Farmer Education and Technology Adoption: The Choice of Education Measures*

Masakazu Hojo†

Abstract

This paper investigates how we should measure farmer education in empirical specifications. Many existing studies find positive effects of education on the adoption of agricultural innovations by farmers. However, the empirical specification of education differs between studies, and most of the studies do not justify the measure of education that is used. In this context, the two relevant issues relate to the level of education and which member of the farm household's education matters. In this paper, I use data on rural Bangladesh to estimate and compare the effects of 14 education measures on the probability of adopting newly disseminated crops. The empirical results suggest that the average and minimum years of schooling and the presence of one literate member in the household have positive effects on technology adoption. By contrast, years of schooling of the most educated person and the household head have no significant effects. These results cast doubt on the arbitrary choices of education measures in existing studies.

JEL classification: I20; Q12; Q16

Keywords: Education; Agriculture; Technology adoption; Bangladesh

---

*I am grateful to Akira Kohsaka, Colin McKenzie, Yasuyuki Sawada, Keijiro Otsuka, and participants of the Fall Meeting of the Japan Economic Association at Hiroshima University on 13–14 October 2002 for their helpful comments.

†Associate Professor of Economics, Faculty of Economics, Niigata University. 8050 Ikarashi-Ninocho, Niigata 950-2181 Japan, Tel/Fax: +81-25-262-6391, E-mail address: hojo@econ.niigata-u.ac.jp

1 Introduction

Economists have paid much attention to the diffusion of new agricultural technologies because most people in developing countries earn their subsistence incomes from farming. Hence, the diffusion of new agricultural technology is expected to raise their incomes and improve their nutrition. In particular, many economists have hypothesized that highly educated farmers tend to adopt productive innovations earlier than those who are relatively poorly educated. Underlying this hypothesis is "the greater education of the more educated farmer has increased his ability to understand and evaluate the information on new products and processes ... The better educated farmer is quicker to adopt profitable new processes and products since, for him, the expected payoff from innovation is likely to be greater and the risk likely to be smaller" (Nelson and Phelps, 1966, p. 70). Having tested this hypothesis, many economists have found that farmer education increases the probability of adopting new agricultural technologies such as High Yielding Varieties (HYV), fertilizers, and pesticides (summarized in Feder et al., 1985).

While the positive role of farmer education in agricultural development seems undoubted, a problem remains: empirical specifications of education differ between studies. In other words, most existing studies do not explain the measurement of farmer education or justify the measure used. Two aspects of this problem are relevant. One concerns how to measure the *level* of education attained by members of the farm household. For example, in the 37 empirical studies of farmer education and farm efficiency summarized in Lockheed et al. (1980), 27 use years of schooling attained by household members, eight use dummy variables that describe some threshold levels of education, and two use an indicator of literacy. The second aspect concerns *whose education matters*, which has recently been discussed in Jolliffe (2002). Of the 37 studies, 15 use the education level of the farm operator or manager, 14 use the average level of education, four use the education level of the household head, one uses the education level of the farm operator's wife, and in three, it is unclear what measure is used. Because different measures of education represent different aspects of farmer behavior, it is important to select the appropriate measure of education in empirical investigations.

This paper investigates which education variable is appropriate for estimating the effect of education on technology adoption by farmers by using data from rural Bangladesh. The two aspects of measuring farmer education are discussed. The empirical results suggest that average and minimum years of schooling in a household capture the positive effect on the probability of adopting a new crop variety while the maximum level and the household head's education have no significant effects.

This paper is organized as follows. In section 2, measures of education used in existing studies are reviewed and summarized. The data used in this paper are described in section 3. In section 4, the empirical methodology is described. Estimation results are reported in section 5. Concluding remarks are presented in section 6.

2 Measures of Education and Existing Studies

2.1 The level of education

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

Among Cotlear's classifications, years of formal schooling is the most widely used measure in empirical studies relating to agriculture. For example, Lin (1991) includes years of schooling of the household head in his regressions and finds that this variable has a positive effect on the probability of adoption of hybrid rice by Chinese farmers. Pitt and Sumodiningrat (1991) find that the same variable has an insignificant effect on the introduction of HYV by Indonesian farmers.

There is evidence that only education above a threshold level positively affects the probability of innovation adoption. For example, Jamison and Lau (1982) find that only more than four years of education affects the probability of adoption of chemical inputs by farmers in Thailand. Recently, Knight et al. (2003) have found that the schooling of the head of the household reduces risk aversion and encourages the adoption of agricultural innovations in rural Ethiopia. In addition to using years of schooling, they also include dummy variables for three threshold levels: whether the household head has any schooling; up to three years of schooling; and more than four years of schooling. It is found that these variables significantly reduce risk aversion and increase the probability of the adoption of new crops and inputs.

Considering the relatively high dropout rate for schools in many developing countries, educational attainment from formal schooling might better be measured by whether an individual has completed particular courses. Foster and Rosenzweig (1996) measure the schooling level of the household by using an indicator variable for whether any individual in the household had completed primary schooling. Using this indicator variable, they show that returns to primary schooling increased during the green-revolution period in India.

The effects of nonformal education have also been estimated. Using data from Bangladesh, Basu et al. (2002) find that literate household members play an important role. These authors estimate wage earnings for illiterate workers by using a dummy variable that indicates whether the illiterate worker lives in a household with at least one literate person. (Other explanatory variables are also included in the regression.) Basu et al. (2002) find that this dummy variable has a significantly positive effect. That is, an illiterate person can benefit from living in a household with literate persons. In addition, several researchers have addressed the issue of measuring the level of informal education. For example, Cameron (1999) explores the dynamic process of innovation adoption by incorporating farmers' past experiences of HYV adoption. She finds that learning is an important factor in the process of innovation adoption by U.S. farmers.

2.2 Whose education matters?

Another aspect of measuring farmer education has been recently discussed by Jolliffe (2002) in his work entitled "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 earnings can reasonably be estimated since both education and wage earnings are measured at the individual level. However, extending the wage regression model to the household-income regression model is difficult because, owing to data limitations in developing countries, household income cannot normally be decomposed into the earnings of each household member.

The structure of the problem raised in Jolliffe (2002) is applicable to agriculture. Because farming is often undertaken by self-employed farm households in many developing countries, outcomes of farming activities are usually observed at the household level. On the other hand, one can measure the education level of each individual in the household. Thus, when we regress outcomes from farming (such as the quantity of output and the adoption of new crops) on the education variable (and other explanatory variables), the variables on the left-hand side are measured at the household level whereas the education variable on the right-hand side is measured at the individual level. Therefore, a variable that represents the *household's* level of education is required.

Jolliffe (2002) proposes three measures of education that 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 assumes that average years of schooling act as a proxy for the "worker effect", while maximum years of schooling in a household proxies the "allocative effect".[2] Jolliffe (2002) tests the effect of the three variables on household income by using data from Ghana and finds that the maximum amount of education in the household has a positive effect on total household income. Average years of schooling within the household has separate effects on farm and non-farm household incomes.

Considering the two aspects already discussed, in this paper, I investigate which education measure(s) can be used to estimate the positive effect of education on the

[1] He also uses the household head's years of schooling.

[2] A more educated worker can acquire more information about inputs. This additional information enables the worker to reduce the cost of production and this may stimulate the adoption of new inputs. This effect is termed the "allocative effect". The "worker effect" implies that education enables a worker to produce more output from a given amount of resources. See Welch (1970) for details of these concepts.

adoption of new technology by farmers. For the empirical analysis of this paper, I select 14 measures of education from existing studies and carefully compare the effect of each variable on the adoption of a new crop variety. The education measures examined in this paper are summarized in Table 1. These are calculated by from the levels of education of all household members over 15 years of age.[3] First, four variables represent formal schooling: the minimum, average, maximum, and the head's years of schooling within each household. The use of years of schooling implicitly assumes that any additional year of schooling, irrespective of the household's existing education level, increases the probability of adoption of the new crop variety at the same rate. Of these four variables, the years of schooling of the household head is the most widely used among existing studies. In addition, eight dummy variables describe the threshold years of schooling of the household head and all household members. These variables indicate whether the household head or at least one member of the household has more than three, four, five, or six years of schooling. The use of the threshold level of schooling is motivated by the recognition that the farmer's attitude to adopting new technology and the associated risks are only affected once a certain level of education has been attained.[4] Lastly, instead of measuring education levels by using formal schooling, I use two variables relating to literacy. These are dummy variables that indicate whether the household head or at least one member of the household can read. If farmers need to understand pamphlets or manuals that explain how to grow new crops or use new inputs, it is reasonable to consider literacy as a potential determinant of innovation adoption.

[3] An alternative is to calculate measures of education for all household members except students and children under five years of age. I found that the estimation results were similar to those reported in section 5.

[4] Given the method discussed in Foster and Rosenzweig (1996), one should use an indicator variable for whether a household member completes primary education. Data limitations prevented this. However, the dummy variable for whether at least one member of the household has more than five or six years of schooling could be interpreted as an indicator of the completion of primary education.

3 Data

The data used in this paper are from four waves of a household survey conducted by the International Food Policy Research Institute (IFPRI) at three sites in Bangladesh in 1996 and 1997 (see Bouis et al., 1998). This survey was conducted to evaluate the effects of new agricultural technologies being disseminated through nongovernmental organizations (NGOs). In Saturia, one of the surveyed sites, commercial vegetable (CV) production technology was disseminated, and in this paper, I use the data from this site.[5] Each household was surveyed four times in approximately 12 months: in mid-1996, late 1996, early 1997, and mid-1997. The data set includes information on literacy, education status, detailed agricultural production module, and demographic composition.

Bangladesh administrative units are at the levels of the division, district, *thana*, union, village, and *para*. There are six divisions in the country. A division is divided into districts, which comprises several *thanas*. *Thanas* are divided into unions, which are composed of villages. A *para* is a subunit of a village. The sampling methods can be summarized as follows. In the Saturia *thana*, five *paras* were selected from those *paras* in which CV production technology had been disseminated by NGOs. This yielded a total of 916 adopting and nonadopting households. All households were eligible for sample selection but with unequal probabilities: 110 households were selected at random from 128 households that adopted the CV production technology, and 55 of 788 nonadopting households were selected at random. This produced a sample of 165 adopting and nonadopting households. However, in the subsequent empirical analysis, 42 households are excluded because of missing observations. Consequently, I have a sample of 123 farm households from five *paras* in Saturia *thana*. Note that the population corresponding to this sample is not the farmers of Bangladesh, but those of the Saturia *thana*.[6]

Descriptive statistics for the measures of education are reported in Table 1. The average years of schooling of the head of the household is about 2.7 years, while the

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

[6] See Bouis et al. (1998) for detailed information on the sampling scheme of this data set.

Table 1
Description of the Education Measures

Definition	Variable	Mean	Std. Err.
Years of Schooling			
head of the household	*yrs_head*	2.670	0.427
maximum member	*yrs_max*	4.578	0.742
average of the household members	*yrs_avg*	2.235	0.408
minimum member	*yrs_min*	0.198	0.116
Dummy = 1 if Schooling of the Head			
more than 3 years	*mt3_head*	0.346	0.061
more than 4 years	*mt4_head*	0.340	0.062
more than 5 years	*mt5_head*	0.290	0.068
more than 6 years	*mt6_head*	0.254	0.060
Dummy = 1 if Schooling of One Member			
more than 3 years	*mt3_all*	0.555	0.077
more than 4 years	*mt4_all*	0.545	0.078
more than 5 years	*mt5_all*	0.485	0.095
more than 6 years	*mt6_all*	0.412	0.079
Literacy (Dummy)			
head of the household	*lit_head*	0.407	0.060
at least one member in the household	*lit_all*	0.591	0.486

Source:
Author's calculation from the survey file. Weighted means are reported. Number of observations = 123.

average of the most (formally) educated member is about 4.6 years.[7] The percentage of household heads with more than three years of schooling is 34.6%. In 55.5% of the sampled households, the years of schooling of the most educated member of the household exceeds three years. The percentage of literate household heads is 40.7%, and in 59.1% of the sampled households, at least one member is literate.

4 Methodology

Given that education facilitates the adoption of agricultural innovations by farmers, as discussed above, one must select appropriate education measures in empirical specifications. Thus, in this paper, I investigate which education measures can capture the positive effect of education on the adoption of CV.

For this purpose, determinants of adoption of commercial vegetables are esti-

[7]The identity of the head of the household is determined by the respondent.

mated. Because my interest is in the choice of education measures in empirical specifications, a simple model of technology adoption is applied. Following earlier studies such as those of Lin (1991) and Knight et al. (2003), the decisions about innovation adoption by farm households i is modeled on the basis of the following utility function for household i:

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

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 that is independent of X. I assume that a household adopts CV if $U_i(1) > U_i(0)$, while the household does not adopt CV if $U_i(1) \leq U_i(0)$. Thus, defining $U_i^*(T) = U_i(1) - U_i(0)$ yields the following 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 to be a continuously distributed variable that is independent of X. I also assume that the distribution of ε_i is symmetric around zero. Thus, the probability of adopting CV is 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 is consistent. However, given the small sample size of 123 households, there is some concern about the distribution of ε_i. Nonnormality in the latent error ε_i implies 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 is inconsistent. However, I am interested in estimating and comparing the effects of different education variables. Therefore, of particular relevance is not the consistent estimation of β as such, but the partial effect of the education variable on the probability of adoption of CV, which is given by $\partial \Pr(T = 1)/\partial x$, where x is the education variable included in X_i. While the small sample size is undesirable, probit estimation is expected to provide good estimates of the partial effects of the education variables.[8]

The explanatory variables, X_i, comprise the measures of education and characteristics of the household. As explained in section 2, I compare the effects of 14 representative education variables. Table A in the Appendix reports the correlation coefficients between these education variables. As expected, the 14 variables are highly correlated with each other, which suggests potential multicollinearity when they are included simultaneously in the same regression. In addition, most of the equations estimated in existing studies include only one education variable. Therefore, in the equations estimated in this paper, I run one regression for each education variable; that is, 14 equations are estimated independently, and each regression includes one education variable. This procedure provides an estimate of the pure effect of each variable rather than an estimate of the combined effect of highly correlated education measures.[9]

Thus, the equations estimated in this paper are summarized as follows:

$$\Pr(T_i = 1) = \beta_0 + \beta_1 education_i + \beta_2 characteristics_i + \beta_3 village_i + \varepsilon_i \tag{4}$$

where the education measures (*education*) are those already discussed, and the characteristics of the household (*characteristics*) comprise the age of the household head, a dummy for whether the head of the household is female, a dummy for the job of the household head (which is unity if the primary occupation of the household head is farming), the demographic structure of the household (that is, the number of adults (aged 15–60), the number of young people (0–14), and the number of old people (over 60)), and characteristics of the type of land owned by the household (area per adult, irrigation status, and soil type).[10] Descriptive statistics on these variables are reported in Table B in the Appendix. I also include village dummies (*village*) to account for the clustered nature of the data.

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

[9]I also ran regressions that included a number of education variables. However, results from these regressions were unreliable. For example, a variable that was positively significant in a simple regression was negatively significant in a multiple regression.

[10]The area of land owned is measured in decimals (1 decimal=435.6 square feet). The irrigation status is indicated by a dummy variable that is unity if the land is well irrigated. The soil types, clay, loam, sandy, clay-loam, and sandy-loam, are represented by dummy variables (clay-loam is excluded).

5 Estimation Results

Table 2 summarizes the marginal effects of the education variables estimated from equation (4) by using the probit estimator. As explained in section 3, households were sampled with unequal probabilities. I adjust for this by including sampling weights. The clustered nature of the data is also taken into account.[11] Recall that since each education measure is included separately in the regressions, 14 separate equations are estimated. To concentrate on the effect of education, the coefficients of the other explanatory variables and the village dummies are not reported in Table 2.

First, consider the years of formal schooling of household members. Of the four variables, the average and minimum years of schooling attained by household members are found to have significantly positive effects on the probability of adopting CV. In particular, an additional year of minimum schooling in the household increases the probability of CV adoption by 12%. However, maximum years of schooling and the head's years of schooling are insignificant. In addition, as the next four rows suggest, all the dummy variables for the threshold years of the head's schooling are insignificant. This is somewhat surprising because the household head's or farm operator's years of schooling is the most widely used education measure among existing studies.

By contrast, a household in which at least one member has more than three or four years of schooling is found to be significantly more likely to adopt CV, as the next two rows show. However, this effect seems to diminish. Households having five or more years of schooling has no significant effect.[12] A household in which at least one member has three or more years of schooling is 15.9% more likely to adopt CV than a household in which all members have less than two years of schooling. These results may indicate the importance of primary (or fundamental) education in household decisions about technology adoption.

The final two rows report the results on literacy. As might be expected from

[11] Stata (version 7.0)'s *dprobit* command and its *pw* and *cl* options were used to estimate all the models in this paper.

[12] To account for the completion of secondary and tertiary education, I also used a dummy variables indicating whether at least one household member had more than nine or 12 years of schooling. These variables were both insignificant. (Results are not reported).

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 above results, literacy of the household head has no significant effect. By contrast, having at least one literate member raises the probability of adoption by about 15.5%. This result confirms the empirical finding of Basu et al. (2002) for Bangladesh that the literacy of one household member benefits illiterate household members.

Although the estimated effects of household characteristics are not reported in Table 2, they can be summarized as follows. Characteristics of the household head such as age, sex, and primary job are insignificant. This corresponds to the insignificant effect of head's education already discussed. The coefficients on the variables representing the number of adults and young people, which can be interpreted as effects of the availability of family labor, are significantly positive in most regressions. A household that owns well-irrigated land is significantly more likely to adopt CV, which reflects the importance of a stable supply of water for growing CV. The effect of farm size (the area of land owned by the household) is negative. This finding is surprising, but confirms those of earlier studies such as that of Hayami (1981).

The estimation results can be summarized as follows. The educational attainment of the head of the household has no significant effect, however it is measured. Years of schooling of the most educated member in the household is also insignificant. By contrast, the household's average, minimum, and its individual member's education (especially at the primary or fundamental level) positively affect the probability of adopting CV. These results may suggest that a farm household in which *all* household members have fundamental education has a higher probability of adopting CV than a farm household in which *one* household member is better educated and other members have little education. These results contrast with the finding of Jolliffe (2002) that the household's maximum education captures the allocative effect and thus increases total household income. It is worth considering the implications of this difference. One possibility is that the results may reflect the structure of decision making in the sampled households. That is, the head or the most educated member of the household may have relatively little influence on decisions about farming activities in the surveyed area. In particular, the insignificant effect of the head's education might be affected by the definition of the head of the household in the data set. That is, because the identity of the household head is determined by the respondent irrespective of the actual roles of household members, it could be that the household head is not the farm operator. For example, the oldest person might be designated as the head of the household. Another possibility relates to the characteristic of the new technology studied; that is, CV. Considering the importance of fundamental education, covering the first three or four years of schooling, and the importance of literacy, CV adoption may only require fundamental knowledge or skills. In any case, the results of this paper cast doubt on the arbitrary choice of education variables in existing empirical studies.

6 Conclusion

Most existing studies of the effect of education on technology adoption by farmers do not explain the choice of education measure. This suggests that the choice is *ad hoc*. Therefore, in this paper, I have focused on finding appropriate measures of farmer education in the context of estimating the effect of education on the adoption of a new crop variety. Two aspects of farmer education were discussed: the level of education and the "whose education matters". In this context, I estimated the effects of 14 education variables on the probability of adopting commercial vegetables among farmers in rural Bangladesh.

The empirical results are clear. The education of the head of the household and that of the most educated member of the household have no significant effects on the adoption of commercial vegetables. On the other hand, the household's average and minimum education levels and the education levels of its individual members (especially primary or fundamental education) have significantly positive effects. These results may suggest that a farm household in which all household members have fundamental education is more likely to adopt CV than a farm household in which one household member is better educated and other members have little education. These results contrast with Jolliffe (2002)'s recent finding that the household's maximum education captures the allocative effect and thus increases total household income. The difference between the results of this paper and those of Jolliffe might be due to differences in the data sets and empirical approaches. Hence, direct comparisons are difficult. Nevertheless, the results of this paper cast doubt on the arbitrary choice of education variables in existing empirical studies.

References

Basu, K., A. Narayan, and M. Ravallion (2002) 'Is literacy shared within households? theory and evidence for bangladesh.' *Labour Economics* 8(6), 649–665

Bouis, H., B. de la Briere, L. Guitierrez, K. Hallman, N. Hassan, O. Hels, W. Quabili, A. Quisumbing, S. Thilsted, Z. Zihad, and S. Zohir (1998) *Commercial Vegetable and Polyculture Fish Production in Bangladesh: Their Impacts on Income,* *Household Resource Allocation, and Nutrition* (Washington, DC: International Food Policy Research Institute)

Cameron, L. A. (1999) 'The importance of learning in the adoption of high-yielding variety seeds.' *American Journal of Agricultural Economics* 81, 83–94

Cotlear, D. (1986) 'Farmer education and farm efficiency in peru: The role of schooling, extension services and migration.' Discussion Paper, Education and Training Series, World Bank,

Feder, G., R. E. Just, and D. Zilberman (1985) 'Adoption of agricultural innovations in developing countries: A survey.' *Economic Development and Cultural Change* 31, 255–298

Foster, A. D., and M. R. Rosenzweig (1996) 'Technical change and human capital returns and investments: Evidence from the green revolution.' *American Economic Review* 86, 931–953

Hayami, Y. (1981) 'Induced innovation, green revolution, and income distribution: Comment.' *Economic Development and Cultural Change* 30, 169–176

Jamison, D. T., and L. J. Lau (1982) *Farmer Education and Farm Efficiency* (Baltimore: Johns Hopkins University Press)

Jolliffe, D. (2002) 'Whose education matters in the determination of household income? evidence from a developing country.' *Economic Development and Cultural Change* 50(2), 287–312

Knight, J., S. Weir, and T. Woldehanna (2003) 'The role of education in facilitating risk-taking and innovation in agriculture.' *Journal of Development Studies* 39(6), 1–22

Lin, J. Y. (1991) 'Education and innovation adoption: Evidence from hybrid rice in china.' *American Journal of Agricultural Economics* 73, 713–723

Lockheed, M. E., D. T. Jamison, and L. J. Lau (1980) 'Farmer education and farm efficiency: A survey.' *Economic Development and Cultural Change* 29(1), 37–76

Nelson, R. R., and E. S. Phelps (1966) ‘Investment in humans, technological diffusion, and economic growth.’ *American Economic Review* 56(1/2), 69–75

Pitt, M. M., and G. Sumodiningrat (1991) ‘Risk, schooling and the choice of seed technology in developing countries: A meta-profit function approach.’ *International Economic Review* 32(2), 457–473

Welch, F. (1970) ‘Education in production.’ *Journal of Political Economy* 78, 35–59

Wooldridge, J. M. (2002) *Econometric Analysis of Cross Section and Panel Data* (Cambridge, MA: MIT Press)

Yang, D. T. (1997) ‘Education and off-farm work.’ *Economic Development and Cultural Change* 45(3), 613–632

Appendix

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 definitions of the variables.

Table B

Descriptive Statistics for the Explanatory Variables other than Education

Variable	Mean	Std. Err.
Characteristics of the head		
Age	47.032	2.701
Dummy =1 if female headed	0.030	0.022
Dummy =1 if primary occupation is farming	0.541	0.063
Demographic Composition		
Number of Adults (15-60 years of age)	3.043	0.088
Number of Young (0-14 years of age)	1.768	0.220
Number of Old (60 or more years of age)	0.266	0.072
Land Owned		
Area per adult (in decimal)	30.170	4.859
Dummy =1 if well irrigated	0.730	0.090
Soil Type of the land (Dummy)		
Clay	0.401	0.086
Loam	0.700	0.039
Sandy	0.163	0.021
Sandy-loam	0.757	0.076

Note:

Number of observations = 123. Weighted means are reported. 1 decimal = 435.6 square feet.