two most powerful determinants of technology adoption appear to be membership in an association and access to credit. Both of these variables may be proxies for unobserved management skill on the part of the farmer assuming that more skilled farmers are simultaneously more likely to form mutually beneficial associations, obtain credit, and adopt new technologies. The formal education of the head of the household also has a consistently positive relationship to most technology adoption decisions (with the exception of improved seed, which we will discuss below). The effect is stronger for higher levels of education. Having at least five years of schooling completed indicates completion of lower primary school. Completion of at least lower primary school implies a much higher propensity to adopt new technology than lower or zero levels of education. This result is consistent with other analyses (World Bank 2007).

As expected, growing cotton and tobacco is strongly associated with fertilizer and pesticide use. Also as expected, easy access to additional land discourages fertilizer and pesticide use, which is land saving technologies. Older household heads are more likely to adopt animal traction and mechanization. The coefficient on gender of the household is positive and significant in five of the ten regressions, indicating that a higher likelihood for men to adopt new technologies, particularly chemical inputs and animal traction. While not presented, agro-ecological differences play a fundamental role in the odds of adopting new technology. The results indicate that households in those areas with high rainfall and endowed with better soils are more likely to adopt new agricultural technologies, particularly improved seeds, than regions with poor and erratic rainfall and predominately sandy soils.

Extension appears to only influence the decision to adopt animal traction. It is possible that extension messages are being passed to leaders of associations and then diffused to farmers. This would disguise the impact of extension behind the association membership variable. Nevertheless, the apparent lack of impact of extension on input use is disconcerting. Other impacts are sporadic or non-existent. The impact of distance is notably weak and sometimes counterintuitive. Farm size mainly influences animal traction and mechanization. Overall, the results point to associations, credit, schooling, and outgrower schemes as the primary forces pushing agricultural technology adoption over the period 2002-05.

A word on seed is worthwhile. Relative to the other technologies, adoption of improved seed is associated with notably few determinants in both 2002 and 2005.[1] Seeds are crucial in agriculture. They are one of the most important determinants of productivity. Hence, the lack of association between use of improved seeds and schooling or extension is potentially disconcerting. This result may be explained in part by the fact that a substantial share of the users of improved seed received the seed via free distribution following an emergency (such as drought or floods).

Separate regressions on the seed adoption decision by crop (not presented but available from the authors) appear to help reduce this noise. For most crops, schooling is associated with the adoption of improved varieties. This result is consistent with Zavale et al (2005) who studied the adoption of improved seed by smallholder farmers in Mozambique and found a positive and significant effect of education on the probability of adoption of improved maize seeds. At the same time, the crop level regressions continue to find no association with extension. While noise in the data due to free distribution of seed following emergencies may be part of the problem, the insignificant effect of extension services might also indicate constraints to adoption due to economic constraints, farmers' perceptions, or ineffective extension.

[1] The results summarized in Table 5 also show that cotton growers are less likely to adopt improved food crops seed, especially improved maize seeds. There are several reasons why cotton growers are less likely to adopt improved maize seeds. Common pests are possible explanations. Cotton and maize share the same pests particularly the American bollworm (*Helicoverpa spp*). Growing maize and cotton in neighboring plots may help spread the pest and thus increase crop damage for both crops. This may explain why farmers growing cotton are less likely to grow maize.

Table 4 Marginal Effects on Probability of Adoption of Factors 2002

Variable	Improved seeds	Fertilizer use	Pesticide use	mechanization	Animal traction
Head gender	-0.0055	0.3283*	0.3704**	0.3938	0.18903**
Head age (40-49)	0.0439	-0.1031	0.0296	0.4166**	0.1815**
Head age (50-59)	-0.0588	-0.1325	-0.0144	0.4925**	0.0755
Head age (>60)	-0.0175	-0.0735	0.1248	0.4879**	0.3089***
Schooling (3-4 yrs)	0.1132	0.1667	0.1968*	0.4078**	0.0795
Schooling (>5 yrs)	0.0142	0.3056**	0.2669*	0.7114***	0.1219
Extension	0.0221	0.1318	0.1142	-0.1722	0.2941***
Membership association	0.5753***	0.8847***	0.6631***	0.7051***	0.1944
Access to credit	0.3306***	0.3573***	0.4481***	0.2778	0.0772
Farm size (0.75-1.75 ha)	0.0024	-0.1174	-0.1237	-0.0023	-0.1501*
Farm size (1.75-5 ha)	0.0244	0.1739	0.0312	0.1153	0.3366***
Farm size (>5 ha)	0.0073	0.1259	0.2730**	0.1494	0.0776
Distance (21-40 km)	-0.0366	0.1651	-0.0894	-0.0343	0.1331*
Distance (>40 km)	-0.0976	0.273*	0.0061	0.0903	0.0149
Easy access to land	0.0350	-0.4001***	-0.2182**	-0.0828	0.0082
Grow cotton	-0.1504	0.9833***	2.3334***	0.1042	-0.4834***
Grow tobacco	0.1996	1.4462***	0.67471***	0.1054	0.2235

Legend: * p<0.05; ** p<0.01; ***p<0.001

Table 5 Marginal effects of Probability of Adoption of Modern Inputs, Animal Traction and Mechanization 2005

Variable	Improved seeds	Fertilizer use	Pesticide use	mechanization	Animal traction
Head gender	0.04298	0.20611	0.2998*	0.3774	0.1280*
Head age (40-49)	0.12983*	-0.07646	0.0544	0.4698**	0.2780***
Head age (50-59)	0.08876	-0.09934	0.0599	0.6308***	0.3093***
Head age (>60)	0.16416*	-0.02283	0.2039*	0.6796***	0.5762***
Schooling (3-4 yrs)	0.08503	0.1435	0.24107**	0.3737**	0.1102
Schooling (>5 yrs)	0.03467	0.30415**	0.3142**	0.6916***	0.1907**
Extension	0.05334	0.16062*	0.1136	-0.1040	0.3209***
Membership association	0.5682***	0.83075***	0.7176***	0.7282***	0.2112*
Access to credit	0.3216***	.47820***	0.5385***	0.3583**	0.2243***
Farm size (0.75-1.75 ha)	-0.03776	-0.1677	-0.1485	-0.1979	-0.1871***
Farm size (1.75-5 ha)	0.0932	0.16872	0.01485	0.0695	0.3792***
Farm size (>5 ha)	-0.0013	0.21102*	0.2845**	0.2797*	0.0025
Distance (21-40 km)	-0.03860	0.35120***	-0.0124	0.0868	0.0747
Distance (>40 km)	-0.06682	0.2042*	-0.0815	0.0208	-0.0587
Easy access to land	0.00131	-0.51091***	-0.26621***	-0.1602	0.0275
Grow cotton	-.047853***	0.52870***	0.2823***	-0.3019	-0.7104***
Grow tobacco	-0.17684	1.6081***	0.7369***	-0.2375	0.0154

Legend: * p<0.05; ** p<0.01; *** p<0.001

Change in Technology Adoption Score

A regression analysis was performed on the "change in technology score" defined as the natural logarithm of the difference in the sum of "technology score" for each household. The explanatory variables included demographics and institutional variables hypothesized to influence household behavior towards new technology discussed in the preceding section. Table 6 reports the results of the first difference model in technology adoption score.

Table 6: First Difference Model of Technology Adoption Score Change.

Variable: Dependent Variable: Change in Score	Coefficient
Initial Level (2002)	
Household Head Age (40-49)	0.0252
Household Head Age (50-59)	0.0315
Household Head Age (>60)	0.0538
Household Head schooling (1-2 yrs)	-0.0060
Household Head schooling (3-4 yrs)	-0.0135
Household Head schooling (>5 yrs)	0.0713
Adult equivalent	-0.0093**
Hired temp labor	-0.0474
Hired permanent labor	-0.2670***
Extension (1 if yes 0 if not)	0.1795***
Association (1 if yes 0 if not)	-0.1643*
Credit access (1 if yes 0 if not)	0.4840***
Drought (1 if yes 0 if not)	-0.0778
Difference between 2005 and 2002	
Adult Equivalent Difference	-0.0080
Perm Labor Difference	0.1254*
Temp Labor Difference	0.1388***
Extension Difference	0.2450***
Association Difference	0.2630***
Credit Difference	0.7776***

Legend: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Changes in access to credit, access to rural extension and membership in an association positively affect the change in technology score. The findings are broadly consistent with the cross section results though with some differences in magnitude of effect. Controlling for unobserved heterogeneity across households notably weakens the impact of membership in an association, which was the strongest indicator in cross section. At the same time, contact with an extension agent comes through more strongly both in terms of initial level and first difference. The primary determinant of adoption shifts from membership in an association to access to credit.

The results of the regression of change in technology score show no statistically significant effect of the schooling level of the household head in 2002 on propensity to adopt between 2002 and 2005 while controlling for other factors. This result, combined with the generally impacts found in cross section, points to access as a key constraint to further technology adoption once a level of technical sophistication (which is associated with education) has been attained.

7. Conclusions

This paper examined the underlying determinants of agricultural technology adoption by rural households in Mozambique. The major findings can be briefly summarized. Access to credit, higher levels of education, access to extension advisory services, and members of agricultural associations are more likely to adopt new agricultural technologies.

The findings with respect to credit are particularly strong and robust. Difficulty in accessing credit appears to be one of the major constraints to technology adoption. This finding is reinforced by the strong association between the use of pesticide and growing cotton and the use of fertilizer and growing tobacco. The monopsony purchase rights granted in outgrower schemes help to overcome credit market failures by substantially increasing the probability that loan will be repaid. Countering credit market failures appears to be a high policy priority.

Membership in an association also appears to positively influence adoption decisions via improved information dissemination. Associations are also a potential for overcoming credit market failures. Uaiene (2006) has argued that inventory credit programs have the potential of creating confidence between farmers and financial institutions thus allowing farmers to have access to farm credit from such institutions using their collective grains in a community warehouse as collateral. Such inventory credit would be facilitated if farmers are grouped in associations.

The results also point to positive impacts of extension contact on adoption of new technologies. The role of extension comes through more strongly when household heterogeneity is accounted for using the panel data approach. Agricultural extension activities of the Ministry of Agriculture are widely recognized as understaffed and under funded. The finding of positive impacts associated with existing extension activities combined with international experience point to a strong rationale for increased efforts in the strategically important areas of public agricultural research and extension. As pointed out earlier, research and extension arguably should be the fundamental core of government support to agriculture.

Finally, the finding that households with easy access to land are less likely to adopt new technologies, particularly purchased inputs, points to the need for selectivity and a firm economic basis for the choice of technology. Land saving technologies, such as fertilizers and pesticides, are less likely to be adopted where land is abundant.

The cautionary tale in the preceding paragraph indicates that new technology adoption is not automatic. In addition, once adopted, the technology must be properly used if agricultural productivity is to increase. Nevertheless, without close attention to the use and adoption of improved agricultural technologies, production growth is likely to slow and rural poverty is likely to remain widespread. Despite more than a decade of effort, improved agricultural technologies currently play only a minor role in Mozambique. To increase the likelihood of adopting modern agricultural technologies by smallholder farmers, policy makers should put emphasis on overcoming credit market failures, access to advice via extension, organization of farmers into associations and improved education. Appropriately implementing these policy recommendations poses a significant challenge. The success of outgrower schemes provides an important model on which to build.

8. References

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