THE ROLE OF SCHOOLING IN THE ALLEVIATION OF RURAL POVERTY IN 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 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.

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?

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, 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. 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. 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.

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. In short, the focus of the paper is to see the role of education in reducing income poverty through the choice of profitable (but risky) activities in Ethiopia.

The paper is organised as follows. In section 2 the conceptual framework is presented. The data used for the study, along with a discussion of farm and non-farm activities in rural Ethiopia, are described in section 3. In section 4 we outline the model and method of estimations. The estimation results are presented in section 5. Section 6 concludes.

MODEL OF PORTFOLIO CHOICE, EDUCATION AND WELFARE

The presence of risk-aversion 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. Risk-aversion, combined with credit and insurance market imperfections, forces a household to diversify its income sources.

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:

$$HRA = h(L, G, K, X, O) \tag{1}$$

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

$$LRA = l(L, G, K, X, O) \tag{2}$$

The farmer allocates his labour among activities so that the marginal productivity of labour (weighted by the marginal utility of income) is equalised across activities.

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

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.

DESCRIPTION OF THE DATA

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.

Detailed summaries of the description of data are given in Table 1. 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. 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.

Table 1. Description of variables.

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

Maize, wheat, *teff* and barley are the most preferred crops in sample sites. The riskiness of activities 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.

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. Hence, it must be grown by relatively less risk-averse farmers. 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. 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. 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.

ECONOMETRIC MODELS AND METHODS OF ESTIMATIONS

Econometric models of technology adoption, entry into high-return/high-risk activities and household welfare are specified. 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:

$$prob(HRA_i = 1) = prob(\varepsilon_{Ci} > -\gamma' X_{Ci}) = 1 - F(-\gamma' X_{Ci}) \tag{8}$$

$$prob(LRA_i = 1) = prob(\varepsilon_{Ci} < -\gamma' X_{Ci}) = F(-\gamma' X_{Ci}) = 1 - F(\gamma' X_{Ci}) \tag{9}$$

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 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;[1] 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); 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* ν_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.[2] 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.

The Durbin-Wu-Hausman test of endogeneity, tests for the relevance of instruments and a test of over-identification are performed (Davidson and MacKinnon 1993, 209-242)[3]. For all models, robust standard errors are ensured by adjusting for the cluster effects.

ESTIMATION RESULTS

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 rarer 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 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.[4] 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.

The estimations result for equation (6) of our theoretical model with technology adoption as the dependent variable are given in Table 2. 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 suggesting that female-headed households are less likely to adopt innovations than male-headed households. Land cultivated per adult equivalent does not show statistically

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

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

[3] 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 $F_{m,\ N\text{-}k}$, where m is the number of endogenous variables, N is the sample size, and k is the number of parameters estimated.[3] 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 $\chi^2(m)$, where m is the number of over-identifying restrictions. A rejection of the null hypothesis casts doubt on the validity of the instruments.

[4] 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.

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.

Table 2. 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.

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.

Schooling and activity choice

To test whether schooling is important to activity choice, we estimated logit models of growing white *teff* (assumed to be highly risky, but with higher return) 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.[5] In addition, the squares of wealth and schooling are included only in the logit model of growing white *teff*.[6]

The Durbin Wu-Hausman test of weak exogeneity was performed to test whether wealth and schooling are endogenous to the models.[7] 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 3, female-headed households are significantly less likely to produce white *teff* than male-headed households. This indicates that households headed by women face constraints which are not encountered by male-headed households.

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[5] Because *teff* (white *teff*) is not grown in Imdibir, this site is dropped from the estimation.

[6] Preliminary regressions showed that the squares of wealth and schooling were not significant in the off-farm work participation equations.

[7] 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.

Table 3. The logit (probability) of growing white teff
(dependent variable = wteffp, n=961).

	Marginal effects	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 and P-value 0.73.
There are 10 site dummies not shown here for the purpose of economising space.

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.

Estimation results for participation in low return and high return off-farm activities are given in Table 4. 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.

Entry into high-return activities requires capital investment. The marginal value (in utility terms) of farm labour increases with skill, capacity to bear risk and farm size. Hence, we expect the probability of entry into high-return off-farm activities to increase with wealth and schooling and to decrease with farm size. We found schooling increase and farm size and wealth decreases the probability of entry into higher-return off-farm activities. However, the coefficients farm size and wealth are not statistically significantly different from zero.

Table 4. The logit (probability) of working in low and high paying off-farm activities (dependent variables = uoffp, soffp, n=1295).

	UOFFP (OLS)			SOFFP (IV estimator)		
	Coef	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.

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.

The Durbin Wu-Hausman test of weak exogeneity was performed to test whether wealth and schooling are endogenous to the models.[8] F-tests reject the null hypothesis that the variables are jointly exogenous for household welfare. Hence, instrumental variable estimation is used for the welfare function. The over identification test indicates also that that the equation is properly specified and the instruments used are valid and they are themselves are not correlated with the error term. The estimation result is given in Table 5

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 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.

[8] 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.

Table 5. 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			

There are 10 site dummies not shown here for the purpose of economising space. N=1241 and wealth and schooling are considered as endogenous variables because they are found to be not exogenous.

CONCLUSIONS

One potentially fertile avenue of research is the relationship between education, innovative behaviour and household income. Using data from the Ethiopia Rural Household Survey, we have been able to consider these questions.

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 poverty or 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 raises household welfare (income per adult equivalent) 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.

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