ISSN 1518-3548

BANCO CENTRAL DO BRASIL

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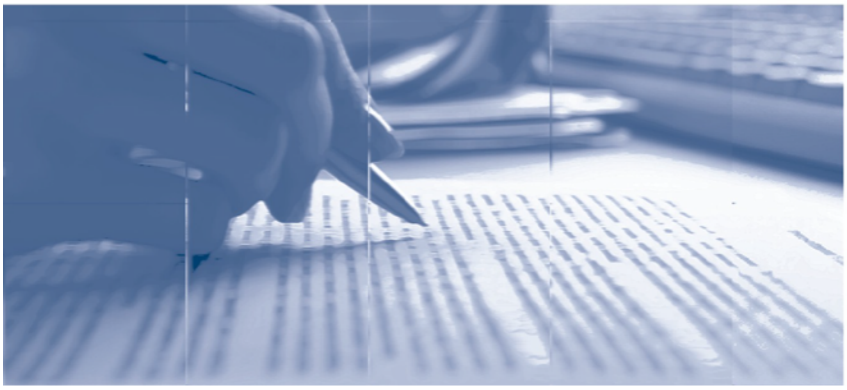
January, 2014

Working Papers



346

ISSN 1518-3548
CGC 00.038.166/0001-05

Working Paper Series	Brasília	n. 346	January	2014	p. 1-15

Working Paper Series

Edited by Research Department (Depep) – E-mail: workingpaper@bcb.gov.br

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The efficiency of Chinese local banks: a comparison of DEA and SFA

Benjamin Miranda Tabak* Daniel Oliveira Cajueiro† Marina V. B. Dias‡

Abstract

This study investigates to which extent results produced by a single frontier model are reliable, based on the application of data envelopment analysis and stochastic frontier approach to a sample of Chinese local banks. Our findings show they do produce a consistent trend on efficiency scores over the years. However, rank correlations indicate they diverge with respect to individual performance diagnosis. This shows that these models provide steady information on the efficiency of the banking system as a whole, but they become inconsistent at individual level.

Keywords: Bank efficiency; Stochastic frontier approach; Data envelopment analysis.

JEL Classification Numbers: G21, G28.

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1 Introduction

This paper applies both data envelopment analysis (DEA) and stochastic frontier approach (SFA) to investigate the efficiency of Chinese local banks. We analyze some features related to the efficiency scores of both approaches. We determine whether the methodology applied is relevant to the determination of best and worst performers and to the conclusions drawn regarding the whole market. These methods are not consistent in the determination of individual performance. Nevertheless, they do produce a similar trend on efficiency over the years.

Efficiency of financial institutions can be measured by parametric or non-parametric models. Both approaches have their features, but few studies apply both types of methodologies to the same sample to investigate the consistency between their results. Some of these studies consider the conditions Bauer et al. (1998) propose to investigate this issue (Fiorentino et al., 2006). There are mixed results regarding the similarity of these models. Some authors find that the consistency between DEA and SFA in ranking banks according to their performance is low or even statistically insignificant (Fiorentino et al., 2006; Ferrier and Lovell, 1990). On the other hand, comparison of their results at industry level can point out the similarities between them (Resti, 1997).

There are two main points we make that differ from previous literature on the comparison of DEA and SFA. First, we do not rule the methodologies as either consistent or inconsistent. We analyze at which level their results are more reliable, produce similar information, and to which extent they must be considered with care. Second, we argue that the comparison of the behavior of efficiency along the sample period is much more relevant to determine the consistency between both models than the average levels of efficiency.

Parametric and non-parametric methodologies are extensively applied to measure the efficiency of financial institutions. In many cases, the purpose of the existing studies is to assist policy makers with relevant information, such as the impact of regulation measures over the performance of these firms (Lee and Chih, 2013; Barth et al., 2013; Gaganis and Pasiouras, 2013). However, it is common to apply only one frontier model, either parametric or non-parametric, to measure efficiency. Investigating if these models are consistent has the purpose of pointing out to which extent results and conclusions obtained from the application of only one frontier method are reliable, especially to assist policy decisions.

Studies of bank efficiency in China are mostly related to the effects of deregulation reforms over the performance of financial institutions (Berger et al., 2009; Sun et al., 2013). Some of them, as Yin et al. (2013), conclude that these reforms led to an improvement on bank efficiency. Our study finds stable efficiency scores over the period 2001-2012, which is not in line with the idea that deregulation reforms still have a positive impact on the efficiency of Chinese financial institutions.

2 Methodology and Data

Bank efficiency can be measured through basically two different types of models: parametric or non-parametric. The most applied parametric model is the stochastic frontier approach and the most applied non-parametric model is data envelopment analysis. In this paper, we apply data envelopment analysis and stochastic frontier approach to measure the efficiency of Chinese commercial banks. The advantages of using DEA is that it does not require prior knowledge of either the distributional form of the inefficiency term or the production technology used in the industry. The main feature of the SFA is that it accounts for random shocks (Berger and Humphrey, 1997; Seiford and Thrall, 1990; Mester, 1996).

2.1 Data Envelopment Analysis

Data envelopment analysis was first proposed by Charnes et al. (1978) and was developed based on the seminal work of Farrell (1957). It uses linear programming techniques to build a non-parametric efficiency frontier of the data sample. Therefore, the frontier is constructed by the practices (combination of inputs and outputs) of the most efficient firms in the sample. The linear programming problem consists of the maximization of the firm's weighted output-input ratio. In this study, we apply DEA to measure input-oriented, output-oriented, economic and allocative efficiencies. We estimate the variable returns to scale model, proposed by Banker et al. (1984). The input-oriented model consists of the following linear programming problem:

$$
\begin{aligned}
&\min_{\phi,z} \phi \\
&\quad \text{s.a} \quad -q_i + Q\lambda_j \geq 0 \\
&\qquad\qquad \phi x_i - X\lambda_j \geq 0 \\
&\qquad\qquad\quad \textstyle\sum_{i=1}^{n} \lambda_i \\
&\qquad\qquad\quad \lambda_i \geq 0
\end{aligned} \tag{1}
$$

in which ϕ is technical inefficiency, q_i are the outputs for firm i, Q and X are matrices of outputs and inputs for all firms, respectively, x_i is the vector of inputs for the i-th firm and λ_i is a vector of weights.

Allocative efficiency measures the quality of the combination of inputs to produce certain outputs considering input prices (Sengupta, 1999). Economic efficiency analyzes both technical and allocative efficiencies (Bauer et al., 1998). They can be measured by a cost minimization problem that determines the optimal levels of inputs to be used given their prices (w_i):

$$\begin{aligned} \min_{w_i,\chi} \; & w_i'\chi_i \\ \text{s.a} \quad & \textstyle\sum_j \lambda_j y_j - y_i \geq 0 \\ & \chi_i - \textstyle\sum \lambda_j x_j \geq 0 \\ & \lambda_j \geq 0 \qquad (2) \\ & \textstyle\sum_i \lambda_i = 1 \qquad (3) \end{aligned}$$

Economic efficiency (EE) will be determined by the following ratio:

$$EE_i = \frac{w_i \chi_i}{w_i' x_i} \tag{4}$$

Allocative efficiency will be measured by the ratio cost efficiency over input-oriented technical efficiency TE_{inputs}:

$$AE_i = \frac{EE_i}{TE_{inputs,i}} \tag{5}$$

2.2 Stochastic Frontier Approach

The stochastic frontier approach was simultaneously developed by Meeusen and Van den Broek (1977) and Aigner et al. (1977) and it estimates a parametric frontier of the best possible practices given a standard cost or profit function. Both cost and profit functions are comparable to DEA economic efficiency measures, since they consider the same efficiency concept (Bauer et al., 1998). We estimate a cost function because it is more commonly applied in the literature (Berger and Mester, 1997).

Since SFA builds a parametric frontier, it is necessary to specify the production technology and the distribution of the inefficiency term. We use a translog form of the cost function, since it is a flexible functional form (Berger et al., 2009; Lozano-Vivas and Pasiouras, 2010). Also, the inefficiency term υ has a half-normal distribution, while the random error ν is normally distributed. The translog cost function is written as follows:

$$\begin{aligned} ln(CT/w_2) = \; & \delta_0 \; + \sum_j \delta_1 ln(y_j)_{it} + \frac{1}{2}\sum_j \sum_k \delta_{jk} ln(y_j)_{it} ln(y_k)_{it} \\ + \; & \beta_1 ln(w_1/w_2)_{it} + \frac{1}{2}\beta_{11} ln(w_1/w_2)_{it} ln(w_1/w_2)_{it} \\ + \; & \sum_j \theta_j ln(y_j)_{it} ln(w_1/w_2)_{it} \\ + \; & ln\upsilon_{it} + ln\nu_{it}. \end{aligned} \tag{6}$$

in which CT is the firm's total costs. i and t stand for bank and time, respectively. In the true fixed effects model, the inefficiency term, υ_{it}, is composed by a set of dummy variables, which determine its behavior across time. This study considers three outputs and two inputs. Thus, w_1 and w_2 are the two inputs used to produce the four outputs, y_j. The normalization by the price of the last input (w_2) guarantees price homogeneity.

In this study, we apply two different specifications of the stochastic frontier model, the true fixed effects model from Greene (2005) and the model proposed by Battese and Coelli (1995). The true fixed effects model fits the sample better, so we refer to this model when considering the parametric efficiency results[1]. We obtain efficiency scores from the Jondrow et al. (1982) estimator.

2.3 Data

Our sample comprises an unbalanced panel with 461 yearly observations from 65 Chinese local commercial banks for the period 2001-2012. The data source is Bankscope. Our definition of local banks includes city commercial banks and rural commercial banks (Berger et al., 2009). To analyze the efficiency trend over the years, we create sub-samples for each year and apply the DEA model for all of them. For the stochastic frontier model, we use the specification of panel data.

This paper uses the intermediation approach to define inputs and outputs for the empirical application, which states that banks capture borrowed funds and use capital and labor to turn them into loans and other assets (Sealey and Lindley, 1977). Therefore, we specify the outputs as deposits, loans and liquid assets. The input quantities are total interest expenses and total non-interest expenses. Input prices are the ratios total interest expenses over deposits and non-interest expenses over fixed assets. Table 1 shows descriptive statistics on these variables.

[Table 1 about here.]

3 Empirical Results

Results regarding the individual performance of firms should be looked into with care, while general results, related to the performance of the whole market, are consistent. Both data envelopment analysis and stochastic frontier approach results show that efficiency scores are roughly stable over the years, which we report on Figure 1.

This finding does not confirm the upward trend Yin et al. (2013) observe for bank efficiency in China after 2001. From the results we report on tables 2 and 3, our scores

[1] The log-likelihood for the true fixed effects model is 249.051, while for the Battese and Coelli (1995) model it is -6179.308.

do seem to vary over the years at first sight. DEA scores seem to show a drawback in the period 2001-2007, with posterior efficiency gains. SFA scores seem to indicate a slight improvement on efficiency over the sample period. However, a closer look into mean efficiency scores and their volatility, which we report on Figure 1, leads to the conclusion that the performance of Chinese local banks does not show a statistically significant change over the years. A possible reason for divergent results is that our sample comprises only Chinese local banks (which includes only city commercial banks and rural commercial banks), while Yin et al. (2013) use a sample with different types of Chinese commercial banks.

[Table 2 about here.]

[Table 3 about here.]

From Figure 1 we observe that efficiency levels are in some periods higher according to results from the parametric methodology. Nevertheless, we point out that this difference is not relevant if both models provide the same conclusion over the banking system's performance. Efficiency levels themselves are not enough to rule for the (in)consistency between different methodologies. In this case, both models indicate that Chinese local banks have not experienced efficiency improvements over the period 2001-2012. This shows that, for this empirical study, DEA and SFA do provide similar conclusions with respect to the performance of the industry of Chinese local banks as a whole

[Figure 1 about here.]

To analyze the consistency between individual efficiency scores produced by the two methodologies, we compute Spearman's rank correlation between DEA economic efficiency and SFA cost efficiency, since they use the same efficiency concept (Bauer et al., 1998). We find a rank correlation of 2.6%, which is not statistically significant at 1% level and is consistent with the findings of Ferrier and Lovell (1990), who compute the correlation of 1.4% [2]. Fiorentino et al. (2006) also find a positive but low correlation between data envelopment analysis and the stochastic frontier approach (between 44% and 58%).

One possible explanation for the difference between both models is that DEA is more sensitive to sample heterogeneity than the SFA (Fiorentino et al., 2006). To check if this argument is plausible, we run a robustness check in which we use the DEA results of efficiency to remove efficient banks from the original sample (Sample A), leaving us with a sample of banks that are originally economically inefficient (Sample B) and a sample of banks that are originally technically inefficient (Sample C). We find that efficiency scores

[2] We compute the spearman rank correlation between scores relative to the year 2009, which is the year which comprises the greater number of observations

do not differ among these samples and, thus, heterogeneity is not the reason why DEA and SFA do not produce similar results. These results are available from the authors upon request. We do not repeat the same to the SFA estimation because we use the results of the true fixed effects model, which already accounts for heterogeneity (Greene, 2005).

It should be expected that DEA and SFA might produce contradictory results in some empirical applications. Berger and Humphrey (1997) point out the conflict between parametric and non-parametric methodologies, based on the fact that they have different degrees of dispersion and rank banks differently. This latter conflict is exactly the inconsistency we report here. From a theoretical perspective, DEA and SFA are very different. Data envelopment analysis considers a deterministic frontier, while the stochastic frontier model considers a parametric one, which incorporates states of nature. For this reason, Bauer et al. (1998) propose some consistency conditions these models should meet in order to be sure they are providing policy makers with reliable information. The fact that DEA does not account for random shocks may be the source of the inconsistency between both models (Fiorentino et al., 2006). The implication of this inconsistency in the framework analyzed here is that individual performance should be analyzed with caution. The application of only one methodology to determine best and worst performers may lead to wrong conclusions, especially when rank correlation among different models are not statistically significant.

4 Conclusions

We apply both data envelopment analysis and the stochastic frontier model to a sample of Chinese local banks. We analyze the consistency between these measures from micro and macro perspectives. The majority of studies on Chinese bank efficiency apply either a parametric or a non-parametric methodology to investigate the performance of the country's financial institutions. Our findings show that these models are not consistent in the individual analysis of efficiency and results obtained at a micro level should be dealt with care. However, they do provide similar results regarding the behavior of average efficiency scores for the whole market over the years. We argue that this behavior is more important to determine the consistency between both models than the average efficiency levels themselves. We also conclude that Chinese local banks do not show improvement on performance over the period 2001-2012.

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Figure 1: Comparison of efficiency levels from DEA and SFA over the years

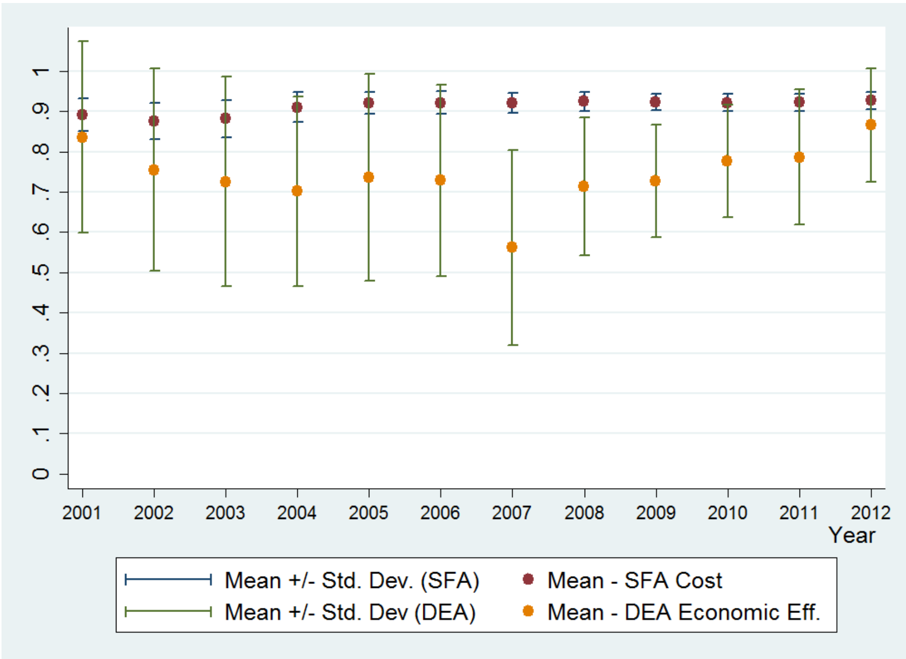

Table 1: Variables used on efficiency estimation

Year		Total Expenses	Loans	Liquid Assets	Deposits	Total interest expenses	Total non-interest expenses	w_1*	w_2**
2001	Mean	61295.1	860217.2	354383.8	1253685	35996.56	25298.54	0.0309	0.0145
	SD	23195.06	285442.3	447405.3	443558.3	19638.2	12011.74	0.0149	0.0023
	N	11	11	11	11	11	11	11	11
2002	Mean	65174.23	1087913	520003.2	1552868	38278.05	26896.18	0.0255	0.0125
	SD	33599.87	531390.6	792499.2	847203.8	23653.01	13560.7	0.0136	0.0043
	N	18	18	18	18	18	18	18	18
2003	Mean	78698.42	1330581	568032.2	1954243	47620.05	31078.37	0.0252	0.0116
	SD	39959.86	710515.8	719897.7	1060500	28368.26	16468.98	0.0129	0.0024
	N	19	19	19	19	19	19	19	19
2004	Mean	78169.5	1439702	521796.8	2179900	45090.97	33078.53	0.0205	0.0121
	SD	48780.2	777170.9	637022.1	1289392	32505.24	21477.64	0.0111	0.0032
	N	22	22	22	22	22	22	22	22
2005	Mean	118563.3	2178598	877169.6	3418808	70117.15	48446.17	0.0235	0.0119
	SD	101892	2021322	1167075	3289473	62991.66	46994.37	0.0147	0.0029
	N	33	33	33	33	33	33	33	33
2006	Mean	129944.5	2449558	843163.6	3727860	75784.04	54160.49	0.0227	0.0119
	SD	122496.1	2367041	1045025	3798744	72481.59	57113.23	0.0122	0.0030
	N	45	45	45	45	45	45	45	45
2007	Mean	169503.5	3093186	1274486	4811405	106348.5	63155.06	0.0234	0.0114
	SD	162724	2988969	1247269	4916175	105660.8	63978.75	0.0098	0.0039
	N	51	51	51	51	51	51	51	51
2008	Mean	269878.7	4219558	2038509	6917867	176589.1	93289.53	0.0265	0.0126
	SD	287657.7	4839686	2912078	8074015	202274.4	94392.54	0.0097	0.0047
	N	60	60	60	60	60	60	60	60
2009	Mean	270343.7	5809675	2693320	9468915	156452.9	113890.7	0.0169	0.0108
	SD	286005.8	6701814	3393745	1.11E+07	177282.9	114011.7	0.0055	0.0028
	N	61	61	61	61	61	61	61	61
2010	Mean	360655	7451999	5140042	1.28E+07	210750.9	149904.2	0.0161	0.00981
	SD	391473.3	8544235	6012537	1.43E+07	242344.6	155516.8	0.0054	0.0026
	N	59	59	59	59	59	59	59	59
2011	Mean	644508.5	9653769	7.45E+06	1.62E+07	431168.3	213340.2	0.0264	0.01068
	SD	690654.5	1.10E+07	8.94E+06	1.73E+07	502389.1	206458	0.0111	0.0027
	N	57	57	57	57	57	57	57	57
2012	Mean	1399510	1.90E+07	1.48E+07	3.04E+07	1008609	390901.5	0.0326	0.0094
	SD	1220445	1.69E+07	1.28E+07	2.55E+07	950192.7	296742.8	0.0075	0.0018
	N	25	25	25	25	25	25	25	25

*Ratio total interest expenses over deposits
**Ratio total non-interest expenses over total assets

Table 2: DEA economic efficiency scores

Year	Mean	Std. Dev	Min	Max
2001	0.84	0.24	0.36	1
2002	0.76	0.25	0.33	1
2003	0.73	0.26	0.33	1
2004	0.70	0.24	0.36	1
2005	0.74	0.26	0.19	1
2006	0.73	0.24	0.28	1
2007	0.56	0.24	0.22	1
2008	0.71	0.17	0.35	1
2009	0.73	0.14	0.48	1
2010	0.78	0.14	0.48	1
2011	0.79	0.17	0.31	1
2012	0.87	0.14	0.60	1

Table 3: SFA efficiency scores

	Cost efficiency			
Year	Mean	Std. Dev	Min	Max
2001	0.89	0.04	0.81	0.93
2002	0.88	0.04	0.75	0.93
2003	0.88	0.05	0.76	0.93
2004	0.91	0.04	0.82	0.96
2005	0.92	0.03	0.85	0.96
2006	0.92	0.03	0.83	0.95
2007	0.92	0.02	0.80	0.95
2008	0.93	0.02	0.79	0.96
2009	0.92	0.02	0.87	0.96
2010	0.92	0.02	0.87	0.96
2011	0.92	0.02	0.86	0.95
2012	0.93	0.02	0.85	0.95