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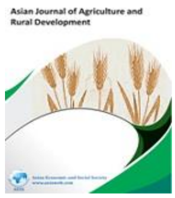

Estimating cost efficiency and sources of inefficiency in paddy farming: A study in Vietnam's Mekong Delta

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ABSTRACT
The misuse of chemical fertilizers, pesticides and herbicides in rice cultivation is leading to low-quality outputs, high production costs, health issues and environmental problems (e.g., degraded soil quality, water pollution and increasing greenhouse gases). The efficient use of production inputs would be a feasible way to mitigate these issues. This paper employed a true random-effects model to measure cost efficiency and investigate the factors affecting cost inefficiency among Vietnamese rice producers. This study used the surveyed data of 350 rice households collected in the Mekong Delta, Vietnam. The findings of this research show that the mean cost efficiency score is 0.92 with a wide variation (0.26 – 0.99). This study indicates that there is still potential for inefficient rice producers to save production costs by improving their cost inefficiency. The study also reveals a positive relationship between cost inefficiency and farm size, natural disasters and rice diseases. This suggests that as farms grow, natural disasters and rice diseases become more prevalent and rice producers become increasingly incapable of managing input costs. This study suggests that supportive policies should focus on improving rice farmers' skills to manage production inputs and deal with rice diseases and natural disasters to minimize rice production costs.

Contribution/Originality: This study uses an accurate random-effect model technique to determine cost efficiency while taking into consideration farm variation which has usually been ignored in past efficiency studies. The findings suggest policy implications for supporting rice households to save production costs and this is also a reference for other paddy-producing countries.

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1. INTRODUCTION
Rice plays an important role in ensuring economic development and food security in developing and underdeveloped countries (Trong, Burton, Ma, & Hailu, 2022). However, the abuse of inputs such as pesticides, herbicides and chemical fertilizers is causing health problems, high production costs, low-quality outputs and environmental problems (e.g., soil quality degradation, water pollution and increasing greenhouse gas emission) (Ho,

Hung, & Tien, 2023). The efficient use of inputs would be a feasible way to mitigate these issues (Ho, 2021; Ho et al., 2023).

There have been several studies conducted worldwide on the estimate of rice production efficiency (Trong et al., 2022). However, researchers seemed to focus primarily on estimating productive efficiency while ignoring the influence of input prices which have a significant effect on household decisions about which inputs to use and in what ways to reduce production costs (Ho, 2021). Some studies have attempted to take price effects into account in measuring efficiency in rice farming using the cost frontier function to estimate cost efficiency (CE) (Coelli, Rahman, & Thirtle, 2002; Huang, Huang, & Fu, 2002; Nguyen, Hoang, & Seo, 2012; Siagian & Soetjipto, 2020; Tu & Trang, 2016). However, farm heterogeneity has not been studied which might result in biassed estimations and cost-efficiency evaluations.

Therefore, the goal of this study is to determine how successfully rice farmers control production costs by measuring and analysing cost efficiency and its influencing elements. We take farm heterogeneity into account using a translog stochastic cost frontier function with the true random-effects (TRE) model approach (Greene, 2005; Greene, 2005). We estimate the pooled and TRE models and use the likelihood ratio test to examine the existence of farm heterogeneity in the current dataset.

This paper makes two contributions to the literature: (i) This study first attempts to employ the true random-effects model to take farm heterogeneity which was always ignored in previous studies related to efficiency measurement into account to obtain robust estimates for measuring cost efficiency and examine the factors affecting cost inefficiency in rice production among Vietnamese rice farmers. (ii) The findings of this paper provide useful policy implications for Vietnamese policymakers to design proper policies for the rice sector to help rice farmers minimize production costs. This study is also a reference for other rice farming countries.

2. LITERATURE REVIEW

The work of Farrell (1957) served as the foundation for empirical efficiency measurement. Since his work, the efficiency measurement method has been widely developed in several approaches. The parametric approach also known as the stochastic frontier analysis (SFA) method (Aigner, Lovell, & Schmidt, 1977; Battese & Corra, 1977) and the non-parametric approach (mathematic programming) also known as the data envelopment analysis (DEA) method are the two methods that are frequently used in empirical studies to estimate efficiency (Charnes, Cooper, & Rhodes, 1978). A comprehensive review of concepts and estimation methods of efficiency measurement is provided by Batiese (1992); Bauer (1990); Førsund, Lovell, and Schmidt (1980) and Greene (2008).

The SFA and DEA methods are two commonly used approaches for measuring efficiency in rice farming (Bravo-Ureta et al., 2007; Trong et al., 2022). The SFA method has the advantage of being able to separate statistical noise from the inefficiency term but its disadvantage is that it requires prior assumptions about the production functional form and the distribution of the error term (Bauer, 1990). On the other hand, the DEA method does not require these assumptions but is limited in its ability to distinguish between statistical noise and inefficiency estimates (Bauer, 1990). In this study, the parametric SFA approach is used for its advantage of separating random noise and heterogeneity from the inefficiency term.

In empirical research, the translog (TL) and Cobb-Douglas (CD) production functions are frequently used when addressing functional form selection. The log-likelihood ratio (LR) test can be used to determine the dataset's optimal functional form.

The truncated normal distribution has been proven to be more acceptable in previous studies. The exponential, half-normal, gamma and truncated normal distributions are the most often used in the literature for the inefficiency term distribution (Baccouche & Kouki, 2003; Ho, 2021). We have examined all three forms of inefficiency distributions in this study and found that the models performed better when the normal distribution was truncated.

Variations in rice farming inefficiency can be affected by farmer and farm characteristics and geographical factors. The present study is based on literature reviews suggests that the cost-inefficiency performance of Vietnamese rice farmers is influenced by various factors including the educational attainment and gender of the household head, the number of household members, the area under rice cultivation, the distance between the house and the rice field, the number of rice-farming training attendances, natural disasters and rice diseases (George Edward Battese & Coelli, 1995; Dhungana, Nuthall, & Nartea, 2004; Ho, 2021; Rahman, 2003; Sherlund, Barrett, & Adesina, 2002; Siagian & Soetjipto, 2020; Trong & Napasintuwong, 2015; Tu & Trang, 2016; Wadud & White, 2000).

3. MATERIALS AND METHODS

3.1. Stochastic Cost Frontier Function

This paper uses the true random-effects model technique to estimate cost efficiency and identify inefficiencies across Vietnamese rice fields as previously indicated. The stochastic true random-effects model of the cost frontier function is expressed as

$$C_{it} = f(W_{it}, Y_{it}, \beta_i) * exp(w_i + \varepsilon_{it}) \quad (1)$$

Where C denotes the variable cost, $i = 1, 2, \ldots, n$ represents the i-th household, $t = 1, 2, \ldots, T_i$ is the time period. $f(\cdot)$ represents the function, Y represents output quantity, W represents a vector of input prices and β denotes a vector of parameters that need to be estimated. w is to capture unobserved farm heterogeneity (Greene, 2005; Greene, 2005), ε_{it} is a composed error term, $\varepsilon_{it} = v_{it} + u_{it}$, while v_{it} captures a random noise term and u_{it} is to capture the cost inefficiency.

To ensure that the estimates of Equation 1 follow economic theory, the stochastic cost frontier function in Equation 1 has to meet the following properties of a cost function: (i) the cost function, *C(Y, W)* is non-negative, continuous, concave and homogeneous of degree one in input prices (*W*) for given output (*Y*); (ii) the cost function, *C(Y, W)* is non-decreasing in input prices (*W*) for given output (*Y*) and (iii) the cost function, *C(Y, W)* is non-decreasing, concave and homogeneous of degree one in output (*Y*) for given input prices (*W*) (Kumbhakar & Lovell, 2003).

The cost inefficiency (u_{it}) among farms is assumed due to the differences in farms and farmers' characteristics. This relationship is written as a linear function.

$$u_{it} = \varphi_0 + \varphi Z_{it} \qquad (2)$$

Where φ_0 and φ are parameters that need to be estimated, Z_{it} is a vector of explanatory factors that include farm and farmer characteristics to capture the cost inefficiency variations among rice farms.

3.2. Data Source and Variable Definition

We used the primary data that was collected in the Mekong River Delta using a face-to-face interview method. We chose to study in the Mekong River Delta because it is the main rice-cultivation area of Vietnam which contributes more than 50% of paddy quantity and harvested rice area (GSO, 2023). After cleaning the data, the final data set used in this study consists of 350 rice farmers with 918 observations as each rice farmer can grow rice in two or three seasons. The variables used in the stochastic cost frontier function include variable cost (*C*), output quantity (*Y*), the prices of seed, fertilizers and labor inputs (*Wseed*, *Wfert* and *Wlab*) and dummy variables to measure rice variety (D_{HQV}) and copping season ($D_{S\text{-}A}$ and $D_{A\text{-}W}$) effects. We use variables related to farmer and farm characteristics including gender, educational levels, rice farming experience, extension, household size, land ownership, farm size, paddy diseases, natural disasters and distance to examine the sources of cost inefficiency among rice farmers. The definition and statistical summary of these variables are given in Table 1.

Table 1. Definition and descriptive statistics of variables.

Variable	Definition	Mean	Std. dev.
Variable cost, input prices and paddy quantity			
VC	Variable cost (USD).	859.01	735.48
Y	Total quantity of harvested paddy (kg).	15,305.26	14,144.24
Wfert	The price of fertilizer (USD/kg).	0.40	0.06
Wlab	Labor wage (USD/working day).	5.77	1.58
Wseed	The price of seed rice (USD/kg).	0.43	0.13
$D_{S\text{-}A}$	Equal to 1 if the summer-autumn season, 0 otherwise.	0.36	0.48
$D_{A\text{-}W}$	Equal to 1 if the autumn-winter season, 0 otherwise.	0.27	0.45
D_{HQV}	Equal to 1 if high-quality rice varieties, 0 otherwise.	0.42	0.49
Factors affecting cost inefficiency			
Gender	Gender of household head (Equal to 1 if male, 0 otherwise).	0.96	0.20
Education	The educational levels of household head (Years).	6.17	3.27
Experience	Paddy production experience of household head (Years).	26.95	12.08
Extension	The number of paddy production extension attendances (Number).	2.45	4.88
House-size	The number of household members (People).	3.75	1.49
Land-own	Percentage of rice land owned by households (%).	75.11	37.41
Farm-size	Farm size (Hectare).	2.38	2.09
Disaster	Paddy loss due to natural disasters (%).	11.00	12.98
Disease	Paddy loss due to paddy diseases (%).	2.86	5.45
Distance	The distance from the house to the rice field (km).	1.47	4.64

4. RESULTS AND DISCUSSION

4.1. Estimates of the Stochastic Cost Frontier Function

The calculated parameters for both models are shown in Table 2 and they were implemented with STATA software (version 17).

Table 2. Estimates of the translog stochastic frontier cost function.

Variable	Pooled		TRE	
	Coefficient	Std. err.	Coefficient	Std. err.
Cost frontier model				
Constant	−0.304***	0.023	−0.320***	0.022
lnWseed	0.252***	0.035	0.250***	0.040
lnWfert	0.587***	0.042	0.555***	0.055
lnY	0.914***	0.013	0.872***	0.015
½lnWseed_sq	0.176	0.107	0.196*	0.109

Variable	Pooled		TRE	
	Coefficient	Std. err.	Coefficient	Std. err.
½lnWfert_sq	0.424	0.274	0.686**	0.328
½lnY_sq	0.091***	0.015	0.113***	0.015
lnWseed_Wfert	−0.118	0.134	−0.201	0.133
lnWseed_Y	0.002	0.027	0.000	0.026
lnWfert_Y	0.104***	0.040	0.074	0.045
D_{S-A}	0.184***	0.017	0.178***	0.010
D_{A-W}	0.205***	0.019	0.180***	0.012
D_{HQV}	−0.047***	0.017	−0.028*	0.016
Cost inefficiency model				
Constant	−3.541***	0.640	−4.500***	0.821
Gender	−0.586	0.506	0.032	0.690
Education	−0.088	0.120	−0.082	0.140
Experience	0.044	0.119	−0.071	0.142
Extension	−0.078	0.109	−0.104	0.136
House-size	−0.197*	0.111	−0.156	0.120
Land-own	−0.178	0.110	0.081	0.136
Farm-size	0.188	0.120	0.299**	0.124
Disaster	1.121***	0.156	1.211***	0.147
Disease	0.231**	0.103	0.219**	0.096
Distance	0.164*	0.091	0.101	0.120
Model properties				
Σ wi	−	−	0.174***	0.009
$E(\sigma_{u_{it}})$	0.163	−	0.139	−
$\sigma_{v_{it}}$	0.192***	0.006	0.106***	0.005
Log-likelihood	130.05	−	286.65	−

Note: *, **, and *** denote the statistically significant levels at 10%, 5%, and 1%, respectively.

We use the LR test to identify the preferred functional form and model. The LR ratio to test the Cobb-Dough functional form against the translog form (H_0: $\alpha_{jk} = \beta_h = \gamma_j = 0$) for pooled and TRE models are 288.68 and 63.44, respectively which are much greater than the critical values at a significant level of 99%, $\chi^2_{0.99}$ (6) = 16.074 (Kodde & Palm, 1986) for all models. This suggests that the translog functional form represents rice production technology better than the Cobb-Dough functional form. Subsequently, we test the absence of farm heterogeneity ($H_0{:}\sigma_{w_i} = 0$) using the LR test of the pooled model against the TRE model with the translog form. The LR statistic is 313.2 much greater than the critical values at a significant level of 99%, ($\chi^2_{0.99}$ (1) = 5.412) confirming that there is strong evidence of the existence of farm heterogeneity among rice farmers. The existence of farm heterogeneity in the present data is also confirmed by the significant estimate of the parameter σ_{w_i}.

The estimated parameters of the cost frontier functions for pooled and TRE models are provided in Table 2. The first-order coefficients of seed price, fertilizer price and output are as expected, positive and statistically significant at 1%. Thus, the parameter estimates of the pooled and TRE models satisfy the properties of the cost frontier function that the optimal variable cost has a positive relationship with output quantity and input prices.

The estimate of the D_{HQV} coefficient is negative and statistically significant in both pooled and TRE models suggesting that the variable production cost of the high-quality rice variety is lower than that of the conventional variety group. The estimates of both models also show that there is strong evidence of the impact of cropping seasons on rice farmers' variable cost frontier. The variable costs for rice production in the summer-autumn (D_{S-A}) and autumn-winter (D_{A-W}) seasons are significantly higher than those in the winter-spring (D_{W-S}) season. The estimate of theta (σ_{w_i}) in the TRE model that measures farm heterogeneity is statistically significant implying that unobserved farm heterogeneity exists among rice farmers that needs to be taken into account. Thus, the use of the TRE model to control the heterogeneity effect is appropriate.

Table 3. Summary of partial cost elasticities with respect to output quantity and input prices.

Variable	Pooled		TRE	
	Mean	Std. dev.	Mean	Std. dev.
Seed price	0.239	0.065	0.239	0.067
Fertilizer price	0.543	0.137	0.521	0.165
Labor price	0.218	0.159	0.240	0.162
Output quantity	0.876	0.093	0.827	0.107

We predicted the partial variable cost elasticities with respect to paddy quantity and input prices to understand how the variable cost varies due to the changes in output quantity and input prices. The results will provide vital information to support policymakers in designing appropriate policies to manage the rice sector based on the input price and quantity instruments. The estimated results for each model are consistent as shown in Table 3. The partial elasticities of variable cost in rice farming with respect to paddy quantity and input prices satisfy the properties of the cost function as mentioned above that they are positive for input prices and output quantity. The results also show that variable cost is more elastic with respect to paddy quantity than input prices. The partial variable cost elasticity with output quantity is 0.827 implying that if output quantity increases by 10%, the variable cost will increase by 8.27% given that other factors remain unchanged. The mean elasticity of variable costs with respect to fertilizer is 0.521, double that of seed and labor prices, 0.239 and 0.24, respectively. Thus, a 10% increase in the input prices of fertilizer, seed and labor will increase the variable cost of rice production on average by 5.21%, 2.39% and 2.4% respectively keeping other factors constant.

4.2. Cost Efficiency Analysis

Table 4 presents a summary of the cost efficiency estimates categorised by rice variety groups and cropping seasons. The average cost efficiency estimates for the pooled model are lower than those of the TRE model, implying that inefficiency levels were overestimated because the pooled model is not able to consider farm heterogeneity. The average cost efficiency over sampled farms is 0.919 with a wide variation in cost efficiency among rice farmers (0.26–0.99) implying that there is room for inefficient rice farms to save production costs if they reduce their inefficiency. Our estimated mean cost efficiency is consistent with the results of Tu and Trang (2016) who showed that the mean cost efficiency in paddy production in An Giang province, Vietnam's Mekong Delta is 0.9 (0.72–0.97). In addition, our result is close to the finding of Siagian and Soetjipto (2020) who found a result of 0.86 for rice households in Indonesia.

Table 4. Statistical summary of cost efficiency scores by cropping seasons and rice varieties.

Variable	Observation	Pooled		TRE	
		Mean	Std. dev.	Mean	Std. dev.
By cropping season					
Winter– spring	339	0.920	0.089	0.936	0.080
Summer–autumn	329	0.905	0.073	0.924	0.062
Autumn–winter	250	0.875	0.115	0.890	0.114
By variety					
High quality rice varieties	384	0.893	0.114	0.909	0.106
Conventional rice varieties	534	0.910	0.074	0.926	0.070
Overall cost efficiency	918	0.903	0.093	0.919	0.087

Table 4 shows that there are differences in the mean cost efficiency among cropping seasons and rice variety groups. The traditional rice variety adopters had an average cost efficiency of 0.926 which is greater than that of the high-quality rice variaty adopters (0.909). This indicates that the high-quality rice variety group performed more inefficiently than the conventional variety group. The mean cost efficiency of the winter-spring cropping season is 0.936, higher than those of the summer-autumn and autumn-winter 0.924 and 0.89, respectively. Thus, we find that seasons considerably affect variable cost frontiers and cost efficiency in rice farming among Vietnamese rice farms.

4.3. Determinants of Cost Inefficiency

An important thing in efficiency measurement is to investigate the factors affecting farmers' inefficiency performance by estimating the inefficiency model. Table 2 presents the estimated outcomes of the cost inefficiency model (described in Equation 1) in the present study. These findings were calculated concurrently with the stochastic cost frontier models (defined in Equation 2).

The results of the inefficiency model indicate that the estimates of educational levels, experience, household size, and extension are negative. However, they are not statistically significant implying that there is no clear evidence of the effects of these factors on farmers' cost inefficiency performance. There is also no statistical evidence on the relationship between gender, rice land ownership, distance and cost inefficiency. We find that farm size has a positive impact on farmers' cost inefficiency indicating that the larger the farm size, the more cost-inefficient farmers are. This finding is consistent with the findings of Tu and Trang (2016) in An Giang, Vietnam and Siagian and Soetjipto (2020) in Indonesia. Our research finds that natural disasters and paddy diseases have a positive impact on cost inefficiency.

5. CONCLUSION AND POLICY IMPLICATIONS

This research measures cost efficiency and investigates the factors that influence the cost inefficiency among paddy households by applying the stochastic frontier analysis approach with a true random effects model. This paper used primary data gathered from 350 paddy households in the Mekong Delta, southern Vietnam. The estimated results confirm that the absence of farm heterogeneity was rejected and is necessary to be controlled. This means that the estimated results of the true random effects model are more plausible than those of the pooled one. The first-order estimates of variable input prices are positive and statistically significant as expected. We also find that variable costs have a positive relationship with paddy quantity.

The partial cost elasticities with respect to paddy quantity and the prices of inputs indicate that variable costs in rice production are inelastic for output quantity and input prices. The partial cost elasticity estimate with respect to fertilizer price is 0.521, double that of seed and labor prices, 0.24 implying that fertilizer is the major input cost of rice farming. The partial cost elasticity estimate with respect to output quantity is 0.827 implying that if output quantity increases by 10%, the variable cost will increase by 8.27% keeping other factors constant.

The estimation of cost efficiency reveals that although rice farmers exhibit a high cost efficiency (0.92) on average, cost efficiency scores among rice farmers have a wide range of variation (0.26 – 0.99). The research results suggest that inefficient rice farmers still have the potential to reduce production costs if they improve their efficiency. The estimates of the cost inefficiency model report that the variation in cost inefficiency among rice farms is due to rice area, natural disasters and rice diseases. The results show that rice areas, natural disasters and rice diseases positively and significantly impact farmers' cost inefficiency. However, there is no evidence on the effects of education, rice farming experience, gender, household size, rice land ownership, extension and distance on farmers' cost inefficiency performance.

This study suggests that training programs should focus on improving the production skills of rice farmers so that they can manage input costs and deal with rice diseases and natural disasters better to reduce paddy losses.

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