The Technical Efficiency Change of

Cooperative Stores in Thailand

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Abstract

This study aims to verify factors determining the level of technical inefficiency of cooperative stores in Thailand from 2017–2021. The balanced panel data of 86 cooperative stores and the stochastic frontier analysis approach were employed to serve the objective. The results indicated the existence of inefficiency among cooperative stores in Thailand. By applying the Translog production function, the estimated technical efficiency scores for most decision-making units had an upward trend during 2017–2018 but slightly decreased during 2018–2020, i.e., the beginning of the COVID-19 pandemic, and finally began to rise again from 2021 after most people had been vaccinated and COVID-19 became endemic. Finally, the significant negative relationships between technical inefficiency and debt-to-equity ratio, reserves, and the location dummy variable suggest that to improve efficiency, cooperative stores should efficiently utilize their debts, maintain the appropriate number of reserves, and exercise the appropriate marketing strategies.

Keywords: cooperative stores, stochastic frontier analysis, technical efficiency change

1. Introduction

Cooperative stores are one form of legal entity of cooperative enterprise. By gathering individuals with the same business purposes, cooperative stores aim at providing quality consumer goods with fair prices and positioning themselves to be the organization promoting the well-being of cooperative members while helping their members solve the problem of high costs of living. Members of cooperative stores not only receive satisfaction from consuming quality products with reasonable prices but also gain benefits in the forms of dividends and average cash back, depending on the amount of share capital and the amount of spent on purchases with stores.

Although cooperative stores in Thailand are practicable, their business operations from 2017–2021 had inferior performance. The shrinkage of their profits, number of stores, and business volumes (Table 1), concomitant with an increase in total liabilities, were the results of (1) severe competition both domestically and internationally from modern trade and electronic commerce, (2) the COVID-19 pandemic causing unemployment rates, followed by the deterioration of consumer purchasing power, and (3) the rise of the inflation rate caused by both demand, i.e., pull inflation via expansionary fiscal policy during the pandemic, and cost, i.e., push inflation due to the war in Ukraine affecting the world prices of oil and animal feed. Additionally, the deficient performance of cooperative stores was due to internal factors, such as a low level of staff quality.

Table 1. Performance of cooperative stores in Thailand (2017–2021)

	2017	2018	2019	2020	2021
Number of Stores	171	176	168	153	152
Number of Members (Persons)	738,573	750,028	749,979	661,353	714,341
Business Volume (Millions of \$)	5,579.70	5,153.73	5,247.29	4,282.25	1,583.81

	2017	2018	2019	2020	2021
Profits (Millions of ₿)	145.26	136.14	219.82	138.61	50.35
Total Liabilities (Millions of \$\mathbb{B})	1,115.79	1,223.96	1,060.78	974.35	484.16
Operating Capital (Millions of \$)	1,785.4	1,744.98	1,905.43	1,883.47	871.39

Source: Cooperative Auditing Department, 2022

Consequently, the objectives of this study were as follows: (1) to measure the technical efficiency of cooperative stores in Thailand by using Stochastic Frontier Analysis (SFA), (2) to determine the factors affecting the technical inefficiency of cooperative stores in Thailand, and (3) to examine the change of efficiency level of cooperative stores in Thailand from 2017–2021. In this study, the parametric method, Stochastic Frontier Analysis (SFA), was applied to the information of 86 cooperative stores in Thailand that were in full operation from 2017–2021.

A contribution of this study to the current empirical papers in this field is by providing the estimated result of the technical efficiency score of cooperative stores and investigating the trend of these scores over time. Moreover, due to the parametric characteristic of SFA, the model can determine the significant sources of cooperative stores' inefficiency, which, in turn, suggests the policy recommendation to close the inefficiency gap of cooperative stores in Thailand.

The remainder of the paper is organized as follows. Section 2 presents reviews of related literature on this topic. The scope of the study and methodology are explained in Section 3. The results and their interpretation are shown in Section 4. Section 5 provides the conclusion and recommendations.

2. Literature Review

Recent studies related to the SFA estimation of the technical efficiency score of cooperatives were found by Qu et al. (2020), where the authors separated cooperatives into two groups: (1) a collective marketing group for farmers and (2) an equivalent non-marketing group that provided no marketing service. By applying the Propensity Score Matching (PSM) method and SFA, they found that the roles of cooperatives' duties directly affected the technical efficiency score for each decision making unit (DMU). The results also showed that being a member of both types of cooperatives would positively enhance DMUs' output quantities. Moreover, the technical efficiency scores of farmers with the memberships of a non-marketing group were higher than those with the memberships of a collective marketing group. The study suggested that policymakers should encourage cooperative members to focus on activities that were not related to market promotion so as to improve the technical efficiency level, in their case, apple producers in China.

Kashiwagi (2020) studied the effects of being a member of agricultural cooperatives on the technical efficiency and total factor productivity of olivegrowing farms in West Bank, Palestine. The author used cross-sectional data from olive-growing farms in Jenin province. The methodology began with propensity score matching to reduce the problem of selection bias in the sample. Then, the author applied SFA to determine the technical efficiency score of DMUs and used the residual approach method to determine the value of total factor productivity. The results showed that participation in cooperatives caused the average technical efficiency score of sample DMUs to increase from 10.16% to 10.52% because of the advantages in loan access, quality of saplings, soil preparation, and other services provided by cooperatives. The study suggested that joining as members of cooperatives was the appropriate strategy to improve

technical efficiency and enhance the competitive capability of olive-growing farms in Jenin.

Ahmad and Ahmad (2018) investigated the dynamics of the technical efficiency of sugar mills in India. The main objectives were to measure the technical efficiency of sugar mills and identify factors influencing the technical efficiency score. The author used SFA to determine the technical efficiency of 115 sugar mills in Uttar Pradesh. The results revealed that among all sugar mills, the ones operating in the form of public limited companies had the highest average value of the technical efficient score, followed by sugar mills operating in the form of individual proprietors, while the lowest average value of technical efficient score was found among the group operating in the form of public corporations. Furthermore, by using entrepreneurship to categorize types of sugar mills, the study expressed that sugar mills that had co-ownership between state and central government and the ones that were private companies had higher technical efficiency scores than sugar mills with other forms of entrepreneurship. Finally, the results indicated that the number of years in operation was the only factor that had a positive impact on technical efficiency, while the location of mills had no significant effect on the technical efficiency score.

The remaining papers applied SFA to measure the technical efficiency score of agricultural business units at the farm level. For example, Abdul-Rahaman (2016) examined the profitability, financial efficiency, and constraints among cotton farmers in three northern provinces in Ghana, i.e., Tolon, Karaga, and Savelugu Nanton, by using SFA. The author used questionnaires to interview 150 smallholder cotton farmers, and the results showed that the estimated technical efficiency scores of cotton farmers ranged between 16.05% and 98.13%, and the average scores of the sample were equal to 15.05%. Moreover, the factors significantly affecting the technical efficiency scores consisted of farm

age, gender, memberships of the farmer group, educational level, size of households, and farmer experiences.

Tuan (2016) examined the characteristics of rice farmers and the problems of rice production in agricultural cooperatives in the Kien Giang province of Vietnam. 276 rice farmers who had memberships in four agricultural cooperatives in the Chau Thanh district were surveyed. The author used SFA with the Cobb-Douglas production function to estimate the technical efficiency scores of rice production for all DMUs and identify the main factors affecting such scores. The results revealed that the average technical efficiency score of rice farmers who were members of cooperatives was equal to 92.4%, and the factors significantly influencing such scores consisted of farmland size, seed quantities, potassium fertilization, and number of laborers. By contrast, the factors affecting the inefficiency of rice production included farmers' experience, technical training in rice production, number of years of cooperative membership, and number of cultivation cycles per year. The study suggested appropriate policies to improve the technical efficiency level of rice production, such as reducing the seed quantity used, increasing potassium fertilizer volume, and regularly monitoring the farms' operation. Moreover, the managerial policies of agricultural cooperatives, such as the enhancement of business knowledge for members and encouragement of minor farmers to work together as large-scale farms, could boost the farms' efficiency.

Chiona et al. (2014) estimated technical efficient scores for smallholder maize farmers in a central province in Zambia, where corn production was the main crop. The author used SFA to estimate the efficiency score and identify factors significantly affecting such scores of maize farmers; primary data on 400 maize farmers were used to estimate the SFA. The results revealed the opportunity for Zambian maize farmers to improve the efficiency of maize

production by reducing the number of factors used in the process. The estimated average technical efficiency score of the sample was equal to 0.50. The lowest and the highest technical efficiency scores were equal to 0.02 and 0.84, respectively. About 14% of Zambian maize farmers in the sample had a technical efficiency score lower than 0.30, while 46% of the sample had technical efficiency scores higher than 0.50. Furthermore, only 14% of the sample had technical efficiency scores higher than 0.70. The study indicated that farmer age, certified seed usage, loan accessibility, consulting on agricultural technology, and revenue from off-farm activities were the factors significantly influencing the technical efficiency score. The study suggested that the Zambian government and stakeholders of maize production should design appropriate policies, such as improving loan accessibility to farmers, consulting on agricultural technology, and encouraging farmers to use hybrid certified seeds.

Finally, Gounder and Xayavong (2004) applied SFA to determine the total factor productivity growth (TFP) of the manufacturing industry in New Zealand from 1978–1998. The authors divided the methodology into two steps. First, the authors applied SFA to estimate technical efficiency scores for DMUs, and second, they used the estimated scores as the dependent variable and regressed them on other explanatory variables to determine the impacts of these variables on efficiency scores. Moreover, the authors decomposed TFP into four parts, representing the following changes: (1) technological progress, (2) technical efficiency, (3) scale efficiency, and (4) allocative efficiency. The results revealed that both technological progress and allocative efficiency of the New Zealand manufacturing industry were improved, especially during the Post-Reform Period (1984–1998), while the technical efficiency had a downward trend in the same period. Finally, the results also showed that scale efficiency was the smallest component in TFP.

3. Research Methodology

3.1 Theoretical Framework

This study employed the technique of stochastic frontier analysis (SFA) (Meeusen & Van den Broeck, 1977; Aigner et al., 1977). SFA is the parametric approach to estimating the technical efficiency score of decision-making units (DMUs). Under this approach, SFA attempts to statistically estimate coefficients and the structure of error terms by decomposing them into the following two components: (1) random effect, representing the uncertainty of DMUs' surroundings, and (2) technical inefficiency, representing the inefficiency of the production process within the DMUs. However, to determine an efficiency score, SFA requires the specification of production function. The general functional forms include Translog and Cobb-Douglas functions. Initially, the production function specified for cross-sectional data under the SFA was in the following form:

$$Y_i = f(X_i; \beta) + \varepsilon_i \tag{1}$$

where, Y_i represents the output of DMU i (i = 1, 2, ..., N), β is the vector of unknown parameters, X_i is the ($K \times 1$) vector of inputs of DMU i, $f(X_i; \beta)$ is the production function that relates number of inputs to the maximum level of output produced, and ε_i are the error terms. As mentioned, the main idea of SFA is the decomposition of ε_i into two terms, as follows:

$$\varepsilon_i = V_i - U_i \tag{2}$$

where, $V_i(-\infty < V_i < \infty)$ is the random variable assumed to be independent and identically distributed with 0 means and constant variance (σ_V^2) or $V_i \sim iidN(0, \sigma_V^2)$, whereas U_i is the non-negative random variables assumed to be independent and identically distributed with 0 means and constant variance (σ_U^2) or $U_i \sim iid|N(0, \sigma_U^2)|$, and independent of V_i . In this case, V_i represents the

random effect on the output outside the control of DMUs while U_i accounts for the inefficiency of production process of DMUs, which measures the shortage of output from the stochastic frontier $f(X_i\beta) + V_i$. As a result, the technical efficiency score of DMU i (TE_i) can be calculated as:

$$TE_i = \frac{Y_i^*}{Y} = \frac{f(X_i; \beta) \exp(V_i - U_i)}{f(X_i; \beta) \exp(V_i)} = \exp(-U_i)$$
 (3)

Equation (3) shows that technical efficiency score is the ratio between the observed output of DMU i (Y_i^*) and the level of output of the same DMU on the production frontier (Y) when DMU uses the same number of inputs. In this case, the frontier output (Y) is equal to the estimated output computed from equation (1) plus the value of respective V_i for each DMU. The estimated values of TE_i from equation (3) range between 0 and 1.

The technique of SFA applied with the unbalanced panel data was found in Battese and Coelli (1995). The authors improved equation (1) to compute the technical efficiency of DMU i (i = 1,2,...,N) over the period t (t = 1,2,...,T) as follows:

$$Y_{it} = f(X_{it}; \beta) \exp(V_{it} - U_{it})$$
(4)

and
$$U_{it} = \eta_{it} U_i = \{ \exp[-\eta(t-T)] \} U_i$$
 (5)

where, Y_{it} is the output level of DMU i in period t, $f(X_{it}; \beta)$ is the production function related to the maximum level of output that can be produced by using a number of inputs (X_{it}) , and X_{it} is the $k \times 1$ vector of inputs used for the production of DMU i in period t. β is the vector of unknown parameters, V_{it} is the random variable assumed to be $V_{it} \sim iidN(0, \sigma_V^2)$ representing uncontrollable effect on the output level of DMU i in period i. i is a non-negative random variable assumed to be i0 by i1 in period i2. Finally, the unknown parameter i1 represents the adjustment of i2 over time. In this model, the value of i3 has an inverse relationship with

the value of U_{it} as follows: $\eta > 0 \rightarrow U_{it}$ tends to decrease when t increases; $\eta < 0 \rightarrow U_{it}$ tends to increase when t decreases; and $\eta = 0 \rightarrow U_{it}$ is stable when t increases.

Furthermore, the overall variance of model (σ^2) can be computed from the variance of V_{it} and U_{it} as:

$$\sigma^2 = \sigma_V^2 + \sigma_U^2 \tag{6}$$

and
$$\gamma = \frac{\sigma_U^2}{\sigma^2} \tag{7}$$

where, γ is coefficients measuring the deviation of observed outputs (Y_i^*) from the frontier output (Y). The value of γ ranges from 0 to 1 ($0 \le \gamma \le 1$). Like the cross-sectional SFA model, the panel version of SFA can compute the technical efficiency score of DMU i in period t TE_{it} by using the formula:

$$TE_{it} = \exp(-U_{it}) \tag{8}$$

Also, the value of computed TE_{it} ranges between 0 and 1.

Generally, when the production process is affected by technical inefficiency, the SFA model from equation (4) can be estimated by the maximum likelihood method (ML). Theoretically, the ML estimators are more consistent than other estimating methods such as ordinary least squares (OLS).

3.2 Data and Model Specification

To define the production function, the output and input variables and their supporting reasons must preliminarily be determined. In this study, revenue from the sale of goods and the rendering of service (R_{it}) is used as the dependent variable, while direct business cost (DB_{it}) , operating expenses (OE_{it}) , and non-current assets (NC_{it}) are treated as the independent variables of the SFA model. Moreover, three other variables, including current liability (CL_{it}) , non-current liability (NCL_{it}) , and amount of share capital (SC_{it}) , are used as the explanatory

variables affecting the inefficiency level of cooperative stores. All variables are computed in terms of per unit of member to remove the bias due to the cooperative sizes. The supporting reasons for all variables are shown in Table 2.

Table 2. Details on output and input variables of SFA model

Outnut Variable	Connection Decree
Output Variable	Supporting Reason
Revenue from the sale of goods and the rendering of service $(R_{it}: Baht/member)$	Income received by cooperative stores from selling their goods or providing services to members and customers. Revenue is gained from the core business of cooperative stores, reflecting firms' ability to create the value added for their business. As a result, R_{it} can be treated as the output variable representing the business performance of cooperative stores.
Input Variables (SFA)	Supporting Reason
Operating Expenses (OE_{it} : Baht/member)	Operating expenses refers to costs that keep cooperative stores running their day-to-day operations, e.g., office supplies, payroll, marketing costs, etc. OE_{it} is treated as an input variable representing other costs that cooperative stores incur while performing their operational activities.
Non-Current Assets $(NC_{it}: Baht/member)$	Non-current assets of fixed assets refers to resources that cooperatives own for the sake of revenue generation. In this case, NC_{it} includes the assets that cooperatives hold for more than 1 year and could not easily be turned into cash, such as store, plant, equipment, land, property, and trademark.
Input Variables (Inefficiency)	Supporting Reason
D/E Ratio $(DE_{it}: Percent)$	The D/E ratio refers to the cooperatives' debt divided by the members' equity. This ratio represents a cooperative's financial leverage. A higher ratio indicates that cooperatives finance their operation through borrowing, while a low ratio indicates that cooperatives use equity to finance their operation. Moreover, the ratio reveals how well the cooperatives finance their operations, hence affecting their inefficiency level.
Reserves $(RS_{it}: Baht/Member)$	Reserves or retained earnings are part of cooperatives' profits used to strengthen cooperatives' financial position (e.g., repaying debt and funding expansion). Holding reserves is quite important to cooperatives since it can help them when unexpected events occur (e.g., cost ascending or revenue reduction without notice). As a result, high reserves mean cooperatives have insulation for unexpected external shocks, thus affecting the efficiency or inefficiency of each coop.
Types of Cooperative Stores $(T_{it}: Dummy)$	In this study, cooperative stores are categorized into 2 groups: (1) cooperative stores related to educational institutions and hospitals $(T_{it} = 0)$ and (2) cooperative stores not related to educational institutions and hospitals $(T_{it} = 1)$. This dummy variable is added to the model to indicate the difference in technical inefficiency between these two groups.

For model specification, this study applied both Cobb-Douglas and Translog production functions for the panel-data version of SFA in equation (4). The SFA production functions in both forms are defined as:

SFA Cobb-Douglas Production Function:

$$\ln R_{it} = \beta_0 + \beta_1 \ln O E_{it} + \beta_2 \ln N C_{it} + V_{it} - U_{it}$$
(9)

SFA Translog Production Function:

$$\ln R_{it} = \beta_0 + \beta_1 \ln OE_{it} + \beta_2 \ln NC_{it} + \frac{1}{2}\beta_3 (\ln OE_{it})^2 + \frac{1}{2}\beta_4 (\ln NC_{it})^2 + \beta_5 (\ln OE_{it}) (\ln NC_{it}) + V_{it} - U_{it}$$
(10)

Equations (9) and (10) assume that the random variable V_{it} independently and identically normally distributes with mean 0 and variance σ_V^2 or $V_{it} \sim iidN(0, \sigma_V^2)$ while the non-negative random variable U_{it} representing inefficiency of the production process of DMUs is assumed to be independently and identically normally distributed and truncated at 0 with mean $z_{it}\delta$ and variance σ^2 or $U_{it} \sim iidN^+(z_{it}\delta,\sigma^2)$, where z_{it} is the 1×3 vector of independent variable affecting the technical inefficiency of DMUs or $z_{it} = [DE_{it} \quad RS_{it} \quad T_{it}]$ and δ is the 3×1 vector of unknown parameters. Random variable V_{it} and U_{it} are assumed to be independently distributed for all t = 1, 2, ..., T, and i = l, 2, ..., N.

Finally, to determine the effects of factors on the inefficiency level of DMUs, Battese and Coelli (1995) defined the technical inefficiency effects as:

$$U_{it} = z_{it}\delta + W_{it} = \delta_0 + \delta_1 D E_{it} + \delta_2 R S_{it} + \delta_3 T_{it} + W_{it}$$
 (11)

where, the random variable W_{it} is normally distributed with mean 0 and variance σ^2 , and truncated at $-z_{it}\delta$ ($W_{it} \ge -z_{it}\delta$).

Equations (9)–(11) are simultaneously estimated by the ML method, and the technical efficiency score can be estimated by:

$$TE_{it} = \exp(-U_{it}) = \exp(-z_{it}\delta - W_{it})$$
 (12)

Under this specification, the model defined the variance parameter $\sigma_S^2 = \sigma_V^2 + \sigma^2$ and parameter γ (deviation of observed outputs form the frontier output), which can be computed by:

$$\gamma = \sigma^2 / \sigma_S^2 \tag{13}$$

3.3 Hypothesis Testing Under the SFA Model

Due to the parametric characteristic of the SFA model, the advantage of SFA relies on the model's ability to test the hypotheses of the estimated parameters. The main hypothesis testing of the SFA model includes the following:

3.3.1 Testing for Existence of Inefficiency in Production Process

Battese and Coelli (1995) revealed numerous ways to test for the existence of inefficiency in the production process. However, the popular and convenient method is to test $H_0: \gamma = 0$ against $H_1: \gamma \ge 0$. In this case, the test statistics consist of Wald Statistics (W) and Likelihood Ratio (LR).

Wald Statistics (W) is defined as

$$W = \hat{\gamma}/S_{\hat{\nu}} \tag{14}$$

where $\hat{\gamma}$ is the estimated parameter of γ from equation (7) and $S_{\hat{\gamma}}$ is the standard deviation of $\hat{\gamma}$. By assuming that $W \sim N(0, 1)$, if $W > Z_{\alpha}$, the decision is to reject H_0 , and the conclusion is that the SFA model is appropriate to estimate the production function of DMU.

Likelihood Ratio (LR) is defined as

$$LR = -2[\log(L_0) - \log(L_1)]$$
 (15)

where, $\log(L_0)$ is the log-likelihood value of the function under the null hypothesis H_0 (e.g., function estimated by OLS), while $\log(L_0)$ is the value of log-likelihood under the condition when H_0 is wrong (when $\gamma \neq 0$ or when

function is estimated by ML). The statistic LR follows the chi-square distribution (Kodde & Palm, 1986) with the degree of freedom N-1 or $LR \sim \chi_{N-1}^2(2\alpha)$. If $LR > \chi_{N-1}^2(2\alpha)$, the decision is to reject H_0 , indicating the existence of technical inefficiency in the production function.

3.3.2 Specification Test of the Production Function

Since the estimated technical efficiency scores are sensitive to the form of production function, the specification test of production is required to determine whether the chosen form is appropriate or not. The likelihood ratio statistic (LR) can be used to serve this objective. In this case, the LR can be computed by:

$$LR = -2[RLLF - ULLF] \tag{16}$$

where RLLF is the log-likelihood value of the restricted frontier model or the production function that is relevant to the null hypothesis H_0 , while ULLF is the log-likelihood value from the unrestricted frontier model or the production function that is relevant to the alternative hypothesis H_1 . LR statistic follows the chi-square distribution $(LR \sim \chi_{df}^2)$ with the degree of freedom equaling the number of restrictions in the model. In this case, if $LR > \chi_{df}^2(\alpha)$, the decision is to reject H_0 and concludes that the model under H_1 is more appropriate to estimate the production function than the model under H_0 .

3.3.3 The Significance Test of β_i

The estimated parameter β_i of each input variable in equation (3.1) can be tested for their significance impacts on the output variable by using the t statistic, which can be computed as follows:

$$t = \hat{\beta}_i / S_{\widehat{\beta}} \tag{17}$$

where, $\hat{\beta}_i$ is the estimated parameter of β_i , and $S_{\widehat{\beta}}$ is standard error of respective β_i . By setting up the hypothesis H_0 : $\beta_i = 0$ against H_1 : $\beta_i \neq 0$, if the computed t from equation (17) is greater than the critical $t_{\alpha/2,df.=N-1}$ or less than $-t_{\alpha/2,df.=N-1}$, the decision is to reject H_0 . This means that the respective input variable has a statistically significant impact on the output variable.

4. Results

Financial panel data of the 86 Thai cooperatives from 2017–2021 were collected to compute the stochastic frontier. Note that all variables in the model except for D/E ratio (DE_{it}) and the dummy variable (T_{it}) representing the type of cooperative stores were computed in terms of per unit of cooperative's members to alleviate the effect of cooperative size and the problem of outliers in the model. The descriptive statistics of all variables in the SFA model are shown in Table 3.

Table 3. Descriptive statistics of all variables included in the SFA model

Variables	R _{it}	ln R _{it}	OE_{it}	$\ln OE_{it}$	NC _{it}	ln NC _{it}	DE_{it}	RS_{it}
Max.	4,021,162.80	15.207	303198.51	12.622	2,160,664.55	14.586	1.380	105,550.663
Min.	58.75	4.073	97.59	4.581	0.136	-1.995	0.000	0.000
Mean	88,140.34	9.653	3822.48	7.273	19,512.036	6.065	0.208	6,367.301
S.D.	332,822.86	1.741	18739.53	1.178	186,036.655	2.164	0.194	11,404.922

Source: Computed data by the author

From Table 3, cooperative stores with the highest revenue, operating expenses, and non-current assets belonged to DMU 21 (The Consumer Cooperative Federation of Thailand LTD.), while the lowest ones were found in DMU 18 (Pattana Cooperative Store), DMU 23 (Nakorn Ping Cooperative Store), and DMU 79 (Mitsubishi Motor Officer Cooperative Store), respectively. Details on all DMUs are shown in Appendix I. Furthermore, the correlation

matrix of all variables used to estimate stochastic frontier and the technical inefficiency effects (Table 4) exhibited a strong correlation between $\ln R_{it}$ and $\ln OE_{it}$.

Table 4. Correlation matrices of variables estimating SFA and the technical inefficiency effects

	ln R _{it}	ln <i>OE</i> _{it}	ln NC _{it}	DEit	RS _{it}
ln R _{it}	1				
ln OE _{it}	0.755768	1			
ln NC _{it}	0.329853	0.448197	1		
DEit	0.262053	0.248333	0.147025	1	
RS _{it}	0.278658	0.267326	-0.01827	-0.20552	1

Source: Computed data by the author

4.1 The Estimation of Stochastic Frontier

The estimated results of SFA Cobb-Douglas and Translog production functions are shown in Tables 5 and 6, respectively. Overall, both functions seemed to be the good representative of the efficiency frontier since the estimated coefficient γ in both functions was statistically significant at a 1% level (by Wald statistic and likelihood ratio), indicating the existence of technical inefficiency among DMUs. A similar conclusion can be confirmed by the LR test of the one-sided error in both functions, which was greater than the critical value $\chi^2(2\alpha)$. Moreover, estimated coefficients of all independent variables in both functional forms were also statistically significant at a 1% level, except for the coefficient of $\ln(NC_{it})$ in the SFA Cobb-Douglas function, and have the expected signs.

However, to choose the best model for computing the technical efficiency, the likelihood ratio statistic from equation (16) can be used to determine the appropriate model. In this case, the SFA Cobb-Douglas production function was the restricted model of the Translog function; thus, the likelihood ratio statistic for model specification can be calculated by:

$$LR = -2[RLLF - ULLF] = -2[-638.4220 - (-619.0517)] = 38.7406$$

Since the critical value of $\chi^2_{df.=3}(\alpha=0.01)$ is equal to 11.43, the conclusion is to reject the null hypothesis $(H_0: \beta_3 = \beta_4 = \beta_5 = 0)$. In other words, the unrestricted model or Translog functional form was more appropriate for estimating the efficiency frontier than the Cobb-Douglas function.

Table 5: Estimated result for the SFA Cobb-Douglas production function equation (9)

Dependent Variable: $ln(R_{it})$ number of cross-sections = 86 number of time periods = 5 total number of observations = 430

Coefficients	S.E.	t Statistics
1.4719	0.1622	9.0743***
1.1758	0.0123	95.7230***
- 0.0024	0.0197	- 0.1223
0.8816	0.0358	24.6146***
- 0.1644	0.0551	- 2.9862***
- 0.00001	0.000003	- 2.8928***
- 0.8610	0.0298	- 28.9300***
1.1144	0.0290	38.4024***
0.000073	0.000013	5.6077***
d Function	- 638.4220	-
ne-sided error	55.0387***	
;	5	
	1.4719 1.1758 - 0.0024 0.8816 - 0.1644 - 0.00001 - 0.8610 1.1144 0.000073 d Function ne-sided error	1.4719 0.1622 1.1758 0.0123 - 0.0024 0.0197 0.8816 0.0358 - 0.1644 0.0551 - 0.00001 0.000003 - 0.8610 0.0298 1.1144 0.0290 0.000073 0.000013 d Function - 638.4220 ne-sided error 55.0387***

Source: Computed data by the author

Note: *, **, *** refer to statistically significant at 0.1, 0.05, and 0.01, respectively

Table 6: Estimated result for SFA Translog production function Equation (10)

Dependent Variable: $ln(R_{it})$ number of cross-sections = 86 number of time periods = 5 total number of observations = 430

- 3.1932 3.0780 - 0.5209 - 0.3656	S. E. 1.1148 0.3780 0.1473	t Statistics - 2.8645*** 8.1419*** - 3.5362***		
3.0780 - 0.5209	0.3780	8.1419***		
- 0.5209				
	0.1473	- 3.5362***		
- 0.3656				
	0.0648	- 5.6454***		
- 0.0437	0.0157	- 2.7783***		
0.1061	0.0220	4.8161***		
1.0783	0.1067	10.1014***		
- 0.9755	0.2412	- 4.0449***		
- 0.00002	0.000005	- 4.2598***		
- 0.7718	0.1011	- 7.6356***		
1.0419	0.0684	15.2235***		
0.00003	0.000006	5.1249***		
tion	- 619.0517			
l error	81.4582***			
	5			
	0.1061 1.0783 - 0.9755 - 0.00002 - 0.7718 1.0419 0.00003	0.1061 0.0220 1.0783 0.1067 - 0.9755 0.2412 - 0.00002 0.000005 - 0.7718 0.1011 1.0419 0.0684 0.00003 0.000006 dion - 619.0517 Herror 81.4582***		

Source: Computed by the author

Note: *, **, *** refer to statistically significant at 0.1, 0.05, and 0.01, respectively

4.2 The Estimated Results of Technical Efficiency and Inefficiency Effect

The technical efficiency scores (TE_{it}) of all cooperative stores estimated by Translog SFA model from 2017–2021 are shown in Table 7.

Table 7: The estimated technical efficiency of cooperative stores from 2017–2021 using SFA Translog production function

DMU	2017	2018	2019	2020	2021	DMU	2017	2018	2019	2020	2021
1	1.0000	1.0000	1.0000	1.0000	1.0000	46	0.4463	0.4465	0.4505	0.4547	0.4487
2	0.8063	0.8035	0.8066	0.7965	0.7949	47	0.4238	0.4099	0.3402	0.4235	0.4412

DMU	2017	2018	2019	2020	2021	DMU	2017	2018	2019	2020	2021
3	0.9577	0.9906	0.9954	0.9991	1.0000	48	0.4215	0.4139	0.4197	0.4220	0.4282
4	1.0000	1.0000	1.0000	1.0000	1.0000	49	0.4459	0.4540	0.4629	0.4776	0.4841
5	1.0000	1.0000	1.0000	1.0000	1.0000	50	0.4098	0.4185	0.4253	0.4344	0.4536
6	1.0000	1.0000	1.0000	1.0000	1.0000	51	0.4047	0.4042	0.4036	0.4047	0.4022
7	0.8796	0.8694	0.8524	0.8749	0.8690	52	0.4295	0.4172	0.4227	0.4315	0.4330
8	0.9986	1.0000	1.0000	1.0000	1.0000	53	0.9486	0.9403	0.8732	0.8379	0.8491
9	0.7908	0.8527	0.8552	0.8783	0.9520	54	0.5072	0.4980	0.4999	0.5272	0.5226
10	1.0000	1.0000	1.0000	1.0000	1.0000	55	0.4259	0.4226	0.4264	0.4547	0.5609
11	1.0000	1.0000	1.0000	0.9965	0.9972	56	0.4835	0.4884	0.5023	0.5059	0.4984
12	0.9263	0.9267	0.9237	0.9424	0.9385	57	0.9091	0.9158	0.8584	0.9213	0.8648
13	1.0000	0.9984	1.0000	0.9964	0.9986	58	0.4920	0.5089	0.5426	0.3616	0.3716
14	0.8483	0.8512	0.8324	0.8190	0.8236	59	0.4308	0.4329	0.4335	0.4348	0.4378
15	1.0000	1.0000	1.0000	0.9993	0.9811	60	1.0000	1.0000	1.0000	1.0000	1.0000
16	0.4239	0.4082	0.4468	0.4497	0.4689	61	0.8862	0.8752	0.8792	0.8731	0.8782
17	0.4092	0.4022	0.4070	0.4056	0.3900	62	0.3975	0.4037	0.4114	0.4032	0.4126
18	0.8889	0.8990	0.8310	0.8284	0.8555	63	0.8338	0.8244	0.8424	0.9067	0.8364
19	0.4048	0.3951	0.3918	0.3816	0.3757	64	0.7951	0.8743	0.8899	0.9162	1.0000
20	0.4360	0.5175	0.4297	0.4458	0.4598	65	0.9430	0.9644	0.9808	0.9713	0.9639
21	1.0000	1.0000	1.0000	1.0000	1.0000	66	0.3906	0.3863	0.3837	0.3673	0.3661
22	1.0000	1.0000	1.0000	1.0000	1.0000	67	0.4882	0.4830	0.4938	0.4895	0.4784
23	0.8374	0.8228	0.8758	0.8375	0.8105	68	1.0000	0.9108	0.8228	0.7858	0.8546
24	0.4425	0.4343	0.4322	0.4257	0.4271	69	0.4046	0.4024	0.4079	0.4110	0.4196
25	0.4222	0.3905	0.3901	0.3919	0.3969	70	0.4316	0.4251	0.4266	0.4318	0.4173
26	1.0000	1.0000	1.0000	1.0000	1.0000	71	1.0000	1.0000	1.0000	1.0000	1.0000
27	0.4897	0.4891	0.4848	0.4864	0.4907	72	0.4262	0.4145	0.4224	0.4166	0.4319
28	1.0000	1.0000	1.0000	1.0000	1.0000	73	0.9160	0.9382	0.9508	0.9505	0.8995
29	0.4545	0.5422	0.4514	0.4488	0.4684	74	0.9981	0.9980	1.0000	1.0000	1.0000
30	0.4115	0.4184	0.4131	0.4064	0.4194	75	0.4771	0.4915	0.4937	0.4886	0.4856
31	0.4716	0.4809	0.4885	0.4903	0.5059	76	0.4411	0.4419	0.4355	0.4832	0.4672
32	0.5181	0.5043	0.4938	0.5217	0.5212	77	0.4501	0.4567	0.4633	0.4632	0.4737
33	0.8955	0.8997	0.9759	0.9923	0.9687	78	0.4421	0.4625	0.4697	0.5026	0.5212
34	1.0000	1.0000	1.0000	1.0000	1.0000	79	0.8495	0.8512	0.8558	0.8704	0.8650

DMU	2017	2018	2019	2020	2021	DMU	2017	2018	2019	2020	2021
35	0.4944	0.4704	0.4902	0.4947	0.4818	80	0.4355	0.4400	0.4087	0.4617	0.4854
36	0.5301	0.5403	0.5308	0.5429	0.5411	81	0.5052	0.4900	0.4825	0.4734	0.4648
37	0.9232	0.9102	0.9860	0.9891	0.9391	82	0.9951	0.9484	0.9170	0.9137	0.9486
38	0.8687	0.8742	0.8679	0.8664	0.9024	83	0.7832	0.7788	0.7763	0.7758	0.7681
39	0.9858	0.9896	0.9895	0.9891	0.9992	84	0.4442	0.4473	0.4524	0.4706	0.4875
40	0.4222	0.4332	0.4413	0.4520	0.4313	85	0.4547	0.4359	0.4292	0.3819	0.3846
41	0.4798	0.4759	0.4978	0.5033	0.5042	86	0.9683	0.9751	0.9390	0.9070	0.8990
42	0.9703	0.9749	0.9805	0.9695	0.9691	Max	1.0000	1.0000	1.0000	1.0000	1.0000
43	0.9613	0.9641	0.9750	0.9664	0.9566	min	0.3906	0.3863	0.3402	0.3616	0.3661
44	0.5829	0.9177	0.8302	0.7424	0.6754	Mean	0.6967	0.7022	0.6992	0.7004	0.7026
45	0.6514	0.6520	0.6643	0.6997	0.7074	S.D.	0.2511	0.2514	0.2516	0.2504	0.2478

Sources: Computed data by the author

Results from Table 7 exhibit some issues worth mentioning here. First, only 12 cooperative stores, including DMUs 1, 4, 5, 6, 10, 21, 22, 26, 28, 34, 60, and 71, operated on the efficient frontier from 2017–2021 (*TE* scores equal to 1 for all years). Second, the average TE score slightly increased during 2017–2018 but began to reduce from 2019 and rebounded back to the initial 2019 level since 2021. This was relevant with the emergence of the COVID-19 pandemic in Thailand in 2019 and the recovery from the situation since 2021. Third, for all periods, about 40% of cooperative stores in Thailand had a TE score below 0.5. About 20% had a TE score ranging between 0.5–0.9, and another 20% had a TE score ranging between 0.9 – 0.99. Thus, only 20% of cooperative stores in Thailand operated efficiently from 2017–2021. Finally, 11 cooperatives stores, including DMUs 2, 7, 12, 18, 20, 23, 65, 66, 67, 81, and 83, showed a downward trend of technical efficiency from 2017–2021.

The technical inefficiency effect from the Translog SFA function was estimated as the following (with standard error in parenthesis):

$$\widehat{U}_{it} = 1.0783 - 0.9755DE_{it} - 0.00002RS_{it} - 0.7718T_{it}$$

$$(0.1067)^{***} \quad (0.2412)^{***} \quad (0.000005)^{***} \quad (0.1011)^{***}$$

The result showed that all three variables had a significant impact on the technical inefficiency of cooperative stores at a 1% level. The negative coefficient of DE_{it} indicated that an increase in debt-to-equity ratio caused the inefficiency to decline. Initially, the sign seemed to contrast with our expectations since cooperative stores with a high D/E ratio would have more of a burden to pay off their principles and interests, and they could have more chance of becoming bankrupt if their business performances were persistently running below target. However, it is possible that a high D/E ratio would refer to the need for cooperative stores to urgently expand their businesses or capacities since their products are in high demand in the market. As a result, a high D/E ratio would possibly lessen the inefficiency level.

Finally, both signs of independent variables RS_{it} and T_{it} are negative, as expected. Cooperative stores with high reserves means, i.e., the ones that earned profits and have a lower level of technical inefficiency, and cooperative stores located in academies or hospitals had the chance to earn high revenues and profits since they had market potential, such as easy accessibility to their customers and a limited number of competitors, which, in turn, decreased the technical inefficiency.

5. Discussion and Conclusion

This study aimed to investigate the technical efficiency change of cooperative stores in Thailand from 2017–2021 and attempted to verify factors determining the level of technical inefficiency of the DMUs. The panel data of related variables included total revenue (R), operating expenses (OE), non-current assets (NC), D/E ratio (DE), reserves (RE), and dummy variable (T),

representing the cooperative stores related to academies and hospitals. The complete data of 86 cooperative stores were used to estimate the efficiency frontier and their technical efficiency scores by applying the parametric technique of stochastic frontier analysis (SFA). Since the estimated results under SFA are quite sensitive to the prespecified forms of production function, the author attempted to choose the appropriate form of production function by selecting Cobb-Douglas and Translog functions and using the likelihood ratio test to determine the proper form. The results revealed evidence of an inefficiency component in the data. However, the suitable form of production function was the Translog function. Thus, this function was employed to estimate the technical efficiency scores (*TE*) and the technical inefficiency effect of Thai cooperative stores.

The estimated results of *TE* indicated that only 12 cooperatives operated on an efficiency frontier for all years. On average, *TE* scores for almost the DMUs were adjusted upward from 2017–2018, then adjusted downward from 2018–2020 (when the COVID-19 pandemic began), and finally begin to adjust upward from 2021 (after most people have been vaccinated and the pandemic becomes endemic). Moreover, about 40% of cooperative stores in Thailand had TE scores below 0.5, and about 12% of the cooperative stores showed a downward trend of *TE* scores in this period. Finally, the estimated results of the technical inefficiency effect showed the significant negative relationships between technical inefficiency and three other explanatory variables, including the D/E ratio, reserves, and dummy variable, representing the location of cooperative stores related to academies and hospitals.

6. Recommendation

6.1 Policy Recommendations

The results from this study indicated the slowdown or stagnation of the technical efficiency of cooperative stores during the COVID-19 pandemic. Although the sign of an upward trend of technical efficiency of cooperative stores existed right after the pandemic became endemic, cooperative stores are still faced with high competition from modern trade. Thus, to survive, cooperative stores must adjust themselves as follows: (1) Although some cooperative stores financed their operations through debt, they should utilize their debt in an efficient way, such as making a difference by introducing goods and services that meet the customer requirements. (2) Cooperative stores should maintain the appropriate number of reserves since reserves help to strengthen the financial position of cooperative stores, especially when faced with paying off debts, buying assets, spending for maintenance, and more. (3) The results showed that the technical efficiency of cooperative stores significantly depended on location. Cooperative stores that are located in academies and hospitals had more advantages due to market potential and the limited number of competitors. For cooperative stores that are poorly located, a wide variety of tactics, both online and offline, exist to overcome this problem, such as offering unique goods and services, participating in key local events, using suitable social media platforms, developing online marketing strategies, and more.

6.2 Recommendations for Further Studies

The evaluation of technical efficiency scores of cooperative stores in this study was based on the stochastic frontier analysis. Since SFA is the parametric method, it has the advantage over the non-parametric method (such as data envelopment analysis) in terms of hypothesis testing of all estimated coefficients,

illustrating the impact of explanatory variables on the dependent variable. However, two disadvantages were obvious about this model. First, SFA can be applied only in the case of one output and multiple inputs to compute the technical efficiency of DMUs but cannot be used when dealing with multiple outputs and multiple inputs. For the latter case, data envelopment analysis (DEA) was much better to serve this objective. Second, the estimated results of coefficients and TE scores were sensitive to the choice of specification; thus, further studies should compare and investigate characteristics and features of other functional forms, e.g., normalized quadratic, non-homothetic CES, CES-Translog, and generalized Leontief functions, before using them to estimate the results. Additionally, further studies should thoroughly consider other explanatory variables affecting the inefficiency of cooperative stores. The sources of low performance probably come from both internal and external factors, such as low staff quality, competitive intensity, and the macroeconomic environment surrounding cooperative stores. As a result, variables such as communication skills, work quality and quantity, teamwork, and switching costs representing staff quality, along with the degree of concentration, degree of differentiation, rate of market growth representing competitive intensity, and macroeconomic environment could be evaluated against the inefficiency level of cooperative stores.

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Appendix I: Details on DMUs

# DM U	Coop.	Name	# DMU	Coop.	Name
1	6	Krung Thep Coop. Store	2	19	Phra Nakorn Coop. Store
3	23	Chanthaburi Coop. Store	4	24	Sing Buri Coop. Store
5	25	Nakorn Ratchasima Coop. Store	6	26	Sara Buri Coop. Store
7	30	Phatthalung Coop. Store	8	32	Ayutthaya Coop. Store
9	35	Kalahom Coop. Store	10	36	Chumphon Coop. Store
11	37	Prachin Buri Coop. Store	12	42	Phuket Coop. Store
13	44	Sakon Nakhon Coop. Store	14	49	Bua Yai District Coop. Store
15	51	Lampang Coop. Store	16	121	CU Coop. Store
17	155	KU Coop. Store	18	416	Pattana Coop. Store
19	469	Pranakorn Commercial and Technical College Coop. Store	20	1877	Ubon Ratchathani Rajabhat University Coop. Store
21	2474	The Consumer Coop. Federation of Thailand	22	3417	Thai Oil Coop. Store
23	3854	Nakornping Coop. Store	24	4242	Bansomdej Chaopraya Rajabhat Coop. Store
25	4926	Nakorn Phanom Coop. Store	26	4929	Dairy Farming Promotion Organization of Thailand Coop. Store
27	5235	Pattani Hospital Coop. Store	28	5352	Pulp and Paper Coop. Store
29	5913	Nakhonsawan Vocational College Coop. Store	30	6141	Trat Hospital Coop. Store
31	6270	Nakhonpathom Vocational College Coop. Store	32	6819	Maharaj Nakhon Si Thammarat Hospital Coop. Store
33	7180	The Second Army Area Coop. Store	34	7211	The First Army Area Coop. Store
35	7269	Kasetsart Coop. Store	36	7313	Nakhon Nayok Hospital Coop. Store
37	7363	Army Aviation Center Coop. Store	38	7457	Lop Buri Anti-Aircraft Artillery Division Coop. Store
39	7573	The Fourth Army Area Coop. Store	40	7576	Phrae Vocational College Coop. Store

# DM U	Coop.	Name	# DMU	Coop.	Name
41	7597	Phuket technical college Coop. Store	42	7621	EGAT Coop. Store
43	7696	Transportation Coop. Store	44	7836	Tak College of Agriculture Coop. Store
45	7861	Chiang Mai Technical College Coop. Store	46	7908	Chachoengsao Vocational College Coop. Store
47	7909	Rajabhat Chatoengsao University Coop. Store	48	7914	Buriram College of Agriculture Coop. Store
49	7966	Saraburi Technical College Coop. Store	50	7969	Surat Thani Hospital Coop. Store
51	8021	Uthai Thani Technical College Coop. Store	52	8098	Pathumthani Technical College Coop. Store
53	8192	Border Patrol Police Coop. Store	54	8288	Chanthaburi Technical College Coop. Store
55	8342	Chonburi Vocational College Coop. Store	56	8366	Lampang Hospital Coop. Store
57	8374	Fort Thanarat Coop. Store	58	8467	Nongkhai Technical College Coop. Store
59	8507	Nakhonrahasima Technical College Coop. Store	60	8547	Fort Surasi Coop. Store
61	8574	Phanuransi Military Camp Coop. Store	62	8687	Vachira Phuket Hospital Coop. Store
63	8729	1 st Combat Service Headquarter Coop. Store	64	8768	BAAC Coop. Store
65	8770	Sawang Daen Din Teachers Coop. Store	66	9009	Chiang Mai Rajabhat University Coop. Store
67	9073	Betong Hospital Coop. Store	68	9111	Fort Chao Phraya Bodindecha Coop. Store
69	9323	Aviation School Coop. Store	70	9599	Ranong Hospital Coop. Store
71	9858	Su-ngai Upe Thung Wa	72	10349	Maharat Nakhon Ratchasima Hospital Coop. Store
73	11286	Bueng Chawak Coop. Store	74	12706	Bang Chun Union Coop. Store
75	13007	Kanchanaburi Rajabhat University Coop. Store	76	13856	Buddhasothorn Hospital Coop. Store
77	15265	Chumphon Khet Udomsak Hospital Coop. Store	78	15319	Phatthalung Hospital Coop. Store
79	16153	Mitsubishi Motor Officers Coop. Store	80	16911	Samutprakarn Hospital Coop. Store

# DM U	Coop.	Name	# DMU	Coop.	Name
81	17005	Romklao Pangtong School Coop. Store	82	17230	SCG Ceramics Public Company Officers Coop. Store
83	17709	B food Lopburi Coop. Store	84	17808	Banphaeo General Hospital Officers Coop. Store
85	18552	Thabo Crown Prince Hospital Coop. Store	86	18736	Burapa Power Broad Industry Coop. Store