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Accounting for Rice Productivity Heterogeneity in Ghana: The Two-Step Stochastic Metafrontier Approach

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***Abstract*—**Rice yields among agro-ecological zones are heterogeneous. Farmers, researchers and policy makers are making frantic efforts to bridge rice yield gaps between agro-ecological zones through the promotion of improved agricultural technologies (*IATs*). Farmers are also modifying these *IATs* and blending them with indigenous farming practices (*IFPs*) to form farmer innovation systems (*FISs*). Also, different metafrontier models have been used in estimating productivity performances and their drivers. This study used the two-step stochastic metafrontier model to estimate the productivity performances of rice farmers and their determining factors in GSZ, FSTZ and CSZ. The study used both primary and secondary data. Farmers in CSZ are the most technically efficient. Technical inefficiencies of farmers are negatively influenced by age, sex, household size, education years, extension visits, contract farming, access to improved seeds, access to irrigation, high rainfall amount, less lodging of rice, and well-coordinated and synergized adoption of technologies. Albeit farmers in CSZ are doing well in terms of rice yield, they still have the highest potential of increasing rice yield since they had the lowest TGR. It is recommended that government through the ministry of food and agriculture, development partners and individual private companies promote the adoption of *IATs* as well as educate farmers on how to coordinate and synergize the adoption of the whole package. Contract farming concept and agricultural extension intensification should be vigorously pursued to the latter.

***Keywords*—**Efficiency, farmer innovation systems, improved agricultural technologies, two-step stochastic metafrontier approach.

I. Introduction

EVIDENTLY, rice yields differ across the agro-ecological zones in Ghana. While farmers in Greater Accra Region (CSZ) always obtained rice yield of 6 Mt/ha, their counterparts in Northern (GSZ), Upper East (Sudan Savannah and GSZ) and Volta (Transitional Savannah) Regions always struggle to obtain 4 Mt/ha [1]. It is clear that over the years, rice yield in Greater Accra Region (CSZ) doubles other regions except the Volta Region and this may be attributed to the fact that rice production in Greater Accra is largely done under irrigation. Aside the differences in agro-ecological zones, the externally developed improved agricultural technologies (*IATs*) and inherently discovered or developed farmer innovation systems (*FISs*) play a critical role in rice productivity heterogeneity. As noted by [2], when high-yielding pest- and disease-resistant varieties are made available, affordable and accessible to smallholder farmers, some will adopt and be able to increase their productivities close to the potential values or even commercial level.

The discrepancies in rice productivities across agro-ecological zones; call for questions on whether the variations are stemming from the following: differences in *IFPs*, *FISs* and *IATs;* efficiencies of farmers in the production process; climatic and soil conditions; regional specific and policy factors. Additionally, efficiency studies on rice in Ghana have been location specific and lack policy credibility for the entire nation. For instance, [3] examined farm-specific technical efficiency of smallholder rice farmers in the Upper East region of Ghana; [4] assessed the extent of exposure and adoption of the NERICA varieties across the rice growing districts (Ejura-Sekyedumase, Hohoe and Tolon-Kumbungu) in Ghana, and determined the key factors that affect adoption; [5] analysed economic efficiency of NERICA rice farms in the Volta Region of Ghana.

Also, [6] analyze the impact of row-planting technology on rice productivity in two districts, Kasena Nankana East and Bawku Districts in the Upper East Region of Ghana. Though, [7] assessed the impact of agricultural extension and fertilizer adoption on rice productivity in Ghana, the analysis was not segregated into agro-ecological zones. Methodologically, all the above-mentioned studies have not examined how cumulatively agro-ecological zone specific factors, institutional and policy factors; farmer specific factors and *FISs* and *IATs* influence productivity performance indices (technical efficiency and metafrontier technical efficiency) of farmers using a new-two step stochastic metafrontier approach.

II. Methodology

A. Analytical Framework of the New Two-Step Stochastic Metafrontier Models

The stochastic metafrontier production function can be estimated using the pooling stochastic metafrontier model, the two-step mixed model or the new two-step stochastic metafrontier model. For the pooling stochastic metafrontier model, all the group data are pooled together and used to

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estimate the stochastic metafrontier. The two-step mixed approach was proposed by [8], [9]. The name two-step mixed approach came from the fact that it combines stochastic frontier and mathematical programming techniques in estimating metafrontier model. However, while the estimated metafrontier technical efficiencies using the pooling stochastic metafrontier model are not exact, the two-step mixed approach violates the standard regularity property. The superiority of the new two-step approach lies in the fact that its estimated metafrontier technical efficiencies are accurate and exact, and also meet all the standard regularity conditions. Therefore, this study employs the new two-step approach in measuring metafrontier estimates of rice production in the agro-ecological zones in Ghana.

The new two-step stochastic metafrontier model proposed by [10] uses two stochastic frontier regressions; thus, the group specific stochastic frontier and the stochastic metafrontier regressions. For the new two-step stochastic metafrontier model, the group specific stochastic frontier is first estimated and the estimated parameters and error terms are pooled together for the estimation of the stochastic metafrontier model. Following the work of [8], [9], the first step of this approach involves the use of maximum likelihood to estimate observed group specific stochastic frontier which is given as:

$$y_i^k = f\left(x_i, \beta_i^k\right)\ell^{V_i^k - U_i^k} = \ell^{x_i\beta_i^k + V_i^k - U_i^k} \qquad (1)$$

where y_i^k denotes the quantity (*kg*) of rice produce by *ith* farmer in *kth* agro-ecological zone, x_i is a $(1\times L)$ vector of quantity of inputs used by the *ith* farmer to produce y_i^k quantity of rice, β_i^k is a $(L\times 1)$ vector of parameters for inputs associated with *kth* agro-ecological zone and $f\left(x_i, \beta_i^k\right)\ell^{V_i^k}$ is the suitable functional form. The error terms are two (V_i^k and U_i^k) and they are assumed to be independent of each other. V_i^k is a symmetric random term which captures the stochastic effects outside the farmer's control (e.g., weather, natural disasters, and luck, measurement errors, and other statistical noise). It is a two-sided random error $\left(-\infty < V_i^k < \infty\right)$. Conversely, U_i^k is a one-sided non-negative $\left(U_i^k \geq 0\right)$ efficiency component that captures the technical inefficiency of the farmer within *kth* agro-ecological zone.

Note that U_i^k is defined by a group technical inefficiency model given as:

$$\mu_i^k = 1 - U_i^k = \varphi_0^k + \sum_{m=1}^{m=M} \varphi_i^k Z_{mi}^k + \omega_i^k \qquad (2)$$

where φ_i^k and ω_i^k, respectively, denote parameters for inputs and error term of the inefficiency model. From the model, Z_m is a vector of explanatory variables which explains technical inefficiency in the production process. From Equation (1), the estimated group specific stochastic frontiers are used to predict the output which is pooled together for the estimation of the stochastic metafrontier model.

B. Empirical New-Two Step Stochastic Metafrontier Translog Model

There are different functional forms used in modelling production functions. Prominent among them are Cobb-Douglas (linear logs of outputs and inputs), quadratic (in inputs), normalized quadratic and transcendental logarithmic (translog) functional forms. Many researchers have resorted to the use of transcendental logarithmic (translog) functional form because of its ability to estimate the interaction terms. Following [11], [10], the empirical group specific stochastic translog model is expressed as:

$$\ln R_i^k = \begin{Bmatrix} \beta_0 + +\Omega_1 D_{F_i}^k + \Omega_2 D_{Pc_i}^k + \beta_1 \ln\left\{Max\left(F_i^k, 1 - D_{F_i}^k\right)\right\} + \\ \beta_2 \ln\left\{Max\left(Pc_i^k, 1 - D_{Pc_i}^k\right)\right\} + \beta_3 \ln L_i^k + +\beta_4 \ln S_i^k + \beta_5 \ln Fs_i^k + \\ \beta_6 \ln K_i^k + \tfrac{1}{2}\beta_{11} \ln\left(NF_i^k\right)^2 + \tfrac{1}{2}\beta_{22} \ln\left(NPc_i^k\right)^2 + \tfrac{1}{2}\beta_{33} \ln\left(L_i^k\right)^2 + \\ \tfrac{1}{2}\beta_{44} \ln\left(S_i^k\right)^2 + \tfrac{1}{2}\beta_{55} \ln\left(Fs_i^k\right)^2 + \tfrac{1}{2}\beta_{66} \ln\left(K_i^k\right)^2 + \beta_{12} \ln NF_i^k \ln NPc_i^k \\ + \beta_{13} \ln NF_i^k \ln L_i^k + \beta_{14} \ln NF_i^k \ln S_i^k + \beta_{15} \ln NF_i^k \ln Fs_i^k + \\ \beta_{16} \ln NF_i^k \ln K_i^k + \beta_{23} \ln NPc_i^k \ln L_i^k + \beta_{24} \ln NPc_i^k \ln S_i^k + \\ \beta_{25} \ln NPc_i^k \ln Fs_i^k + \beta_{26} \ln NPc_i^k \ln K_i^k + \beta_{34} \ln L_i^k \ln S_i^k + \\ \beta_{35} \ln L_i^k \ln Fs_i^k + \beta_{36} \ln L_i^k \ln K_i^k + \beta_{45} \ln S_i^k \ln Fs_i^k + \beta_{46} \ln S_i^k \ln K_i^k \\ + \beta_{56} \ln Fs_i^k \ln K_i^k + V_i^k - U_i^k \end{Bmatrix} \qquad (3)$$

where: Ω_1^k, Ω_2^k and are the coefficients for the dummy variables fertilizer (F_i^k) and pesticides $\left(Pc_i^k\right)$ respectively; β_1^k to β_6^k are own first derivatives; β_{11}^k, β_{22}^k, …, β_{66}^k are own second derivatives. Also, $\beta_{12}^k, \ldots, \beta_{17}^k$; $\beta_{23}^k, \ldots, \beta_{26}^k$; $\beta_{34}^k, \ldots, \beta_{36}^k$; $\beta_{45}^k, \ldots, \beta_{46}^k$; and β_{56}^k are cross second derivatives. Note that $\beta_{12} = \beta_{21}$. Also, F_i^k, Pc_i^k, L_i^k, S_i^k, Fs_i^k and K_i^k, respectively denote quantity of fertilizer (kg), quantity of pesticides (liters), quantity of labor (mandays), seed planted (kg), farm size (acres) and capital (Ghana cedis) for ith farmer in kth agro-ecological zone.

During data collection, it was realized that some of the farmers do not apply fertilizer and pesticides. Therefore, there are zero observations for quantity of fertilizer and pesticides used. In order to deal with the biases associated with estimating a production function with some variables having zero observations, the model used by [11] was adopted. Therefore, $D_{F_i}^k$, and $D_{Pc_i}^k$ were added to the original translog model and $\ln\{Max\,(F_i^k, 1-D_{F_i}^k)\}$ and $\ln\{Max\,(Pc_i^k, 1-D_{Pc_i}^k)\}$ were used to replace $\ln F_i^k$ and $\ln Pc_i^k$ respectively. The replacement of $\ln F_i^k$ and $\ln Pc_i^k$ with, $\ln\{Max(F_i^k, 1-D_{F_i}^k)\}$ and $\ln\{Max(Pc_i^k, 1-D_{Pc_i}^k)\}$ in the model was to minimise biases in the coefficients of some of the variables due to zero observations of fertilizer and pesticides. On the other hand, the dummy variables $D_{F_i}^k$ (1 if applied fertilizer, 0 otherwise), $D_{Pc_i}^k$ (1 if used pesticides, 0 otherwise) dealt with changes in the intercept as a result of zero observations [11], [12]. Also, $\ln\{Max(F_i^k, 1-D_{F_i}^k)\}$ and $\ln\{Max(P_i^k, 1-D_{Pc_i}^k)\}$ indicate the natural log of F_i^k and Pc_i^k variables generated by adding 1 to the original variables of fertilizer and pesticides respectively. Note that in the own products and cross products, $\ln NF_i^k$ and $\ln NPc_i^k$ is respectively the same as $\ln\{Max(F_i^k, 1-D_{F_i}^k)\}$ and $\ln\{Max(Pc_i^k, 1-D_{Pc_i}^k)\}$. This is for simplification.

Whether a farmer is technically efficient or not depends on farmer-specific, farm-specific, location-specific and institutional as well as policy variables. It also depends on the types and levels of technology adoption. The index measuring technical inefficiency of the farmers in *k-th* agro-ecological zone is given as:

$$TI_i^k = U_i^k = \left\{ \varphi_0^k + \sum_{m=1}^{m=5} \varphi_m^k FC_{mi}^k + \sum_{m=6}^{m=11} \varphi_m^k IPV_{mi}^k + \sum_{m=12}^{m=13} \varphi_m^k EF_{mi}^k + \sum_{m=14}^{m=17} \varphi_{14}^k RPT_i^k + \omega_i^k \right\} \tag{4}$$

where φ_S^k denote parameter estimates and FC_i, IPV_i, EF_i, RPT_i, respectively denote farmer characteristics, institutional and policy variables, environmental factors and rice production technologies of *ith* farmer. The farmers' characteristics used in the study are number of years of formal education (*Eduyrs*), age (*Age*), household size (*HHS*), rice farming experience (*FarmExp*) and sex (*Sex*). The institutional and policy variables included in the inefficiency model are number of visits by AEAs with advice on rice production (*ExtVisits*), credit access (*CredAcc*), contract farming (*ContFarm*), membership of farmer based organization (*FBO*), access to improved seed (*ImpvSeed*) and access to formal irrigation facility (*IrrigAcc*). Lodging of rice (*LodgRice*) and low amount of rainfall (*LowRain*) are the environmental factors considered in the study. Lastly, rice production technologies which are hypothesized to have influence on technical inefficiency are adoption of *IATs* (*Adopt_IATs*), adoption of *FISs* (*Adopt_FISs*), PC index of *IATs* (*IATs_PC_Index*) and PC index of *FISs* (*FISs_PC_Index*). Note that ω_i^k is the two sided error term which is independently and normally distributed with zero expectation and homoscedastic variance N(0, 1).

Each of the estimated group specific stochastic translog models is used to predict rice outputs. The predicted rice outputs ($\hat{R}_i^*$) are pooled together and used to run the metafrontier model.

C. Data Description and Sampling

Ghana is divided into six agro-ecological zones namely, Sudan Savannah Zone (SSZ), Guinea Savannah Zone (GSZ), Forest Savannah Transition Zone (FSTZ), Semi-Deciduous Rain Forest Zone (SDRFZ), High Deciduous Rain Forest Zone (HDRFZ) and Coastal Savannah Zone (CSZ). Through stratified sampling technique, GSZ, FSTZ and CSZ were selected for the study. Primary data for 2015/16 cropping season and secondary data on climatic variables (rainfall and temperature) in each of the study districts were collected.

In determining the sample size for the study, Slovin's formula used by [13] was adopted. It is expressed as:

$$n = \frac{N}{1 + Ne^2} \tag{5}$$

where *n* is the sample size, *N* is the population size and *e* is the percentage of imprecision of sampling that can be tolerated. This study used 8% as the percentage of imprecision. From [14], 929493, 81001 and 8515 rice farmers were extrapolated for GSZ, FSTZ and CSZ, respectively. Using these populations, the respective sample size of 377, 359 and 171 were obtained for GSZ, FSTZ and CSZ. Through stratified sampling, Tolon, Kumbungu, Savelugu, Kasena-Nankana, West Mamprusi, Chereponi and Builsa South Districts were selected in GSZ and North Tongu, Ketu North, Krachi Nchumburu, Pru and Hohoe Districts were selected from FSTZ. Shai Osudoku, Ningo Prampram and Ashaiman Districts were included in CSZ. Systematic sampling technique was then used to select houses and one rice farmer was randomly selected from each house. In some of the communities, the enumerators visited rice farms and the rice farms were systematically selected and the owners interviewed.

III. Empirical Results and Discussions

A. Summary Statistics of Variables

The summary statistics of continuous and discrete variables used in the new-two step stochastic metafrontier are respectively presented in Tables I and II. The average age of farmers in the GSZ, FSTZ and CSZ are 39.4years, 45.4years and 46.6years respectively. Farmers in GSZ have the largest average household size of 9.4 with low education level, low experience in the cultivation of rice and few number of extension visits. Averagely, farmers in the CSZ are closer to agricultural extension officers, rice output market and Accra, the capital of Ghana, as compared to those in GSZ. Also, FSTZ recorded the highest amount of mean annual rainfall (1150.9mm) followed by GSZ recording 984.7mm with CSZ having the least (800.0mm). The average amount of temperature increases as one moves from southern to northern Ghana.

TABLE I
SUMMARY STATISTICS OF CONTINUOUS VARIABLES

Continuous Variables	GSZ (n = 377)			FSTZ (n = 359)			CSZ (n = 171)			Pooled (N = 907)		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Rice output (Kg)	1966.2	102.0	8862.0	2988.1	336.0	14532.0	5405.5	1008.0	19320.0	3019.1	102.0	19320.0
Farmer characteristics												
Age (years)	39.4	18.0	65.0	45.4	21.0	70.0	46.6	27.0	71.0	43.1	18.0	71.0
Household size	9.4	1.0	30.0	6.8	1.0	17.0	5.6	1.0	12.0	7.7	1.0	30.0
Education years	3.8	0.0	16.0	8.0	0.0	19.0	9.6	0.0	20.0	6.5	0.0	20.0
Rice farming experience (years)	12.8	1.0	41.0	15.6	1.0	50.0	13.7	2.0	36.0	14.1	1.0	50.0
Institutional and policy variables												
Extension visits	2.1	0.0	14.0	2.4	0.0	9.0	3.9	0.0	8.0	2.5	0.0	14.0
Amount of credit (Gh¢)	120.6	0.0	2000.0	647.2	0.0	5500.0	1433.4	0.0	6500.0	576.5	0.0	6500.0
No. of FBO advice	1.2	0.0	24.0	1.0	0.0	8.0	1.4	0.0	7.0	1.2	0.0	24.0
Infrastructure												
Distance from office of AEAs to community (km)	11.5	0.0	67.9	5.7	0.0	32.0	2.5	0.1	12	7.5	0.0	67.9
Distance from community to market centers of rice (km)	11.9	0.0	131.0	4.3	0.0	32.0	2.6	0.0	12	7.1	0.0	131.0
Distance from Accra to Community (km)	699.8	608	777.0	273.0	95.0	520.0	62.7	29.0	81.0	410.8	29.0	777.0
Distance from farm to the house (km)	4.3	0.1	80.0	3.7	0.1	22.0	4.6	0.2	18.0	4.1	0.1	80.0
Inputs												
Labor (mandays)	40.8	8.0	205.0	44.9	10.0	183.0	52.1	10.0	158.0	44.5	8.0	205.0
Farm size (acres)	2.4	0.5	10.0	2.6	0.5	12.0	2.9	1.0	8.7	2.6	0.5	12.0
Seed (kg)	76.9	8.0	1000.0	85.5	20.0	1200.0	84.6	20.0	450.0	81.7	8.0	1200.0
Fertilizer (kg)	144.5	0.0	700.0	218.5	0.0	2300.0	310.4	0.0	1200.0	205.1	0.0	2300.0
Pesticides (kg)	2.9	0.0	60.0	4.6	0.0	36.0	4.3	0.0	40.0	3.8	0.0	60.0
Capital (Gh¢)	336.3	6.1	3324.0	807.2	7.5	5726.4	1668.0	196.8	6252.9	773.8	6.1	6252.9

The average quantity of rice produced by farmers in GSZ, FSTZ and CSZ are 1966.2 kg, 2988.1 kg and 5405.5 kg respectively. Averagely, among all the three agro-ecological zones, farmers in CSZ used the largest quantity of each of the inputs (i.e. labor, seed, fertilizer, pesticides, and capital) followed by farmers in FSTZ with those in GSZ employing the least quantity. In terms of the technologies, farmers in CSZ were the highest adopters (60.8%) of superior technologies (*IATs*). The GSZ recorded the lowest adopters of *IATs*. On the other hand, the FSTZ recorded the highest percentage (18.9%) of farmers who adopted *FISs,* suggesting that farmers in this zone are the most innovative compared to others. GSZ recorded the lowest proportion of farmers (15.7%) adopting *FISs*.

B. Test for Specifications of Models

For appropriateness of the models, the hypotheses in Table III were tested using generalized likelihood-ratio test statistic which is distributed as a chi-square. From Table III, the null hypothesis that the Cobb-Douglas functional form is appropriate is rejected for all the zones. This is a justification for the use of translog functional form since it accurately and better represents the data for all the zones than the Cobb-Douglas production function. Also, the null hypothesis that technical inefficiency is absent is rejected since the test is significant at 1% for all the models. Thus, a significant number of rice farmers operate under the respective group frontiers, and hence, below the metafrontier. As a result, the used of OLS or average production response model would be inappropriate [15]. The last and the principal hypothesis of this study, which states that the technologies used by farmers in the three agro-ecological zones are homogenous, was rejected. Therefore, the technologies used by farmers in the three agro-ecological zones differ justifying the use of the metafrontier model. The use of a new-two step stochastic metafrontier translog estimation technique rather than the pooled stochastic frontier would better show the efficiency comparison among farmers in these three agro-ecological zones [16], [10].

TABLE II
SUMMARY STATISTICS OF DISCRETE VARIABLES

Variables	GSZ (n = 377)		FSTZ (n = 359)		CSZ (n = 171)		Pooled (N = 907)	
	Freq	%	Freq	%	Freq	%	Freq	%
Farmer Characteristics								
Sex: Female	94	24.93	134	37.33	63	36.84	291	32.08
Male	283	75.07	225	62.67	108	63.16	616	67.92
Institutional and Policy Variables								
Credit access: No	299	79.31	229	63.79	76	44.44	604	66.59
Yes	78	20.69	130	36.21	95	55.56	303	33.41
Contract farming: No	303	80.37	257	71.59	36	21.05	596	65.71
Yes	74	19.63	102	28.41	135	78.95	311	34.29
FBO membership: No	158	41.91	155	43.18	60	35.09	373	41.12
Yes	219	58.09	204	56.82	111	64.91	534	58.88
Improved seed: No	242	64.19	215	59.89	75	43.86	532	58.65
Yes	135	35.81	144	40.11	96	56.14	375	41.35
Input subsidy: No	291	77.19	274	76.32	164	95.91	729	80.37
Yes	86	22.81	85	23.68	7	4.09	178	19.63
Access to irrigation: No	246	65.65	236	65.74	30	17.54	512	56.45
Yes	131	34.75	123	34.26	141	82.46	395	43.55
Environmental Shock Factors								
Lodging of rice: No	242	64.19	247	68.80	117	68.42	606	66.81
Yes	135	35.81	112	31.20	54	31.58	301	33.19
Low rains: No	188	49.87	195	54.32	140	81.87	523	57.66
Yes	189	50.13	164	45.68	31	18.13	384	42.34
Affected by diseases: No	236	62.60	249	69.36	156	91.23	641	70.67
Yes	141	37.40	110	30.64	15	8.77	266	29.33
Infrastructure								
Motorable road to district capital: No	123	32.63	107	29.81	56	32.75	286	31.53
Yes	254	67.37	251	70.19	115	67.25	621	68.47
Technologies								
Adopters only *FISs*: No	318	84.35	291	81.21	144	84.21	753	83.02
Yes	59	15.65	68	18.94	27	15.79	154	16.98
Adopters only *IATs*: No	275	72.94	200	55.71	67	39.18	542	59.76
Yes	102	27.06	159	44.29	104	60.82	365	40.24

TABLE III
HYPOTHESES FOR THE USE OF STOCHASTIC FRONTIER AND METAFRONTIER MODELS

Null Hypothesis	n	DF	χ^2-cal	LR χ^2-crit	P-Value
Cobb-Douglas functional form is appropriate					
GSZ	377	21	126.45	38.93	0.0000
FSTZ	359	21	43.62	38.93	0.0026
CSZ	171	21	46.20	38.93	0.0012
Metafrontier	907	21	530.73	38.93	0.0000
No inherent inefficiency					
GSZ	377	17	192.16	33.41	0.0000
FSTZ	359	17	173.95	33.41	0.0000
CSZ	171	17	69.77	33.41	0.0009
Metafrontier	907	17	134.55	33.41	0.0000
Homogeneous technologies					
There is no differences in technologies used in GSZ, FSTZ and CSZ	907	49	147.12	74.92	0.0001

C. Determinants of Output in the New-Two Step Stochastic Metafrontier Translog Model

Table IV shows the maximum likelihood estimates of the new-two step stochastic metafrontier translog model. In order to interpret the first-order parameter estimates as partial production elasticities at the sample mean. The study followed the work of [17], in which all the inputs and output variables were normalized (divided) by their respective sample means. The monotonicity condition was checked and it was observed that all the models were monotonic since the respective sums of the estimated first-order coefficients of all the logarithmic inputs were positive. Since the agro-ecological specific production functions were used to estimate the metafrontier, the definition that metafrontier is an envelope of the group frontiers is valid. The convexity and no free lunch property of all the production functions were met since the use of translog is valid and no farmer indicated that he/she harvested rice from an uncultivated field.

The estimated total variances are all statistically significant at 1%. GSZ has the widest variation across farms, an implication that there is great opportunity on the average for them to raise their technical efficiency levels. From the gamma values, the inefficiencies in the usage of the inputs and other farm practices accounts for 92.99%, 75.46% and 81.81%

deviations between actual and frontier rice output in GSZ, FSTZ and CSZ agro-ecological zones, respectively. This suggests that GSZ has the highest levels of inefficient usage of inputs and other farm practices. From the Table IV, random shocks outside the control of farmers (e.g. unfavorable weather conditions, floods, bushfires, diseases and measurement errors) account for 7.01%, 24.54%, and 18.19% of inefficiencies in the deviations of the actual rice output from the frontier output in GSZ, FSTZ and CSZ agro-ecological zones, respectively [18], [19]. On average, farmers in Ghana have inefficiencies in their usage of inputs and other farming practices, explaining 79.36% deviations of their actual rice output from the metafrontier rice output.

The effect of two inputs on output is complementary if the interaction term has significant positive coefficient and the opposite is true for significant negative coefficient of the interaction term. The intercept coefficient of fertilizer is statistically significant in all the agro-ecological zones' specific frontier models as well as the metafrontier model. The intercept coefficient of pesticide is only significant in the metafrontier model. This revelation means that the estimation of the parameters of the frontier production function would have been biased if the specifications of the dummy for fertilizer were eliminated in the models. Principally, the estimation of the new two-stage stochastic translog metafrontier model would have given bias maximum likelihood parameter estimates if the dummies of the fertilizer and the pesticides were not included in the model [11], [12].

TABLE IV
MAXIMUM LIKELIHOOD ESTIMATES OF THE NEW-TWO STEP STOCHASTIC METAFRONTIER TRANSLOG MODEL

Variables	GSZ Model		FSTZ Model		CSZ Model		Metafrontier Model	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	0.0718	0.0596	-0.1358	0.0888	-0.1203	0.0755	0.0948***	0.0192
DF	-0.4143***	0.0985	-0.1460*	0.0749	-0.2462*	0.1366	-0.2555***	0.0216
DPc	0.0011	0.0641	-0.0059	0.0689	0.0448	0.0745	-0.0510***	0.0184
ln(F)	0.6449**	0.2864	0.6009***	0.2117	0.6669*	0.3891	0.5352***	0.0617
ln(Pc)	0.0449	0.1388	0.0030	0.1931	0.2321	0.1684	0.1505***	0.0411
ln(L)	-0.1060	0.1090	0.3456*	0.1970	0.2697*	0.1405	0.0375	0.0346
ln(S)	-0.1041	0.0902	-0.4290***	0.1580	-0.5670***	0.1255	-0.2666***	0.0282
ln(Fs)	0.7062***	0.1454	0.9552***	0.2721	1.1695***	0.1937	0.8324***	0.0423
ln(K)	0.3697***	0.0467	0.0257	0.0485	0.0690	0.1153	0.2204***	0.0121
ln(F)ln(F)	0.2182	0.3876	0.2158	0.2431	-0.7731	0.5528	0.0387	0.0822
ln(Pc)ln(Pc)	-0.0942	0.1015	0.1246	0.1660	-0.1255	0.2008	-0.0695*	0.0360
ln(L)(ln(L)	-0.0751	0.1154	0.5920*	0.3026	0.3195	0.2353	0.0524	0.0461
ln(S)ln(S)	-0.0411	0.0455	0.1020	0.1093	0.2307	0.1541	0.0044	0.0168
ln(Fs)ln(Fs)	0.3643*	0.2194	0.6111	0.5546	-0.0685	0.6189	0.5609***	0.0715
ln(K)ln(K)	0.1617***	0.0255	0.0476**	0.0221	0.1495	0.1746	0.1196***	0.0058
ln(F)ln(Pc)	0.1817	0.1147	-0.0356	0.1722	0.0274	0.1877	0.0751**	0.0333
ln(F)ln(L)	0.3085**	0.1507	-0.2360	0.2345	-0.0190	0.1922	0.1365***	0.0480
ln(F)ln(S)	-0.0272	0.1302	0.5019**	0.2267	0.1901	0.1838	0.2776***	0.0387
ln(F)ln(Fs)	-0.3209	0.2068	-0.5567	0.3519	-0.1959	0.2837	-0.4369***	0.0618
ln(F)ln(K)	-0.3129***	0.0653	0.0389	0.0444	-0.0980	0.1101	-0.0921***	0.0154
ln(Pc)ln(L)	-0.0238	0.1332	-0.2076	0.1958	-0.1242	0.2053	-0.0108	0.0407
ln(Pc)ln(S)	0.1375	0.0894	0.0975	0.1182	0.2060	0.1742	0.0487**	0.0246
ln(Pc)ln(Fs)	-0.2097	0.1586	-0.2144	0.1967	-0.2310	0.2743	-0.2150***	0.0422
ln(Pc)ln(K)	-0.0360	0.0482	0.0475	0.0449	0.2152	0.1310	0.0039	0.0124
ln(L)ln(S)	0.1480	0.0926	-0.2326	0.1751	-0.2546	0.1661	0.0169	0.0299
ln(L)ln(Fs)	-0.3459***	0.1109	0.1231	0.2734	0.4254	0.2688	-0.1531***	0.0380
ln(L)ln(K)	0.0071	0.0570	-0.0766*	0.0422	-0.2080	0.1659	-0.0241*	0.0134
ln(S)ln(Fs)	0.0406	0.1083	-0.2013	0.2562	-0.1612	0.2721	-0.0779**	0.0347
ln(S)ln(K)	-0.1189***	0.0418	-0.0522	0.0505	0.0983	0.1089	-0.0627***	0.0106
ln(Fs)ln(K)	0.0995	0.0702	0.0001	0.0735	-0.2219	0.2448	-0.0070	0.0170
σ_v^2	0.0151		0.0423		0.0148		0.0058	
σ_u^2	0.2015		0.1302		0.0665		0.0224	
σ_s^2	0.2166		0.1725		0.0813		0.0282	
γ_u^2	0.9299		0.7546		0.8181		0.7936	
Log-Lik	40.7859		15.1670		73.5596		735.0145	
Wald χ^2 *(29)*	1679.18***		1400.2***		1336.06***		17389.73***	

, ** and * significant at 10%, 5% and 1%, respectively.*

1. Determinants of Rice Output in Guinea Savannah Zone

The factors that significantly determine rice output in GSZ are fertilizer, farm size and capital. The effects of these three inputs on rice output are consistent with *a priori* expectation (economic theory) since they all have a positive influence. Fertilizer is significant at 5%, while farm size and capital are significant at 1% each. This suggests that fertilizer, farm size and capital increase rice output holding other factors constant with the direction of the effects of fertilizer and farm size, confirming the work of [20]. Comparing the impacts, farm size has the highest impact on rice output, followed by fertilizer. For fertilizer, the elasticity of 0.6449 implies that a 100% increase in fertilizer will increase mean rice output by 64.5%, *ceteris paribus*. The sum of first order elasticities measures the returns to scale. From Table V, the sum of first order elasticities is 1.5556 implying on average, farmers in GSZ are enjoying increasing returns to scale (IRS). This means that on average, the quantity of inputs used by farmers are below the efficient level, and hence, a farmer can increase rice output by 155.6% if all the inputs are jointly increased by 100%.

2. Determinants of Rice Output in Forest Savannah Transition Zone

From Table IV, the first order elasticities of fertilizer, seed and farm size are highly significant at 1% each, while labor is significant at 10% in the FSTZ. The findings reveal that pesticides and capital are not significant. The maximum likelihood elasticity estimates of fertilizer, labor and farm size are positive implying that a 100% increase in fertilizer, labor and farm size each will respectively increase rice output by 60.1%, 34.6% and 95.5% *ceteris paribus*. These significant and positive impacts of fertilizer, labor and farm size are in tandem with the findings of [20]. Also, a 100% increase in quantity of seed planted will result in a 42.9% decrease in rice output, and this, negative relationship confirms a study by [20]. From the results of the group specific stochastic translog model of FSTZ, the returns to scale is 1.5014% indicating that when all the inputs (fertilizer, pesticides, labor, seed, farm size and capital) are jointly increased by 100%, there will be more than proportionate increase in the quantity of rice produced by 50.1% (150.14% minus 100%). Therefore, farmers in the FSTZ are also underutilizing inputs as observed in GSZ. This suggests that farmers should increase the quantity of inputs used so as to enjoy a more than proportionate increase in rice output.

3. Impacts of Factor Inputs on Rice Output in Coastal Savannah Zone

Rice production in the CSZ depends on fertilizer, labor, seed and farm size. This is because fertilizer and labor significantly affect rice output at significant levels of 10% each, while seed and farm size significantly influence rice production at significant levels of 1% each. Statistically, pesticides and capital do not influence rice output in the study area. The fertilizer, labor and farm size positively affect rice output, while seed negatively affects rice output in CSZ. A 100% increase in fertilizer, labor and farm size each will result in an increase the quantity of rice produced by 66.7%, 27.0% and 117.0%, respectively. On the contrary, rice output will decline by 0.5670% when a farmer increases the quantity of seed planted by 1%. While fertilizer, labor and farm size are underutilized, seed is over utilized. Farmers overcrowd the rice plot with seed through broadcasting method and should rather reduce the quantity of rice seed they plant on the field since that will result in an increase in rice output. The total elasticity of output is 1.8402% implying that farmers underutilize most of the inputs, and hence, are operating at increasing returns to scale level. In other words, a 100% increase in all the inputs will result in 184.0% increase in rice output which is 84.0% more than the proportionate increase in inputs. This means farmers can still increase rice output by jointly increasing the quantity of all the inputs.

4. Determinants of Rice Output in the Metafrontier

From the results of the metafrontier as shown in Table IV, all the inputs, except labor, are significantly different from zero, and hence, significantly affect the quantity of rice produced. Statistically and coincidentally, fertilizer, pesticides, seed, farm size and capital each are highly significant at 1% each. The direction of the effects corroborates with the *a priori* expectation since fertilizer, pesticides, farm size and capital have positive, while seed has a negative relationship with the quantity of rice produced. The partial elasticity values indicated that a 100% increase in the quantity of fertilizer, pesticide, farm size and capital each will result in 53.5%, 15.1%, 83.2% and 22.0% increase in rice output, respectively, holding other factors constant. On the other hand, rice output will decrease by 26.7% when the quantity of rice seed used for planting increases by 100% *ceteris paribus*. The positive relationship between fertilizer and rice output in this study is consistent with the findings of [21]. On the other hand, the negative relationship between seed and rice output in this study contradicts the findings of [21].

On average, the sampled farmers involved in rice production in Ghana operate in the first stage of production function, i.e. they are operating at increasing returns to scale (returns to scale value of 1.5094). This means that if all the inputs are jointly increased by 100%, quantity of rice produced will increase by 151.0%. This increase in rice output is more than a proportionate joint increase in fertilizer, pesticides, labor, seed, farm size and capital. This justifies the need for rice farmers to continue to expand their production activity by increasingly employing more factor inputs until they reach constant returns to scale. From the results of the metafrontier model, there are significant input complementary effects between fertilizer and pesticides; fertilizer and labor; fertilizer and seed; and pesticides and seeds. This implies, when the quantities of the pairs of inputs are jointly increased, rice output will increase in Ghana. The inputs that are substitutes are fertilizer and farm size; fertilizer and capital; pesticides and farm size; labor and farm size; labor and capital; seed and farm size; and seed and capital.

D. Distributions of Technical Efficiency Scores and TGRs

The minimum, maximum, and the mean technical efficiency scores in GSZ are 10.0%, 99.0% and 82.2%, respectively. In the FSTZ, the minimum technical efficiency score is 23.0%, while the average is 83.6%. Farmers in CSZ have average technical efficiency score of 89.1% with the minimum score value of 31.0%. The maximum technical efficiency scores for farmers in all the three agro-ecological zones are equal i.e. 99.0% suggesting no farmer has a technical efficient score of 100%. It is not surprising since it is practically impossible to have technical efficiency of 100%. On average, the farmers in CSZ have the highest technical efficiency score value of 89.1%, while farmers in GSZ have the lowest technical efficiency score value of 82.2%. Given the available technologies and managerial skills, rice farmers in GSZ, FSTZ and CSZ, respectively, produce 17.8%, 16.4% and 10.9% below their potential rice output. On average, farmers in CSZ are 5.5% and 6.9% more productive than farmers in FSTZ and GSZ, respectively. This revelation confirms MoFA data on rice yield which indicates that farmers in Greater Accra have the highest yield of 6.45 Mt/ha, followed by Volta Region with yield values of 3.6 Mt/Ha [1]. The low level of technical efficiency of rice farmers in Northern Ghana confirms the findings of [19].

The average estimated TGRs for farmers in GSZ, FSTZ and CSZ are 92.6%, 91.1% and 84.4%, respectively. TGRs are contingent on the technology available for rice production in Ghana. On average, rice farmers in GSZ achieved 92.6% of the potential output given the technology available to the whole rice production subsector. On the other hand, farmers in FSTZ and CSZ produced on average 91.1% and 83.5%, respectively, of their potential output given the technology available to the entire rice farming industry. Since none of the agro-ecological zones had an average TGR of 1, it suggests that none of the group specific frontiers is tangential to the metafrontier. This implies that given the status quo in terms of the available inputs and technology, on average, farmers in the three agro-ecological zones have not been able to produce the potential metafrontier output in Ghana. The reason could be that farmers are not fully using the available technology for rice production. Notwithstanding that, the environmental conditions also prevent them from producing on the metafrontier. As noted by [10], technology gap exists because of the choice of a particular technology which actually depends on the environmental factors.

E. Determinants of Technical Inefficiency across the Agro-Ecological Zones

As noted by [15], estimates of the level of technical inefficiency of firms are necessary but not sufficient to provide information for the researcher to make any meaningful policy recommendations. As such, identifying the factors causing the variations in the technical inefficiencies is very important. Aside from the farmer characteristics (age, sex, household size, years of education, rice farming experience), institutional and policy variables (extension visits, credit access, contract farming, farmer based organization membership and access to formal irrigation), environmental factors or shocks (lodging of rice, low rainfall amount), the principal component indices of *IATs* and *FISs* were used as the explanatory variables in the inefficiency models.

TABLE V
DETERMINANTS OF TECHNICAL INEFFICIENCY ACROSS THE AGRO-ECOLOGICAL ZONES

Variables	GSZ Model		FSTZ Model		CSZ Model		Metafrontier Model	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
$ln(\sigma_v^2)$	-3.7636***	0.1669	-3.4287***	0.1215	-4.1166***	0.1919	-5.1947***	0.1330
			Farmer Characteristics					
Age (+)	0.0058	0.0167	0.0358	0.0218	0.0569	0.0363	0.0316***	0.0093
Sex (-)	-0.7271**	0.3006	-0.1154	0.2861	-0.0017	0.5031	-0.0221	0.1451
HHS (-)	-0.0190	0.0300	-0.0798*	0.0408	-0.0139	0.1037	-0.0663***	0.0237
Eduyrs (-)	0.0019	0.0366	-0.0699**	0.0338	-0.0390	0.0780	-0.0251	0.0178
FarmExp (-)	-0.0069	0.0206	0.0022	0.0211	-0.0690	0.0503	0.0020	0.0110
			Institutional and Policy Variables					
ExtVisits (-)	-0.1120	0.1199	-0.2546**	0.1000	-0.2842	0.1749	0.1468***	0.0392
CredAcc (-)	-0.5862	0.5010	0.7042	0.4520	1.4712	1.0486	-0.2179	0.1689
ContFarm (-)	-0.9801	0.9193	-2.4043*	1.4533	-1.5050**	0.6857	0.2701	0.1908
FBO (-)	-0.3007	0.3042	-0.5991*	0.3360	-0.1611	0.5909	0.0185	0.1500
ImpvSeed (-)	0.2895	0.4806	-1.7176***	0.5123	1.4985**	0.7033	-0.1262	0.1892
IrrigAcc (-)	-0.9617**	0.4194	-2.0761***	0.7297	-0.5482	0.6353	-0.2143	0.1820
			Environmental Factors					
LodgRice (-)	1.9192***	0.3317	1.1944***	0.3259	0.7233	0.5790	0.6865***	0.1598
LowRain (-)	0.4737*	0.2766	0.5457*	0.2964	1.0055*	0.5820	-0.2768*	0.1546
			Rice Production Technologies					
Adopt_IATs (-)	-0.1833	0.4740	-0.7374*	0.4176	-2.0342***	0.7216	0.0937	0.1883
Adop_FISs (-)	0.3718	0.3523	-0.3205	0.3239	0.3044	0.5234	-0.0760	0.1561
IATs _PC_Index (+)	0.8194***	0.2501	0.7976***	0.2459	0.3941	0.2551	-0.0281	0.0819
FISs_PC_Index (+)	-0.4458*	0.2561	0.4256*	0.2376	-0.4159	0.3670	-0.4694***	0.1050
Constant	-2.4488***	0.7645	-1.9134**	0.9671	-3.6772**	1.7271	-5.2873***	0.4924

, ** and * significant at 10%, 5% and 1% respectively.*
The a priori expectaions are shown in the parenthesis

1. Determinants of Technical Inefficiency in Guinea Savannah Zone

From Table V, it is observed that factors which significantly cause technical inefficiency in GSZ are sex, access to irrigation facilities, farmers' perception on lodging of rice, and farmers' perception on the amount of rainfall, as well as *IATs'* index and FISs' index. The direction of the effects of all these significant variables is consistent with the *a priori* expectations except *FISs* index. In terms of the direction of the effects, the findings in GSZ showed that male farmers, farmers who have access to irrigation facilities, farmers who have not experienced lodging of rice, farmers who perceived that they have received high rainfall amount and farmers who are well-coordinated and more synergized adopted *IATs* and are more technically efficient than their counterparts with opposing features holding other factors constant. Also, farmers who are males, have access to irrigation facilities, have not experienced lodging of rice and perceived high rainfall amount are respectively more efficient than their farmer colleagues with contrasting characteristics.

The result that male farmers are more efficient than female farmers was confirmed by [22], [23]. According to [22], women are engaged in unmeasured non-economic activities (such as child care, cooking, cleaning, etc) in the household coupled with some traditional beliefs which reduced their ability to be more efficient. The revelation that farmers who perceived they have received high annual rainfall amount are more technically efficient corroborates with the findings of [24] about rice growth in Central Uganda. This finding is also consistent with [25], who argued that rice yield increases by 1.7% for a 20% increase in rainfall in Tanzania. In recent times, a research entitled "Effects of Climate and Conflict on Technical Efficiency of Rice Production, Northern Uganda" by [26] found out that as rainfall increases, the efficiency of farmers producing rice increases.

It is important to note that PCA index is a weight which shows the degree of correlation or distribution. When the innovation systems or technologies are more unequally distributed, they have high standard deviations, and hence, farmers who uniformly synergize the adoption of *IATs* have respectively lower PC indices. Therefore, as shown in Table V, a negative sign of the *IATs*_index suggests that farmers who uniformly synergize the adoption of *IATs* (i.e. have lower PC index) are more technically efficient than their counterparts. Therefore, farmers who are well-coordinated and synergized adopted the *IATs* and have high technical efficiency scores than those with other features in GSZ *ceteris paribus*. This corroborates with the *a priori* expectations since it pays when a farmer uniformly and synergized the adoption of the superior technology, *IATs*.

2. Determinants of Technical Inefficiency in Forest Savannah Transition Zone

From the finding of this research, contract farming, FBO membership, the use of improved rice seed, access to irrigation facilities, non-lodging of rice, perceived high rainfall amount, and adoption of *IATs* improve technical efficiency of farmers, holding other factors constant. While more uniformly, well-coordinated and synergized adoption of *IATs* increases farmers' technical efficiency, more uniform and synergized adoption of *FISs* decreases technical efficiency ceteris paribus. The direction of effects of all these variables is consistent with economic theory, except *FISs' index*. The positive contribution of the number of extension visits to technical efficiency is plausible and confirmed the work of [19]. With agricultural extension advice, farmers are able to acquire knowledge on improved technologies, which in turn effects, improves their efficiency levels. The study reveals that it is not enough to adopt *IATs,* the synergy of the adopted *IATs* is also key to improving farmers' technical efficiency.

3. Determinants of Technical Inefficiency in Coastal Savannah Zone

In the CSZ agro-ecological zone, the estimated coefficients of contract farming and adoption of *IATs* are negatively signed and statistically significant at 5% and 1%, respectively. The direction of the effects confirms the *a priori* expectations that farmers engaged in contract farming and who adopted *IATs* are more technically efficient than their counterparts who did otherwise. Perceived low rainfall amount is statistically significant at 10% and agrees with the economic theory since it has a negative sign. Therefore, farmers who perceived high rainfall amount are more technically efficient than farmers who perceived a low amount of rainfall. The reasons for this outcome are the same, as explained under the technical inefficiency model of GSZ. The use of improved seed is statistically significant at 5% but does not meet the *a priori* expectations.

4. Determinants of Metafrontier Technical Inefficiency

Holding other factors constant, age, household size, extension visits, perceived lodging of rice, perceived low amount of rainfall, as well as uniform and well-coordinated adoption of *FISs* statistically and significantly influence technical inefficiencies of rice farmers in Ghana. Farmers who are more statistically technically efficient are younger farmers, farmers who have larger household sizes and farmers who perceived that their rice did not lodge. These factors are statistically significant at 1% and their directions of effects meet the *a priori* expectation. It is not surprising to observed that as farmers grew older, their inefficiencies increased because similar findings were made by [27] among selected wheat farmers in Kenya. This is contingent on the fact that the elderly farmers are so stuck to their old system of farming that they fail to adhere to the advice of the agricultural extension officers on the need to use *IATs*. Also, most of them do not have access to current information on *IATs,* as compared to younger farmers.

As noted by [19], farmers with larger families have a variety of labor (children, youth, men and women), which leads to division of labor and specialization. Division of labor and specialization result in overall improvement of the technical efficiencies of farming operations. Also, farmers with larger household sizes may have enough family labor, and therefore, do not need to spend unproductive time in searching for laborers to hire. The time for supervising hired laborers may be used in productive activities as well. This may be the reason why farmers with larger household sizes are more technically efficient than their counterparts. In the metafrontier model, the number of extension visits, low amount of rainfall received and uniform synergized adoption of *FISs* statistically and significantly influence the technical efficiency of rice farmers but do not meet *a priori* expectations.

IV. Conclusions

Stakeholders in agriculture (i.e. the government, through MoFA, development partners and individual private companies) should not only seek to promote the adoption of *IATs,* but also, they should educate farmers on how to coordinate and synergize the adoption of the whole package.

The designed policy for the promotion of this superior technology should be intensified and farmer targeted in the whole country, especially GSZ. In the short term, private rice processing companies, rice marketing companies, financial institutions etc. should engage farmers in contract farming to help them get access to improved farming inputs, which in effect will enhance their productivity performances. Agricultural extension agents should also intensify the extension activities to farmers by advising them on good agronomic practices in rice production.

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