Chapter 3

Literature Review on Bank Efficiency

I. Introduction

This study will measure the efficiency of Thai commercial banks using different frontier approaches. The frontier analysis can provide an overall, objectively determined, numerical efficiency value of firms, which is also called X-efficiency of the firm. This chapter will review the literature on three different approaches: parametric frontier approach, non-parametric frontier approach, and the combination of parametric and non-parametric frontier approach. First, three main parametric frontier approaches (the stochastic frontier approach, the distribution–free approach, and the thick frontier approach) are introduced and reviewed. Then two main non-parametric frontier approaches are discussed in detail: data envelopment analysis and free disposal hull analysis. Further, the combination approach is reviewed. Since the real efficiency frontier of the commercial banking is unknown, only the correlation analysis between the efficiency and other factors such as environmental factors and bank specific characteristics can be found in the literature.

The rest of this chapter is organized as follows: section II, III, and IV will review the literature on parametric approach, non-parametric approach, and the combination approach respectively; section V reviews the correlated factors, and the most related papers are discussed in section VI.

II. Parametric frontier approach

Academic research has put effort on efficiency measurement since late 1970s. Later frontier analysis techniques have been used to study the efficiency of financial institutions. Berger and Humphrey (1997) surveyed 130 studies on financial institutions. Multiple time periods data from 21 countries was used in frontier efficiency analysis. The various financial institutions studied include commercial banks, bank branches, savings and loans, credit unions, and insurance companies. There are two main streams of research direction. One is parametric frontier analysis and the other is non-parametric analysis. The survey found that the various efficiency methods did not necessarily yield consistent results, and there was no consensus on the preferred method for determining the best-practice frontier against which relative efficiencies of decision making units were measured. Each approach has its advantages and disadvantages. The advantage of parametric frontier approach is that it allows random error. The parametric frontier approach imposes a particular functional form and associated behavioral assumptions that predefines the shape of the frontier, which is also the drawback of the parametric approach. The advantage of the non-parametric frontier approach is that it imposes less structure on the frontier, but the key disadvantage is that it does not allow for random error. No measurement error, luck, or data problems are assumed. Any of these errors that does exist in an inefficient decision making unit's data may be reflected as a difference in its measured efficiency. If any of these errors exists in one of the units on the efficient frontier, then the measured efficiency of all decision making units that are compared to this unit or linear combinations involving this unit may change.

As mentioned in the introduction above, there are three main parametric frontier approaches: the stochastic frontier approach (SFA), the distribution–free approach (DFA), and the thick frontier approach (TFA).

Among three parametric frontier approaches, the most popular one is the SFA. It was first introduced by Aigner, Lovell, and Schmidt (1977) and then applied and developed further by others such as Battese and Coelli (1992; 1995), Mester (1993; 1996), Berger and Mester (1997), Berger and De Young (1997), De Young and Hasan (1998), Bos and Kool (2006), and etc. SFA specifies a functional form for the cost or profit relationship among inputs, outputs, and environmental factors, and a composed error term. Hence, the resulting inefficiency scores are defined as cost inefficiency or profit inefficiency. For the convenience to compare scores among different methods, efficiency ratios are constructed by other researchers. Berger and Mester (1997) provided more detailed definitions of different bank efficiency concepts:

1. Cost efficiency: the cost efficiency of a particular bank is defined as the ratio of the estimated cost needed to produce the bank's output vector if the bank were as efficient as the best-practice bank in the sample facing the same exogenous variables to the predicted actual cost of the particular bank, net of random error.

It is derived from a cost function. The cost function is specified as follows: the dependent variable is total variable costs, and independent variables are the prices of variable inputs, the quantities of variable outputs and any fixed inputs or outputs, environmental factors, random error, and inefficiency.

2. Standard profit efficiency: the standard profit efficiency is defined as the ratio of the predicted actual profits to the predicted maximum profits for a best-practice

bank, adjusted for random error, or the standard profit efficiency is the proportion of maximum profits that are actually earned.

It is derived from a profit function. The profit function is specified as follows: the dependent variable is variable profits, and independent variables are the prices of variable inputs and variable outputs, environmental factors, random error, and inefficiency. Notice that output prices are taken as exogenous in this specification.

3. Alternative profit efficiency: the alternative profit efficiency is defined as the ratio of predicted actual profits to the predicted maximum profits for a best-practice bank, adjusted for random error.

It is derived from the profit function that the dependent variable is the same as the standard profit function whereas the independent variables are the same as the cost function. i.e., it is a measure of how close a bank comes to earning maximum profits given its output levels rather than its output prices. This is a recent development in efficiency analysis, which is useful when some of the assumptions underlying cost and standard profit efficiency are not met.

In regard to the functional form which the stochastic frontier approach (SFA) specifies, the most popular one is the translog function. Translog model is the most often used flexible functional form which is interpreted as a second-order approximation (by expanding the function in a second-order Taylor series) to an unknown functional form (Greene, 2003). For example, if the function is $y = f(x_1, \ldots, x_k)$, then the translog model is

$$\ln y = \alpha_0 + \sum_{k=1}^{k} \alpha_k \ln x_k + \frac{1}{2}\sum_{k=1}^{k}\sum_{l=1}^{k} \beta_{kl} \ln x_k \ln x_l + \varepsilon$$

where α and β are unknown parameters to be estimated, and ε is the error term.

However, the translog function is a local approximation model. It is criticized that it may not fit the data very well (Gallant, 1981; Berger and Humphrey, 1997). Later development attempts to specify more globally flexible form, such as the Fourier flexible functional form which adds Fourier trigonometric terms to a standard translog function (Mitchell and Onvural, 1996; Berger and DeYoung, 1997; Berger and Mester, 1997; Williams and Nguyen, 2005). However, this functional form includes more parameters to be estimated and thus requires a larger sample size than the standard translog form does. For instance, the model applied in Berger and Mester (1997) includes 122 net free parameters after imposing symmetry. The results showed that there was only a small difference in average efficiencies and very little difference in efficiency dispersion or rank dispersion between the Fourier-flexible specification and the translog functional form.

In regard to the error term, there are various techniques to distinguish the inefficiency term from the random error term. SFA imposes a composite error term. For instance, if the dependent variable is the cost, then the error term is $\varepsilon = u + v$; if the dependent variable is profit, then the error term is $\varepsilon = -u + v$. Where "v" is the random error term (therefore, the frontier is called stochastic frontier) and "u" is the cost inefficiency or profit inefficiency respectively. "u" measures the percentage by which the particular decision making unit fails to achieve the frontier, i.e. the ideal cost or profit level. It is assumed to be nonnegative, therefore the cost inefficiency will increase the cost and the profit inefficiency will decrease the profit. The random error term usually follows the standard normal distribution. Two popular possible distributions for the inefficiency term are assumed to be half-normal distribution and the exponential distribution. Jondrow, Lovell, Materov, and Schmidt (1982) have derived an explicit formula to approximate the expected value of the inefficiency for the half-normal and exponential cases, which is now the standard measurement used in the literature. Take the profit stochastic frontier as an example, $\varepsilon = -u + v$, where $v \sim N(0, \sigma_v^2)$ and $u \geq 0$. Let u follows the half normal distribution and the standard deviation is σ_u, and let $\lambda = \sigma_u/\sigma_v$, $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$, $z = \varepsilon\lambda/\sigma$, $\phi(z)$ be the standard normal density function and $\Phi(z)$ be the cumulative normal density function. Then the expected profit inefficiency can be approximated as:

$$E(u \mid \varepsilon) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(z)}{1-\Phi(z)} - z\right]$$

The distribution–free approach (DFA), and the thick frontier approach (TFA) also specify a similar functional form as SFA for the frontier, but they differ in how to separate the inefficiency term from the random error term.

The DFA frontier approach assumes that the random error tends to average out to zero, whereas the inefficiency of each decision making unit tends to be stable over time. Since the random error tends to average out to zero, therefore the average of the particular bank's residuals from all of the regressions will be an estimate of the inefficiency level of that particular decision making unit. Thus, this approach is usually applied for each sub-period of a panel data set. However, if the full period is too long, the efficiency of the bank might not be stable; if the full period is too short, the random errors might not average out to zero. The literature indicates that six-year time period might be a reasonable horizon (DeYoung, 1997; Berger and Mester, 1997). Berger and Humphrey (1997) point out that DFA measures the average deviation of each bank from the best average-practice frontier, rather than the efficiency at any one point in time if the efficiency of bank is shifting overtime due to regulatory reform, technical change, or other influences.

The TFA frontier approach measures the inefficiency against a thick frontier rather than a precise frontier edge (Berger and Humphrey, 1991). First, it divides the sample into cost or profit quartiles after the sample is divided into size classes, which is to ensure the reasonable representation of all sizes of decision making units across quartiles. The lowest cost quartile or the highest profit quartile can be thought of as a "thick frontier". The decision making units in the lowest cost quartile or the highest profit quartile are considered to have the greater than average efficiency, whereas the decision making units in the highest cost quartile or the lowest profit quartile are considered to have the lower than average efficiency. Second, the cost or profit function is estimated for both of the highest and lowest quartiles. Then TFA assumes that differences in predicted cost or profit between the highest and lowest quartiles represent inefficiencies, while differences in predicted cost or profit values within the highest and lowest quartiles of decision making units represent random error. The advantage of TFA is that no distributional assumption is imposed on either inefficiency or random error term. The drawback of TFA is that it only provides an estimate of the general level of overall efficiency rather than point estimates of efficiency for individual decision making units.

Other sophisticated models also take into account other factors such as the quality of banks' outputs and the bank risk (Mester, 1996; Berger and Mester, 1997). The quality and riskiness are proxied by average nonperforming loans and average equity capital. The fixed equity capital is treated as an input to control for heteroskedasticity and scale biases in estimation, and to give more economic interpretation.

III. Non-parametric frontier approach

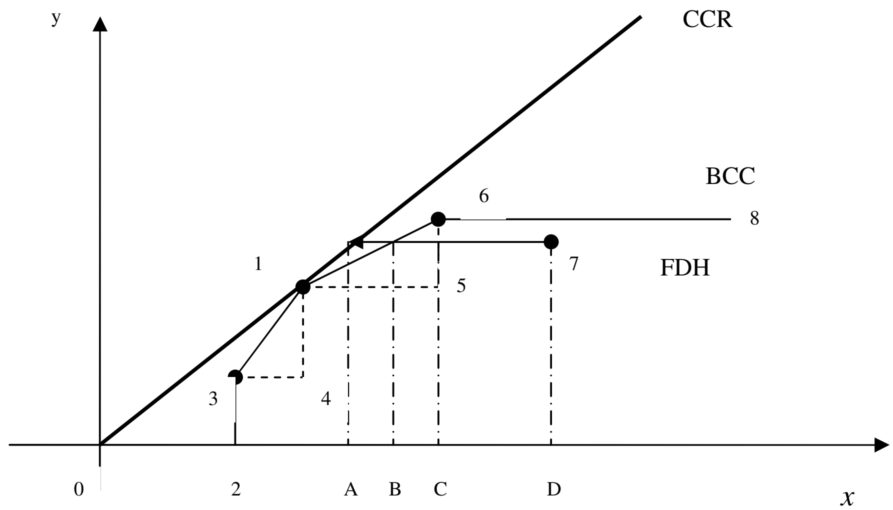
There are two main non-parametric approaches used to measure the efficiency of the bank in the literature. The popular one is the data envelopment analysis (DEA). And the other one is free disposal hull (FDH).

DEA is a linear programming technique. The DEA frontier is a convex production possibility set formed as the piecewise linear combinations that connect the set of best-practice observations. The best-practice frontier observations are those for which no other decision making unit or linear combination of units has as little or less of every input (given outputs) or as much or more of every output (given inputs). Therefore, DEA does not require the explicit specification of the form of the underlying production relationship. There are several DEA models. This paper will focus on CCR and BCC models. Different model assumes different production possibility set. The following Figure 3.1 (assuming only one input x and one output *y*) shows alternative shapes of the boundaries of different reference production sets.

CCR model is one of the most basic DEA models, which was initially proposed by Charnes, Cooper and Rhodes in 1978 (Charnes, Cooper, and Rhodes, 1981). The CCR model is the same as the one of Farrell in 1957, which is called "Farrell cone" because it has the form of a cone issued from the origin of the space of input and output quantities (Tulkens, 1993). The model implies constant returns to scale. In Figure 3.1, the shape of CCR production set is a ray issued from the origin and passed through point 1. Any decision making unit falls on this ray will be CCR efficient.

Figure 3.1

Different reference production sets and the respective efficiency measurements



Source: Tulkens (1993)

Note:

1. It is assumed that only one input x and one output y exist; and there are 4 observed decision making units: 1, 3, 6, and 7.
2. Different reference production sets are: CCR frontier is represented by the ray 01; BCC is represented by the piecewise linear frontier 23168; and FDH is represented by the staircase line 2341568.
3. The efficiency measures (input-oriented) of observation 7 with different models are: 0A/0D = CCR measure; 0B/0D = BCC measure; 0C/0D = FDH measure.

BCC model was developed by Banker, Charnes, and Cooper (1984) to relax the constraint of constant returns to scale. It exhibits varying returns to scale, usually first increasing and then decreasing returns to scale. It can be seen from Figure 3.1 that the shape of the BCC reference production set is a convex piecewise linear frontier linking the points 2, 3, 1, 6, and 8.

FDH (Fee disposal hull) was first developed by Deprins, Simar and Tulkens (1984). It is a special case of the DEA model where the points on lines connecting the DEA vertices are not included in the frontier. The shape of the frontier is the staircase line. The basic motivation is to ensure that efficiency evaluations are affected from only actually observed decision making units. Hence, the FDH production set consists only of the DEA vertices and the free disposal hull points interior to these vertices. It is represented in Figure 3.1 by the staircase line 2341568.

All of the above three models define the efficiency in a range of 0 to 1, where 0 means the least efficiency and 1 stands for the highest efficiency. In Figure 3.1, it is assumed that there are 4 observed decision making units: 1, 3, 6, and 7. Unit 1 is on the CCR frontier, therefore it has the CCR efficiency of 1. Whereas unit 3 and 6 are on the BCC and FDH frontier, hence they have the BCC and FDH efficiency of 1. To measure the CCR, BCC, and FDH efficiency of any other unit that is not on the frontier, the virtual decision making unit (the one that is on the frontier but is not observed) is required for CCR and BCC methods. In this case, decision making unit 7 is not on any frontier, therefore, the input-oriented efficiency is measured as follows: CCR measure = 0A/0D; BCC measure = 0B/0D; and FDH measure = 0C/0D. Obviously, it can be seen from Figure 3.1 that the FDH production set is nested in the BCC production set, and BCC production set is nested in the CCR production set. Hence, let θ be the efficiency measure, then the relationship among three efficiency measures is:

$$\theta_{FDH} \geq \theta_{BCC} \geq \theta_{CCR}.$$

The linear programming model is utilized to find the virtual decision making unit. The CCR model is set as the following linear programming problem:

CCR model:

$$\begin{aligned} \text{maximize} \quad & u\, y_0 \\ \text{subject to} \quad & v x_0 = 1 \\ & -vX + uY \leq 0 \\ & v \geq 0,\ u \geq 0. \end{aligned}$$

where X and Y are input and output matrices of all decision making units; x_0 and y_0 are the inputs and outputs of the particular decision making unit (DMU) being studied. v is the row vector of input multipliers and u is the row vector of output multipliers.

However, it is the dual problem of the above model that is often used to measure the efficiency of the DMU.

The dual problem of CCR model:

$$\begin{aligned} \text{minimize} \quad & \theta_{CCR} \\ \text{subject to} \quad & \theta_{CCR} x_0 - X\lambda \geq 0 \\ & Y\lambda \geq y_0 \\ & \lambda \geq 0 \end{aligned}$$

where θ_{CCR} is a real variable representing the CCR efficiency score and λ is a nonnegative scalar vector, represents the percentages of other DMUs used to construct the virtual DMU.

The optimal solution θ^* is referred to as "technical efficiency" of the DMU. The range of θ^* is (0, 1]. For a DMU to be CCR-efficient, two conditions must be satisfied together: (1), $\theta^* = 1$; and (2), all slacks (input excesses and output shortfalls) are zero. Otherwise, the DMU is called CCR-inefficient. If only (1) is satisfied, then it is also called weak efficient (Cooper, Seiford and Tone, 2000).

To test whether a DMU is CCR-efficient, a second linear programming problem must be solved:

maximize $w = es^{-} + es^{+}$

subject to $s^{-} = \theta^{*}x_0 - X\lambda$

$s^{+} = Y\lambda - y_0$

$\lambda \geq 0, s^{-} \geq 0, s^{+} \geq 0$

where e is a vector of ones, θ^{*} is the optimal solution from the first linear programming problem, s^{-} and s^{+} are the slack vectors representing input excesses and output shortfalls respectively.

The definition of BCC-efficiency is the same as the CCR-efficient. But the linear programming (LP) model is slightly different. BCC model imposes one more constraint: $e\lambda = 1$, where e is a vector of 1s. For instance:

BCC model

minimize θ_{BCC}

subject to $\theta_{BCC}x_0 - X\lambda \geq 0$

$Y\lambda \geq y_0$

$e\lambda = 1$

$\lambda \geq 0$

Once again, the BCC model requires solving two LP problems or two phases to reach the definition of BCC-efficient. Tone (2001) developed a slack-based model (SBM) which can deal directly with the input excesses and output shortfalls of the DMU concerned. Thus only one LP problem or only one phase is to be solved. Later, SBM technique was applied to a three-stage DEA approach, which incorporates the effect of environmental factors on efficiency, to study the efficiency of financial service sector (Drake, Hall and Simper, 2006).

The FDH efficiency of a DMU can be measured by using the following mixed integer programming problem (one more constraint added to the BCC model):

FDH model:

$$\begin{aligned} \text{minimize} \quad & \theta_{FDH} \\ \text{subject to} \quad & \theta_{FDH} x_0 - X\lambda \geq 0 \\ & Y\lambda \geq y_0 \\ & e\lambda = 1 \\ & \lambda \in \{0, 1\} \end{aligned}$$

where the last constraint ensures that efficiency evaluations are affected from only actually observed decision making units.

IV. <u>Combination of parametric and non-parametric frontier approach</u>

Berger and Humphrey (1997) reviewed 130 studies that apply frontier efficiency analysis on financial institutions in 21 countries. Overall, there were 60 applications of parametric approach and 69 of non-parametric approach. Among the 60 parametric applications, there were 24 of SFA, 20 of DFA, and 16 of TFA. Of the 69 nonparametric applications, 62 were DEA, 5 were FDH, and 2 were other approaches. There was no evidence that whether the parametric approach is better than the non-parametric approach or not since the true level of efficiency of financial institutions was unknown. The only conclusion can be drawn is that DEA and SFA are popular methods among the researchers.

Both parametric and nonparametric approaches have advantages and disadvantages over each other. The parametric approach imposes a particular functional form that predefines the shape of the unknown frontier. If the functional form is misspecified, then the measured efficiency may be biased. The advantage of the parametric approach is that it allows random error in the functional form. The nonparametric applications impose less structure on the unknown frontier, but the disadvantage is that it does not allow random error such as data problems, luck, or other measurement errors. Research effort has been put on how to alleviate the disadvantages of each approach. For instance, researchers have attempted to seek more flexible functional forms for SFA, and to develop a stochastic version of DEA.

Another way to relieve the disadvantages of two approaches is to combine the parametric and nonparametric approaches. The early effort was done by Thiry and Tulkens (1992). They studied urban transit firms in Belgium. They proposed a two-stage method for estimating production characteristics from efficient observations only. First, the non-parametric FDH method was employed to identify the efficient and inefficient observations. Then, parametric production frontiers were obtained by estimating translog production function through OLS applied to the subset of efficient observations only. It was concluded that the estimates of parametric functions on filtered out data sets did yield better results than usual methods in the sense that they were more consistent with the predictions of economic theory.

Later, Bauer and Hancock (1993) applied the Thiry and Tulken's two-stage method (it was called FDH Filter technique in Bauer and Hancock's paper) to estimate the efficiency of the Federal Reserve in providing check processing services. A variety of frontier estimation techniques were applied to estimate the efficiency. It was found that the estimate of the potential increase in efficiency or reduction in costs is much more sensitive to the choice of frontier estimation technique. However, the FDH methods were concluded to be the best at discriminating between efficient and inefficient production sites, and at measuring efficiency when the number of observations for similar levels of output was large.

DEA has also been incorporated in this combination effort. Arnold, Bardhan, Cooper, and Kumbhakar (1996) introduced a new way to combine DEA and regression approaches in a two-stage process: first, the DEA was applied to identify which DMUs (public secondary schools in Texas) were efficient and which were inefficient. Second, the results were transformed into a dummy variable which was included in OLS regressions and the stochastic frontier estimation. Bardhan, Cooper, and Kumbhakar (1998) applied this two-stage method on simulated data. The DEA was combined with OLS and SFA regressions (using different forms of production functions with different error distributions). The results indicated that the estimates generated by the two-stage DEA-dummy variable approach did not differ significantly from the true parameters. Whereas traditional single-stage regression approaches failed to perform satisfactorily and yielded biased parameter estimates in every cases.

The DEA-dummy variable approach is preferable to the FDH Filter technique if the sample size of observations is relatively small. However, since the FDH boundary is nested in the DEA boundary, the FDH method will identify more efficient DMUs.

V. Correlated factors

After the inefficiency or efficiency scores are generated or computed from the model, most researchers attempt to find the correlation between inefficiency or efficiency scores and other factors such as bank specific characteristics, environmental factors, and etc. Different techniques are applied in this stage, such as ordinary least squares (OLS) (Williams & Nguyen, 2005; Kwan, 2006), logistic functional form (Mester, 1993; 1996), Tobit estimation technique (DeYoung and Hasan, 1998), and ordered probit model (Narongtanupon, 2000).

The correlated factors usually consist of 4 groups: macroeconomic environmental factors, banking industry environmental factors, bank general and financial characteristics, and governance indicators.

1. Macroeconomic factors: these factors are included to test whether they have any effects/correlation on/with banking efficiency. Examples are: the growth rate of the GDP, the overall country risk, and the crisis dummy (Narongtanupon, 2000).

2. Banking industry environmental factors: these factors are considered since the industry competition will have some correlation with the efficiency. Factors in the literature include: the Herfindahl index (HHI) (DeYoung and Hasan, 1998), the degree of competition in the lending business measured by the percentage of total loans made by the largest banks to total loans in the banking industry, the market concentration in the borrowing business measured by the percentage of total deposits in largest banks to total deposits in the banking sector (Narongtanupon, 2000), average nonperforming loan (DeYoung and Hasan, 1998; Berger and Mester, 1997).

3. Bank general and financial characteristics: these factors will surely have the relationship with the efficiency. Variables include: age of the bank (Mester, 1996; Berger and Mester, 1997; DeYoung and Hasan, 1998), deposit to total liability ratio, capital to total asset ratio, ratio of foreign borrowing to total liabilities, loan to total asset ratio, ratio of fee based income to total revenue (Narongtanupon, 2000), bank size (usually classified by total assets or net income), deposit to asset ratio, loan loss provision to total loans, off-balance sheet activities to total assets, loan growth rate (Kwan, 2006), net income to total assets, nonperforming loan to total assets (Mester, 1993), and number of bank offices (Mester, 1996).

4. Governance indicators: since the banking industry is subject to heavy regulations and banks have gone through many changes especially after the financial crisis, governance of many banks have changed, which can play a role in changes of efficiency. Governance indicators include: dummy variable indicates whether a bank is private- or state- or foreign-owned, dummy variable indicates whether a bank is closed down or assets and liabilities are transferred to another bank, dummy variable indicates whether a bank has gone through a foreign acquisition or domestic M&A (William and Nguyen, 2005).

VI. **Most related papers**

Most SFA studies use data from the United States and European countries. Few studies draw data from Asia. Examples are as follows: Kwan (2006) applied the SFA (the standard multiprodcut translog function) to investigate the cost efficiency of commercial banks in Hong Kong; Williams and Nguyen (2005) used the SFA (the

Fourier-flexible form) to measure the alternative profit efficiency of commercial banks operating in Southeast Asia; Shanmugam and Das (2004) applied SFA (the Cobb-Douglas functional form) to a panel data to measure the profit efficiency of Indian commercial banks. Reynaud and Rokhim (2004) employed the SFA (translog cost function) to show that the inefficiency increased after the financial crisis in both Turkish and Indonesian banking industry.

Similarly, fewer researches apply the DEA to Asian data. It was used by Laeven (1999) to estimate a "grand frontier" to measure the inefficiencies of banks in five East Asia countries: Indonesia, Korea, Malaysia, the Philippines, and Thailand. The pre-crisis period of 1992-1996 was studied. The results indicated a substantial increase in efficiency for Indonesia, the Philippines, and Thailand, and an insignificant change for Korea and Malaysia. Further, a two-factor fixed effects model with ownership dummies was regressed to explain the variation in changes in output efficiencies.

To the author's knowledge, there are only six previous papers studied the Thai commercial banks' efficiency. Four of them utilized SFA and two others applied DEA approach. None of the papers employed the combination approach.

Okuda and Mieno (1999) estimated cost efficiencies of Thai domestic commercial banks during the 1985-1994 period using the translog functional form. The focus of their paper was the microeconomic analysis of Thai banking industry. Their results showed that the inefficiency seemed to increase in the 1990s compared with the 1980s; and for the 1985-1994 period, the inefficiency was the highest for the medium-sized banks and lowest for the large-sized banks. Jayapani (1997) applied the translog functional form to estimate the production efficiency of Thai commercial banks for the deregulation period. The results showed that the efficiency was increased as a result of deregulation.

Both papers of Williams and Intarachote (2002) and Narongtanupon (2000) analyzed the alternative profit efficiencies of domestic and foreign commercial banks in Thailand. The difference is that the study period for the former paper is 1990-1997, whereas the latter is 1989-1998. The results of the two papers (with different functional forms) supported the global advantage hypothesis that foreign banks from strong home environment might have efficiency advantage over host-country banks. Williams and Intarachote (2002) showed that the average profit inefficiency was increasing for both Thai and foreign banks from 1990 to 1997. For Thai banks, the inefficiency score was 0.0266 in year 1990, 0.1939 in 1995, 0.2771 in 1996, and 0.3850 in 1997. Whereas for foreign banks, the inefficiency score was 0.0262 in year 1990, 0.1906 in 1995, 0.2720 in 1996 and 0.3769 in 1997. Both showed a big fall of efficiency from 1996 to 1997. Narongtanupon (2000) computed the average X-efficiency scores for Thai and foreign banks. The efficiency score of Thai banks was generally higher than 60 percent from 1989 to 1997, and only 35.30 percent in year 1998. The efficiency score of foreign banks was generally slightly higher than that of the Thai banks, and 0.5383 percent in year 1998. Again both indicated a big decrease in efficiency after the crisis.

One paper used the DEA to measure the productive efficiency of both Thai and foreign commercial banks operating in Thailand during the 1989-1994 period (Leightner and Lovell, 1998). The other study applied a constrained multiplier, input-oriented DEA to evaluate the productive efficiency and performance of 12 Thai commercial banks during the 1990-2003 period (Chunhachinda and Srisawat, 2007).

The results showed that the large Thai-owned banks were the most efficient banks while the small foreign-owned banks were the least efficient banks. Also, the efficiencies of Thai commercial banks reduced significantly after the 1997 financial crisis.