The Role Schooling in the Choice of Activities and Alleviation of Poverty in Rural Ethiopia

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Abstract

The impact of education on farmers' choice of activities and household welfare are modelled and estimated using farm household data for rural Ethiopia. We find that education has significant effects on household welfare. Schooling increases the adoption of new technologies and facilitates entry into highly profitable farm and non-farm activities, all of which may increase welfare and help farm households escape out of income poverty. An additional year of schooling in a household increases the welfare (measured in terms of consumption per adult equivalent) by 8.5 Percent. These findings provide a rationale to governments and donor organisations to include the expansion of rural schooling (through encouragement of parents to send their children to school) in their policy reform as a means of reducing material deprivation.

Keywords: Education, welfare, poverty and rural Ethiopia.

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1. Introduction

There is a growing concern that resources have to be mobilised in such away to have greater impact on poverty reduction so that poor countries can have long-term food security (World Bank, 2000). Long-term food security requires that farmers produce a surplus, which can be saved and invested. However, certain questions have to be answered first in order to design a mechanism on how to promote investment, bring economic growth and reduce income poverty. What are the factors that motivate farmers to adopt new technologies and to enter into profitable, but risky activities? Does education help farmers adopt new technologies, invest in profitable activities and there by reduce income poverty? What other factors determine income poverty?

Hence, it would be useful to know whether or not education (other factors) helps to raise rural incomes (and reduce income poverty) by encouraging the adoption of new technologies and enabling farmers to undertake risky, high-return activities. Such research is particularly timely for Africa, where food security is a persistent problem and where, to our knowledge, there have been no previous studies of the relationship between schooling and income poverty based on a well formulated representative data set.

There are several avenues by which education increases income and reduce income poverty. Education may lessen the inherent riskiness of agricultural activities by reducing uncertainty, (Knight, Weir and Woldehanna, 2003), as literacy and numeracy enhance the ability to receive, decode and understand information. Education also has non-cognitive effects upon attitudes and practices, which may enhance a farmer’s willingness to take on risk. For example, education may increase achievement-orientation and facilitate openness to new ideas and modern practices. Education also helps to increase farm productivity and household income available from various sources, acting as a substitute for (or complement to) access to credit and providing a buffer against the danger of starvation if a prospective innovation is unsuccessful and there by reduce vulnerability of households to risk.

The objective of the study is to consider whether schooling (education) is correlated with household welfare and to analyse the role of education in the adoption of new technologies and in undertaking higher-risk and higher-return activities and in reducing poverty. The paper is organised as follows. In section 2 the conceptual framework is presented. In section 3 previous studies are reviewed. The data used for the study, along with a discussion of farm and non-farm activities in rural Ethiopia, are described in section 4. In section 5 we outline our hypotheses and methodology. The estimation results are presented in section 6. Section 7 concludes.

2. Conceptual Frame Work

2.1. Poverty

Poverty has many dimensions (World Bank, 2000): material deprivation (measured by an appropriate concept of income or consumption); low achievement in education and health; vulnerability (exposure to risk) and voicelessness (and powerlessness). These four dimensions of poverty might interact and reinforce to each other (World Bank, 2001). Low level of education and health can lead to low level of income and hence might lead to material deprivation. Reducing vulnerability may allow people to take advantage of higher-risk, higher-return opportunities and there by decrease the material deprivation by increasing income and welfare. Here in this paper the relationship between the income poverty and education as well as the role of education in reducing vulnerability of people and in encouraging entry into higher-risk, higher-return activities are assessed. Consumption (rather than income) is viewed as the preferred welfare indicator in this paper as consumption better captures the long-run welfare level than current income, better reflect households' ability to meet the basic needs and reflects the household's access to credit and saving at times when their income is very low. In most developing countries, an income report of households is understated compared to consumption expenditure report. Here in this paper, the objective is not to estimate the level of poverty, but to assess the determinants of poverty. Hence we use consumption as indicator of poverty for our econometric model estimation.

2.2. Portfolio Choice, Education and Welfare

The presence of risk-preference in a farmer's behaviour means that risk factors may affect production and investment decisions. All else being equal, risk-averse households will diversify more, choose a lower-risk/lower-return portfolio of activities, and have lower average incomes, particularly if individuals have few opportunities to smooth consumption given income (Alderman and Paxon 1994). Risk averse farmers may smooth their income ex ante through income diversification and/or through adoption of drought resistant seeds, or crop diversification. Risk-aversion, or credit and insurance market imperfections may force a farm household to diversify its income sources (Eswaran and Kotwal, 1989). Risk-averse farmers will be willing to trade lower incomes for lower variability of incomes. Lower variability may be achieved by engaging in activities, which are negatively correlated with farm income and wealth, such as low-payng off-farm work and migration to towns. It is useful to distinguish between lower and higher return off-farm activities in order to determine whether risk factors or income factors prompt diversification of income.

Farmers often make adjustments within their cropping systems to reduce income risk. The cultivation of different crops or combining crop and livestock farming may be important risk management strategies.[1] Varying attributes of crops, such as the maturity period, drought tolerance, and the timing and quantity of labour and other inputs required, can affect the choice of crops.

Suppose that a farm household follows a von Neuman-Morgenstern utility function (*U=Eu(w)*), which is monotonically increasing with wealth (w), $Eu'(w) > 0$, and $Eu''(w) < 0$. Let us categorise household productive activities into two types: (1) those which are high-return and risky; and (2) those which are low-return and less risky. Assume that these two activities have distinct characteristics. Production in high return/risky activities (*HRA*) are characterised by constant returns to scale with labour (*L*), land (*G*), fixed capital (*K*), variable inputs (*X*), and others inputs (*O*) as the factors of production:

$$HRA = h(L, G, K, X, O) \qquad .(1)$$

Similarly, production in low return and less risky activities (*LRA*) are characterised by constant returns to scale with the same factors of production:

$$LRA = l(L, G, K, X, O) \qquad (2)$$

The farmer allocates his labour among activities (or chooses among the activities) so that the marginal productivity of labour (weighted by the marginal utility of income) is equalised across activities. In other words, the first order optimal condition for labour allocation will equalise the marginal product of labour (weighted by the expected marginal utility) to each activity (see for example, Dercon and Krishnan 1995; Dercon 1996):

$$Eu'(w).\left(\frac{\partial h(.)}{\partial L}\right) = Eu'(w).\left(\frac{\partial l(.)}{\partial L}\right) \qquad (3)$$

[1] Diversification of crops, while helping to lower income variability, can also increase farm income if crop diversification improves the match of crops with soil type.

If the farmer involve in high-return/risk activities only, the first order optimal condition for labour allocation can be written as:

$$Eu'(w).\left(\frac{\partial l(.)}{\partial L}\right) < Eu'(w).\left(\frac{\partial h(.)}{\partial L}\right) \tag{4}$$

The implications of this model are that (1) farmers' choice between these two activities can be attributed to their capacity to bear risk and (2) risk aversion. The impact of risk-aversion is shown in the model through the expected marginal utility of wealth ($Eu'(w)$). If a farm household is less risk-averse and is not constrained by capital and skill (education and/or ability), the utility of using labour in the higher-return, capital and skill intensive activities is higher than in low-return/less-risky activities. Farm households, which are relatively less risk-averse are most likely to be engaged in higher-return, risky activities. Furthermore, those with higher levels of education are likely to face fewer resource and skill constraints to investment in profitable activities. Hence, less risk-averse and more educated farmers will enjoy higher income. On the other hand, uneducated farmers are more likely to be employed in low-return/less risky activities and command lower returns to their labour and hence lower income.

3. Literature

In Tanzania, Dercon (1996) finds that there is a relationship between liquid assets and choice of less risky crops. Assets per adult decreases and the land-labour ratio increases the proportion of land allocated to the less risky crop (sweet potato), although the effect of the land-labour ratio is not statistically significant. The determinants of farmers' entry into cattle production, which is a higher-return activity (requiring lumpy investment and possibly entailing risk), are analysed for Tanzania by Dercon (1998). He finds those richer households own substantial cattle herds, while poor households specialise in low-return, low-risk activities. Households with lower endowments are less likely to own cattle, and the returns to their endowment are lower. The schooling of the household head increases income per adult in the cattle-owning group, but not in the non-owning group. The schooling of female adults increases the income of both the cattle-owning and non-owning groups, but the effect is three times larger for those who own cattle. The mean marginal return to male adult labour and land are considerably higher for cattle-owning households than for non-owners. This implies that cattle owners can allocate labour and land to higher return activities, both because they are able to enter into cattle-rearing and because they are less concerned with risk in their activity mix. Dercon and Krishnan (1995) also analyse the portfolio choice of Tanzanian and Ethiopian farmers. However, they do not use education as an explanatory variable, owing to the absence of data.

Feder, Just and Zilberman (1985) review a few studies on the effects of risk, uncertainty and human capital on the adoption of technology. Among them only Binswanger et al. (1980), using data on Indian farmer, estimates risk-aversion and uses it to explain the adoption of fertiliser. However, their results are mixed. The review concludes that empirical studies have very rarely treated the role of subjective risk.

The human capital empirical literature relating to the adoption of new technologies is well integrated with theory. This literature is inspired by the writings of Schultz (1964) who argues that the introduction of new technologies results in disequilibrium and sub-optimal use of inputs and technologies, and those changes in technology increase the value of farmer's entrepreneurial ability. Welch (1970) extended and applied the concepts of Schultz, suggesting that formal schooling plays a role in determining allocative ability and that the value of education increases with technology. Lockhead, Lamison and Lau (1980), in their review of 18 studies representing 37 data sets, find that education has a positive and significant effect on output in areas where farmers are modernising. Phillips (1994) extended their review (with 12 additional studies) and concluded that the effect of schooling varies across regions, being stronger in Asia than in Latin America, irrespective of the degree of mechanisation in those regions. Ram (1976) finds that the returns to education are higher in the progressive districts of India than in the backward districts. Rosenzweig (1978) finds that the probability of adoption of high-yield grain in the Punjab Region of India was positively related to education of the farmers. Jamison and Lau (1982), using a logit model of adoption of chemical inputs, find for Thailand that education affects the probability of adoption positively, but only above a threshold level of four years of schooling. Appleton and Balihuta (1996) review several African studies and find that the effect of schooling on agricultural output is usually not significant, though in some cases it can be large. Gerhart (1975) finds that the likelihood of adoption of hybrid maize in Kenya is positively related to education. Croppenstedt et al. (1998), using data from a 1994 USAID fertiliser marketing survey, find that literate farmers in Ethiopia are more likely to adopt use of fertiliser than those who are illiterate.

This review of previous studies indicates that, despite the well-formulated theory of human capital, empirical evidence on the role of human capital in raising the return to labour in peasant farming and consequently increasing the choice of high-return (but risky activities) is scarce. Furthermore, most of the literature is confined to Asia and Latin America. The mechanism by which education increases income and welfare of farm households and acts to encourage the choice of high-retun (but risky) activities has not yet been adequately explored. Therefore, the role of education in reducing poverty through the choice of profitable (but risky) activities will be the focus of this paper.

4. The Data Set

The data for this study are drawn from the Ethiopia Rural Household Survey (ERHS) conducted by the Department of Economics, Addis Ababa University, in collaboration with the Centre for the Study of African Economies (CSAE), Oxford, in 1994. The survey covers 1477 household in 18 *Peasant Associations* (each composed of several villages) spanning 15 w*oredas* (districts) in six regions. The 15 sites represent the most important agro-ecological zones in Rural Ethiopia.[2] The number of households surveyed in each site reflects the size of the *Peasant Association* (PA) in relation to the total size of all PA's surveyed. Female-headed households were also proportionally represented. Households were selected randomly using the PA registers. Each household was surveyed three times within approximately twelve months (early 1994, later in 1994 and early 1995), providing a picture of both current production and consumption activities and household characteristics. Topics covered included production, consumption, assets, credit, off-farm activities, migration, and livestock ownership. The first round also included a few questions on educational status and attainment. Further information on education, as well as historical recall on agricultural innovations, was provided in the second round of the survey (Dercon and Krishnan 1994).

Sixty-nine percent of farmers in the sample adopted new inputs such as fertiliser, insecticide, herbicide and fungicide, and 48 percent adopted more than one input at a time (Table 1). A negligible number of farmers stopped using the inputs adopted (2.7 percent). A large proportion of farmers also adopted a new crop, such as a vegetable, fruit (e.g., avocado) or cash crop (e.g., coffee and chat). The proportion of farmers who have adopted both inputs and a crop was 43 percent.

Maize, wheat, *teff* and barley are the most preferred crops in the four sites (Table 2). Among cereals, barley and maize are the most frequently grown crops. The riskiness

[2] Bevan and Pankhurst (1996) provide detailed information on each of the sites.

of activities can be partly evaluated using farmers' responses to the question "which crop is the worst affected by drought, pests and diseases"? Among the cereals, *teff*, maize and wheat are the worst affected (listed by 21, 25, and 30 percent of the respondents, respectively), while millet and barley are the least affected. Beans and sorghum are also quite vulnerable. Among the cash crops, coffee is the worst affected, but chat and *enset* are also mentioned.

Table 1: Adoption rate (percent) of new technology (1995)

Technology	Percent
Adoption of at least one new input	52.4
Stop using new inputs	2.9
Adoption of more than one new input	22.4
Currently using fertiliser	45.9
Currently using fungicide	2.6
Currently using herbicide	10.2
Currently using pesticide	5.4
Currently using innovative crops	65.2
Stop growing at least one adopted crop	30.2
Adoption of avocado	7.9
Adoption of chat	17.5
Adoption of coffee	26.8
Adoption of potato	14.4
Adoption of sugarcane	12.1
Adoption of vegetables	18.1
Adoption of both new crop and inputs	42.3
Currently use both new crop and inputs	37.5

Most extension activities in Ethiopia are related to crop production. Although Ethiopian agricultural research covers all crops and livestock production, the diffusion of technologies is limited at present to certain crops, such as *teff*, wheat and maize. The new technologies include fertiliser, improved seeds, fungicides and insecticides. *Teff*, which is the second most important crop (after maize), in terms of production output and the first in terms of area coverage, accounts for the highest share in total fertiliser consumed by farmers (Degefe and Nega 1999/2000). There are two types of *teff*: white *teff* and black (mixed) *teff*. Most of the fertiliser and almost all of the improved seeds are applied on white *teff*. The price of white *teff* is higher than the price of black *teff*, wheat and maize. Wheat also has a relatively high rate of input utilisation. Although maize is not characterised by high fertiliser application, it is second in the use of improved seeds. For barley and sorghum, the rate of application of fertiliser and the use of improved seed is very low.

We can surmise that white *teff* is a high-return/risky crop given that it commands the highest (but most volatile) price and the highest use of fertiliser and improved seeds and that it less drought-tolerant than other crops. If there is a failure in rainfall, farmers' investment in fertiliser and improved seeds is lost. Hence, it must be grown by relatively less risk-averse farmers. If farmers are highly risk-averse they may prefer to plant black teff or another cereal, which does not require high use of fertiliser and is more drought-tolerant. Hence, white *teff* is the best candidate to test whether risk-averse farmers have a lower probability of growing a high-return/risky crop.

Table 2: The percentage of farmers growing crops and riskiness of crops in Rural Ethiopia (n=1477)

	Percentage of farmers growing the crop	Percent reporting problem of drought, pest and disease
White teff	26.3	21.0
Black teff	19.5	-
Wheat	27.0	30
Barley	37.4	6
Maize	40.8	26
F. Millet	4.5	0
Coffee	25.5	52
Chat	12.4	18
Sorghum	20.9	20
Enset	28.6	45
Linseed	6.4	0
Lentils	3.7	-
Beans	20.7	18.1
Potato	5.9	54.0
Onion	5.2	

Livestock production is another potential candidate for testing the impact of schooling on entry into higher-return/higher-risk activities. However, livestock production in Ethiopia is not riskier than crop production. Although capital is required to enter, risk associated with livestock is lower than risk associated with crop production. Most Ethiopian farmers keep livestock to hedge against risk. During drought years, farmers sell cattle to feed their families. In our data, no adoption of new technologies related to livestock husbandry is reported. Hence investment in livestock may indicate risk-aversion. Indeed the preliminary model estimation shows that schooling increases to entry into livestock production activity, but not statistically significant.

Beyond crop and livestock production, farmers participate in various off-farm activities (Table 3). We choose to distinguish between low-return and high-return off-farm activities. Employment as a farm worker by another household, unskilled wage employment, domestic wage employment, and food-for-work programme employment are categorised as low-paying off-farm activities. Those categorised as high-paying off-farm activities include skilled wage employment (e.g., carpentry and masonry), teaching, employment as a soldier, driver, or mechanic, as well as employment in own off-farm businesses, such as weaving/spinning, milling, handicrafts/pottery, trading, pack animal transportation and traditional healing. Participation of farmers in high-paying off-farm activities is more common than participation in low-paying off-farm activities both in terms of participation and income share. Detailed summaries of the description of the data are given in Tables 4. Grain trade is the most popular activity among the high paying off-farm activities in terms of participation and share of income. Farmers' rate of participation in off-farm activities is very low in general because they are rationed in the off-farm labour market (Table 3c) and constrained by start up capital for high paying off farm activities. A considerable number of farmers can not work off-farm because their labour is needed on the farm.

Table 3a: Summary of education, off-farm work participation, adoption, and sex of the head (percent)

	Percent of participation
Percent of HHs with 1-3 years of sch.(Ed1_3)	41.3
Percent of HHs with 4-6 years of sch. (Ed4_6)	11.5
Percent of HHs with >6 years of sch.(Ed12)	3.2
Percent of HHs with 6-7 years of sch. (ED7)	1.1
Percent of HHs with >7 years of sch. (ED8)	1.8
Percent of female headed households (fehh)	20.7
Low paying off-farm work participation	20.0
High paying off-farm work participation	42.3
Over all off-farm work participation	57.1
Off-farm wage employment	22.2
Off-farm own business	38.9

Table 3b: Participation rates of various off-farm activities

Off-farm activities	%
Weaving	5.4
Milling	0.5
Handicraft	5.8
Trade in grain	10.5
Trade in livestock	1.0
Transport in pack animal	0.8

Table 3c: Reasons for not seeking off-farm employment

Reasons	%
No opportunity	47.9
Needed on the farm	23.4
Jobs to far away	2.0
Wages too low	1.5

Table 4: Description of variables

Variable	Description	Mean
ADOPINCR	Rate of technology adoption	0.42
GROWUSE	Rate of technology adoption and still using r	0.38
Aequ	Adult equivalent family size	4.85
Agehead	Age of the household head	46.26
AWTEFF	Area allocated for white teff (hectare)	0.18
Cons	Total consumption (USD)	445.59
Consae	Consumption per adult equivalent (in USD)	103.34
Conspa	Income per working family members (in USD)	155.17
Deprat	Dependency ratio	0.43
Ed1_3	Percent of HHs with 1-3 years of sch.(Ed1_3)	41.3
Ed12	Percent of HHs with >6 years of sch.(Ed12)	3.2
Ed4_6	Percent of HHs with 4-6 years of sch. (Ed4_6)	11.5
Ed7	Percent of HHs with 6-7 years of sch. (ED7)	1.1
Ed8	Percent of HHs with >7 years of sch. (ED8)	1.8
Fehh	Dummy for female headed household	0.21
Hhsize	Household size	6.10
Nudehh1	Number household members ≤ 15years old	1.71
Nufehh	Number female household members > 15 years old	1.66
Nufehh2	Number female household members > 15 years old squared	
Numahh	Number male household members > 15 years old	1.57
Numahh2	Number male household members > 15 years old squared	
School	The average number of schooling for a household	1.7
Soffin	Income from high-return off-farm work	81.45
Soffp	Participation in high-return off-farm activities (1 if household participates)	0.42
Tlandpa	Total land per adult equivalent in hectare	0.49
TOTLAND	Total land cultivated in hectare (a measure of farm size)	2.03
Totland2	Total land cultivated squared	
Uoffin	Income from low-return off-farm work	30.78
Uoffp	Participation in low-return off-farm activities (1 if household participates)	0.20
Wealth	Wealth (value of livestock and farm implements) measured in Birr	2292.48
Wealthpa	Wealth per adult equivalent	482.73
Wteffp	Participation rate in growing of white teff (1 if a household grows white teff	0.26

5. Econometric Models and Methods of Estimation

The following hypothesis is tested: does schooling increases household welfare by enabling farmers to enter higher-risk/higher-return agricultural and non-agricultural activities? To answer this question, econometric models of technology adoption, entry into high-return/high-risk activities and household welfare are specified following the theoretical models discussed in section 2.

The adoption of new technologies by farmers can be modelled as:

$$U_i(A) = \alpha' X_{Ai} + e_{Ai} \tag{5}$$

where U_i is the net utility gain of a household from using a new technology (*A*); X_{Ai} is a vector of location, farm and household characteristics, physical capital (e.g., wealth) endowments, human capital endowments; and e_{Ai} is an independently and identically distributed household specific *ex ante* shock. If $U_i > 0$, a household adopts the new technology, whereas if $U_i \leq 0$, the household does not adopt. Consequently, the probability of adopting a new technology is given by:

$$prob(A_i = 1) = prob(e_{Ai} > -\alpha' X_{Ai}) = 1 - F(-\alpha' X_{Ai}) \tag{6}$$

where A_i is an index of technology adoption which is equals 1 if the household adopts the new technology and zero if the household does not adopt the new technology; and *F* is the cumulative probability distribution function of e_{Ai}.

The model of portfolio choice can be used to build an econometric model of farmers' entry into high-return/high-risk activities. Assume that the expected marginal utility of allocating labour to high-return/high-risk activities is given by *U'(HRA)* and the expected marginal utility of allocating labour to low-return/low-risk activities is given by *U'(LRA)*. Assume also that

$$U'(HRA)\text{-}U'(LRA) = \gamma' X_{Ci} + e_{Ci} \tag{7}$$

where X_{Ci} are variables affecting the expected marginal utility of undertaking both the high-return/high-risk activities and the low-return/low-risk activities; and ε_{Ci} are identically and independently distributed household specific shocks. Consequently, the probability that a farm household will undertake high-return/high-risk activities is given by:

$$\begin{aligned} prob(HRA_i = 1) &= prob(U'_i(HRA) - U'_i(LRA) > 0) \\ &= prob(\varepsilon_{Ci} > -\gamma' X_{Ci}) = 1 - F(-\gamma' X_{Ci}) \end{aligned} \tag{8}$$

$$\begin{aligned} prob(LRA_i = 1) &= prob(U'_i(HRA) - U'_i(LRA) < 0) \\ &= prob(\varepsilon_{Ci} < -\gamma' X_{Ci}) = F(-\gamma' X_{Ci}) = 1 - F(\gamma' X_{Ci}) \end{aligned} \tag{9}$$

where HRA_i and LRA_i are index of activity choices of higher return and lower return, respectively, F is the cumulative distribution function of e_{Ci}. In the probability models of (6), (8) and (9), the functional form of F will depend on assumptions made about the error terms. Assuming the cumulative distributions of the error terms (e_i) are logistic, we utilise logit models (Maddala 1983, 22) of subjective risk-aversion, technology adoption and entry into high-return/high-risk activities. For (8), for example, the logit probability model is given by:

$$prob(HRA_i = 1) = 1 - F(-\gamma' X_{Ci}) = \frac{\exp(\gamma' X_{Ci})}{1 + \exp(\gamma' X_{Ci})} \tag{9}$$

in which the parameters γ (α in the case of (6)) can be estimated using the maximum likelihood estimator (MLE).

The household welfare (C), measured as household consumption per adult equivalent is modelled as:

$$\log C_i = b_0 + \sum_{j=1}^{6} b_j X_{ij} + u_i \tag{10}$$

where

C_i = natural logarithm of consumption per adult equivalent;[3]

X_{i1} = environmental factors (captured by site dummies);

X_{i2} = physical capital (livestock and farm implements), and physical capital squared;

X_{i3} = human capital (such as schooling, experience (age), and schooling and age squared);

X_{i4} = farm characteristics (such as farm size, farm size squared and use of new technology);

[3] Adult equivalent family size is computed based on the calorie requirement given by the food composition table prepared by West (1987).

X_{i5} = household characteristics (such as the number of working male and female household members and the number of working male and female household members squared, the number of dependants and sex of the household head);

u_i *and* v_i = error terms.

In all models, schooling is defined as average years of schooling of adults in the household. The use of individual education (such as that of the head or wife) may obscure the relationship between human capital, on the one hand, and technology adoption, risk-aversion, and activity choice, on the other.[4] Owing to traditional ties and the lack of a highly developed division of labour, members of a household are likely to share ideas with each other. In addition, since farming is a family enterprise, it is likely that farm decisions are taken following discussion among household members.

If any of the explanatory variables in an econometric model are endogenous, they will be correlated with the error term, and the parameter estimates will be biased. Hence, the Durbin-Wu-Hausman test of endogeneity, tests for the relevance of instruments and a test of over-identification must be performed (Davidson and MacKinnon 1993, 209-242). For a continuous dependent variable, the test involves regression of each endogenous variable on the instruments and other exogenous variables in the model. Next, the original dependent variable is regressed on the original regressors, augmented by the residuals from the first stage instrumental variable regressions. Under the null hypothesis, the coefficients of the residuals are jointly zero and OLS estimation of the model yields consistent estimates. The alternative hypothesis is that the coefficients of the residuals are not zero and OLS estimation of the model will not yield consistent estimates. The test statistic is distributed as $F_{m,\ N-k}$, where m is the number of endogenous variables, N is the sample size, and k is the number of parameters estimated.[5] The relevance of the instruments is tested by regressing each of the suspected endogenous variable on instruments and other exogenous variables in the model and performing F-tests of the joint significance of the instruments. The validity of the choice of instruments may be tested, at least to a limited extent, by an over-identification (OID) test. Following Davidson and MacKinnon (1993, 236), a regression of the instrumental-variables residuals on the full instrument matrix gives rise to a Lagrange multiplier test statistic (R-squared multiplied by N) for the joint null hypothesis that the equation is properly specified and the instruments are valid (i.e. uncorrelated with the error term). The test statistic, under the null, is distributed as

[4] We have tried to use the schooling of the household head alone, but it was not significant in any of the estimations.

[5] The same procedure can used to test the endogeneity of explanatory variables in limited dependent models, such as logit, probit and tobit models (Smith and Blundell 1986).

$\chi^2(m)$, where m is the number of over-identifying restrictions. A rejection of the null hypothesis casts doubt on the validity of the instruments.

For all models, robust standard errors (from which the t-ratios are derived) are ensured by adjusting for the cluster effects (see Deaton 1997, 73-78 for a discussion and formulas used to derive standard errors). The ERHS used stratified random sampling in which Peasant Associations were first selected and farm households were then chosen randomly from each site. The peasant associations selected for the survey are widely separated geographically and may have distinct characteristics. There may be more homogeneity within peasant associations than between them. Hence, we control for cluster effects in the econometric estimation.

6. Estimation Results

6.1. Schooling and Technology Adoption

Equation of technology adoption is specified as a dichotomous variable set equal to one if a farmer has adopted at least one innovative input and at least one innovative crop and zero if the farmer did not adopt both an innovative input and an innovative crop. This fairly strict definition of technology adoption was chosen because many households have adopted either a new input or a new crop but adopting both is more rare and indicates a greater commitment to innovation than having adopted only one or the other.

Innovation adoption is assumed to be dependent on the sex and age of the household head, land owned per adult equivalent and schooling. Site-specific fixed effects are also expected to play an important role. Hence, we will control for these using site dummy variables. We do not control for other potentially relevant variables, such as household income and land quality, because of possible endogeneity and because current values of such variables may not reflect conditions at the time when the adoption decision was made. Land quality may have been improved but, since it cannot be bought or sold, land quantity is likely to be exogenous.

The Durbin Wu-Hausman test was performed to determine whether schooling is endogenous to the model.[6] However, the null hypothesis that the suspected endogenous variables are at least weakly exogenous cannot be rejected. The *p-value* is very high (0.76). Hence, the logit model of technology adoption is estimated without instruments.

[6] The instruments used are: the average age of adult members, the number of household members who can read and write, a dummy for whether the head of the household can read and write, and the number of extension visits.

The estimations result for equation (6) of our theoretical model with technology adoption as the dependent variable are given in Table 5. The probability of adopting new technologies increases with the age of the household head, but not statistically significant. The coefficient on the dummy for being a female-headed household is negative and significant. This suggests that female-headed households are less likely to adopt innovations than male-headed households. Land cultivated per adult equivalent does not show statistically significant effect on technology adoption. Once again, the site dummies are highly significant, indicating that there are important site fixed effects, which determine whether or not households will adopt innovations.

Controlling for other factors, which affect adoption, schooling has a statistically significant influence on the willingness of farmers to adopt new technologies. The higher is the average of years of schooling of adults in the household, the greater the probability of adopting innovations. Re-estimating the model with years of schooling replaced by a series of dummy variables to indicate whether average education in the household is between 1 and 3 years, 4 to 6 years or more than 6 years, we find that households where average education is at the secondary level are more than twice as likely to have adopted new technologies as are households where average education is at the primary level. The positive effect of education on technology adoption may be related to the existence of credit constraints which may be less binding for more educated people. Moreover, education is positively associated with technology adoption as educated farmers are less subjectively risk averse than the uneducated ones (Knight, Weir and Woldehanna, 2003),

Table 5: The effect of schooling on technology adoption (dependent variable = ADOPINCR, n=1043)

	Version one			Version two		
ADOPINCR	**Coefficient**	**T-ratio**	**Marginal eff.**	**Coefficient**	**T-ratio**	**Marginal eff.**
Fehhh	-0.788	-2.940	-0.197	-0.710	-2.579	-0.177
Agehead	0.003	0.432	0.001	0.003	0.440	0.001
School	0.102	1.138	0.025			
ed1_3				0.591	3.713	0.148
ed4_6				0.440	1.110	0.110
ed12				0.965	1.663	0.241
Tlandpa	-0.039	-1.000	-0.010	-0.041	-1.079	-0.010
Constant	-1.558	-3.817	-0.389	-1.819	-4.880	-0.455
Pseudo R2	0.469			0.725		
Log likelihood	-383.480			-380.980		
Hausman test of endogeneity	$\chi^2(1)$=0.094; p-value=0.759					

There are 10 site dummies not shown here for the purpose of economising space. Site 14 drops because it predicts failure completely. Hence 113 observations were dropped.

6.2. Schooling and Activity Choice

Estimation results for equation (10) in our model (predicting the probability of growing white *teff* and participating in unskilled and skilled off-farm work) are presented in Tables 6 and 7. Since white *teff* commands one of the highest (but the most volatile) cereal prices and is highly associated with extension activities, schooling should influence the decision to grow this crop. If farmers are less educated, they can choose low-paying/low-risk activities. To test whether schooling is important to activity choice, we estimated logit models of growing white *teff* and of working in low-return and high-return activities.

In all three logit models, we use sex of the household head, age of the household head, the square of age, wealth, farm size, the square of farm size, the number of male and female working family members, the square of number of male and female working family members, the number of dependants, average years of schooling of adults in the household, and site dummies.[7] In addition, the squares of wealth and schooling are included only in the logit model of growing white *teff*.[8]

The Durbin Wu-Hausman test of weak exogeneity was performed to test whether wealth, and schooling are endogenous to the models.[9] F-tests reject the null hypothesis that the variables are jointly exogenous for the probability of participating in high-paying off-farm activities, but not for the probability of growing white *teff* and participating in low-paying off-farm activities. Hence, instrumental variables estimation is used for the logit model of high-return off-farm work participation. For the others, we use uninstrumented logit models.

The probability of growing white *teff* is estimated, and the results are presented in Table 6, female-headed households are significantly less likely to produce white *teff* than male-headed households. This indicates that households headed by women

[7] Because *teff* (white *teff*) is not grown in Imdibir, this site is dropped from the estimation.
[8] Preliminary regressions showed that the squares of wealth and schooling were not significant in the off-farm work participation equations.
[9] Instruments include: the number of household members who can read and write, a dummy for whether the head of the household can read and write, the average age of adults in the household, the average age of the household's dependants, a dummy indicating whether or not the father of the household head was a farmer, a dummy for whether the household has a house made from cement and a metal roof, the amount of grazing land available to the household, and consumption per adult equivalent.

face constraints which are not encountered by male-headed households. Age of the head is not significant. Farm size and wealth, all influence the probability of growing white *teff* positively, but at a diminishing rate. Farm size has positively affects the probability of growing white *teff*, reaching a maximum at 2.8 hectares of land (above mean farm size). The positive effect of farm size and wealth might be due the fact that wealthy farmers are less risk averse and have the capacity to cope up with risk. Schooling affects the probability of growing *white teff* positively, but at a diminishing rate. However, the coefficient of the average years of schooling of adults is not statistically significant. Using a series of dummy variables do not affect the result either.

Table 6: The logit (probability) of growing white teff (dependent variable=wteffp, n=961)

	Coef_OLS	T-ratio
Fehhh	-0.407	-1.220
Agehead	-0.041	-1.017
age2	0.001	1.357
TOTLAND	1.337	6.143
totland2	-0.114	-4.638
Numahh	-0.070	-0.226
Nufehh	-0.147	-0.458
numahh2	-0.001	-0.019
nufehh2	0.029	0.514
nudehh1	-0.095	-1.187
School	**0.170**	**1.207**
School squared	**-0.026**	**-1.592**
Wealth/100	0.036	3.819
Wealth/100 squared	-0.0001	-2.017
Constant	-0.233	-0.230
N	961	
Log likelihood	-318.233	
Pseudo R^2	0.484	
Hausman test of endogeneity	$\chi^2(4)$ =2.03; P-value 0.73	

Estimation results for participation in low return and high return off-farm activities are given in Table 7. Female-headed households and those with lower adult household members have a lower probability of participation in these low-return off-farm activities than male-headed households and those with higher adults. Farmers with more land are expected to have a lower probability of working in low-return off-farm activities. This is found to be the case. However, the coefficient on farm size is not statistically significant. Not surprisingly, the site dummy variables are also important. This may reflect differences in opportunities or in the necessity for such activities between the sites. Schooling is found to decrease the probability of entry into low-return off-farm work.

There are 10 site dummies not shown here for the purpose of economising space. Site8~=0 predicts failure perfectly, site8 dropped and 93 obs not used, site14~=0 predicts failure perfectly, site 14 dropped and 114 obs not used; site16~=0 predicts failure perfectly, site16 dropped and 62 obs not used; Note: site12~=0 predicts failure perfectly and site12 dropped and 63 obs not used

6.3. Human Capital and Household Welfare

To test the effect of schooling, wealth and other household and farm characteristics on household welfare, equation (10) is estimated with consumption per adult equivalent as the dependent variable. Consumption per adult equivalent is used as a proxy for welfare. The explanatory variables used are site dummies, age, the square of age, farm size, the square of farm size, the numbers of working male and female family members and the squares of the numbers of working male and female family members, the number of dependants, wealth, the square of wealth, schooling, the square of schooling, and a dummy variable for the adoption of new technologies.

Table 7: The logit (probability) of working in low and high paying off-farm activities (dependent variables = uoffp, soffp, n=1295)

	UOFFP (ols)			SOFFP (IV estimator)		
	Coefficient	Marginal effect	T-ratio	Coefficient	Marginal effect	T-ratio
Agehead	0.056	0.006	1.478	0.054	0.013	2.071
age2/100	-0.072	-0.007	-2.091	-0.058	-0.014	-2.272
Fehhh	-0.758	-0.076	-2.592	-0.174	-0.041	-0.821
Wealth/100	-0.024	-0.002	-3.739	-0.004	-0.001	-0.358
TOTLAND	-0.090	-0.009	-1.048	0.026	0.006	0.337
totland2	0.001	0.0001	1.202	-0.0002	-0.00004	-0.352
Numahh	0.539	0.054	1.680	0.241	0.056	1.193
Nufehh	0.456	0.046	1.658	0.012	0.003	0.057
numahh2	-0.087	-0.009	-1.617	-0.042	-0.010	-1.288
nufehh2	-0.064	-0.006	-1.150	0.034	0.008	1.494
nudehh1	-0.104	-0.010	-2.604	-0.023	-0.005	-0.512
School	-0.124	-0.012	-1.951	0.255	0.060	2.235
Constant	-2.082	-0.209	-2.308	-3.225	-0.754	-3.587
Log likelihood	-473.751			-693.524		
PseudoR2	0.242			0.294		
N	1295			1455		
Hausman test of endogeneity	Ch(2)=3.743; P-value = 0.1589			Ch(2)=9.139; P-value = 0.0104		

There are 10 site dummies not shown here for the purpose of economising space.

Table 8: Determinants of welfare (dependent variable = natural logarithm of consumption per adult equivalent)

Explanatory variables	Version 1		Version 2	
	Coefficient	T-ratio	Coefficient	T-ratio
Agehead	-0.015	-1.923	-0.020	-2.746
age2/100	0.013	1.825	0.016	2.451
Wealth/100	0.011	1.199	0.012	1.364
Wealth/100 squared	0.000	-0.947	0.000	-1.124
School	**0.077**	**3.120**		
School squared	**0.005**	**1.063**		
ed1_3			**0.090**	**2.856**
ed4_6			**0.176**	**3.869**
ed7			**0.623**	**4.601**
ed8			**0.47875**	**2.882**
ADOPINCR	**0.157**	**2.199**	**0.150**	**2.097**
TOTLAND	0.025	2.326	0.023	1.968
totland2	-0.0002	-2.429	-0.0001	-2.054
Numahh	-0.112	-1.590	-0.109	-1.660
Nufehh	-0.199	-3.564	-0.204	-3.404
numahh2	0.002	0.372	0.006	0.982
nufehh2	0.028	3.387	0.029	3.132
Nudehh1	-0.098	-3.184	-0.100	-3.328
Constant	4.898	7.915	5.001	8.561
R^2	0.297		0.298	
Durbin Wu-Hausman test	F(5,1207) = 2.95; P-value =0.012			
Over-identification test	$\chi^2(1)$ = 1.806; P-value = 0.179			

The effect of technology adoption, area of land cultivated, and labour endowments on household income (welfare) are positive, and statistically significant. The effect of wealth is not found to be statistically significant, possibly due to multicollinearity. Controlling for other factors, schooling significantly explains the variation in the welfare level of households in rural Ethiopia. Schooling significantly increases household income and hence welfare. On the average one year of schooling is calculated to increase household welfare by 8.5 percent. The possible mechanism for schooling to increase household income (and hence welfare) is by enabling household to adopt new technologies and to enter into profitable off-farm activities.

7. Conclusions

Using data from the Ethiopia Rural Household Survey, we have been able to assess the effects of schooling and innovative behaviour upon household consumption per adult equivalent (a proxy for household welfare and poverty) are considered. We found evidence to suggest that human capital have both direct and indirect effects on income poverty (household welfare). Schooling affects poverty indirectly through its effects upon increasing the adoption of innovations. The other mechanism by which schooling reduces poverty is by enabling farmers to enter into profitable non-farm activities. In total, an extra year of schooling raise household welfare (income per adult equivalent and hence reduce poverty) by 8.5 percent. Furthermore, strengthening the extension system, increasing endowment of quality of labour and assets might help to reduce income poverty.

Given the evidence on the role of schooling on entry into higher-return/high-risk investment activities and the adoption of technologies, education will have far reaching effects in rural Ethiopia. By investing more in human capital, farmers become more willing and more able to adopt technology and consequently earn higher income and escape out of income poverty. Hence expansion of education can be used a mechanism to reduce rural poverty in Ethiopia. These findings may provide an incentive to governments and donor organisations to expand rural schooling and encourage parents to send their children to school as a means of reducing material deprivation (income poverty).

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