Impact of improved varieties on the yield of rice producing households in Ghana

A.N. Wiredu,[1*] *K.O. Gyasi,*[1] *K.A. Marfo,*[2] *S. Asuming-Brempong,*[3] *J. Haleegoah,*[2] *A. Asuming-Boakye*[3] *and B.F. Nsiah*[2]

[1]Council for Scientific and Industrial Research – Savanna Agricultural Research Institute, Tamale, Ghana; [2] Council for Scientific and Industrial Research – Crop Research Institute, Kumasi, Ghana; [3] University of Ghana, Accra, Ghana.

Abstract

Farm households in Ghana have benefited from the programs that promote high-yielding crop varieties and other complementary technologies. The use of these improved agricultural technologies is expected to enhance performance through increased yields and incomes. Despite the expected gains, these households operate at low levels of productivity. Evidence of the impact of such interventions on performance and livelihood in the country is limited. With data from 489 randomly selected rice producers, the study applied the average treatment effect (ATE) methodology to examine the impact of adoption of new improved rice varieties on yield. Profiling the rice-producing households, it was discovered that the rate of adoption varied by location. The rate of adoption of improved rice varieties is estimated at about 46%. Adoption had positive impact on farmers' rice yields. Experience, gender (male) and expectations about the yield and performance of improved technologies had positive effect on yield. Proper targeting of beneficiaries of interventions and effective training in good agricultural practices are expected to increase adoption rates and improve the level of performance.

Introduction

Research suggests that there is good potential for improving performance and productivity in the agricultural sector in Ghana (Appiah, 1990). This can only be attained through positive transformation of the sector, including increased availability and use of improved technologies (Ampofo, 1990). The agricultural sector has benefited from myriad interventions that seek to improve yield, reduce poverty and increase incomes (ISSER, 2006, 2007, 2008). Farmers (including rice producers) have benefited from the dissemination of high-yielding crop varieties in addition to other complementary technologies (Jatoe, 2002; Al-hassan *et al.*, 2004; Langyintuo and Dogbe, 2005; Faltermeier, 2007).

Despite the expected gains from the numerous interventions, the level of adoption of improved technologies among these farmers is reportedly low. Most of these farmers use low-yielding crop varieties and poor agronomic practices. Farm households, especially those in northern Ghana, are still operating at low levels of productivity (Langyintuo and Dogbe, 2005).

Interventions are designed with the objective of improving food security, increasing incomes and reducing poverty via improved farm-level performance (Norton, 2004). The impact of interventions, such as the effect of the use of the improved technologies, is channeled through the behavioral and decision-making processes of farmers. The behavioral changes and decisions that are made are subsequently translated into high-level performance (Wu, 2005). Adoption of these technologies is therefore expected to enhance productivity and consequently increase incomes, reduce poverty and consequently ensure equity among beneficiaries (Asante *et al.*, 2004).

A handful of the rapidly growing literature on the impact of anti-poverty programs has focused on performance, rural poverty and income. Most of these impact studies have revealed positive relations between technology adoption and livelihoods (Winters *et al.*, 1998; Mwabu *et al.*, 2006; de Janvry and Sadoulet, 2002; Mendola, 2006; Kijima *et al.*, 2008; Hossain *et al.*, 2003; Bourdillon *et al.*, 2002). Mendola (2006) and Kijima *et al.* (2008), for example, identified a positive relationship between the adoption of improved crop varieties and wellbeing. Meanwhile, Bourdillon *et al.* (2002) observed that the adoption of improved maize varieties increased the crop incomes of adopters only modestly in Zimbabwe. Hossain *et al.* (2003), however, found the adoption of improved rice varieties had positive effect on wealthy households, but negatively affected poor households in Bangladesh.

These conflicting findings justify further research on the impact of improved technologies. Research scientists, policy-makers, donor agencies and all other stakeholders need clear understanding of the linkages between adoption and impact of improved behavior on performance of farm households. Most of the impact studies have used regression procedures to examine the differences in mean outcomes of adopters and nonadopters. The results from such analyses have been shown to be characterized by self-selection bias and are therefore not able to adequately identify the causal effect of adoption (Imbens and Wooldridge, 2009; Lee, 2005; Imbens, 2004; Rosembaum, 2002; Heckman and Robb, 1985; Rosembaum and Rubin, 1983; Rubin, 1974).

* Corresponding author (email: nanayawnimowiredu@yahoo.co.uk).

In order to correct for the possible effect of selection bias, Mendola (2006) uses the propensity score matching (PSM) method to estimate the average treatment effect (ATE) impact of improved varieties on income. The approach controls for the observable covariates that are partly responsible for self-selection and therefore removes that part of the selection bias called 'overt bias' (Lee, 2005; Rosenbaum, 2002). In reality, however, self-selection may also be affected by some unobservable covariates. Also in the case of adoption, treatment is endogenous and there is the possibility of noncompliance. Some participants may opt out of their treatment even when randomly assigned (Imbens and Rubin, 1997; Moffitt, 1996; Angrist *et al.*, 1996; Imbens and Angrist, 1994). Diagne *et al.* (2009) used the counterfactual outcomes framework, but estimated the parameters of local average treatment effect (LATE) of NERICA adoption on household expenditure and calorie intake in Benin. The LATE parameter is the ATE for the complying sub-population. Diagne *et al.* (2009) argue that the ATE parameter estimated with the PSM method does not identify the causal effect of adoption, but rather the impact of supplying a technology. They further argue that the parameter estimate from the LATE identifies the causal effect of adoption in the presence of noncompliance (Imbens and Angrist, 1994). In the adoption context, the sub-population of compliers corresponds to that of potential adopters of the technology (Diagne *et al.*, 2009).

This paper also uses the counterfactual outcome framework to estimate the causal effect of adoption of improved rice varieties on the incomes of rice-producing households in northern Ghana.

Methodology

Conceptual basis of local average treatment effect

The basic principle underlying the treatment effect estimation methodology is the assumption of a counterfactual outcome for every event (Diagne and Demont, 2007). This assumption implies two possible outcomes for every event. With respect to this study, any randomly selected rice farmer has two potential outcomes from adopting improved rice varieties. If y_1 represents the potential outcome of adopting improved variety and y_0 otherwise, then the expected population impact of adoption, which is also referred to as the average treatment effect (ATE), can be derived as follows:

$$TE_i = y_{i,1} - y_{i,0} \tag{1.0}$$

$$ATE = E(y_i - y_0) \tag{2.0}$$

where TE_i denotes 'treatment effect' and represents the effect of adoption on farmer i, $y_{i,1}$ the potential impact for adopters, and $y_{i,0}$ as the potential impact for nonadopters of improved varieties.

In reality, an outcome and its counterfactual cannot be observed and so $y_1 - y_0$ is undefined for farmer i. Since adoption is a necessary condition for impact, then $y_0 = 0$ for a randomly sampled farmer. This implies that the impact on farmer i is $y_{i,1}$ and the average adoption impact $ATE = E(y_1)$. This actually underestimates the true population impact because y_1 is observed for only the adopting, a situation that may result in the problem of selection bias. If $T_A = 1$ denotes adoption and $T_A = 0$ otherwise, the impact on the adopting sub-population or ATE on the treated (ATE1) can be obtained as a conditional expected value (Φ). In the same way, the expected impact on the nonadopters on the untreated (AET0) can be derived. These are given as follows:

$$ATE1 = E(\Phi_1 | T_A = 1) \tag{3.0}$$

$$ATE0 = E(\Phi_1 | T_A = 0) \tag{4.0}$$

Two broad approaches have been used in the quest to deal with selection bias associated with the noncompliance or endogenous treatment variable (Imbens, 2004). One of the approaches is based on the assumption of conditional independence (Diagne and Demont, 2007), which postulates the existence of a set of observed covariates k, which, when controlled for, renders the treatment status a independent of the two potential outcomes y_1 and y_0. The ATE parameter estimates under the conditional independence assumptions can be obtained by either pure parametric regression or two-stage procedure. In the pure parametric regression-based method, the covariates are further assumed to interact with the treatment status variable to account for heterogeneous responses. With the two-stage estimation procedure, the conditional probability of treatment or the propensity score, $\pi(T_A = 1|\mathrm{x}) \equiv \pi(\mathrm{x})$, is estimated in the first stage. In the second stage, the ATE parameters are estimated by either parametric regression-based methods or nonparametric methods (Diagne *et al.*, 2009).

The second approach, the instrumental variable (IV) based methods, assumes the existence of an instrumental variable that explains the treatment status but not the expected outcome of the treatment (Diagne *et al.*, 2009). In addition to minimizing the disturbances associated with overt bias, the IV-based method also minimizes the disturbances associated with hidden biases when treatment is endogenous (Heckman and Vytlacil, 2005; Imbens 2004; Abadie, 2003; Imbens and Angrist, 1994).

The IV-based methods assume the existence of at least one variable z called instrument that explains variations in the treatment status and not the potential outcomes, once the effects of the covariates x are controlled for. Different IV-based estimators are available, depending on functional form assumptions and assumptions regarding the instrument and the unobserved heterogeneities.

Empirical framework

This paper applies the conditional independence-based method to estimate ATE, ATE1 and ATE0 with a two-stage estimation procedure. In the first stage, a Probit adoption model is estimated to correct for the heteroscedasticity in the dichotomous dependent variable. The adoption model is explicitly expressed as:

$$T_{A,i} = \alpha_0 + \sum_{k=1}^{K} \alpha_{h,k} H_{k,i} + \sum_{k=1}^{K} \alpha_{X,k} X_{k,i} + \sum_{k=1}^{K} \alpha_{y,k} Y_{k,i} + \gamma_i \qquad (5)$$

where $H_{k,j} = (h_1, h_2, h_3, h_4, h_5, h_6)$, the variable h_1 denotes the age of household head, h_2 the gender of the household head, h_3 the number of years spent by the household head in formal education, h_4 the years of experience in rice cultivation, h_5 credit accessibility, and h_6 access to extension services. $X_{k,I} = (X_{land}, X_{lab})$, the variable X_{land} represents the size of land resource used for rice production and X_{lab} the work-days of labor resources used for rice production. $Y_{k,i}$ is a vector of variables that measures the expectation of farmers about the returns that accrue to rice production. The coefficients (α) represent the relative responses of the dependent variable to changes in the right hand side variables.

With the assumption of interaction between the k factors affecting both adoption and impact, the second stage is parametrically estimated with an ordinary least square (OLS) regression model as follows:

$$y_i = \alpha_0 + \sum_{k=1}^{K} \alpha_{h,k} H_{k,i} + \sum_{k-1}^{K} \alpha_{X,k} X_{k,i} + \sum_{k=1}^{K} \alpha_{j,k} Y_{k,i} + \alpha_{T_A,k} T_{A,i} + \gamma_i \qquad (6)$$

Data and descriptive statistics

The study involved 489 rice farmers from three districts in Ghana. The districts Ejura-Sekyedumase, Hohoe and Tolon-Kumbungu represent key rice-producing districts in the country. The three districts are located in the transitional, forest and guinea savannah agro-ecological zones, respectively. The districts are also part of the areas where improved rice varieties and other complementary technologies are being promoted.

A three-stage random sampling procedure was applied for the selection of the rice farmers. At each stage, a list of rice-producing communities and households was generated and then a statistically representative sample drawn out of the list. The listing was done at the district, community and household levels.

The majority of the interviewed farmers were male. The average age of farmers was about 41 years. They managed an average household size of about 9 persons. More than half of the interviewed farmers were educated. Access to extension services varied widely across the districts, with an average of about 2 extension contacts per year. A typical farmer had up to 12 years of experience (Table 1).

Table 1. Characteristics of rice-producing households

Characteristic	Ejura	Hohoe	Tolon	Overall
Sample size (N)	115	203	171	489
Female (%)	46.09	65.02	2.92	38.85
Male (%)	53.91	34.98	97.08	61.15
Educated (%)	53.04	59.11	53.8	55.83
Extension (%)	58.26	67.49	22.81	49.69
Extension contacts (per year)	2	2	1	2
Age (years)	44.37	44.17	33.79	40.58
Household size	7	6	15	9
Experience (years)	9	12	12	11.5

Results

Adoption of improved rice varieties

Over the years, researchers in Ghana and their international collaborators have been promoting adoption of improved rice varieties. Despite this effort, studies suggest that farmers continue to produce local varieties of rice in addition to some of the improved varieties. The results of this study suggest diverse adoption rates across the study areas.

The study had two categories of improved rice varieties:New Rice for Africa (NERICA) and national-program (NARS) varieties. About 46% of the interviewed farmers had adopted at least one of the improved varieties. A little over 90% of the rice farmers in Tolon-Kumbungu used at least one of the improved varieties. Adoption was lower among the rice farmers in Ejura-Sekyedumase and Hohoe (Table 2).

Table 2. Percentage adoption of improved rice varieties

Variety	Ejura	Hohoe	Tolon	Overall
Improved	29.57	16.75	90.64	45.6
NERICA	17.92	2.03	1.22	5.74
NARS	13.91	15.27	90.64	41.31

Overall, the rate of adoption of the NERICA varieties was very low, less than 10%, across the districts. Adoption of improved rice varieties developed by the NARS was higher (except in Ejura-Sekyedumase), yet less than 50% of the farmers had adopted these. The rate of adoption of the NARS varieties was a little over 90% among the farmers in Tolon-Kumbungu district. This situation is attributable to the fact that the promotion of improved varieties in the north of Ghana, including Tolon-Kumbungu, is very vigorous through the Council for Scientific and Industrial Research – Savanna Agricultural Research Institute.

Impact of adoption on farmers' rice yields

The results suggest significant differences between the yields of adopters and nonadopters. While adopters recorded an average yield of about 0.18 tonnes per hectare, nonadopters recorded about 0.06 t/ha. This confirms the expectation that adoption of improved rice varieties has positive impact on yield or land productivity (Wu, 2005). For any randomly selected household in the study areas, adoption of improved varieties increased yield by 0.024 t/ha. Within the sub-sample of adopters, yield was expected to increase by 2.41 t/ha. Among the nonadopters, improved rice varieties were expected increase their yield by 0.004 t/ha (Table 3).

Table 3. Impact and determinants of rice yield

ATE	Parameters	Variable	Parameters
ATE	0.0240438	Adoption	0.024044
ATE1	2.4110438	Age	0.0012829*
ATE0	0.0042404	Male	0.0508729*
PSB	–4.12E–11	Household size	0.000754
		Education	0.003356
		Yield in 2004	0.8827604*
		Extension contacts	0.036384

ATE, average treatment effect; ATE1, average treatment effect on adopters; ATE0, average treatment effect on nonadopters; PSB, population selection bias.

In order to determine the factors affecting the yields, an OLS estimation procedure was applied. In addition to farm-level characteristics, it was assumed that some idiosyncratic factors affect yield. Gender was shown to be an important determinant of yield among the rice farmers in the study area. Rice yields increased when farms are managed by male farmers.

Age of farmers was used as a proxy for experience in rice cultivation and had positive effect on yield. Experience in rice cultivation implies accumulated knowledge in rice production. This can be useful for proper management of the rice fields to ensure higher yields (Wiredu, 2009).

The expectation of rice farmers about yield of rice also had positive effect on the actual yield. This is represented by the yield from previous harvest (a lag variable that captures the expectation of farmers). Farmers obtain knowledge from previous production, which can be applied to improve yield. Moreover, if farmers expect higher yields from rice production they have incentives to invest in more productivity-enhancing practices to enhance their yields.

Conclusion

This study contributes knowledge by applying an innovative analytical procedure to determine the impact of improved technologies on performance.

The study showed, among other things, that adoption of improved technologies — including improved varieties — had positive impact on rice productivity and yield. Moreover, apart from farm-level characteristics, productivity was also affected by idiosyncrasy, which suggests the importance of the managerial expertise of the rice producer.

From the results of the study, I make a number of recommendations. In order to encourage wide adoption of improved rice varieties,promotional activities must be improved. This requires proper targeting of beneficiaries,complemented by training in good agricultural practices. Proper targeting and training of beneficiaries of interventions can help improve exposure and adoption and hence improve productivity.

References

Abadie A. 2003. Semi-parametric instrumental variable estimation of treatment response models. *Journal of Econometrics*113: 231–263.

Angrist DJ, Imbens GW and Rubin DB. 1996. Identification of causal effects using instrumental variables. *Journal of the American Statistical Association*91(434): 444–455.

Al-hassan S, Sarpong DB and Al-Hassan R. 2004. Allocative efficiency, employment and rice production risk: An analysis of small holder paddy farms in the Upper East Region of Ghana. *Ghana Journal of Development Studies* 64(1): 73–94.

Ampofo ST. 1990. Farmers' adoption of recommended practices. Paper presented at Farmer–Extension: The First Farming Systems Workshop, Accra.

Appiah MR. 1990. CRIG [Cocoa Research Institute in Ghana]. Experience in off-station research fertilizer trials. Paper presented at Farmer–Extension: The First Farming Systems Workshop, Accra.

Asante EG, Appiah MR, Ofori-Frimpong K andAfrifa AA. 2004. The economics of fertilizer use on some peasant cocoa farms in Ghana. *Ghana Journal of Agricultural Science* 33: 183–190.

Bourdillon M, Hebinck P, Hoddinott J, Kinsey B, Marondo J, Mudege N and Owens T. 2002. Assessing the impact of HYV maize in resettlement areas of Zimbabwe. *Discussion Paper* 161. International Food Policy Research Institute, Washington, DC.

de Janvry A and Sadoulet E.2002 World poverty and the role of agricultural technology: Direct and indirect effects. *Journal of Development Studies*38(4): 1–26.

Diagne A, Adekambi SA, Simtowe FP and Biaou G. 2009. Impact of agricultural technology adoption on poverty: The case of NERICA rice varieties in Benin. Paper presented at the 27th Conference of the International Association of Agricultural Economists, Beijing.

Diagne A and Demont M. 2007. Taking a new look at empirical models of adoption: Average treatment effect estimation of adoption rates and their determinants. *Agricultural Economics* 37: 201–210.

Faltermeier L. 2007. Adoption of water conservation and intensification technologies in the lowland rice production system of northern Ghana. Paper presented at the MEIDE Conference, Maastricht, Netherlands.

Heckman J and Robb R. 1985. Alternative methods of evaluating the impact of interventions. *In:* Heckman J and Singer B eds. *Longitudinal Analysis of Labor Market Data*. Cambridge University Press, Cambridge, UK.

Heckman J and Vytlacil E. 2005. Structural equations, treatment effects, and econometric policy evaluation. *Econometrica*73: 669–738.

Hossain M, Lewis D, Bose ML and Chowdhury A. 2003. Rice research, technological progress, and impacts on the poor: the Bangladesh case. *Discussion Paper 110*. International Food Policy Research Institute (IFPRI), Washington, DC.

Imbens G. 2004. Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics* 86: 4–29.

Imbens GW and Angrist JD. 1994. Identification and estimation of local average treatment effects. *Econometrica*62: 467–476.

Imbens GW and Rubin DB. 1997. Estimating outcome distributions for compliers in instrumental variable models. *Review of Economic Studies*64: 555–574.

Imbens G and Wooldridge JM. 2009. Recent developments in the econometrics of program evaluation. *Journal of Economic Literature* 47(1): 5–86.

ISSER. 2006. *The State of the Ghanaian Economy 2005*. Institute of Statistical, Social and Economic Research (ISSER), University of Ghana, Legon, Accra.

ISSER. 2007. *The State of the Ghanaian Economy 2006*. Institute of Statistical, Social and Economic Research (ISSER), University of Ghana, Legon, Accra.

ISSER. 2008. *The State of the Ghanaian Economy 2007*. Institute of Statistical, Social and Economic Research (ISSER), University of Ghana, Legon, Accra.

Jatoe JBD. 2002. The determinants of adoption and impact of improved sorghum varieties in the Upper West Region, Ghana. MPhil Thesis. Department of Agricultural Economics & Agribusiness, University of Ghana, Legon, Accra.

Kijima Y, Otsuka K and Sserunkuuma D. 2008. Assessing the impact of NERICA on income and poverty in central and western Uganda. *Agricultural Economics*38:327–337.

Langyintuo AS and Dogbe W. 2005. Characterizing the constraints for the adoption of a *Callopogonium mucunoides* improved fallow in rice production systems in northern Ghana. *Agriculture, Ecosystems & Environment* 110: 78–90.

Lee M-J. 2005. *Micro-Econometrics for Policy, Program and Treatment Effects*. Advanced Texts in Econometrics. Oxford University Press.

Mendola M. 2006. Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. *Food Policy* 32: 372–393.

Moffitt RA. 1996. Identification of causal effects using instrumental variables: Comments. *Journal of the American Statistical Association* 91(434): 5.

Mwabu G, Mwangi W and Nyangito H. 2006. Does adoption of improved maize varieties reduce poverty? Evidence from Kenya. Paper presented at the International Association of Agricultural Economists Conference, Gold Coast, Australia, 12–18 August. 15 p.

Norton DR. 2004. *Agricultural Development Policy: Concepts and expectations*. John Wiley & Sons, Chichester, UK. 528 p.

Rosenbaum PR. 2002. *Observational Studies*(2nd edn). Springer-Verlag, New York.

Rosenbaum PR and Rubin DR. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*70: 41–55.

Rubin D. 1974. Estimating causal effects of treatments in randomized and non-randomized studies. *Journal of Educational Psychology*66: 688–701.

Winters P, de Janvry A, Saudolet E and Stamoulis K. 1998. The role of agriculture in economic development: Visible and invisible surplus transfers. *Journal of Development Studies*345: 71–97.

Wiredu AN, Gyasi KO and Abdoulaye T. 2009. Characterization of Maize Producing Households in the Northern Region. Drought Tolerant Maize for Africa (DTMA) Project Country Report – Household Survey, Ghana.

Wu Z. 2005. Does size matter in Chinese farm household production. Paper prepared for the Agricultural Economics Society Annual Conference, University of Nottingham, Nottingham, UK.