Banking Efficiency in China: Application of DEA and Tobit Analysis

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Abstract: In this paper, Data Envelopment Analysis (DEA) and super efficient DEA (SE-DEA) are employed to measure the efficiency of Chinese commercial banks. Incorporating Tobit regression analysis, the determinants of banking efficiency are investigated based on Panel data. Overall, the DEA results show relatively low average efficiency levels and state-owned banks are more inefficient than that of joint-equity banks. And Tobit regression indicates that bank size and ownership are the main influencing factors on banking efficiency, while little evidence suggests that the capital ratio can explain the bank efficiency levels.

Key Words: Commercial banks, Data Envelopment Analysis, Super efficient DEA, Tobit regression

1 Introduction

The banking industry is of great importance to every one of us. Firstly, China’s bond and equity markets are not well developed, thus intensifying the importance of the banking sector. Secondly, Chinese banks are increasingly facing competition from their foreign rivals with China entry into WTO. Major domestic banks continue to pursue all the opportunities available to enhance their competitiveness. Consequently, performance analysis in the banking industry has become part of their management practices. Top bank management wants to identify and eliminate the underlying causes of inefficiencies and helping their firms to gain competitive advantage, or at least meet the challenges from others.

Traditionally, banking performance evaluation mainly focused on various profitability measures. Usually multiple ratios are selected to analyze the different aspects of the operations. However, ratio analysis provides relatively insignificant amount of information when considering the effects of economies of scale, the identification of benchmarking policies, and the estimation of overall performance. As alternatives to traditional bank management tools, Data Envelopment Analysis (DEA), originally proposed by Charnes, Cooper and Rhodes [1], allows management to objectively identify best practices in complex operational environments. Compared to conventional methods, DEA is a better way to analyze the data since it allows handling multiple inputs and outputs (with different units) in a noncomplex way and requires no prior assumption about a specific functional form linking inputs and outputs. Therefore, DEA is a leading approach for the performance analysis in banking industry in literature.

Sherman and Gold [2] were one of the first researchers to use DEA to evaluate and compare the performances of banks. Thereafter this approach has become increasingly popular in measuring efficiency in different national banking industries. And recently, a number of domestic studies have attempted to analyze efficiency issues using the non-parametric techniques. LI Xi-yi and REN Ruo-en [3] used input-oriented DEA method to analyze the technical efficiency and efficiency change of Chinese stated-owned commercial banks over the 1994-2001 period. They found that the technical efficiency of state-owned commercial banks was very low during the periods of Asian financial crisis. This is different from the finding of ZHAO Xu [4] who reported the efficiency increasing with fluctuation. HE Ren [5] employed DEA to evaluate the performance of commercial banks in shanghai from 2000 to 2003, the results indicated that the efficiency of four state-owned banks was higher than that of joint-equity.

From above-mentioned, we can see that no agreement conclusion has been reached on the issue of banking efficiency. Moreover, all studies existed are based on traditional DEA method. The main weakness of traditional DEA is that it leaves the efficient units of the product set undifferentiated. And evidence suggests that relatively little empirical investigations have been made into the determinants of efficiency by using censored regression techniques.
So, in this paper, the technical efficiency of individual commercial banks is evaluated first. And to overcome the weakness of traditional DEA, the super efficiency DEA (SE-DEA) model is introduced to rank all evaluated banks including the efficient ones. Then, the determinants of efficiency of commercial banks are investigated using the censored regression technique. The rest of this paper is organized as follows. The following section is the methodology, which presents the DEA and Tobit models. The data and specification of the relevant variables are discussed in Section 3. Section 4 summarizes the efficiency results of the DEA. The determinants of efficiencies are explained in Section 5. Section 6 concludes.

2 Methodology
2.1 The CCR Model

Consider \( n \) DMUs to be evaluated, DMU \( j (j = 1, 2, \ldots, n) \) that consumes the amounts \( X_j = \{x_{ij}\} \) of \( m \) different inputs \( (i = 1, 2, \ldots, m) \) and produces the amounts \( Y_j = \{y_{rj}\} \) of \( r \) outputs \( (r = 1, \ldots, s) \). The efficiency of a particular DMU \( 0 \) under the assumption of constant returns to scale (CRS) can be obtained from the following linear programs (input-oriented CCR model)

\[
\begin{align*}
\text{m in} & \quad \left[ \theta - \varepsilon \left( \sum_{i=1}^{m} s_{i}^{-} + \sum_{r=1}^{s} s_{r}^{+} \right) \right] \\
\text{s.t.} & \quad \sum_{j=1}^{n} \lambda_{j} x_{ij} + s_{i}^{-} = \theta x_{ij0}, i = 1, 2, \ldots, m \\
& \quad \sum_{j=1}^{n} \lambda_{j} y_{rj} - s_{r}^{+} = r_{rj0}, r = 1, 2, \ldots, s \\
& \quad \theta, \lambda_{j}, s_{i}^{-}, s_{r}^{+} \geq 0, j = 1, 2, \ldots, n \\
\end{align*}
\]

(1)

Where \( \theta \) is the efficiency score and \( \lambda_{j} \) is the weights for the inputs and outputs of the DMUs. \( \varepsilon \) is a non-Archimedean infinitesimal, \( s_{i}^{-} \) and \( s_{r}^{+} \) are input and output slack variables respectively.

By solving model (1) \( n \) times (each time evaluating different DMU at the objective function) we can get relative efficiency for all the DMUs. These scores assign the DMUs into two groups: the efficient ones lying on the “efficient frontier” and the inefficient ones that fall below the frontier. A DMU is termed efficient if and only if the optimal value \( \theta^{*} \) is equal to 1 and all the slack variables are zero.

2.2. The Super Efficiency Model

The main weakness of standard DEA is that it leaves the efficient units of the product set undifferentiated. To overcome this problem, an extension of the basic DEA methodology, called super efficiency DEA (SE-DEA) model was provided by Andersen and Petersen [6], which listed as model (2):

\[
\begin{align*}
\text{m in} & \quad \left[ \theta - \varepsilon \left( \sum_{i=1}^{m} s_{i}^{-} + \sum_{r=1}^{s} s_{r}^{+} \right) \right] \\
\text{s.t.} & \quad \sum_{j=1,j \neq 0}^{n} \lambda_{j} x_{ij} + s_{i}^{-} = \theta x_{ij0}, i = 1, 2, \ldots, m \\
& \quad \sum_{j=1,j \neq 0}^{n} \lambda_{j} y_{rj} - s_{r}^{+} = r_{rj0}, r = 1, 2, \ldots, s \\
& \quad \theta, \lambda_{j}, s_{i}^{-}, s_{r}^{+} \geq 0, j = 1, 2, \ldots, n \\
\end{align*}
\]

(2)

Compared model (1) and (2), we find that the core idea of SE-DEA is to exclude the decision-making unit (DMU) from the reference set when its own relative efficiency is being evaluated. The advantage of SE-DEA over the conventional DEA method is that SE-DEA provides a ranking
procedure for all DMUs, not only the inefficient DMUs, but the efficient ones as well.

2.3 The Tobit Model

To investigate the determinants of efficiency, the Tobit model (also known as truncated or censored regression model) is employed. The standard Tobit model can be defined as follows:

\[ Y_j = \begin{cases} \beta^T X_j + \varepsilon_j, & \beta^T X_j + \varepsilon_j > 0 \\ 0, & \beta^T X_j + \varepsilon_j \leq 0 \end{cases} \]

(3)

Where \( \varepsilon_j \sim N(0, \sigma^2) \), \( \beta \) is the coefficient parameter for independent variable \( X_j \). When the DEA scores are transformed, the coefficient of the Tobit model can be interpreted as if it is a coefficient of an ordinary least squares regression. That is, it indicates the expected proportionate change of dependent variable with respect to one unit change in independent variable \( X_j \), holding other factors constant.

3 Data and the Speciation of Variables

Commercial banks, as a dominant part of Chinese banking system, consist of 4 state-owned banks, 10 joint-equity banks, 107 city commercial banks and 2 housing saving banks until 2001. In terms of total assets, the share of 4 state-owned banks and 10 joint-equity banks can be reached more than 90%. The efficiency of them can reflect the competitiveness of banking industry. So, the 4 state-owned banks and 10 joint-equity banks were chosen as our DMUs.

Table 1: Inputs and Outputs Descriptive Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Med</th>
<th>Max</th>
<th>Min</th>
<th>Std.</th>
<th>Variables</th>
<th>Mean</th>
<th>Med</th>
<th>Max</th>
<th>Min</th>
<th>Std.</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>11.76</td>
<td>0.99</td>
<td>49.09</td>
<td>0.31</td>
<td>18.51</td>
<td>X1</td>
<td>11.40</td>
<td>1.04</td>
<td>48.09</td>
<td>0.425</td>
<td>17.83</td>
</tr>
<tr>
<td>X2</td>
<td>188.37</td>
<td>41.56</td>
<td>636.75</td>
<td>10.72</td>
<td>261.2</td>
<td>X2</td>
<td>196.72</td>
<td>42.33</td>
<td>695.08</td>
<td>13.31</td>
<td>270.32</td>
</tr>
<tr>
<td>X3</td>
<td>355.45</td>
<td>69.74</td>
<td>1572.46</td>
<td>10.72</td>
<td>501.45</td>
<td>X3</td>
<td>339.20</td>
<td>77.62</td>
<td>1503.71</td>
<td>55.19</td>
<td>466.78</td>
</tr>
<tr>
<td>Y1</td>
<td>397.64</td>
<td>89.41</td>
<td>1624.07</td>
<td>38.86</td>
<td>532.61</td>
<td>Y1</td>
<td>397.45</td>
<td>97.85</td>
<td>1593.40</td>
<td>516.08</td>
<td>466.78</td>
</tr>
<tr>
<td>Y2</td>
<td>24.03</td>
<td>12.96</td>
<td>96.6</td>
<td>4.15</td>
<td>26.88</td>
<td>Y2</td>
<td>26.92</td>
<td>17.11</td>
<td>109.97</td>
<td>4.59</td>
<td>516.03</td>
</tr>
</tbody>
</table>


In the banking literature, three main approaches, namely the production approach, the intermediation approach, and the asset approach have been developed to define the input-output relationship. We follow the production method with a small modification for the definition of inputs and outputs. Concretely, this study uses three input and two output measures for evaluating these banks’ performance. Three inputs selected for the DEA analysis are: the number of employees (X1), capital expenditures on fixed assets (X2) and operating expense (X3). Two outputs include operating income (Y1), and profit before tax (Y2). All variables except X1 are measured in billions of RMB. X1 is measured in billions of persons. Table 1 presents the statistics for two samples (2001 and 2002).

To further investigate the effects of environmental variable on the efficiency of these commercial banks, we follow with a Tobit regression. Using the efficiency scores obtained from SE-DEA evaluations as the dependent variable, we then estimate the following regression model

\[ \theta_j = \beta_0 + \beta_1 EOTA + \beta_2 TA + \beta_3 SO + \epsilon_j \]

(4)

These variables represent aspects of the bank’s environments that may influence efficiency, but which are outside the immediate control of management. There is clearly the potential for disagreement on exactly what kind of variables can meet these criteria. We consider the effects of capital adequacy ratio (EOTA), bank size (TA), and ownership (SO) on technical efficiency. EOTA is the ratio of equity to total assets. Size is measured in total assets (billions of RMB). We introduce the dummy variable SO to detect whether ownership influences efficiency. SO equals to zero if state-owned and equals to one otherwise.
4 Efficiency Estimations

4.1 The Results of CCR Model

Following the methodology described in Section 2, we evaluate the efficiency of all 14 banks in the estimation set by running a CCR input oriented DEA. Table 2 summaries the efficiency scores.

<table>
<thead>
<tr>
<th>DMUs</th>
<th>Results of CCR</th>
<th>Results of SE-DEA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2001</td>
<td>2002</td>
</tr>
<tr>
<td>Industrial and commercial Bank of China</td>
<td>0.5713</td>
<td>0.6094</td>
</tr>
<tr>
<td>Agricultural Bank of China</td>
<td>0.4448</td>
<td>0.4507</td>
</tr>
<tr>
<td>Bank of China</td>
<td>0.5905</td>
<td>0.5907</td>
</tr>
<tr>
<td>China Construction Bank</td>
<td>0.5770</td>
<td>0.5931</td>
</tr>
<tr>
<td>Bank of Communications</td>
<td>0.7723</td>
<td>0.9769</td>
</tr>
<tr>
<td>China Merchants Bank</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Shenzhen Development Bank</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Shanghai Pudong Development Bank</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>CITIC Industrial Bank</td>
<td>0.8664</td>
<td>0.8831</td>
</tr>
<tr>
<td>China Minsheng Bank</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Industrial Bank</td>
<td>0.8331</td>
<td>0.8636</td>
</tr>
<tr>
<td>Hua Xia Bank</td>
<td>0.9453</td>
<td>1</td>
</tr>
<tr>
<td>China Everbright Bank</td>
<td>0.8181</td>
<td>0.8417</td>
</tr>
<tr>
<td>Guangdong Development Bank</td>
<td>0.8011</td>
<td>0.8175</td>
</tr>
</tbody>
</table>

It is evident from table 2 that Chinese banking industry displays significant variations in efficiency levels. The overall efficiency has a mean score of 80% for all banks in 2001 and only four banks (out of 14) achieve CRS efficiency. While the remaining of the 10 banks exhibits varying degrees of inefficiencies, which implies that some latent and enterprise special resources are still not being penetrated and not being fully utilized. So they need to rearrange inputs (especially the number of employee for state-owned banks) to improve their performance.

It is noteworthy that the mean value of state-owned banks in 2001 and 2002 is only 0.5535, which is much lower than the average 92% observed in the joint-equity banks. Nevertheless, it is possible to detect a slight improvement in the efficiency levels through time.

4.2 The Results of SE-DEA Model

The results of CCR model indicate that four commercial banks are efficient in 2001. And in 2002 the number of efficient banks becomes 5 in addition the former 4 banks to Hua Xia bank. Even calculate the average score of the two years, we can’t identify which one is the most efficient. So, we introduce the super efficiency DEA (SE-DEA) model and provide a ranking for all banks, including the efficient ones. And the results of the calculation shows that China Merchants Bank is the most efficient bank, followed by China Minsheng Bank in 2001 and 2002, while the 4 state-owned banks are the most inefficient banks.

5 Explaining the Determinants of Efficiency

To examine the differences among banks, we estimate the Tobit regression described in equation (4) by panel data of 2001 and 2002. The results of the Tobit regression are summarized as equation (5)

\[ \theta_j = -0.7391 \text{EOTA} + 0.0663 \text{LTA} - 0.5979 \text{SO} + \varepsilon_j \]

\[ (-0.1555) \quad (2.5620) \quad (5.4778^{**}) \]

\[ R^2 = 0.40 \quad \text{Adj. } R^2 = 0.33 \quad \text{D.W.} = 2.1 \]

It is noted that capital ratio (EOTA) has a sign of negative influence on banks’ efficiency. However the negative coefficient is not statistically significant at the selected level. This means that the capital ratio is not an influencing factor on the bank efficiency during the period of analysis. For the case of relationship between bank size and efficiency we find that positive relation between of them is existed.
However, a smaller coefficient (0.069) indicates relative insignificant effects on banking efficiency. SO, representing the ownership dummy has a positive sign and is statistically significant at 99 percent level. This means that banks with controlling state ownership are likely to be more inefficient than their joint-equity counterparts. There are many possible explanations for this result. The first relates to the nature of joint-equity bank customers. Unlike the four state-owned banks, joint-equity banks mainly serve profitable private enterprises, which may have been less affected by the macroeconomic turmoil than the SOEs. Another possible and related explanation is that joint-equity banks exhibit lower non-performing loan ratios. In contrast, the state banks provide policy lending to SOEs, therefore they are more influenced by bad loans. On the other hand, joint-equity banks perform more like profit-seeking financial institutions, and so grant loans according to economic criteria. Thus, they are less affected by bad loans. Finally, most of joint-equity banks have less administrative pressure from government and similarly would seem better placed to learn quickly about advanced technology. They are thus expected to have a relatively high efficiency level.

6 Conclusions

This study is to measure and to explain the measure differences in the performance of Chinese commercial banks. Firstly, a non-parametric approach, in the form of Data Envelopment Analysis (DEA) and its modified model super efficiency DEA are applied. And then using efficiency measures derived from SE-DEA estimation we also evaluate the determinants of Chinese bank efficiency by the Tobit regression model approach.

Overall, banking industry displays significant differences in efficiency levels, the average efficiency of the state-owned banks is only 0.5535, which is much lower than that of joint-equity banks. Tobit results suggest that the efficiency differences are affected by many environmental variables. Bank size and ownership have positive effects on the banking efficiency, while little evidence suggests that the capital ratio (EOTA) can explain the bank efficiency levels.

So, to improve the performance of commercial banks, we need not only to reduce the inputs (such as the number of employee) to achieve the efficiency frontier, but also to consider the effects of environmental factors.

References