The Adoption of Water Conservation and Intensification Technologies and Farm Income: A Propensity Score Analysis for Rice Farmers in Northern Ghana

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Abstract

This study uses cross-sectional data of 342 small-scale lowland rice farmers in Northern Region of Ghana to analyze the impact of the adoption decision of bund construction and seed dibbling on net returns, input demand and output supply. Matching was conducted based on Mahalanobis distance combined with propensity score. Balancing tests by checking the mean standardized absolute bias in the matched sample were conducted as well as sensitivity analysis to check for hidden bias due to unobservable selection. The empirical results of impact assessment using propensity score matching controlling for self-selection bias suggest that input demand is significantly higher for adopters of bunds, but not statistically different for adopters and non-adopters of dibbling seed. However, output supply and net returns were not found to be statistically different for adopters and non-adopters of bunds. Adopters of dibbling were found to have higher output supply while no statistically significant difference was found for net returns of adopters and non-adopters of dibbling. The results were found to be relative insensitive to hidden bias.

JEL classification:

Keywords: Propensity score matching, evaluation, sensitivity analysis, Rosenbaum bounds, water conservation methods, bunds, rice production

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1. Introduction

The adoption of new agricultural technologies continues to play a key role in increasing agricultural productivity and food security in developing countries and to stimulate overall economic growth through intersectoral linkages (e.g. Hazell and Hojjati, 1995), while conserving natural resources. Given the close link between poverty, farming and environmental degradation the impact of cultivation practices has received significant attention in the last two decades. New cultivation techniques have been introduced to contribute to increasing sustainable agricultural production. However, most of the new technologies introduced in the agricultural sector have been only partially successful, due to low rates of adoption. This observation has generated increased interest in issues related to innovation and dissemination of improved agricultural technologies.

Rice is an important cereal to Ghana's economy and agriculture, accounting for nearly 15% of the agricultural Gross Domestic Product (Kranjac-Berislavjevic 2000). Rice is the major cash crop in northern Ghana. Northern Region was a main producer of paddy rice with a share of 60 percent of total rice production in the 1970s (Kranjac-Berisavljevic 2001), supplying the rest of the country and beyond, mainly due to relatively high subsidies on agricultural inputs including machinery and equipment. As subsidies were gradually removed as a result of the structural adjustments implemented in 1983, rice profitability declined, due to the increasing prices of agricultural inputs relative to nominal prices of rice (Asuming-Brempong 1998).

Similar to the dietary shift towards rice consumption in West African countries, rice consumption has increased up to 25 kg/capita/year (Lançon and Benz 2007) in Ghana compared to 7.4 kg/capita/year in the period 1982 to 1985 (MOFA 2004). Rice consumption is predicted to increase further due to an increasing food demand in general (due to high human population growth rate of 2.8% and income-driven expansion) and a shifting demand to high value staples (MOFA 2001). On the supply side, the average annual production growth rate of rice decreased to 1.8% in 1998-2003 compared to 1993-1998 from 5.0% due to declining rice-fertilizer price ratio caused by the liberalization policy. The observed growth rates can be attributed to area expansion, with yield gains playing a minor role (MOFA 2004).

The average yield of paddy rice under rain fed conditions was 2.0 Mt/ha in 2003, stagnating since 1993 (Seini and Nyangteng 2003), compared with average yields of 6.5 Mt/ha achievable under more effective extension and use of recommended technologies (MOFA 2004). As a result, rice imports have increased steadily since the 1970s. In 2006, 64% of Ghana's need had to be imported, weighting heavily on the country's currency reserve (US$ 120 million) (Asubonteng et al. 2006).

The key constraints to rice production in the Northern Region are erratic rainfall during the uni-modal rainfall season from April – and low soil fertility. However, Ghana was found to have a comparative advantage in the production of paddy rice over other countries in the sub-region (Asuming-Brempong 1998). Northern Region has a relatively high annual rainfall of 1100 mm compared to neighboring countries and a huge potential for the development of lowland rice as inland valleys exceeds 400,000ha, while only a small proportion of this is currently under cultivation (Mercer-Quarshie 2000). Thus, there is urgent need for water conservation and yield increasing intensification methods in lowland rice production in Northern Region to boost productivity and output.

The Lowland Rice Development Project (LRDP), aimed at the development of a profitable and sustainable intensive rice production system focusing on small scale farmers, first introduced and disseminated construction of earthen bunds as water conservation method[1] and dibbling as yield increasing but labor-intensive planting method in lowland rice production in three valleys in the in the Northern Regione from 1999 to 2003[2]. LRDP itself developed 1040 ha of lowland area through provision of water harvesting structures in form of contour bunds. Yields increased from 1 Mt/ha to 2.5 Mt/ha (LRDP 2004). Despite contribution bund creation was found to be yield increasing by the

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[1] It has been shown for inland valleys in West Africa that the 'period of positive water balance can be extended by about 20 days in wet years' in Bida, Nigeria or by about 50 days in both wet and dry years in Makeni, Sierra Leone by properly constructed bunds (Gunneweg et al. 1986).

[2] Other components of the technological package introduces are intensified weeding (double manual weeding), use of improved varieties, two rounds of fertilizer application with dibbling of first fertilizer.

LRDP and the fact that the construction of intermediary bunds was highly encouraged during LRDP, it appears the dissemination of dibbling has been more successful than the dissemination of bund construction among the farmers (LRDP 2004). However, the reasons for the low adoption rate of the technology of bund construction remains unclear and have so far not been investigated (FSRPOP 2005).

The present study examines the impact of the adoption decision of bund construction and seed dibbling on input demand, output supply and net returns in the lowland rice production among a sample of rice farmers in the Northern Region of Ghana. A propensity score model is employed to control for self-selection that normally arises when technology adoption is not randomly assigned and self-selection into treatment occurs.

The remainder of the paper is organized as follows. The next section outlines the theoretical framework and empirical specification for the study. The third section provides a description of the data and definition of the variables. The empirical results from the analysis are presented in section four. A final section presents concluding remarks.

2. Theoretical model and empirical specification

Given the objective of the study, which is to examine bunds as a water conservation method and dibbling as a yield-increasing seeding method, we assume that farmers choose between construction of bunds or non-construction, and on the other hand between dibbling seed or not dibbling. Assuming that farmers are risk neutral, it may be assumed that in the decision making process on whether to adopt or not, they compare the expected utility of wealth from adoption denoted as $U_A^*(\pi)$ against the expected utility of wealth from non-adoption represented as $U_N^*(\pi)$, with profits (π) representing wealth. Adoption then occurs if $U_A^*(\pi) > U_N^*(\pi)$. Farmer's expected utility of adoption can be related to a set of explanatory variables (Z) as follows: $U_A^*(\pi) = \gamma' Z_i + \varepsilon_i$ with γ being a vector of parameters. The error term ε with mean zero and variance σ_ε^2 captures measurement errors and factors unobserved to the researcher but known to the farmer. Variables in

Z include determinants of the adoption decision such as plot characteristics, characteristics of the farm (e.g. farm size) as well as socio-economic characteristics of the farmer and the farm family such as education, age or household size. Policy variables and characteristics of the village may also be included in the vector Z. The farmer's utility from choosing adoption is not observable but the choice of adoption or non-adoption: $U(\pi)=1$ if $U_A^*(\pi) > U_N^*(\pi)$ and $U(\pi)=0$ if $U_A^*(\pi) \le U_N^*(\pi)$. The probability of adoption may then be expressed as:

$$\Pr(U=1) = \Pr(U_A^*(\pi) > U_N^*(\pi)) = \Pr(\varepsilon_i > -\gamma' Z_i) = 1 - F(-\gamma' Z_i) \qquad (1)$$

where F is the cumulative distribution function for ε. The assumptions made on the functional form of F result in different models.

To link the adoption decision process to the input demand and output supply, it is assumed that farmers are risk-neutral and that they maximize expected net returns instead of expected utility.

$$\max_w E(PQ(W,Z)) - R'W \qquad (2)$$

where E is the expectation operator conditional on information currently available to farmers; P is the output price and Q is the expected output level; W is a column vector of inputs and Z a vector of household endowments and characteristics, and R is a column vector of input prices. Net returns can be expressed as a function of the variable inputs, the output price, the household endowments and characteristics, and the technology d, i.e. bund construction and dibbling, respectively as follows:

$$\pi = \pi(R,d,P,Z) \qquad (3)$$

Following Abdulai and Binder (2006), we start with any well-specified normalized profit function, direct application of Hotelling's Lemma to equation (2) yields the corresponding input demand and output supply equations:

$$\frac{\partial \pi(P,R)}{\partial R_i} = -W_i^* \quad \text{for all } i \qquad (4)$$

$$\frac{\partial \pi(P,R)}{\partial R_i} = -Q_i^* \quad \text{for all } i \qquad (5)$$

Where W^* and Q^* are the optimal input demand and output supply levels. The explicit functions in reduced forms for a variable input and output supply, as well as net returns, are then given as

$$W = W(R, d, P, Z) \quad \text{for all } i \tag{6}$$

$$Q = Q(R, d, P, Z) \quad \text{for all } i \tag{7}$$

Thus, equations (6) and (7) indicate that input demand, output supply and net returns are influenced by the technology choice, household characteristics, output price, and input prices.

To analyze the impact of technology adoption on input demand, output supply and net returns, this study employs a non-experimental evaluation method which allows for causal inference even for observational data under certain conditions. Propensity Score Matching (PSM) controls for self-selection by creating the counterfactual for the group of adopters. The problem of selection bias arises as the treatment assignment is not random, but there is self-selection into treatment and factors of the treatment or adoption decision are also relevant to the process determining the outcome. Then, the groups of adopters and non-adopters might be systematically different. PSM constructs a statistical comparison group by matching every individual observation on adopters with individual observation from the group of non-adopters with similar characteristics. Thus, the matching process tries to create an experimental dataset in that, conditional on observed characteristics, the selection process is random. Based on these groups of farmers having similar behavior, the 'Average Treatment Effect on the Treated' (ATT) $\tau_{ATT} = E\{Y_{1i} - Y_{0i} \mid D_i = 1\}$ can then be estimated.

The matching approach tries to balance the distribution of X, as in non-random data sets the covariates do not have an identical distribution in the two groups. Thus, matching on X is based on the assumption that the selection bias is zero, as conditioning on (observable) X eliminates the bias (Heckman et al. 1997). This assumption is called the 'conditional independence assumption' (CIA) or 'strong unconfoundedness' (Imbens 2004) and can be given as follows:

$$Y_1, Y_0 \coprod D \mid X \tag{8}$$

The CIA states, that technology adoption is random und uncorrelated with the outcome once controlled for X (Mendola 2007). Thus, technology adoption is a function of observable characteristics and can be explained purely by observables. The CIA is more plausible than in case of OLS, as the technology effect among groups of farmers having similar behaviour (same propensity score) is evaluated. ATT is only defined within the region of common support. This is because only in the overlapping subset of the comparison group and treatment group comparable observations can be matched (Heckman et al. 1997). The common support condition (CSC) is defined as follows:

$$0 < P(D = 1 \mid X) < 1 \tag{9}$$

By the overlap condition, the propensity score is bounded away from 1 and 0, excluding the tails of the distribution of p(X). This assumption ensures that persons with the same X values have a positive probability of being both participants and no-participants (Heckman et al. 1997). If there are regions where the support of X does not overlap for the different groups, matching is only justified when performed over the common support region. A violation of the CSC is a major source of bias due to comparing incomparable individuals (Heckman et al. 1997). Individuals that fall outside of the region of common support have to be disregarded and the treatment effect cannot be estimated (Bryson et al. 2002).

The propensity score matching is a new approach of single index matches instead of high-dimensional matches. The propensity score is defined by Rosenbaum and Rubin (1983) as the conditional probability to adopt the new technology given the control of X as follows:

$$p(X) \equiv P(D = 1 \mid X) = E(D \mid X) \tag{10}$$

where $D = \{0,1\}$ is the indicator of exposure to treatment and X is the multidimensional vector of pre-treatment characteristics. The propensity score is a function such that the conditional distribution of X given $p(X)$ is the same in both groups, i.e. conditional to $p(X)$, X and D are independent. This balancing property of propensity score can be expressed as follows (Lee 2006):

$$D \amalg X \mid p(X) \tag{11}$$

Hence, if the unconfoundedness assumption holds, all biases due to observable components can be removed by conditioning on the propensity score (Imbens 2004).

Given the propensity score, which can be estimated by any standard probability model, ATT can be estimated under CIA as follows (Becker and Ichino 2002):

$$\begin{aligned}\tau_{ATT} &= E\{Y_{1i} - Y_{0i} \mid D_i = 1\} = E\{E\{Y_{1i} - Y_{0i} \mid D_i = 1, p(X_i)\}\} = \\ &E\{E\{Y_{1i} \mid D_i = 1, p(X_i)\} - E\{Y_{0i} \mid D_i = 0, p(X_i)\} \mid D_i = 1\}\end{aligned} \tag{12}$$

There are different methods for cross-sectional data to find the 'closest' neighbour as matching partner. The present study employs the multivariate covariate matching with replacement based on Mahalanobis distance with the p-score as additional variable to put greater emphasis on specific variables. The distances are calculated as follows:

$$d(i, j) = (u - v)^T C^{-1} (u - v) \tag{13}$$

where u and v are values of the matching variables for treated subject i and non-treated subject j, and C is the sample covariance matrix of the matching variables from the full set of non-treated subjects (Guo et al. 2006). The non-treated subject j, which has the minimum distance $d(i, j)$ to the treated within calipers defined by p-score, is chosen as match for the treated.

It is significant to mention that the main purpose of the propensity score estimation is not to precisely predict selection into treatment, but to balance the observed distribution of covariates across the treated and the non-treated groups[3]. The success of propensity score estimation is therefore assessed by the resulting balance (rather than by the fit of the models used to create the estimated propensity scores) (Lee 2006). Thus, after matching balancing tests check for the extent to which differences in the covariates in the two groups in the matched sample have been

[3] As noted by Mendola (2007), it is the objective to 'well' specify the propensity scores for treatment variable, but 'too good' data is not helpful as this makes it more and more complicated to find matching partners when the overlap between both groups became very limited.

eliminated, thus whether the matched comparison group can be considered as plausible counterfactual (Lee 2006). Multiple versions of balancing tests exit in the literature. The standardized mean difference '(or standardized bias') between treatment and control sample, recommended by Lee (2006), which is a suitable way to quantify the bias between treatment and control sample was suggested by Rosenbaum and Rubin (1985). For each variable, the mean standardized difference is computed before and after matching as:

$$B(X) = 100\frac{\overline{X}_T - \overline{X}_C}{\sqrt{\frac{V_T(X)+V_C(X)}{2}}} \tag{14}$$

where $\overline{X}_T$ and $\overline{X}_C$ are the sample means for the full treatment and comparison groups, while $V_T(X)$ and $V_C(X)$ are the corresponding sample variances (Lee 2006). Total bias is then estimated as an unweighted average of all covariates (Hujer et al. 2004) and bias reduction can be computed as:

$$BR = 100\left(1 - \frac{B_{after}}{B_{before}}\right) \tag{15}$$

Sensitivity analysis can be conducted to ascertain the robustness of the estimates. Given that matching only balances the distribution of observed characteristics, if there are unobserved variables that simultaneously affect assignment into treatment and the outcome variable, a hidden bias might arise (Rosenbaum 2002). This study addresses this problem with the bounding approach suggested by Rosenbaum (2002).

The participation probability for an individual i with observed characteristics x_i in a program is $\pi_i = \Pr(D_i = 1 \mid x_i) = F(\beta x_i + \gamma u_i)$, where u_i the unobserved variable is and γ is the effect of u_i on the adoption decision. If the study is free of hidden bias, γ will be zero and the participation probability will solely be determined by x_i. If there is hidden bias, two individuals with the same observed covariates x differ in their chances of receiving treatment. Under the assumption of a matched pair of individuals i and j, and that F is the logistics distribution, the odds that the individual receive treatment is then given by $\pi_i/(1-\pi_i)$ and $\pi_j/(1-\pi_j)$. The odds ratio is then:

$$\frac{\frac{\pi_i}{1-\pi_i}}{\frac{\pi_j}{1-\pi_j}} = \frac{\pi_i(1-\pi_j)}{\pi_j(1-\pi_i)} = \frac{\exp(\beta x_j - \gamma u_j)}{\exp(\beta x_i - \gamma u_i)} = \exp[\gamma(u_i - u_j)] \tag{16}$$

The x-vector cancels in case that both units have the same observed covariates (as implied by the matching procedure). Then, the individuals differ in their odds of adoption decision only by a factor that involves the parameter γ and the difference in their unobserved covariates u. The sensitivity analysis evaluates how inference about the adoption is altered by changing the values of γ and $(u_i - u_j)$, thus, how large $\Gamma = e^{\gamma}$ have to be (as a measure of the degree of departure from a study with random assignment of treatment) (Rosenbaum 2002). For each value of Γ, bounds on the significance levels of the treatment effect in the case of endogenous self-selection into treatment status and confidence intervals can be derived (Caliendo and Kopeinig 2006).

In the base scenario e^{γ} = 1, the lower and upper bounds are equal to each other and they equal the usual significance level from the randomization distribution (Rosenbaum 2003). By comparing the Rosenbaum bounds on treatment effects at different levels of Γ, it is possible to assess the strength such unmeasured influences would require in order that the estimated treatment effect from propensity score matching would have arisen purely through selection effects (DiPrete and Gangl 2004).

3. Data and definition of variables

The data used in the study were collected from a survey between October 2005 and April 2006. Data collection was conducted in 24 communities located in four neighboring districts of Northern Region, covering three river valleys (Kulda-Yarong valley, Zuwari valley and Sillum valley). A stratified random sample of 342 farmers was selected from the four districts to ensure representation of major land holdings, adopters and non-adopters of the two identified technologies and household types. Information from the households was gathered through interviews. Additional information was obtained from the Northern Region Ministry of Food and Agriculture. The data covered information on production systems, input use, costs, nature and extent of adoption, adoption history, socio-economic characteristics of farmers and compound family[4], as well as plot level characteristics.

Table 1 presents the definitions and sample characteristics of the variables used in the analysis. It can be observed from Table 1 that 48.53% adopted bund technology, while a higher percentage of farmers (67.83%) adopted the technology. Among the LRDP participants, 61% constructed bunds and 80% of farmers used the dibbling technique as a planting method. The average farm size was 7.35 acres. The average size of lowland rice was 2.17 acres, while the average size cultivated with other crops was 5.18 acres. Average household size was 19 persons and farmers were on average 37 years. The average number of years of schooling among those with formal schooling is 9.28 years. 47.37% of farmers participated in the LRDP project. 23.68% out of 342 farmers indicated that they were supported by the FSRPOP project[5]. 79.01% FSRPOP farmers also indicated that they formerly participated in the LRDP.

In the overall sample, average application rate of nitrogen was 28.32 kg/ha. This appears to be high, especially when compared to the national average of 6 kg/ha and 21.6 kg/ha in sub-Saharan Africa. Controlling for the use of dibbling, there is no significant difference in the demand for nitrogen between users and non-user of bunds technology. On the other hand, a significant difference in fertilizer demand can be found between adopters and non-adopters of the dibbling technology. The data also indicate that among the non-user of bunds, the use of dibbling increases average nitrogen demand by 4.51 kg per acre (significant at the 1% level), while among users of

[4] The basic unit of social organization is the compound household. Its nucleus is an elementary or polygynous family, to which may be attached the descendants of the head's grandfather. Dependent men (married or unmarried) live in the compound household under the household head (Abu 1992).

[5] From 2003, the LRDP collaborated with the Food Security and Rice Producers Organization Project (FSRPOP). The objective of FSRPOP is mainly to sustain the rice intensive cropping scheme by building the capacities of farmer based organizations to fulfill some of the tasks ensured previously by LRDP (organize access to inputs and credits, marketing of paddy, monitor cropping activities and manage and sustain collective structures as storage or water).

bunds, the adoption of dibbling increases the demand for nitrogen by 3.64 kg per acre (significant at the 5% level).

The average sample yield was 7.20 bags per acre in 2005. Average output of bund adopters was 7.59 bags per acre and 6.84 bags per acre for non-adopters. Controlling for the use of dibbling seed, there is no significant difference in the average output between adopters and non-adopters of bund technology. The average yield of adopters of dibbling seed is 7.91 bags per acre, while the average yield among non-adopters of dibbling seed is 5.71 bags per acre, showing a significant difference. In the group of non-users of bunds, the difference of output resulting from dibbling seed is 2.1 bags per acre (significant at the 1% level). Among the adopters of bunds technology, the dibbling technology appears to increase output by 2.41 bags in average (significant at 1% level). Descriptive statistics show no significant difference in net returns between adopters and non-adopters of bund technology, even if controlled for the use of dibbling. Meanwhile, among users of bunds, the t-test shows significantly higher net returns for dibbling seed (322,703.6 GHC per acre[6]). For non-users of bunds the net returns are significantly higher for dibbling seed (248,817.8 GHC per acre). This result suggests that complementary adoption of bunds and dibbling gives the highest increase in net returns.

Three major categories of explanations are available in the adoption literature to explain adoption decisions. These include the innovation-diffusion paradigm, the resource-constraint paradigm and the adopters' perception paradigm. Derived from these theories, some groups of factors have been found to be determinants of adoption in previous studies: farm and farmers' attributes, external support systems, perception of or attributes associated with the technology and the farming objective. Specifically, agricultural adoption literature found variables as age, experience, gender and education of the decision maker, labor endowment, farm size, information availability, access to credit, wealth, land tenure, transportation infrastructure, complementary input supply, perception of needs and of technology to be important variables for adoption decisions in

[6] GHC= (Old) Ghanaian Cedi, substituted by new Ghanaian Cedi (GHS) since 1st July 2007

developing countries (Huffman (2001), Feder, Just and Zilberman (1985); Feder and Umali (1993), Abdulai and Huffman (2005)). Guided by economic and social theory, matching should be based on all variables that influence both treatment assignment and outcomes and are not affected by the treatment (Caliendo and Kopeining 2006). In the present study, the choice of variables is based on previous empirical results of the determinants of the adoption decision of bund construction and dibbling seed.

4. Empirical results

The empirical results from the matching models are presented in Table 4 and Table 5 and the estimated propensity scores are given in Table 2 and Table 3. The estimates from the propensity score matching procedure suggest that input demand is significantly higher for adopters of bund construction by 3.045 bags per acre, using a very stringent caliper of 0.01. As indicated earlier, the main purpose of the propensity score estimation is not to predict selection into treatment as well as possible, but to balance the distributions of relevant variables in both groups. The balancing powers of the estimations are ascertained by considering the reduction in the median absolute standardized bias between the matched and unmatched models. These differences are shown in the fourth and fifth columns of Table 5. Estimation of the treatment effect of bund adoption on input demand reduces the median absolute standardized bias from 19.926 to 7.600. In case of net returns, matching reduces median absolute standardized bias from 18.547 to 6.089 and in case of output from 16.881 to 5.783, indicating adequate balancing of covariates by the chosen matching algorithm. This clearly indicates the significance of matching in reducing biases in the estimates. However, no significant difference of output (ATT= -0.403 bags per acre) and net returns (ATT= 146,618.363 GHC per acre) could be found between adopters and non-adopters of bunds.

It turns out that balancing the distribution of the covariates indicate no statistically significant difference in net returns between adopters and non-adopters of dibbling (ATT= 149,944.257 GHC per acre). Balance checks indicate adequate removing of bias, median standardized absolute bias declines from 23.309 to 10.231. However, by implementing the matching procedure, output was found to be significantly higher for adopters of dibbling seed (ATT=1.945 bags per acre). Median absolute standardized bias was halved from 22.427 to 10.251. Just adopting dibbling of seed, seem not to result in different input demand for adopters and non-adopters. An ATT of 0.262 bags per acre was found with a bias reduction to 6.600 from 20.630.

Additionally, a comparison of the pseudo R^2 from a probit of treatment status on regressors X before matching and after matching on the matched samples shows that in all cases the variance of the treatment status explained by the regressors X declined substantially after matching. The corresponding P-values of the likelihood-ratio test of the joint insignificance of all the regressors X before and after matching also show, that after matching, the significance of regressors on treatment status could always be rejected. Before matching, it was never rejected at the 1% level (see Table 5). The common support condition is satisfied for all estimations.

Table 4 also presents the (upper) Rosenbaum bounds for treatment effects that are significantly different from zero. As noted by Hujer et al. (2004), sensitivity analysis for insignificant effects is not meaningful and is therefore not considered here. Given that the estimated (significant) treatment effects are positive, the (lower) bounds under the assumption that the true treatment effect has been under-estimated are less interesting (Becker and Caliendo 2007). The upper bounds results are obtained under the assumption that the estimated treatment effects overestimate the true treatment effects (due to positive unobserved selection), resulting in an upward bias in the estimated treatment effects (Becker and Caliendo 2007). Then, the reported test statistic is too high and should be adjusted downwards. The significant positive impact of dibbling on output would no longer be significant at a level of Gamma (the odds ratio of differential treatment assignment due to an unobserved covariate) of 1.45. In case of the positive and significant impact of bund construction on input demand, it would require a hidden bias of Gamma between 1.4 and 1.45 to render spurious the conclusion of a positive effect.

The results obtained from matching are in the range of findings of other studies and are relatively insensitive to hidden bias. In fact, the Rosenbaum bounds are a worst-case scenario

(DiPrete and Gangl 2004). The results mean that the confidence interval for the treatment effect would include zero if an unobserved variable caused the odds ratio of treatment assignment to differ between treatment and control groups by 1.45 and if this variable's effect on the outcome was so strong as to almost perfectly determine whether the outcome would be bigger for the treatment or the control case in each pair of matched cases in the data. In the case where a confounding variable had an equally strong effect on assignment but only a weak effect on the outcome variable, the confidence interval for the outcome variable would not be zero.

5. Concluding remarks

The study employed a seemingly unrelated bivariate probit estimation procedure to examine the adoption decisions of bunds and dibbling in Northern Ghana.

The impact of adoption decision on net returns, output supply and input demand found by conducting propensity score matching may explain the differing adoption rates of bunds and dibbling of seed in the study region. While output and net returns seem not to be statistically higher for adopters of bunds, output is found to be higher for adopters of dibbling seed. Thus, dibbling of seed might be more attractive to farmers than bund construction.

References

Abadie, A. and Imbens, G (2001) Simple and Bias-Correct Matching Estimators for Average Treatment Effects. Technical Working Paper 283. National Bureau of Economic Research.

Abdulai, A. and Binder, C.R. (2006) Slash-and-burn Cultivation Practice and Agricultural Input Demand and Output Supply. *Environment and Development Economics* 11: 201-220.

Abdulai, A. and Huffman, W.E. (2005) The Diffusion of New Agricultural Technologies: The Case of Crossbred-Cow Technology in Tanzania. *American Journal of Agricultural Economics* 87: 645-659.

Abu, Katie (1992) GGAEP – Target Group Survey. Tamale, Ghana

Asubonteng, K.O.; Adiyiah, B. Masunaga, T. And Wakatsuki, T. (2006) Meeting the Rice Production and Consumption Demand of West Africa with Improved Soil and Water (Sawah) and Nutrient Management Technologies. Paper presented at 18th World Congress of Soil Science. July 9-15, 2006, Philadelphia, Pennsylvania, USA

Asuming-Brempong (1998) Profitability, Competitiveness and Welfare Effects of Trade Liberalization on the Rice Sub-sector in Ghana. Structural Adjustment and Agriculture in West-Africa. COPESRIA Book Series, Senegal

Becker and Caliendo (2007) Mhbounds – Sensitivity Analysis for Average Treatment Effects. Discussion Paper No. 2542. IZA, Bonn

Bryson, A. Dorsett, R. and Purdon, S. (2002) The Use of Propensity Score Matching in the Evaluation of Active Labour Market Policies. Working Paper Number 4, Policy Studies Institute and National Centre for Social Research, London

Caliendo, M. and Kopeinig, S. (2008) Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys* 22:1, 31–72

DiPrete, T.A. and Gangl, M. (2004) Assessing Bias in the Estimation of Causal Effects: Rosenbaum Bounds on Matching Estimators and Instrumental Variables Estimation with Imperfect Instruments. *Sociological Methodology* 34: 271-310

FAO (2002) FAO/WFP Crop and Food Supply – Assessment Mission to Northern Ghana, Special Report. FAO Global Information and Early Warning System on Food and Agriculture, World Food Programme

Feder, G. and Umali, D. (1993) The Adoption of Agricultural Innovations: *A Review. Technol. Forecast. Social Change* 43: 215-239

Feder, G; Just, E and Zilberman, D. (1985) Adoption of Agricultural Innovations in Developing Countries: A Survey. Economic Development and Cultural Change 33: 255-298

FSRPOP (2005) Complement Survey of Intensive Rice Cropping in LRDP Catchment Area.

Gunneweg, H.A.M.I., Evers, A. and Huizing, A. (1986) A model to assess proposed procedures for water control: Application and results for two small inland valleys, in: A.S.R. Juo and J.A. Lowe, eds., The Wetlands and Rice in Subsaharan Africa , IITA, Ibadan, Nigeria

Guo, S., Barth, R.P. and Gibbons, C. (2006) Propensity score Matching Strategies for Evaluation Substance Abuse Services for Child Welfare Clients. Children and Youth Services Review 28:357-383

Hazell, P. and Hojjati, B. (1995) Farm / Non-farm Growth Linkages in Zambia. *Journal of African Economies* 4: 406-435

Heckman, J., Ichimura, H. and Todd, P. (1997) Matching as An Econometric Evaluation Estimator. *Review of Economic Studies* 65 (2): 261–294

Huffman, W.E. (2001) Human capital: Education and agriculture, in: G.L. Gardner and G.C. Rausser, eds., *Handbook of Agricultural Economics*, Vol.1B, Amsterdam, The Netherlands: Elevier Science.

Hujer, R.; Caliendo, M. and Thomsen, S.L. (2004) New Evidence on the Effects of Job Creation Schemes in Germany – A Matching Approach with Threefold Heterogeneity. *Research in Economics* 58(4):257-302

Imbens, G.W. (2004) Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review. *The Review of Economics and Statistics* 86(1):4-29

Kranjac-Berislavjevic, G.; Blench, R.M. and Chapman, R. (2003) Multi-Agency Partnerships (MAPS) for Technical Change in West African Agriculture. Rice Production and Livelihoods in Ghana. ODI, UDS

Kranjac-Berislavjevic, G. (2000) Some Features of Rice Production in Ghana. Multiagency Partnerships for Technical Change in West African Agriculture. National Workshop on Rice Production in Ghana. Held at Ho, Upper East Region, Ghana.

Lançon, F. and Benz, H.D. (2007) Rice Imports in West Africa: Trade Regimes and Food Policy Formulation. Poster prepared for Presentation at the 106th Seminar of the EAAE, 25-27.10.2007, Montpellier, France

Lechner. M: (2001) A Note on the Common Support Problem in Applied Evaluation Studies. Discussion Paper, University of Gallen, SIAW

Lee, W. (2006). "Propensity Score Matching and Variations on the Balancing Test," 3rd Conference on Policy Evaluation, ZEW, Mannheim (Germany), 27-28 October.

LRDP (2004) Final Report

Mendola, M. (2007) Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. *Food Policy* 32 (3): 372-393

Mercer-Quarshie, H. (2000) The Lowland Rice Development Project. Multiagency Partnerships for Technical Change in West African Agriculture. National Workshop on Rice Production in Ghana. Held at Ho, Upper East Region, Ghana, November 2000

MOFA (2005) Mid-term Report 2005, Ministry of Food and Agriculture, Northern Region

MOFA (2004) Agriculture in Ghana. Facts and Figures 2003. SRID, Ministry of Food and Agriculture

MOFA (2001) Accelerated Agricultural Growth and Development Strategy in Support of Ghana's Vision 2020. Republic of Ghana

Rosenbaum, P.R. (2002) Observational Studies. Second Edition. New York: Springer

Rosenbaum, P.R. and Rubin, D.B. (1985) Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. *The American Statistician* 39: 33-38.

Rosenbaum, P.R. and Rubin, D.B. (1983) The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* 70(1): 41-50

Seini, A. W.; Nyanteng, V. K. (2003) Afrint Macro Study: Ghana Report (Revised). ISSER, University of Ghana, Legon

Table 1: Variable definitions and descriptive statistics

Variable Name	Variable definition	Sample mean	Standard deviation
Dependent variables			
USE_B	Farmer uses bunds:1=Yes, 0=No	0.49	0.50
USE_D	Farmer dibble seed:1=Yes, 0=No	0.68	0.47
OUT_AC	Output of lowland rice production (bag per acre)	7.20	4.19
N_KG_AC	Application of nitrogen per acre in lowland rice cultivation (kg)	11.46	9.30
NRET_AC	Net returns (GHC) per acre in lowland rice cultivation	738,130.9	651,831.4
Independent Variables			
GEQ_HH	Number of labor equivalents living in the compound household.	13.40	9.46
GEQ_ILL	Number of labor equivalents regularly helping in lowland rice production, suffering from frequent illness	2.07	2.80
AGE_R	Age of respondent in years	37.31	10.82
AGE2_R	(Age of respondent in years)*2		
AV_FSZ	Family land in acres per labor equivalent of household[7]	1.28	1.01
AV_FSZ_2_100	((AV_FSZ)*2)/100		
CROP_SZ	Area cultivated by rice farmer under other crops (acre)	5.18	4.53
R_SZ	Total area cultivated by respondent with lowland rice (acres)	2.17	1.37
FSZ	Total area cultivated by respondent (acres)	7.35	5.29
FSZ2	((FSZ)*2)/100		
USE_IMPV	Farmer cultivated improved rice variety in 2005: 1=Yes, 0=No	0.91	0.29
BULL	Number of bullocks (pair) owned by the farmer	0.15	0.40
bike	Number of bicycles owned by the farmer	1.03	0.53
TRACTOR	Farmer owned tractor: 1=Yes, 0=No	0.03	0.18
INFS_R	Educational level of farmer: 0=none, 1=literate	0.29	0.46

[7] Labor equivalents are calculated with following factors: men (14-60)=1; women (14-60)=0.75; elderly / children=0.5

Variable Name	Variable definition	Sample mean	Standard deviation
EDUC_R	Educational level of farmer: 0=no education, 1=literacy, 2=formal school education	0.49	0.80
CREDIT	Farmer obtained any credit: 0=no, 1=yes	0.40	0.49
OFF_R	Farmer has any off-farm income: 0=no, 1=yes	0.36	0.48
FSRPOP	Farmer participates in FSRPOP: 0=no, 1=yes	0.24	0.43
LRDP	Farmer participated in LRDP as project farmer: 1=Yes, 0=No	0.47	0.50
HEAD	Farmer is head of the household: 0=no, 1=yes	0.42	0.49
CGROUP2	Farmer is in any organization related to crop production (other than FSRPOP): 1=Yes, 0=No	0.38	0.49
CGROUP3	Farmer is in crop related group (excluding working groups): 1=Yes, 0=No	0.074	0.261
KY	District dummy: 1=farmer is located in Kulda-Yarong valley, 0=otherwise	0.12	0.33
ZUWARI	District dummy: 1=farmer is located in Zuwari valley, 0=otherwise	0.11	0.32
SH_VSOIL	Share of area cultivated with lowland rice in 2005 with very good soil	0.51	0.48
SH_VRET	Share of area cultivated with lowland rice in 2005 with very good water retention	0.52	0.48
SH_LOAM	Share of area cultivated with lowland rice in 2005 with loamy soil	0.17	0.36
SH_BUND	Share of area cultivated with lowland rice in 2005 with and bunds	0.56	0.47
SH_LRDP	Share of area cultivated with lowland rice in 2005 with LRDP bunds	0.28	0.39
DROUGHT	Drought in early growing stage of rice plant in 2005: 1=Yes, 0=No	0.47	0.50
PRICE_AV	Average price per kg nitrogen (GHC)	19,596.77	4,209.70

Table 2: Estimation of propensity scores for bund technology

	Net returns		Input demand		Output supply	
Variable Name	Coefficients	t value	Coefficients	t value	Coefficients	t value
AGE_R	-0.003	-0.22	-0.001	-0.04	-0.004	-0.29
GEQ_HH	0.024	1.53	0.025*	1.66	0.027*	1.83
GEQ_ILL	-0.057	-1.48	-0.055	-1.49	-0.048	-1.38
PRICE_AV	-0.000	-0.51	-0.000	-0.11	-0.000	-0.09
HEAD	0.175	0.56	0.078	0.27	0.226	0.83
BULL	-0.568	-1.44	-0.229	-0.75	-0.302	-1.06
bike	-0.071	-0.31	-0.088	-0.41		
CROP_SZ	-0.149	-1.14	-0.124	-1.01	-0.034	-0.30
FSZ	0.094	0.85	0.077	0.73	-0.010	-0.10
AV_FSZ	0.289*	1.87	0.259*	1.76	0.256*	1.88
INFS_R	0.157	0.62				
EDUC_R			-0.013	-0.10	1.259	1.62
EDUC2_R					-0.634	-1.62
OFF_R	-0.255	-0.96	-0.125	-0.51	-0.421*	-1.84
CREDIT	0.336	1.10	0.404	1.55	0.254	0.93
TRACTOR	1.241	1.26	1.024*	1.70	0.904	1.60
FSRPOP	0.072	0.24	0.248	0.88	0.273	1.05
LRDP					0.335	1.29
SH_LRDP			-0.072	-0.21		
USE_IMPV	0.856	1.53	0.506	1.04	0.720	1.60
USE_D	1.291***	4.29	1.435***	5.07		
CGROUP2	-0.009	-0.03	-0.058	-0.25	-0.001	-0.01
SH_VSOIL	-0.445*	-1.76	-0.541**	-2.30	-0.236	-1.08
SH_LOAM	-0.405	-1.33			-0.160	-0.61
SH_VRET	-0.153	-0.60	-0.116	-0.50	-0.202	-0.89
KY	1.653***	3.25	1.554***	3.26	0.675*	1.71
ZUWARI						
CONST	-1.624	-1.59	-1.687*	-1.82	-0.806	-0.97
Obs.	186		218		216	
Pseudo-R^2	0.2468		0.2518		0.1668	

* Significant at 10%, ** significant at 5%, *** significant at 1%
Source: Own calculation

Table 3: Estimation of propensity scores for dibbling seed

	Net returns		Input demand		Output supply	
Variable Name	Coefficients	t value	Coefficients	t value	Coefficients	t value
AGE_R	0.002	0.13	0.012	0.16	-0.000	-0.00
AGE2_R			-0.000	-0.19		
GEQ_HH	0.021	0.84	0.010	0.42	0.022	0.99
GEQ_ILL	0.027	0.51				
PRICE_AV	0.000	0.78	-0.000	-0.35	0.000	0.40
HEAD	0.243	0.62	0.440	1.27	0.266	0.77
BULL	-0.532	-1.00			-0.532	-1.29
bike	0.581*	1.88			0.483*	1.72
R_SZ	-0.019	-0.11			-0.112	-0.78
FSZ	-0.049	-0.92	-0.054*	-1.83	-0.004	-0.11
AV_FSZ	0.090	0.26	0.189	0.58	-0.017	-0.12
AV_FSZ_2_100	-1.758	0.13	-2.947	-0.61		
INFS_R					0.098	0.34
EDUC_R	-0.071	-0.38	0.166	0.96		
OFF_R	-0.850**	-2.53	-0.894**	-2.76	-0.609**	-2.08
CREDIT	-0.136	-0.33	0.338	1.03	-0.244	-0.61
TRACTOR	-0.098	-0.110	0.927	1.10	0.284	0.37
FSRPOP	0.589	1.33	0.700*	1.80	0.596	1.59
LRDP	0.913**	2.26			0.719*	1.84
SH_LRDP			-0.239	-0.47		
USE_IMPV	0.736	1.19	0.886	-3.79	0.742	1.30
SH_BUND	0.793**	2.62	1.143***	3.39	0.903**	3.13
CGROUP2			0.296	0.92		
CGROUP3	0.121	0.24				
SH_VSOIL			0.970**	3.12		
SH_LOAM	0.243	0.62			0.391	1.08
SH_VRET			-0.106	-0.36	0.333	1.28
DROUGHT	0.597*	1.89	0.547*	1.77	0.503*	1.71
KY	-2.628***	-3.88	-2.310***	-3.79	-2.337***	-4.13
ZUWARI	-0.333	-0.89	-0.240	-0.64	-0.288	-0.83
CONST	-1.772	-1.44	-1.272	-0.69	-1.612	-1.54
Obs.	177		208		206	
Pseudo-R^2	0.4184		0.3821		0.3765	

* Significant at 10%, ** significant at 5%, *** significant at 1%
Source: Own calculation

Table 4: Average treatment effects and results of sensitivity analysis

	Outcome	Caliper	ATT	t-stat.	Critical level of Γ (hidden bias)	No. Treated No. Controls	Loss of observations due to common support
Bund construction	Net returns (GHC per acre)	0.075	146,618.363	0.91	–	49 90	47
	Demand for N (kg per acre)	0.01	3.045	1.88	1.45	67 98	53
	Average output (bags per acre)	0.05	-0.403	-0.40	–	63 97	56
Dibbling seed	Net returns (GHC per acre)	0.1	149,944.257	0.66	–	48 50	79
	Demand for N (kg per acre)	0.1	0.262	0.13	–	55 54	99
	Average output (bags per acre)	0.075	1.945	2.14	1.45	44 54	108

*Significant at 10%, ** significant at 5%, *** significant at 1%
Source: Own calculation

Table 5: Indicators of covariate balancing, before and after matching

	Outcome	Caliper	Median absolute bias (before matching)	Median absolute bias (after matching)	Pseudo R^2 (unmatched)	Pseudo R^2 (matched)	P value of LR (unmatched)	P value of LR (matched)
Bund construction	Net returns (GHC per acre)	0.075	18.547	6.089	0.247	0.109	0.000	0.870
	Demand for N (kg per acre)	0.01	19.926	7.600	0.252	0.078	0.000	0.881
	Average output (bags per acre)	0.05	16.881	5.783	0.168	0.107	0.000	0.665
Dibbling seed	Net returns (GHC per acre)	0.1	23.309	10.231	0.418	0.193	0.000	0.303
	Demand for N (kg per acre)	0.1	20.630	6.600	0.382	0.166	0.000	0.196
	Average output (bags per acre)	0.075	22.427	10.251	0.376	0.149	0.000	0.589

* Significant at 10%, ** significant at 5%, *** significant at 1%
Source: Own calculation