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An Analysis of Technical Efficiency of Rice Production in Indonesia

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Abstract

The objectives of this paper are to estimate technical efficiency in rice production and to assess the effect of farm-specific socio-economic factors on the technical efficiency using survey data from 15 provinces in Indonesia, collected in 2008. A stochastic frontier production function model is used to estimate the technical efficiency of rice farms in each province, and using the model, the influence of socio-economic factors on efficiency is also measured. This study finds that there is a sizeable degree of variation of inefficiency between the 15 provinces. It also finds that factors like land size, income and source of funding are influential determinants of technical efficiency. In terms of age, it also found that younger farmers tend to be more efficient. Expanding the agricultural area, especially outside Java and Sumatera Islands, improving farmers' income and giving an incentive to young people to work in the agricultural sector will enhance technical efficiency and thus productivity, as well as the overall rice output

Keywords: rice production, technical efficiency, stochastic production function

1. Introduction

Currently, in the Indonesian context, the technical efficiency of rice farming is an important concern mainly because of its important role in maintaining domestic food security and as well as improving agricultural development. Rice is staple food that consumed by most Indonesian and the per capita consumption shows that it is higher compared to neighbouring countries. With a total population of approximately 235 million in 2007, the per capita rice consumption reached approximately 130-139 kilograms per year, while in Thailand and Japan the consumptions are 79 and 52 kilograms respectively (BPS, 2007).

Despite the important of rice sector in the Indonesian economy, this sector has been facing a significant challenge, especially in increasing the production at the level above the domestic consumption rate. Recent figures show that not only rice, but most of Indonesia's agricultural products, experience slower growth in total factor productivity (TFP) (World Bank, 2010). The agricultural TFP growth fell from 2.35 per cent per year in 1968-92 to annual contractions of 0.58 per cent from 1993 to 2001 (World Bank, 2010). Such conditions eventually contribute to the slow growth of job creations in rural areas.

Based on the above unfavourable condition especially in the productivity of rice farming and agricultural sector in Indonesia, it is then very important to improve the sectoral performance, not only in the context of food security and jobs creation, but also from the perspective of rural areas development. The objective of this paper is to quantify the technical efficiency of rice farm by using survey data from 15 provinces in Indonesia in 2008, as well as to assess the factors that contribute to the technical efficiency. To achieve this objective, this paper employs stochastic production function and inefficiency effect model. In the context of literature on technical efficiency of rice farming in Indonesia, the present study extends the literatures in two ways. First, it utilizes the survey data from 15 provinces, which mainly become the major regions of rice farming in the country. Second, based on the quantification of technical efficiency, this paper tries to analyse both factors of production as well as socio-economic characteristics, contributes to the efficiency of rice farming.

This paper is organized as follows. Section 2 reviews the relevant literatures on efficiency studies in rice farming. Section 3 explains briefly the stochastic frontier model and specification of the functional forms. The empirical results are presented in section 4 and some conclusions are drawn in section 5.

2. A Brief of Literature

Frontier models have been widely applied in agricultural studies (for example: Battese & Coelli, 1992; Bravo-Ureta & Pinheiro, 1993; and Xu & Jeffrey, 1998). In the context of South and South-East Asian regions, rice production efficiency study has recieved a substantial attention (see for example: Balcombe et al., 2007; Coelli, et al., 2002; Dhungana, et al., 2004; Rahman, 2010; Rahman & Rahman, 2009; Rahman, et al., 2009; Tan, et al., 2010; Wadud & White, 2000; Yao & Shively, 2007). In the case of India, some studies were also conducted, including by Battese et.al (1989), Battese and Coelli (1992), and Battese & Coelli (1995). All three of these studies has a common approach which was using stochastic frontier production function. The results of these studies also showed some similarities, although in Battese & Coelli (1995), the research not only focusing on the estimation of frontier production function, but also tries to develop the inefficiency effects model. From the inefficiency effects model, Battese & Coelli (1995) found that age and education level of farmers, farm size and years of observation significantly affect agricultural production inefficiencies in the two villages were examined, namely Kanzara and Shirapur. While in the other villages, Aurepalle, the inefficiency were not significantly influenced by age and education variables farmers, farm size.

Bravo-Ureta and Pinheiro (1997) conducted a study on efforts to increase productivity by improving the efficiency of small-scale farming in the Dajabon region, Dominican Republic. The study uses two stages, where the first stage of Bravo-Ureta and Pinheiro (1997) estimate the stochastic production function to obtain the technical efficiency, allocative and economic efficiency levels by using maximum-likelihood method. In the second stage, Bravo-Ureta and Pinheiro (1997) used Tobit models to estimate the effect of various attributes of farmers on efficiency.

In the case study in China, Xu and Jeffrey (1998) and Tian and Wan (2000) estimate the efficiency of rice farming. Xu and Jeffrey (1998) try to analyse the differences in the production of conventional rice and hybrid rice farming by using a dual decomposition efficiency stochastic frontier models. The model involves several variables of which the location, chemical fertilizers, bio fertilizers, machinery, and pesticide. The results of the study showed significant differences in technical and allocative efficiency between conventional rice farming and the production of hybrid rice. Xu and Jeffrey (1998) and Tian and Wan (2000) found that education has a positive effect on technical efficiency of rice farming. Tian and Wan (2000) also found that multi-cropping index has a negative effect on the level of technical efficiency. Several other studies using the same method in analysing technical efficiency and inefficiency effects, such as Idiong (2007) in the case in Nigeria, Khan *et al.* (2010) in Bangladesh, and Khai and Yabe (2011) in Vietnam.

In other studies, Krasachat (2003) and Dhungana et al (2004) measure and investigate technical efficiency in Thailand and Nepal, respectively. Both use deterministic models to measure the level of technical efficiency, while the inefficiency effects obtained from the Tobit models. In the case of Thailand, Krasachat (2003) found the average overall technical efficiency is 0.71 and the variable of land affect significantly the level of efficiency. Meanwhile, in the case of Nepal, Dhungana et al (2004) found that differences in the level of inefficiency among farmers are the result of differences in the intensity of the use of resources such as seed, labour, fertilizer and mechanical equipment.

The same method is used by Javed et al (2010) in the analysis of rice and wheat farming in Pakistan. The results of the study revealed that the average technical efficiency in rice-wheat farming system is 0.83, and the result from inefficiency models indicate that length of study, the number of contacts with advisor, and access to credit have a negative effect on inefficiency.

In the context of Indonesia, there is only a few empirical studies concerning technical efficiency of rice farming. Some that can be mentioned are Fabiosa, Jensen, and Yan (2004), Rada, Buccola, and Fuglie (2010), and Brazdik (2006). Brazdik (2006) evaluates the technical and scale efficiency of rice farms in West Java and to identify determinants affecting farms' efficiency and the result shows that farm size is one of the most important factors of farm's technical efficiency and that high land fragmentation was the main source of the technical inefficiency during the final period of the intensification era. Furthermore, Fabiosa *et.al* (2004) examine the impact of macroeconomic shocks on the efficiency of small farmers and conclude that productive efficiency declined by 7 to 22 percent during the crisis, largely because of a decline in technical efficiency and a relatively large volatility in efficiency.

However, in the context of Indonesia, there is no study that compare the rice farming technical efficiency of each region in Indonesia and identify the common and specific characteritics which influence its technical efficiency. Consequently, this paper contributes to fill the the current gap by estimating and comparing technical efficiency among regions and identify the common and specific characteristics which contribute to the technical efficiency in each region.

3. Model and Data

3.1 The Basic Model

The stochastic frontier model which also called composed error model was introduced by Aigner *et al*. (1977) and Meeusen and van den Broeck (1977). The basic model of stochastic frontier can be represented as follows.

$$y_i = g(x_i, \beta) + \varepsilon_i \text{ for i = 1, 2, …, N} \tag{1}$$

where y = output, x = input vector, β = parameter vector, ε = *error term*, i = firm or production unit. The error term ε, consists of two independent components,

$$\varepsilon_i = v_i - u_i \tag{2}$$

where v_i is two-sided error term which represents statistical noise which is assumed to be *i.i.d* $N(0, \sigma_v^2)$ and $u_i \geq 0$ is one sided error term that represents technical inefficiency, assumed to be independent to v_i and x_i. Another assumption is that error component $u_i = |U_i|$, where U_i is *i.i.d* $N(0, \sigma_u^2)$. This assumption implies that u_i is half-normal. However, the assumption can be replaced by other assumption such as truncated-normal (Stevenson, 1980; Battese and Coelli, 1992) and two-parameter gamma (Greene, 1990).

Based on those assumptions, the model can be estimated using Maximum-Likelihood Estimation (MLE). Aigner *et al*. (1977) derives log likelihood function based on the following:

$$\ln(y_i) = g(x_i, \beta) + v_i - u_i \tag{3}$$

Furthermore, ALS (1977) expresses the likelihood function in the form of two variance parameters, which are $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u / \sigma_v$. λ is an indicator of variability in two sources' random errors, which then differentiate one production unit to the other. The likelihood function therefore can be expressed as follow.

$$\ln L(y|\beta, \lambda, \sigma^2) = N \ln \frac{\sqrt{2}}{\sqrt{\Pi}} + N \ln \sigma^{-1} + \sum_{i=1}^{N} \ln[1 - F(\varepsilon_i \lambda \sigma^{-1})] - \frac{1}{2\sigma^2} \sum_{i=1}^{N} \varepsilon_i^2 \tag{4}$$

where, $\varepsilon_i = y_i - x_i \beta$ and F are standard normal conditional distribution function (cdf). The ML estimator is derived from the maximization of (4) with respect to the parameters β, λ, σ.

If y in logarithm, hence the technical efficiency of production unit i can be expressed as follow

$$TE_i = exp(-u_i) \tag{5}$$

and technical inefficiency is $1 - TE_i$. The prediction of the above technical efficiency requires estimates of the u_i. The best predictor for u_i is conditional expected value of u_i given ε_i. This condition was stated and applied in the stochastic frontier model of Jondrow et.al (1982). Jondrow et.al (1982) show that

$$E(u|\varepsilon) = \sigma_* \left[\frac{f(\varepsilon\lambda/\sigma)}{1 - F(\varepsilon\lambda/\sigma)} - \left(\frac{\varepsilon\lambda}{\sigma} \right) \right] \tag{6}$$

where $\varepsilon\lambda/\sigma = -\mu_*/\sigma_*$ and $\lambda = \sigma_u/\sigma_v$, while f and F are *cdf* respectively. Since μ_* and σ_* are unobservable, hence the parameters can be replaced by the estimates of respective parameters. Referring to Battese and Coelli (1988), the technical efficiency of production unit of i is

$$TE = E[\exp(-u_i|\varepsilon_i)] = \left\{ \frac{1 - \Phi[\sigma_* - (\mu_i^*/\sigma_*)]}{1 - \Phi(-\mu_i^*/\sigma_*)} \right\} exp\left(-\mu_i^* + \frac{1}{2}\sigma_*{}^2 \right) \tag{7}$$

where $\Phi(\cdot)$ is the *cdf*.

3.2 Functional Forms and Variables

This paper will use the most appropriate functional forms by employing the log likelihood ratio test to the Cobb-Douglas and translog models. The Cobb-Douglas specification is presented as follow.

$$y_i = \beta_0 \prod_{j=1}^{n} x_{ij}^{\beta_{ij}} e^{\varepsilon_i} \qquad \text{For } i = 1, 2, ..., n \tag{8}$$

where y = output, x_j= the *j-th* input, i = i-th farmer, $\varepsilon_i = v_i - u_i$, and β_0, β_{ij} = parameters. Transforming into logarithm form yields;

$$\ln y_i = \ln \beta_0 \sum_{j=1}^{n} \beta_{ij} \ln x_{ij} + v_i - u_i \tag{9}$$

The detail model specification for the case of paddy production is:

$$ln(y_i) = ln\beta_0 + \beta_1 ln(land_i) + \beta_2 ln(seed_i) + \beta_3 ln(fertilizer_i) + \beta_4 ln(pesticide_i) + \beta_5 ln(labor_i) + \beta_6(cost_i) + v_i - u_i \tag{10}$$

where y represents the quantity of freshly threshed rice paddy (in tonnes); $land_i$ is the harvest area (in hectares); $seed_i$ is quantity of seeds used in the farming areas (in kilograms); $fertilizer_i$ is fertilizer (in kilograms); $pesticide_i$ is pesticide applied (in kilograms); $labor_i$ is hired labourers input (person-days); $family_i$ labour input by family (person-days); $cost_i$ is dummy variable for other cost of rice farming, such as land rent, farming equipment, credit interest, land tax, fuels, and others (D = 1, if other costs are positive, D = 0 otherwise); v_i is stochastic noise, assumed to be *i.i.d* $N(0, \sigma_v^2)$; u_i is non-negative random variable which is called inefficiency effect, assumed to be distributed as absolute value from $N(0, \sigma_u^2)$; and β is unknown parameter to be estimated along with the variance parameters, which is formulated in the form: $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u / \sigma_v$.

The second specification is the translog model, which is given by:

$$lny_i = \alpha_0 + \sum_{j=1}^{6} \alpha_{ji} \ln x_{ji} + 0.5 \sum_{j=1}^{6} \alpha_{ji}\, lnx_{ji}^2 + \sum_{j=1}^{6} \sum_{k}^{6} \alpha_{jk}\, lnx_{ji}\, lnx_{ki} + v_i - u_i \tag{11}$$

where the variables are as previously defined.

As a special case of translog model, the Cobb-Douglass functional form imposes restrictions on the technology by imposing constant production elasticity and elasticity of input substitution equals to unity. Therefore, this paper will test the Cobb-Douglas against the translog function to determine whether it is an adequate representation of the data.

Based on the appropriate model, the next procedure will be hypothesis test for λ which will determine whether there is inefficiency effect or not. Given the result of hypothesis test procedure, the technical inefficiency model is defined as follow (Battese & Coelli, 1995):

$$u_{it} = \delta_0 + \sum_{j=1}^{11} \delta_j Z_{ji} \tag{12}$$

Where the δ_js are unknown parameters; Z_1 is income of farmer million rupiah per month); Z_2 is dummy for farmer's education attainment (1 if farmer finishes high school, 0 otherwise); Z_3 is farmer's age (year); Z_4 is dummy for farmer's other job (1 if farmer has other job, 0 otherwise); Z_5 is dummy for irrigation facility (1 if rice field irrigated, 0 otherwise); Z_6 is dummy for financial source for farming (1 if self-funding, 0 otherwise), Z_7 is dummy for government assistance (1 if government assisted, 0 otherwise); Z_8 is dummy for dry season (1 if production in drought condition, 0 otherwise); Z_9 is dummy for rainy season (1 if production in rainy season, 0 otherwise); Z_{10} is dummy for cultivating area (1 if area more than 5000 m2, 0 otherwise); and Z_{11} the ratio of labour per hectare.

3.3 Descriptive Statistics

Table 1. Sample distribution based on province

No	Province	Farm Sample (n)
1	Nanggroe Aceh Darussalam (NAD)	186
2	Sumatera Utara (SUMUT)	274
3	Sumatera Barat (SUMBAR)	217
4	Sumatera Selatan (SUMSEL)	238
5	Lampung	230
6	Jawa Barat (JABAR)	345
7	Jawa Tengah (JATENG)	337
8	Jawa Timur (JATIM)	339
9	Banten	216
10	Bali	133
11	Nusa Tenggara Barat (NTB)	185
12	Kalimantan Barat (KALBAR)	152
13	Kalimantan Selatan (KALSEL)	199
14	Sulawesi Tengah (SULTENG)	128
15	Sulawesi Selatan (SULSEL)	275
Total		3454

This study uses data from the 3454 rice farmers in 15 provinces in Indonesia based on a survey of business cost structure of rice plants (SOUTP) conducted by the Central Statistics Agency (BPS) of Indonesia in 2008.

Descriptive statistics of all variables included in the model are presented in Table 2. The descriptive statistics are calculated based on provincial basis. From production perspective, the production of rice in 15 provinces is at an average of 2 tons per hectare, where Sumatera and Sulawesi became the two highest rice producers. The average labour use in all provinces was approximately 51 person-days per hectare, while in terms of fertilizer used the mean value was 177 kilograms per hectare. From age perspective, most of age of the farmers is more than 45 years.

Table 2. Descriptive statistics of all variables included in the stochastic frontier production models and inefficiency models

Province	Component	Output	Land	Seed	Fertilizer	Pesticide	Labour	Other cost	Other income	Age
NAD	N	179	179	179	179	179	179	179	179	179
	Min	210	400	3	8	2	8	15	159	21
	Max	4600	12500	100	400	1500	103	3700	8735	86
	Mean	1218	2524	19	78	184	29	612	1736	50
	Stdev	874	1882	15	62	231	15	660	1423	12
SUMUT	N	638	638	638	638	638	638	638	638	638
	Min	220	430	2	5	3	4	2	38	17
	Max	35000	100000	800	2100	64000	499	22572	44553	85
	Mean	2918	6387	39	190	970	47	1136	4438	49
	Stdev	3075	7689	53	195	3711	32	1449	5151	12
SUMBAR	N	196	196	196	196	196	196	196	196	196
	Min	160	648	3	7	2	10	2	60	23
	Max	4644	14000	68	570	7000	201	6785	8007	88
	Mean	1410	4125	22	94	367	39	714	1940	50
	Stdev	937	2704	14	88	960	27	798	1658	14
SUMSEL	N	484	484	484	484	484	484	484	484	484
	Min	450	900	2	23	50	9	53	63	18
	Max	16000	40000	245	2150	120000	292	5418	21715	85
	Mean	3608	9926	56	241	3391	74	817	5906	46
	Stdev	2476	7362	45	174	6666	70	824	4704	12
LAMPUNG	N	504	504	504	504	504	504	504	504	504
	Min	250	400	3	15	2	8	7	26	22
	Max	12200	27500	150	4100	16000	258	7166	15038	93
	Mean	2238	5013	21	273	665	55	709	2792	49
	Stdev	1726	3831	17	299	1080	42	887	2342	13
JABAR	N	1454	1454	1454	1454	1454	1454	1454	1454	1454
	Min	112	280	2	5	2	6	2	2	15
	Max	25800	43000	105	2900	45000	424	25325	50137	90
	Mean	1757	3730	13	185	1022	52	647	2232	51
	Stdev	2383	4785	13	241	2838	39	1422	3837	12
JATENG	N	1320	1320	1320	1320	1320	1320	1320	1320	1320
	Min	90	375	2	10	2	7	2	3	24
	Max	12000	20000	150	1830	20000	297	10162	25141	88
	Mean	1301	2657	14	194	424	40	391	1421	51
	Stdev	1185	2247	12	237	959	26	682	1603	12
JATIM	N	1197	1197	1197	1197	1197	1197	1197	1197	1197
	Min	99	260	2	6	2	4	2	7	15
	Max	22000	35000	200	5800	20000	344	13310	27753	98
	Mean	1683	3238	17	228	278	43	470	2020	51
	Stdev	1698	2977	17	308	696	34	761	2290	12
BANTEN	N	342	342	342	342	342	342	342	342	342
	Min	150	400	2	8	2	12	4	67	12
	Max	9800	25700	75	900	1800	220	4612	18421	90
	Mean	1569	3287	11	113	258	47	308	2169	48
	Stdev	1330	3087	10	111	269	29	453	2301	12
BALI	N	117	117	117	117	117	117	117	117	117
	Min	180	300	2	10	5	12	17	277	29
	Max	9000	18000	70	1400	2400	194	7384	13477	81
	Mean	2105	3793	17	197	273	53	1071	2659	51
	Stdev	1580	2612	12	201	315	38	1362	2374	11
NTB	N	174	174	174	174	174	174	174	174	174
	Min	160	400	2	15	50	9	8	51	20

Province	Component	Output	Land	Seed	Fertilizer	Pesticide	Labour	Other cost	Other income	Age
	Max	8100	20000	160	770	15000	171	2800	15604	90
	Mean	2220	5365	35	168	735	48	560	2940	47
	Stdev	1677	3972	29	135	1772	31	507	2709	13
KALBAR	N	163	163	163	163	163	163	163	163	163
	Min	450	900	5	15	2	12	10	535	26
	Max	8730	35000	110	550	15000	391	1730	17815	82
	Mean	2106	6127	22	129	1923	96	191	4068	48
	Stdev	1304	4142	14	90	2116	69	263	2868	12
KALSEL	N	292	292	292	292	292	292	292	292	292
	Min	189	723	4	15	2	8	10	11	19
	Max	7430	20230	103	720	6000	202	3930	13814	82
	Mean	1624	4539	24	130	933	61	625	2295	46
	Stdev	1135	3026	16	105	1025	33	682	2099	12
SULTENG	N	146	146	146	146	146	146	146	146	146
	Min	257	500	3	10	40	4	27	61	20
	Max	30000	60000	480	1800	53100	316	36300	40299	81
	Mean	3162	7683	50	252	3014	35	2532	4071	46
	Stdev	4056	8117	53	266	5709	29	5052	5185	13
SULSEL	N	729	729	729	729	729	729	729	729	729
	Min	114	300	2	8	4	6	10	30	19
	Max	17470	30000	240	1450	6500	186	17646	26090	85
	Mean	2574	5403	23	179	547	51	1664	2755	47
	Stdev	2208	4456	21	175	691	25	2240	2740	13
Mean value of each variables		**2099.53**	**4919.80**	**25.53**	**176.73**	**998.93**	**51.33**	**829.80**	**2896.13**	**48.67**

Note, N: number of farm samples; stdev: standard deviation

4. Empirical Result

4.1 Production Frontier Estimates

A likelihood ratio (LR) test can be employed to determine which model specification is better. In this study, the LR test was conducted to compare the Cobb-Douglas production function model against the translog model. The null hypothesis of the test is that the appropriate model is Cobb-Douglas production function, while the alternative hypothesis is that the translog model is more representative in explaining production function of rice farming in all 15 provinces. The chi-square values obtained from the test are presented in Table 3. The test result shows that in most of the cases the null hypothesis was rejected (except for Bali, Nusa Tenggara Barat, and Kalimantan Barat) and it was concluded that in 12 provinces, the translog specification fitted the data better than the Cobb-Douglas counterpart.

Table 3. Likelihood ratio test on Cobb-Douglas production function model against the translog model

No	Province	Log Likelihood Function		LR-stat	Critical Value	Decision	Appropriate Model
		Cobb-Douglas	Translog		$\alpha = 0.05$		
1	NAD	33.62	75.02	82.81	32.67	Reject H_0	Translog
2	SUMUT	44.36	67.66	46.61	32.67	Reject H_0	Translog
3	SUMBAR	10.11	25.92	31.61	32.67	Reject H_0	Translog
4	SUMSEL	7.95	69.53	123.16	32.67	Reject H_0	Translog
5	LAMPUNG	-79.74	-54.18	51.12	32.67	Reject H_0	Translog
6	JABAR	136.66	170.72	68.13	32.67	Reject H_0	Translog
7	JATENG	483.59	665.55	363.94	32.67	Reject H_0	Translog
8	JATIM	1.85	38.92	74.14	32.67	Reject H_0	Translog
9	BANTEN	9.91	36.16	52.50	32.67	Reject H_0	Translog
10	BALI	36.21	33.35	-5.71	32.67	Accept H_0	Cobb-Douglas
11	NTB	-24.35	-12.43	23.84	32.67	Accept H_0	Cobb-Douglas
12	KALBAR	96.59	-34.99	-263.14	32.67	Accept H_0	Cobb-Douglas
13	KALSEL	30.91	57.62	53.42	32.67	Reject H_0	Translog
14	SULTENG	0.40	35.95	71.10	32.67	Reject H_0	Translog
15	SULSEL	43.42	88.39	89.94	32.67	Reject H_0	Translog

Based on the above result, the maximum likelihood estimates of the parameters from the most appropriate model are presented in Table 4.

Table 4. Maximum-likelihood estimates for parameters of the stochastic frontier production models in 15 provinces

Variable	Parameter	ACEH	SUMUT	SUMBAR	SUMSEL	LAMPUNG	JABAR	JATENG	JATIM	BANTEN	BALI	NTB	KALBAR	KALSEL	SULTENG	SULSEL
Constant	β_0	-2.252**	-0.144	-3.648***	-8.633***	-3.668*	-1.537*	-0.528**	3.965***	-5.087***	0.389	2.234***	6.766***	3.093	8.893***	2.320**
		(1.080)	(1.689)	(1.057)	(1.243)	(2.594)	(1.041)	(0.265)	(1.599)	(1.930)	(0.682)	(0.536)	(0.262)	(2.853)	(1.114)	(1.082)
Land	β_1	1.137*	0.411	1.807***	4.466***	2.494***	1.769***	0.990***	0.190	2.476***	0.825***	0.301***	0.149***	-0.549	-3.730***	-0.285
		(0.717)	(0.571)	(0.531)	(0.433)	(0.852)	(0.399)	(0.095)	(0.566)	(0.714)	(0.129)	(0.093)	(0.032)	(1.020)	(0.678)	(0.315)
Seed	β_2	-3.482***	-0.015	1.361*	-1.862***	-1.080*	-0.627**	0.015	0.422	-1.105*	0.139*	0.169**	-0.033**	0.027	2.185***	0.142
		(1.322)	(0.408)	(0.905)	(0.466)	(0.706)	(0.349)	(0.083)	(0.461)	(0.746)	(0.093)	(0.074)	(0.018)	(0.730)	(0.920)	(0.320)
Fertilizer	β_3	2.329**	0.946***	-1.426**	-0.940***	-0.579**	-0.411**	-0.031***	-0.173	0.319	0.062*	0.301***	0.069***	0.679	1.058*	-0.034
		(1.349)	(0.266)	(0.804)	(0.402)	(0.321)	(0.180)	(0.012)	(0.209)	(0.253)	(0.038)	(0.054)	(0.020)	(0.551)	(0.773)	(0.249)
Pesticide	β_4	0.340	0.165*	0.364	0.047	0.369**	-0.124**	-0.001	-0.019	-0.162	-0.027*	0.023	0.009*	0.007	-0.306	0.054
		(0.786)	(0.105)	(0.303)	(0.250)	(0.208)	(0.074)	(0.013)	(0.131)	(0.202)	(0.019)	(0.026)	(0.006)	(0.191)	(0.410)	(0.101)
Labour	β_5	0.723	0.326**	0.125	-0.787***	-0.144	0.195*	-0.003	-0.290**	0.078	-0.041	0.085**	0.063***	0.779***	-0.204	0.295
		(0.731)	(0.190)	(0.491)	(0.263)	(0.315)	(0.129)	(0.013)	(0.170)	(0.247)	(0.039)	(0.038)	(0.013)	(0.327)	(0.538)	(0.282)
Oth cost	β_6	0.018	-0.273**	0.145	-0.073	-0.014	0.0003	0.044***	-0.259***	-0.058	0.041	0.092***	0.036***	0.015	1.808***	0.715***
		(0.469)	(0.142)	(0.283)	(0.244)	(0.194)	(0.090)	(0.010)	(0.098)	(0.179)	(0.034)	(0.033)	(0.007)	(0.236)	(0.492)	(0.168)
0.5(land)^2	β_{11}	0.117	0.197**	-0.089	-0.533***	-0.294**	-0.245***	-0.001	-0.015	-0.260**				0.303*	0.822***	0.308***
		(0.281)	(0.112)	(0.144)	(0.071)	(0.152)	(0.081)	(0.017)	(0.109)	(0.148)				(0.199)	(0.235)	(0.061)
0.5(seed)^2	β_{22}	-0.833**	-0.032	0.740***	-0.358***	-0.098	-0.125**	0.007	0.017	-0.309**				-0.148	0.610***	0.091*
		(0.487)	(0.069)	(0.271)	(0.108)	(0.137)	(0.073)	(0.012)	(0.085)	(0.140)				(0.142)	(0.233)	(0.058)
0.5(fertilizer)2	β_{33}	-0.346***	0.109***	0.077*	0.222***	-0.050*	-0.082***	0.001	-0.074***	-0.110**				-0.161**	0.093	0.063*
		(0.096)	(0.042)	(0.058)	(0.076)	(0.031)	(0.022)	(0.003)	(0.022)	(0.049)				(0.089)	(0.130)	(0.047)
0.5(pesticide)2	β_{44}	-0.027**	-0.004	-0.003	0.029	0.018	-0.001	-0.001*	0.006	0.019				0.025**	-0.047**	0.007
		(0.014)	(0.006)	(0.015)	(0.022)	(0.015)	(0.005)	(0.001)	(0.007)	(0.020)				(0.013)	(0.028)	(0.009)
0.5(labour)2	β_{55}	0.098**	0.016	0.070	0.024	-0.051**	0.024*	-0.001	0.029**	-0.076**				0.026	-0.084*	0.059**
		(0.047)	(0.021)	(0.056)	(0.025)	(0.030)	(0.016)	(0.001)	(0.016)	(0.035)				(0.041)	(0.064)	(0.032)
0.5(oth cost)2	β_{66}	-0.011	0.026**	0.035**	0.059**	0.022	0.019***	0.002***	0.015**	-0.028**				0.012	0.148***	0.022*
		(0.035)	(0.012)	(0.017)	(0.035)	(0.020)	(0.007)	0.000	(0.007)	(0.013)				(0.020)	(0.052)	(0.017)
Land x seed	β_{12}	0.388	-0.048	-0.252*	0.449***	0.223**	0.124**	-0.012	-0.005	0.045				-0.061	-0.496***	-0.086**
		(0.315)	(0.079)	(0.180)	(0.078)	(0.127)	(0.068)	(0.012)	(0.087)	(0.142)				(0.141)	(0.199)	(0.046)
Land x fertilizer	β_{13}	-0.392*	-0.205***	0.198*	-0.025	0.082*	0.133***	0.010***	0.070**	-0.012				-0.035	-0.127	-0.096***
		(0.269)	(0.054)	(0.123)	(0.045)	(0.057)	(0.036)	(0.004)	(0.037)	(0.059)				(0.097)	(0.172)	(0.040)
Land x pesticide	β_{14}	-0.079	-0.014	-0.068	-0.033	-0.073**	0.035**	0.002	-0.001	0.044				-0.037	0.037	-0.028**
		(0.155)	(0.021)	(0.055)	(0.048)	(0.039)	(0.016)	(0.002)	(0.026)	(0.046)				(0.039)	(0.086)	(0.017)
Land x labour	β_{15}	-0.212*	-0.045*	0.013	0.101**	0.048	-0.054**	0.007***	0.033	0.037				-0.105**	0.207**	-0.036
		(0.150)	(0.035)	(0.076)	(0.052)	(0.055)	(0.028)	(0.003)	(0.033)	(0.048)				(0.061)	(0.093)	(0.052)
Land x oth cost	β_{16}	0.049	0.019	-0.051	-0.082*	-0.03	0.003	-0.006***	0.059***	0.029				-0.048	-0.208**	-0.098***
		(0.087)	(0.026)	(0.049)	(0.051)	(0.035)	(0.019)	(0.002)	(0.018)	(0.029)				(0.050)	(0.096)	(0.028)
Seed x fertilizer	β_{23}	0.572***	0.096***	-0.276**	-0.033	-0.047	-0.008	-0.001	0.027	0.290***				0.070	0.151	-0.016
		(0.227)	(0.038)	(0.130)	(0.065)	(0.053)	(0.032)	(0.004)	(0.032)	(0.070)				(0.111)	(0.155)	(0.035)
Seed x pesticide	β_{24}	0.047	0.014	0.054	-0.047	0.032	-0.014	0.000	-0.018	0.011				-0.004	-0.057	-0.024**
		(0.141)	(0.015)	(0.054)	(0.043)	(0.034)	(0.014)	(0.002)	(0.021)	(0.037)				(0.034)	(0.083)	(0.014)
Seed x labour	β_{25}	-0.007	0.048**	-0.115	-0.061	-0.063*	0.062***	0.000	-0.049**	0.080*				0.097*	-0.023	0.152***
		(0.125)	(0.026)	(0.096)	(0.050)	(0.046)	(0.025)	(0.003)	(0.028)	(0.054)				(0.064)	(0.089)	(0.042)
Seed x oth cost	β_{26}	0.011	-0.036**	-0.028	-0.037	-0.037	-0.025*	0.010***	-0.062***	-0.044**				0.043	-0.02	0.01
		(0.085)	(0.019)	(0.048)	(0.039)	(0.035)	(0.016)	(0.003)	(0.016)	(0.022)				(0.042)	(0.077)	(0.024)
Fertilizer x pesticide	β_{34}	0.093***	0.000	-0.004	-0.007	0.016	-0.018**	0.002	0.003	-0.062**				0.046**	0.076*	0.045***
		(0.027)	(0.012)	(0.037)	(0.037)	(0.019)	(0.011)	(0.001)	(0.012)	(0.029)				(0.025)	(0.048)	(0.015)
Fertilizer x labour	β_{35}	0.164***	-0.015	0.071*	-0.003	0.042**	-0.013	-0.009***	0.023*	-0.079**				-0.062	-0.177***	0.006
		(0.056)	(0.022)	(0.052)	(0.036)	(0.023)	(0.022)	(0.001)	(0.016)	(0.041)				(0.050)	(0.069)	(0.045)
Fertilizer x oth cost	β_{36}	-0.042	0.018	0.041	0.044	0.031*	0.002	-0.005***	-0.011	0.040**				0.034	-0.127**	0.059***
		(0.047)	(0.015)	(0.035)	(0.040)	(0.022)	(0.011)	(0.001)	(0.012)	(0.017)				(0.033)	(0.063)	(0.020)
Pesticide x labour	β_{45}	0.011	-0.014**	-0.03	-0.004	-0.041***	0.012**	-0.003***	0.006	0.015				-0.009	0.019	-0.01
		(0.021)	(0.008)	(0.026)	(0.017)	(0.017)	(0.007)	(0.001)	(0.008)	(0.030)				(0.017)	(0.034)	(0.013)
Pesticide x oth cost	β_{46}	-0.031**	-0.001	0.031*	0.047**	0.016*	-0.007**	-0.002***	0.003	-0.011				-0.006	0.016	0.004
		(0.015)	(0.005)	(0.020)	(0.021)	(0.012)	(0.004)	0.000	(0.006)	(0.014)				(0.009)	(0.035)	(0.008)
Labour x oth cost	β_{56}	-0.003	0.007	-0.044*	0.021	0.024	0.003	0.002***	-0.004	-0.013				0.026	-0.062*	-0.081***
		(0.022)	(0.011)	(0.032)	(0.019)	(0.020)	(0.008)	(0.001)	(0.008)	(0.018)				(0.020)	(0.048)	(0.022)

(***), (**) (*) indicates respectively that the value of the statistic is significant at 1, 5 and 10 percent

The result of parameter estimates for land area variable shows a positive and statistically significant coefficient in 11 provinces, which means that an increase in land area will have a positive impact on rice farming. Since the coefficient is obtained from the log-log model, then the coefficient can be interpreted as land area elasticity of rice farming. This elasticity varies in each province, and is in the range 0.3 to 4.4. It means that in some provinces the relationship between the land area and rice farming is inelastic, but in some other provinces, is quite elastic. The coefficients of square of land size are negatively significant in the case of SUMSEL, LAMPUNG, JABAR, and BANTEN, which imply that the rice farming function in those province exhibits diminishing return. This means that adding more land area will reduce the marginal productivity of land at some point.

An interesting result is shown by the coefficients of fertilizer in 11 provinces. Although the coefficients are statistically significant, the signs are not consistent from one province to other. For example, in the case of SUMSEL, LAMPUNG, JABAR, and JATENG, the coefficients are negative, which mean that an increase in the use of fertilizer in the production process will have a negative impact on rice farming. One possible explanation for this result is that the fatigue condition of land. It is because all the provinces above have intensively used fertilizer in rice farming more than other province. Hence the impact of additional use of fertilizer might harm the productivity capacity of rice farming. This notion is also supported by the coefficients of square of fertilizer that are negatively significant in 5 provinces, implying diminishing return.

In the case of pesticide use in rice farming process, the coefficients are not significant in most of all provinces, except for SUMUT, LAMPUNG, JABAR, BALI, and KALBAR. The coefficients' sign also show mixed result but in all, the pesticide elasticity of rice farming is very low.

Another interesting result is shown by coefficient of labour, where there are only 7 provinces in which labour has an impact to rice farming. Even, in the case of 2 provinces, SUMSEL and JATIM, the labour coefficient is negative, implying that an increase in labour hour in production process will have a negative impact on output. Moreover, in the case of JATIM, it can be seen that the use of labour in the paddy production exhibits the minimum function since the parameter of squared land is positive. It may be concluded that at some stage after passing the minimum amount of labour required, an increase of this input will increase the output.

Additionally, the cross effect coefficient indicates the relationship between two inputs. The result shows that generally land and seed, land and fertilizer, seed and fertilizer, seed and labour, fertilizer and pesticide, fertilizer and labour are complementary inputs. Whereas, on average land and pesticide, land and labour, land and other cost, seed and pesticide, seed and other cost, pesticide and other cost and labour and other cost are substitution inputs.

4.2 Inefficiency Effect Estimates

Moving forward into the analysis of inefficiency model, it is required to identify whether the inefficiency model can accurately represent the rice production function characteristics. In order to meet that condition, it is necessary to conduct Likelihood Ratio (LR) test. In LR test, the efficiency model becomes the unrestricted model, whereas the standard model (without inefficiency effect) becomes the restricted one. The result of the LR test is represented in Table 5. The LR test shows that inefficiency effect exists in the rice stochastic frontier production model in all provinces. The inefficiency effect is also supported by the value of gamma parameter which is quite big and statistically significant.

Table 5. LR test efficiency model versus standard model

Province	LR stat	Critical Value*		Decision	Remark
		df	$\alpha = 0.01$		
ACEH	125.729	13	27.026	Reject H_0	inefficiency effect
SUMUT	164.938	13	27.026	Reject H_0	inefficiency effect
SUMBAR	47.208	13	27.026	Reject H_0	inefficiency effect
SUMSEL	151.908	13	27.026	Reject H_0	inefficiency effect
LAMPUNG	185.152	13	27.026	Reject H_0	inefficiency effect
JABAR	495.310	13	27.026	Reject H_0	inefficiency effect
JATENG	1042.368	13	27.026	Reject H_0	inefficiency effect
JATIM	376.815	13	27.026	Reject H_0	inefficiency effect
BANTEN	133.867	13	27.026	Reject H_0	inefficiency effect
BALI	66.378	13	27.026	Reject H_0	inefficiency effect
NTB	66.717	13	27.026	Reject H_0	inefficiency effect
KALBAR	306.246	13	27.026	Reject H_0	inefficiency effect
KALSEL	85.566	13	27.026	Reject H_0	inefficiency effect
SULTENG	45.231	13	27.026	Reject H_0	inefficiency effect
SULSEL	179.553	13	27.026	Reject H_0	inefficiency effect

The maximum likelihood estimates of inefficiency effects model is presented in Table 6. From the table it can be seen that the coefficients of income in all provinces, are found to have the expected signs. The income variable has a significant positive association, indicating that as the income of farmer increased, the farmer has the ability to use better inputs in the production process, which in turn increase the production efficiency.

In the context of education variables, the estimation results show that in almost all provinces, the coefficient of education has no significant effect on the level of efficiency of rice farming. There are only 4 provinces that show a negative effect of education on rice farming efficiency. These results may be attributed to the age background of the majority of farmers that are above 45 years, so that the effect of education is not significant on the production efficiency changes.

The analysis of the education variable above is confirmed by the estimates of age coefficient, which show that the age variable has a significant negative association, indicating that younger farmers tend to be more efficient. Moreover, having another job for farmer has influence to the production efficiency only in a few provinces. In some provinces such as SUMSEL and JATENG, having another job improves the efficiency through improvement of income and skill of farmer, while in other provinces, the job in fact has a negative impact on efficiency.

Table 6. Maximum-likelihood estimates for parameters of the inefficiency effects model

Variable	Parameter	ACEH	SUMUT	SUMBAR	SUMSEL	LAMPUNG	JABAR	JATENG	JATIM	BANTEN	BALI	NTB	KALBAR	KALSEL	SULTENG	SULSEL
Income	δ_1	-0.220***	-0.394***	-0.200***	-0.187***	-0.198***	-0.250***	-0.439***	-0.452***	-0.270***	-0.372***	-0.19***	-0.709***	-0.091***	-0.127***	-0.321***
		(0.063)	(0.117)	(0.038)	(0.033)	(0.036)	(0.038)	(0.023)	(0.101)	(0.093)	(0.137)	(0.042)	(0.023)	(0.018)	(0.037)	(0.063)
Education	δ_2	-0.041	-0.004	0.166**	0.223*	0.097	0.078	0.087	0.215**	0.063	0.170	-0.180	-0.025	-0.038	-0.032	0.112*
		(0.127)	(0.095)	(0.092)	(0.146)	(0.125)	(0.110)	(0.074)	(0.119)	(0.298)	(0.164)	(0.216)	(0.037)	(0.072)	(0.133)	(0.085)
Age	δ_3	0.004	0.019***	0.010***	0.006***	0.010***	0.015***	0.006***	0.016***	0.007**	0.004	0.011***	0.000	0.004**	0.006***	0.009***
		(0.005)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.009)	(0.004)	(0.001)	(0.002)	(0.002)	(0.003)
Oth job	δ_4	0.013	0.226***	-0.024	-0.083	0.026	-0.017	-0.080***	0.230***	0.072	-0.111	0.072	0.043*	0.033	0.135*	0.008
		(0.103)	(0.087)	(0.066)	(0.111)	(0.078)	(0.043)	(0.037)	(0.079)	(0.096)	(0.124)	(0.115)	(0.032)	(0.045)	(0.093)	(0.062)
Irrigation	δ_5	-0.475***	-0.441***	0.369***	-0.776***	0.051	0.090**	-0.127***	-0.068	-0.176*	2.344*	0.009	0.028	0.078*	0.272**	-0.038
		(0.119)	(0.170)	(0.073)	(0.252)	(0.073)	(0.041)	(0.035)	(0.060)	(0.118)	(1.525)	(0.132)	(0.028)	(0.057)	(0.137)	(0.076)
Financial	δ_6	1.062*	0.218**	-0.001	-0.033	0.124*	0.143**	1.607***	0.811***	1.455***	0.236	0.567***	6.661***	0.133*	-0.124*	-0.047
		(0.652)	(0.104)	(0.102)	(0.058)	(0.086)	(0.063)	(0.108)	(0.225)	(0.461)	(0.220)	(0.183)	(0.224)	(0.088)	(0.079)	(0.078)
Govt assist	δ_7	0.229**	-0.289**	0.033	0.250***	-0.109	-0.166***	-0.016	-0.097	-0.161*	0.121	0.018	0.046*	0.090*	0.052	-0.203*
		(0.138)	(0.135)	(0.150)	(0.069)	(0.104)	(0.057)	(0.037)	(0.079)	(0.114)	(0.131)	(0.121)	(0.030)	(0.062)	(0.109)	(0.126)
Drought	δ_8	0.056	0.335***	-0.173*	-0.127*	0.330***	-0.030	-0.045	0.175**	0.022	0.859**	0.302**	-0.098***	-0.024	0.606***	0.193**
		(0.150)	(0.109)	(0.113)	(0.089)	(0.076)	(0.055)	(0.097)	(0.098)	(0.148)	(0.394)	(0.136)	(0.030)	(0.062)	(0.133)	(0.102)
Flood	δ_9	-0.206	0.423***	0.208*	0.132*	0.465***	0.000	0.371***	0.271**	-0.339	0.000	0.445***	-0.033	-0.499***	-0.580***	0.148*
		(0.281)	(0.148)	(0.143)	(0.093)	(0.144)	(0.098)	(0.062)	(0.126)	(0.283)	(1.000)	(0.168)	(0.028)	(0.212)	(0.145)	(0.098)
Cult area	δ_{10}	0.199	0.498***	-0.417***	1.074***	0.203**	0.596***	0.762***	1.357***	-0.156	0.634***	0.325**	0.026**	0.176***	0.054	0.194**
		(0.242)	(0.176)	(0.128)	(0.168)	(0.105)	(0.117)	(0.074)	(0.313)	(0.522)	(0.153)	(0.157)	(0.015)	(0.068)	(0.087)	(0.099)
Labor ratio	δ_{11}	0.906***	1.425***	0.917***	0.669***	1.086***	0.832***	-0.001	1.046***	-0.088	-0.303	0.612***	0.342***	0.715***	0.642***	1.824***
		(0.274)	(0.381)	(0.192)	(0.148)	(0.170)	(0.111)	(0.077)	(0.207)	(0.271)	(0.344)	(0.223)	(0.066)	(0.131)	(0.158)	(0.303)
Sigma-squared	σ^2	0.058***	0.268***	0.069***	0.082***	0.167***	0.208***	0.346***	0.299***	0.267***	0.079***	0.084***	0.018***	0.046***	0.053***	0.169***
		(0.023)	(0.067)	(0.012)	(0.008)	(0.029)	(0.033)	(0.018)	(0.072)	(0.077)	(0.024)	(0.020)	(0.002)	(0.009)	(0.012)	(0.046)
gamma	γ	0.818***	0.938***	0.475***	0.699***	0.912***	0.951***	0.999***	0.930***	0.991***	0.886***	0.184	0.080	0.445	0.473***	0.882***
		(0.107)	(0.018)	(0.129)	(0.051)	(0.042)	(0.011)	(0.000)	(0.019)	(0.008)	(0.076)	(0.234)	(2.014)	(0.384)	(0.149)	(0.057)
Log-likelihood		75.02	67.66	25.92	69.53	-54.18	170.72	665.55	38.92	36.16	36.21	-24.35	96.59	57.62	35.95	88.39

Note, (***), (**) (*) indicates respectively that the value of t statistic is significant at 1, 5 and 10 percent, figure in parantheses is standar error

In terms of source of financing, the financial coefficients show significant and positive signs, which mean that as the source of financing comes from farmer, the production will be less efficient compared to the case of external source of financing. A limited amount of fund of farmer will constrain farmer in applying better inputs such seeds, fertilizer, tractor machine, and other materials in the rice farming, therefore the source of financing in rice farming influences efficiency. Furthermore, the government assistance has a different effect on technical efficiency. In SUMUT, JABAR, BANTEN and SULSEL government has a positive influence to increase the efficiency. On the other hand, in the others, the government assistance may not have impact to improve the efficiency.

Another appealing result is that the cultivated area and labour ratio have a similar effect on technical efficiency. On average, a wider land area a lower technical efficiency will be. It could occur because an increase of land used may not be followed by an increase of other important inputs hence the economic scale cannot be exhibited. This circumstance supports the diminishing return condition resulted from production function estimation. Similarly, when the ratio of labour engaged is higher, the technical efficiency tends to be lower.

Climatic factors or the season is also a factor that is important in the process of rice farming in Indonesia. This factor indicated by the dummy variable of dry season and the rainy season. Based on the estimates, when there is a dry season, some provinces experience a lower efficiency in rice farming. Meanwhile, during the rainy season, the impact varies among provinces. But in general, in the case of flood, the level of production efficiency is also decreased significantly.

4.3 Technical Efficiency Indexes

The average farm-level technical efficiencies of the 15 provinces are predicted based on the maximum-likelihood estimates. The estimates are presented in Table 7. The results show a wide variation in the level of technical efficiencies across provinces. For example, the minimum and maximum technical efficiencies in the 15 provinces are 11 per cent and 100 per cent, respectively. With respect to mean value, out of the sample of 15 provinces, 47 per cent have technical efficiency of 80 per cent or below, while the remaining 53 per cent have technical efficiency of higher than 81 per cent. Overall, the mean technical efficiency is about 77 per cent, indicating that the average farm produced only 77 per cent of the maximum attainable output for given input levels in 2008. This shows that there is considerable possibility for enhancing the technical efficiency, and thus productivity as well as the overall rice output. The higher degree of variability of technical efficiency estimates between provinces can be attributed to the instability of farming conditions.

Table 7. Descriptive statistics of predicted technical efficiency indexes

Province	Mean	Minimum	Maximum	Standard deviation
ACEH	0.816	0.290	0.981	0.164
SUMUT	0.809	0.319	0.967	0.138
SUMBAR	0.863	0.468	0.980	0.112
SUMSEL	0.819	0.397	0.980	0.141
LAMPUNG	0.694	0.285	0.959	0.184
JABAR	0.783	0.311	0.975	0.151
JATENG	0.810	0.331	1.000	0.157
JATIM	0.805	0.304	0.967	0.141
BANTEN	0.750	0.279	0.984	0.174
BALI	0.799	0.341	0.972	0.145
NTB	0.850	0.333	0.986	0.145
KALBAR	0.317	0.106	0.986	0.154
KALSEL	0.776	0.432	0.980	0.138
SULTENG	0.879	0.516	0.982	0.111
SULSEL	0.820	0.311	0.970	0.125
Average	**0.77**	**0.33**	**67.58**	**0.15**

5. Conclusion

This study uses stochastic production frontier to estimate farm level technical efficiency using input and output data from 15 provinces in Indonesia in 2008. The results indicate sizeable degree variation of inefficiency in all provinces, which imply considerable possibility for enhancing the technical efficiency, and thus productivity as well as the overall rice output. In general, land input has a significant contribution in most of the provinces. However in some provinces there is a tendency of diminishing return, especially in Java and Sumatera islands.

The study also analyses the inefficiency effects to evaluate the factors influencing the inefficiency. Results indicate that improving farmer's income will increase the technical efficiency of rice farming by allowing farmer to improve the quality of their production factors. Further results also show that giving incentive to people in productive age to work in the rice farming will enhance the technical efficiency as well as productivity of rice production. The improvement of government assistance, especially with respect to financial aspect will also enhance the technical efficiency, since the assistantships will reduce the farmer's constraint in applying better inputs such seeds, fertilizer, tractor machine, and other materials in the rice farming.

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