The Role of NGO Involvement in Agricultural Development : An Econometric Analysis using Household Data from Bangladesh

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Abstract

This study assesses the effect of participation in NGO programs on agricultural productivity in Bangladesh. Using data from the study "Long-term Impact of Antipoverty Interventions in Bangladesh, 2006−07," farm-level productivity is estimated by stochastic frontier analysis, and the effect of participation is estimated econometrically in four dimensions of participation using OLS, instrumental variable and the control function approaches. Participation in NGO programs improves technical efficiency as measured by total factor productivity. The intensity of participation is important for productivity improvement, but the duration is not. Participants in international NGO programs have higher productivity than those in national NGO programs.

Keywords : NGO programs, agricultural productivity, treatment effects model

JEL Classification Numbers : I38, O13, Q12, Q16, Q18

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1. Introduction

As Bangladesh is an agricultural country, increasing productivity in its agricultural sector should be a priority as a strategy for boosting the country's economic growth. Although Bangladesh's economy has undergone considerable diversification over the years, the agricultural sector remains the largest sector in the economy, currently contributing 23.5% of GDP (MOA, 2011). The sector accounts for 42.1% of the total employed labor force and constitutes the largest source of foreign exchange earnings by serving as the base sector for the country's main industries such as textiles. Agriculture also contributes to growth by providing raw materials as well as a market for industrial products. Thus, agricultural productivity is the primary driver of the economic development of the country. However, Bangladesh is encountering problems such as a decrease in arable land and insufficient resources for production (Robbani et al., 2007). Agricultural extension is the principal means for boosting agricultural development by assisting farmers to make efficient, productive and sustainable use of their land and other resources. Through this educational process, information is generated, shared and used for the improvement of the livelihoods of farmers and their families.

In particular, agricultural extension is an important development intervention for increasing the growth of the agricultural sector in light of rising demand and supply-side pressure and promotion of sustainable, inclusive and pro-poor agriculture and, hence, economic development. Under the extension system, agents interact with farmers to provide them with information and aid the development of their managerial skills (Birkhaeuser et al., 1991). Extension agents disseminate information on agricultural practices and optimal input use, and advise farmers directly on specific production problems, thus facilitating a shift to more efficient methods of production. In this way, the extension mechanism not only accelerates the diffusion process and the adoption of new varieties and technologies but also improves farmers' managerial ability and encourages the efficient use of existing technologies by improving farmers' know-how. These two distinct roles of agricultural extension may have different effects on farmers' performance in attempting to close management and technology gaps (Dinar et al., 2007).

The extension system in Bangladesh comprises a multitude of governmental and nongovernmental organizations. Nongovernmental organizations (NGOs) traditionally provide advice to farmer groups allied to the provision of microcredit and/or target their services to agricultural development. Such NGOs have become the main service providers in countries where the governments are unable to fulfill their traditional role because of limited human resources and service capacity (World Bank, 2005). In Bangladesh, where increasing urbanization is reducing the amount of agricultural land, increasing the efficiency of the agricultural sector is important, as increasing the sector's productivity and growth potential will create opportunities to achieve food security and reduce rural poverty. Currently, about 400 international, national and local NGOs are directly engaging in the agricultural sector with the aim of achieving these goals

(Anonymous, 2003); they are mainly engaged in extension services and capacity building.

The aim of the Bangladeshi government's agricultural policy is to increase productivity so that the country can achieve self-sufficiency in food and foreign exchange earnings through agricultural exports. As part of its strategy to achieve this goal, the government is seeking to adopt macroeconomic policies that encourage the involvement of the nongovernment sector in the supply of inputs and technology, and to develop policies and regulations that will ensure the sustainability of this involvement for a productive agricultural sector. Thus, the role of NGOs in supporting resource-poor farmers with appropriate technology and adequate funding is an important aspect of the country's agricultural development.

Demonstrating the impact of NGOs in the agricultural sector has become an increasingly important challenge in recent times, especially in relation to making a significant impact on poverty reduction. Questions persist about the effectiveness of the nongovernment sector's contribution to productivity improvement. NGOs also must assess their own impact, both for organizational learning and for strategy development. The results of such assessments are likely to reveal a need among NGOs to engage in policy interventions and initiatives to promote and sustain their activities for improving the socioeconomic well-being of the farming community.

In view of these issues, the present study examines the role of NGOs in improving productivity in Bangladesh. The study's specific objectives are: 1) to estimate the productivity of farm-level agricultural production; and 2) to assess the impact of participation in NGO extension programs on household agricultural productivity. The impact is measured in four dimensions: i) participation in NGO programs; ii) duration of participation in NGO programs; iii) NGO program participation index; and iv) NGO type (local, national, international). Understanding the importance of productivity and exploring ways to increase it are essential in identifying effective agricultural policies. The present study provides policy guidelines for sustaining productivity improvements through NGO extension programs.

2. Study area and data

This study uses data from the project "Long-term Impact of Antipoverty Interventions in Bangladesh" (LIAIB), conducted by a research group guided by International Food Policy Research Institute (IFPRI) in 2006–07. The survey covered three districts of Bangladesh: Manikganj, Mymensingh and Jessore. The survey adopted a stratified multistage design for selection of sample farm households. This study considers a sample of 1,393 households engaged in agricultural activities for their livelihoods. The sample includes both participants and nonparticipants in NGO programs.

3. Productivity estimation

We use total factor productivity (TFP) per farm household as the measure of farm household performance. The measures of TFP are intended to provide an indication of the state of the production function (frontier). TFP reflects the extent to which increased amounts of output are feasible from given inputs. A higher productivity level of one farm household compared with others is necessarily a sign that this one is “performing better” than the others. Therefore, for a farm household to be operating at a lower level of productivity indicates that there is scope for productivity improvement. We use a stochastic frontier model to measure TFP because it allows us to separate the stochastic error term into two components: a systematic random error to account for statistical noise and a technical inefficiency component (Battese and Coelli, 1992). In cross-sectional frameworks, technical efficiency is customarily interpreted as TFP (Otsuki, 2010). The stochastic frontier analysis (SFA) also provides the basis for conducting statistical tests of hypotheses regarding production structure and degrees of inefficiency.

The stochastic frontier model for the i^{th} production unit is defined by

$$\ln Output_i = \beta_0 + \beta_1(\ln Land_i) + \beta_2(\ln Labor_i) + \beta_3(\ln NonLabor_i) + v_i - u_i, \tag{1}$$

where ln denotes the natural logarithm; *Output* is the total receipts obtained from output; *Land* is the total number of hectares under cultivation; *Labor* is the wage expenditures for both regular and casual agricultural labor; *NonLabor* is the expenditures for nonlabor inputs (seed, fertilizer, pesticides, water); and *i* is the individual farm household. Here, the v_i s are assumed to be identically and independently distributed errors that represent random variations in output that are assumed to be normally distributed with a mean of 0 and variance σ_v^2. Following Battese and Coelli (1995), the u_i s are assumed to be nonnegative random variables that represent technical inefficiency, i.e., the stochastic shortfall of output from the most efficient production. The stochastic disturbance term v_i is assumed to be distributed independently of u_i. Thus, the error term $(v_i - u_i) = \varepsilon_i$ is not symmetric because $u_i \geq 0$. Assuming that v_i and u_i are distributed independently of the explanatory variables, estimation of the parameters in equation (1) by ordinary least squares (OLS) will provide consistent estimates of all parameters except the intercept term because $E(\varepsilon_i) = -E(u_i) \leq 0$. Moreover, OLS cannot isolate technical efficiency in the residual term. A different estimation technique with additional assumptions is required for a consistent estimate of the intercept and technical efficiency of each producer. The maximum likelihood method is appropriate under the assumption that the v_i s are normally distributed, while the u_i s are defined by the half-normal distribution, which ensures that technical efficiency estimates fall between 0 and 1. The half-normal distribution works best and is used most often because the standard deviation of the normal (truncated at zero) is able to concentrate efficiencies near zero or spread them out (Greene, 1990). Other empirical studies using different distributional assumptions for comparison show that both rankings and efficiency scores are generally similar across distributions (Fuiji, 2001; Street, 2003).

The technical efficiency of production for the i^{th} farm can be defined as

$$TE_i = \exp(-u_i) = Y_i / Y_i^*, \tag{2}$$

where Y_i is its observed output and Y_i^* is its maximum possible output given the available inputs.

3-1 Estimation results of the stochastic frontier model

The empirical results obtained for the stochastic frontier model of equation (1) using the maximum likelihood method are presented in Table 1. The intercept, land and nonlabor variables are statistically significant at the 1% level and labor is significant at the 5% level with the expected signs. The largest elasticity is observed for land, indicating that land is indispensable for agricultural output. The nonlabor input variable has the second largest elasticity, confirming the importance of other customary agricultural inputs. Labor also has a substantial elasticity, indicating its importance too.

Table 1 : Results of the stochastic frontier analysis

Variable	Coefficient	Std. error
Constant	3.7554***	0.1713
ln Land	0.5838***	0.0351
ln Labor	0.0427**	0.0193
ln Non Labor	0.3755***	0.0313
σ_u	0.2858	0.0518
σ_v	0.3137	0.0181
σ^2	0.1801	0.0217
λ	0.9115	0.0671
γ	0.1976	
Wald χ^2	2985.32***	
No. of observations	661	
LR statistic	4.37**	

Source : Author's estimation based on LIAIB (2006–07) data for Bangladesh
Note : The symbols ** and *** indicate significance at the 5% and 1% levels, respectively.
The "frontier" command in Stata version 11 was used for the estimation.

The results presented in Table 1 indicate that the parameter λ is 0.9115, which estimates the ratio of the standard deviation of the inefficiency component to the standard deviation of the idiosyncratic component. The likelihood ratio (LR) is significant at the 5% level, indicating the effects of technical inefficiency. Technical efficiency is calculated for each sample once the inefficiency term u_i is adjusted so that technical efficiency scores do not exceed the range $[0, 1]$. The parameter γ, which measures the variability of the two sources of error (white noise disturbance and unilateral error), reached 0.1976 (19.76%). The total composed error variance of the production function is explained by the variance of the technical inefficiency term. These terms represent the importance of incorporating technical inefficiency into the production function.

Descriptive statistics for the technical efficiency measure indicate that the mean is about 81% (Table 2). These statistics imply substantial potential to improve efficiency among sampled farmers and, hence, improve production output and/or reduce production costs.

Table 2 : Descriptive statistics of technical efficiency

Mean	Std. deviation	Median	Minimum	Maximum
0.8083	0.0622	0.8159	0.3203	0.9308

Source: Author's estimation based on LIAIB (2006–07) data for Bangladesh

4. Estimation of the impact of NGO programs

We estimated the impact of participation in an NGO program under four dimensions: participation, using a dummy variable; duration of participation, using the number of years affiliated; participation index, as the number of meetings attended during the last month of the survey period; and NGO type (local, national or international). The estimation methods employed for comparing the results were the OLS, instrumental variable (IV) and control function approaches. In the OLS analysis, we regress the technical efficiency from SFA on the explanatory variables. The OLS model is

$$TE_i = \beta_0 + \beta_1 NGO_i + \beta_2 Age_i + \beta_3 Age_i^2 + \beta_4 Sex_i + \beta_5 Edu_i + \beta_6 FamIncome_i + u_i. \quad (3)$$

However, when we omit any relevant variable (e.g., motivation, managerial capability) from the regression, we create dependence between the error term and the other explanatory variables in the model. If we use OLS to estimate such a model, we end up with omitted variable bias and inconsistency of the estimates. Therefore, employing the IV method would involve leaving the unobserved factor in the error term. Although this measure is less efficient, it creates an alternative estimation technique to OLS that recognizes the presence of endogenous variable(s).

The IV estimation relies on the existence of valid instruments that satisfy the following two requirements. First, valid instruments should be relevant, i.e., they should be substantially correlated with the endogenous regressors. Second, they should be exogenous, i.e., they should be uncorrelated with the outcome except through their effects on the endogenous regressors. In this context, we considered which variable 1) is predictive of an individual's participation in an NGO program, but 2) is not associated with any of the potential unobserved covariates that influence that outcome. Moreover, given the limited dataset available, there are few available variables to choose from.

We hypothesized that family landholding along with other covariates of the structural equation would make a good instrument for the following reasons: 1) living in an NGO service area would make an individual eligible for program participation (assuming that person met all the participation criteria), but would not necessarily ensure that the individual enrolls, and 2) possessing a given block of land may be independent of specific unobserved covariates. Part of the reason for using family landholding as an IV is the belief that landholding will make participants and nonparticipants more similar on unmeasured confounders. This is certainly true for measured demographics. Therefore, the effect of family landholding on a given technical efficiency is indirect, interceded by the probability of program participation. We estimated the IV model by using the reduced form equation

$$NGO_i = \gamma_0 + \gamma_1 Land_i + \gamma_2 Age_i + \gamma_3 Age_i^2 + \gamma_4 Sex_i + \gamma_5 Edu_i + \gamma_6 FamIncome_i + \varepsilon_i \tag{4}$$

and the structural equation

$$TE_i = \beta_0 + \beta_1 NGO_i + \beta_2 Age_i + \beta_3 Age_i^2 + \beta_4 Sex_i + \beta_5 Edu_i + \beta_6 FamIncome_i + u_i. \tag{5}$$

If we consider that unconfoundedness, or selection on unobservables, holds, then it allows units to select into treatment based on unobservables that affect the response. Even if eligibility is randomly assigned, actual enrollment in programs may suffer from self-selection. However, randomized eligibility can often be used as an IV. Lack of a counterfactual further exacerbates the problem of consistent impact estimation. The control function approach is the classic way of dealing with the problem of selection on unobservables (Heckman, 1979). Selection on unobservables occurs when the error term in the outcome equation is correlated with the treatment, or with selection into the sample being used for estimation.

As noted, most models that are linear in parameters are estimated using standard IV methods. However, the control function approach offers some distinct advantages where differences exists for models that are nonlinear in the endogenous variables, even if they are linear in parameters. Nevertheless, the control function approach, while likely more efficient than a direct IV approach, is less robust, although the control function estimator is generally more precise than the IV estimator and, compared with the IVs, imposes the strongest assumptions. Three assumptions are distinct: 1) joint normality of the distribution of the error terms in the participation and outcome equations; 2) both error terms are independent of both sets of observables; and 3) standard normalization for the probit selection equation, which is identified only up to scale.

In practice, control function approaches, specifically the treatment effects model, permit the comparison of real outcomes with the counterfactual case. They have been used widely in the program evaluation literature. A standard treatment effects model is given as

$$Y_i = \delta T_i + \beta X_i' + v_i \ , \tag{6}$$

where Y_i, $i = 1, 2, ..., N$, is the outcome variable; T_i is the binary treatment assignment (T=1 if participation occurs, otherwise $T = 0$); δ is a coefficient estimator for T_i that is interpreted as a treatment effect; X_i is a vector of exogenous variables; β is a vector of coefficient parameters for X_i; and v_i is an error term that has normal distribution with mean 0 and variance σ_v^2. The participation of individuals based on a set of determinants Z_i is specified as

$$T_i^* = \gamma Z_i' + \upsilon_i \ , \tag{7}$$

where T_i^* is a latent variable, γ is a vector of coefficient parameters and υ_i is an error term. The latent variable is unobservable and its relationship with T_i is specified by

$$T_i = 1 \text{ if } T_i^* > 0, \text{ otherwise } T_i = 0. \tag{8}$$

If unobserved factors in (7) are correlated with v_i, the correlation coefficient between υ_i and v_i (denoted by ρ) is nonzero, and, thus, the OLS estimate is inconsistent (Greene, 2008). Then, the expected outcome assuming a normal distribution for T become

$$\begin{aligned} E[Y_i | T_i, X_i, Z_i] &= X_i'\beta + \delta T_i + E[v_i | T_i, X_i, Z_i] \\ &= X_i'\beta + \delta T_i + \left[\rho_1 \sigma_{v_1} \{\phi(Z_i'\gamma)/\Phi(Z_i'\gamma)\}\right] P(T_i = 1|X) + \left[\rho_0 \sigma_{v_0} \{-\phi(Z_i'\gamma)/1 - \Phi(Z_i'\gamma)\}\right][1 - P(T_i = 1|X)], \end{aligned} \tag{9}$$

where the expected outcome for the participants is

$$E[Y_i | T_i, X_i, Z_i] = X_i'\beta + \delta T_i + \left[\rho_1 \sigma_{v_1} \{\phi(Z_i'\gamma)/\Phi(Z_i'\gamma)\}\right] \tag{10}$$

and the expected outcome for the nonparticipants is

$$E[Y_i | T_i, X_i, Z_i] = X_i'\beta + \left[\rho_0 \sigma_{v_0} \{-\phi(Z_i'\gamma)/1 - \Phi(Z_i'\gamma)\}\right]. \tag{11}$$

Here, $\rho_1 \sigma_{v_1}$ equals the covariance between v_i and υ_i for participants; $\rho_0 \sigma_{v_0}$ equals the covariance between v_0 and υ_0 for nonparticipants; $\phi(Z_i'\gamma)$ is the marginal probability of the standard normal distribution at $Z_i'\gamma$; and $\Phi(Z_i'\gamma)$ is the cumulative probability of the standard normal distribution at $Z_i'\gamma$. The third term of (10) and second term of (11) include the inverse Mill's ratio to control for possible sample selection bias. The difference in the expected outcome between participants and nonparticipants then becomes

$$E[Y_i | T_i = 1, X_i, Z_i] - E[Y_i | T_i = 0, X_i, Z_i] = \delta + \text{ selection term.} \tag{12}$$

The positive (negative) sign of the selection term implies that OLS overestimates (underestimates) δ and the sign of the selection term depends on that of ρ. Maximum likelihood estimation is employed because it produces consistent estimators (Maddala, 1983; Greene, 2008). It also jointly estimates the participation and productivity equations and allows the testing of the significance of cross-equation correlation, ρ. We estimated the treatment effects model by using the participation equation

$$NGO_i = \gamma_0 + \gamma_1 Land_i + \gamma_2 Age_i + \gamma_3 Age_i^2 + \gamma_4 Sex_i + \gamma_5 Edu_i + \gamma_6 FamIncome_i + \varepsilon_i \quad (13)$$

and the productivity equation

$$TE_i = \beta_0 + \beta_1 NGO_i + \beta_2 Age_i + \beta_3 Age_i^2 + \beta_4 Sex_i + \beta_5 Edu_i + \beta_6 FamIncome_i + u_i . \quad (14)$$

4-1 Estimation results for participation in an NGO program

Table 3 provides the empirical estimates of the OLS, IV and treatment effects models for the effect of participation on technical efficiency. Participation in an NGO program appeared to have a significant effect on household productivity in the treatment effects model and the IV model, but this was not significant in the OLS case. The level of significance is lower in the selection model than in the IV model. The magnitude of productivity improvement by participation is high in the treatment effects model compared with the IV model. The LR statistic is significant, indicating that the participation equation and the outcome equation are not independent. Thus, the selection model produces more efficient estimates compared with the IV model.

Table 3 : Effect of participation in an NGO program on productivity (dependent variable = technical efficiency)

Variables	OLS	IV	Treatment effects model
Constant	0.8243***	0.7877***	0.7805***
Participation	0.0011	0.0303*	0.0350***
Age	0.0015*	0.0027**	0.0030***
Age^2	-0.00002*	-0.00003**	-0.00003***
Sex	0.0179**	0.0113	0.0115
Education	0.0001	-0.0006	-0.0007*
Family net income	-4.24e-07	3.44e-08	1.04e-07
Observation number	549	546	546
F statistics/Wald χ^2	1.88*	1.51	58.31***
First-stage estimation			
Constant		1.4300***	2.4053*
Age		-0.0410**	-0.1034**
Age^2		0.0004***	0.0010**
Sex		-0.0738	-0.2597
Education		0.0165***	0.0458***
Family net income		-0.00002***	-0.00004**
Family land		0.0006***	0.0015***
DWH test statistics		4.69**	
Sargan test		Exactly identified	
ρ			-0.7237
σ			0.0301
λ			-0.0218
LR statistic			15.08***

Source : Author’s estimation based on LIAIB (2006–07) data for Bangladesh
Note : The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The “treatreg” command in Stata version 11 was used for the treatment effects model estimation.

In this study, we considered mainly crop productivity. Overall, participation in an NGO program improves crop productivity at the household level: crop productivity is 3.5% higher for participants compared with nonparticipants, based on the treatment effects model. Similar findings are reported by Davis et al. (2010) for a farmers' field school operated by NGOs in Uganda and Kenya and by Godtland et al. (2004) in the Peruvian Andes. An explanation for this result may be that NGOs working in the study area are supporting farmers with demand-led agricultural information, which might improve farmers' production skills and ultimately their agricultural productivity.

4-2 Estimation results for duration of participation in an NGO program

We considered the duration variable as a measure of the extent of participation in an NGO program. Duration refers to affiliation with the NGO in year(s). Our hypothesis was that long-term affiliation improves the participant's productivity, possibly because of improvement in adaptability or development of a technology information network. As with participation, discussed above, we considered the results from the OLS, IV and selection models for comparison. The empirical results are given in Table 4.

Table 4 : Effect of duration of participation in an NGO program on productivity (dependent variable = technical efficiency)

Variables	OLS	IV	Selection model
Constant	0.8267***	0.7808***	0.8251***
Participation duration	0.0001	-0.0051	0.0003
Age	0.0014	0.0040*	0.0012
Age^2	-0.00001*	-0.00004**	-0.00001
Sex	0.0178**	0.0195	0.0120
Education	0.0001	-0.0009	-0.00003
Family net income	-4.58e-07	6.42e-07	1.08e-07***
Observation number	549	546	701
F statistics/Wald χ^2	1.86*	1.00	19.25***
First-stage estimation			
Constant		-9.7703**	-4.7744***
Age		0.4853***	0.1636***
Age^2		-0.0048***	-0.0016***
Sex		2.0213	0.6934**
Education		-0.1670***	-0.0443***
Family net income		0.0002***	0.00003**
Family land		-0.0038**	-0.0009**
DWH test statistic		5.19**	
Sargan test		Exactly identified	
ρ			0.3865
σ			0.0242
λ			0.0094
LR statistic			2.32

Source : Author's estimation based on LIAIB (2006–07) data for Bangladesh
Note : The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The "heckman" command in Stata version 11 was used for the selection model estimation.

The results presented in Table 4 indicate that duration of participation in an NGO program has no effect on productivity. All three models verify this result. Having found that the duration of participation is not important for productivity, in the next subsection, we examine the importance of intensity of participation for productivity improvement, using the program participation index.

4-3 Estimation results for the NGO program participation index

The NGO program participation index is the number of group meetings attended during the last month of the survey period. As most NGOs use a group approach for transferring information and technology to the participants, we considered the number of group meetings attended to be a measure of intensity of participation. The empirical results are presented in Table 5.

Table 5 : Effect of the NGO program participation index on productivity (dependent variable = technical efficiency)

Variables	OLS	IV	Selection model
Constant	0.8326***	0.9066***	0.9773***
Participation index	0.0013**	0.0584	0.0012*
Age	0.0008	-0.0050	-0.0028*
Age^2	-8.15e-06	0.00005	0.00002*
Sex	0.0242***	-0.0528	-0.0060
Education	0.0008**	0.0033	0.0004
Family net income	-7.92e-07*	1.43e-06	-1.01e-07
Observation number	346	343	407
F statistics/Wald χ^2	3.86***	0.07	10.00
First-stage estimation			
Constant		-1.2127	-5.2602***
Age		0.1065	0.1782***
Age^2		-0.0010	-0.0016***
Sex		1.1011	0.6388
Education		-0.0479	0.0128
Family net income		-0.00004	-0.00004**
Family land		0.0004	0.0021***
DWH test statistic		4.97**	
Sargan test		Exactly identified	
ρ			-0.8933
σ			0.0307
λ			-0.0274
LR statistic			15.78***

Source : Author’s estimation based on LIAIB (2006–07) data for Bangladesh
Note : The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The “heckman” command in Stata version 11 is used for the selection model estimation.

The results of Table 5 indicate that the participation index has a significant effect on household productivity in the selection model and OLS results, but not in the IV results. The level of significance is lower in the OLS results. The magnitude of productivity improvement according to the participation index is slightly greater in the OLS results than in the selection model results. The LR statistic is significant, indicating that the participation equation and productivity equation are not independent. Hence, the selection model produces more efficient estimates compared with those of the OLS estimates. Thus, a 1% increase in NGO meeting participation is estimated to increase productivity by 0.12% for participants in NGO programs.

4-4 Estimation for each NGO type

We compared the OLS and IV results for each type of NGO (local, national, international) using dummy variables. We also employed a model with multinomial treatments and continuous outcomes using maximum simulated likelihood (Deb and Trivedi, 2006). The model considers the effect of an endogenously chosen multinomial-valued treatment on an outcome variable, conditional on two sets of independent variables. The treatment choice is assumed to follow a mixed multinomial logit distribution. We specify the model with a latent factor structure that allows idiosyncratic influences on treatment choice to affect outcomes. The model is adopted from Deb and Trivedi (2006) and Deb (2009); the details are given as follows.

Considering individual i, who chooses one treatment from a set of four choices, one of which is a control group, implying a multinomial choice model. Let U_{ij}^{*} denote the indirect utility obtained by selecting the j^{th} treatment, $j=0,\ 1, 2, ..., J$ and $U_{ij}^{*}=z_i^{'}\alpha_j+\delta_j l_{ij}+\eta_{ij}$, where z_i denotes exogenous covariates with associated parameters, α_j and η_{ij}, which are independently and identically distributed error terms. The indirect utility function includes a latent factor l_{ij} that includes unobserved characteristics common to individual i's treatment choice and outcome and that is assumed to be independent of η_{ij}. Let $j=0$ denote the control group for which the utility is $U_{ij}^{*}=0$ for generality. Let t_j be binary variables representing the observed treatment choice and $\mathrm{t}_i=(t_{i1},t_{i2},...,t_{iJ})$. Also let $\mathrm{l}_i=(l_{i1},l_{i2},...,l_{iJ})$. Then, the probability of treatment is represented as

$$\Pr(\mathrm{t}_i|z_i,\mathrm{l}_i)=\mathrm{g}(z_i^{'}\alpha_1+\delta_1 l_{i1},z_i^{'}\alpha_2+\delta_2 l_{i2},...,z_i^{'}\alpha_J+\delta_J l_{iJ}) \ , \tag{15}$$

where g is an appropriate multinomial probability distribution. Specifically, we assume that g has a mixed multinomial logit structure, defined as

$$\Pr(\mathrm{t}_i\left|z_i,\mathrm{l}_i\right.)=[\exp(z_i^{'}\alpha_j+\delta_J\, l_{iJ})]/[1+\sum_{k=1}^{J}\exp(z_i^{'}\alpha_k+\delta_k\, l_{ik})] \ . \tag{16}$$

Now the outcome equation for individual i, $i=1,...,N$, is

$$E(y_i\left|\mathrm{t}_i,x_i,\mathrm{l}_i\right.)=x_i^{'}\beta+\sum_{j=1}^{J}\gamma_j\, t_{ij}+\sum_{j=1}^{J}\lambda_j l_{ij} \ , \tag{17}$$

where x_i is a set of exogenous covariates with associated parameter vectors, β and γ_j, designating the treatment effects relative to the control. $E(y_i\left|\mathrm{t}_i,x_i,\mathrm{l}_i\right.)$ is a function of each of the latent factors l_{ij} , i.e., the outcome is affected by unobserved characteristics that also affect selection into treatment. If the factor-loading parameter, λ_j, is positive (negative), the selection is positively (negatively) correlated through unobserved characteristics.

Again, the joint distribution of the treatment and outcome variables, conditional on the common latent factors, can be written as

$$
\begin{aligned}
\Pr(y_i, \mathrm{t}_i \mid \mathrm{x}_i, z_i, \mathrm{l}_i) &= f(y_i \mid \mathrm{t}_i, x_i, \mathrm{l}_i) \times \Pr(\mathrm{t}_i \mid z_i, \mathrm{l}_i) \\
&= f(\mathrm{x}_i'\beta + \mathrm{t}_i'\gamma + \mathrm{l}_i'\lambda) \times \mathrm{g}(z_i'\alpha_1 + \delta_1 l_{i1}, \ldots, z_i'\alpha_J + \delta_J l_{iJ})
\end{aligned} \tag{18}
$$

The simulated log-likelihood function for the dataset is

$$
\ln l(y_i, \mathrm{t}_i \mid \mathrm{x}_i, z_i) \approx \sum_{i=1}^{N} \ln[\frac{1}{S} \sum_{s=1}^{S} \{f(\mathrm{x}_i'\beta + \mathrm{t}_i'\gamma + \tilde{\mathrm{l}}_{is}'\lambda) \cdot \mathrm{g}(z_i'\alpha_1 + \delta_1 \tilde{l}_{i1s}, \ldots, z_i'\alpha_J + \delta_J \tilde{l}_{iJs})\}]. \tag{19}
$$

Provided that S (the total draws) is sufficiently large, maximizing the simulated log-likelihood is equivalent to maximizing the log-likelihood.

Table 6 compares the OLS and IV estimates for the effect of NGO type on technical efficiency, with the results for the treatment effects model given in Table 7. In Table 6, only the OLS estimates for national NGOs indicate a significant effect on household productivity.

Table 6 : Effect of NGO type on productivity (OLS and IV estimates) (outcome variable = technical efficiency)

Variables	NGO type					
	Local NGO		National NGO		International NGO	
	OLS	IV	OLS	IV	OLS	IV
Constant	0.8302***	0.8356***	0.8296***	0.8333***	0.8311***	0.7474
NGO coefficient	0.0019	-0.0689	-0.0045*	-0.0369	0.0036	-0.3394
Age	0.0013	0.0019	0.0015	0.0022*	0.0013	0.0045
Age^2	-0.00001	-0.00002*	-0.00002*	-0.00002**	-0.00001	-0.00004
Sex	0.0160*	0.0062	0.0159*	0.0070	0.0158*	0.0304
Education	0.00005	-0.0005	-8.63e-06	-0.0004	0.00005	-0.0016
Family income	-3.77e-07	1.55e-07	-3.59e-07	-3.02e-07	-3.79e-07	1.10e-06
Observation number	500	498	500	498	500	498
F statistic	1.54	0.87	2.04*	1.09	1.59	0.13
First-stage estimation						
Constant		-0.0278		-0.1145		-0.2656
Age		0.0062		0.0210		0.0091
Age^2		-0.00006		-0.0002		-0.00007
Sex		0.0134		0.0480		0.0742
Education		-0.0055		-0.0068		-0.0043
Family income		7.78e-06**		2.14e-06		4.37e-06
Family land		-0.0002**		-0.0004**		-0.00004
DWH test statistic		2.84*		2.18		2.75*
Sargan statistic		Exactly identified		Exactly identified		Exactly identified

Control group (base category) = No participation
Source : Author's estimation based on LIAIB (2006–07) data for Bangladesh
Note : The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

In the treatment effects model (the multinomial logit model), there is one equation for each treatment relative to the control (nonparticipants). We excluded the variable "Sex" from the participation equation; otherwise, convergence would not have been possible for the maximum likelihood estimation. The model estimates in Table 7 indicate that family land, which is omitted from the productivity equation, is negatively associated in all treatment equations, although it is not significant for international NGOs. Households having smaller farms are more likely to participate in an NGO program than households with large farms. Education is negatively significant for all types of NGOs in the participation equation, indicating that illiterate and less educated farmers are more likely to participate in NGO programs.

Table 7 : Effect of NGO type on productivity (multinomial logit model) (outcome variable = technical efficiency)

Variables	Productivity equation	Participation equation		
		Local NGO	National NGO	International NGO
Constant	-7.4203***	-5.0020	-3.9056	-11.1047*
Age	0.0017	0.1545	0.1670*	0.3186
Age^2	-0.00002*	-0.0015	-0.0017*	-0.0027
Sex	0.0068	-	-	-
Education	-0.00008	-0.0991**	-0.0619**	-0.1088*
Family income	-4.07e-07	0.0001**	0.00004	0.0001*
Family land	-	-0.0052***	-0.0035***	-0.0016
Treatment effect:				
Local NGO	0.0006			
National NGO	0.0112***			
International NGO	0.0122*			
ln alpha	7.2488***			
λ Local NGO	0.0002			
λ National NGO	0.0090***			
λ International NGO	-0.0106**			
Observation number	498			
Wald χ^2	59.60***			

Source: Author's estimation based on LIAIB (2006–07) data for Bangladesh
Note: The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The "mtreatreg" command in Stata version 11 is used for the estimation of the treatment effects model.

The results of Table 7 also show significant treatment effects for national and international NGOs. Because the conditional mean for the outcome is exponential, the parameter estimates can be interpreted directly in percent changes in the mean outcome. Therefore, participants in programs by international NGOs have 1.2% more technical efficiency than nonparticipants, whereas those participants in national NGO programs have 1.1% more technical efficiency than nonparticipants. There is also significant evidence of selection on unobservables for participation in programs by national and international NGOs. The selection bias is positive for participation in national NGO programs, suggesting a positive correlation between the unobserved determinants of participation and productivity; this is the reverse in the case of participation in international

NGO programs. The chi-square test rejects the independence of the productivity and participation equations at the 1% level of significance.

Overall, the results suggest that participation in NGO programs improves agricultural productivity. Intensity of program participation is important for productivity improvement, but duration is not. This might be because participation gives farmers technological information as well as solutions to their farming problems. More intense participation allows farmers to share their problems with each other as well as with the experts and to receive updated solutions and technological information, thus helping to improve their productivity. Participants in programs by international NGOs have higher productivity than participants in national NGO programs, indicating that international NGOs perform better than national NGOs in terms of farm-level productivity. This might be due to their technological advancement for supporting farmers. This suggests that, to improve farm-level agricultural productivity, the government should relax operational rules and regulations related to NGO activities. Government agricultural programs should be implemented in a way that engages multiple stakeholders, including NGOs. Village-level engagement might be most effective in this context. Field-level NGO workers need logistic support from the government as well as from their respective organizations—a role that local governments can perform with proper guidelines. The finding that local NGOs are less important for productivity improvement indicates that local NGOs should intensify their programs by targeting farmers' most pressing problems.

5. Conclusions

By employing survey data on the long-term impact of antipoverty interventions in Bangladesh, from 2006–07, this study investigated whether participation in NGO extension programs improves farm-level agricultural productivity in Bangladesh. The OLS, IV and the control function approaches were applied, considering four dimensions of participation in NGO programs. We found that there is scope for farms to achieve further productivity improvements. We also found that participation in an NGO program improves agricultural productivity and that the intensity of participation is more important than the duration. International NGOs have a greater effect on improving productivity than national NGOs. Local NGOs do not make a significant contribution to productivity improvement. Participation in an NGO program enhances productivity mainly through supporting farmers by solving farm problems and transferring updated technologies in the study areas. These findings highlight the importance of supporting NGOs as a major vehicle for farmer development. Government extension programs should involve NGOs in implementation at the field level. NGO staffs need greater local government support to perform their activities and overcome operational obstacles. Future research should investigate the farm-level operational obstacles encountered by NGOs as well as strategies for overcoming them.

References

Anonymous (2003). "Existing Extension System: Strengths, Weaknesses and Proposed Reforms in Bangladesh." Country Paper: Paper Presented in Regional Workshop on Operationalizing Reforms in Agricultural Extension in South Asia, held on 6-8 February, 2003 at New Delhi, India.

Battese, G. E., and T. J. Coelli (1992). "Frontier Production Function Technical Efficiency and Panel Data with Application to Paddy Farmers in India." *Journal of Productivity Analysis*, Vol.3, No.1-2, pp.153-169.

Battese, G. E., and T. J. Coelli (1995). "A Model for Technical Inefficiency in a Stochastic Frontier Production Function for Panel Data." *Empirical Economics,* Vol.20, pp. 325-332.

Birkhaeuser, D., R. E. Evenson, and G. Feder (1991). "The economic impact of agricultural extension: a review." *Economic Development and Cultural Change*, Vol.39, pp. 610-650.

Davis, K., E. Nkonya, E. Kato, D. A. Mekonnen, M. Odendo, R. Miiro, and J. Nkuba (2010). "Impact of Farmer Field Schools on Agricultural Productivity and Poverty in East Africa." IFPRI Discussion Paper, 00992, International Food Policy Research Institute.

Deb, P., and P. K. Trivedi (2006). "Maximum Simulated Likelihood Estimation of a Negative Binomial Regression Model with Multinomial Endogenous Treatment." *The Stata Journal*, Vol.6, No.2, pp. 246-255.

Deb, P. (2009). "MTREATREG: Stata Module to Fits Models with Multinomial Treatments and Continuous, Count and Binary Outcomes Using Maximum Simulated Likelihood." Available: http://ideas.repec.org/c/boc/bocode/s457064.html (accessed October 24, 2011).

Dinar, A., G. Karagiannis, and V. Tzouvelekas (2007). "Evaluating The Impact of Agricultural Extension on Farms Performance in Crete: A Nonneutral Stochastic Frontier Approach." *Agricultural Economics*. Vol.36, pp. 133-144.

Fuiji, A. (2001). "Determinants and Probability Distribution of Inefficiency in the Stochastic Cost Frontier in Japanese Hospitals." *Applied Economics Letters*, Vol.8, No.12, pp. 807-812.

Godtland, E. M., E. Sadoulet, A. de Janvry, R. Murgai, and O. Ortiz (2004). "The Impact of Farmer-Field-Schools on Knowledge and Productivity: A Study of Potato Farmers in the Peruvian Andes." *Economic Development and Cultural Change*, Vol.53, No.1, pp. 63-92.

Greene, W. H. (1990). "A Gamma Distributed Stochastic Frontier Model." *Journal of Econometrics,* Vol.46, pp. 141-164.

Greene, W. H. (2008). *Econometric Analysis (6th Edition)*. New Jersey: Prentice-Hall, Upper Saddle River.

Heckman, J. J. (1979). "Sample Selection Bias as a Specification Error." *Econometrica*, Vol.47, No.1, pp. 153-161.

Maddala, G. S. (1983). *Limited-Dependent and Qualitative Variables in Econometrics*. New York, Cambridge University Press.

MOA (Ministry of Agriculture) (2011). "Bangladesh Agriculture at a Glance." http://www. moa.gov.bd/statistics/bag.htm (accessed: July 7, 2011).

Otsuki, T. (2010). "Estimating Agroforestry's Effect on Productivity in Kenya: An Application of a Treatment Effects Model." OSIPP Discussion Paper, DP-2010-E-001.

Owens, T., J. Hoddinott, and B. Kinsey (2003). "The Impact of Agricultural Extension on Farm Production in Resettlement Area of Zimbabwe." *Economic Development and Cultural Change*, Vol.51, pp. 337-357.

Robbani, M., S. U. Siddiquee, S. Zaman, and H. Nakamura (2007). "Agriculture in Bangladesh: Recent Trend and Agroenvironment toward Sustainability." *Journal of the Faculty of Agriculture Shinshu University*, Vol.43, No.2, pp. 17-25.

Street, A. (2003). "How Much Confidence Should We Place in Efficiency Estimates?" *Health Economics,* Vol.12, No.11, pp. 895-907.

World Bank (2005). "Revitalizing the Agricultural Technology System in Bangladesh." Bangladesh Development Series, Paper No.7, The World Bank Office, Dhaka.