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Technical efficiency of the Malaysian commercial banks: a stochastic frontier approach

Abstract

The purpose of this study is to examine the technical efficiency of the Malaysian commercial banks over the period of 2000-2006, using the stochastic frontier approach (SFA). The findings show that Malaysian commercial banks have exhibited an average overall efficiency of 81 percent implying an input waste of 19 percent. The results also found that the level of efficiency has increased during the period of study. Finally, domestic banks are found to be more efficient relative to foreign banks.

Keywords: technical efficiency, commercial banks, SFA, domestic banks, foreign banks.
JEL Classification: C21, H21, E59.

Introduction

The structure of the Malaysian financial institutions has changed dramatically for the last twenty years. In addition, global trend towards liberalization in banking has led to the blurring of demarcation lines separating activities of the different groups of financial institutions and the removal of artificial barrier to competition. Similarly, deposit taking, credit granting, investment, insurance and financial advisory services are being bundled into one financial conglomerate of financial supermarkets. The integration of financial markets within and across borders as well as mergers among banks, reflect attempts to increase the financial industry efficiency. The Malaysian experience on the merger exercise is a good example. From 58 financial institutions, the number has to reduce to 10 anchor banks and this is to be completed by 31 December 2000. This was the result of the financial crisis which has weakened the domestic banking sector and the move towards consolidation is hoped to improve the efficiency of the banking sector.

The commercial banks have undergone a tremendous development with the merger exercise. Theoretically, bank merger could broaden the product mix and reduce cost, and definitely large size capital and asset are crucial for a bank to become efficient, competitive and powerful one. These elements with good quality service will enable banks to compete with foreign institutions at local as well as at international levels.

The objective of this paper is to investigate the level of technical efficiency among commercial banks in Malaysia for the period of 2000-2006. The paper is structured as follows: the next section will discuss efficiency measurement in banking followed by model development and data. Empirical findings are discussed in section 3 followed by conclusion.

1. Efficiency measurement in banking

Generally, efficiency means the maximum output that can be produced from any given total of inputs. This refers to the efficiency of a firm which allocates resources in such a way as to produce the maximum quantity of output. In the context of resource allocation efficiency, Shepherd (1997) pinpoints two categories: internal efficiency and allocative efficiency. Internal efficiency refers to effective management within the firm itself; for example, the ways in which management inspires the staff, controls costs and keeps operations lean. However, when a company is increased in size, profit flows are expected to increase too. Hence, management tends to become less effective. Such shortcomings in management are known as X-inefficiencies and can be attributed to the excess of actual costs over the minimum possible costs. In other words, X-inefficiency may be measured as excess costs divided by actual costs.

Early research in banking industry was mainly concerned with estimating the average productivity, using some sort of indices and with cost comparison (Farrell, 1957). Subsequently, researchers tended to proxy efficiency by market share. They assumed that banks with large market shares are expected to earn higher profits because of lower unit costs (Smirlock, 1985; Evanoff and Fortier, 1988). In other words, banks with lower cost structures could maximize their profits either by maintaining the current level of prices and size or reducing the price levels and expanding a positive relationship between firms' profits and market structures being attributed to the gains made by more efficient firms.

The financial indicators of bank's operating performance, such as operating costs divided by total assets or the return on equity or assets, have also been used to compare efficiencies; for example, Rhoades (1986), Cornett and Tehranian (1992) and Srinivisan and Wall (1992) studied the effect of mergers among banks on efficiency. However, the use of financial ratios has its limitations. According to Berger et al. (1993), the first problem is that financial ratios are regarded as misleading indicators of efficiency because they do not control for product mix or input prices. Secondly, using the cost-to-asset ratio assumes that all assets are equally costly to produce and all locations have equal costs of doing business. Finally, the use of simple ratios cannot distinguish between X-efficiency gains and scale and scope efficiency gains.

Recent approaches to measure bank efficiency include the parametric and non-parametric approaches. These efficiency measurements differ primarily in how much shape is imposed on the frontier and the distributional assumptions imposed on the random error and inefficiency (Berger and Humphrey, 1997). In the research literature, both parametric and non-parametric approaches have been widely used but there is no consensus which of these major approaches is superior (Berger and Humphrey, 1997). There are three main parametric approaches used to estimate relative efficiency: the stochastic frontier approach, the thick frontier approach, the thick frontier and distribution-free estimates approach.

The stochastic frontier approach (SFA) sometimes also referred to as the econometric frontier approach (EFA), was developed by Aigner, Lovell and Schmidt (1977), and Meeusen and Van den Broeck (1977). In this approach, the SFA specifies a functional form for the cost, profit or the production frontier and allows for random error. The SFA modifies a standard cost (production) function to allow inefficiencies to be included in the error term. The predicted standard cost function is assumed to characterize the frontier while any inefficiency is captured in the error term, which is construction orthogonal to the predicted frontier. This assumption forces any measured inefficiencies be uncorrelated with the regressors and any scale or product mix economies derived linearly from these explanatory variables (Ferrier and Lovell, 1990).

Another assumption needed in the SFA is to distinguish the inefficiencies from random components of the error terms. The random components include short-term luck which places individual banks in relatively high or low cost positions and measurement error from excluded explanatory variables, misspecification etc. These two components are separated by assuming that inefficiencies are drawn from asymmetric half-normal distribution, and that random errors are drawn from a symmetric normal distribution. However, it is not possible to decompose individuals' residuals into inefficiency or random variation; therefore, estimating technical inefficiency by observation is impossible. Okuda et al. (2003) use SFA to estimate the cost function of the Malaysian commercial banks from 1991-1997 and its impact on bank restructuring. The study observed economies of scale but not economies of scope and suggested that Malaysian domestic banks were making unproductive capital investments.

The thick frontier approach (TFA) has been applied to banking by Berger and Humphrey (1991, 1992). This approach, instead of estimating a frontier edge, compares the average efficiencies of groups of banks. A cost function for the lowest average cost quartile of banks is estimated and banks in this quartile are assumed to have greater than average efficiency and form a 'thick frontier'. Similarly, a cost function is also estimated for the highest average cost quartile and banks in this quartile presumably have less than average efficiency. Differences in error terms within the highest and lowest performance quartile of observations (stratified by size class) are assumed to represent random error, while the predicted cost differences between the highest and lowest quartile are assumed to reflect inefficiencies. This inefficiency residual is then decomposed into several types of inefficiencies. The TFA thus imposes no distributional assumptions on either inefficiency or random error except to assume that inefficiencies differ between the highest and lowest cost quartile and that random error exists within these quartiles.

In the distribution-free approach (DFA), a functional form for the frontier is also specified but inefficiencies are separated from random error in a different way. Unlike the SFA, the DFA makes no strong assumptions regarding the specific distributions of the inefficiencies or the random errors. The identifying assumption is that efficiency of each bank is stable over time, while random errors tend to average out over time. The estimate of inefficiency for each bank in a panel data set is then determined as the difference between its average residual and the average of the bank on the frontier with some truncated measure performed to account for the failure of the random error to fully average out. The truncation procedure is similar to the TFA treatment of outliers[1]. Therefore, the truncation procedure is used to remove some of the effects of the extreme observations by treating all the most efficient firms alike and, similarly, all the most inefficient firms alike[2]. Berger (1993) has applied the DFA to banking in the study of the US banking industry. He finds that the frequency distribution of inefficiencies appears to be closer to the shape of symmetric nor-

[1] In the TFA approach, data are averages within the very highest and lowest average cost quartile.

[2] Lang and Welzel (1996) used a fixed effects model where a dummy variable is specified for each bank in a panel data set. Differences in the fixed effects estimated across banks represent bank inefficiencies. Berger (1993) finds that the fixed effects approaches (under Method 2) were confounded by large differences in scale.

mal distribution than an asymmetric half-normal distribution. Yildrim and Philippatos (2007) use both SFA and DFA to examine the cost and profit efficiency of banking sectors in twelve countries in Europe and find that the average cost efficiency level was 72 percent by DFA and 77 percent by SFA.

Unlike the parametric approach, the non-parametric approach assumes that random error is zero so that all unexplained variations are treated as reflecting inefficiencies. Non-parametric approaches such as Data Envelopment Analysis and Free Disposal Hull, put relatively little structure on the specification of the best-practice frontier. Data Envelopment Analysis (DEA) is rooted in the work of Farell (1957), who used the economic concept of the production frontier and the production possibility set to define technical and allocative efficiencies and later proposed measures of relative inefficiencies. DEA was first introduced by Charnes, Cooper and Rhoades (1978) to describe an application of mathematical programming to observe data to locate frontier which can then be used to evaluate the efficiency of each of the organizations responsible for the observed output and input quantities. The concept of DEA is similar to that of technical efficiency in the microeconomic theory of production. However, the main difference is that the DEA production frontier is not determined by some specific equation; instead it is generated from the actual data for the evaluated firms (DMUs). Therefore, the DEA efficiency score for a specific firm is defined not by an absolute standard but relative to the other firms under consideration. DEA also assumes that all firms face the same unspecified technology, which defines their production possibility set. The main objective of DEA is to determine which firms are operating on their efficient frontier and which firms are not. If the firm's input-output combination lies on the DEA frontier, the firm is considered efficient; and the firm is considered inefficient if the firm's input-output combination lies inside the frontier.

The basic DEA model (CCR model) implied the assumption of constant returns to scale. This assumption was later relaxed to allow for the evaluation of variable returns to scale and scale economies. Specifically, the efficient frontier may be derived using four alternative returns to scale assumptions; constant returns to scale (CR); variable returns to scale (VR), non-increasing returns to scale (NI); and non-decreasing returns to scale (ND). Yue (1992) defines the following assumptions. A bank exhibits increasing returns to scale if a proportionate increase in inputs and outputs places it inside the production frontier; and constant returns to scale if a proportionate increase or decrease in inputs or outputs move the firm either along or above the frontier. A bank which is not on the frontier is defined as experiencing non-increasing returns to scale if the hypothetical bank with which it is compared, exhibits either constant or decreasing returns to scale. A similar definition applies for non-decreasing returns to scale. A firm which is efficient under the assumption of variables return to scale (VRS) is considered technologically efficient; the VRS score represents pure technical efficiency (PT), whereas a firm which is efficient under the assumption of constant returns to scale (CRS) is technologically efficient and also uses the most efficient scale of operation.

There are a number of studies examining relative efficiency using DEA (Sufian and Abdul Majid, 2007; Li, 2006; Sufian, 2006; Sufian, 2004; Katib and Mathews, 2000). Sufian and Abdul Majid (2007) analyze efficiency change of Singapore commercial banks during the period of 1993-2003. They find that commercial banks in Singapore exhibited an average overall efficiency of 95.4 percent. Li (2006) investigates the scale-efficiency and technology-efficiency of 14 Chinese commercial banks. She concludes that most banks have low comparative efficiency. She also finds that inefficient banks generally have input surplus. Sufian (2006) investigates the efficiency of non-bank financial institutions in Malaysia for the period of 2000-2004. The study finds that finance companies were more efficient than merchant banks and that the inefficiency was the result of pure technical inefficiency rather than scale inefficiency. Using DEA to examine the efficiency effects of bank mergers and acquisition in Malaysia, Sufian (2004) finds that Malaysian banks have exhibited a commendable overall efficiency level of 95.9 percent during 1998-2003 which indicates that merger program was successful. Katib and Mathews (2000) also use DEA to estimate the efficiency of 20 Malaysian commercial banks from 1989 to 1995. The results suggest that whilst efficiency ranges between 68 percent and 80 percent, the trend in efficiency is downwards.

Free Disposal Hull is a special case of the DEA model where the points on lines connecting the DEA vertices are not included in the frontier. Instead, the FDH production possibility set is composed of only the DEA vertices and the Free Disposal Hull point interior to these vertices. Because the FDH frontier is either congruent with or interior to the DEA frontier, FDH will typically generate larger estimates of average efficiency than DEA. The FDH approach therefore allows for a better approximation or 'envelopment' of the observed data.

2. Model specification and data

This study will use the intermediation approach. Under the intermediation approach, banks are treated as financial intermediaries that combine deposits, labor and capital to produce loans and investments. The values of loans and investments are treated as output measures; labor, deposits and capital are inputs; and operating costs and financial expenses comprise total cost.

Technical efficiency (TE) has two types of measure: output-oriented and input-oriented measures. If it is an output-oriented measure, TE is a bank's ability to achieve maximum output given its sets of inputs. Whilst, an input-oriented TE measure reflects the degree to which a bank could minimize its inputs used in the production of given outputs. Our study adopts an output-oriented measure. A value of 1 indicates full efficiency and operations on the production frontier. A value of less than 1 reflects operations below the frontier. The wedge between 1 and the value observed measures the technical efficiency.

The technical efficiency of the bank can be written in a natural logarithm form as follows:

$$InQ = f(x) + InU_t - InV_t, \tag{1}$$

where InQ is the observed outputs in natural log, f denotes some functional form, x is the vector of inputs, U_t is the inefficiency error term, V_t is random error term which accounts for measurement of error on the value of output.

To put it simply, the production function describes the relationship between the output variables with quantities of input variables plus the inefficiency and random error.

$$InQ = \alpha_0 + \sum_{i=1}^{n} \alpha_1 Inx_i + E_t, \tag{2}$$

Where InQ is the natural log of output variable for production function, Inx_i is the vector of quantities of variable inputs in natural log, E_t is the stochastic error term where

$$E_t = U_t - V_t. \tag{3}$$

Following Aigner, Lovell and Schmidt (1977), this study assumes the distribution of the error term or statistical noise, V_i, to be two-sided normal distribution while the inefficiency term, U_i, is assumed to be one sided (*half normal distributed*).

The full model thus

$$\begin{aligned} \ln Q_{it} = \beta_0 + \alpha_1 \ln X_1 + \alpha_2 \ln X_2 + \alpha_3 \ln X_1 \ln X_1 + \\ + \alpha_4 \ln X_2 \ln X_2 + \alpha_5 \ln X_1 \ln X_2 + \upsilon_{it} + v_{it}, \end{aligned} \tag{4}$$

where Q_{it} is outputs: total earning assets (financing, dealing securities, investment securities and placements with other banks), X_i s are inputs: total deposits (deposits from customers and deposits from other banks) and total overhead expenses (personnel expenses and other operating expenses).

Our sample is an unbalanced panel of 22 commercial banks (9 domestic banks and 13 foreign banks) during the period from 2000 to 2006, totalling 147 observations. The basic data source is BANKSCOPE – Fitch's International Bank Database.

The computer program, FRONTIER Version 4.1 developed by Coelli (1996), has been used to obtain the maximum likelihood estimates of parameters in estimating the technical efficiency. The program can accommodate cross sectional and panel data; cost and production function; half-normal and truncated normal distributions; time-varying and invariant efficiency; and functional forms which have a dependent variable in logged or original units. These features of what Frontier 4.1 can and cannot do are not exhaustive, but provide an indication of program's capabilities.

Table 1 presents the descriptive statistics of banks' inputs and outputs used in this study.

Table 1. Commercial bank's input and output variables 2000-2006 (in RM million)

	Variable	N	Mean	Median	Minimum	Maximum	Std. dev.
All							
	Q	147	28300.14	19669.00	508.90	189518.10	34256.54
	X_1	147	24477.63	17172.50	190.10	164392.60	29819.88
	X_2	147	1073.91	825.20	6.60	2784.00	1212.98
Domestic banks							
	Q	59	53196.17	38644.60	8826.00	189518.10	40747.25
	X_1	59	46037.12	33733.30	6955.90	164392.60	35478.75
	X_2	59	761.70	571.90	124.20	2784.00	572.60
Foreign banks							
	Q	88	11608.48	3124.30	508.90	39324.00	12660.97
	X_1	88	10022.98	2614.20	190.10	35417.30	11249.28
	X_2	88	191.09	63.25	6.60	875.10	231.24

Notes: Q = Total earning assets, X_1 = Total deposits, X_2 = Total overhead expenses.
Source: Authors' estimation.

3. Empirical findings

A firm is regarded as technically efficient if it is able to obtain maximum outputs from given inputs or minimize inputs used in producing given outputs. Therefore firms on the production frontier are labelled as 'best practice' and they demonstrate optimum efficiency in the utilization of their resources. A value of 1.0 indicates that a firm lies on the best-practice frontier or full efficiency. A value of less than 1.0 indicates operations below the frontier or inefficient utilization of resources. In Table 2, the average technical efficiency score of Malaysian banks for the 147 observations over the years 2000-2006 ranges between 77 percent to 84 percent and increases over the years. Katib and Mathews (2000) find the score ranges between 68 percent and 80 percent but on a decreasing trend whilst Sufian (2004) finds Malaysian banks exhibited 95.9 percent. As an overall, the efficiency score is 81 percent. In other words, the sample banks have wasted on average 19 percent of their inputs.

Looking at the efficiency scores in Table 3, both domestic banks and foreign banks average efficiency is on increasing trend. The scores for domestic banks on average ranged between 88.8 percent and 92.8 percent whilst that of foreign banks ranged between 69.7 percent and 78.2 percent. The overall efficiency level for domestic banks was higher (90.9 percent) compared to that of foreign banks (74.4 percent) suggesting that domestic banks are on average more efficient than foreign banks. The results also suggest that there is significant mean difference between technical efficiency of domestic and foreign banks.

Table 2. Technical efficiency: summary of SFA results

	2000	2001	2002	2003	2004	2005	2006	All
Mean	0.771	0.790	0.791	0.811	0.822	0.832	0.842	0.810
Median	0.840	0.849	0.858	0.867	0.876	0.884	0.891	0.871
Maximum	0.942	0.946	0.949	0.99	0.992	0.992	0.993	0.993
Minimum	0.432	0.457	0.481	0.506	0.529	0.552	0.575	0.432
S. D.	0.159	0.145	0.143	0.139	0.132	0.126	0.119	0.137
Skewness	-0.811	-0.974	-0.801	-0.801	-0.813	-0.825	-0.836	-0.844
N	18	20	21	22	22	22	22	147

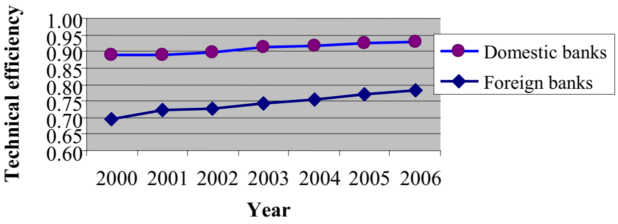
Notes: N = Number of banks, S.D. denotes standard deviation.
Source: Authors' own estimates.

This is perhaps the results of the merger waves of the 1990's that has completed its exercise in 2000, leaving domestic banks to only 9 banks. In addition, foreign banks have been prohibited to open new branches since 1971 while that of domestic banks were given competitive advantage and support from the government.

Table 3. Technical efficiency scores by ownership, 2000-2006

	2000	2001	2002	2003	2004	2005	2006	All
Domestic banks								
Mean	0.888	0.889	0.896	0.913	0.918	0.923	0.928	0.909
Median	0.893	0.894	0.900	0.912	0.917	0.923	0.928	0.909
Maximum	0.942	0.946	0.950	0.992	0.993	0.993	0.994	0.994
Minimum	0.840	0.845	0.854	0.863	0.872	0.880	0.888	0.840
Std. dev.	0.038	0.038	0.036	0.043	0.041	0.038	0.036	0.040
Skewness	-0.126	0.126	0.123	0.567	0.562	0.557	0.552	0.267
N	7	8	8	9	9	9	9	59
Foreign banks								
Mean	0.697	0.724	0.727	0.742	0.756	0.769	0.782	0.744
Median	0.646	0.722	0.683	0.701	0.718	0.734	0.749	0.713
Maximum	0.901	0.907	0.913	0.919	0.924	0.929	0.934	0.934
Minimum	0.432	0.457	0.482	0.506	0.530	0.553	0.575	0.432
S. D.	0.164	0.154	0.148	0.141	0.135	0.128	0.122	0.139
Skewness	0.005	-0.023	-0.024	-0.038	-0.051	-0.064	-0.075	-0.161
N	11	12	13	13	13	13	13	88

Notes: N = Number of banks, S. D. denotes standard deviation.
Source: Authors' own estimates.



Note: Figure 1 depicts the graphical presentation of the mean efficiency scores for both domestic and foreign banks.

Fig. 1. Technical effciency for domestic and foreign banks

Analyzing the technical efficiency at bank level throughout 2000 to 2006, the impact of merger upon domestic banks can be seen from the increase of efficiency scores of domestic banks (Table 4). By comparing the performance of domestic banks based on the mean efficiency scores, the results show that AmBank Malaysia Berhad, the leading service provider in Malaysia, appears to perform well with 99.3 percent, outperforming the largest bank, Malayan Banking Berhad, which is ranked third (93.4 percent). RHB bank is ranked second (95.3 percent). The disparity between the highest (99.3 percent) and the lowest (86.7 percent) was quite small. Both Hong Leong Bank and Public bank have improved their efficiency levels significantly during the period.

Looking at the performance of foreign banks, banks which experience high levels of technical efficiency include United Overseas Bank (91.8 percent), OCBC bank (91.7 percent) and Citibank (90.3 percent). However, the disparity between the highest (91.8 percent) and the lowest (50.5 percent) was quite large. The Royal Bank of Scotland and JP Morgan Chase Bank have both improved their efficiency levels significantly throughout the period observed.

Table 4. Mean technical efficiency of individual banks, 2000-2006

Banks	2000	2001	2002	2003	2004	2005	2006	Average
Domestic banks								
Affin Bank Berhad	0.841	0.850	0.860	0.868	0.877	0.884	0.892	0.867
Alliance Bank Malaysia Bhd	NA	0.845	0.854	0.863	0.872	0.880	0.888	0.867
AmBank Malaysia Berhad	NA	NA	NA	0.992	0.993	0.993	0.994	0.993
CIMB Bank Berhad	0.903	0.909	0.915	0.921	0.926	0.930	0.935	0.920
EON Bank	0.840	0.850	0.860	0.868	0.877	0.884	0.892	0.867
Hong Leong Bank Berhad	0.881	0.888	0.895	0.902	0.908	0.914	0.920	0.901
Malayan Banking Berhad	0.920	0.925	0.930	0.934	0.938	0.942	0.946	0.934
RHB Bank	0.942	0.946	0.950	0.953	0.956	0.959	0.962	0.953
Public Bank	0.893	0.899	0.906	0.912	0.917	0.923	0.928	0.911
Foreign banks								
The Royal Bank of Scotland	0.593	0.614	0.635	0.654	0.673	0.691	0.709	0.653
Bangkok Bank Berhad	0.432	0.457	0.482	0.506	0.530	0.553	0.575	0.505
Bank of America	0.560	0.582	0.604	0.625	0.645	0.664	0.682	0.623
The Bank of Nova Scotia	0.579	0.600	0.621	0.641	0.661	0.679	0.697	0.640
Bank of China	NA	NA	0.579	0.601	0.622	0.642	0.661	0.621
Bank of Tokyo-Mitsubishi UFJ	0.765	0.779	0.792	0.805	0.817	0.828	0.838	0.803
Citibank Berhad	0.883	0.890	0.897	0.904	0.910	0.916	0.921	0.903
HSBC Bank	0.826	0.837	0.847	0.856	0.865	0.874	0.882	0.855
United Overseas Bank	0.901	0.907	0.913	0.919	0.924	0.929	0.934	0.918
Standard Chartered Bank	NA	0.849	0.859	0.868	0.876	0.884	0.891	0.871
JP Morgan Chase Bank	0.581	0.603	0.624	0.644	0.663	0.682	0.699	0.642
OCBC Bank	0.899	0.906	0.912	0.917	0.923	0.928	0.932	0.917
Deutsch Bank	0.646	0.665	0.683	0.701	0.718	0.734	0.749	0.699

Note: NA denotes data not available.
Source: Authors' own estimates.

Conclusions

As in most previous studies on bank efficiency, we find that on average, bank deviates substantially from the best-practice frontier. The technical efficiency for the whole sample on average was 81 percent suggesting an input waste of 19 percent. Overall, the level of efficiency has slightly increased over the period of study.

Our results also suggest that domestic banks on average were found to be relatively more efficient compared to foreign banks, 90.1 percent and 74.4 percent respectively. According to our results, AmBank, RHB and Malayan Banking appear to be the most efficient domestic banks while Affin, Alliance and EON Bank were the least efficient banks. As for foreign banks, United Overseas, OCBC and Citibank were the most efficient banks while Bangkok Bank, Bank of America and Bank of China were the least efficient.

As a caveat, the results should be interpreted with great caution since previous researches differ substantially across different estimation procedures. Further study should use other estimation approaches and look at the cost and profit efficiency and results thus can be compared.

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Appendix. Stochastic technical frontier maximum likelihood parameter estimates

Parameter	Variable	Coefficient	Standard error	T-ratio
β_0	Constant	4.9481	0.4401	11.2434
β_1	lnX_1	-0.0095	0.1614	-0.0588
β_2	lnX_2	0.2307	0.1447	1.5947
β_3	$lnX_1\ lnX_1$	0.0582	0.0202	2.8840
β_4	$lnX_2\ lnX_2$	0.0165	0.0184	0.8927
β_5	$lnX_1\ lnX_2$	-0.0405	0.0374	-1.0834
Sigma-square	$\sigma^2 = \sigma^2_v + \sigma^2_u$	0.0914	0.1173	0.7797
Gamma	$\gamma = \sigma^2_u / (\sigma^2_v + \sigma^2_u)$	0.9838	0.0209	47.1492
Log likelihood function		218.8504		

Notes: X_1 = Total deposits (deposits from customers and deposits from other financial institutions), X_2 = Total Overhead Expenses (personnel expenses and other operating expenses). Dependent variable is Q, Total Earning Assets (financing, dealing securities, investment securities and placements with other banks).