Extension Participation and Improved Technology Adoption: Impact on Efficiency and Welfare

by Sadick Mohammed and Awudu Abdulai

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Abstract:

Examining the welfare impact of agricultural development interventions that incorporate diffusion of improved production technologies to farmers within extension delivery programs can be challenging, because of the difficulty in ascertaining the individual impacts of the production technology and the extension delivery program. Using recent farm level data from extension dissemination program of legume inoculant technology in Ghana, we employ a novel approach to investigate, simultaneously, the impact of the inoculant technology adoption and the extension program participation on farmers' productivity, efficiency and welfare. We decompose each of these impact measures into subcomponents whose causal paths can be traced to both the adoption of the production technology and the extension delivery program. We find that improved technology adoption alone contributes 72% directly to farm productivity and 73% indirectly due to improved farmer efficiency, leading to 77% improvement in farmers' welfare. On the other hand, extension delivery program participation alone contributes 28% directly to farm productivity and 27% indirectly due to improved farmer efficiency, resulting in 23% improvement in farmers' welfare.

Keywords: Stochastic Frontier Analysis, Mediation Analysis, Treatment Effect, Impact Assessment, Inoculant Technology Adoption.

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1. Introduction

The increasing global food demand calls for adoption of new agricultural technologies to increase food production. Similar concerns in the past led to the introduction of the green revolution, a policy that advocated for intensifying the use of high yielding varieties, mineral fertilizers and tractors among smallholder farmers in developing countries (Pingali, 2012). Although the policy led to an increase in agricultural productivity and food supply, it also contributed to environmental impacts such as degraded lands, impoverish soils and adverse climatic conditions due to reactive nitrogen released from agriculture production activities (Pingali 2012; Zhang *et al.*, 2015). Increase in food production cannot be achieved without sufficient nitrogen supply, as nitrogen allows farmers to increase crop production per unit area of land (Zhang *et al.*, 2015). To mitigate the effect of pollution from reactive nitrogen while ensuring sufficient food production, a new paradigm shift is required (Mutuma *et al.*, 2014; Zhang *et al.*, 2015).

The Integrated Soil Fertility Management (ISFM) is one of such new approaches employed to promote soil fertility enhancing technologies for resource-poor farmers in developing countries (Crowley and Carter, 2000). A technology promoted under the program among smallholder soybean farmers in northern Ghana is the legume inoculant technology. The soybean is targeted due to its potential to undergo sustainable intensification, its industrial value and nutritional quality (Heerwaarden *et al.*, 2018; Foyer *et al.* 2018). The inoculant technology is an organic input containing isolates of an elite strain of bacterial (*Bradyrhizobium japonicum*) and organic carrier material (Lupwayi, *et al.*, 2000). The inoculant technology is seen as cost-effective alternative to rehabilitating poor soils by enhancing the build-up of biological nitrogen fixation (BNF) organisms in the soil (Giller, 2001). Empirical evidence of potential productivity gains from inoculant is reported in the literature (see Rurangwa *et al.*, 2018; Heerwaarden *et al.*, 2018; Chibeba *et al.*, 2018). Notably, grain yield of soybean increased by 20 – 29 percent in Mozambique (Chibeba *et* *al.*, 2018) and 12 – 19 percent in the northern region of Ghana (Ulzen *et al.*, 2016), relative to uninoculated fields. Yield response to inoculant significantly varies across agro-ecological zones in Africa and depend on agronomic practices and varietal promiscuity to the strain of the *Rhizobia* in the inoculant (Heerwaarden *et al.*, 2018). To improve efficiency, organizations involved in the dissemination of the inoculant technology employ several innovative extension methods[3] to school farmers on good agronomic and crop management practices on the inoculant technology.

Our goal in this study is to simultaneously assess the impact of the inoculant technology adoption and the extension participation on farmers' productivity and efficiency. Usually, agricultural development programs such as the inoculant dissemination program often have a dual goal of inducing an upward shift in the production frontier and promoting better management, which incorporates two potentially endogenous treatments in a single program (Bravo-Ureta, 2014). The treatment of a new superior technology and that of building human capital, each having the potential to influence both the technology frontier function and the inefficiency function independently (Huang and Liu, 1994; Kumbhakar *et al.*, 2009). However, empirical studies often overlook the double treatment endogeneity, most often addressing one of them, and subsuming the other into distributional assumptions of the model. For instance, in Dinar *et al.* (2007) study on the impact of extension service in Greece, extension participation is analyzed as performing a dual role, an input in the production function and a factor narrowing the technology gap, exerting direct and indirect effects in the production process. Their approach implicitly assumed homogeneous technology and fail to account for selection bias in the extension participation. In the event that farmers self-select into an extension program or adopt superior production technology, the direct and indirect effects due to heterogeneity in technology or enhanced farmer capacity will be

[3] The extension channels employ are video documentaries, radio listening clubs, on-farm and off-farm trials, field days, brochures, use of community volunteers.

unaccounted for and the impact will be incomplete. Other studies following the seminal work of Dinar *et al*. (2007) employ a mixed multi-stage approach to address the issue of selectivity and technology heterogeneity (e.g. Bravo-Ureta, *et al*., 2012; Villano *et al*., 2015; Abdulai and Abdulai, 2016; De los Santos-Montero and Bravo-Ureta, 2017; Abdul-Rahaman and Abdulai, 2018; Bravo-Ureta, *et al*., 2020). Even though the mixed multi-stage approach accounts for selection bias, it fails to account for the direct and indirect impacts that heterogeneous production technologies may have on both the production frontier and the efficiency function. The mixed multi-stage approach also attempts to address technology heterogeneity among production units by estimating group-specific frontiers for different groups of production units and further use the group frontiers to obtain the meta-frontier for comparison. However, because the maximum likelihood estimates of the predicted group-specific frontier is neither known a prior nor estimated relative to the same frontier, some degree of biasness in this approach is unavoidable and difficult to ascertain (Huang *et al.*, 2014). Moreover, as indicated by Triebs and Kumbhakar (2018), the approach subsumes observed variables like extension service with the potential to augment the farmer's managerial ability in the inefficiency parameter of the model. On the contrary, the managerial ability does not only influence the inefficiency function but also the technology frontier, resulting in non-neutrality of the production function (Huang and Liu, 1994; Triebs and Kumbhakar 2018). Also, the endogeneity issues address in the mixed multi-stage approach center mainly on the feedback between the technology choice and the production model residuals, but not on accounting for endogeneity, which could separately and simultaneously affect the technology frontier and the production inefficiency function (Chen *et al.,* 2020).

The present study attempts to fill the gap and contribute to the above literature on impact assessment and technical efficiency, using survey data of 600 farm households from northern Ghana. Specifically, we employ the stochastic frontier model with endogenous treatment and mediator effect (Chen *et al.,* 2020), to estimate the impact of dual purpose development interventions, and to decompose the impact into direct and indirect effects. This novel approach brings together mediation analysis[4], treatment effect and that of the stochastic frontier models in a single framework. Using this approach, we are able to disentangle the dual purpose development interventions' impact into four components. That is, the direct effects on the technology frontier, the indirect effects on the technology frontier that go through the mediator, the direct effects on the technical inefficiency, and the indirect effects on the technical inefficiency that go through the mediator. Our approach departs from the conventional approaches in the literature (e.g. Bravo-Ureta, *et al*., 2012; Villano *et al*., 2015; Abdulai and Abdulai, 2016; De los Santos-Montero and Bravo-Ureta, 2017; Bravo-Ureta *et al.*, 2020), in which a conventional SPF model that corrects for sample selection bias is estimated. In particular, we estimate a treatment effect model using the stochastic frontier regression framework, while addressing endogeneity from selection bias, endogenous treatment and mediator variables. We also account for treatment heterogeneities among production units.

The rest of the paper is organized as follows: In sections 2 and 3, we present the conceptual and empirical framework and empirical identification of causal impact respectively, section 4 discusses the empirical specification and the estimation procedure, while section 5 describes the data and descriptive Statistics. The empirical results are presented in section 6, while section 7 contains the conclusion and policy implications.

2. Conceptual and Empirical Framework

In agriculture, new production technologies such as high yielding varieties, complementary inputs like fertilizer, or as in our case, the inoculant technology have the potential to shift the production

[4] The mediation analysis is also known as the Baron-Kenny models in the statistics literature.

frontier upwards. Also farmers who receive extension services or technical training on the new technology may experience further shift in the production frontier upwards by reducing production inefficiencies. The two shifts envisage two potentially endogenous treatments in a single agricultural development intervention that incorporates dissemination of new production technologies and training of farmers. First, adoption of a new superior technology that affects both the production frontier function and the inefficiency function (Kumbhakar *et al.,* 2009), and extension training that builds human capital with the potential to influence both the production frontier function and the inefficiency function (Huang and Liu, 1994; Triebs and Kumbhakar, 2018).

To represent both frontiers, let Y denote individual farmer i observed output under a given technology and X be a vector of observed covariates. We express the farmer's observed output in a conventional stochastic frontier form (Kumbhakar and Lovell, 2000) as;

$$Y = Y^* - u, \quad u \geq 0 \tag{1}$$

where Y^*, is the unobserved stochastic frontier that may be influenced directly by the new technology and indirectly by extension training and $u \geq 0$, is the unobserved production inefficiency assumed to be randomly distributed, which may be influenced directly by extension training and indirectly by the new technology. The expression in equation 1 indicates that Y^* and u are two distinct unobserved random components, which can be separately identified. In line with Chen *et al.* (2020), we stochastically express each unobserved function in terms of observed covariates in a system of equations as follows;

$$Y = \begin{cases} Y^* = h(X, \beta^h) + v \\ u = g(X, \beta^g) + \tilde{u} \end{cases} \quad \text{and} \tag{2}$$

$E[Y^*|X] = h(X, \beta^h)$, and $E[u|X] = h(X, \beta^g)$, $E[v|X] = 0$, $E[\tilde{u}|X] = 0$

where X is a vector of covariates, $h(.)$ is the frontier function with parameter vector β^h and $g(.)$ is a non-negative inefficiency function with parameter vector β^g, while v and $\tilde{u}$ are error terms assumed to be independently and identically distributed. $E[.]$ is the expectation operator which identifies the conditional mean expectations of the equations in the system. To relate the effect of the production frontier and the inefficiency to observed farmer-specific potential outcome, given his observed characteristics and inputs, we express equation 1 in terms of its conditional mean representation as follows;

$$E[Y|X] = h(X, \beta^h) - g(X, \beta^g) \tag{3}$$

By letting Y_1 to be the potential outcome of a farmer who adopts the technology (i.e. the inoculant technology) and Y_0 be the potential outcome, if the same farmer did not adopt, then, the average treatment effect on the treated (ATT) for adopters can be specified as;

$$ATT = E(Y_1 - Y_0|D = 1) = E(Y_1|D = 1) - E(Y_0|D = 1) \tag{4}$$

where D is a binary adoption indicator, with $D = 1$ if the farmer adopts and 0 otherwise.

3. Impact Identification Strategy

In observational data situation like ours, evaluating the impact of the inoculant dissemination program on farmers' welfare and the shifts in the production technology and inefficiency functions may suffer serious identification problems, resulting in biased estimates. However, with good and valid instruments, it is possible to categorize the whole population into a well identified mutually disjoint sub-population of adopters who are compliers of the instrument (Imbens and Angrist, 1994; Angrist et al., 1996).

In our setting, we use rural electrification as the most likely exogenous instrument that can identify various sub-population of inoculant adopters. Given that the rhizobia in the inoculant survive within a temperature limit of about 25^0C, it requires a controlled temperature storage facility.

Hence, it is expected that farmers who live in communities connected to the national grid of electricity supply may have access to the technology, compared to their counterparts who live in communities without electricity supply. If we let Z_1 represent an instrumental variable (IV) that takes a value of 1, if the farmer's village is connected to national electricity grid, and 0 otherwise, the propensity of a farmer adopting the technology can be specified in the following latent variable (i.e., D^*) discrete choice model;

$$D^* = \gamma_{z_1} Z_1 + \gamma_x X + U_D, \text{ with } D = \begin{cases} 1, & if\ D^* \geq 0 \\ 0, & otherwise \end{cases} \quad \text{and}$$

$$D = 1(\gamma_{z_1} Z_1 + X\gamma_x + U_D \geq 0) \tag{5}$$

where D is a discrete adoption decision indicator, with $D = 1$ if the farmer adopts inoculant and 0 otherwise, X is a vector of covariates, γ is the parameter of interest and U is the error term.

Naturally, it is expected that the effect of extension service participation (i.e. the managerial skills) is mainly observed after the farmer adopts the technology on which the extension training is based on. That is, when the farmer uses or adopts the inoculant technology. As such, the extension functions as a post-adoption mediator and can be modelled as a function of adoption. With a potentially endogenous binary mediator, such as the extension service participation in this case, the mediation effect can be identified with a continuous exogenous variable with known distribution and whose level differs with adoption status (Frölich and Huber, 2017; Chen *et al.*, 2020). In this circumstance, we rely on farmer's distance to the nearest extension office as a possible exogenous continuous instrument. We expect that farmer's propensity to participate in extension service programs increases as the distance decrease and decreases as the distance increase. If we let Z_2 be a continuous instrumental variable (IV) whose distribution and level decrease as mediation takes the value of 1, and increase as mediation goes to 0, then, the propensity of a farmer who adopts the technology to also participate in the extension program can be expressed in a latent variable (i.e., M^*) model as follows;

$$M^* = \alpha_d D + \alpha_{z_2} Z_2 + X\alpha_x + U_M, \text{ with } M_i = \begin{cases} 1, & if\ M^* \geq 0 \\ 0, & otherwise \end{cases} \quad \text{and}$$

$$M = 1(\alpha_d D + \alpha_{z_2} Z_2 + X\alpha_x + U_M \geq 0) \qquad (6)$$

where M is a binary mediation indicator, with $M = 1$ if the farmer participates in extension program and 0 otherwise, D is the adoption status indicator, X is a vector of covariates, α is the parameter of interest and U is the error term. Considering altogether equations 5 and 6, (which identify both the potentially endogenous adoption and extension decisions), suggest that the post-mediation potential outcome Y is a function of D and M, pre-supposing that, the post-mediation potential outcome can be represented as $Y(D, M(D))$. Where $M(D)$ is the mediator function whose effect depends on the adoption status of the farmer.

Given a binary adoption indicator (i.e., D(1), D(0)) and a binary IV ($Z_1 \in \{0,1\}$), four potential outcomes representing four mutually disjoint sub-population of farmers can be identified as follows (Angrist *et al.*, 1996; Imbens and Angrist, 1994);

$$(D(1), D(0)) = \begin{cases} (1,1), & always\ takers, \\ (1,0), & compliers\ (\boldsymbol{C}), \\ (0,1), & defiers, \\ (0,0), & never\ takers. \end{cases} \qquad (7)$$

where $\boldsymbol{C}$ is an indicator of instrument compliers, who are induced to adopt the technology based on the instrument. This sub-population of farmers, no matter the circumstance, does not change adoption status with the assigned status by the instrument (Angrist *et al.* 1996). Due to this known behavior, their potential impact better approximates that of causal estimates from a full compliance experimentation. Therefore, by conditioning on the observed covariates of farmers X and their complier status $\boldsymbol{C}$, the average treatment effect on the treated as expressed in equation 4 can be identified (Chen *et al*., 2020) as follows;

$$CLATE = E\left[Y\left(1, M(1)\right)\middle|X = x, \boldsymbol{C}\right] - E[Y(0, M(0))|X = x, \boldsymbol{C}] \qquad (8)$$

where $CLATE$ is the conditional local average treatment effect. Also, because the levels of the continuous instrumental variable for identifying the mediation effect varies with adoptions status, it is possible to decompose the unconditional local average treatment effect into direct and indirect effects as in Chen *et al.* (2020);

$$CDLATE = E\left[Y\left(1, M(1)\right)\middle|X = x, \boldsymbol{C}\right] - E[Y(0, M(1))|X = x, \boldsymbol{C}] \qquad (9)$$

$$CILATE = E\left[Y\left(0, M(1)\right)\middle|X = x, \boldsymbol{C}\right] - E[Y(0, M(0))|X = x, \boldsymbol{C}] \qquad (13)$$

where $CDLATE$ is the conditional direct local average treatment effect and the $CILATE$ is the conditional indirect local average treatment effect. Conversely, the unconditional average treatment effect can also be derived from the conditional local average treatment effects, by conditioning on only the sub-population of farmers who are compliers as follows;

$$LATE = E[CLATE(X)|\boldsymbol{C}] = E\left[Y\left(1, M(1)\right)\middle|\boldsymbol{C}\right] - E[Y(0, M(0))|\boldsymbol{C}] \qquad (11)$$

$$DLATE = E\left[Y\left(1, M(1)\right)\middle|\boldsymbol{C}\right] - E[Y(0, M(1))|\boldsymbol{C}] \qquad (12)$$

$$ILATE = E\left[Y\left(0, M(1)\right)\middle|\boldsymbol{C}\right] - E[Y(0, M(0))|\boldsymbol{C}] \qquad (13)$$

where LATE is the local average treatment effect which captures the total effect, while DLATE and ILATE are direct and indirect local average treatment effects respectively, that capture the impact due to technology adoption and mediation.

4. Empirical Specification and Estimation

A farmer's propensity to participate in extension services (i.e. the potential mediation model) may correlate with his inoculant adoption decision (i.e. the potential treatment model) either due to observed or unobserved factors. We assume that the error terms are independently and identically distributed and follow a bivariate normal distribution. In line with Chen *et al*. (2020), we specify the joint extension participation and inoculant adoption decisions as a bivariate probit, with a bivariate normal distribution and CDF $F_{U_{M,D}}(.,.,\rho_{md})$ as follows;

$$P(M, D|Z_1, Z_2, X, \eta), \text{ and } \quad \begin{bmatrix} U_M \\ U_D \end{bmatrix} |(Z_1, Z_2, X) \sim N\left(\begin{bmatrix} U_M \\ U_D \end{bmatrix}, \begin{bmatrix} 1 & \rho_{md} \\ \rho_{md} & 1 \end{bmatrix}\right) \quad (14)$$

where $\eta \equiv (\alpha_d, \alpha_{z_2}, \alpha_x, \gamma_{z_1}, \gamma_x, \rho_{md})$ is a maximum likelihood estimator of a vector of parameters. In a first-stage estimation, a bivariate probit model is estimated to control for selection bias from both observables and unobservables. To unify the impact assessment and mediation analysis within the stochastic frontier analysis framework, we represent the frontier function of Aigner *et al*. (1977) and Meeusen and van den Broeck (1977) in the form of Chen *et al.* (2020), for $d, d' \in \{0,1\}$[5], as follows;

$$Y\big(d, M(d')\big) = \breve{h}\big(d, M(d'), X, \beta_{dj}^{h}\big) - \breve{g}\Big(d, M(d'), X, \beta_{dj}^{g}\Big) + U_Y(v\big(d, M(d')\big) + \tilde{u}\big(d, M(d')\big)) \quad (15)$$

where $\breve{h}(d, M(d'), X)$ and $\breve{g}(d, M(d'), X)$ are potential frontier and non-negative potential inefficiency functions, respectively; X is a vector of covariates; β is a parameter of interest; while $v\big(d, M(d')\big)$ and $\tilde{u}\big(d, M(d')\big)$ are potential random error terms. The binary adoption indicator is $D = d, d' \in \{0,1\}$ and $j = M(d')$ is the mediator function whose distribution varies with adoption status. The conditional mean expectation of equation (15) combines the potential output model and the potential mediator model as;

5 The observed binary adoption decision indicator d varies as d', taking the value of 1, if a farmer adopts the inoculant technology and 0, otherwise.

$$E\left[Y(d, M(d'))|X, \boldsymbol{C}\right] = h_{d'}\left(X, \alpha_m, \beta_{dj}^h\right) - g_{d'}\left(X, \alpha_m, \beta_{dj}^g\right) \quad \text{and} \quad (16)$$

$$E\left[v\left(d, M(d')\right)\middle|X, \boldsymbol{C}\right] = 0,\ E\left[\tilde{u}\left(d, M(d')\right)\middle|X, \boldsymbol{C}\right] = 0, \text{ and } E[M(d')|X, \boldsymbol{C}] = m_{d'}(X, \alpha_m)$$

where $m_{d'}(.)$ is a non-negative function of the potential mediator model in {0,1} with a parameter vector α_m. To reflect variations in the distribution of the non-negative potential mediator model as the adoption indicator takes the value within {0,1} in the estimated parameters of interest, we rewrite equation 16 as;

$$E\left[Y(d, M(d'))|X, \boldsymbol{C}\right] = h_{d'}\left(X, \alpha_m, \beta_{d1}^h, \beta_{d0}^h\right) - g_{d'}\left(X, \alpha_m, \beta_{d1}^g, \beta_{d0}^g\right) \quad (17)$$

We estimated the parameters in equation (17) using a two-stage weighted nonlinear least squares (WNLS) method. Let the individual farmer's observed outcome (Y), extension service participation (M), inoculant adoption (D) and covariates (X) be a weighted random vector $W \equiv (Y, M, D, X)$ with sample size N, and $\beta_d \equiv (\beta_{d1}^h, \beta_{d0}^h, \beta_{d1}^g, \beta_{d0}^g)$ be an arbitrary vector space of a weighted nonlinear least squares estimator (WNLSE) observed as $b_d \equiv (b_{d1}^h, b_{d0}^h, b_{d1}^g, b_{d0}^g)$. The parameter space can be expressed as the minimizer of the weighted mean square error (MSE) of the observed outcomes of interest (Frölich and Huber, 2014; Chen *et al.*, 2020) as follows;

$$\beta_d \equiv \underset{b_{d\in\beta_d}}{\operatorname{argmin}} \sum\nolimits_{d'=0,1} E[w(d, d', \alpha_w)(Y - h_{d'}\left(X, \alpha_m, b_{d1}^h, b_{d0}^h\right) + g_{d'}(X, \alpha_m, b_{d1}^g, b_{d0}^g)^2] \quad (18)$$

where $w(d, d', \alpha_w) \equiv w(1,1, \alpha_w)$, $w(1,0, \alpha_w)$, $w(0,1, \alpha_w)$, and $w(0,0, \alpha_w)$ is a weighted function of (D, Z_1, Z_2, X), with a parameter vector α_w obtained from the first-stage estimation. The weighting function $w(d, d', \alpha_w)$ accounts for heterogeneities within the production units that may be due to observed and unobserved firm-specific factors influencing production (or outcomes, which in our case is yield and farm net returns). The WNLS is estimated using the generalized method of moment (GMM) approach. The generalized moment-based approach overcomes the restrictiveness in forcing the traditional parametric family of production functions (such the Cobb-Douglas, Translog, and others) in assuming specific distributions, which is sometimes inappropriate leading to modelling bias and misleading conclusions (Giannakas et al., 2003; Vidoli and Ferrara 2015; Ferrara and Vidoli 2017; Ferrara 2020).

5. Data and Descriptive Statistics

The present study uses farm level data obtained from a recent survey conducted in the northern region of Ghana from June to August 2018. The sample was drawn using a multi-stage sampling technique. Based on the proportion of beneficiary communities (78%) in the inoculant dissemination program and intensity of soybean production in Ghana, northern region was purposively selected. Cluster sampling technique was used to zone the region into two clusters, consisting of eastern corridor zone (ECZ) and western corridor zone (WCZ). Based on dissemination program participation status of districts and intensity of soybean production at the district level within the clusters, eight (8) districts, comprising four (4) from each cluster were purposively sampled. From the ECZ: Yendi, Saboba, Chereponi and Karaga districts were selected, while in the WCZ: East Mamprusi, East Gonja, Savelugu and Kumbungu districts were selected. In consultation with the field officers and agriculture extension agents (AEAs) in the selected districts, 5-7 communities were proportionally sampled, based on the extension channel received, dissemination program participation, and farmer population. One farmer-based organization (FBO) was randomly selected from a list of FBOs that were exposed to the inoculant technology and another randomly selected from a list of unexposed FBOs for each community. Using a lottery approach, we randomly drew five farmers from each FBO. After a preliminary interview session with each of the selected farmers, using a computer assisted personal interview (CAPI), a list of the farmers' information network members (INMs) was compiled. The CAPI random number generator then used farmers' unique identification numbers to randomly sample three network members from each farmer's INMs for interview. A total of 600 farm households, consisting of 325 inoculant exposed farmers and 275 unexposed farmers, were interviewed in a face-to-face session. The data collected include inoculant adoption status, dissemination program participation status, household demographic characteristics, location characteristics, input used, crop yield and farm net returns, plot level precipitation and soil quality.

Definitions and summary statistics of the variables used in the empirical analysis are presented in Table 1. It shows that 54% of our sampled farmers participated in the inoculant extension program. Table 1 also shows that 51% of farmers adopted the inoculant with an average yield of 830kg/ha soybeans and net returns of 840GHC/ha. The population of farmers in our sample are quite young with an average age of 42 years and predominantly male farmers 71%, with very low level of education, averaging 3 years of schooling.

As shown in Table 1, average land cultivated to soybeans is 5ha, using an average total labor supply of 8 persons hours per day/ha and 4kg/ha of agrochemicals in the process. It further shows that 57% of the farmers are located in the western corridor zone. Table 1 again, shows that 51% of the farmers live in communities that are connected to the national grid of electricity supply, and located at an average distance of 19km to the nearest extension office and 2km to the nearest market. In terms of inoculant knowledge test score, Table 1 reveals that farmers obtain an average of 56% inoculant knowledge score from participating in the dissemination program.

6. Empirical Results

First, we present the results of the first-stage bivariate probit estimates, as the identification of the model hinges on it and present the estimates in the appendix due to space limitation[6]. Next, we present and discuss estimates of the weighted nonlinear least-squares, estimated via the generalized method moments procedure.

6.1 First-Stage Bivariate Probit Estimates

Table A2 presents estimates from the bivariate probit model. The model is used to account for selection bias and for identification of the instrumental variable (IV) regression. Table A2 shows that, both the extension participation model (i.e. the mediation model) and the adoption model are highly correlated due to unobserved heterogeneities. The *p*-value for the null hypothesis shows that ρ_{md} is significantly different from zero (at 1% level), indicating that farmers' extension participation and inoculant adoption decisions may be correlated due to unobserved heterogeneities. However, the sign for ρ_{md} is negative, suggesting that farmers are likely to substitute adoption of new technologies (such as the inoculant) with knowledge acquisition from extension participation (Huth and Allee 2002). This observation is intuitive, because extension services and adoption of improved technologies tend to enhance farmers' production efficiency (Huang and Liu, 1994; Kumbhakar *et al.,* 2009; Triebs and Kumbhakar, 2018). The significance of ρ_{md} also suggests that farmers may have self-selected into the extension program or adoption of the inoculant technology.

Table A2 also shows that, the two instrumental variables are both significantly different from zero (at 1 % level). In particular, distance to the nearest extension office (Z_2), which is used to identify extension program participation, is negative and significant at 1% level. More importantly, farmer's community connection to the national electricity grid (Z_1), which we used to identify the

6 Although the covariates in the bivariate probit model can be considered as determinants of inoculant adoption and extension participation, we focus on its identification properties, because the primary interest in this study is for proper model identification, and not to model determinants of participation and adoption decisions.

inoculant adoption model, is positive and highly significant at 1% level. This implies that one percent increase in rural electrification of communities, increases the likelihood of inoculant adoption by 320%. Intuitively, this makes sense, because the rhizobia used in formulating the inoculant survive in a particular temperature range (25^0C), which stands to reason that, communities with access to constant electricity supply could well operate cold storage facilities. As a result, farmers in such communities may have access to the inoculant, hence, are more likely to adopt, compared to farmers living in communities without constant electricity supply (Dzanku *et al.,* 2020). Our finding of positive effect of community electricity connectivity on farm households' production activities is consistent with existing literature on rural electrification impact on households' economic activities (see Thomas *et al.,* 2020; IEG-World Bank, 2008; Cabraal *et al.,* 2005; Martins, 2005). It is, however, unique by linking rural electrification to agricultural technology adoption.

The validity of the instrument for identification of local average treatment effect in our IV regression estimation strategy requires that the instrument be monotonic increasing function of the level of the instrumental variable (Z_1), and the level of the treatment (*D*) (see Chen *et al.,* 2020). As shown in Table A2, both the instrument in the treatment model and the treatment indicator *D* in the mediation model have positive signs and highly significant (at 1% conventional level), suggesting that our instrument is valid and strong. Intuitively, what it means is that, inoculant adoption increases with increasing extension participation and community electricity connectivity.

6.2 Determinants of Technology and Inefficiency Frontiers

Tables 2 and 3 present factors that affect the production technology and inefficiency frontiers with respect to yield (lnKg/ha), for the case scenario that farmers' adopt the inoculant technology with mediation and the counterfactual scenario of non-adoption nor mediation, respectively (see Tables 4 and 5, for that of farm net returns). The factors explain the observed yield and net returns variabilities in each scenario among farmers with different adoption and mediation conditions in our sample. For the sake of brevity, we focus the discussion on the yield, which can be extended to that of the net returns.

The model estimated is a weighted nonlinear least-squares regression using generalized method of moment. As such, it does not represent any specific conventional production function model, and as such does not depend on any functional form distribution assumptions. Though we estimate a nonlinear regression model with most of the covariates being log and log-squares, the parameter estimates can be interpreted as in a linear regression estimates (Chen *et al.*, 2020). Our approach of estimating the stochastic production frontier is akin to that of the generalized additive models (GAMs) approach that fits a response variable on a sum of smooth functions of explanatory variables in a regression context with normal distribution (Ferrara, 2020; Ferrara and Vidoli 2017). This specification is preferred to the conventional functional form specifications, due to its flexibility in relaxing the need to impose perfect linearity condition on the underlying stochastic frontier function between the explanatory variables and the outcomes of interest (Ferrara, 2020).

Each Table contains two columns corresponding to two different adoption scenarios. In Table 2, column one contains estimates for the case of adoption with mediation (i.e. Adopters^{M}), henceforth, mediated-adopters (MA). This category represent the scenario that farmers participated in the extension program and also adopted the inoculant technology, while column two represents the counterfactual case scenario for farmers who neither participated in the extension program nor adopted the inoculant technology, henceforth refer to as non-mediated-non-adopters (NM-NA). In

Table 3, column one represents the case scenario of farmers, who did not participate in the extension program but adopted the inoculant technology (i.e. Adopters^{N}), hereafter, non-mediated-adopters (NM-A), whereas column two represents the counterfactual case of farmers who participated in the extension program but did not adopt the inoculant technology (i.e. Non-Adopters^{M}), hereafter refer to as mediated-non-adopters (M-NA).

The estimates for the constant term in Table 2 captures the effect of unobserved farmer-specific characteristics on the production function, are all positive and statistically significant across all farmers. These results suggest that farmers may have certain unobserved characteristics that enhance or limit their ability to push the production frontier upward, irrespective of the superiority of the production technology being employed. Similar trend is observed in Table 3. The results also show that observed farmer-specific characteristics such as education, gender and age have significant impact in shifting the production frontier of farmers. In particular, for NM-NA farmers, education is positive and significant at 5% level, while education square is negative and significant 1% level, suggesting that an increase in education pushes the production frontier of this category of farmers upwards, with the maximum effect occurring at 2 years of schooling. On the other hand, education is negative and significant at 1% level for M-NA farmers, while that of the squared term is positive, suggesting that this category of farmers require more years of schooling, in order for education to have positive impact on their production frontier.

Also in Table 2, gender (i.e. being a male farmer) has positive coefficient across all farmers, but statistically significant (at 10% and 5% levels) for only NM-A and M-NA farmers respectively, suggesting that being a male farmer within our study area generally improve ones' productivity. This observation may be due to the fact that male farmers in most parts of developing countries have better access to family labor, quality land and other resources than female farmers, a finding that is in line with Gebre *et al.* (2019) in their study of gender differences in agricultural productivity among maize farmers in Ethiopia. However, the reverse is observed for the net returns in Tables 4 and 5, suggesting that in terms of net returns, female farmers' are able to push their net returns frontier upwards, compared to their male counterparts. This observation is intuitive as female farmers are more likely to have good marketing skills, compared to their male counterparts, as such are more likely to bargain for good prices.

Table 2 also shows that among the conventional inputs (land, labor, agrochemicals and improved seed variety), land has the highest effect on the production frontier. Land is positive and statistically significant at 1% level across all category of adopters (except NM-NA which is not statistically significant), suggesting that a unit increase in land cultivated to soybean under the inoculant technology leads to increase in yields ranging between 72kg/ha to 96kg/ha across various category of farmers. Similar but greater effect is observed in terms of net returns per hectare of land (see Tables 4 and 5). The results further reveal that the effect of labor on the production frontier is positive and statistically significant at 1% level for MA farmers, suggesting that this group of farmers benefited from labor availability.

Also in Tables 2 and 3, the quantity of agrochemicals used is positive and significant at 1% and 10% for NM-NA and NM-A farmers respectively, indicating that the quantity of agrochemicals applied to control weeds shifts the production frontier of this category of farmers upwards. It is possible that some farmers may not have used agrochemicals, which if not accounted for could bias the results. Following Battese (1997), we included a dummy variable for chemical usage and did not find any statistical significant effect at any conventional level.

In addition to the conventional and farmer-specific characteristics, we also controlled for environmental and geographical factors using zonal dummies, plot level soil quality and precipitation. The results reveal that the zonal dummy which indicates whether the farmer is located in the western corridor zone (WCZ) or eastern corridor zone (base category) is negative across all category of adopters but statistically significant for NM-NA and M-NA farmers only, suggesting that the eastern corridor zone has high potential for soybean production, compared to the WCZ, since being in that zone shifts the production frontier upwards relative to being in WCZ. Tables 2 and 3 also reveal that soil quality at the farm level plays significant (at 1% level of statistical significance) role in shifting the production frontiers upwards across all category of adopters. The results further show that insufficient precipitation at the plot level significantly shifts the production frontier downwards. In particular, that of MA (at 1% level of significance), a finding which is consistent with adverse effects of rainfall on productivity in the literature.

In the last two rows of Tables 2 and 3, we present estimates of post-mediation factor(s) that influence farmers' level of (in)efficiency in the usage of the inoculant technology that could have great impact on yields obtained from adoption. We conducted an inoculant technical knowledge quiz and use the test scores to proxy the post-mediation factors in the inefficiency frontier function. As shown in the Tables, the coefficient of a constant only inefficiency frontier model (represented as $\beta^{g}_{(0)}$) is positive and statistically significant at 1% level across all adopters, suggesting that adopting the inoculant technology without sufficient technical knowledge on its usage makes farmers highly inefficient and less beneficial. On the other hand, the coefficient of the inefficiency model, with inoculant knowledge test score (represented as $\beta^{g}_{(ts)}$) is negative and statistically significant at 1% level across all adopters, indicating that adopting the technology with sufficient technical knowledge increases farmers' production efficiency (i.e. reduces farmers' inefficiency). Similar results pattern is obtained for net returns in Tables 4 and 5. This finding learns credence to Dzanku *et al.* (2020), who argued that effective application of the inoculant technology requires knowledge on proper storage and inoculation procedures in order to replicate the effective experimental results of the inoculant technology by farmers.

6.3 Impact of Mediation and Inoculant Adoption on Productivity, Efficiency and Welfare

In this section, we report estimates of the treatment effects derived in equations 11 – 13. The results for yields and net returns are presented in Tables 6 and 7, respectively. Focusing on Table 6, the first column contains total impact of program participation on the farm household's welfare, decomposed into welfare contribution coming directly from adoption of new technology and indirectly from participation in the extension program. The second column contains total impact of inoculant adoption on the production frontier of inoculant adopters' relative to non-adopters, decomposed into the portion due directly to technological change which shifts the observed production frontier closer to the ideal production frontier (i.e. the potential yield frontier), and indirectly due to improvement in adopters' technical knowledge in shifting the production frontier. The estimates in the third column represent the total impact on the production efficiency of inoculant adopters relative to non-adopters, decomposed into efficiency gained due to technological change and indirectly due to improvement on inoculant adopters' technical knowledge.

The results in column one of Table 6 show that, the total treatment effect (measured as the local average treatment effect (LATE)) on yields is positive and statistically significant at the 1% level. Specifically, the impact on yield is 52kg/ha (and 46GHC/ha for net returns), suggesting that farmers who participate in the extension program and adopt the inoculant technology increased their yields (and net returns), compared to if they had neither participate in the extension program nor adopt the inoculant technology. This finding implies that farmers who have access to constant electricity supply and extension information achieve higher welfare benefits, compared to farmers who do not have access to both electricity and extension information. A decomposition of the welfare benefits due to mediation indicate that 77% (i.e. DLATE = 40kg/ha) of the welfare benefits, in terms of marginal gains in yield, can be attributed to the farm household's adoption of improved technology (i.e. the inoculant), while 23% (ILATE = 12kg/ha) is due to the farm household's participation in inoculant extension dissemination program.

The total treatment effect on the production frontier in column two of Table 6 shows that, the technological change led to a reduction in the yield gap between the production frontier of adopters and that of the best production frontier by 203kg/ha. In order words, farmers who participate in the extension program and adopt the inoculant technology increased their yields by 203kg/ha, which agrees with Ulzen *et al.* (2018) who reported that farmers' soybean yield increased by 200kg/ha with inoculant application in northern Ghana. Further decomposition of the impact on the shift of the production frontier shows that 72% (i.e. $DLATE_h$ =146kg/ha) is due to adoption of the improved technology, while 28% ($ILATE_h$ = 58kg/ha) of the shift is due to enhancement in farmers' technical knowledge on the improved technology usage. Intuitively, the total effect is an interaction of adoption of the improved technology and technical knowledge in the management of the new technology that leads to realization of the full potential of the technology. This finding is in line with Takahashi *et al.* (2020), who in a recent review of the literature on technology adoption and extension, highlight the need to collaborate the two in a single study.

In column three of Table 6, the total effect on the technical efficiency shows that improvement in technical efficiency of farmers led to an increase in yield of about 256kg/ha. This indicates that farmers who participate in the extension program and adopt the inoculant technology are able to cut down their inefficiency up to 256kg/ha (i.e. yield that would have been lost due to inefficiency) by adopting improved technology with technical knowledge. The marginal gain due to technical efficiency appears to outweighs that of yield at the production frontier (i.e. 203kg/ha). This finding is consistent with the argument by Huang and Liu (1994) that farmers who acquire technical knowledge on a new technology prior to adoption of the technology tend to benefit more. A decomposition of the total effect of technical efficiency shows that 73% (i.e. $DLATE_g$ =186kg/ha) of the improvement comes from the farmer's adoption of improved technology, while 27% ($ILATE_g$ = 70kg/ha) comes from technical knowledge on the technology, implying that the synergic effect of better technology and technical knowledge is required for farmers to be fully technically efficient. However, greater proportion of technical efficiency is achieved by adopting improved technology, which is consistent with Kumbhakar *et al.* (2009) argument that some technologies inherently make the farmer efficient or inefficient. We find similar patterns of impact on the production technology frontier and the technical efficiency frontier in the net returns model presented in Table 7.

6.4 Production and Technology Gap Profiles

In Figures 1 and 2, we present the conditional (i.e. condition on being a complier) mean yield estimates in deciles across various sub-population of adopters at the production technology and technical inefficiency frontiers, respectively. This is important in characterizing the production and technology gap between the sub-population of adopters and non-adopters, since adoption of an improved technology may induce inequalities in the production structures of farmers, due to heterogeneity in production technology and technical efficiency of farmers at the respective frontiers. Recent literature in the stochastic frontier analysis employ quantile regression to profile the production and technology gap among firms for structural analysis (e.g. Lai *et al.,* 2020; Huang *et al.,* 2017). However, the quantile regression approach is somehow restrictive as it allows for characterization of firms only at the quantile means and not at the individual firm level means, as in the case of standard regression (Fortin *et al.* 2011), the approach employed in this paper.

Figure 1shows that, the yield distance of farmers who participate in the extension program and adopt the inoculant technology – (i.e. the MA farmers (H-11)) at every decile is more closer to zero, compared to farmers who neither participate in the extension program nor adopt the technology (i.e. the NM-NA farmers (H-00)). Similarly, the MA farmers yield gap is also narrower, compared to farmers who participate in the extension program but did not adopt inoculant (i.e. the M-NA farmers (H-01)), suggesting that the yield gap of farmers who participate and adopt the inoculant technology is more closer to farmers producing soybeans at the best production technology frontier.

Also in Figure 2, the conditional mean plot of the yield at the technical efficiency frontier shows that, the average yield distance of MA farmers (G-11) at every decile is almost on the zero line, as compared to that of NM-NA (G-00) and M-NA (G-01) farmers respectively, indicating that farmers who participate in the extension dissemination program and adopt the inoculant are technically more efficient than farmers who neither adopt nor participate in the dissemination program. However, a comparison of the yield distance at both the production frontier and the technical efficiency frontier between farmers who participated in the extension dissemination program but did not adopt the inoculant (i.e. the M-NA farmers – (H-01 and G-01)) is also lower, when compared to that of NM-NA farmers (i.e. H-00 and G-00), suggesting that, extension participation even without adoption of a new technology may still be effective in improving farmers' efficiency. We find similar production and technical efficiency profile patterns in the net returns.

Figures 3 and 4 show the full conditional mean yield distributions for MA farmers (H-11) in panel (a), compared to NM-NA farmers (H-00) in panel (b) and also that of M-NA (H-01) farmers in panel (a), compared to NM-NA (H-00) farmers in panel (b), respectively. The mean yield distribution at the production technology frontier of MA farmers is much lower, and appears to be densely skewed to the left (i.e. towards zero), compared to that of the distributions of NM-NA and M-NA farmers. This finding in an indication that a greater percentage of the yield variability among the farmers may be attributed to technology heterogeneity, which greatly minimizes the yield distance between farmers who participate in the extension program and adopt the technology and those who did not. Similar pattern of distribution is observed in respect of the net returns.

Conversely, the mean yield distribution at the technical efficiency frontier in Figures 5 and 6 show that the distribution for MA farmers (i.e. G-11) is also densely skewed to the left (i.e. towards zero), compared to that of NM-NA (i.e. G-00) and M-NA (G-01) farmers, respectively. These results indicate that conditional on participating in the extension dissemination program and adopting the inoculant technology, all else being equal, greater percentage of yield variability at the frontiers may be due to random noise rather than technical inefficiency. We observed similar distribution patterns in the net returns.

7. Policy Implications and Conclusions

Analyzing the welfare impacts of improved agricultural technologies and extension delivery programs can be challenging, because either of them can lead to welfare gains. The approach often employed in empirical analysis is to focus on one component and subsume the other in statistical distributional assumptions. In this study, we employ a new approach that evaluates simultaneously the two components and decomposes the welfare impacts attributable to each of the two components. We use recent farm level data of soybean farmers who participated in the extension dissemination program of legume inoculant technology in Ghana. We investigate, simultaneously, the impact of the inoculant technology adoption and the extension program participation on farmers' productivity, efficiency and welfare. We also decompose each of these impact measures into subcomponents whose impact paths can be traced to inoculant technology adoption, extension delivery that enhances farmers' technical knowledge, and the program participation decision.

Our findings revealed that investing in either development of improved agricultural technologies such as the inoculant or intensifying extension delivery programs lead to increased productivity, as well as efficiency and welfare gains. We also found that the contribution of adoption of improved agricultural technologies alone (i.e. inoculant adoption) can improve farm productivity by 72%, productivity gain due to improved farmer efficiency by 73%, and improvement in welfare by 77%. On the other hand, extension delivery program participation alone improved productivity by almost 28%, productivity gain due to improved farmer efficiency by 27%, and improvement in welfare by 23%. Although the results suggest that improved agricultural technologies impact is greater than extension delivery, we found that the synergic effect of the two is far greater than the individual effects.

Our findings show that investment in research development aimed at developing new agricultural technologies for farmers in developing countries such as Ghana can contribute to poverty alleviation. In the same vain, our results confirm the significance of improving farmers' access to extension services, given that extension agents provide farmers with detailed knowledge on new technologies. Our findings also reveal the significance of rural electrification in enhancing the diffusion of new agricultural technologies, suggesting that state sponsored rural electrification programs will go a long way to contribute to the adoption of new agricultural technologies, thereby increasing farm incomes and reducing rural poverty. This will also facilitate the deployment of new channels of extension delivery via information and communication technologies (ICT) channels which mostly use electricity for effective functioning. As argued in this study, investment in rural electrification will also drive the development and expansion in rural enterprises such as sales of agro-inputs and perishable agro-based products, which must be stored under specific storage conditions.

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List of Tables

Table 1. Definition and Summary Statistics.

Variable	Definition	Mean	SD	Min	Max
Outcomes					
Yield	Soybean yield per hectare (lnKg/ha)	829.64	888.24	32.41	5703.87
Farm Net Return	Gross revenue less variable cost (lnGHC/ha)	840.26	762.11	75.11	4229.89
Treatment Variable					
Adopt-Inoculant	1 If farmer adopts inoculant, Otherwise=0	0.510	0.500	0	1
Mediator Variable					
AES-Part	1 If farmer participated in dissemination program, Otherwise=0	0.542	0.499	0	1
Production Inputs					
Land	Area of land planted with soybean (ha)	5.045	4.371	5.045	4.371
Labor	Total labor used in soy cultivation (Worker-days/ha)	7.808	24.23	0.198	274.73
Agrochem	Total amount of active ingredient in chemical used (kg/ha)	4	7.186	0	87.22
Chemdumy	1 If farmer uses agrochemical, Otherwise=0	0.025	0.156	0	1
Improvar	1 If farmer uses improve seed variety, Otherwise=0	0.700	0.459	0	1
Creditconst	1 If farmer is not credit constrained, Otherwise=0	0.828	0.377	0	1
Farmer-Specific Characteristics					
Age	Age of farmer (years)	41.56	13.32	18	87
Gender	1 If farmer is male, 0 for female	0.708	0.455	0	1
Edu	Years of schooling	2.792	4.687	0	21
Location					
WCZ	1 If farmer is in Western Corridor Zone, Eastern Corridor Zone = 0	0.567	0.496	0	1
Distmarket	Distance to nearest market (km)	2.362	4.137	0.100	50.10
Soilqual	1 If soil quality is good, Poor soil quality=0	0.508	0.500	0	1
Rainfall	Amount of rainfall in (%)	61.63	16.24	20	100
Instrumental Variables					
Distextoff (Z_2)	Distance to nearest extension office in (km)	18.90	25.10	0.016	160.93
Electgrid (Z_1)	1 If community is connected to the national grid for electricity supply, Otherwise = 0	0.512	0.500	0	1
Other Control Variables					
Testscore	Inoculant knowledge test score (%)	56.091	23.75	2	98
Resemtech	1 If inoculant usage resembles existing inputs usage, Otherwise=0	34.933	35.22	0	100
Techdiff	1 If inoculant application process is considered difficult, Otherwise=0	0.278	0.267	0	1
Dislang	1 If dissemination language is in farmer's mother tongue, Otherwise=0	0.695	0.461	0	1
Comextoff	1 if community has extension agent, Otherwise = 0	0.625	0.485	0	1

Note: SD is standard deviation; Min and Max are minimum and maximum values respectively.

Table 2. Adoption with Mediation – (Weighted Nonlinear Least-Squares) – Yield (lnKg/Ha)

Variables	**Adopters^{M}** *(d, M(d'))=(1,1)*	**Non-Adopters^{N}** *(d, M(d'))=(0,0)*
	Coeff.(S.E)	*Coeff.(S.E)*
Age	0.009*(0.005)	0.021(0.016)
Gender	0.096(0.128)	0.350(0.379)
Edu	0.017(0.046)	0.204**(0.095)
Edusq	-0.003(0.003)	-0.016***(0.006)
lnland	0.717***(0.101)	0.098(0.332)
lnlaborsq	0.037***(0.012)	-0.042(0.045)
lnagrochem	-0.031(0.023)	0.328***(0.113)
Chemdumy	-0.440(1.487)	1.244(1.497)
Improvar	-0.168(0.158)	-0.516(0.408)
WCZ	-0.073(0.138)	-1.384***(0.336)
Distmarket	-0.005(0.017)	-0.008(0.041)
Soilqual	0.341***(0.115)	0.506(0.378)
Rainfall	-0.008***(0.003)	-0.007(0.012)
Creditconts	-0.194(0.123)	-0.006(0.542)
Tsresid	-0.652***(0.179)	-4.271***(0.936)
Const.	5.604***(0.458)	264.037***(54.392)
Inefficiency		
$\beta^{g}_{(ts)}$	-10.281***(4.284)	-0.015***(0.006)
$\beta^{g}_{(0)}$	0.457***(0.171)	5.786***(0.207)
Observ. (N)	*306*	*294*

*Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors. Columns one and two represents farmers who participate in the extension program and adopt the inoculant (i.e. Adopters^{M} = Mediated-Adopters, abbreviated as (MA)) and farmers who neither participate nor adopt the inoculant (i.e. Non-Adopters^{N} = Non-Mediated-Non-Adopters, abbreviated as (NM-NA)), respectively.*

Table 3. Adoption without Mediation – (Weighted Nonlinear Least-Squares) – Yield (lnKg/Ha)

Variables	**Adopters^{N}**	**Non-Adopters^{M}**
	(d, M(d'))=(1,0)	*(d, M(d'))=(0,1)*
	Coeff.(S.E)	*Coeff.(S.E)*
Age	-0.0003(0.020)	0.019(0.015)
Gender	0.490*(0.280)	1.050**(0.524)
Edu	-0.051(0.107)	-0.593***(0.208)
Edusq	0.004(0.006)	0.046***(0.017)
lnland	0.958***(0.291)	0.862***(0.363)
lnlaborsq	-0.021(0.032)	-0.067(0.066)
lnagrochem	0.100*(0.060)	-0.246**(0.126)
Chemdumy	-0.156(13.989)	-12.237(7.661)
Improvar	0.411(0.449)	-0.211(0.536)
WCZ	0.441(0.477)	-1.510***(0.474)
Distmarket	-0.003(0.025)	-0.065(0.055)
Soilqual	0.635***(0.267)	1.201***(0.496)
Rainfall	0.002(0.011)	-3.3-e5(0.014)
Creditconts	-0.518(0.374)	0.810(0.697)
Tsresid	-0.223***(0.077)	-3.403***(0.933)
Const.	5.595***(1.227)	102.035***(2.270)
Inefficiency		
$\beta^{g}_{(ts)}$	-7.980***(2.112)	-0.016**(0.008)
$\beta^{g}_{(0)}$	0.080(0.247)	4.862***(0.025)
Observ. (N)	*306*	*294*

*Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors. Columns one and two represents farmers who did not participate in the extension program but adopt the inoculant (i.e. Adopters^{N} = Non-Mediated-Adopters, abbreviated as (NM-A)) and farmers who participate in the extension program but did not adopt the inoculant (i.e. Non-Adopters^{M}, abbreviated as M-NA)), respectively.*

Table 4. Adoption with Mediation – (Weighted Nonlinear Least-Squares) – Farm Net Returns (lnGHC/Ha)

Variables	**Adopters^{M}** *(d, M(d′))=(1,1)* *Coeff.(S.E)*	**Non-Adopters^{N}** *(d, M(d′))=(0,0)* *Coeff.(S.E)*
Age	0.002(0.002)	-0.065*(0.037)
Gender	-0.157***(0.062)	-0.635(0.754)
Edu	-0.005(0.019)	0.231(0.205)
Edusq	0.0002(0.001)	-0.009(0.014)
lnland	1.108***(0.042)	1.185*(0.674)
lnlaborsq	-0.009(0.006)	0.154*(0.091)
lnagrochem	-0.016(0.010)	-0.094(0.141)
Chemdumy	-0.366(0.464)	-3.434(3.090)
Improvar	-0.094(0.066)	1.078(0.921)
WCZ	-0.103*(0.057)	0.001(0.674)
Distmarket	-0.006(0.006)	0.028(0.074)
Soilqual	0.007(0.051)	0.373(0.761)
Rainfall	-0.006***(0.002)	-0.013(0.022)
Creditconts	-0.013(0.053)	6.478***(1.315)
Tsresid	0.014(0.071)	-15.578***(3.401)
Const.	5.699***(0.236)	254.477***(53.500)
Inefficiency		
$\beta^{g}_{(ts)}$	-8.430**(3.616)	-0.007***(0.001)
$\beta^{g}_{(0)}$	-0.538***(0.091)	5.730***(0.209)
Observ. (N)	*306*	*294*

*Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors. Columns one and two represents farmers who participate in the extension program and adopt the inoculant (i.e. Adopters^{M} = Mediated-Adopters, abbreviated as (MA)) and farmers who neither participate nor adopt the inoculant (i.e. Non-Adopters^{N} = Non-Mediated-Non-Adopters, abbreviated as (NM-NA)), respectively.*

Table 5. Adoption without Mediation – (Weighted Nonlinear Least-Squares) – Farm Net Returns (lnGHC/Ha)

Variables	**Adopters^{N}**	**Non-Adopters^{M}**
	(d, M(d'))=(1,0)	*(d, M(d'))=(0,1)*
	Coeff.(S.E)	*Coeff.(S.E)*
Age	-0.009(0.007)	-0.085***(0.030)
Gender	0.202**(0.088)	-5.664***(1.270)
Edu	-0.003(0.034)	0.161(0.325)
Edusq	0.0001(0.004)	0.006(0.027)
lnland	1.136***(0.104)	1.962***(0.649)
lnlaborsq	-0.024**(0.010)	-0.029(0.137)
lnagrochem	0.012(0.019)	-0.362*(0.195)
Chemdumy	-0.193(4.158)	-11.631(16.412)
Improvar	0.095(0.148)	-5.725***(1.211)
WCZ	0.238*(0.139)	-0.531(0.935)
Distmarket	0.001(0.008)	0.011(0.095)
Soilqual	0.146*(0.088)	-2.129**(0.920)
Rainfall	-0.001(0.003)	0.011(0.029)
Creditconts	-0.336***(0.129)	-6.223***(1.693)
Tsresid	-0.493**(0.232)	-2.509(2.121)
Const.	5.557***(0.480)	96.343***(30.533)
Inefficiency		
$\beta^{g}_{(ts)}$	-15.551*(8.707)	-0.040***(0.008)
$\beta^{g}_{(0)}$	-1.720***(0.647)	4.441***(0.426)
Observ. (N)	*306*	*294*

*Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors. Columns one and two represents farmers who did not participate in the extension program but adopt the inoculant (i.e. Adopters^{N} = Non-Mediated-Adopters, abbreviated as (NM-A)) and farmers who participate in the extension program but did not adopt the inoculant (i.e. Non-Adopters^{M}, abbreviated as M-NA)), respectively.*

Table 6. Productivity, Efficiency and Welfare Estimates on Soybean Yield - (lnKg/ha)

Impact on: Welfare	Technology Frontier	Inefficiency Frontier
LATE	$LATE_h$	$LATE_g$
52.296***(0.496)	-203.283***(1.987)	-256.086***(2.333)
DLATE	$DLATE_h$	$DLATE_g$
40.218***(0.427)	-145.942***(1.633)	-186.199***(2.010)
ILATE	$ILATE_h$	$ILATE_g$
12.071***(0.281)	-57.884***(1.337)	-69.915***(1.579)

*Note: *** indicates 1% level of significance; Values in brackets are bootstrapped standard errors from 1,000 re-samples. LATE is local average treatment effect, representing the total effect of participation in the extension dissemination program and inoculant adoption; DLATE is direct local average treatment effect, representing the component of the total effect that comes from inoculant adoption; ILATE is indirect local average treatment effect, representing the component of the total effect that comes from extension participation.*

Table 7. Productivity, Efficiency and Welfare Estimates on Net Returns – (lnGHC/ha)

Impact on: Welfare	Technology Frontier	Inefficiency Frontier
LATE	$LATE_h$	$LATE_g$
46.026***(0.573)	-185.568***(2.333)	-231.511***(2.245)
DLATE	$DLATE_h$	$DLATE_g$
26.478***(0.492)	-124.835***(1.998)	-151.354***(2.402)
ILATE	$ILATE_h$	$ILATE_g$
19.543***(0.466)	-60.683***(1.418)	-80.189***(1.805)

*Note: *** indicates 1% level of significance; Values in brackets are bootstrapped standard errors from 1,000 re-samples. LATE is local average treatment effect, representing the total effect of participation in the extension dissemination program and inoculant adoption; DLATE is direct local average treatment effect, representing the component of the total effect that comes from inoculant adoption; ILATE is indirect local average treatment effect, representing the component of the total effect that comes from extension participation.*

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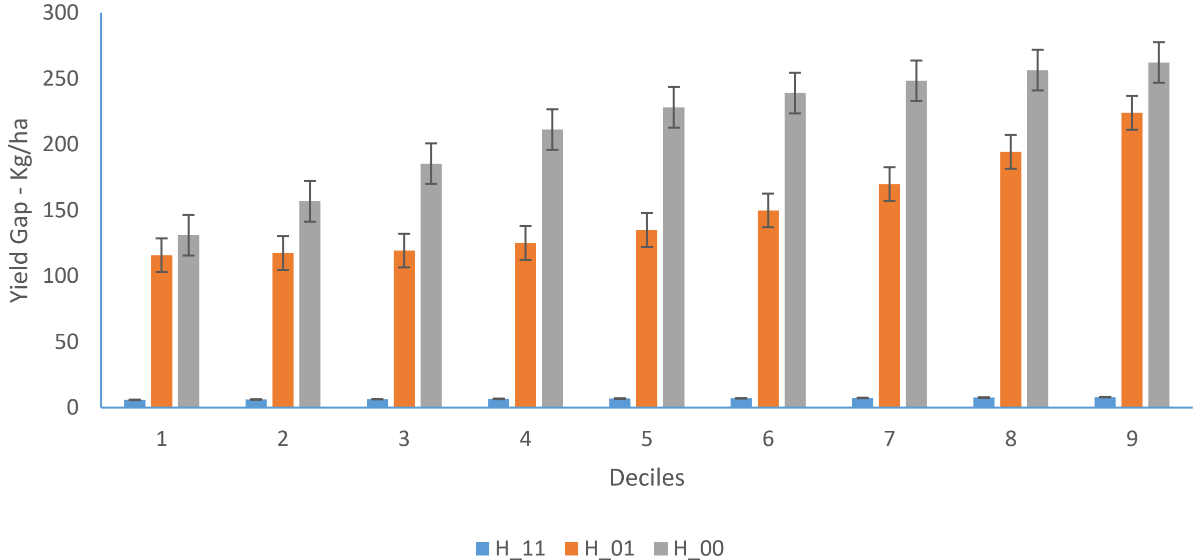

Figure 1. Yield Gap Profile at the Production Technology Frontier (lnKg/Ha).
Where H-11, H-00 and H-01 01 indicates mediated-adopters, non-mediated-non-adopters and mediated-non-adopters, respectively at the production technology frontier function of yield. The figure illustrates the yield gap profile in deciles of farmers operating at different production technology frontiers, compared to farmers at the best production frontier operating at zero technological inefficiency.

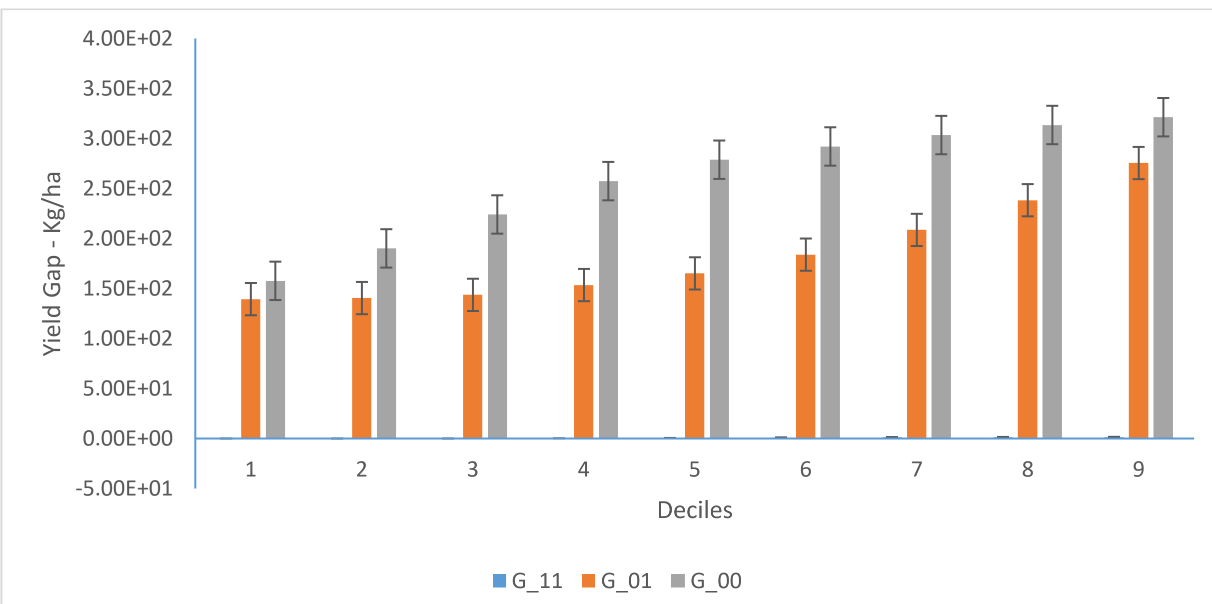

Figure 2. Yield Gap Profile at the Inefficiency Frontier (lnKg/Ha).
Where G-11, G-00 and G-01 indicates mediated-adopters, non-mediated-non-adopters and mediated-non-adopters, respectively at the technical inefficiency function of yield. The figure illustrates the yield gap profile in deciles of farmers operating at different levels of technical inefficiency, compared to farmers operating at zero technical inefficiency.

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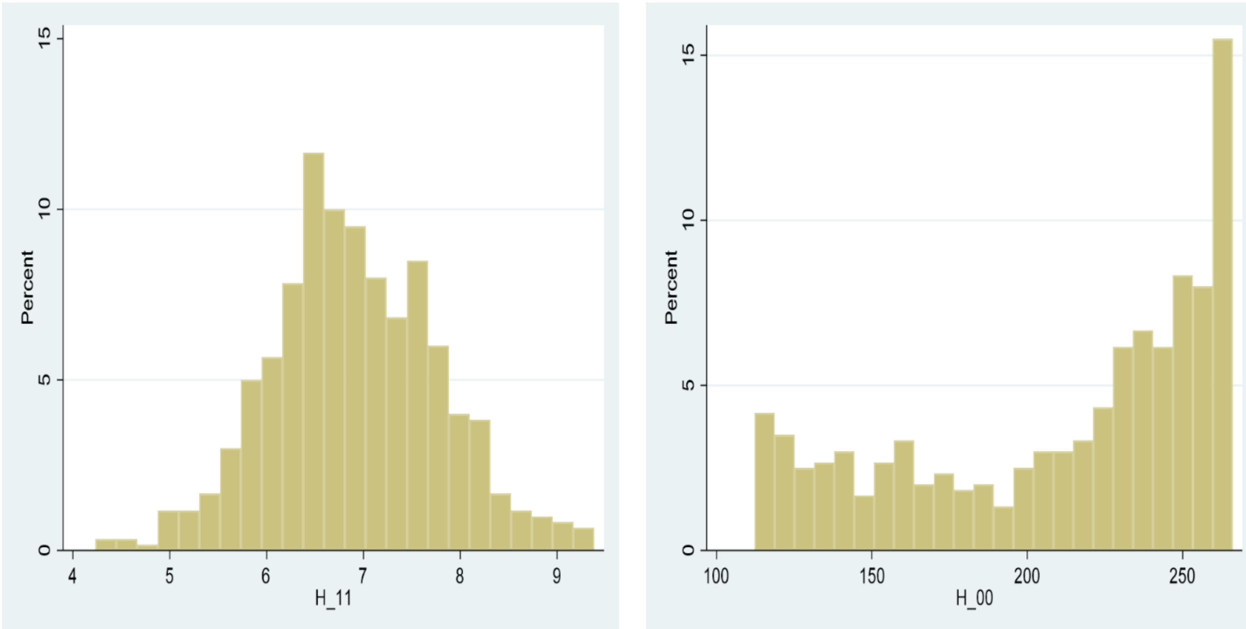
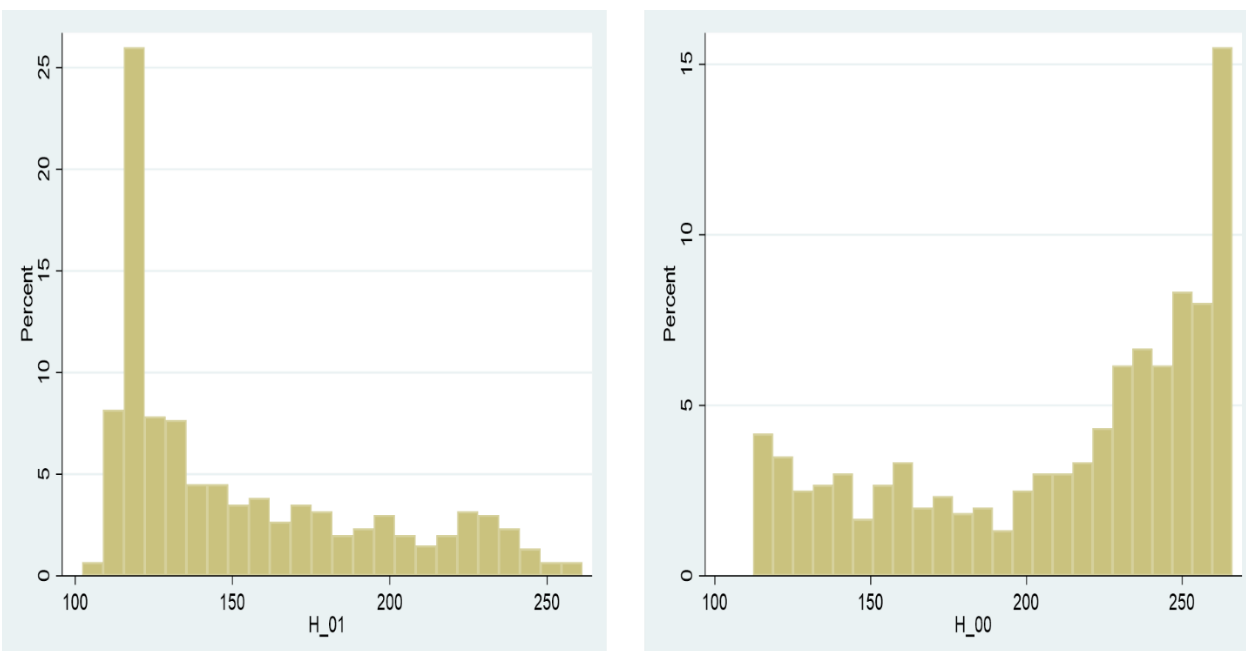


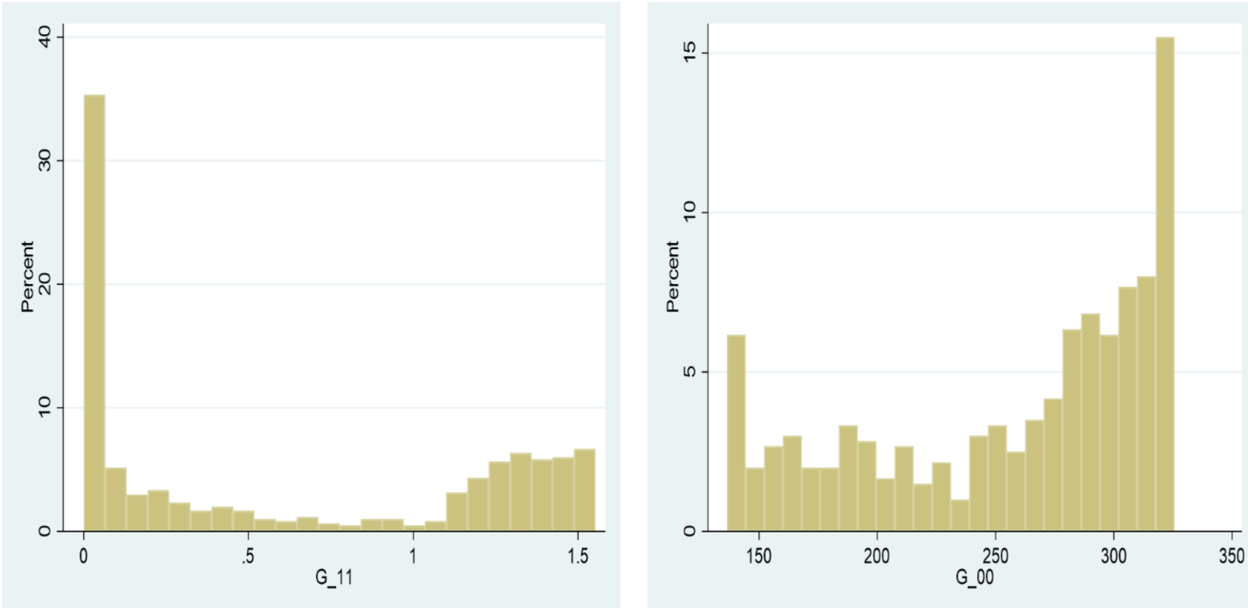
(a) Mediated-Adopters (b) Non-Mediated-Non-Adopters

Figure 3. Comparison of Yield (lnKg/Ha) Distributions at the Technology Frontier – Direct Effect



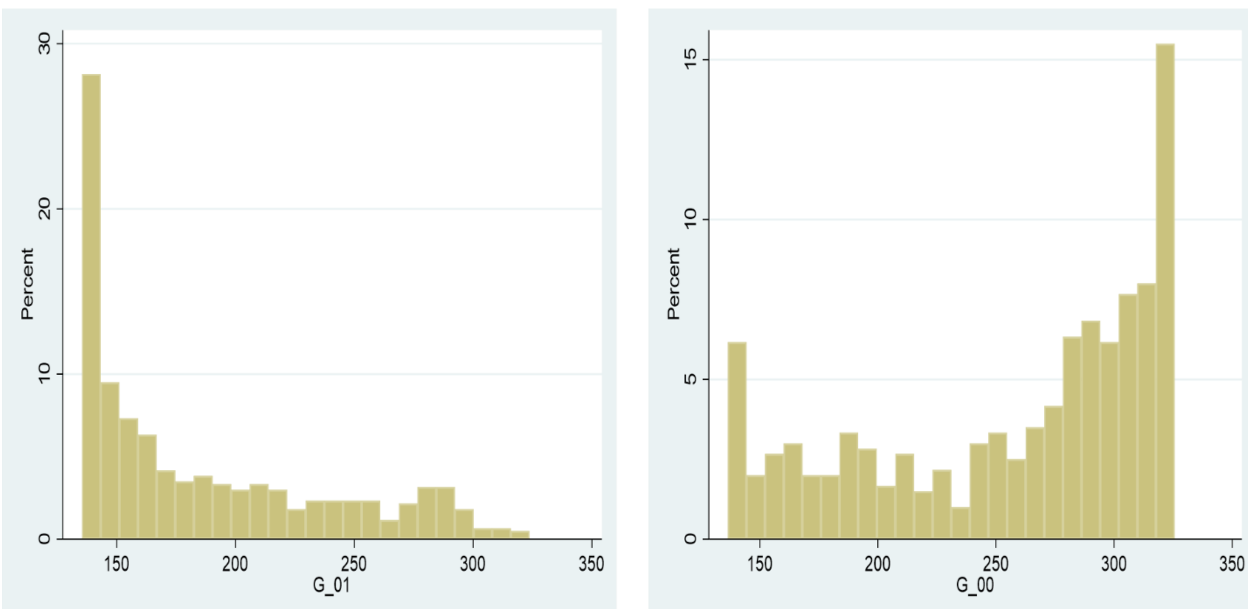
(a) Mediated- Non-Adopters (b) Non-Mediated-Non-Adopters

Figure 4. Comparison of Yield (lnKg/Ha) Distributions at the Technology Frontier – Indirect Effect



(a) Mediated-Adopters (b) No-Mediated-Non-Adopters

Figure 5. Comparison of Yield (lnKg/Ha) Distributions at the Inefficiency Frontier – Direct Effect



(a) Mediated- Non-Adopters (b) No-Mediated-Non-Adopters

Figure 6. Comparison of Yield (lnKg/Ha) Distributions at the Inefficiency Frontier – Indirect Effect

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Table A1. Comparison of Adopters and Non-Adopters.

Variables	**Adopters Mean(S.E)**	**Non-Adopters Mean(S.E)**	**Mean Diff (S.E)**
Yield	962.35(53.453)	691.53(47.57)	270.82***(71.75)
Farm Net Return	802.20(40.586)	879.87(47.37)	-77.67(62.21)
Age	43.133(0.727)	39.929(0.803)	3.205***(1.081)
Gender	0.696(0.026)	0.721(0.026)	-0.025(0.037)
Edu	2.853(0.271)	2.728(0.271)	0.125(0.383)
Land	4.88(0.235)	5.214(0.270)	-0.332(0.357)
Labor	7.649(1.980)	7.973(1.327)	-0.323(1.980)
Agrochem	3.726(0.343)	4.286(0.481)	-0.560(6.685)
Chemdumy	0.029(0.010)	0.020(0.008)	0.009(0.013)
Improvar	0.706(0.026)	0.694(0.027)	0.012(0.037)
Creditconst	0.797(0.023)	0.861(0.020)	-0.063**(0.031)
WCZ	0.565(0.028)	0.568(0.029)	-0.003(0.041)
Distmarket	2.372(0.261)	2.352(0.212)	0.020(0.338)
Soilqual	0.542(0.029)	0.473(0.029)	0.070*(0.041)
Rainfall	61.503(0.924)	61.769(0.953)	-0.265(1.327)
Comextoff	0.621(0.028)	0.629(0.028)	0.008(0.040)
Distextoff	15.78(1.155)	22.07(1.694)	-6.295***(2.037)
Electgrid	0.941(0.013)	0.949(0.013)	-0.008(0.019)
Testscore	61.692(1.647)	48.979(2.157)	12.713***(2.666)
Resemtech	38.824(2.017)	30.884(2.027)	7.939***(2.860)
Techdiff	0.307(0.015)	0.247(0.016)	0.060***(0.022)
Dislang	0.725(0.026)	0.663(0.028)	0.062*(0.038)
Comextoff	0.621(0.028)	0.629(0.028)	-0.008(0.040)
Observ. (N)	**306**	**294**	

Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors.

Table A2. Participation and Adoption Decisions (First-Stage Bivariate Probit Estimates).

Variables	**AES-Participation (M)**	**Inoculant-Adoption (D)**
	Coeffs.(S.E)	*Coeffs.(S.E)*
Const.	-3.061***(0.487)	-1.407**(0.611)
Age	0.022***(0.005)	0.007(0.007)
Gender	0.365***(0.152)	-0.397**(0.204)
Edu	0.014(0.048)	-0.017(0.058)
Edusq	-0.003(0.003)	0.0003(0.004)
lnland	-0.167(0.110)	0.003(0.135)
lnlaborsq	-0.015(0.019)	0.011(0.024)
Creditconst	-0.502***(0.179)	-0.009(0.231)
lnagrochem	0.013(0.032)	-0.028(0.040)
Chemdumy	0.059(0.454)	0.664(0.552)
Improvar	0.016(0.141)	-0.008(0.180)
WCZ	-0.209(0.137)	-0.127(0.179)
Distmarket	-0.008(0.015)	0.004(0.020)
Soilqual	0.619***(0.140)	0.229(0.172)
Rainfall	-0.006(0.004)	-0.003(0.005)
lntestsq	2.275***(0.200)	-0.038(0.202)
Tsresid	-2.861***(0.221)	0.023(0.209)
Adopt-inoculant *(D)*	1.657***(0.160)	-
Electgrid (Z_1)	-	3.200***(0.186)
Distextoff (Z_2)	-0.041***(0.013)	-
ρ_{md}	-0.715***(0.189)	
Wald test of ρ_{md}*=0*	18.27***	
LL	-359.078	
Wald Chi-sq	543.22***	
Observ.(N)		600

Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors.