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Production risk and technical inefficiency of smallholders' rubber production in Indonesia

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Abstract

This study estimates the technical efficiency of smallholder's rubber production attributed to output risks and inefficiencies. Three hundred eighty-four (380) respondents were selected and surveyed in South Sumatra, Indonesia, using a multi-stage random sampling procedure. This study adopted an integrated stochastic frontier technique and the Just-Pope model by employing the maximum likelihood estimation. The results indicated that rubber yield variation came from inefficiencies rather than random variability. The mean technical efficiency was estimated at 0.72, suggesting that there is still a possibility to enhance rubber production if risks and inefficiencies are reduced. Labour was a significant risk-reducing input for rubber farms. The determinants of farming experience, extension visit, tapping system, and planting material significantly influenced technical inefficiency. This finding reveals that technical efficiency of rubber production could be enhanced by improving these factors. Therefore, more extension knowledge to farmers on recommended tapping systems and rubber clonal is recommended.

Keywords: smallholders' rubber, output risk, technical efficiency, stochastic frontier technique, Just-Pope model

Full length article *Corresponding Author, e-mail: lina_fsy@yahoo.com

1. Introduction

In Indonesia, natural rubber is an essential commodity as it contributes to the country's revenue (US$3.25 billion), and in 2019 it provided income for more than 2.59 million rural households. In 2020, most rubber plantations in Indonesia were rubber smallholdings which constitute about 88 percent (i.e., 3.26 million hectares) of the total rubber planted in Indonesia. Government estates make up 5 percent, and private estates 7 percent [1]. In recent years, Indonesian rubber has fluctuated in production, productivity, and export. National rubber production declined from 2016-to 2020 by 3.73 percent per annum. Furthermore, the growth of rubber productivity in Indonesia has also fluctuated over the years. During 2016-2020, the average growth of rubber productivity in Indonesia was 1.20 percent per year. In 2020, rubber productivity reached 1,158 kilograms per hectare. Also, Indonesian smallholder's rubber have much lower yields than estates [1].

In Indonesia, particularly South Sumatra, rubber production was characterized by risk. Hazards include adverse weather, weeds, pests, and diseases, in addition to various socioeconomic and cultural constraints, which in turn lead to production and market uncertainty [3]. This variation is reflected by Indonesian rubber production, productivity, and export fluctuations. Furthermore, the Indonesian rubber industry faces the problem that low productivity on rubber smallholdings results in low income. Therefore, the productivity of rubber smallholdings should be improved substantially to be an essential engine of welfare growth and poverty alleviation. According to [4], the best and most effective way to improve productivity is to allocate resources more efficiently. This effort can be implemented if the empirical knowledge regarding the technical efficiency of resource allocation, production risk, and the factors affecting technical efficiency is provided. Taking this into consideration, it is necessary to calculate the level of farm's technical efficiency to estimate output losses attributed to output risks and inefficiencies.

There are many studies on the technical efficiency of Indonesian agricultural production. However, few examine technical efficiency in producing perennial tree crops, mainly rubber. [5] studied the technical efficiency of smallholder oil palm production in West Sumatra. Their estimation showed that the technical efficiency estimate for all smallholders was 66 percent. The findings also indicated that education was negatively related to technical efficiency. [6], conducted a study to calculate the technical efficiency of oil palm smallholdings in Riau Province, Indonesia. Their estimation indicated that, on average, the technical efficiency was 83%. The factors of farmers groups, education level, farmer's age, and farm diversification significantly affected technical efficiency. [7] estimated the technical efficiency of smallholder cocoa farmers in Lampung Province, Indonesia. Their findings revealed that the technical efficiency of cocoa farms was 82%. Factors such as farmers' age, family size, farmers' groups, and side grafting application have significant effects related to technical efficiency. Most of these studies only focused on socioeconomic characteristics as determinants of inefficiency, but none included the risk effect on technical efficiency estimates. The existence of risk ultimately affects the level of technical efficiency achieved. Denying the presence of risk can lead to biased estimations of technical efficiency [8-9]. Moreover, the studies that analyzed the technical efficiency of Indonesian rubber are still limited. Therefore, this study bridges the research gap by including output risk's effect on technical efficiency estimates of rubber production. This study is also meant to contribute to the limited literature on the technical efficiency and risk analysis of perennial tree crop production, mainly rubber in Indonesia.

Output risks are an important influence on farmers' input allocation and production supply [3]. Therefore, farmers' technical efficiency performance could change significantly if these risks are identified. It is suggested that production risk and technical inefficiency are integrated into a single framework by incorporating the stochastic frontier model into the Just-Pope Model. Empirical studies by [10];[11]; [9] revealed that it is possible to incorporate the stochastic frontier model into the Just-Pope production function.

2. Materials and methods

2.1. Data Source

In this study, South Sumatra Province, Indonesia, was selected as the study area. It covers an area of approximately 8,701,742 square kilometers and has a total population of 7.701.528 persons that live in 17 districts/cities [20]. A structured questionnaire was used to obtain the cross-sectional data of output and production inputs and farmers' demographic and socioeconomic characteristics. The target population for the study was rubber smallholders in South Sumatra Province. The number of rubber farmers were obtained from the Directorate General of Estate Crops, Indonesia's Ministry of Agriculture. A combination of purposive, multi-stage, and random sampling procedures was employed in this study. In the first stage, South Sumatra, the biggest rubber producer in Indonesia, was purposively selected. In the second stage, 11 out of 17 districts were also chosen because they were prominent rubber production areas with 411,336 involved in the rubber industry. Then, the sample size of 384 respondents was formed by using table 1 of Krejcie and Morgan [21]. In the third stage, a random selection of rubber farmers from each district was conducted in a ratio proportional to the size of the population of rubber farmers in each section. Due to inconsistencies in some of the data collected, it was only possible to analyze the data from 380 farmers.

2.2. Preliminary Analysis

The first step in the preliminary analysis was generating a variable of rubber-weighted trees. One of the difficulties faced in estimating the technical efficiency of perennial tree crops is accounting for the differences in the number and the age of trees. The sampled farms in this study have different numbers and periods of trees. Different aged trees have further yield potential, and these differences may cause bias in estimating the production function and technical efficiency model. To eliminate this bias, it is necessary to generate a new variable which can capture the effect of tree age and the number of trees. Therefore, the two variables of tree age and the number of trees were integrating into a new variable [6];[5]; [22]; [23]. The new variable is rubber-weighted trees (W.R.T.).

The rubber trees produce latex at six years of age and reach a yield peak between 15 and 18 years. The age of the rubber trees in this study was between 6 and 30 years. During the production period, rubber trees have a six-stage bark consumption period. The bark consumption period represents the potential rubber yield based on the tree's age. It is represented by the different types of bark consumption panels: B0-1 panel represents rubber trees aged 6- 10 years; B0-2 panel represents rubber trees aged 11-14 years; B1-1 panel represents rubber trees aged 15-18 years, B1-2 panel represents rubber trees aged 19-22 years, H0-1 and H0-2 panels represent rubber trees aged 23-26 years, and free tapping panels represent rubber trees aged 27-30 years. When smallholders adopt good agronomic practices, rubber trees can reach their highest production at between 15 and 18 years. Afterwards, rubber trees’ output starts to dwindle gradually [24]. Therefore, following [22], the W.R.T. variable of rubber is given by:

$$WRTi = W1RT1i + W2RT2i + W3RT3i + W4RT4i + W5RT5i + W6RT6i$$

Where:

WRT**_i* represents total weighted rubber trees on the i-farmer's plot; RT_{1i} represents the number of trees aged 6-10 years; RT_{2i} represents the number of rubber trees aged 11-14 years; RT_{3i} represents the number of rubber trees aged 15-18 years; RT_{4i} represents the number of rubber trees aged 19-22 years; RT_{5i} represents the number of rubber trees aged 23-26 years; RT_{6i} represents the number of rubber trees aged 27-30 years, and ***W's are the weights to be estimated.

Using data obtained from the yield profile of rubber [24], the average weight of rubber (kilogram/hectare) is calculated for each age group. Rubber trees aged 15-18 years are at their yield peak; thus, $W_3 = 1$. Then, the average rubber weight for each age group was divided by the average weight for those at yield peak (i.e., RT_3) to obtain the weights (W's) estimates [22]. In this study, the average rubber weight for RT_1; RT_2; RT_3; RT_4; RT_5 and RT_6 are 800; 1,775; 1,800; 1,675; 1,600 and 1,350 kilogram per hectare respectively, thus, the estimated W's are as follows:

W1 = 800/1800 = 0.44; W2 = 1775/1800 = 0.98; W3 = 1800/1800 = 1

W4 = 1675/1800 = 0.93; W5 = 1600/1800 = 0.89; W6 = 1350/1800 = 0.75

Subsequently, it is necessary to test Cobb-Douglas against translog functional forms to determine the best fit model for data analysis using a generalized likelihood-ratio (L.R.) test. The L.R. test suggests that translog frontier function was the best fit model for the data analysis since the null hypothesis of Cobb-Douglas was rejected at 16 degrees of freedom and 5% level of significance because the generalized likelihood-ratio (L.R.) test statistic of 65.782 is higher than the critical chi-square table value of 25.689.

2.3. Empirical Model of Integrating Risk into Stochastic Frontier Analysis (SFA)

The study integrated the Just and Pope (J-P) model into the stochastic frontier technique, as suggested by [9], by employing the maximum likelihood estimation. According to [25] stochastic frontier production function, can be expressed by:

$$yi = f\ (xi\ ;\beta)\ \exp(vi - ui\ )\ i = 1, 2, \dots, I \quad (1)$$

Where: Y_i represents the output which is restricted by quantity of stochastic. Then, $\mathbf{f}(x_i;\beta)\exp(V_i - U_i)$ is the term stochastic frontier, where β is a vector of technology parameters to be estimated. V_i is a random noise that is associated with measurement error and uncontrollable factors. V_i are under assumption that they are independently and identically distributed as $\mathbf{N}(\mathbf{0},\sigma_V^2)$ random variables. While, the $\mathbf{U_i's}$ have assumption that they are non-negative truncation of the $\mathbf{N}(\mathbf{0},\sigma_u^2)$ distribution or half normal distribution which captures the technical inefficiency. So that, in SFA, error term can be measured for each observation to capture random noise term (i.e measurement error and factors that out of farm's control), while, the one-sided error term, captures the technical inefficiency.

Since the translog model is the best fit model, thus it was employed to analyze the technical efficiency of rubber production. The translog production function could be specified by:

$$\ln y_i = \beta_0 + \sum_{j=1}^{4}\beta_j \ln x_j + 0.5\sum_{j=1}^{4}\beta_{jj}\ln x_i^2 + \sum_{j=1}^{4}\sum_{k=1}^{4}\beta_{jk}\ln x_{ji}\ln x_{ki} + v_i - u_i \quad (2)$$

where the variables are input variables, i.e. i.e. X_1= weighted rubber trees (RWT) (number), X_2 = fertilizer (Kg/year), X_3 = herbicide (liter/year) and X_4 = labour (man-hours/year). Following [19], a flexible approach suggested by [9] was employed to integrate risk into a stochastic model. This approach can be specified as:

$$y_i = f(x_i;\beta) + g(x_i;\gamma)v_i - q(z_i;\delta)u_i \quad (3)$$

Based on this approach, when v_i and u_i were specified in equation (2), therefore the risk function and the inefficiency function are specified as follows, respectively:

$$\sigma_v^2 = g\left(\prod_{k=1}^{3} x_k^{\gamma k}\right) \quad (4)$$

$$u_i = q\left(\sum_{i=1}^{7}\delta_i Z_i\right) \quad (5)$$

where X_k refers to the input variables that explain the production risk, i.e., X_1 = fertilizer, X_2 = herbicide and X_3 = labour; Z_i is vector of determinant that refers to demographic and socio-economic characteristics of rubber farmers i.e. Z_1 = age of household head (years), Z_2 = education level of household head (scoring), Z_3 = family size (number), Z_4 = extension visit (dummy variable), Z_5 = farming experience (years), Z_6 = tapping system (dummy variable), and Z_7 = planting material (dummy variable).

Then, one-step SFA approach using the maximum likelihood estimator was employed to estimate the parameters in equation (2), (4) and (5) simultaneously.

2.4. Partial Elasticity

In the case of a translog form, the production elasticity cannot be directly interpreted from the translog production frontier because of the presence of interaction coefficients; then partial elasticity was estimated [26] ; [27]; [28]. The partial elasticity is given by:

$$\frac{\partial InE(Yj)}{\partial InE(Xk)} = \beta_k + 2\beta_{kk}\, In(X_{ki}) + \sum_{j\neq k} \beta_{kj} In(X_{ji}) \tag{6}$$

Thus, the scale coefficient (β) is given by:

$$\beta = \sum_k^n =_1 \left[\frac{\partial InE(Yj)}{\partial InE(Xk)}\right] \tag{7}$$

The β is the proportional change in output obtained from a unit proportional increase in all inputs. If β is more significant than one, the farms have an increasing return to scale. The farms have constant returns to scale if β equals one. In contrast, if β is less than one, rubber farms have a decreasing return to scale.

3. Results and discussion

3.1. Estimation of Translog Production Function

In this study, risk function was incorporated into stochastic frontier analysis (S.F.A.) using a flexible approach as proposed by [9] Kumbhakar (2002). The method was used to estimate parameters for the production function, technical efficiency, production risk, and technical inefficiency model simultaneously using maximum likelihood estimation (MLE). Table 1 presents the estimation results of the translog production function. Table 1 showed that the lambda (λ) estimate of 3.089 reveal that rubber output variation, which comes from inefficiency, was more pronounced than output due to random variability. Moreover, the gamma (γ) estimate of 0.898 indicates that 89.8% of random variation in rubber production is explained by inefficiency.

Table 1: Maximum-likelihood Estimation for Parameter of Stochastic Frontier Production

Variable	Parameters	Translog model	
		Coefficient	t-value
Constant	β_1	-7.577	-3.76
Ln WRT	β_2	4.477	4.71***
Ln fertiliser	β_3	-0.792	-1.45
Ln herbicide	β_4	-0.784	-1.98**
Ln labour	β_5	0.508	0.61
lnWRT Square	β_6	-1.277	-4.02***
lnFertiliser Square	β_7	-0.012	-0.12
ln Herbicide Square	β_8	-0.051	-0.76
ln Labour Square	β_9	-0.224	-2.40*
lnWRTx ln Fertiliser	β_{10}	0.354	2.56**
lnWRT x ln Herbicide	β_{11}	0.081	0.61
lnWRT x ln Labour	β_{12}	0.271	1.56
ln Fertiliser x ln Herbicide	β_{13}	-0.177	-2.61***
ln Fertiliser x ln Labour	β_{14}	-0.125	-1.35
ln Herbicide x ln Labour	β_{15}	0.190	1.89*
Variance Parameters			
Log likelihood		262.189	
Sigma^2 (σ^2) = $\sigma_u^2 + \sigma_v^2$		0.061	
Lambda (λ) = σ_u / σ_v		3.089	
Gamma (γ) = $\sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$		0.898	

* Indicates significant at 10%, ** significant at 5%, *** significant at 1%

Source: Authors' estimation

Because the coefficients in the translog model are not directly interpretable as the production elasticity, partial elasticity was estimated instead. From Table 2, it can be observed that the partial elasticity for W.R.T., fertilizer, labor, and Herbicide were 0.512%, 0.168%, 0.096%, and 0.042%, respectively. The positive sign means an increase in output when all inputs are increased. This finding implies that W.R.T. is the essential production input in rubber production, followed by fertilizer, labor, and Herbicide. The sum of elasticity or return to scale coefficient was less than 1 (i.e., 0.820), indicating a decreasing return to scale in rubber production. A decreasing return to scale implies that the increase of rubber output is less than the increase of the input.

Table 2: Partial elasticity in Translog function

Variable of Inputs	Elasticity (Percent)
WRT	0.512
Fertiliser	0.168
Herbicide	0.042
Labour	0.096
Return to Scale	0.820

Source: Authors' estimation

Table 3: Frequency distributions of technical efficiency scores

Efficiency Class	Frequency (n)	Percentage (%)
<0.2000	0	0.00
0.2001-0.3000	1	0.30
0.3001-0.4000	9	2.40
0.4001-0.5000	32	8.40
0.5001-0.6000	53	13.90
0.6001-0.7000	85	22.40
0.7001-0.8000	82	21.60
0.8001-0.9000	45	11.80
0.9001-0.9999	73	19.20
1.0000	0	0.00
Total summary		380
Mean		0.72
Std. Deviation		0.17
Min		0.30
Max		0.99

Source: Authors' estimation

3.2. Technical Efficiency

Table 3 presents the frequencies and percentages corresponding to the range of efficiency scores for Indonesian rubber smallholders. The technical efficiencies of rubber farmers vary from one farmer to another in 0.2000 to 0.9999. The results showed that, on average, the technical efficiency score of sampled farms was estimated at 0.72. It suggested that, on average, rubber farms were only producing 72% of the output of best-practice farmers for the given inputs. According to [30], a farm is technically efficient if a technical efficiency scores higher than 82%. Based on this standard, the number of technically efficient rubber farms is only 27.4% of the total sample.

3.3. Production Risk Function

Table 4 provides the results of the production risk effect model. This study presents production inputs such as fertilizer, Herbicide, and labor. The finding of this study shows that the information on fertilizer was positive, suggesting that this input is risk-increasing. This result is similar to [15] and [31]. It may be attributed to misuse in fertilizer application as many farmers are not made aware of information regarding the correct use of fertilizers. This lack of knowledge can lead to farmers using more fertilizer than is necessary, which can cause an increase in the growth of rubber, poison the crop, and eventually decrease yields. In this study, fertilizer did not have a significant risk-increasing effect.

The herbicide had a negative sign about the production risk model. However, the results show that the input of Herbicide was not significantly risk-decreasing. In this study, the results show that labor had a negative effect with a 5% level of significance concerning the production risk effect model, suggesting that labor is a risk-reducing input for rubber farms. This result aligns with a prior assumption that rubber farms are very dependent on labor, especially for tapping activities.

Table 4: Production risk function

Variables	Parameters	Coefficients	Standard Error	t-ratio
Constant	$\psi 1$	48.206	41.332	1.17
Ln fertiliser	$\psi 2$	13.782	9.543	1.44
Ln herbicide	$\psi 3$	-0.666	8.204	-0.08
Ln labour	$\psi 4$	-22.919	11.359	-2.02**

* Indicates significant at 10%, ** significant at 5%, *** significant at 1% Source: Authors' estimation

3.4. Factors Affecting Technical Inefficiency

The results reveal that rubber farms were not operating at total efficiency. Therefore, it is necessary to determine the factors that could improve the technical efficiency of rubber farms. Table 5 provides the results of the technical inefficiency model. The results show that all of the determinants had expected signs. Four of the determinants were statistically significant concerning technical inefficiency, i.e., extension, experience, tapping system, and planting material.

The age of farmers had a positive sign concerning technical inefficiency, suggesting that technical efficiency likely decreases as the farmers grow older. This result is in line with findings by [32]. This finding may be caused by the fact that older farmers are more conservative and traditional in their methods and are more reluctant to embrace new technology. In this study, the farmer's age did not influence technical inefficiency significantly. Family size and education factors were negative and were not compelling about technical inefficiency effect. [33] also found similar results.

The negative coefficient of extension visits concerning the inefficiency model suggests that the extension service enables the farmers to learn better farming methods and be more efficient at using limited resources. The determinant of the extension was statistically significant in influencing technical inefficiency at a 5% level of significance. This result is in line with findings by [19]. However, 64% of the sampled farmers had never received extension visits. The lack of extension service for rubber farmers is a severe hindrance to increasing the productivity levels of smallholdings. Thus, government policy is urgently required to optimize the effectiveness of the extension visit system for the smallholders. The determinant of experience has a negative sign and was statistically different from zero at a 1% level of significance on technical inefficiency. The result is similar to those obtained by [34]. It suggests that as the smallholder's experience in rubber farming increases, their technical efficiency in rubber production also increases because experienced farmers apply better practices and therefore suffer fewer losses.

Table 5: The technical inefficiency model

Variables	Parameters	Coefficients	Std. Error	t-ratio
Constants	$\delta 0$	0.464	0.493	-0.94
Age of farmer	$\delta 1$	0.004	0.011	0.36
Family size	$\delta 2$	-0.075	0.073	-1.03
Education level	$\delta 3$	-0.052	0.088	-0.59
Extension visits	$\delta 4$	-0.483	0.199	-2.42**
Experience of farming	$\delta 5$	-0.119	0.017	-7.23***
Tapping system	$\delta 6$	-0.652	0.237	-2.75***
Planting material	$\delta 7$	-0.382	0.175	-2.19**

* Indicates significant at 10%, ** significant at 5%, *** significant at 1%,Source: Authors' estimation

The determinant of the tapping system had a negative sign and was statistically significant at 1% about technical inefficiency. It suggested that the recommended tapping system S/2 d2 could increase technical efficiency. The result is in line with the study conducted by [33]. Planting material had a statistically significant difference at 5% in relation to technical inefficiency. This finding is similar to those made by [35]. The negative sign of planting material suggested that the use of clonal rubber leads to a higher average technical efficiency than the use of non-clonal rubber.

4. Conclusions

This study concludes that variation in output due to technical inefficiency is more pronounced than the variation in the production due to random variability. The production input factors of rubber weighted trees (W.R.T.), fertilizer, Herbicide, and labor are essential in the development of rubber production and increase mean output positively. The sum of elasticity or return to scale coefficient was 0.820, indicating a decreasing return to scale in rubber production. A decreasing return to scale implies that the increase of rubber output is less than the increase of the inputs. The level of technical efficiency was estimated at 0.72, implying that smallholder's rubber production still could be enhanced by about 28% using the same level of input use.

The study results showed that labor was estimated to be a significant risk-reducing input. The determinants of farming experience, extension visits, tapping system, and planting material of rubber clonal had significant negative relationships on the inefficiency effect model. It suggests that technical efficiency of smallholder's rubber production could be enhanced by improving these factors. Therefore, more extension knowledge to farmers on recommended tapping systems and clonal rubber is recommended. The government should improve the extension visit system for farmers and organize training, seminars, or workshops to enhance the farmers` knowledge. To produce new high-yielding rubber clones distributed to rubber smallholders, research and development activities should also be increased.

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References

[1] Directorate General of Estate Crops. (2019). Tree crop estate statistics of Indonesia. Rubber 2015-2017. Directorate General of Estate Crops, Ministry of Agriculture, Jakarta.

[2] Pusat Data dan Sistem Informasi Pertanian. (2019). Outlook karet. Komoditas Pertanian Subsektor Perkebunan. Sekretariat Jenderal-Kementerian Pertanian. Jakarta.

[3] R.A. Villano & E. Fleming (2006). Technical inefficiency and production risk in rice farming: Evidence from Central Luzon Phillipines. Asian Economic Journal. 20(1): 29-46.

[4] Y. Kaka, M.N. Shamsudin, A. Radam, & I.A. Latif, (2016). Profit efficiency among paddy farmers: A Cobb-Douglas stochastic frontier production function analysis. Journal of Asian Scientific Research. 6(4): 66-75.

[5] Hasnah., E. Fleming & T. Coelli (2004). Assessing the performance of a nucleus estate and smallholder scheme for oil palm production in West Sumatra: A stochastic frontier analysis. Agricultural Systems. 79: 17-3.

[6] W. Alwarritzi, T. Nanseki, & Y. Chomei (2015). Analysis of the factors influencing the technical efficiency among oil palm smallholder farmers in Indonesia. Procedia Environmental Sciences. 28: 630-638.

[7] D.M. Sari, A. Fariyanti, & N. Tinaprilla, (2017). Analysis efisiensi teknis perkebunan kakao rakyat di Provinsi Lampung (Technical efficiency analysis of smallholder cacao plantations in Lampung Province). Jurnal Tanamana Industri dan Penyegar (Journal of Industrial on Beverage Crops). 4(1): 31-40.

[8] R. Bokusheva, & H. Huckmann (2006). Production risk and technical inefficiency in Russian agriculture. European Review of Agricultural Economics. 33(1): 93-118.

[9] S.C. Kumbhakar (2002). Specification and estimation of production risk, risk prefernces and technical efficiency. American Journal of Agricultural Economics. 84:8-22.

[10] G.E. Battese, A.N. Rambaldi, & G.H. Wan (1997). A stochastic frontier production function with flexible risk properties. Journal of Productivity Analysis. 8:269-280.

[11] S.C. Kumbhakar (1993). Production risk, technical efficiency and panel data. Economics Letter. 41: 11-16.

[12] F. Asche, & R. Tveteras (1999). Modelling production risk with a two-step procedure. Journal and Resource Economics. 24:424-439.

[13] B. Fufa, & R.M. Hassan (2003). Stochastic maize production technology and production risk analysis in dadar district, East Ethiopia. Agrekon, 42 (2): 116-128.

[14] S.C. Kumbhakar & E.G. Tsionas, E.G (2010). Estimation of production risk and risk preference function: a nonparametric approach. Annals of Operations Research. 176: 369- 378.

[15] R.E. Just & R.D. Pope (1978). Stochastic specification of production functions and economic implication. Journal of Econometrics. 7:67-86.

[16] T. Tiedemann & U. Latacz-Lohmann (2013). Production risk and technical efficiency in organic and conventional agriculture—The case of Arable

farms in Germany. Journal of Agricultural Economics. 64:73–96.
[17] R.E. Just, & R.D. Pope (1979). Production function estimation and related risk considerations. American Journal of Agricultural Economics. 61:276-284.
[18] A.G. Guttormsen, & K.H. Roll (2013). Production risk in subsistence agriculture. Journal of Agricultural Education and Extension. 1-13.
[19] Z. Yang, A.W. Mugera, & F. Zhang (2016). Investigating yield variability and inefficiency in rice production: A case study in Central China. Sustainability. 8(8): art 787.
[20] BPS-Statistics Sumatera Selatan Province. (2017). Provinsi Sumatera Selatan Dalam Angka (Sumatera Selatan Province in Figures) 2016. Palembang, Indonesia: BPS-Statistics Sumatera Selatan Province Publisher.
[21] R.V. Krejcie, & D.W. Morgan (1970). Determining sample size for research activities, Educational Psychological Measured. 30:607-610.
[22] A. Ofori-Bah & J. Ashafu-Adjaye (2011). Analysis of scope economies and technical efficiency of cocoa agroforestry system in Ghana. Journal of Ecological Economics. 70:1508- 1518.
[23] T.V.H. Son, T. Coelli, & E. Fleming (1992). Analysis of the technical efficiency of state rubber farms in Vietnam, Agricultural Economics. 9:183-201.
[24] Kuswanhadi & E. Herlinawati (2012). Penyadapan. In M. Lasminingsih, H. Suryaningtyas, C. Nancy, & A. Vachlepi (Eds), Sapta Bina Usaha Tani Karet Rakyat. Sembawa: Pusat Penelitian Karet-Balai Penelitian Sembawa.
[25] G.E. Battese & T.J. Coelli (1995). Model for technical inefficiency effects in a stochastic frontier production function for panel data, Empirical Economics. 20: 325-32.
[26] S. Chiona, T. Kalianda, & G. Tembo (2014). Stochastic frontier analysis of the technical efficiency of smallholder maize farmers in Central Province, Zambia. Journal of Agricultural Science. 6(10):108-118.
[27] A. Nchare (2007). AERC Research Papers, No.163: Analysis of factors affecting technical efficiency of Arabica Coffee producers in Cameroon. Nairobi: African Economic Research Consortium.
[28] K.R. Sharma, P. Leung, & H.M. Zalenski (1999). Technical, allocative and economic efficiencies in swine production in Hawaii: A Comparison of Parametric and Nonparametric Approaches, Agricultural Economics, 20:23-35.
[29] T. Wijaya, R. Ardika, & J. Saputra (2014). The effect of omission fertilizer application on rubber yield of PB 260. Current Agriculture Research Journal. 2(2): 68-72.
[30] R. Grabowski, S. Kraft, C. Pasurka, & A. Hassan, (1990). A ray-homothenic and efficiency: grain farms in Southern Illinois, European Review Agricultural Economics. 17:435-448.
[31] G.H. Wan, & J.R. Anderson (1990). Estimating risk effects in Chinese food grain production. Journal of Agricultural Economics. 41:85–93.
[32] S. Poungchompu, & S. Chantanop, S. (2015). Factor affecting technical efficiency of smallholder rubber farming in Northeast Thailand. American Journal of Agricultural and Biological Sciences. 10(2):83-90.
[33] A. Aliyu, I.A. Latif, M.N. Shamsudin, & N.M. Nawi, (2016). Factors affecting technical efficiency of rubber smallholders in Negeri Sembilan, Malaysia. Journal of Agricultural Science, 9(5), 226-232. Available at: https://doi.org/10.5539/jas.v9n5p226
[34] G. Danso-Abbeam, R. Aidoo, K.O. Agyemang, & K. Ohene-Yankyera. (2012). Technical efficiency in Ghana's cocoa industry: Evidence from Bibiani-Anhwiaso-Bekwai District. Journal of Development and Agricultural Economies. 4(10):287-294.
[35] T. Haryanto, B.A. Talib, & N.H.M. Salleh (2015). An analysis of technical efficiency variation in Indonesian rice farming. Journal of Agricultural Science. 7(9):144-153.