EFFICIENCY OF FOOD INDUSTRY IN VIETNAM: AN APPLICATION OF LATENT CLASS STOCHASTIC FRONTIER ANALYSIS

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Abstract : *Food industry plays an important role in meeting economic development goals and increasing demands of processed food. However, there have been no studies considering the performances of food industry over time was found in Vietnam. Therefore, the study used a data set of 340 food processing companies from the small and medium enterprise (SME) surveys in 2007, 2009 and 2013. By applying latent class stochastic frontier analysis for a balanced panel data, the study found that the average technical efficiency of food processing companies was 91.5%, suggesting that they could expand their output level about 9% while keeping inputs constant. The study also found that the technical efficiency has been improved over time at annual growth rate of 1.47%. The firms in Ha Noi, Ho Chi Minh and Quang Nam had the lowest technical efficiency score while that of the firms in Lam Dong, Hai Phong and Ha Tay provinces were the highest.*

Keywords: *Food industry; Latent class stochastic frontier analysis; Technical efficiency; heterogeneity*

I. INTRODUCTION

Since the reform policy namely "*Doi Moi*" in 1986, the Vietnamese economy has achieved significantly positive changes in terms of economic growth and poverty reduction. The total nominal GDP has increased steadily at an average growth rate of 17.8% year^{-1} for the period 2006-2014 (GSO, 2014). The poverty rate was reduced from 60% in 1990 to 18% in 2010 based on the poverty line of General Statistics Office of Vietnam. Such achievements were originated from the significant contribution of small and medium enterprises (Harvie, 2004, 2007).

In Vietnam, Company Law and Private Enterprise Law were, respectively passed in 1990 and 1991, it created better environment for private enterprises. These laws have resulted in the dramatically increased number of SMEs from about 3000 in 1992 to more than 80,000 registered enterprises in 2010, suggesting an annual growth rate of 20% (AED, 2011; Le & Harvie, 2010). However, the number of enterprises which got bankrupt also increased because of various reasons such as capital shortage, high competition, limited access to markets, institutional weaknesses (Carlier & Tran, 2004; Sakai & Takada, 2000). These constraints have affected significantly the technical performance of firms over time. So far, there have been some studies considering technical efficiency of SMEs in Vietnam, but they normally applied stochastic frontier analysis and used cross-sectional data. Thus, these findings did not reflect the technical efficiency changes and the heterogeneity among firms, particularly the case of pooled data of firms in different regions. Le and Harvie (2010) has applied stochastic frontier analysis to estimate technical efficiency scores of manufacturing SMEs in Vietnam. Although the study used the unbalanced panel data of manufacturing SMEs in 2002, 2005 and 2007, the study estimated separately the production functions and the estimate technical efficiency scores for each year. The mean technical efficiency scores were 84.25, 92.55 and 92.34% for years 2002, 2005 and 2007, respectively. However, this study did not take heterogeneity into account and estimated the production frontiers by using cross-sectional data approach instead of panel data approach. Tran, Grafton, and Kompas (2008) also applied stochastic frontier analysis to estimate technical efficiency for five kinds of SMEs (i.e. food processing, chemicals, manufactured foods, machinery and miscellaneous industries). The study used data from SME surveys in 1996 and 2001 and estimated separately the production frontiers for each year. Similarly, this study also ignored heterogeneity and panel data approach. After more than three decades, stochastic frontier analysis which had been first developed by Aigner, Lovell, amp, and Schmidt (1977); Meeusen and Van den Broeck (1977) was employed in thousands of studies. However, these studies normally assumed that the underlying production frontier was the same for all observations. Therefore, the current study used the latent class stochastic frontier analysis (LCSFA) to estimate technical efficiency of firms with the assumption of time-varying inefficiencies (i.e. panel data approach). The LCSFA approach can take heterogeneity into account (Barros, de Menezes, & Vieira, 2013; J. W. Bos, Economidou, Koetter, & Kolari, 2010; J. Bos, Economidou, & Koetter, 2010; W. Greene, 2002, 2005; Orea & Kumbhakar, 2004). By using LCSFA, a mixture of production frontiers will be estimated simultaneously, from which we can estimate the shortfall (technical inefficiency) from the observed output to a latent production frontier.

The objective of this current study is to investigate the technical efficiency scores and technical efficiency changes for food industry in Vietnam by using LCSFA. The study provides updated information about food industry's performance over time. These results are important policy implications to promote the development of food industry.

The remainder of this paper was organized as follows. Section 2 presents the analytical framework of LCSFA and data used for this study. Section 3 provides results and discussions, followed by conclusions in section 4.

II. METHODOLOGY

2.1 Analytical framework

The data on firms' production technology was collected in 10 provinces/cities/capital, suggesting that the heterogeneity exists among firms. In the other words, it means that they do not share the same underlying production technology. To deal with this real situation, the study applied the latent class stochastic frontier analysis to seperate heterogeneity apart from inefficiency term. The heterogeneity results in biased estimation of technical efficiency by using traditional assumption (i.e. all firms share the common frontier) because the unobserved technological differences are not taken into account. Reviews of literature indicate that there have been two main approaches to consider heterogeneity: two-stage (known as priori sample separation) and single-stage approach. With the former, cluster analysis was employed to classify observations into several groups, then production technology is estimated seperately for each class. Such applications can be found in the studies of Grifell-Tatjé and Lovell (1997); Kolari and Zardkoohi (1995); Mester (1993, 1997). With the latter, the heterogeneity and stochastic frontier are simultaneouly considered to estimate the mixture of production functions (Barros et al., 2013; W. Greene, 2002, 2005; Orea & Kumbhakar, 2004). Such approach is preferable because it relies on goodness of fit, leading the estimated results are superior.

To estimate technical efficiency for each firm, it is necessary to specify the underlying production technology or the latent class that the firms belong to. The technical efficiency was asummed to be time-variant in the balanced panel data. The model with such assumption (time-variant) is sometimes known as time-varying inefficiency model or time decay model. Assume the production technology for each class is presented in translog form as follows

$$Y_{it} = f\left(X_{it}, \beta_j\right)|j \exp(v_{it|j} - u_{it|j}) \tag{1}$$

where subscripts *i* = 1,…, N stands for firms; *j* = 1,…, J indicates latent classes; Y_i and X_i are vectors of the observed output and inputs, respectively; β_j are parameters to be estimated for each class, and *t* = 1,…, *T* indicates time period.

The composed error terms ($E_{it|j} = v_{it|j} - u_{it|j}$) which are the difference of noise effect ($v_{it|j}$) and technical inefficiency ($u_{it|j}$) terms for class *j*. The former ($v_{it|j}$) indicates the statistical noise effect for class *j*, which is normally distributed at zero mean and is assumed to be independent of the non-negative technical inefficiency component ($u_{it|j}$). The term $u_{it|j}$ which follows a half-normal distribution is calculated based on the conditional expectation of $u_{it|j}$, given the value of the composed error term (Jondrow, Knox Lovell, Materov, & Schmidt, 1982). The expression of $u_{it|j}$ is presented as

$$E\left(u_{it|j}|\varepsilon_{it|j}\right) = \sigma^* \left[\frac{\phi\left(\varepsilon_{it|j}\lambda_j/\sigma_j\right)}{\left(1 - \Phi\left(\varepsilon_{it|j}\lambda_j/\sigma_j\right)\right)} - \left(\frac{\varepsilon_{it|j}\lambda_j}{\sigma_j}\right)\right] \tag{2}$$

where $\sigma^* = \sqrt{\sigma_{u|j}^2 \sigma_{v|j}^2/\sigma^2}$; and $\phi(.)$ and $\Phi(.)$ represent the standard normal density and cumulative distribution functions.

According to W. Greene (2002, 2005); W. H. Greene (2008), the likelihood function for each firm in class *j* is given by

$$LF_{ij} = f\left(X_{it}, \beta_j, \sigma_j, \lambda_j\right) = \frac{\Phi\left(\lambda_j.\varepsilon_{it|j}/\sigma_j\right)}{\Phi(0)} . \frac{1}{\sigma_j} . \phi\left(\frac{\varepsilon_{it|j}}{\sigma_j}\right) \tag{3}$$

where

$$\varepsilon_{it|j} = \ln Y_{it|j} - \beta_j' X_{it};\ \sigma_j = \sqrt{\sigma_{u|j}^2 + \sigma_{v|j}^2};\ \lambda_j = \sigma_{u|j}/\sigma_{v|j}$$

$\phi(.)$ and $\Phi(.)$ denote the standard normal density and the cumulative distribution function, respectively.

By applying the time-varying inefficency model devised by George E Battese and Coelli (1992); George Edward Battese and Coelli (1995), the output-oriented technical efficiency (OTE) of the i^{th} farm in *t* period belonging to class *j* is obtained by the expression

$$\mathrm{OTE}_{it|j} = \exp(-u_{it|j}) = \exp[-\eta(t - T)]|U_i| \tag{4}$$

where $\boldsymbol{\eta}$ which is an unkonw scalar indicates the improvement of technical efficiency over time if $\boldsymbol{\eta}$ is positive; *T* is the number of time periods.

The remaining task is to specify the class probabilities and the class membership for each firm. According to W. Greene (2002); Orea and Kumbhakar (2004), multinomial logit model can be used to perform such estimation.

The appropriate number of classes is determined by using the testing down approach proposed by W. Greene (2005); Orea and Kumbhakar (2004). The AIC (Akaike Information Criterion) is the most widely used to select the preferred model. The best model is the one with the lowest AIC value.

2.2 Data collection

The study used data from the small and medium enterprise (SME) surveys in 2007, 2009 and 2013. The food processing enterprises in this study was selected from the SME surveys in 2007, 2009 and 2013 based on 2-digit economic sectors which was classified in decision No. 10/2007/QĐ-TTg on 23rd January 2007. Total 340 firms that had been operating food processing industry were selected for this study. It means that 1020 observations in a balanced panel were used for estimating production frontiers. The number of food processing firms that was interviewed by SME surveys was greater than the sample size in this current study. However, in order to get the balanced panel data, the study only selected 340 firms for estimation. In this study, we used total output value to be the dependent variable in production function because the data of output quantity was unavailable for years 2007 and 2009. Such application of output value was found in many previous studies to estimate technical efficiency in panel data because of unavailability of quantity data (Badunenko & Stephan, 2004; Sun, Hone, & Doucouliago, 1999; Tran et al., 2008; Zheng, Liu, & Bigsten, 1998). Regarding to the independent variables, the study considered five main inputs (i.e. energy and water cost, raw material, labor cost, capital and operation cost) to estimate production frontiers. The detail description of these variables is presented in Table 1.

Table 1. Descriptive statistics of variables used for production function

	Variable description	Mean	Min	Max	SD
Output					
Y	Output value	3,027,222	13,000	290,000,000	15,737,853
Inputs					
X_1	Energy and water cost	77,291	120	5,885,000	318,780
X_2	Material	1,016,465	100	101,900,000	5,776,310
X_3	Labor cost	239,840	720	29,200,000	1,534,747
X_4	Capital	258,389	50	12,200,000	908,914
X_5	Operation cost	181,683	60	37,000,000	1,423,498

Note: These values of input and output were measured in thousand VND (1 USD = 22,260 VND).
SD stands for standard deviation

Source: The small and medium enterprise (SME) surveys in 2007, 2009 and 2013

Table 1 shows that the variations of all output and inputs was quite large because the current study considered both medium and small enterprises. According to the decree No. 56/2009/NĐ-CP, small and medium enterprises were classified into three levels: micro-small, small and medium scales based on number of labors or total capital. Such classification is described in table 2.

Table 2. Classification of small and medium enterprises in Vietnam

Sectors	Micro-small	Small scale		Medium scale	
	Labor	Labor	Capital	Labor	Capital
Agriculture, forestry and fishery	Under 10 persons	10-200 persons	Under 20 billion VND	200-300 persons	20-100 billion VND
Industry and construction	Under 10 persons	10-200 persons	Under 20 billion VND	200-300 persons	20-100 billion VND
Trade and services	Under 10	10-50	Under 10	50-100	10-50 billion

	persons	persons	billion VND	persons	VND

Source: Decree No. 56/2009/NĐ-CP

III. RESULTS AND DISCUSSIONS

As mentioned, for LCSFA, we had to select the best model based on AIC and log-likelihood. Table 3 presents AIC indexes and log-likelihood for each model.

Table 3. AIC and log-likelihood values of models

Indicator	One class SFA	Two class SFA	Three class SFA
AIC	2222.1	2091.8	2204.2
Log-likelihood	-1087.0	-996.9	-1028.1

Table 3 shows that LCSFA is the best model for this study with AIC = 2091.8, which is the smallest among concerned models. In addition, although we can't use LR test in LCSFA due to inconsistent degrees of freedom, the log-likelihood values reflects that the model with two latent classes is best fit.

Now we turn to estimate the parameters of production frontiers. For comparison, the study provides both parameters of one class (i.e. the underlying production frontier is the same for all observations) and two class SFA (i.e. two different frontiers was estimated). The estimated parameters of one class and two class models are presented in table 4.

Table 4. Estimated parameters of LCSFA

Parameters	One class		Two classes			
			1st Class		2nd Class	
	Coefficients	**S.E**	**Coefficients**	**S.E**	**Coefficients**	**S.E**
$\ln X_1$	0.5650***	0.2122	0.6838	1.2458	0.8392***	0.1258
$\ln X_2$	-0.4860***	0.1163	-0.1863	0.5484	-0.5595***	0.0950
$\ln X_3$	-0.4114***	0.2243	-0.4797	0.8489	-0.3257***	0.1483
$\ln X_4$	0.2561*	0.1337	0.2626	0.9610	0.2272**	0.1088
$\ln X_5$	0.3303*	0.1760	-0.0831	1.0152	0.1492	0.1111
$(\ln X_1 \ln X_1)/2$	0.0964**	0.0393	0.8039***	0.3692	0.0850***	0.0181
$(\ln X_2 \ln X_2)/2$	0.0838***	0.0132	0.1670***	0.0655	0.1244***	0.0087
$(\ln X_3 \ln X_3)/2$	-0.0364	0.0480	-0.6078***	0.2638	-0.0225	0.0286
$(\ln X_4 \ln X_4)/2$	-0.0035	0.0179	0.3129***	0.1368	-0.0137	0.0116
$(\ln X_5 \ln X_5)/2$	0.0357	0.0275	0.2972	0.2023	0.0169	0.0155
$\ln X_1 \ln X_2$	-0.1131***	0.0176	-0.3547*	0.2011	-0.1257***	0.0104
$\ln X_1 \ln X_3$	0.0052	0.0293	0.2070	0.2158	-0.0108	0.0168
$\ln X_1 \ln X_4$	0.0022	0.0200	-0.4352***	0.1584	0.0415***	0.0106
$\ln X_1 \ln X_5$	0.0090	0.0255	-0.1337	0.2102	-0.0287***	0.0135
$\ln X_2 \ln X_3$	0.1123***	0.0237	0.2215*	0.1254	0.0845**	0.0115
$\ln X_2 \ln X_4$	0.0042	0.0111	0.2652***	0.0881	-0.0386***	0.0062
$\ln X_2 \ln X_5$	-0.0291**	0.0127	-0.3511***	0.1292	0.0337***	0.0089
$\ln X_3 \ln X_4$	-0.0360*	0.0190	-0.1236	0.0945	-0.0187	0.0124
$\ln X_3 \ln X_5$	-0.0444*	0.0239	0.3730**	0.1766	-0.0434***	0.0148
$\ln X_4 \ln X_5$	0.0246*	0.0135	-0.1109*	0.0667	0.0251***	0.0076
Intercept	7.9942***	1.1918	8.0713	6.2036	7.8276***	0.7691
σ	0.7684		0.0851	0.1517	0.0047	0.0551
$\lambda = (\sigma_u / \sigma_v)$	0.5509***	0.1086	1.0928*	0.5644	0.2224***	0.0831
σ_u	0.3708	0.0447				
σ_v	0.6730					
$\boldsymbol{\eta}$	-1.1096	1.0484	0.3092	0.8734	0.6818	2.0298
Propabilities						
Class 1					21.980***	
Class 2					78.020***	

Observations	1020	102	918

Note: *, ** and *** indicate the significant levels at 10%, 5% and 1%, respectively.
Source: The small and medium enterprise (SME) surveys in 2007, 2009 and 2013

As shown in table 4, η was negative in one class model but positive in two class model, suggesting that if we estimates the frontier by one class model, the technical efficiency reduced over time for individual firm. However, in case of two class model, the study indicated an opposite trend that the technical efficiency increased over period. Such biased estimation leads to serious policy implications for small and medium enterprises, particularly food processing companies in Vietnam.

Table 4 also shows that λ were significant at 10% for both one class and two class models, suggesting that the null hypothesis of inefficiency absence is rejected. In the other words, the food processing firms were technically inefficient. This finding is consistent with previous studies (Le & Harvie, 2010; Tran et al., 2008). Prior to estimate technical efficiency of firms, the study classified observations into groups based on posterior probabilities in LCSFA. Table 5 presents observations by classes.

Table 5. Observations by class

Area	**One class**		**Two classes**			
			1st class		**2nd class**	
	Count	**%**	**Count**	**%¹**	**Count**	**%²**
Ha Noi	36	3.53	6	0.59	30	2.94
Phu Tho	126	12.35	9	0.88	117	11.47
Ha Tay	129	12.65	6	0.59	123	12.06
Hai Phong	81	7.94	3	0.29	78	7.65
Nghe An	243	23.82	18	1.76	225	22.06
Quang Nam	93	9.12	24	2.35	69	6.76
Khanh Hoa	54	5.29	3	0.29	51	5.00
Lam Dong	24	2.35	0	0.00	24	2.35
Ho Chi Minh	159	15.59	30	2.94	129	12.65
Long An	75	7.35	3	0.29	72	7.06
Total	**1020**	**100**	**102**	**10**	**918**	**90**

Note: $\%^1 + \%^2 = 100\%$
Source: The small and medium enterprise (SME) surveys in 2007, 2009 and 2013

Table 5 shows that within 1020 observations (340 firms in three time periods), the largest proportion of observations (90%) was stick to class 2 while only 102 observations (10%) belonged to class 1. The majority of observations belonging to class 1 was food processing firms in Ho Chi Minh, Quang Nam and Nghe An provinces. The explanation of such posterior probabilities is an interesting topic. However, it is beyond the scope of this study.

Now we turn to estimate the technical efficiency scores for each class, year and technical efficiency changes over time.

Table 6. Output-oriented technical efficiency scores by LCSFA

Efficiency score	**Pooled data**		**1st Class**		**2nd class**	
	Count	**%**	**Count**	**%**	**Count**	**%**
<50%	9	0.88	9	8.82	0	0
50-70%	50	4.90	50	49.02	0	0
70-90%	149	14.61	43	42.16	106	11.55
>90%	812	79.61	0	0.00	812	88.45
Mean	91.50		66.84		94.24	
Max	99.00		89.30		99.00	

Min	31.00	31.00	87.06
SD	9.47	11.81	3.02

Source: The small and medium enterprise (SME) surveys in 2007, 2009 and 2013

Table 6 indicates that the average technical efficiency of food processing companies was 91.5%, suggesting that these firms could expand their output about 9% while keeping inputs constant. The majority of firms (79.6%) had the technical efficiency scores distributed above 90%. However, the variation of technical efficiency was quite large, ranging from 31% to 99%. Regarding to class 1, the average technical efficiency was 66.84%, which is much smaller than that of class 2 (94.24%). The variation of technical efficiency in class 1 was the biggest with the standard deviation of 11.81%, suggesting that these firms' performances were diverse or unidentical. With regard to class 2, the variation of technical efficiency was quite small, indicating the identical performances among firms.

As mentioned above, the η value was positive, indicating the improvement of technical efficiency over time. The results of technical efficiency over time are presented in Table 7.

Table 7. Technical efficiency scores by year

Efficiency score	Pooled data		1st Class		2nd class	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
2007	87.16	10.23	58.61	11.45	90.34	1.09
2009	92.20	8.88	67.30	9.85	94.97	0.51
2013	95.14	7.31	74.61	8.15	97.42	0.27
Efficiency change	1.47%		4.11%		1.27%	

Source: The small and medium enterprise (SME) surveys in 2007, 2009 and 2013

The average technical efficiency of food processing companies increased steadily over year at 1.47%, 4.11% and 1.27% in case of pooled observations, class 1 and class 2, respectively. The firms belonging to class 1 had the highest technical efficiency improvement. These results suggest that food processing companies' performances improved over time. The possible explanations for such improvement are easier access of information, market opportunities, increasing demands on processed foods, better environment of investment and credit accessibility (Le & Harvie, 2010; Tran et al., 2008).

Table 8. Technical efficiency by area

Area	Technical efficiency				Ranking
	Mean	**Min**	**Max**	**SD**	
Ha Noi	88.19	43.21	97.78	14.71	9
Phu Tho	92.79	60.47	97.93	6.30	4
Ha Tay	93.14	61.58	97.89	6.11	3
Hai Phong	93.17	54.47	98.00	6.69	2
Nghe An	92.28	50.86	99.00	7.67	7
Quang Nam	86.45	30.99	97.65	16.01	10
Khanh Hoa	92.58	55.49	97.85	7.70	5
Lam Dong	94.56	89.11	97.89	2.91	1
Ho Chi Minh	89.51	48.72	98.14	11.25	8
Long An	92.53	47.95	97.85	7.93	6

Source: The small and medium enterprise (SME) surveys in 2007, 2009 and 2013

Table shows that although Ha Noi capital and Ho Chi Minh city are the two biggest cities in Vietnam, its average technical efficiency was, respectively ranked at 9 and 8th position, suggesting that the food processing firms in these areas had lower performances compared to the other areas. Quang Nam province had the lowest technical efficiency score at 86.45%, showing that the firms in this area could expand their output level about

14%, given inputs constant. Lam Dong, Hai Phong and Ha Tay provinces had the highest technical efficiency at 94.56%, 93.17% and 93.14%, respectively.

IV. CONCLUSIONS

By using latent class stochastic frontier analysis, the study shows that the two class model is the best fit for food industry in Vietnam. Food processing companies were technically inefficient. The average technical efficiency of pooled observations was 91.5%, suggesting that they could expand their output level about 9% while keeping inputs constant. The firms belong to class 1 had the lowest technical efficiency. The study also found that the technical efficiency has been improved over time at annual growth rate of 1.47%. The firms in Ha Noi, Ho Chi Minh and Quang Nam had the lowest technical efficiency score while that of the firms in Lam Dong, Hai Phong and Ha Tay provinces were the highest.

The current study poses two questions for further studies. Firstly, considering the characteristics of firms belonging to class 1 is crucial for policy recommendations as they had the lowest technical efficiency. Secondly, it is also important to provide answers to the question why the food processing firms in Ha Noi, Ho Chi Minh had the lowest technical efficiency as these two areas are the top cities of Vietnam in terms of economic achievements.

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