Discussion Papers In Economics And Business

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Abstract

Education levels of farmers have been measured in a variety of ways in preceding studies. In order to examine whether or not different measures of education have different effects on the behavior of farmers, I first summarize the measures of education and then perform an empirical analysis. Although education measures examined in this paper have been used in many studies, their effects are shown to differ significantly in my empirical analysis: some variables have positive impacts on farmer's behavior while others do not. This result suggests we have to pay more attention to selecting measures of education in empirical investigations.

JEL classification: I20; Q12; Q16

Keywords: Education; Agriculture; Technology adoption; Bangladesh

*The author is grateful to Akira Kohsaka, Colin McKenzie and participants of the Fall Meeting of the Japan Economic Association at Hiroshima University on 7-8 October 2001 for their helpful comments on a draft of this paper.

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I. Introduction

Education has been shown to facilitate the productivity of farming activities in both developed and developing countries. A great number of empirical studies have tested the effects of farmer's education on the efficiency of agricultural production, as summarized in Lockheed et al. (1980) and Feder et al. (1985). Judging from these studies, there seems no room to throw doubt on the important role played by education in agricultural development.

The importance of farmer's education has been demonstrated in many empirical studies, however, another problem remains: How should we measure farmer's education? In other words, the way of measuring the level of education is not common across studies. Of course, because the measurement of the level of education by an researcher is subject to the availability of the data, it might be the case that only one measure of education was available to the researcher. However, due to recent development of the household-level data collected in developing countries, more detailed information on farmers have become available and, as the result, we can measure the level of farmers' education in several ways. Consequently, we have several alternative measures of education and, if different measures have different effects on farmers' behavior, we have to select an appropriate measure. The purpose of this paper is to summarize measures of education used in preceding studies and investigate whether different measures of education have different impacts on farmers' behavior.

Two aspects should be considered when measuring farmer education. One is the *level* of education. We can measure the level of education by, say, years of formal/non-formal schooling, completion of primary/higher education, literacy, and so on. Another aspect is recently discussed by Jolliffe (2002) and known as "Whose education matters?" To understand this, suppose our interest is in the effect of education on efficiency of farm production. Because farming is typically carried out by self-employed households in many developing countries, production efficiency is observed at the household level. In contrast, we can observe the education level of each individual in the household. Thus, when we regress production efficiency on the education variable (of course with other explanatory variables), the dependent variable is observed at the household level while explanatory variable (education) is measured at the individual level. Therefore, we should find a variable which represents the level of education of a *household*. Jolliffe (2002) proposes three variables as proxies for the education level of a household.

According to the two aspects discussed above, we select 14 representative measures of education from preceding studies. To examine whether different measures have different impacts on farmers' behavior, an empirical analysis is performed. We estimate the effect of each education variable on the probability of adoption of a new crop variety, using household data from rural Bangladesh. Estimation results are mixed. Some variables are found to have strong positive impacts while others have insignificant impact. This result strongly suggests that careful choice of education measures are needed before empirical investigations. Note that the purpose of this paper is not to demonstrate the validity (or invalidity) of a specific variable among others in the general context, but to emphasize the importance of careful choice of education variables in individual cases.

This article is organized as follows. In section II, measures of education used in the preceding studies are reviewed and summarized. The data used in this paper are described in section III. Section IV presents empirical methodology. Estimation results are reported in section V. Some concluding remarks are found in section VI.

II. Measures of Education and the Related Studies

Level of Education

One aspect of measuring the education of a household is the level of education attained by household members. Cotlear (1986) classify three types of education: formal, non-formal and informal. Formal education consists mainly of schooling; non-formal education includes different kinds of extension, adult literacy training and organized apprenticeships; and informal education refers to a wide definition of learning-by-doing, which may include not only direct experience in a particular job but also various learning processes that arise from being exposed to different circumstances.

Among Cotlear's classification, years of formal schooling is the most commonly used measure in empirical studies concerning agriculture. For example, Lin (1991) includes years of schooling of the household head in his regressions and finds a positive effect of this variable on the probability of adoption of hybrid rice by Chinese farmers; Pitt and Sumodiningrat (1991) employ the same variable but find an insignificant impact on the introduction of High Yielding Varieties (HYV) by Indonesian farmers.

There are some evidence that only above a threshold level of education positively affects the probability of adoption. Jamison and Lau (1982) find that only above a threshold level (four years) of education affects the probability of adoption of chemical inputs by farmers in Thailand. Recently, Knight et al. (2003) find that schooling of the head of the household decreases risk-aversion and encourages adoption of agricultural innovations in rural Ethiopia. In addition to using the years of schooling as such, they alternatively include dummy variables which indicate three threshold levels: whether or not schooling of the household head exceeds zero years, is up to three years, and is more than four years. All these variables are found to have significantly positive effects on reducing risk aversion and increasing the probability of adoption of new crops and inputs.

Furthermore, considering the higher rate of dropping out from school in many developing countries, educational attainment from formal schooling might better be measured by whether or not an individual completed a certain class. Foster and Rosenzweig (1996) measure the schooling level of the household by creating an indicator variable for whether or not any individual in the household had completed primary schooling. Using this indicator variable, they show that returns to primary schooling increased in the green-revolution period in India.

Apart from formal schooling, evidence for non-formal education has also been presented. Basu et al. (2002) find an important role played by a literate member in a household, using data from Bangladesh. They estimate wage of illiterate workers on a dummy variable for whether or not the illiterate worker is living with at least one literate person (of course other explanatory variables are also included in the regression). Basu et al. (2002) find a significantly positive effect of this dummy variable, that is, an illiterate person can benefit from literate persons within the household. On the other hand, several researchers have addressed measuring the level of informal education. For example, Cameron (1999) explores the dynamic process of innovation adoption by incorporating farmers' past experience of HYV adoption. She finds learning is an important factor in the process of innovation adoption by U.S. farmers.

Whose Education Matters?

Another aspect of measuring education of a household is recently discussed in Jolliffe (2002) and known as "Whose education matters?" Jolliffe's focus is on whose education is important in determining household income in developing countries.

He points out that, the effect of education on individual wage income can reasonably be estimated since both education and wage income are measured at the individual level; On the other hand, extending the wage regression model to the household income regression model leads to the difficulty because household income cannot usually be decomposed into the earning of each household member, due to the limitation of data in developing countries.

The structure of the problem raised in Jolliffe (2002) seems applicable to the context of agriculture. Because farming is typically carried out by self-employed farm households in many developing countries, outcomes from farming activities are usually observed at the household level. On the other hand, we can measure the education level of each individual in the household. Thus, when we regress outcomes from farming (e.g., quantity of output, adoption of new crops, etc) on the education variable (of course with other explanatory variables), the left-hand side is measured at the household level while the education variable in the right-hand side is measured at the individual level. Therefore, we should find a variable which represents the level of education of a *household*.

Jolliffe (2002) proposes three measures of education which can represent the level of education of a household: the minimum, average, and maximum years of schooling within each household.[1] According to Welch (1970) and Yang (1997), Jolliffe presumed that the average level of education proxies for the worker effect while the maximum value of education in a household proxies for the allocative effect.[2] Jolliffe (2002) tests the effect of the three variables on household income using data from Ghana, and finds that the maximum and average years of schooling within the household have positive impacts on household income.

Except for Jolliffe (2002), the preceding studies cited above do not discuss the reason why the author employs a particular measure of education. In other words, there may be several alternative measures and, these alternatives might have different effects on the dependent variable. As long as each education variable can have a different effect on farmers' behavior, we should examine the validity of using a particular measure of education. To investigate whether or not different measures

[1] He additionally examines the years of schooling of the household head.

[2] Increased education can permit a worker to produce more with the given resources (worker effect). On the other hand, a more educated worker can acquire more information about inputs. The increased information can reduce the cost of production and may enhance the adoption of some new inputs (allocative effect). See Welch (1970) for the detailed concepts of these effects.

of education have different impacts on farmers' behavior or ability, we perform an empirical analysis.

In the empirical analysis below, we select 14 representative measures of education from preceding studies and then carefully compare the effect of each variable on the adoption of a new crop variety. Education measures examined in this paper are summarized in Table 1. These are calculated by the level of education of all household members over 15 years old.[3] First, we have four variables concerning the years of schooling: the minimum, average, maximum and head's years of schooling within each household. The use of years of schooling implicitly assumes that an additional year of schooling of the household member encourages the adoption of the new crop variety. Among the four variables, the years of schooling of the head of the household have been most popularly used in the earlier studies. Next, we have eight dummy variables. These dummy variables describe the threshold years of schooling concerning the household head and all members: whether or not the household head or at least one member in the household have more than three, four, five and six years of schooling. The use of the threshold level of schooling is motivated by the recognition that at least a certain level of education is needed to affect the farmer's attitude towards adoption and risk of new technologies.[4] Last, in lieu of measuring education level by formal schooling, we examine two variables concerning literacy. These are dummy variables which equal to one if the household head or at least one member in the household have ability to read. If farmers needs to understand pamphlets or manuals which explain the way of growing new crops or using new inputs before adoption, it is reasonable to employ the variable concerning literacy.

III. Data

The data used in this paper are from four rounds of a household survey conducted by International Food Policy Research Institute (IFPRI) in three sites in Bangladesh in 1996 and 1997 (see Bouis et al., 1998). This survey was conducted in order to

[3]Alternatively, we can calculate measures of education of all household members without students and children (less than five years old). I checked this calculation, but the estimation results which will be reported in chapter V are essentially similar.

[4]If we follow the method discussed in Foster and Rosenzweig (1996), we should create the indicator variable which represents whether or not a household member completes primary education. I could not do this due to limitation of data, however, the dummy variable that whether or not at least one member in the household have more than five or six years of schooling can be interpreted as indicating the completion of primary education.

Table 1
Description of the Education Measures

Definition	Variable	Mean	Std. Dev.
Years of Schooling			
head of the household	*yrs_head*	2.496	3.823
maximum member	*yrs_max*	4.732	4.115
average of the household members	*yrs_avg*	2.242	2.338
minimum member	*yrs_min*	0.358	1.216
Dummy = 1 if Schooling of the Head			
more than 3 years	*mt3_head*	0.325	0.470
more than 4 years	*mt4_head*	0.301	0.460
more than 5 years	*mt5_head*	0.276	0.449
more than 6 years	*mt6_head*	0.220	0.416
Dummy = 1 if Schooling of One Member			
more than 3 years	*mt3_all*	0.634	0.484
more than 4 years	*mt4_all*	0.593	0.493
more than 5 years	*mt5_all*	0.528	0.501
more than 6 years	*mt6_all*	0.415	0.495
Literacy (Dummy)			
head of the household	*lit_head*	0.390	0.490
at least one member in the household	*lit_all*	0.691	0.464

Note: Number of observations = 123.

evaluate the impacts of new agricultural technologies being disseminated through non-governmental organizations (NGOs). In Saturia, one of the surveyed sites, commercial vegetable (CV) production technology was disseminated, and we use the data from this site.[5] Each household was surveyed four times within approximately twelve months: middle 1996, later in 1996, early 1997 and middle 1997. The dataset provides literacy, enrollment status, detailed agricultural production module, demographic compositions, and so on.

Bangladesh administrative units are division, district, *thana*, union, village and *para*. There are six divisions in the country. A division is then divided into districts, which comprise several *thanas*. *Thanas* are divided into unions, which are composed of villages. A *para* is a subunit of a village. Sampling methods can be summarized as follows: In Saturia *thana*, five *paras* are selected from all *paras* where the CV production technology had been disseminated by NGOs. This gave a total of 916 adopting and non-adopting households. All households were eligible

[5]In the other two sites, Jessore and Mymensingh, group and individual fishponds technologies were disseminated.

for sample selection, although with unequal probabilities: 110 households were selected at random from 128 households which adopted CV production technology, and 55 out of 788 non-adopting households were selected randomly. This gave a total of 160 adopting and non-adopting households. In the empirical analysis below, however, thirty-seven households are excluded due to missing observations. As a result, we have a sample of 123 farm households in five *paras* in Saturia *thana*. Note that the population of this sample is not the farmers in Bangladesh, but those in Saturia *thana*.[6]

Descriptive statistics for the measures of education are shown in Table 1. The average years of schooling of the head of the household is about 2.5 years, while the average of the most (formally) educated member is about 4.7 years.[7] The percentage of the household head who has more than three years of schooling is 32.5%. In 63.4% of the sample households, years of schooling of the most educated member in the household exceeds three years. The percentage of literate household head is 39%, and in 69.1% of the sample households, at least one member is literate.

IV. Hypothesis and Methodology

Given that education facilitates the adoption of agricultural innovations by farmers, we face, as discussed above, the choice of education measures in empirical investigations. So the hypothesis tested here is: whether or not different measures of education have different effects on the adoption of commercial vegetables by sample households.

To test the hypothesis, we estimate the determinants of adoption of commercial vegetables. Because our interest is in the choice of education measures in empirical formulation, we employ a simple model. Following the earlier studies such as Lin (1991) and Knight et al. (2003), the decision of innovation adoption by a farm household i is modeled as follows. The utility function of a household i is

$$U_i(T) = X_i\gamma_T + \varepsilon_{Ti} \tag{1}$$

where T is an indicator of technology adoption ($T = 1$ when CV is adopted and $T = 0$ otherwise), $U_i(T)$ is the utility gain from adopting technology T, X_i is a vector of education variables and characteristics of household i, γ_T is a vector of unknown parameters, and ε_{Ti} is a household-specific shock independent of X. We

[6]See Bouis et al. (1998) for detailed information on the sampling frame of this data set.
[7]The head of the household is determined by the respondent.

assume that a household adopts commercial vegetable if $U_i(1) > U_i(0)$, whereas if $U_i(1) \leq U_i(0)$, the household does not adopt. Thus, defining $U_i^*(T) = U_i(1) - U_i(0)$, we have a familiar latent variable model:

$$U_i^*(T) = X_i\beta + \varepsilon_i, \qquad T = 1 \text{ if } U_i^* > 0 \text{ and } T = 0 \text{ otherwise} \tag{2}$$

where $\beta = \gamma_1 - \gamma_0$ is a vector of unknown parameters and $\varepsilon_i = \varepsilon_{1i} - \varepsilon_{0i}$ is assumed a continuously distributed variable independent of X. We also assume that the distribution of ε_i is symmetric about zero. Thus, the probability of adoption of commercial vegetables can be expressed as follows.

$$\Pr(T_i = 1) = \Pr(U_i^* > 0) = \Pr(\varepsilon_i > -X_i\beta) = 1 - F(-X_i\beta) = F(X_i\beta) \tag{3}$$

where $F(\cdot)$ is the cumulative distribution function for ε_i evaluated at $X_i\beta$.

The distribution of F depends on the distribution of ε_i. If ε_i is normally distributed, then $F(X\beta) = \Phi(X\beta)$ where $\Phi(\cdot)$ is a cumulative normal distribution, and the probit estimator for β would be consistent. Given the small sample size of the data (123 households), however, some readers might concern about the distribution of ε_i. Actually, non-normality in the latent error ε_i means that $F(X\beta) \neq \Phi(X\beta)$, and therefore $\Pr(T_i = 1) \neq \Phi(X\beta)$. In this case, the probit estimator for β will be inconsistent. But, recall that our interest here is estimating and comparing the effects of various education variables. Therefore, we should not pursue the consistent estimation of β as such, but pay attention to the partial effect of the education variable on the probability of adoption of commercial vegetables, $\partial \Pr(T = 1)/\partial x$, where x is an education variable included in X_i. The small sample size is certainly undesirable, but I think the probit provides good estimates of the partial effects of education variables.[8]

The explanatory variables, X_i, are composed of the measures of education and the characteristics of the household. As discussed in section II, we consider 14 representative education variables and compare the effects of them. Table A in the Appendix reports the correlation coefficients between the education variables. As might be expected, the 14 variables seem highly correlated with each other. In addition, most of the equations estimated in the preceding studies include only one education variable. Therefore, in the estimations below, we run one regression for one education variable, that is, 14 equations in total are independently estimated,

[8] For the problem of non-normality in the latent variable model, see Wooldridge (2002, chapter 15).

and each regression includes one measure of education. This procedure, I expect, can provide pure effect of each variable rather than including other education measures which are highly correlated.[9]

As the result, the equations to be estimated in this paper can be summarized as follows.

$$T_i = \beta_0 + \beta_1 education_i + \beta_2 characteristics_i + \beta_3 villagedummy_i + \varepsilon_i \tag{4}$$

where education measures (*education*) are those discussed above, and the characteristics of the household (*characteristics*) are composed of: age of the head of the household; whether or not the head of the household is female (dummy variable which equals one if female headed); the job of the head of the household (dummy variable which equals one if the primary occupation of the head is farming); the demographic structure in the household (the number of adults (15-60 years of age), young (0-14) and old (60-)); and the characteristics of the land owned by the household (area per adult, irrigation status and the soil type of the land).[10] Descriptive statistics for these variables are reported in Table B in the Appendix. We also include village dummies (*villagedummy*) to account for the clustered nature of the data.

V. Estimation Results

Table 2 summarizes the marginal effects of education variables estimated from equation (4) by probit. As discussed in Section III, the sample households are selected with unequal probabilities. We adjust this by including sampling weights. Clustered nature of the data is also taken into account.[11] Recall that each measure of education is separately included in the regression, therefore 14 equations in total are estimated independently. To concentrate on the effect of education, results on other explanatory variables and village dummies are not reported in table 2.

[9] I also run regressions which include multiple education variables. However, the results of these regressions are fairly unreliable. For example, a variable which is positively significant when only this variable is included becomes negatively significant when included with other education measures.

[10] The area of owned land is measured in Decimal (1 Decimal=435.6 Sq.Ft.). Irrigation status is described as a dummy variable which equals one if the land is well irrigated. Soil types are clay, loam, sandy, clay-loam and sandy-loam, and these are also expressed as dummy variables (clay-loam is excluded).

[11] The *dprobit* command of Stata version 7.0 with *pw* and *cl* options is used to estimate all the models in this paper.

First, we consider the years of formal schooling of household members. Among the four variables, the average and minimum years of schooling attained by the household members are found to have significantly positive effects on the probability of adoption of commercial vegetables. Especially, An additional year of the minimum schooling in the household increases the probability of adoption by 12 percent. On the other hand, the maximum and head's years of schooling are insignificant. In addition, as the next four rows suggest, dummy variables which indicate the threshold years of schooling of the head of the household are all insignificant. This is somewhat surprising because the years of schooling of the head of the household have been most frequently used in the preceding studies.

In contrast, a household in which at least one member has more than three or four years of schooling is found to adopt CV with significantly higher probability, as shown in the next two rows. This effect, however, seems to be decreasing. Five or more years of schooling in a household do not have any significant effects.[12] A household in which at least one member has three or more years of schooling adopts commercial vegetables with higher probability (15.9 percent) than a household in which all members have less than two years of schooling. These results may indicate the important role of primary (or fundamental) education in the decision of technology adoption by sample households. The last two rows report the results on literacy. As might be expected from the above results, literacy of the head of the household do not have any significant impacts. By contrast, the probability of adoption significantly increases by about 15.5 percent when a household has at least one literate member. This result seems to correspond to the empirical evidence found by Basu et al. (2002), in which they show that literacy of one member is shared with the illiterate members within the household using data from Bangladesh.

Estimates on the characteristics of the household are not reported in the table, but can be summarized as follows. The characteristics of the head of the household such as age, sex and primary job are all insignificant. This seems to correspond to the insignificant effects of head's education reported above. The coefficients of the number of adults and young members, which can be interpreted as the availability of family labor, are significantly positive in most of the regressions. A household which has well-irrigated land is found to adopt CV with significantly higher probability, and this reflects the importance of the stable supply of water in growing up

[12]To account for the completion of the secondary and tertiary education, the author also examine the dummy variables which indicate at least one member in a household has more than nine or twelve years of schooling. These variables are both insignificant (results are not shown).

Table 2
The Probit Marginal Effects of the Education Variables

Variable	$\partial \Pr(T = 1)/\partial x$	Std. Error
Years of Schooling		
head of the household	-0.001	0.008
maximum member	0.005	0.008
average of the household members	0.015 **	0.006
minimum member	0.120 ***	0.045
Dummy = 1 if Schooling of the Head		
more than 3 years	-0.015	0.056
more than 4 years	-0.045	0.054
more than 5 years	-0.023	0.074
more than 6 years	-0.078	0.120
Dummy = 1 if Schooling of at least One Member		
more than 3 years	0.159 *	0.077
more than 4 years	0.113 **	0.053
more than 5 years	0.058	0.060
more than 6 years	-0.013	0.070
Literacy (Dummy)		
head of the household	-0.027	0.033
at least one member in the household	0.155 ***	0.021

Note: Number of observations = 123. Each education variable is separately estimated with common explanatory variables and village dummies (results are not shown). Clustering robust standard errors are reported. Stars indicate significance as follows: *** = 0.01; ** = 0.05; * = 0.10.

the commercial vegetables. On the other hand, the effect of farm size (the area of land owned by the household) is found negative. This is somewhat controversial, but the negative sign of this variable is also reported in the earlier studies such as Hayami (1981).

After all, our estimation results can be summarized as follows: The educational attainments of the head of the household are found to have insignificant effect irrespective of the way of measuring the level of education. In contrast, the household average, minimum and one member's education (especially primary or fundamental level) have positive effects on the probability of adoption of commercial vegetables. Thus, it is shown that different measures of education have different impacts on farmers' behavior. We should consider the implications of this result. One possibility is that the results may reflect the structure of decision making in the sample households: The head of the household may have relatively lower bargaining power in the decision of farming activities. Another possibility is the characteristic of the new technology, commercial vegetables: considering the importance of fundamental education such as three or four years of schooling and literacy, the introduction of CV may require only fundamental knowledge or skills. In any case, the results of this paper throw doubt on the arbitrary choice of education variables in the preceding empirical studies.

VI. Conclusion

Many researchers have shown the important role of education on farming activities in both developed and developing countries, however, the way of measuring the level of education is not common across studies. If we have several measures of education, we have to select an appropriate measure from them. In this paper, I first summarized measures of education used in recent empirical studies and then performed an empirical analysis, in order to investigate whether or not different measures of education have different effects on farmers' behavior.

Empirical results are mixed. Education of the head of the household do not have any significant effects on the adoption of commercial vegetables, irrespective of the way of measuring the level of education. On the other hand, the household average, minimum and one member's education (especially primary or fundamental level) are found to have significantly positive impacts. Therefore, it is found that different measures of education have different effects on the behavior of farmers. This result strongly suggests we should pay more attention to selecting the appropriate education measures. Also, if an education variable which is significant in one data set becomes insignificant in another data set, it is fruitful to investigate the implication of this change. This paper contributes to this area of research using a data set on commercial vegetables in rural Bangladesh. Future researches using data set on other countries, other kinds of technology, or other contexts (e.g., effect of education on productivity of farming) should clarify the appropriate way of measuring the level of farmer education.

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Appendix

Table A reports the correlation coefficients between the education variables. Table B contains descriptive statistics for the explanatory variables other than education.

Table A

Correlation Coefficients between the Education Variables

	yrs_head	*yrs_max*	*yrs_avg*	*yrs_min*	*mt3_head*	*mt4_head*	*mt5_head*	*mt6_head*	*mt3_all*	*mt4_all*
yrs_head	1.000									
yrs_max	0.688	1.000								
yrs_avg	0.794	0.894	1.000							
yrs_min	0.466	0.359	0.616	1.000						
mt3_head	0.903	0.638	0.723	0.397	1.000					
mt4_head	0.916	0.653	0.733	0.377	0.945	1.000				
mt5_head	0.918	0.653	0.744	0.403	0.890	0.942	1.000			
mt6_head	0.901	0.605	0.674	0.314	0.764	0.809	0.858	1.000		
mt3_all	0.471	0.844	0.704	0.224	0.527	0.498	0.470	0.403	1.000	
mt4_all	0.504	0.863	0.736	0.245	0.539	0.543	0.512	0.439	0.918	1.000
mt5_all	0.538	0.872	0.748	0.252	0.552	0.549	0.584	0.501	0.804	0.876
mt6_all	0.619	0.868	0.779	0.283	0.578	0.599	0.624	0.630	0.639	0.697
lit_head	0.802	0.549	0.642	0.369	0.868	0.820	0.773	0.663	0.435	0.459
lit_all	0.420	0.751	0.629	0.198	0.464	0.439	0.413	0.355	0.880	0.808

	mt5_all	*mt6_all*	*lit_head*	*lit_all*
mt5_all	1.000			
mt6_all	0.795	1.000		
lit_head	0.455	0.477	1.000	
lit_all	0.708	0.563	0.535	1.000

Note: Number of observations = 123. See Table 1 for the definition of the variable.

Table B

Descriptive Statistics for the Explanatory Variables other than Education

Variable	Mean	Std. Dev.
Characteristics of the head		
Age	46.122	12.858
Dummy =1 if female headed	0.033	0.178
Dummy =1 if primary occupation is farming	0.577	0.496
Demographic Composition		
Number of Adults (15-60 years of age)	3.179	1.499
Number of Young (0-14 years of age)	1.870	1.101
Number of Old (60 or more years of age)	0.268	0.513
Land Owned		
Area per adult (in Decimal)	28.974	25.282
Dummy =1 if well irrigated	0.715	0.453
Soil Type of the land (Dummy)		
Clay	0.366	0.484
Loam	0.683	0.467
Sandy	0.122	0.329
Sandy-loam	0.732	0.445

Note: Number of observations = 123. 1 Decimal = 435.6 Sq. Ft.