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

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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; Roseambaum, 2002; Heckman and Robb, 1985; Roseambaum and Rubin, 1983; Rubin, 1974).

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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:

\[
\begin{align*}
TE_i &= y_{1,i} - y_{0,i} \\
ATE &= E(y_{1} - y_{0})
\end{align*}
\]

where \( TE_i \) denotes ‘treatment effect’ and represents the effect of adoption on farmer \( i \), \( y_{1,i} \) the potential impact for adopters, and \( y_{0,i} \) 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 \( y_{1,i} \) 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 (\( \Phi \)). In the same way, the expected impact on the nonadopters on the untreated (ATE0) can be derived. These are given as follows:

\[
\begin{align*}
ATE_1 &= E(\Phi|T_A = 1) \\
ATE_0 &= E(\Phi|T_A = 0)
\end{align*}
\]

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, \( \pi(T_A = 1|x) \equiv \pi(x) \), 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:

$$T_{Ad} = \alpha_0 + \sum_{k=1}^{K} \alpha_{h,k} H_{k,i} + \sum_{k=1}^{K} \alpha_{X,k} X_{k,i} + \sum_{k=1}^{K} \alpha_{Y,k} Y_{k,i} + \gamma_i$$  \hspace{1cm} (5)

where $H_{k,i} = (h_1, h_2, h_3, h_4, h_5, h_6)$, 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, $h_5$ the years of credit accessibility, and $h_6$ access to extension services. $X_{land} = (X_{land}, X_{lab})$, 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. $Y_i$, is a vector of variables that measures the expectation of farmers about the returns that accrue to rice production. The coefficients ($\alpha$) 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:

$$y_i = \alpha_0 + \sum_{k=1}^{K} \alpha_{h,k} H_{k,i} + \sum_{k=1}^{K} \alpha_{X,k} X_{k,i} + \sum_{k=1}^{K} \alpha_{Y,k} Y_{k,i} + \alpha_{T,k} T_{Ad} + \gamma_i$$  \hspace{1cm} (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

<table>
<thead>
<tr>
<th>Variety</th>
<th>Ejura</th>
<th>Hohoe</th>
<th>Tolon</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Improved</td>
<td>29.57</td>
<td>16.75</td>
<td>90.64</td>
<td>45.6</td>
</tr>
<tr>
<td>NERICA</td>
<td>17.92</td>
<td>2.03</td>
<td>1.22</td>
<td>5.74</td>
</tr>
<tr>
<td>NARS</td>
<td>13.91</td>
<td>15.27</td>
<td>90.64</td>
<td>41.3</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>ATE Parameters</th>
<th>Variable Parameters</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATE</td>
<td>0.0240438</td>
<td>Adoption</td>
</tr>
<tr>
<td>ATE1</td>
<td>2.4110438</td>
<td>Age</td>
</tr>
<tr>
<td>ATE0</td>
<td>0.0042404</td>
<td>Male</td>
</tr>
<tr>
<td>PSB</td>
<td>–4.12E–11</td>
<td>Household size</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Education</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Yield in 2004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Extension contacts</td>
</tr>
</tbody>
</table>

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


