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ACCOUNTING FOR NON-EXPOSURE BIAS, SELF-SELECTION, AND HETEROGENEITY IN PRODUCTION TECHNOLOGY: EVIDENCE FROM RICE CULTIVATION IN GHANA

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Abstract

This study applied stochastic metafrontier whilst correcting for non-exposure and selection bias to assess the adoption of improved rice varieties on output and technical efficiency of Ghanaian households. Varietal awareness was estimated to account for non-exposure bias and adoption using treatment effect. The exposure and adoption rates of improved rice varieties were 82.5% and 67.2%. Adoption was influenced by rice projects, agricultural extension, higher yield motive, and irrigated production. Application of herbicides, fertilizer, seed, labour and farm size raised rice output amongst adopters. The difference in metafrontier technical efficiency of adopters (42.7%) and non-adopters (44.5%) was statistically insignificant, albeit adopters had higher metatechnology ratio (0.909) compared with non-adopters (0.785). Therefore, adopters applied the best production technology than non-adopters. Weeding twice with herbicides, managing plot water levels and agricultural extension raised the technical efficiency amongst adopters. This study recommends cultivation of improved rice varieties whilst improving technical efficiency.
Key words: *Adoption, Ghana, Non-exposure bias, Rice, Stochastic Metafrontier.*
Jel Codes: *D24, O33, Q12, Q16*

1. Introduction

Agriculture in Ghana accounts for more than 19% of GDP (MoFA, 2021) and three-quarters of export earnings. Nonetheless, Ghana's self-sufficiency in rice production has been in decline as domestic production is able to meet less than 50% of demand (Amanor-Boadu, 2012; Bruce *et al*., 2014; MoFA, 2018 & 2021). Meanwhile, rice consumption per capita has more than tripled from 13.3kg to 51.6kg between 1990-2020 (MoFA, 2016 & 2021). Currently, average rice yield (4mt/ha) is below achievable yield of 6–8mt/ha (MoFA, 2019; Ragasa *et al.,* 2013).

Against this background, Ghana's Rice Development Strategy (MoFA, 2009) aims to raise domestic output by 10% annually. For this reason, improved rice varieties have been released for cultivation in Ghana with desirable traits such as high yield, early maturity, disease resistance, aromatic and parboiling qualities. However, these improved rice varieties have not been widely disseminated and commercialised (Tripp & Mensah-Bonsu, 2013) to convince farmers of profitable returns from cultivating them. Ragasa *et al*. (2013) conducted a descriptive analysis of cultivation of improved rice varieties in Ghana. This study expands the scope by assessing improved rice varietal exposure and adoption, and the effect on output, whilst disaggregating production technology gap from technical inefficiency by estimating a stochastic metafrontier.

2. Materials and Methods

2.1 Description of Study Area and Sampling Approach

This study uses data provided by the International Food Policy Research Institute Ghana office. The survey collected data on rice and maize production from 576 households during the 2012/2013 cropping season in the Northern, Upper East, Upper West, Ashanti, Greater Accra, Volta, Western, and Eastern Regions. The eight regions constitute 79.29% of Ghana's total land area (MoFA, 2016). Proportional probability sampling was used that gave more weight[1] to districts with higher rice output whereas random sampling was used in final selection of districts, communities and households.

2.2 Treatment Effect of Improved Rice Varietal Adoption with Correction for Exposure

Following Diagne & Demont (2007), exposure is defined as a household being aware that improved rice varieties exist. Exposure precedes adoption, and households unaware cannot make adoption decisions regarding improved rice varieties (Diagne, 2006). Therefore, estimating adoption without first estimating exposure produces results of joint probability of exposure and adoption, JEA $[P(\omega y = 1) \ = P(\omega = 1, y = 1)]$ and not adoption alone. The JEA is the average adoption rate under partial exposure because it contains both exposed and non-exposed households. Following Diagne (2006), the probability of exposure is estimated using a probit model as:

$$\omega_i^* = k_i' \beta + u_i \tag{1}$$

ω_i^* is a latent continuous variable related to the observed binary variable, ω_i: $\omega_i = \begin{cases} 1 \ if \ \omega_i^* < 0 \\ 0 \ if \ \omega_i^* \geq 0 \end{cases}$ that determines treatment, k_i comprises the vector of covariates that determine exposure, β is vector of unknown parameters, u_i is a disturbance term which is $u_i \sim IIND(0, \sigma^2)$ and y is adoption status (0,1).

Employing the average treatment effect $[ATE(x)]$ proposed by Wooldridge (2002) and Diagne & Demont (2007) based on the conditional independence assumption (Rosenbaum & Rubin, 1983), that exposure treatment status ω is independent of subsequent adoption outcomes once the observed set of covariates that determine exposure are controlled. $ATE(x)$ is estimated conditional on exposure (Diagne, 2006; Diagne & Demont, 2007), and is written as:

$$ATE\ (x) = E(\ y/z\ , \omega = 1) = g(z, \beta) \tag{2}$$

Adoption is estimated using the exposed households only, and the average of $g(z;\hat{\beta})$ is obtained for the ATE, and respective subsamples for the adopters (ATE1) and non-adopters (ATE0). The ATE measures the adoption outcome of a rice farming household randomly drawn from the population when every rice farming household is exposed to the improved rice varieties.

The estimates of JEA and ATE are used to calculate the non-exposure bias (NEB), the potential additional adoption by the population hampered by incomplete diffusion as:

$$N\hat{E}B = J\hat{E}A - A\hat{T}E \quad (3)$$

Lastly, population selection bias, PSB (Diagne & Demont, 2007) is due to over-estimation of the ATE1 because of likely targeting and self-selection in varietal exposure is given as:

$$P\hat{S}B = A\hat{T}E1 - A\hat{T}E \quad (4)$$

2.3 Correcting for Sample Selection in Stochastic Frontier Analysis

This study applies Greene (2010) who attributes selectivity bias to the correlation of unobserved factors in the noise component, v_i of the stochastic frontier with the error term of the selection equation (w_i) as:

Probit sample selection: $d_i = 1[\alpha' z_i + w_i > 0]$ (5)

Stochastic production frontier: $y_i = \beta' x_i + v_i - u_i$ (6)

$$E[\, y_i | x_i, d_i = 1\,] = \beta' x_i + E[\varepsilon_i | d_i = 1] = \beta' x_i + \frac{\rho\sigma_\varepsilon \phi(\alpha' z_i)}{\Phi(\alpha' z_i)} = \beta' x_i + \theta\lambda_i \quad (7)$$

where, $\varepsilon_i = v_i - u_i$

u_i follows a half-normal distribution: $u_i \sim |N(0, \sigma^2{}_u)|$, $(w_i\,, v_i)$ have a bivariate normal distribution: $(w_i\,, v_i) \sim N_2[(0,1), (1, \rho\sigma_v, \sigma_v^2)]$, and a maximum simulated likelihood is used to integrate out the unobserved random variable using halton draws since there is no closed form (Greene, 2010).

Observable bias can be controlled using propensity score matching [PSM] (Bravo-Ureta *et al.,* 2012). The PSM matches farmers of improved rice varieties with the counterfactual non-adopters based on similar observable characteristics using propensity scores. Correcting for observable and unobservable bias produces consistent and unbiased results of the determinants of rice output and technical efficiency (Kumbhakar *et al*., 2009; Greene, 2010). Separate stochastic production functions are estimated for adopters and non-adopters conditional on adoption decision, d_i (0,1) as:

$$d_i = \alpha_0 + \sum_{j=1}^{15} \alpha_j Z_{ji} + w_i \quad (8)$$

$$lnY_i = \beta_0 + \sum_{k=1}^{5} \beta_k \, lnX_{ik} + {}^1\!/_2 \sum_{k=1}^{5} \sum_{j=1}^{5} \beta_{kj} \, lnX_{ik} \, lnX_{ij} + D_i + v_i + u_i \quad (9)$$

where Z_i is the vector of observable characteristics of adopters and non-adopters of improved rice varieties; α is the estimated parameter; ln represents logarithm to base $\boldsymbol{e}$; Y is rice output; X_i represents the five inputs for the translog model. Following Battese (1997), a dummy variable (D_i) is introduced to account for zero quantities of fertilizer because natural logarithm of fertilizer is taken only when it is positive. Households that planted any of these improved rice varieties (FARO 15, GR varieties [GR 17 to GR 22], GRUG7, Digang, NERICA varieties, Jasmine 85, Togo Marshall, WITA 7, Jet 3, Aromatic Short, Sikamo, Bumbaz, Bodia, IR20, Sakai) in 2012/2013 season were regarded as adopters whereas those who cultivated any of these traditional varieties (Mandii, Mr. Moore, Mr. Harry, Anyofula, Paul/Adongadonga, Salma saa, Muikpong, Wariwari) were treated as non-adopters. The estimations are performed using Limdep 11.

Technical efficiency, TE is measured as a ratio of actual to potential output as:

$$TE = \frac{y_i^*}{y_i} = \frac{f(x_i\beta)\exp(v_i - u_i)}{f(x_i\beta)\exp(v_i)} = \exp(-u_i) \tag{10}$$

Technical inefficiency occurs when a given set of inputs produces less output than what is possible given the available production technology. The determinants of technical inefficiency are estimated using Jondrow *et al.* (1982) conditional expectation procedure where u is $E[u|(\varepsilon - u)]$ with a distribution of $N(\mu^*, \sigma_*^2)$ as follows:

$$u_i = M_i\delta + w_i \tag{11}$$

where M_i are socioeconomic, institutional and farm-specific variables in Table 1 that explain technical inefficiency, δ includes parameters to be estimated, w_i is an unobservable random variable.

Table 1. Summary Definition of Variables

Variable	Notation	Description
Exposure model		
Community involvement in rice projects	K_1	Dummy; 1, community participated in rice project, 0, otherwise
Presence of agro-input shop in community	K_2	Dummy; 1, agricultural input shop exists in community, 0, otherwise
Model farmer	K_3	Dummy; 1, household has been a model farmer, 0, otherwise
Block farming	K_4	Dummy; 1, household participated in block farming, 0, otherwise
Membership of farmer-based organization	K_5	Dummy; 1, household belongs to a farmer-based organization, 0, otherwise
Agricultural extension services	K_6	Dummy; 1, household accesses agricultural extension services, 0, otherwise
Adoption model		
Adoption	d_i	Dummy; 1, household cultivated improved rice variety, 0, otherwise
Community involvement in rice projects	Z_1	Dummy; 1, yes, 0, otherwise
Presence of agro-input shop in community	Z_2	Dummy; 1, yes, 0, otherwise
Model farmer	Z_3	Dummy; 1, yes, 0, otherwise
Block farming	Z_4	Dummy; 1, household participated in block farming, 0, otherwise
Agricultural extension services	Z_5	Dummy; 1, yes, 0, otherwise
Sex of household head	Z_6	Dummy; 1, household head is female, 0, male
Forest zone	Z_7	Dummy; 1, agro-ecological area of rice farm is forest, 0, coastal zone
Guinea savannah zone	Z_8	Dummy; 1, agro-ecological area of rice farm is guinea savannah, 0, coastal zone

Lowland rain-fed	Z_9	Dummy; 1, rice cultivation is lowland rain-fed, 0, upland rain-fed
Irrigated production	Z_{10}	Dummy; 1, rice cultivation by irrigation, 0, upland rain-fed
Higher yield	Z_{11}	Dummy; 1, farmer seeking higher rice yield, 0, otherwise
Market demand	Z_{12}	Dummy; 1, farmer producing rice to sell, 0, otherwise.
Own consumption	Z_{13}	Dummy; 1, farmer producing rice for household consumption, 0, otherwise
Use of farm saved seed	Z_{14}	Number of years current rice variety has been continuously cultivated.
Size of farm	Z_{15}	Total of hectares (ha) of cultivated rice
Stochastic Frontier		
Rice output	Y	Rice output (in kg)
Farm size	X_1	Hectares of rice plot
Rice seed	X_2	Quantity of rice seed (in kg) planted
Fertilizer	X_3	Quantity of fertilizer used (in kg)
Farm labour	X_4	Farm labour (person-days) used
Herbicides	X_5	Herbicides (in litres) used on plot
Fertilizer application	D_i	Dummy; 1, household applied fertilizer on rice farm, 0, otherwise
Technical Inefficiency		
Sex of household head	M_1	Dummy; 1, household head is female, 0, male
Age	M_2	Total years of household head
Agricultural extension services	M_3	Dummy; 1, household has agricultural extension access, 0, otherwise
Educational Status	M_4	Total years of formal education of household head
Rice seed priming	M_5	Dummy; 1, practising seed priming, 0, otherwise
Row planting	M_6	Dummy; 1, practising row planting, broadcasting, 0
Seedling transplanting	M_7	Dummy; 1, seedling transplanting, direct sowing, 0
Sawah system	M_8	Dummy; 1, practise sawah system, 0, otherwise
Land preparation with herbicides	M_9	Dummy; 1, land preparation using herbicides, 0, otherwise
Weeding using herbicides	M_{10}	Dummy; 1, used herbicides for weed control, 0, hand hoe weeding
Weeding frequency	M_{11}	Number of times rice plot was weeded
Actyva fertilizer use	M_{12}	Dummy, 1, applied on rice farm, 0, otherwise
Ammonia fertilizer use	M_{13}	Dummy; 1, applied on rice farm, 0, otherwise
Fertilizer rate	M_{14}	Dummy; 1 if recommended rate of at least 350kg/ha is applied, 0, otherwise
Rice harvesting method	M_{15}	Dummy; 1, combine harvester, 0, sickle
Land preparation	M_{16}	Dummy; 1, herbicide applied, 0, otherwise
Pesticide use	M_{17}	Dummy; 1, pesticide applied, 0, otherwise

Source: Author's construction based on survey data set.

2.5 The Stochastic Metafrontier

The stochastic metafrontier is used to estimate and compare the technical efficiency scores of non-adopters and adopters of improved rice varieties. The metafrontier envelopes the group frontiers (adopters and non-adopters) and estimates the technology gap between the metafrontier and the group frontiers facing different production possibilities. Following Amsler, O'Donnell, & Schmidt (2017), the stochastic metafrontier is given as:

$$f_i = \max[f_{i1}, \ldots . f_{iS}\ ] \qquad s = 1, .. S \qquad (12)$$

Subject to $f_i d_i \leq f_i$

It is stochastic metafrontier because the group frontiers $f_{is} = x_i' \beta_s + v_{is}$ are stochastic. $f_i d_i$ is the vector of inputs for each group, d_i ; β_s and β^* are the vectors of group and metafrontier coefficients to be estimated. The metatechnology ratio (MTR) is estimated as:

$$MTR_i = \frac{exp(x_i' \beta_{d_i})}{exp(x_i' \beta_s\ )} \times \frac{exp(v_i d_i)}{exp(v_{is})} \qquad (13)$$

The MTR measures the closeness of the group frontier to the metafrontier and it depends on the group frontier's input-output combination (Battese *et al.,* 2004). A higher MTR implies a lower gap between the group frontier and the metafrontier. The metafrontier, TE_i^* is:

$$TE_i^* = TE_i \times MTR_i \qquad (14)$$

The metafrontier is estimated using R econometric software following Amsler *et al*. (2017).

3. Results and Discussion

3.1 Exposure Rate, Adoption Rate, and Joint Exposure and Adoption Rate

The results in Table 2 are predictions from estimation of determinants of exposure to improved rice varieties, the $ATE(x)$ adoption model and joint exposure and adoption explained in section 2.2. The exposure rate of 0.833 implies widespread diffusion of the improved rice varieties amongst the population. Exposure was enhanced by involvement of communities in rice projects and presence of community agricultural input shops.

Table 2. Predicted Estimates of Improved Rice Varietal Exposure and Adoption

Name of estimate	Estimate	Standard error
Predicted exposure rate	0.833***	0.015
Predicted joint exposure and adoption rate (JEA) within non-exposed subpopulation	0.559***	0.017
Predicted population potential adoption rate (ATE)	0.672***	0.017
Predicted potential adoption rate within exposed subpopulation (ATE1)	0.797***	0.014
Predicted potential adoption rate for exposed non-adopters (ATE0)	0.416***	0.027
Estimated population adoption gap:		
Non-exposure bias, $N\hat{E}B = J\hat{E}A - A\hat{T}E$	-0.113***	0.003
Population selection bias, $P\hat{S}B = A\hat{T}E1 - A\hat{T}E$	0.125***	0.010

Notes: *** indicate values statistically significant at 1%. Standard errors are calculated using the delta method (Wooldridge, 2002, p. 44).

The predicted adoption within the non-exposed population in Table 2 was 0.429. This estimate was calculated using the non-exposed subsample from the JEA estimation. This means the adoption rate for the non-exposed would have been 42.9% if those households knew about these improved rice varieties. The JEA adoption rate of 55.9% was predicted using the JEA results obtained under partial improved rice varietal awareness. This JEA exceeds the 4% reported by Diagne & Dermont (2007) on Nerica rice adoption in Ivory Coast involving 1,500 rice farmers. The higher JEA rate was partly a result of widespread varietal diffusion (83.3% exposure rate) in the study area. The JEA treats the non-exposed as non-adopters although, they have the potential to adopt when exposed and thus produces biased results by under-estimating the adoption rate.

The consistent and unbiased average treatment effect (ATE) of improved rice varietal adoption was 67.2%. This estimate is higher than the 37% adoption rate in Diagne & Dermont (2007) study on improved rice variety adoption in Ivory Coast. The predicted ATE obtained from the $ATE(x)$ adoption estimation measures the adoption outcome of a rice farming household randomly drawn from the population assuming every rice farmer is aware of the improved varieties. Therefore, under complete diffusion, the average adoption rate (ATE) would be 67.2%, and not the JEA adoption rate of 55.9% under partial exposure. This produces a non-exposure bias [$N\hat{E}B = J\hat{E}A - A\hat{T}E$] of -11.3%, which implies a gap in adoption because of partial diffusion of the improved rice varieties. As more households are exposed, the adoption gap narrows. The predicted average treatment effect on the treated (ATE1) of 79.7% is the adoption rate amongst the exposed that actually cultivated improved rice varieties. This is higher than the 37% adoption rate by rice farmers in Ivory Coast (Diagne & Demont, 2007). The predicted average treatment effect for non-adopting households (ATE0) despite being aware of the improved varieties was 41.6%. This means constraints other than exposure influenced their non-adoption decisions. The population selection bias, PSB ($A\hat{T}E1 - A\hat{T}E$) was 12.5%. It stems from over-estimation of the true population adoption rate because of potential self-selection and targeting bias in improved rice variety exposure. This PSB is lower than the 18% reported by Diagne & Demont (2007) for Nerica rice adoption in Ivory Coast.

3.2 Controlling Observable Bias in Stochastic Production Frontier Estimation

Adoption was estimated using probit model for households with knowledge about improved rice varieties from which propensity scores were predicted. Imposing a common support condition (Leuven & Sianesi, 2003), the propensity scores were matched using nearest neighbour with replacement (Cameron & Trivedi, 2005) of up to 4 matches per adopter to the counterfactual non-adopter within a caliper distance of 0.025^2 to control observable bias (Dehejia & Wahba, 2002). Matching with replacement improves the quality of matches by allowing a given non-adopter counterfactual to be matched to more than one adopter which further reduces observable bias by avoiding bad matches (Smith & Todd, 2005). In Figure 1, the region of common support of the propensity scores ranged from 0.015 to 0.948. The propensity scores of adopters outside the common support interval were excluded from the matching procedure (Leuven & Sianesi, 2003). The standardized mean difference (Rosenbaum & Rubin, 1985) in Table 3 reveals significant observable bias in the covariates of adopters and non-adopters before matching.

The bias was eliminated after matching, producing an appropriate counterfactual (Lee, 2008) within the common support region (Leuven & Sianesi, 2003; Caliendo & Kopeinig, 2008). Moreover, joint significance of the regressors after matching was rejected. The lower pseudo R^2 after matching means all systematic differences in the covariates between adopters and non-adopters of improved rice varieties was eliminated (Faltermeier & Abdulai, 2009).

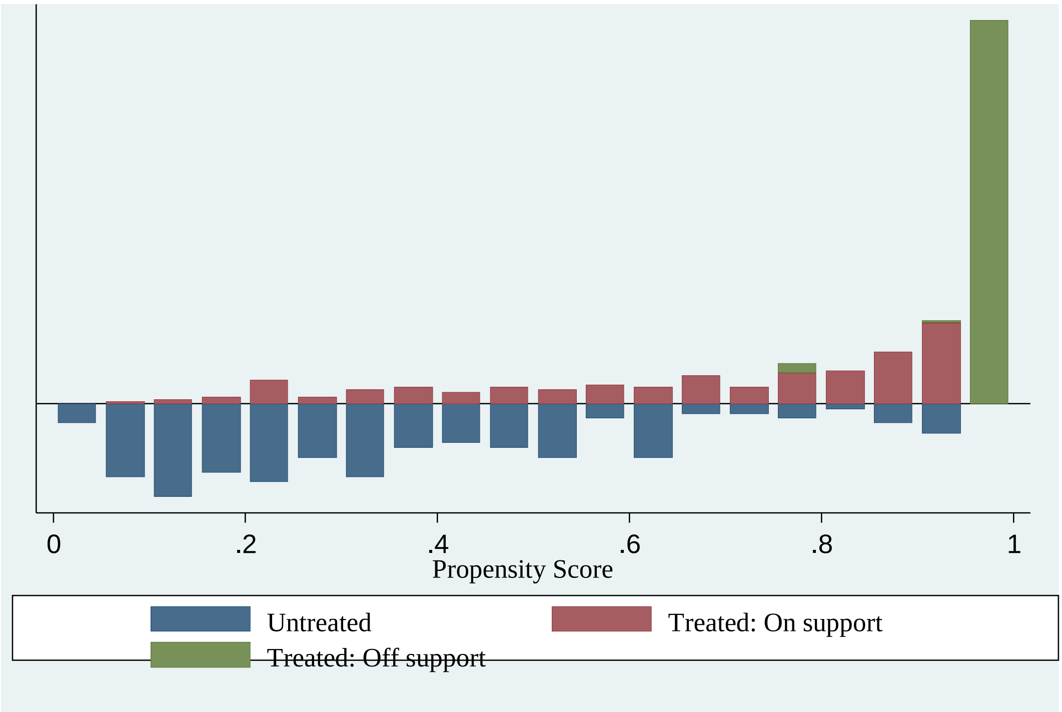

Figure 1. Distribution of Propensity Scores and Region of Common Support

Table 3. Standardized Mean Difference of Covariates Between Non-Adopters and Adopters Before and After Matching

Variable Unmatched (U) Matched (M)		Sample mean: Adopters	Sample mean: Non-adopters	% bias	(Total) % |bias | reduction	t-test t value	V(T)/V(C)
Community involvement in rice projects	U	0.291	0.049	68.0	91.1	6.44***	-
	M	0.168	0.189	-6.0		-0.51	-
Presence of agro-input shop in community	U	0.393	0.251	30.6	56.7	3.14**	-
	M	0.287	0.349	-13.3		-1.20	-
Model farmer	U	0.246	0.037	62.9	94.3	5.92***	-
	M	0.120	0.108	3.6		0.34	-
Block farming	U	0.129	0.018	43.3	97.3	4.05***	-
	M	0.072	0.069	1.2		0.11	-
FBO membership	U	0.480	0.423	11.5	59.0	1.20	-
	M	0.461	0.485	-4.7		-0.43	-
Forest agro-ecological zone	U	0.195	0.135	16.2	66.0	1.66*	-
	M	0.204	0.183	5.5		0.47	-
Guinea savannah agro-ecological zone	U	0.456	0.804	-76.9	83.9	-7.76***	-
	M	0.645	0.703	-12.4		-1.09	-
Lowland rain-fed production system	U	0.541	0.859	-73.9	77.0	-7.31***	-
	M	0.719	0.645	17.0		1.44	-

Irrigated production system	U	0.426	0.049	98.7	78.2	9.30***	-
	M	0.222	0.304	-21.5		-1.71*	-
Seeking higher rice yield	U	0.688	0.479	43.3	61.4	4.59***	-
	M	0.587	0.668	-16.7		-1.53	-
Producing rice to meet market demand	U	0.559	0.282	58.2	91.5	5.99***	-
	M	0.437	0.414	4.9		0.43	-
Producing rice for own consumption	U	0.237	0.196	9.9	67.1	1.03	-
	M	0.252	0.265	-3.3		-0.28	-
Use of farmer saved seed	U	3.961	5.282	-31.4	55.4	-3.53***	0.45*
	M	4.255	4.844	-14.0		-1.49	0.78
Agricultural extension access	U	0.372	0.123	60.3	97.5	5.94***	-
	M	0.236	0..242	-1.5		-0.13	-
Sex of respondent	U	0.216	0.184	8.0	90.3	0.83	-
	M	0.205	0.202	0.8		0.07	-
Education (years)	U	5.592	3.239	45.1	67.7	4.73***	0.97
	M	4.435	3.673	14.6		1.37	1.13
Farm size (ha)	U	3.812	5.697	-31.9	99.5	-3.62***	0.39*
	M	4.182	4.191	-0.2		-0.02	1.80*
Seed quantity (kg)	U	313.670	584.060	-39.6	68.6	-4.62***	0.28*
	M	349.690	434.690	-12.5		-1.39	1.30
Fertilizer quantity (kg)	U	612.530	265.690	88.1	96.6	8.62***	2.39*
	M	386.860	375.120	3.0		0.32	0.84
Farm labour (person-days)	U	1171.6	592.13	4.8	85.7	0.44	44.87*
	M	239.14	322.25	-0.7		-0.62	0.28*
Herbicides use (litres)	U	6.860	5.244	25.0	18.0	2.60**	1.06
	M	6.118	7.444	-20.5		-1.51	0.72
Rice output (kg)	U	9538.50	6919.20	17.3	54.4	1.64	4.70*
	M	6122.70	7317.10	-7.9		-1.28	2.28*
Fertilizer rate use	U	0.267	0.043	65.1	99.5	6.15***	-
	M	0.081	0.080	0.3		0.03	-
Actyva fertilizer use	U	0.024	0.018	3.9	44.7	0.40	-
	M	0.031	0.028	2.2		0.16	-
Ammonia fertilizer use	U	0.712	0.429	59.4	79.1	6.31***	-
	M	0.615	0.556	12.4		1.07	-
Rice harvesting method	U	0.075	0.006	35.4	93.2	3.26**	-
	M	0.006	0.002	2.4		0.67	-
Land clearing herbicide	U	0.655	0.270	39.8	90.2	4.20***	-
	M	0.534	0.515	3.9		0.34	-
Weed control herbicide	U	0.667	0.521	29.8	52.9	3.12**	-
	M	0.584	0.652	-14.0		-1.26	-
Weeding times	U	2.084	1.957	16.0	38.8	1.66*	1.12
	M	1.919	1.997	-9.8		-0.93	1.05
Pesticide use	U	0.489	0.135	82.6	91.2	8.15***	-
	M	0.286	0.317	-7.2		-0.61	-
Rice seed priming	U U	0.438	0.110	78.9	83.7	7.70***	-
	M M	0.335	0.389	-12.8		-0.99	-
Seedling transplanting	U U	0.360	0.080	71.9	79.5	6.93***	-

	MM	0.255	0.312	-14.7		-1.14	-
Row planting	UU	0.228	0.098	35.7	79.3	3.54***	-
	MM	0.174	0.147	7.4		0.66	-

Sample	Pseudo R^2	LR chi^2	p value
Unmatched	0.435	273.36	0.000***
Matched	0.088	40.82	0.196

Notes: ***, **, *, indicate statistically significant at 1%, 5% and 10% respectively.

3.3 Determinants of Adoption of Improved Rice Varieties

Following Bravo-Ureta *et al*. (2012), a stochastic production frontier that corrects unobservable bias was estimated after the PSM. The chi-squared test statistics in Table 4 were statistically significant implying the joint significance of the parameters in determining adoption decisions. Community involvement in rice projects implementation influenced households' adoption of improved rice varieties at 10% significance level. Over 20 rice related projects have been implemented across the country in nearly two decades (Ragasa *et al*., 2013). These projects created improved rice varietal awareness and encouraged their cultivation. Moreover, being a model farmer positively and statistically influenced adoption. The rice project implementers worked with farmers, some of whom participated in varietal trials and demonstrations that influenced their adoption. Access to agricultural extension service had positive influence on cultivation of improved rice at 1% level of significance. Doss and Morris (2001) explained that farmers' contact with agricultural extension officers facilitated adoption of new technologies.

Similarly, irrigated rice cultivation statistically influenced adoption of improved rice varieties at 1% level of significance. In comparison with upland rice cultivation, adoption was higher amongst irrigated rice producers. Irrigated rice production gives the highest yield of 4.5mt/ha (CARD, 2010), and accounts for 16% of national output (MoFA, 2009). Meanwhile, Ghana has not fully exploited its irrigation potential, with irrigated land representing 3.4% of total land area under cultivation (MoFA, 2016).

Table 4: Results of the adoption selection model for the stochastic frontier

Variable	Unmatched sample	Matched sample
	Coefficient	Coefficient
Constant	0.225 (0.381)	0.029 (0.405)
Community involvement in rice projects	0.509* (0.264)	0.535* (0.296)
Presence of agrochemical shop in community	0.136 (0.169)	0.024 (0.184)
Model farmer	0.822*** (0.278)	0.594* (0.316)
Block farming	0.638* (0.354)	0.513 (0.406)
Agricultural extension	0.662*** (0.194)	0.565*** (0.212)
Sex of respondent	0.060	0.110

	(0.194)	(0.202)
Forest zone	-0.619** (0.256)	-0.372 (0.334)
Guinea savannah zone	-0.908*** (0.255)	-0.571** (0.291)
Lowland rain-fed production	0.335 (0.280)	0.266 (0.283)
Irrigated production	1.154*** (0.336)	1.142*** (0.363)
Higher rice yield	0.391** (0.179)	0.296 (0.188)
Rice market demand	0.089 (0.179)	0.096 (0.190)
Own consumption of rice	0.084 (0.189)	0.108 (0.199)
Rice seed recycling	-0.06*** (0.019)	-0.059*** (0.020)
Farm size	-0.025** (0.013)	-0.023* (0.014)
Log-likelihood function	-204.556	-190.897
Chi-squared test statistic	219.025***	75.634***
No. of rice plots	496	330

Notes: ***, **, *, indicate statistically significant at 1%, 5% and 10%. Figures in brackets represent the standard errors.

The coefficient of rice farm located in the guinea savannah agro-ecological zone was negative. This means adoption was lower in the guinea savannah zone relative to the coastal zone. Although the guinea savannah zone produces 53% of national output (MoFA, 2016), many farmers still cultivate traditional varieties. Meanwhile, farm size had an inverse relationship with adoption of improved rice varieties. This implies adoption was higher amongst households with smaller plot sizes. The mean farm size in this study for adopters was about 4.0 ha. This is consistent with Faltermeier & Abdulai (2009) that rice cultivation in Ghana is mainly by smallholders. The longer a particular rice variety was continuously planted, the less willing was a household to cultivate a new variety. Households continuously cultivated a particular variety for at least 4 years. Indeed, 73.5% of plots were planted with farmer saved seeds from previous harvest. It is recommended that farmers renew their seeds at least once every three years (Ragasa *et al.*, 2013).

3.4 Determinants of Rice Output

The statistical significance of the correlation coefficient [$\rho(w, v)$] between the error term of the adoption model and the stochastic frontier in both adopters and non-adopters in Table 5, indicate the presence of selection bias due to unobservable characteristics. Therefore, the stochastic production frontier with sample selection correction in columns 5 and 6 of Table 5 are discussed.

The coefficients of farm size and fertilizer had positive and statistically significant effect on the rice output of non-adopters. Farm size had the highest partial production elasticity of 0.805 on output, followed by 0.463 for fertilizer. The first term coefficients of the translog stochastic frontier for adopters were all positive and statistically significant in fulfilment of the monotonicity condition (Sauer *et al.,* 2006). For example, the coefficient of 0.043 for seed, implies a 100% increase in quantity of seed *ceteris paribus*, leads to a 4.3% increase in rice output. Similar interpretation applies to labour, herbicides and fertilizer with coefficients of 0.038, 0.195 and 0.057 respectively.

Table 5. Results of the Stochastic Production Frontier for The Matched Sample

	Conventional SPF			Sample selection SPF	
Variable	Pooled	Adopters	Non-adopters	Adopters	Non-adopters
Constant	8.885*** (0.075)	9.078*** (0.094)	8.814*** (0.100)	9.452*** (0.016)	8.685*** (0.110)
Farm size (ha)	0.653*** (0.072)	0.757*** (0.081)	0.691*** (0.130)	0.803*** (0.016)	0.805*** (0.127)
Seed (kg)	0.127** (0.059)	0.105* (0.063)	0.098 (0.109)	0.043*** (0.012)	0.088 (0.107)
Fertilizer (kg)	0.227** (0.099)	0.127 (0.123)	0.505*** (0.166)	0.057*** (0.020)	0.463** (0.199)
Labour (person days)	0.009 (0.044)	0.020 (0.054)	-0.018 (0.069)	0.038*** (0.010)	-0.023 (0.070)
Herbicides (litres)	0.149*** (0.049)	0.118** (0.057)	0.302*** (0.095)	0.195*** (0.013)	0.206 (0.126)
Farm size squared	-0.263* (0.148)	-0.423** (0.207)	-0.204 (0.253)	-0.839*** (0.043)	0.027 (0.279)
Seed squared	0.150*** (0.049)	0.068 (0.155)	0.164** (0.064)	-0.142*** (0.024)	0.133 (0.096)
Fertilizer squared	-0.002 (0.150)	-0.327 (0.199)	0.353 (0.250)	-0.481*** (0.043)	0.431 (0.290)
Labour squared	-0.080*** (0.030)	-0.130* (0.074)	-0.030 (0.052)	-0.112*** (0.018)	-0.014 (0.074)
Herbicides squared	0.100 (0.069)	0.079 (0.086)	-0.024 (0.149)	0.056** (0.028)	0.016 (0.152)
Farm size*seed	0.026 (0.068)	0.123 (0.152)	-0.012 (0.113)	0.478*** (0.019)	-0.034 (0.153)
Farm size*fertilizer	-0.043 (0.112)	0.414** (0.165)	-0.119 (0.169)	0.437*** (0.049)	0.112 (0.239)
Farm size*labour	0.140** (0.057)	0.158 (0.113)	0.123 (0.087)	0.027 (0.018)	0.006 (0.101)
Farm size*herbicides	-0.048 (0.087)	-0.240** (0.104)	0.043 (0.177)	-0.525*** (0.027)	0.270 (0.212)
Seed* fertilizer	-0.033 (0.086)	-0.138 (0.136)	-0.094 (0.122)	-0.221*** (0.037)	-0.192 (0.188)
Seed* labour	-0.026 (0.031)	-0.083 (0.113)	0.009 (0.042)	-0.062*** (0.020)	-0.010 (0.068)
Seed* herbicides	0.047 (0.068)	0.036 (0.088)	-0.087 (0.101)	0.368*** (0.023)	-0.114 (0.160)
Fertilizer*labour	0.171** (0.076)	0.156* (0.091)	0.094 (0.132)	0.180*** (0.023)	0.005 (0.142)

Fertilizer*herbicides	0.037 (0.113)	0.104 (0.118)	0.079 (0.176)	-0.133*** (0.036)	-0.117 (0.223)
Labour*herbicides	0.043 (0.054)	0.214** (0.077)	0.057 (0.800)	0.421*** (0.016)	-0.011 (0.083)
Fertilizer Use (0,1)	0.267*** (0.086)	0.322** (0.139)	0.210* (0.118)	0.158*** (0.009)	0.285*** (0.116)
Adoption	0.653** (0.064)				
Lambda (λ)	4.212*** (0.089)	5.593*** (0.120)	3.782*** (0.142)		
Variance (σ^2)	1.056*** (0.112)	1.050*** (0.149)	0.979*** (0.159)		
Sigma-u				1.259*** (0.009)	1.005*** (0.064)
Sigma-v				0.030*** (0.006)	0.279*** (0.061)
Selectivity bias $\rho(w, v)$				-0.749*** (0.243)	0.997*** (0.031)
Mean efficiency	0.551	0.579	0.582	0.467	0.518
Returns to scale	1.165	1.127	1.578	1.136	1.360
Log-likelihood function	-283.182	-116.935	-133.288	-227.001	-236.215
No. of observations	330	167	163	167	163

Notes: ***, **, *, indicate values statistically significant at 1%, 5% and 10%. Figures in brackets denote standard errors.

In keeping with regularity conditions (Sauer *et al.*, 2006), coefficients of the square of seed, fertilizer, labour and farm size were negative and significant at 1%, fulfilling the diminishing marginal productivity condition for these inputs relative to the adopters. For example, the squared of seed, fertilizer, labour and farm size, were -0.142, -0.481, -0.112 and -0.839 respectively. This implies that continuously increasing fertilizer by 100% would in the long run decrease output by 48.1%. The interaction terms of the inputs explain whether they were substitutes or complements in rice production. For instance, farm size and fertilizer with positive coefficient of 0.437 were complements whilst farm size and herbicides with negative coefficient of -0.525 were substitutes. There was increasing returns to scale in both adopters and non-adopters of improved rice varieties.

3.6 Determinants of Technical Inefficiency in Rice Production

The unbiased results in columns 6 and 7 of the matched sample in Table 6 are discussed. The results in the unmatched columns are biased as they have not been corrected for differences in observable characteristics likely to influence technical inefficiency. Variables with negative coefficients have negative relationship with technical inefficiency and vice versa.

Access to agricultural extension services, practice of sawah system, weeding using herbicides, weeding frequency and sex of household head statistically influenced the technical inefficiency of adopters of improved rice. Male household heads amongst the adopters were less technically inefficient than females. Adopter households with access to agricultural extension services were technically efficient than households without access. Out of 216 farmers that accessed agricultural extension services, 207 acted on the advice received.

Agricultural extension delivers improved production technologies to farmers (Gautam, 2000; Evenson, 2001). Adopters of improved rice varieties that practiced plot water management strategies known as sawah system (Buri *et al*., 2012; Abdulai *et al*., 2018) increased their technical efficiency than those that did not. Bam *et al*. (2010) reported increased yield by Ghanaian farmers that practiced the sawah system.

Similarly, adopters that applied herbicides as opposed to weeding using hoes reduced their technical inefficiency. Nearly half (49.6%) of all rice plots applied herbicides, 20.1% practiced hand pulling of weeds and 17.3% weeded using hoes. The frequency of weeding had a negative coefficient, implying adopters who weeded their plots more than once within the season were technically efficient than those that weeded once. In this study, 22.5%, 48.1% and 24.3% of adopter plots were weeded once, twice and thrice. Herbicides are increasingly being applied in Ghana and requires farmer education on their correct application and safe use (Abdulai, 2015).

Regarding non-adopters, the determinants of technical inefficiency were application of sulphate of ammonia fertilizer and weeding frequency. The negative coefficient means the application of ammonia fertilizer reduced technical inefficiency for the non-adopters. About 46% of farms applied ammonia fertilizer at the recommended 7-8 weeks after planting (Abdulai *et al*., 2018). The coefficient of weeding frequency was positive implying technical inefficiency was associated with increased weeding for the non-adopters. The recommended practice is weeding twice within the cultivation season (Ragasa *et al.*, 2013). About 26.7%, 49.7% and 19.6% of non-adopter plots were weeded once, twice and thrice within the season.

Table 6. Results of determinants of technical inefficiency in rice production

	Unmatched sample			**Matched sample**		
Variable	Pooled	Adopters	Non-adopters	Pooled	Adopters	Non-adopters
Constant	0.526 (0.459)	1.493** (0.763)	-0.577 (0.782)	0.526 (0.459)	1.728** (0.716)	-0.577 (0.782)
Sex of household head	0.485** (0.240)	0.821** (0.381)	0.013 (0.409)	0.485** (0.240)	0.633* (0.351)	0.013 (0.409)
Age of household head	0.001 (0.008)	0.005 (0.013)	9.561E-04 (0.014)	0.001 (0.001)	0.003 (0.011)	9.561E-04 (0.014)
Agricultural extension	-0.307 (0.257)	-0.977** (0.508)	0.237 (0.466)	-0.307 (0.257)	-1.011** (0.370)	0.237 (0.466)
Household head level of education	0.000 (0.017)	-0.022 (0.033)	-0.010 (0.026)	0.000 (0.017)	-0.020 (0.031)	-0.010 (0.026)
Rice seed priming	0.229 (0.289)	-0.352 (0.421)	-0.407 (0.675)	0.229 (0.289)	-0.048 (0.344)	-0.407 (0.675)
Seedling transplanting	-0.392 (0.328)	-0.564 (0.462)	-0.487 (1.091)	-0.392 (0.328)	-0.041 (0.397)	-0.487 (1.091)
Row planting	0.059 (0.285)	-0.254 (0.421)	-0.577 (0.563)	0.059 (0.285)	0.115 (0.392)	-0.577 (0.563)
Sawah system	-0.436** (0.212)	-0.920** (0.371)	-0.288 (0.408)	-0.436** (0.012)	-0.964** (0.318)	-0.288 (0.408)
Land preparation using herbicide	-0.425** (0.208)	-0.497 (0.343)	0.057 (0.362)	-0.425** (0.208)	-0.397 (0.311)	0.057 (0.362)
Weeding using herbicide	-0.365* (0.206)	-0.727** (0.358)	-0.423 (0.335)	-0.365* (0.026)	-0.671** (0.306)	-0.423 (0.335)

Weeding frequency	0.061 (0.130)	-0.505** (0.220)	0.462* (0.252)	-0.061 (0.130)	-0.469** (0.182)	0.462* (0.252)
Use of Actyva[3] fertilizer	0.759 (0.582)	0.843 (0.919)	0.063 (1.173)	0.759 (0.582)	0.637 (0.791)	0.063 (1.173)
Use of ammonia fertilizer	-0.384* (0.200)	-0.152 (0.323)	-1.006*** (0.340)	-0.384* (0.200)	-0.095 (0.301)	-1.006*** (0.340)
Fertilizer rate	0.597 (0.383)	0.291 (0.412)	-0.303 (0.685)	0.597 (0.383)	0.754 (0.563)	-0.303 (0.685)
Method of rice Harvesting	-2.993 (3.096)	-4.750 (6.570)	-24.695 (1423.203)	-2.993 (3.096)	0.254 (1.607)	-24.695 (1423.203)
Pesticide use	-0.012 (0.254)	-0.012 (0.375)	-0.105 (0.478)	-0.012 (0.254)	0.025 (0.334)	-0.105 (0.478)
No. of observations	496	333	163	330	167	163

Notes: ***, **, * indicate values statistically significant at 1%, 5% and 10%. Figures in brackets are the standard errors.

Table 7. Estimates of group and metafrontier TEs and metatechnology ratios

Category	Mean	Standard deviation	Maximum	Minimum
Adopters matched sample				
Group TE-Conventional SPF	0.555	0.244	0.923	0.047
Group TE-Sample selection SPF	0.467	0.253	0.969	0.032
Metatechnology ratio (MTR)	0.909	0.106	1.000	0.236
TE relative to stochastic metafrontier	0.427	0.224	0.929	0.031
Non-adopters matched sample				
Group TE-Conventional SPF	0.581	0.218	0.992	0.079
Group TE-Sample selection SPF	0.518	0.232	0.927	0.063
Metatechnology ratio (MTR)	0.785	0.166	1.000	0.150
TE relative to stochastic metafrontier	0.445	0.217	0.919	0.038
Paired t-test of the mean stochastic metafrontier estimates				
	T statistic		*Decision*	
Metafrontier TE diff = mean (Adopters-Non-adopters) = 0.018	0.741 (1.96)		Do not reject H_0	
Metafrontier MTR diff = mean (Adopters-Non-adopters) = 0.124	8.107 (1.96)		Reject H_0: mean (diff) $\neq 0$	

Notes: Critical value in brackets is at 5% significance level. Source: Author's computation based on survey data.

3.7 Summary of Groups and Metafrontier Technical Efficiencies

Consistent with theory, the metafrontier TEs of adopters and non-adopters in Table 7 were less than the group TEs from the sample selection SPF. The stochastic metafrontier allows direct comparison of the TEs of non-adopters with adopters of improved rice varieties. A t-test of the difference (0.018) in mean metafrontier TE between the adopters (0.427) and non-adopters (0.445) was not statistically significant.

Regarding the MTR, the null hypothesis [Ho: mean (diff) =0] was rejected in favour of the alternative [Ha: mean (diff) $\neq$ 0]. Therefore, the MTR for the adopters (0.909) and non-adopters (0.785) were statistically different. An MTR of 1 implies there is no gap between the group frontier and the metafrontier. Over 60% of adopters and non-adopters respectively had metafrontier TEs of 50% or less. In the group sample selection SPF about 56% (adopters) and 47% (non-adopters) had TEs below 50%. The lower TEs are attributed to differences in managerial practices, socioeconomic and environmental characteristics. Farmers can attain higher metafrontier TEs by learning from the best practice farmers. For instance, 7 adopters and 1 non-adopter had metafrontier TEs between 91-100%.

4. Conclusion and Recommendations

This study analysed the adoption of improved varieties and its effect on rice output and technical efficiency of 576 Ghanaian households for 2012/2013 using a stochastic production frontier that accounts for non-exposure and selection bias. Exposure to improved rice varieties was estimated to account for non-exposure bias, followed by the determinants of adoption for the exposed households using treatment effect. A metafrontier was estimated to separate production technology gaps from technical inefficiencies after correcting selectivity bias. Adoption under partial rice varietal exposure under-estimated the adoption rate as 55.9%, producing a non-exposure bias of 11.3%. The average exposure rate of the improved rice varieties was 82.5% whilst adoption rate was 67.2%. Exposure was enhanced by rice projects and agricultural input shops in communities. Rice projects, being a model farmer, agricultural extension, seeking higher yield, and cultivating rice through irrigation influenced adoption.

The metafrontier TE for non-adopters (44.5%) and adopters (42.7%) were not statistically different. Nonetheless, adopters produced closer to the metafrontier given their higher MTR (0.909) than the non-adopters' MTR (0.785). Labour, herbicides, fertilizer, seed and farm size increased the output of adopters whilst farm size and fertilizer raised the output of non-adopters. Agricultural extension, managing rice field water levels, and weeding twice with herbicides increased the technical efficiency of adopters. Relative to non-adopters, ammonia fertilizer application and weeding increased their technical efficiency. This study recommends the cultivation of improved varieties of rice and improving technical efficiency.

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[1] A higher probability of being sampled.

[2] The maximum distance of a propensity score to find a nearest matched neighbour within the common support region.

[3] Actyva is a fertilizer brand name in Ghana.