Productivity and Land Enhancing Technologies in Northern Ethiopia:

Health, Public Investments, and Sequential Adoption

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ABSTRACT

The adoption of more efficient farming practices and technologies that enhance agricultural productivity and improve environmental sustainability is instrumental for achieving economic growth, food security and poverty alleviation in sub-Saharan Africa. Our research examines the interaction between public investments, community health, and adoption of productivity and land enhancing technologies by households in the northern Ethiopian state of Tigray. Agricultural technology adoption decisions are modeled as a sequential process where the timing of choices can matter. We find that time spent sick and opportunity costs of caring for sick family members are significant factors in adoption. Sickness, through its impact on household income and labor allocation decisions for healthcare and other activities, significantly reduces the likelihood of technology adoption. Our findings suggest that agencies working to improve agricultural productivity and land resource conservation should consider not only the financial status of potential adopters, but also their related health situation.

Keywords: Microdam, Tigray, Ethiopia, Health, Sequential Adoption

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Developing countries face the dual tasks of increasing agricultural productivity and ensuring sustainability of the resource base on which agriculture fundamentally depends. The usual means to achieve these goals are through public investments with financial support from government agencies or non-governmental organizations (NGOs). Often, these investments take the form of incentives to adopt improved technologies, the argument being that growth in agricultural production should come from yield increases rather than area expansion (Eicher). For most sub-Saharan African countries, adoption of more efficient farming practices and technologies that enhance agricultural productivity and improve environmental sustainability remains the most practical option for achieving economic growth, food security, and poverty alleviation.

The northern Tigray region of Ethiopia provides a recent example. Tigray is the most land-degraded state of Ethiopia, with seriously eroded and nutrient-deficient arid lands (Hurni). The region is characterized by subsistence farm households raising predominantly cereal and vegetable crops for local consumption and sale. Crop production has declined during the last several decades due to the region's recurrent drought and heavy in-migration following recent civil wars. In response to these conditions, the government of Ethiopia initiated a major rural development program over a decade ago, called SAERT (Sustainable Agricultural and Environmental Rehabilitation in Tigray). Through SAERT, the government has installed several permanent microdams throughout the region. These microdams are for public use and are intended to bring irrigated agriculture to surrounding villages. The choice of location and costs associated with building microdams are the responsibility of the government, with help from external donors.

These partnerships and investments are targeted at adoption of technologies complementary to irrigated agriculture. Dams in Tigray are also afforested to serve as an alternative source of fuel, and therefore might complement technologies related to fuel use. However, microdam creation in Tigray might not always lead to widespread technology adoption or increases in agricultural productivity. The World Health Organization is concerned that these new sources of standing water may increase the prevalence of water-borne diseases. Two such diseases, malaria and shistosomiasis, are already present in Tigray, and microdams are feared to have increased their incidence (MUC). People with either disease may still be able to function in a household production role, but productivity in fields is lower, income may be lower, and more household time may be devoted to caring for the sick.

These diseases may affect technology adoption decisions through their impacts on household time and income. Households may have fewer resources to invest in new technologies. Or they may not have the opportunity to learn about new technologies, given the financial constraints and reduced work time that increased disease brings. Furthermore, farmers may view the technology decision as a sequential one, choosing to adopt one technology before another, given their need to balance income with demands of failing health. This important interaction between health and adoption behavior is missing from much of the development literature. In this paper we study the interaction of public investments, health, and technology adoption within the Tigray region.

Agricultural adoption has been studied extensively (see, for example, Griliches; Just and Zilberman; Feder, Just and Zilberman; Leathers and Smale; Caswell and Zilberman). This work generally focuses on adoption of a single new technology or a set of new technologies viewed by farmers as a single unit. The objective is to find what determines whether producers adopt or reject an innovation, or to examine the pattern of diffusion of innovations (Feder, Just and Zilberman). Commonly explored farm characteristics influencing adoption include farm size, land tenure, and other biophysical traits (Rahm and Huffman; Nowak; Baidu-Forson). Household characteristics include gender, age and education of household head, family size and other demographic traits. Institutional factors such as credit constraints, availability of information, and availability of extension services have also been examined.

There has been some research in the area of "technology packaging," where many agricultural technologies are made available at a given time as a package (Lele and Goldsmith). Byerlee and Polanco and Mann observed that farmers often choose only part of a given technology package, as opposed to the whole, and that they generally followed a stepwise process of adopting different pieces even though the components were strongly complimentary. Leathers and Smale present a theoretical model showing it can be rational for imperfectly informed farmers to undertake stepwise adoption, even when farmers are risk neutral and the entire package would be more profitable if adopted. Others have used conceptual models to identify profitability, riskiness, uncertainty, lumpiness of investment, and institutional constraints as possible explanations for sequential adoption (see Ghadim and Pannell; Feder and Slade; Ryan and Subrahmanyam; Mann).

Although this literature is extensive, little attention has focused on the effects of health on adoption. No work we are aware of addresses how technology adoption depends on the incidence of disease or health-related labor time adjustments. Furthermore most previous empirical studies in developing countries have assumed that farmers do not view the timing of technology adoption as important. These are the issues we focus on in this study. As we will demonstrate, health effects and the sequential nature of adoption are critical for the future packaging of technologies and water development projects in countries where water-borne diseases pose threats to the population.

The Case of Northern Ethiopia

Technologies for sustainable agricultural development programs may be classified roughly as *Resource Conserving* (RC) or *Productivity Enhancing* (PE). In Tigray, PE technologies include high yield crop varieties along with in-place irrigation schemes and fertilizers, while RC technologies include terraces and bands to control erosion, planting of multipurpose trees, and inter-cropping techniques. There have been few incentives for immediate adoption of either technology types. Most Tigray farming households have few resources to finance adoption, and the previous communist regime was not forthcoming with information. The fact that the government owns all land has further compromised adoption. A study of land tenure structure in Tigray by Gebremedhin, Pender and Ehui indicates that tenure security is highly likely to affect farmers' incentives to invest in their land.

Figure 1 summarizes the technology choices when timing of adoption is taken into account. We classify a farmer adopting high yield varieties as a 'PE-technology' adopter. A farmer practicing bands and terraces to control soil erosion is classified as a 'RC-technology' adopter.

We begin with the premise that because of profitability, risk, resource constraints, and limited information, sequential adoption is central to household decisions. For some farmers, the RC technology may be adopted first. For others, the PE technology may precede the RC technology. Others may choose to adopt everything at once or nothing at all. If farmers view these technologies as distinct pieces to be adopted in some order, then all must be treated as potential choice options. Ignoring the possibility of sequencing would erroneously reduce the available choices.

Data and Descriptive Statistics

Our data come from a World Health Organization (WHO) sponsored project undertaken in cooperation with the Mekele University College in Tigray, Ethiopia. The project involved a cross sectional survey of 800 households spread across the entire Tigray region during one major cropping season in 1996. Eight public microdams and twenty-nine surrounding villages were included in the sample. Fifteen of the twenty-nine villages were classified as intervention areas (those impacted by the dams due to their proximity to irrigation water). The rest were considered control villages not impacted due to their distance from the dams. This designation of intervention and control villages was made to ensure enough variation in the data and better link microdams and health to adoption. After missing data were discarded, 483 and 247 observations remained for intervention and control villages, respectively.

The survey was recall questionnaire-based and administered by enumerators trained and accompanied by the authors. Enumerators were chosen through an interview process conducted in cooperation with Mekele University College. Surveys were conducted on household heads and contained a detailed list of questions on household production, consumption, natural resource use, adoption rate and time of adoption of different agricultural and forestry technologies. Surveys also included questions on the health impact of microdams. There was a detailed list of questions on health, number of days a household member was sick, as well as demographic information and other characteristics important to decisions and preferences.

Table 1 presents definitions of variables and selected descriptive statistics. As shown in the table, our data are adopter-characteristic based, i.e., family and demographic attributes of the farm household such as age or education; physical characteristics of the farm such as farm size or its topography; economic factors such as input and output prices, household income; and institutional factors such as access to extension and information services. We augmented these typical variables with measures of health, home health care time, age and proximity of microdams, and access to natural resources and hired labor markets. In addition, data on technologies included the time different technologies were adopted, so that ordering could be identified.

Descriptive statistics are presented in table 1 for control and intervention villages. The average age of microdams is 5 years, although ages range from 1 year to 15 years old. Households in intervention villages appear more likely to engage in irrigation technologies and use improved stoves, compared to those living in control villages. Microdams also appear to be located where access to health centers is better, as the distance to health centers is on average two kilometers closer for intervention villages than control villages.

Now consider the health/sickness variables. We have two measures of disease, a personal assessment of each person as to the number of days suffered due to disease (the time sick variables), and a person's assessment of whether they were suffering from malaria. Given that people may not know what disease they have, the total time sick is a more reliable variable for establishing a link between productivity and health. However, malaria is a fairly recognizable ailment with clear symptoms. Nearly all individuals who reported being sick in our sample indicated that they were suffering from malaria or schistosomiasis-related ailments.

The prevalence of disease appears higher in intervention villages. Not surprisingly, the time household females spend at home caring for sick family members is three times higher in microdam areas than in control villages, which suggests there is a connection between disease and dams. Notice also that medical expenses are twice as high in these locations.

Hired labor use by households is greater in intervention areas. Fuelwood collection appears twice as high in control areas, perhaps because the opportunity cost of shifting labor away from crop production is lower there given that family members are less likely to become sick, or the decreased time females spend caring for sick family members frees them to engage in greater fuel collection and cooking activities.

Econometric Model

While sequential adoption and the impact of health on adoption could be treated as separate issues, we anticipate that sequencing is a better approach of modeling technology adoption behavior for resource-poor farmers in disease-prone areas such as Tigray. Ignoring whether farmers view technologies as pieces, adopted sequentially, may lead to inconsistent estimation of the effects of household characteristics on adoption. For example, a non-sequential adoption model would treat a bundle of two technologies adopted at different times as a single alternative, whereas a sequential model would rely on treating the bundle as two different choices depending on which technology was adopted first (see figure 1).

Our econometric specification takes into account the sequencing of technology adoption choices. We use a multinomial logit (MNL) model and explicitly allow for the fact that farmers may view adoption of one technology before another as a choice that is distinct from adopting in another sequence or adopting all technologies in the package.

Assume the utility of household i choosing technology j U_{ij} is a linear stochastic function of exogenous household characteristics X and endogenous household choices Z:

$$(1) \qquad U_{ij} = \alpha_j X_i + \beta_j Z_i + \varepsilon_{ij}$$

Assuming the errors ε_{ij} are independently and identically distributed with an extreme value distribution, the probability that alternative j is chosen from n alternatives can be represented by an MNL function (McFadden):

$$(2) \qquad \text{Prob(choice j)} = \frac{\exp(\alpha_j X_i + \beta_j Z_i)}{\sum_j^n \exp(\alpha_j X_i + \beta_j Z_i)}$$

Several econometric issues need to be addressed before estimation and analysis of the adoption model. As table 1 demonstrates, our data consist of household-based characteristics and choice variables. Exogenous variables include the market wage for hired labor, which reflects the opportunity cost of household time when labor markets are well defined, as they are in Tigray. However, home health care labor is an activity for which the household's own labor is preferred. A suitable wage rate is therefore not observed for this activity. Instead, the appropriate opportunity cost for home health care labor is an implicit wage that is a function of household characteristics and preferences. This cost can be estimated using a shadow wage rate (Thornton; Jacoby). Following Thornton and Jacoby, an agricultural production function was estimated, and then the lost marginal value product of time spent caring for sick members was calculated based on these estimates and time spent caring for the sick. The marginal value product is the shadow wage rate for males and females and serves as an instrument for the unobserved opportunity cost of male and female home health care time when estimating our model.

Other variables used, such as household labor and sick time, rental land holding and household income, are likely to be endogenous. Endogeneity arises because some of these variables represent household choices that could be correlated with the error in the adoption model. Similarly, time sick and income could be affected by adoption decisions and vice versa. In place of actual female and male hours worked, we use market wages for market labor activities and predicted shadow wages for household health care labor. Instead of total income, we use only a non-labor component of household income. This is unrelated to household production activities and composed of income households receive from non-labor activities and outside sources such as transfers and remittances from family members and relatives.

The endogeneity of time sick and rented landholding is addressed by using instrumental variables, where a predicted value of each variable is first estimated using a regression of the endogenous variable on all exogenous variables and suitable instruments. Then, the prediction is used in place of the endogenous variable when the adoption models are estimated.[1] This approach requires that appropriate instruments exist, i.e., the instruments employed are relevant (Bound, Jaeger, and Baker) and conditions for identification hold (Davidson and MacKinnon). We use the land rental fee as an instrument for rented land holdings. The average age of children, adult male and female members of the household, and distance to health center are used as instruments for adult and child time sick variables. These instruments are assumed to have a direct impact on time sick but only affect household technology adoption decisions through their impact on illness. The age of children is related to disease incidence but has no plausible direct association with adoption outcomes.

We employ several tests to examine the validity of our instrumental variables estimation (see table 3). Our relevance test involves testing whether the instruments are significant in explaining the endogenous variables. The test result strongly supports the relevance of our instruments (p-value = 0.00001). The overidentification test examines the joint null hypothesis that the excluded instruments are valid and correctly excluded from the estimated structural equation. We fail to reject the null hypothesis, lending further credence to the validity of the instruments (p-value = 0.300). An overall test of the instrumental variable approach using the standard Durban-Hausman-Wu test also shows that instrumental variables estimation was appropriate (p-value = 0.002).

Finally we accommodate heteroskedasticity of unknown a priori form (White; Greene), and adjust standard errors to account for our two-stage sampling procedure, given that villages were stratified according to proximity to microdams. This allows for robust estimation in cases where multi-stage sample designs are used (see Deaton).

Tests for Sequential Adoption

In this section we outline two tests for sequential adoption behavior. First, we employ a likelihood ratio test to determine whether MNL models based on sequential and non-sequential choices are equivalent. Secondly, we perform a Wald test on the null hypothesis that the coefficients of the two sequential choices (j = 4,5) are equal. Rejection of the null hypothesis will suggest whether farmers view the sequencing of one technology before the other as distinct from the opposite order.

If sequencing is ignored, the adoption model for Tigray includes only four alternative choices, j = 0, 1, 2, 3 (see figure 1). This implies the last two sequential alternatives (j = 4, 5) can be lumped with (j = 3) into a single choice. We can therefore undertake a likelihood ratio test by ignoring the timing of adoption and re-estimating the restricted model with just four alternatives. If the sequential model does not outperform the non-sequential one, then sequencing is irrelevant and there is no gain by incorporating the timing of adoption choices.[2]

Table 3 presents the likelihood ratio test for sequential adoption. The likelihood ratio test lends strong evidence against the restricted model (p-value = 0.0001), indicating that sequential adoption characterizes Tigray farmers' behavior. It confirms that a model accommodating sequential adoption will have better explanatory power than the traditionally estimated adoption models, which rely on lumping technology choices adopted at varying times into single alternative.

Result for the Wald test is also reported in table 3. We reject the null hypothesis that the coefficients of sequential choices (j = 4, 5) are equivalent (p-values = 0.001). This implies that households in the study area indeed view the choice of (j = 4) different than that of (j = 5). Clearly, ordering is important in our sample.

Both tests indicate that sequential decisions are important, and that farmers view different sequences of technologies as different choices. These results are expected. Most Tigray farmers have few resources to finance adoption of complete packages of technologies, and risk considerations are central in the decision to use new untested technologies with uncertain outcomes. Moreover, our descriptive statistics suggest that health seems to be an important factor in areas affected by microdams. We investigate these linkages below.[3]

Explaining Adoption Choices

We now turn to studying how the choice between alternatives in figure 1 depends on household and resource characteristics. Table 2 presents the results of the MNL estimation. Included are estimated coefficients and marginal probabilities for all choices. The marginal probabilities measure the expected change in the probability of a particular choice being selected with respect to a unit change in an independent variable (see Greene, 1995). Note that the sum of marginal probabilities with respect to a particular explanatory variable must equal zero, since the effects on mutually exclusive decisions must cancel out. This implies that, as an increase in a particular characteristic variable increases the adoption rate for some bundles, the adoption rate must decrease for others in the set of possible choices.

Many of the explanatory variables are statistically significant at a 10% significance level or less and had expected signs in most adoption choice equations. Household head education is positively related to adoption of the PE technology; however, education has an even stronger influence on sequential adoption of both technologies (see the marginal effects of household head education under (j = 4) and (j = 5) in table 2). Farmers with some education attainment are also less likely to go without adopting one or more of the technology choices: the marginal effect of the education variable is significantly negative for the probability of 'no adoption'. More educated households are commonly well informed and receptive, which translates to a higher likelihood of engaging in new technologies. This finding is in line with several previous studies which point out innovation is positively related to farmers' abilities to decipher and analyze information.

Landholding, the main resource of farmers, is highly and positively significant for all adoption choices. This result comes as no surprise, because farm size figures prominently in most adoption decisions (see, for example, Dorfman; Smale and Heisey; Pitt and Sumodiningrat). What is more interesting and informative of Tigray farmers is that their RC technology adoption responsiveness increases with higher access to the rental land market. Larger amounts of leased land are associated with increased adoption and inversely correlated with the baseline 'no adoption' probability. Adoption of resource conserving techniques are land intensive, and availability of rented land allows farmers more flexibility to experiment on their own land.

Limited access to input and output markets (measured by distance to market) has a negative effect on adoption probabilities. Farmers living far from markets face high transaction and information costs that may influence their adoption decisions. Perceptions of the profitability of new technologies are influenced by prices of inputs and outputs. Household exogenous income plays an important role in adoption decision. Households with higher non-labor incomes are less likely to adopt individual technology components separately; rather they choose the adoption of both technology types in sequential fashion. Recall this was one reason for sequential adoption behavior discussed earlier.

The marginal probabilities of predicted female and child sick time (the number of hours spent sick and not working) show that sickness has a significantly negative effect on adoption of all technology choices (see table 2). Higher cost for health care in terms of time spent taking care of sick family members, as measured by the shadow wage for male health care labor, implies that households with sick members are less likely to adopt both technology components. These findings show that household labor time sick, and opportunity costs incurred caring for the sick, significantly affect technology adoption. Note that time sick has a more pronounced negative effect on the adoption of productivity-enhancing technologies which usually tend to be more labor intensive. Projects with health side effects, through their impact on household labor allocation decisions for health care and other activities, reduce the likelihood of adoption.

Results for the sequential adoption choices, (j = 4) and (j = 5) are perhaps the most revealing. These decisions are significantly influenced by many household characteristic variables and in particular health factors. Household head education level significantly affects the decision to choose the PE followed by RC technology choice (j = 4), as well as the decision to choose the RC followed by PE choice (j = 5). More education makes farmers more likely to adopt a combination of RC and PE technologies, but less likely to report no adoption or adopt individual components separately. Thus, the education variable provides strong support for sequential adoption. Sequential choices (j = 4, 5) are significantly and positively affected by own landholding. This result reinforces our motivation for sequential adoption stated earlier. Farmers who decide to adopt a certain technology package would probably prefer to experiment with the components before fully committing to adopting the whole package. On the other hand, access to rented land appears to only affect choice (j = 5), particularly because this technology is more land intensive. Female labor time sick leads to a decline in adoption of choice (j = 4) but has no significant effect on choice (j = 5).

For Tigray farmers, the factors most important to technology adoption decisions are landholding, education, health, and the availability of own and hired labor. Sickness discourages farmers from adopting improved technologies, including both sequential choice alternatives (j = 4 and 5). This is especially important in Tigray, because microdam construction program is already feared to have caused serious side effects on the health of farming communities. Thus, policies targeted at health care infrastructure improvement or accessibility may improve the adoption of water and tree development programs. Greater access to healthcare and market centers will make farmers more likely to adopt both technology components, albeit in a sequential fashion. This result reinforces our motivation for accommodating sequential adoption. Farmers who decide to adopt a certain technology package would probably prefer to experiment with the components before fully committing to adopting the whole package. Finally, education also is consistently significant in all of the adoption choices. Increasing the awareness among farmers of new technologies will likely increase adoption rates.

Summary and Conclusions

Our study examines technology adoption decisions of farmers in the Northern state of Tigray, Ethiopia. Microdams in Tigray improve irrigation possibilities but also may reduce health of the population through increased water borne diseases. This may make simultaneous adoption of many technology packages infeasible, as poor health reduces income and increases time household labor must stay at home caring for the sick. These latter effects may reduce adoption incentives and also lead farmers to adopt technologies in a sequence.

Our empirical tests demonstrate strong evidence supporting the importance of accounting for sequential adoption. The most striking aspect of our study is examining the importance of health on adoption behavior. Sickness significantly reduces the likelihood of technology adoption. Households with poor health and high opportunity costs of diverting labor to health care activities appear less likely to adopt productivity enhancing as well as resource conserving technologies. Health care provision is especially critical in Tigray, because malaria and schistosomiasis are now feared to be perennial problems due to construction of microdams by the government during the past two decades.

We also find that microdams have some positive influences. Older and nearer microdams are correlated with higher adoption levels, perhaps because of improved irrigation possibilities. However, the positive effect on adoption of technologies due to these irrigation opportunities is partially offset by the negative health side effects.

This work has significant policy implications. Resource-poor farm households such as those in Tigray, who earn their livelihood in environments prone to disease risk, view sequencing as important in their adoption decisions. Agencies involved in improving adoption of productivity enhancing and resource conserving technologies thus need to emphasize stepwise dissemination. More importantly, our work underscores the importance of efforts to minimize health side effects of new technologies in order to achieve a higher rate of adoption. In the northern Ethiopian case, this requires recognizing how poor health and the increased costs of health care (in terms of both household time and expenditures) reduce adoption, and understanding how irrigation from microdams complements adopted technologies. Finally, our results make clear that steps to improve land and labor market function will likely increase adoption, thus helping to enhance productivity and resource conservation.

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Notes

[1] Because they are not the focus of our paper, the first stage and production function regression results are not reported in this paper; however, they are available from the authors up on request.

[2] Few households (only 9) reported simultaneous adoption of both technologies (j=3). This case is removed from further econometric analysis due to degrees of freedom concerns, making the number of alternatives in the sequential model 5 instead of 6.

[3] Please refer to Ersado et.al (2002) for the analysis of the impact of microdams on health.

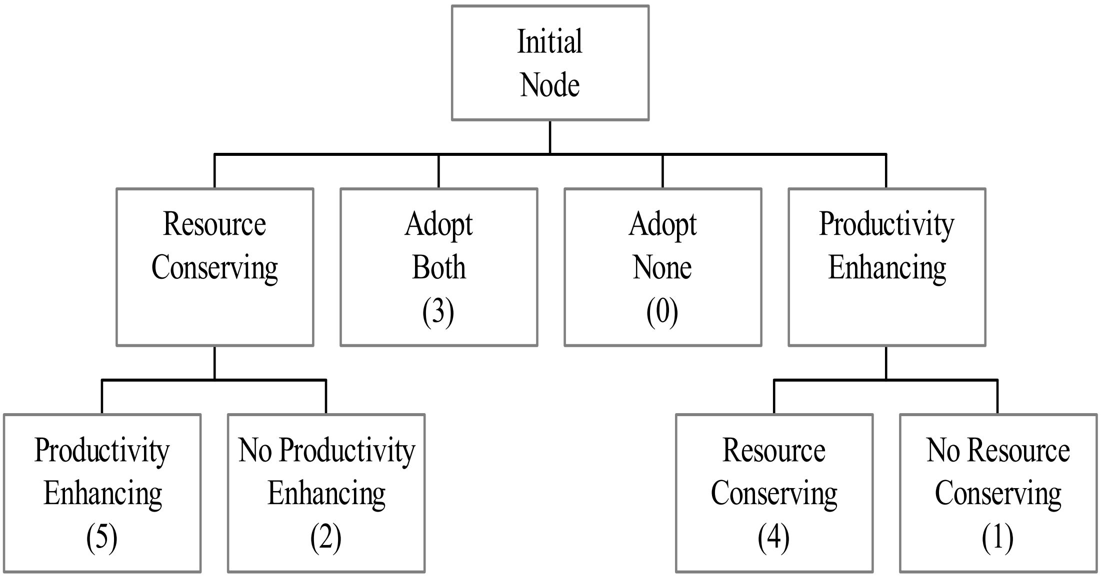

Figure 1. Sequential decision-making tree for technology adoption.

Table 1. Descriptive Statistics

Variable	Measured in	Control		Intervention	
		Mean	St. Dev.	Mean	St. Dev.
Micro dam age (in years)	Years	--	--	5.08	3.22
Household total income[1]	Birr[a]	1046.76	708.68	1080.72	854.92
Medical expenses for health care	Birr	13.68	46.69	23.10	55.23
Total fuelwood collected	DL[b]	16.46	14.49	11.23	15.22
Total own landholding	Timad[c]	4.61	3.30	4.73	2.47
Total rental landholding	Timad	0.84	1.89	1.60	3.43
Irrigation dummy	(Yes=1, No=0)	0.05	0.22	0.16	0.37
Cereal land area	Timad	4.04	2.78	4.05	2.21
Vegetable land area	Timad	0.33	0.71	0.32	0.90
Animal unit	Index[d]	3.70	2.76	3.64	3.63
Hired labor	Persondays[e]	4.40	15.27	12.99	44.05
Male labor wage rate	Birr/ day	9.34	2.56	9.04	2.55
Female labor wage rate	Birr/ day	6.74	1.65	6.63	2.21
Male off-farm wage labor	Persondays	16.31	30.47	5.63	22.29
Male labor time spent sick	Persondays	6.09	13.83	11.85	28.34
Male time taking care of sick	Persondays	0.17	1.25	0.98	7.92
Female off-farm wage labor	Persondays	7.27	15.19	1.55	11.01
Female time taking care of sick	Persondays	0.70	4.60	1.16	7.29
Female labor time spent sick	Persondays	9.74	19.11	16.70	36.85
Child labor time spent sick	Persondays	3.27	9.58	2.46	8.82
Malaria incidence dummy	(Yes =1, No=0)	0.19	0.40	0.32	0.47
Distance to market	Kilometers (KM)	9.63	4.45	7.03	4.14
Distance to health center	Kilometers (KM)	11.15	5.36	6.47	4.06
Distance to microdam	Kilometers (KM)	5.52	1.87	1.86	1.08
Harvest time cereal price	Birr per KG	1.68	0.37	1.77	0.43
Harvest time vegetable price	Birr per KG	2.16	0.47	2.23	0.54
Fuelwood price	Birr per DL	13.33	4.09	14.20	5.89
Agricultural residue price	Birr per sack	15.00	5.72	15.17	5.42
Ownership of improved stove	(Yes =1, No=0)	0.07	0.26	0.18	0.38
No. of household members	Number	5.26	2.23	5.09	2.25
Male labor for cereal production	Persondays	38.15	33.08	38.28	45.03
Vegetable production	Persondays	0.89	5.40	1.68	8.89
Fuelwood collection	Persondays	11.83	24.52	6.16	12.60
Female labor, cereal production	Persondays	17.73	23.79	17.63	26.59
Vegetable production	Persondays	0.39	2.75	0.40	3.78
Fuelwood collection	Persondays	12.38	23.54	8.11	21.39

[a]Exchange rate between Ethiopian Birr and US Dollar is about 1USD: 8.50 Ethiopian Birr); [b]DL stands for Donkey Load, which is about 25 Kilograms; [c]Timad,a traditional land measurement unit in Ethiopia, is about half hectare; [d]Animal unit index represents household livestock capital (ox, horse, donkey, cow, mule, sheep, goat, etc.); [e] one personday is equivalent to 8 hours of work a day.

Table 2: Estimates of Multinomial Logit Model Based on Sequential Choices.

Variable	Sequential Adoption Category				
	(j = 0) [a]	(j = 1)		(j = 2)	
	Marginal Effect (t-value)	Marginal Effect (t-value)	Coefficient (t-value)	Marginal Effect (t-value)	Coefficient (t-value)
Constant			.613 (.72)		-.422(.19)
Household size	.012(.75)	.000(.04)	.009(.11)	-.014(.96)	-.064(.79)
Household head sex (1=male, 0=female)	-.218(2.63)	.106(1.66)	1.14(2.39)	-.009(.13)	.457(1.13)
Household head education	-.033(1.95)	.021(1.64)	.213(2.00)	-.012(.60)	.002(.02)
Household head age	.146(1.56)	-.128(1.80)	-1.11(2.04)	.007(.10)	-.496(1.03)
Microdam age	-.040(2.20)	-.019(1.35)	.014(.16)	.057(3.44)	.303(4.04)
Household own tree holding	.000(1.76)	.0(.47)	-.001(1.00)	.0(.74)	-.001(1.18)
Animal unit	.020(1.45)	.002(.18)	.141(1.37)	-.006(.59)	-.137(1.35)
Distance to market	.030(2.65)	-.026(2.26)	-.145(2.02)	.013(1.97)	.008(.13)
Own landholding	-.062(3.45)	.004(.46)	.109(1.28)	.026(2.24)	.274(3.19)
Predicted rental landholding	-.047(2.15)	-.049(1.73)	-.262(1.22)	.068(1.73)	.408(1.87)
Wage rate	.010(1.37)	.004(.56)	.006(.07)	.097(1.13)	.058(.73)
Shadow price male healthcare labor	.050(1.80)	.012(1.40)	.012(.21)	-.026(2.05)	-.080(.59)
Shadow price female healthcare labor	.007(.31)	.018(1.47)	.121(1.25)	-.002(.07)	-.148(1.03)
Predicted male sick time	.055(2.65)	-.026(1.21)	.132(.80)	-.031(1.23)	.687(3.67)
Predicted female sick time	.067(2.27)	.048(1.84)	.033(.28)	-.109(2.84)	-.461(3.98)
Predicted child sick time	.062(1.95)	-.038(1.48)	-.323(1.93)	-.085(3.28)	-.329(2.17)
Household non-labor Income	-.028(2.23)	-.019(1.90)	-.119(1.70)	-.032(1.12)	-.186(2.70)
Number of Observations	240	113		108	

Note: The estimates of standard errors are adjusted for stratified two-stage sample design. The marginal probabilities are reported for all adoption choices including 'no adoption' (j = 0), unlike the coefficient estimates for which 'no adoption' is a normalized category in order to identify the MNL model parameters.

[a] (j = 0) ≡ Farmers with 'no adoption' of either technology

(j = 1) ≡ Farmers with adoption of *Productivity-Enhancing* (PE) technology only

(j = 2) ≡ Farmers with adoption of *Resource-Conserving* (RC) technology only

Table 2. Estimates of Multinomial Logit Model Based on Sequential Choices. (Cont…)

Variable	Sequential Adoption Category			
	(j = 4) [a]		(j = 5)	
	Marginal Effect (t-value)	Coefficient (t-value)	Marginal Effect (t-value)	Coefficient (t-value)
Constant		.294(1.34)		-.360(1.55)
Household size	.003(.95)	.182(1.23)	-.001(.19)	-.052(.42)
Household head sex (1=male, 0=female)	.013(.86)	1.06(1.26)	.108(2.32)	2.91(2.57)
Household head education	.014(2.13)	.473(2.87)	.010(1.86)	.369(2.65)
Household head age	-.022(2.06)	-1.73(1.83)	-.003(.08)	-.087(.11)
Microdam age	-.005(.77)	-.130(.51)	.008(1.12)	.220(1.83)
Household own tree holding	.000(1.13)	-.004(1.68)	.000(1.35)	-.003(1.83)
Animal unit	-.007(1.41)	-.011(.06)	-.010(1.78)	-.200(1.24)
Distance to market	-.005(1.11)	-.454(4.48)	-.012(1.67)	-.292(3.45)
Own landholding	.015(1.94)	.459(3.73)	.016(1.85)	.637(4.70)
Predicted rental landholding	.005(1.27)	.065(.19)	.027(1.73)	.421(1.77)
Wage rate	-.120(1.43)	-.134(.76)	.009(.24)	-.049(.37)
Shadow price male healthcare labor	-.010(2.06)	-.812(2.12)	-.019(1.95)	-.804(2.32)
Shadow price female healthcare labor	-.011(1.14)	-.119(.62)	.007(.86)	.032(.20)
Predicted male sick time	-.001(.48)	.227(1.34)	.003(.21)	.255(1.08)
Predicted female sick time	-.014(2.25)	-.627(3.02)	-.002(.29)	-.151(1.01)
Predicted child sick time	-.071(1.83)	-.359(1.98)	.010(1.11)	-.004(.02)
Household non-labor Income	.038(1.98)	.389(2.86)	.041(1.95)	.319(2.73)
Number of Observations	25		38	

Note: The estimates of standard errors are adjusted for stratified two-stage sample design.

[a] (j = 4) ≡ Farmers who adopted PE technology followed by RC technology

(j = 5) ≡ Farmers who adopted RC technology followed by PE technology

Table 3. Tests for Sequential Adoption and Instrumental Variables

Sequential Adoption Tests
Sequential choice model: Log-L = -439.46, restricted Log-L = -632.67, Chi-square statistic= 386.42 Non-sequential choice model: Log-L function = -504.84 restricted Log-L = -684.43, Chi-square statistic= 359.18 **Likelihood ratio test** of difference between sequential and non-sequential models): Chi-Square statistic=13.76, p-value = 0.00001 **Wald test** of difference between coefficients of the sequential choices (j=4 and j=5): Chi-Square statistic= 98.64, p-value = 0.00001
Instrumental Variables Tests
Relevance test (i.e., test the significance of instruments in first stage regressions): F-statistic is greater than 15.00 in all cases, p-value =0.00001 **Over-identification test** (i.e., instruments are uncorrelated with error terms and the model is correctly specified): Chi-square statistic =1.05, p-value =0.300 **Durban-Hausman-Wu test** (i.e., test whether the instrumental variables estimation made a difference): Chi-square statistic = 16.95, p-value =0.002