Evaluating Agricultural Banking Efficiency Using the Fourier Flexible Functional Form

By

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Abstract:

This study applied more flexible cost functional form, Fourier Flexible Functional Form, and tested the validity of the Translog cost functional form as to estimate the cost function incorporating risk and loan's quality for banking industry. Meanwhile, the study extended four different cost efficiency measures for banking industry not only among different sized banks but also between commercial banks and agricultural banks. And thereafter, by evaluating these efficiency measures, banks will identify sources of inefficiency, which should aid banks in developing approaches to improve their operational policies, procedures, and performance.

Key words: Fourier Flexible Functional Form, Cost efficiency, Bank efficiency

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1. Introduction

Rural financial markets are undergoing a period of rapid transition. Changes in the agricultural economy, technological advances, the competitive structure in the financial services industry and changes of borrower demands have collectively influenced the delivery of credit to agriculture (Ellinger, 1994). In addition, banking deregulation since 1990s expedited the considerable change of the competitive environment among rural financial markets. Meanwhile, commercial banks have increasingly been involved in farm lending as agricultural debt comprised 37% of their total loan portfolio (Walraven et al., 1993). These lenders, however, have to contend with competitive pressures from fellow commercial banks as well as captive finance companies and input supply firms which face fewer regulatory hurdles compared to the highly regulated banking industry and Farm Credit System (Ellinger, 1994).

Agricultural banks need to function efficiently in order to survive in the increasingly competitive financial environment. It is vital to the health of the rural economy since these banks play a vital role in influencing regional flows of funds (Samolyk, 1989).

Over the past several years, substantial studies have been conducted to measure the efficiency of financial institutions, particularly of commercial banks. Many studies found large cost inefficiencies in those institutions. In general, the cost due to inefficiency accounts for at least 20% of total banking industry costs and about 50% of the industry’s potential profits (Berger and Mester, 1997). In the perfectly competitive market, the inefficient firms would be driven out by the efficient firms. In this regard, a study on banking efficiency will not only be beneficial to the banks to identify strategies to survive in a competitive market but will also be useful for the general public, whose confidence in the economy will be affected by the expectation of the safety in those financial institutions, and policymakers, who are responsible formulating more appropriate new bank legislations.

This issue, however, has not been well studied among agricultural banks. Compared to the regular commercial banks, agricultural banks usually have more concerns on liquidity. One third of all agricultural debts are held by rural banks with assets of less than $50 million (Ellinger, 1994). Thus, agricultural banks are unable to diversify their clientele by including other non-agricultural business clientele due to the shortage of lending funds. The specialized nature of their lending operations results in greater risks and uncertainty. In this regard, results of efficiency analyses based on commercial banking operations have less relevance to agricultural banks as no parallel conclusions can be drawn given these banks' different styles of lending operations.

In general, there are three methodologies used to solve the efficiency problems: Parametric approach, Semi-Nonparametric approach, and Nonparametric approach. The Parametric approach assumes the most strictly specific functional form. The proper assumptions of the functional form and curvature would be the prerequisite to get unbiased estimates for Parametric method. The Semi-Nonparametric approach relaxes the strict functional form requirement of the Parametric approach. Particularly, the minimal *a priori* assumptions would have to be imposed to guarantee the unbiased estimates (Gallant, 1982). But no matter how few *a priori* assumptions would be imposed, Semi-Nonparametric, like Parametric approach, would have to assume certain specific functional forms. Compared with these two approaches, the Nonparametric technique will not require to specify an explicit functional form. Therefore, the problems associated with the potentially wrong functional forms imposed would be avoided.

However, typically, Nonparametric techniques only focus on the technological optimization but neglect economic optimization by ignoring the prices information. In addition, Nonparametric method assumes a deterministic procedure instead of a stochastic procedure. In other words, another drawback of this method is that it usually does not allow for random errors in the data. Thus, there is no way to derive inferences of the estimated parameters or conduct the statistical hypothesis tests (Berger and Mester, 1997; Coelli et al., 2003).

Stochastic Frontier Analysis (SFA), one of most widely used econometrics methods applied to the Parametric approach, was introduced to the efficiency studies by Aigner et al in 1977. Fourier Flexible Functional Form (FF) is the most used functional form in the Semi-Nonparametric approach (Mitchell and Onvural, 1996; Huang and Wang, 2004). Data envelopment analysis (DEA) is a nonparametric method to measure the efficiency of a decision-making unit (DMU). DEA was initiated by Charnes and et al. in 1978 and then it was developed to accommodate technologies that exhibit variable returns of scale by Banker et al. in 1984. Since then, the DEA has been widely applied to efficiency analysis. Recently, some studies are exploring some simulation methods to overcome the drawback of DEA's deterministic approach (Ray, 2004). In this study, we will focus on the comparison of efficiency measurements derived from Translog functional form, representing the Parametric method, and Fourier Flexible functional form, representing the Semi-Nonparametric method.

Since both Parametric and Semi-Nonparametric approaches would rely on the validation of assumed functional forms, it is necessary to explore the advantages and disadvantages of available functional forms. In existing efficiency analysis studies, the most widely used cost functional forms are either Cobb-Douglas or Translog functions because those two functional forms have good characteristics to explain the economic theory and are comparatively simple and easier to estimate (Berger and Humphrey, 1991; Gilligan and Smirlock, 1984; Gropper, 1991; Hunter et al., 1990; Noulas et al., 1990). However, some other researchers challenged the validation of these two general functional forms. For example, Coelli et al.(2003) pointed out that the assumptions of Cobb-Douglas functional form require that all firms have the same production elasticities and the substitution elasticities must equal to one. But in the real world, these are too restrictive requirements to satisfy. McAllister and McManus (1993) questioned the suitability of the Translog cost function for different banking sectors. They concluded that the Translog functional form represents a second-order Taylor series approximation of an arbitrary function at a point. This function, however, forces a symmetric U-shaped average cost curve to both large and small banks without differentiation, which leads to poor approximation of results. Considering the fact that agricultural banks are relatively smaller operations, the Translog functional form might not be ideal for efficiency analyses in the agricultural banks category[1].

The Fourier Flexible (FF) form represents a Semi-Nonparametric approach, using data to infer relationships among variables when the true functional form of the relationships is unknown. In addition, FF functional form can potentially approximate any function well globally for the orthogonality of the trigonometric functions, such as a linear combination of sine and cosine functions named as the Fourier series (Gallant, 1982; Huang and Wang, 2004; Mitchell and Onvural, 1996). So we do not need, when using FF form, to specify the real function form or impose the curvature assumptions before estimating the cost function. Another advantage of FF functional form is that it can measure the bias resulting from use of the Translog form since the Translog form can be viewed as a special case nested in the FF form. Despite of the advantages of FF, very limited studies on FF have been conducted in banking performance analysis.

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[1] Although the Translog functional form might not be represent the cost curve, it does not indicate it would definitely bad in all cases in which the Translog functional form would fit the data very well.

Furthermore, all the existing limited FF studies have been carried out on commercial banks so far (Mitchell and Onvural, 1996; Huang and Wang, 2004). It therefore remains to be seen how FF would fare in agricultural banks' efficiencies analysis. In addition, it is hard or even impossible to identify an appropriate cost functional form for agricultural banks in most cases. Even if some functional forms have already been verified as applicable for certain time periods, their consistency over time might be difficult to establish. This difficulty is partly due to the fact that farmers' needs would be diversified and be prone to change through time given the uncertainties in agricultural production. So it would be interesting and valuable to study the FF functional form on agricultural banks' production and test its performance on agricultural banks, and compare the results between agricultural banks and commercial banks.

Furthermore, some researchers claimed that it would be meaningless to study and measure the banking efficiencies if risks are not considered. Thus, this study would also analyze the effects of loan quality and financial risks on the banking operational cost estimation, which will in turn affect banking operational performance.

2. Model and Methodology

The Fourier Flexible cost function can be expressed as:

$$LnC = \beta_0 + \mathbf{x\beta} + (1/2)\mathbf{xAx'} + \mathbf{z\gamma} + \sum_{h=1}^{H}[u_h \cos(\mathbf{xk_h}) + v_h \sin(\mathbf{xk_h})] + \boldsymbol{\varepsilon} \qquad (1)$$

Where

β_0 is a constant to be estimated;

$\boldsymbol{\beta} = [\beta_{l1},...\beta_{lN}, \beta_{q1},...\beta_{qM}]'$ is a $(N+M)\times 1$ vector of coefficients to be estimated. N is the number of inputs and M is the number of outputs;

$\mathbf{x} = [\mathbf{l'}, \mathbf{q'}]$ is a QT$\times (N+M)$ matrix of rescaled log-input prices $\mathbf{l} = (l_1,...l_N)'$ and scaled log-output quantities $\mathbf{q} = (q_1,...q_M)'$[2]. Q is the number of firms in each year and T is the number of years in panel data;

The rescaling formulas can be expressed as followings:

$$l_i = \lambda(Lnp_i + w_{pi}) \tag{2}$$

$$q_j = \lambda\mu_j(Lny_j + w_{yj}) \tag{3}$$

$$w_{pi} = 0.00001 - \min(Lnp_i) \tag{4}$$

$$w_{yj} = 0.00001 - \min(Lny_j) \tag{5}$$

$$\lambda = \frac{(2\pi - \varepsilon)}{D} \cong \frac{6}{D} \qquad (6)^3$$

$$\mu_j = \frac{(2\pi - \varepsilon)}{\lambda[\max(Lny_j) + w_{yj}]} \cong \frac{6}{\lambda[\max(Lny_j) + w_{yj}]} \tag{7}$$

$$D = \max\{\max(Lnp_i) + w_{pi}\} \tag{8}$$

Where i=1,…, N , j=1,…, M, p_i is the price for input i, *and* y_j represents the output j.

Substituting equations (5) (6) (7) (8) into (2) and (3) to calculate the rescaled data which lie within$[0,2\pi]$.

$\mathbf{A} = \boldsymbol{\beta\beta}' = [a_{ij}]$ is a $(N+M)\times(N+M)$ symmetric matrix of coefficients to be estimated;

$\mathbf{z} = [z_1,...z_w]$ is a $QT \times W$ matrix of exogenous variables which can capture the financial risks and loan quality;

$\boldsymbol{\gamma} = [\gamma_1,...\gamma_w]'$ is a $W \times 1$vector of the coefficients to be estimated for $\mathbf{z}$;

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[2] Gallant (1982) claimed that rescaling the data within $[0,2\pi]$ is important for accurate Fourier series to compensate the so-called Gibb's phenomenon.

[3] ε in equation (6) and (7) is an arbitrary infinitive small number.

u_h, v_h are the coefficients to be estimated for Fourier series cosine and sine accordingly;

$\mathbf{k}_h = [k_{h1},...k_{hN}, k_{h,N+1},...k_{h,N+M}]'$ is a $(N+M)\times 1$ elementary multi-index vector with integer components chosen by researchers to satisfy the following three criteria (Huang and Wang, 2004): (i) k_{hi} ,where *i=1,…,N+M,* cannot be a zero vector and its first non-zero element must be positive; (ii) its elements do not have a common integer divisor; (iii) $|\mathbf{k}_h| \le K$ (a constant) are non-decreasing in h, where *h=1,…,H;*

$\boldsymbol{\varepsilon}$ is a $QT \times 1$ random error vector.

Assume that the cost function must be linearly homogeneous in input prices (based on microeconomic theory), the constraints are set as:

$$\lambda \sum_i^N \beta_{li} = 1 \tag{R1}$$

$$\sum_j^N a_{ij} = 0\,, \quad i = 1,..., N+M \tag{R2}$$

$$u_h = v_h = 0 \;\text{ if }\; \sum_j^N k_{hj} \neq 0 \tag{R3}$$

Constraint (R3) requires the sum of the coefficients of input prices for trigonometric functions of sin(.) and cos(.) in equation (1) to be zero (Huang and Wang, 2004).

As many studies suggested, estimating the cost equation altogether with *N-1* cost share equations could increase the efficiency of estimation for the correlation of the disturbances across equations (Mitchell and Onvural, 1996; Huang and Wang, 2004). The i^{th} cost share equation can be denoted as:

$$S_i = \frac{C_i}{C(\mathbf{p,y})} = \frac{p_i x_i}{C(\mathbf{p,y})}\,, \quad i = 1,...,N \tag{9}$$

Where x_i is the cost-minimizing quantity of input i.

By Shephard's Lemma, x_i can be derived as:

$$x_i = \frac{\partial C(\mathbf{p},\mathbf{y})}{\partial p_i}, \qquad i = 1,\ldots,N \quad . \tag{10}$$

Substituting (11) into (10), the cost share equations would become:

$$S_i = \frac{p_i\left[\dfrac{\partial C(\mathbf{p},\mathbf{y})}{\partial p_i}\right]}{C(\mathbf{p},\mathbf{y})} = \frac{\partial \ln C(\mathbf{p},\mathbf{y})}{\partial C(\mathbf{p},\mathbf{y})}\cdot\frac{\partial C(\mathbf{p},\mathbf{y})}{\partial p_i}\cdot\left(1\Big/\frac{\partial \ln p_i}{\partial p_i}\right) = \frac{\partial \ln C(\mathbf{p},\mathbf{y})}{\partial \ln p_i} \quad , \qquad i = 1,\ldots,N \tag{11}$$

Implementing the first partial derivative of the log-cost function, equation (1), to the i^{th} input log-price, $\ln p_i$, and then substituting the result into equation (11), the expression of cost share equations would change to:

$$S_i = \frac{\partial \ln C(\mathbf{p},\mathbf{y})}{\partial l_i}\cdot\frac{\partial l_i}{\partial \ln p_i} = \lambda\left\{\beta_{li} + \sum_{j=1}^{N} a_{ij} l_j + \sum_{j=N+1}^{N+M} a_{ij} q_{j-N} + \sum_{h=1}^{H}\left[-u_h k_{hi}\sin(\mathbf{x}\mathbf{k_h}) + v_h k_{hi}\cos(\mathbf{x}\mathbf{k_h})\right]\right\} \quad , \qquad i = 1,\ldots,N \tag{12}$$

To avoid the problem of a singular covariance matrix for the disturbances caused by the perfect collinearity of N cost share equations, one of them must be dropped when estimating the equation system composed by log-cost function, equation (1), and N-1 cost share equations expressed by equation (12)[4] . The nonlinear iterative Zellner's seemingly unrelated regression (ITSUR) is applied to the panel data in this study. This estimation method is asymptotically equivalent to the maximum likelihood method.

Since data in this study are panel data, the assumptions of fixed effect model need to be tested before implementing the nonlinear ITSUR to estimate the cost and shares equations system. The Hausman specification test compares the fixed versus random effects under the null

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[4] Which cost share equation is dropped would affect the estimation very little.

hypothesis that the individual effects are uncorrelated with the other regressors in the model (Hausman, 1978). If the null hypothesis is rejected, the random effect model would produce biased estimators. Thus the fixed effect model would be preferred. Hausman's essential result is that the covariance of an efficient estimator with its difference from an inefficient estimator is zero (Greene, 2003).

The number of Fourier series chosen for FF cost functional form would affect the strengths of FF form. Gallant (1981) showed that increasing the number of trigonometric terms included in FF would reduce the approximation error. But too many sine and cosine terms would lead to the over identification and multicollinearity problems. Eastwood and Gallant (1991) found the rules to produce the consistent and asymptotically normal parameter estimates in FF function: the number of parameters to be estimated in FF function should be equal to the number of sample observations raised to the two-thirds power. In this study, there are N equations in the similar seemingly unrelated regression (SUR) equation system, each equation has QT observations. In total $N \cdot QT$ effective observations are used in the analysis. Therefore, the number of parameters, based on the suggestions made by Eastwood and Gallant, would be:

$$NB = \left(N \cdot QT\right)^{\frac{2}{3}} \tag{13}$$

Considering constraints (R1),(R2), and (R3), the total free unknown parameters to be estimated in Translog part $\beta_0 + \mathbf{x\beta} + (1/2)\mathbf{xAx'} + \mathbf{z\gamma}$ for FF log-cost function would be reduced to:

$$\begin{aligned} NB\_Trans\log &= 1 + (N+M) - (N+M) + \left[\frac{(N+M)(N+M)-(N+M)}{2} + (N+M)\right] \\ &= 1 + \frac{(N+M)(N+M+1)}{2} \end{aligned} \tag{14}$$

Where 1 is the number of estimate for β_0; the first (N+M) is the number of estimates of $\boldsymbol{\beta}$; the $-(N+M)$ is due to the homogeneity constraints imposed by (R1) and (R2); the rest part in [.] gives the number of estimates for $\mathbf{A}$ when the symmetric constraints is imposed on $\mathbf{A}$.

By equation (13) and (14) and considering the numbers of sin(.) and cos(.) are the same, we would get the proper number of Fourier series included in equation (1) as:

$$H = \frac{1}{2}(NB - NB\_Trans\log) = \frac{1}{2}\left[\left(N \cdot QT\right)^{\frac{2}{3}} - \frac{(N+M)(N+M+1)}{2} - 1\right] \tag{15}$$

3. Efficiency Measures

The primary benefits of efficiency analysis can be separated into the efficiencies generated by the scale of production, joint production of outputs, and deviations from an efficient frontier (Ellinger, 1994). In this section, four well-known efficiencies are introduced (Mitchell and Onvural, 1996).

(1) Overall scale economy measure (RSE)

RSE is developed by Baumol et al. (1982) and it is defined as the elasticity of cost with respect to output holding output bundle composition:

$$RSE = \sum_{j=1}^{M} \frac{\partial \ln C}{\partial \ln y_j} = \sum_{j=1}^{M} \frac{\partial \ln C}{\partial q_j} \cdot \frac{\partial q_j}{\partial \ln y_j} \tag{16}$$

Calculating the $\frac{\partial q_j}{\partial \ln y_j}$ from equation (3) and substituting it into equation (16), RSE can be rewritten as:

$$RSE = \lambda \sum_{j=1}^{M} \mu_j \cdot \frac{\partial \ln C}{\partial q_j} \, . \tag{17}$$

RSE measures the percentage change in total costs due to one percent increase in all outputs. Change in output only alters the scale of outputs’ bundle but the proportion of the outputs' bundle will remain the same. Return to scale is increasing, constant, or decreasing when RSE is less than, equal to, or greater than one, respectively. It is most useful if banks grow by changing their scales but not the compositions of their output bundles. However, RSE would provide limited insight into cost efficiency when product mixes are allowed to vary.

(2) Expansion path scale economies ($EPSE^{AB}$)

Detecting the limitation of RSE and considering the facts that, as banks enlarge in size, banks move along expansion paths connecting output bundles of increasingly larger size and different product mixes, Berger et al. (1986 and 1987) proposed a new measure, expansion path scale economies ($EPSE^{AB}$), which allows banks to vary both in product quantities and in product mixes. $EPSE^{AB}$ is the elasticity of incremental cost with respect to incremental output allowing variation in proportion to the output mixes.

$$EPSE^{AB} = \sum_{j=1}^{M}\left[\frac{y_j^B - y_j^A}{y_j^B}\cdot\frac{C(\mathbf{y}^B,\mathbf{p})}{C(\mathbf{y}^B,\mathbf{p}) - C(\mathbf{y}^A,\mathbf{p})}\cdot\frac{\partial \ln C(\mathbf{y}^B,\mathbf{p})}{\partial \ln y_j}\right] \qquad (18)$$

where y_j^A and y_j^B are the j^{th} outputs in the output bundles at banks A and B respectively. And $C(\mathbf{y}^A,\mathbf{p})$ and $C(\mathbf{y}^B,\mathbf{p})$ are the total costs to produce the output bundle $\mathbf{y}^A$ in bank A and $\mathbf{y}^B$ in bank B, respectively.

$EPSE^{AB}$ measures the return to scale when expanding from a smaller output bundle $\mathbf{y}^A$ to a larger output bundle with a different product mix, $\mathbf{y}^B$. Return to scale are increasing, constant, or decreasing when $EPSE^{AB}$ is less than, equal to, or greater than one along the expansion path spanning $\mathbf{y}^A$ and $\mathbf{y}^B$.

(3) Economies of Scope (SCOPE)

The cost function of the multi-product bank is said to be sub additive if the cost of joint production is cheaper than its separate production, E.g. $C(\mathbf{y}) < \sum_j C(y_j)$, where $\mathbf{y} = \sum_j y_j$.

Knowledge of the degree of subadditivity of bank cost functions is important for regulatory purposes since an industry is a natural monopoly if all points along the cost manifold in the relevant range of output are sub additive.

Hunter et al. (1990) pointed out that the existence of either increasing RSE or EPSE is neither necessary nor sufficient to explain the subadditivity of the banks' cost functions. Originated from the definition of the subadditivity, several studies applied the concept of the economies of scope, which is a necessary condition for subadditivity, to banking issues (Baumol et al., 1982; Kim, 1986; Mester, 1996; Mitchell and Onvural, 1996; Huang and Wang, 2004). Following the definition in their studies, the overall economies of scope at output bundle $\mathbf{y}$ can be written as:

$$\begin{aligned} SCOPE &= \frac{1}{C(\mathbf{y},\mathbf{p})}\left[\sum_{j=1}^{M} C(y_j,\mathbf{p}) - C(\mathbf{y},\mathbf{p})\right] \\ &\cong \frac{1}{C(\mathbf{y},\mathbf{p})}\left[\sum_{j=1}^{M} C(y_j - 2y_j^m, \tilde{\mathbf{y}}_j^m, \mathbf{p}) - C(\mathbf{y},\mathbf{p})\right] \end{aligned} \tag{19}$$

where $y_j^m = \min(y_j)$, and $\tilde{\mathbf{y}}_j^m = (y_1^m,..., y_{j-1}^m,..., y_M^m)'$ is the output vector whose elements are the minimum values of all M outputs except for y_j.

SCOPE measures the percentage of cost saving from joint (multi-firm) versus specialized (single firm) production. Scope economies or diseconomies exist if SCOPE is greater than or less than zero respectively. SCOPE is the most useful efficiency measure if extreme product specialization is a viable business strategy. However, banks are rarely engaged in extreme specialization. Further more, there are some other problems associated with this measure, especially if the cost function is estimated using the standard Translog (Hunter et al., 1990; Berger et al., 1987; Mester, 1987; White, 1980).

(4) Expansion path subadditivity (EPSUB)

Berger et al. (1987) observed that the banks categorized in different sized groups would have the different proportion of specialization in the product mixes. After he realized the limitations of SCOPE to measure the degree of subadditivity of bank cost functions, he proposed a more general measure of scope economies, Expansion path subadditivity (EPSUB).

$$EPSUB^{AB} = \frac{C(\mathbf{y}^A, \mathbf{p}) + C(\mathbf{y}^D, \mathbf{p}) - C(\mathbf{y}^B, \mathbf{p})}{C(\mathbf{y}^B, \mathbf{p})} \quad (20)$$

where $\mathbf{y}^B$ and $\mathbf{y}^A$ are output bundles for banks B and A respectively, the residual output bundles $\mathbf{y}^D = \mathbf{y}^B - \mathbf{y}^A$ are produced by bank D. $C(\mathbf{y}^B, \mathbf{p})$, $C(\mathbf{y}^A, \mathbf{p})$, and $C(\mathbf{y}^D, \mathbf{p})$ are the total costs to produce the product mixes in bank B, A, and D, respectively.

EPSUB measures the percentage decreasing in total costs resulted from "joint" production of an output bundle $\mathbf{y}^B$, which represents for bank B's size category, compared to a pair of small "specialized" banks, which produce the same total amount of the output bundles. The logic behind the EPSUB is to divide $\mathbf{y}^B$ into two smaller "competing banks" including the representative bank producing $\mathbf{y}^A$ along the expansion path connecting $\mathbf{y}^A$ and $\mathbf{y}^B$.

If $EPSUB^{AB}$ is greater than zero, costs are said to be "subadditive" and it means the scope economies for bank B, implying that bank B cannot be driven from the market by two smaller "specialized" banks A and D. By contrast, if $EPSUB^{AB}$ is less than zero, costs are said to be "superadditive" and it means the scope diseconomies for bank B, implying that bank B cannot survive in the competitive market since it is more cost efficient to produce output bundle $\mathbf{y}^B$ separately by two smaller competitive banks A and D.

4. Data

This study will utilize a panel data set collected from the Call Report Database from 2000 to 2005 published online by the Federal Reserve Board of Chicago. Data were collected on a quarterly basis and are annualized for the purpose of this study. This study's data were obtained from consolidated banking financial statements that summarized the annual financial performances of all branches. Only banks that continuously reported their financial conditions in the database during the six-year period were included in this study. Banks with any zero observations for any variable or in any year were discarded. Given these conditions, a total of 383 banks were identified in each year, with 2298 observations in total across 6 years.

We define "agricultural banks" based on the criterion that the agricultural loan ratio was 25% or higher. The percentages of the agricultural banks are comparatively stable across 6 years, varying from 16.2% to 17.75%. Some studies found that the bank size would also influence the cost efficiencies. This study will, therefore, focus on the effect of size on banking cost efficiencies. In this study, banks are divided into 5 groups using total assets as the classification criterion: Banks with total assets less than \$1 billion are classified as group 1; Banks with total assets between \$ 1 billion and \$ 2 billion are classified as group 2; Banks with total assets between \$ 2 billion and \$ 5 billion are classified as group 3; Banks with total assets between \$ 5 billion and \$ 10 billion are classified as group 4; Banks with total assets over \$ 10 billion are classified as group 5. The distribution of sample banks by specialization (agricultural banks vs. commercial banks) is listed in table1.1 and the distribution of sample banks by total assets (five groups) is listed in table 1.2 and printed in figure 1.

Bank output data collected include Agricultural Loans (y_1), Non-Agricultural Loans (y_2), Consumer Loans (y_3), Fee-based Financial Services (y_4), and Other Assets that cannot be properly included in any other asset items in the balance sheet (y_5). The main input price data categories considered in this study are: Labor-related Measures (salaries and employee benefits divided by number of full-time equivalent employees, p_1), Physical Capital (occupancy and fixed asset expenditures divided by net premises and fixed assets, p_2), Purchased Financial Capital Inputs (expense of federal funds purchased and securities sold and interest on time deposits of $100,000 or more divided by total dollar value of these funds, p_3), and Deposits (interest paid on deposits divided by total dollar value of these deposits, p_4). As described in section 2, following equation (2) to equation (8), all output variables and input price variables are rescaled within $[0,2\pi]$ as $\mathbf{q} = (q_1,...q_5)'$ and $\mathbf{l} = (l_1,...l_4)'$ respectively. In order to calculate the cost share, the cost of each input is also collected and denoted C_1 to C_4 respectively. Then the cost share, S_i , can be calculated as $S_i = \dfrac{C_i}{\sum_{i=1}^{N=4} C_i}$.

The loan quality index z_1 and financial risk index z_2 are included in this study to capture the loan quality and financial risks, respectively. The index z_1 is derived from the ratio of non-performing loans to total loans (NPL) and used to capture the loan quality[5] (Stirob and Metli, 2003). In contrast to the NPL and some other debts status, the equity capital is often ignored (Hughes et al., 2000). Actually, in addition to an important source of loanable funds, equity capital can also be thought of as a cushion to protect banks from loan losses and financial distress. Banks with a lower capital to asset ratio (CAR) would need more debt financing and

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[5] $z_1 = 10000 \times \text{NPL} = 10000 \times \dfrac{\text{nonaccrual loans} + \text{loans 90 days or more past due}}{\text{total loans}}$. The reason to use z_1 but instead of NPL is because $\ln z_1$ is a monotonic transformation of NPL which will only change the magnitude of the NPL but still keep all other properties of NPL. In addition, after the transformation, $\ln z_1$ would be all positive numbers with less extreme values.

therefore have a higher risk of insolvency. So CAR can be good a proxy to measure the financial risk levels for banks. However, in stead of using CAR, we developed another financial risk index z_2 [6]from CAR in this study.

The comparisons of the statistics summaries before and after data transformation for the variables selected are listed in Table 2. Transformed data satisfy the data requirement to estimate the FF log-cost function (equation 1).

The number of Fourier series included would be determined by equation (15). In this study, N=4, M=5, Q=383, T=6. Substituting those numbers into equation (15), we can calculate $H \cong 197$. Then 197 elementary multi-index vectors $\mathbf{k}_h$ s are chosen according to three criteria discussed in section 2.

5. Empirical Estimation and Results

The Hausman hypothesis test for random effects results in the test statistics 123.21 with p-value less than 0.001, showing that the null hypothesis for random effects is rejected. This result suggests that the nonlinear ITSUR is appropriate to estimate the coefficients in the equation system with fixed effects. In order to compare the differences between the FF and Translog cost functional forms, both results are provided in Table 3[7]. In addition, the hypothesis that all coefficients of the Fourier series equal to zero is rejected at 0.01 significant level by LM test (p-value<0.0001). This result indicates that the FF is significantly different from the Translog function and FF cost function is likely to be a proper functional form to estimate the cost function in this case.

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[6] $z_2 = 1000 \times CAR = 1000 \times \frac{\text{Equity Capital}}{\text{Total Assets}}$. The reason to develop z_2 is the same as z_1 .

[7] To save the space, the coefficients of Fourier series would not be presented in Table 3.

Moreover, based on the information presented in Table 3, we found that the theoretical assumptions[8] for cost function are generally true for both FF and the Translog cost functional forms, except for the unexpected negative signs of Purchased Financial Capital Input's price for both Fourier cost and Translog functional forms; and the unexpected negative signs of Consumer Loans for FF cost functional form and Agricultural Loans for Translog cost functional form respectively. Since the unexpected coefficients are either very small in scale to affect the cost function or are insignificant at all, the theoretical assumptions of non-decreasing in input prices and outputs in this case might only be barely violated. In addition, the unexpected signs of the coefficients reveal that it might not always true for the banks to pursue the minimum cost (or maximum profit)[9]. In another aspect, the unexpected coefficient sign of the Agricultural Loans for Translog functional form does provide the empirical proof that it is improper to apply the Translog cost function to measure the agricultural banks' performance as contended by McAllister and McManus (1993).

Another important result revealed in Table 3 is that the coefficients of loan quality index z_1 and financial risk index z_2 are significant for both of the two functional forms as to estimate the cost function. The positive sign of z_1 indicates that a deterioration in the quality of loans will cause an increase in total operational cost for banks. The negative sign of z_2 indicates that banks under higher financial risks are bearing more operational costs. These two reasonable empirical findings show the necessity to involve quality of loans and financial risk levels when estimating the banks' operational costs and, further measuring the operational performance. In addition, the scales of z_1 and z_2 are both larger in Translog cost functional form than they are in FF cost

[8] The microeconomic theory requires the cost function should satisfy: (i) nondecreasing in input prices, (ii) homogeneous of degree one input prices, (iii) concave in input prices, and (iv) nondecreading in outputs.
[9] Compared with the cost function, cost distance function would relax the assumption of cost minimizing behavior (Rodriguez-Alvarez et al. , 2003).

functional form. This implies that Translog functional form would be more sensitive to capture the influences of loan quality and financial risks when the cost function for banking industry is estimated.

Table 4 presents the overall scale economy measure (RSE) for both FF and Tanslog cost functional form. All RSEs are significantly less than one at 1% significant level except for FF cost function for banks in group 5. It implies that almost all banks in this study are experiencing increasing returns to scale if only expanding outputs bundles proportionally without altering the products mixes. The overall banking industries in this study are operating under increasing returns to scale from 2000 to 2005. The trends across the bank groups or bank specializations are similar no matter which of the two cost functional forms is used. Across the bank groups, the scales of the returns to scale are higher in larger bank groups. It indicates that smaller banks benefit more from the increasing returns to scale than larger banks when they expand the outputs in the same proportion. In other words, it indicates that expanding outputs would not be an effective method for larger banks to enhance the cost efficiency. Specifically, if banks are in group 5, the increasing returns to scale will reduce to the constant returns to scale and there will be no benefits from expanding the production at all. Similarly, agricultural banks would benefit more from increasing returns to scale compared to the commercial banks because the latter are generally larger than the former in terms of total assets. So if expanding outputs in the same proportion, the agricultural banks would be anticipated to improve the operational performance much better than commercial banks. The differences in RSEs between FF and Translog cost functional form reflect the differences in the accuracy to approximate the banks' cost function. Overall, the scales of the RSEs are slightly larger in Translog cost function compared to FF cost function. So generally speaking, using the FF cost function would reflect the higher level of increasing returns to scale based on the overall scale economy measure.

Table 5 presents the expansion path scale economies (EPSE) for both FF and Translog cost functional form. All EPSEs in Table 5 are significantly less than one, indicating increasing returns to scale along the expansion path from one smaller sized bank group to its adjacent larger sized bank group (i.e., from group 1 to group 2, or from group 2 to group 3, etc.), which may have different product mixes. EPSE reveals consistent results as RSE.

Table 6 presents the traditional scope economy measure (SCOPE) for both FF and Translog cost functional form. The SCOPE measures for all banks are both significant different from zero and the negative signs indicate that the diseconomies of scope no matter using FF or Translog cost function. However, the SCOPE measure for all 5 bank groups is not statistically different from zero, which implies neither economies nor diseconomies of scope when the FF cost function is applied. Comparatively, when applying the Translog cost function, only banks in group 2 show neither economies nor diseconomies of scope. In contrast, banks in group 1 display economies of scope and the banks in group 3 to group 5 are all diseconomies of scope. If adopting the banks specialization criterion, commercial banks show the diseconomies in both FF and Translog cost function. On the other hand, agricultural banks show neither economies nor diseconomies of scope when applying the FF cost function and diseconomies of scope when applying Translog cost function, respectively. In addition, the change in the sign from positive to negative of the estimates (both FF and Translog cost functions) and the increasing magnitude in the negative coefficients indicate that the pattern of economies of scope would disappear and finally change to diseconomies when bank size is expanded. Compared to the agricultural banks, the commercial banks would be inclined to demonstrate more diseconomies of scope. So agricultural banks would prefer specialized production more than joint production. This result explains why agricultural banks, more "specialized" in agricultural loans, can still survive in the financial markets.

Table 7 presents the Expansion path subadditivity (EPSUB) for both FF and Translog cost functional form. All EPSUBs are not statistically different from zero when applying the FF cost function. This indicates that neither scope economies nor scope diseconomies along the expansion path connecting a smaller bank group and a larger bank group. This finding based on the FF cost function can explain the fact why the percentage of banks in each group is comparatively stable across 6 years (see Figure 1). In addition, this finding is consistent with the results measured by SCOPE. On the other hand, when applying the Translog cost function, EPSUBs suggested that the costs are slightly "superadditive" along the expansion path from group 2 to group 3 and from group 4 to group 5. The different findings based on FF and Translog cost functions might also indicate the inaccuracy when applying the improper cost functional form, Translog, instead of the likely correct cost functional form, FF.

5. Conclusions

This study made three major contributions. First**,** this study applied more flexible functional form, FF, and tested the validity of the Translog cost functional form as to estimate the cost function for banking industry. Second, this study introduced two index variables to measure the effects of the loans' quality and the financial risks in estimating the cost function. Third**,** this study extended four different cost efficiency measures for banking industry not only among different sized banks but also between commercial banks and agricultural banks. This study's results indicate that banks within the same category tend to have homogeneous results to the extent in the largest possibility to assure the robustness of this study's results. Fourth, this study applied the nonlinear ITSUR econometrics method to the panel data to get more efficient coefficients estimates.

Results of this study imply that the FF cost function is likely to be a more appropriate functional form to estimate the banks' cost function. The estimation of the FF cost function also reveals that deterioration in the quality of loans will cause the significant increasing of total operation cost for banks. In addition, banks under higher financial risks are bearing more operational costs.

There are several findings after studying four different cost efficiency measures in this paper: (1) The overall banking industry has been operating under increasing returns to scale from 2000 to 2005. So it is reasonable to expand the quantities of different types of loans to improve the cost efficiency for banking industry in the past 6 years. However, increasing the outputs affects the cost efficiency of different categories of banks to different extent. Specifically, expanding outputs enhance the cost efficiency more efficiently for smaller banks and agricultural banks. (2) Along the expansion path from one smaller sized bank group to its adjacent larger sized bank group with different product mixes would result in the increasing returns to scale. (3) Bank specialization tends to result in scope of diseconomies based on the SCOPE measure. This finding suggests that expanding branches for different specialized business is not an effective resolution for higher operational efficiency in this study. However, using a different criteria, the conclusion might be different. Specifically, neither economies nor diseconomies of scope are discovered across different bank groups and for agricultural banks but diseconomies of scope are found for commercial banks. These findings explain the greater incidence of mergers among commercial banks as well as consolidation into more specialized banking business while agricultural banks, which are more "specialized" in agricultural loans, can still survive in the financial markets. (4) Product mixing is not always an effective method to save costs. Specifically, neither scope economies nor scope diseconomies occurs along the expansion path connecting a smaller bank group and a larger bank group. This finding also explains the fact why the percentage of banks in each group is comparatively stable across six years. In summary, the finding of scale economies in this study suggests that expanding the bank's scale of production, through merging for instance, can reduce the average costs.

Finally, it is important to notice that the conclusion of neither scope economies nor scope diseconomies of joint production in this study is drawn without considering uncertainty, transactions costs, and inputs shareability in banks' operations. For further studies, it may be interesting to incorporate these factors in the efficiency analysis to analyze how joint production may affect scope economies.

Table 1.1. Distribution of Sample Banks by Specialization

Bank Specialization	Years						Average Across Years
	2000	2001	2002	2003	2004	2005	
Agricultural Bank	68 (17.75%)	62 (16.19%)	63 (16.45%)	63 (16.45%)	64 (16.71%)	63 (16.45%)	64 (16.67%)
Commercial Bank	315 (82.25%)	321 (83.81%)	320 (83.55%)	320 (83.55%)	319 (83.29%)	320 (83.55%)	319 (83.33%)
Total	383	383	383	383	383	383	383

Note: In each cell, the upper number is the number of banks in each bank category and the lower number in parenthesis is the percentage of banks in each bank category respectively.

Table 1.2. Distribution of Sample Banks by Total Assets

Bank Group	Years						Average Across Years
	2000	2001	2002	2003	2004	2005	
Group1	47 (12.27%)	40 (10.44%)	34 (8.88%)	30 (7.83%)	25 (6.53%)	23 (6.01%)	33 (8.66%)
Group2	84 (21.93%)	75 (19.58%)	67 (17.49%)	63 (16.45%)	65 (16.97%)	64 (16.71%)	70 (18.19%)
Group3	140 (36.55%)	144 (37.60%)	147 (38.38%)	143 (37.34%)	137 (35.77%)	130 (33.94%)	140 (36.60%)
Group4	50 (13.05%)	57 (14.88%)	62 (16.19%)	69 (18.02%)	68 (17.75%)	71 (18.54%)	63 (16.41%)
Group5	62 (16.19%)	67 (17.49%)	73 (19.06%)	78 (20.37%)	88 (22.98%)	95 (24.80%)	77 (20.15%)
Total	383	383	383	383	383	383	383

Note: In each cell, the upper number is the number of banks in each bank group and the lower number in parenthesis is the percentage of banks in each bank group respectively.

Table 2. Summary of Statistics for Selected Variables

Summary Before Data Transformation						Summary After Data Transformation					
Var.	Obs.#	Sample Mean	Std. Deviation	Minimum	Maximum	Var.	Obs.#	Sample Mean	Std. Deviation	Minimum	Maximum
y1	2298	30402.670	46496.240	74.000	586842.750	q1	2298	3.460	0.941	6.68E-06	6.000
y2	2298	472100.910	879381.000	7819.500	12123239.500	q2	2298	2.692	0.986	8.17E-06	6.000
y3	2298	65577.740	134120.090	905.500	1323394.500	q3	2298	2.729	1.050	8.23E-06	6.000
y4	2298	8050.260	22644.190	56.250	384910.000	q4	2298	2.535	0.998	6.79E-06	6.000
y5	2298	24272.180	51296.880	337.250	713923.500	q5	2298	2.593	0.992	7.84E-06	6.000
p1	2298	27.590	5.211	12.761	74.829	L1	2298	0.833	0.199	1.1E-05	1.953
p2	2298	0.171	0.239	0.029	6.592	L2	2298	1.791	0.517	1.1E-05	6.000
p3	2298	0.022	0.009	0.005	0.061	L3	2298	1.607	0.459	1.1E-05	2.823
p4	2298	0.016	0.007	0.002	0.033	L4	2298	2.031	0.506	1.1E-05	2.979
z1	2298	95.668	77.732	3.277	1038.160						
z2	2298	94.858	23.394	48.674	253.241						
c1	2298	8372.640	16467.720	195.750	151362.000						
c2	2298	2290.190	4678.480	30.000	46518.500						
c3	2298	3069.290	6373.110	48.000	73470.250						
c4	2298	8825.110	15287.650	268.750	196816.750						
c	2298	22557.230	39979.300	849.000	393659.250						

Note: Data transformation follows the equation (2) to (8).

where $\lambda = 1.1$,

$\mu_1 = 0.61$, $\mu_2 = 0.74$, $\mu_3 = 0.75$, $\mu_4 = 0.62$, $\mu_5 = 0.71$,

$w_{y1} = -4.3$, $w_{y2} = -8.96$, $w_{y3} = -6.81$, $w_{y4} = -4.03$, $w_{y5} = -5.82$,

$w_{p1} = -2.55$, $w_{p2} = 3.55$, $w_{p3} = 5.35$, $w_{p4} = 6.1$

Table 3. Estimates of the Fourier cost function and the Translog cost function

Parameter	Estimates		Parameter	Estimates		Parameter	Estimates	
	Fourier Cost Function	Tanslog Cost Function		Fourier Cost Function	Tanslog Cost Function		Fourier Cost Function	Tanslog Cost Function
Intercept	5.972*** (0.224)	6.125*** (0.110)	L1*L2	0.025*** (0.003)	0.010*** (0.001)	L1*q4	0.042*** (0.005)	0.046*** (0.003)
L1	0.510*** (0.018)	0.537*** (0.008)	L1*L3	-0.052*** (0.010)	-0.025*** (0.002)	L1*q5	0.001 (0.005)	-0.015*** (0.003)
L2	0.100*** (0.008)	0.101*** (0.004)	L1*L4	-0.081*** (0.007)	-0.117*** (0.002)	L2*q2	-0.011*** (0.003)	0.004** (0.002)
L3	-0.021*** (0.003)	-0.020*** (0.002)	L2*L3	-0.008*** (0.002)	-0.002** (0.001)	L2*q3	-0.001 (0.002)	-0.002** (0.001)
L4	0.317*** (0.018)	0.288*** (0.008)	L2*L4	-0.023*** (0.002)	-0.030*** (0.001)	L2*q4	0.012*** (0.003)	0.004 (0.001)
q1	0.072 (0.075)	-0.043 (0.027)	L3*L4	0.041* (0.024)	-0.026*** (0.003)	L2*q5	0.002 (0.002)	-0.003** (0.001)
q2	0.176 (0.181)	0.318*** (0.047)	q1*q2	-0.043* (0.023)	-0.022* (0.011)	L3*q3	0.005 (0.004)	0.001 (0.002)
q3	-0.134 (0.100)	0.031 (0.028)	q1*q3	0.035*** (0.012)	0.003 (0.006)	L3*q4	-0.008* (0.005)	-0.011*** (0.003)
q4	0.333** (0.153)	0.242*** (0.040)	q1*q4	-0.044** (0.018)	0.015* (0.009)	L3*q5	0.001 (0.006)	0.008*** (0.003)
q5	0.272* (0.161)	0.105*** (0.034)	q1*q5	0.039** (0.020)	0.001 (0.008)	L4*q4	-0.046*** (0.005)	-0.039*** (0.003)
L1^2	0.108*** (0.011)	0.132*** (0.001)	q2*q3	-0.078 (0.058)	-0.041*** (0.013)	L4*q5	-0.004 (0.006)	0.010*** (0.003)
L2^2	0.006** (0.003)	0.022*** (0.001)	q2*q4	0.056 (0.092)	0.009 (0.016)	L2*q1	0.001 (0.002)	-0.003*** (0.001)
L3^2	0.032 (0.027)	0.071*** (0.003)	q2*q5	-0.089 (0.237)	-0.053** (0.022)	L3*q1	-0.004 (0.003)	0.010*** (0.002)
L4^2	0.063** (0.025)	0.173*** (0.002)	q3*q4	-0.156*** (0.060)	-0.062*** (0.012)	L3*q2	0.024*** (0.007)	0.024*** (0.004)
q1^2	0.005 (0.026)	0.030*** (0.008)	q3*q5	0.092 (0.068)	0.026** (0.011)	L4*q1	0.000 (0.003)	0.000 (0.002)
q2^2	0.311 (0.245)	0.223*** (0.031)	q4*q5	-0.005 (0.087)	0.019 (0.016)	L4*q2	0.042*** (0.007)	0.014*** (0.004)
q3^2	0.156** (0.071)	0.084*** (0.011)	L1*q1	0.003 (0.003)	-0.007*** (0.002)	L4*q3	0.004 (0.004)	0.001 (0.002)
q4^2	0.115 (0.135)	0.003 (0.018)	L1*q2	-0.055*** (0.006)	-0.042*** (0.004)	z1	0.012*** (0.003)	0.017*** (0.003)
q5^2	-0.114 (0.256)	-0.011 (0.024)	L1*q3	-0.008** (0.003)	0.000 (0.002)	z2	-0.090*** (0.016)	-0.111*** (0.016)

Note: The 394 coefficients of the Fourier series (sin(.) and cos(.)) do not be reported in this table.

*** Significant different from zero at the 1% level.

** Significant different from zero at the 5% level.

* Significant different from zero at the 10% level.

Table 4. Overall scale economy measure (RSE) for both FF and Translog cost functional form

		FF cost function		Translog cost function	
		Estimate	Standard Errors	Estimate	Standard Errors
Bank Group	Group1	0.634***	0.116	0.670***	0.017
	Group2	0.688***	0.082	0.727***	0.014
	Group3	0.754***	0.046	0.791***	0.011
	Group4	0.797***	0.035	0.837***	0.010
	Group5	0.881	0.088	0.936***	0.015
Bank Specialization	Agricultural Bank	0.680***	0.075	0.745***	0.014
	Commercial Bank	0.814***	0.043	0.859***	0.010
All Banks		0.803***	0.040	0.850***	0.010

Note: RSEs are measured at sample mean.

*** Significant different from one at the 1% level.

** Significant different from one at the 5% level.

* Significant different from one at the 10% level.

Table 5. Expansion path scale economies (EPSE) for both FF and Translog cost functional form

	FF cost function		Translog cost function	
	Estimate	Standard Errors	Estimate	Standard Errors
$EPSE^{12}$ (Group1-Group2)	0.579**	0.179	0.669***	0.024
$EPSE^{23}$ (Group2-Group3)	0.575***	0.147	0.658***	0.024
$EPSE^{34}$ (Group3-Group4)	0.542***	0.127	0.629***	0.027
$EPSE^{45}$ (Group4-Group5)	0.696***	0.034	0.760***	0.016

Note: EPSEs are measured at sample mean.

*** Significant different from one at the 1% level.

** Significant different from one at the 5% level.

* Significant different from one at the 10% level.

Table 6. Economies of Scope (SCOPE) for both FF and Translog cost functional form

		FF cost function		Translog cost function	
		Estimate	Standard Errors	Estimate	Standard Errors
Bank Group	Group1	0.428	0.326	0.523***	0.098
	Group2	-0.001	0.495	0.087	0.097
	Group3	-0.241	0.652	-0.157*	0.097
	Group4	-0.565	0.502	-0.384***	0.086
	Group5	-0.769	0.503	-0.721***	0.068
Bank Specialization	Agricultural Bank	-0.113	0.484	-0.160**	0.074
	Commercial Bank	-0.739**	0.329	-0.667***	0.074
All Banks		-0.726**	0.323	-0.657***	0.072

Note: SCOPEs are measured at sample mean.

*** Significant different from zero at the 1% level.

** Significant different from zero at the 5% level.

* Significant different from zero at the 10% level.

Table 7. Expansion path subadditivity (EPSUB) for both FF and Translog cost functional form

	FF cost function		Translog cost function	
	Estimate	Standard Errors	Estimate	Standard Errors
EPSUB^{12} (Group1-Group2)	-0.010	0.281	0.052	0.043
EPSUB^{23} (Group2-Group3)	-0.153	0.355	-0.115**	0.053
EPSUB^{34} (Group3-Group4)	-0.112	0.437	-0.073	0.061
EPSUB^{45} (Group4-Group5)	-0.161	0.272	-0.130***	0.039

Note: EPSUBs are measured at sample mean.

*** Significant different from zero at the 1% level.

** Significant different from zero at the 5% level.

* Significant different from zero at the 10% level.

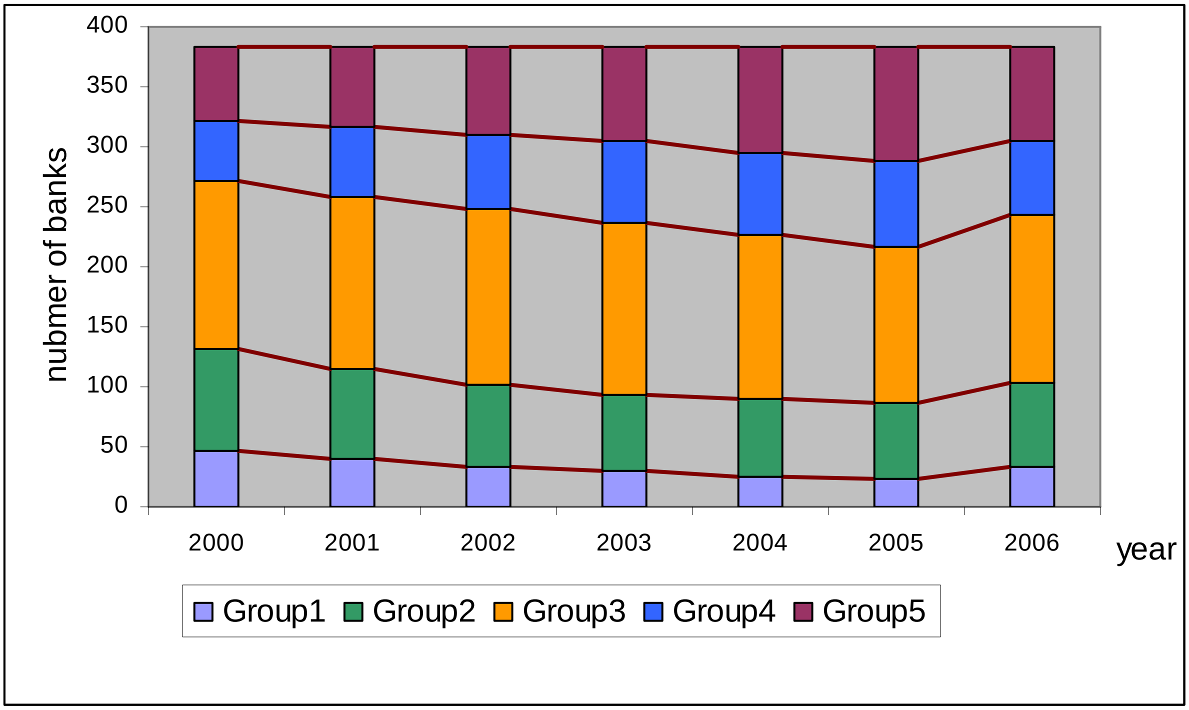

Figure 1. Distribution of Sample Banks by Total Assets

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