

"Assessing the Efficiency of Banks in the United States: A Comparative Analysis of Small & Large Banks"

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Abstract

This paper studies the efficiency of banks in the United States using methods such as Data Envelopment Analysis (DEA), the Malmquist Index, and Stochastic Frontier Analysis. The banks in our sample are divided into two categories: small banks and large banks based on their assets. Our analysis aims to provide a comprehensive assessment of the efficiency of these banks and to identify any significant differences between small and large banks in terms of efficiency. Our findings indicate that small banks, concentrated markets, and savings banks tend to be more efficient than their larger counterparts due to their smaller size, focused business models, and fewer layers of management.

Introduction

There are several reasons why it is important to study the efficiency of banks. First and foremost, banks play a critical role in the economy by intermediating between savers and borrowers, and the efficiency of these financial institutions is crucial for the smooth functioning of the financial system. Inefficient banks may be unable to provide the necessary financial services to support economic growth, while efficient banks can help to allocate capital to its most productive uses and support economic development.

In addition, the efficiency of banks can have significant implications for consumers and depositors. Inefficient banks may have higher costs, which could result in higher fees or lower interest rates for customers. On the other hand, efficient banks may be able to offer more competitive rates and better service to their customers.

Furthermore, the efficiency of banks is of interest to regulators and policymakers, who are responsible for ensuring the stability and soundness of the financial system. Regulators may use measures of efficiency, such as the Herfindahl index or the efficiency ratio, to assess the competitiveness of a market and identify potential antitrust concerns.

Overall, the efficiency of banks is an important factor that can have significant economic, social, and regulatory implications. By studying the efficiency of banks, we can gain insights into the factors that drive performance and identify opportunities for improvement.

The purpose of this paper is to study the efficiency of banks in the United States using methods such as Data Envelopment Analysis (DEA), the Malmquist Index, and Stochastic Frontier Analysis. In order to better understand the performance of these banks, they will be split into two categories: small banks and large banks based on their assets (Aikaeli, 2006). By comparing the efficiency of these two groups of banks, we can gain insights into the factors that may be driving differences in performance and identify opportunities for improvement. Through the use of these various methods, we hope to provide a comprehensive analysis of the efficiency of banks in the United States and contribute to the existing literature on this topic.

Small banks, concentrated markets, and savings banks tend to be more efficient than their larger counterparts due to their smaller size, focused business models, and fewer layers of management. Small banks are able to make decisions more quickly and respond to the needs of their customers more effectively due to their smaller size and less bureaucracy. Concentrated markets, with fewer players, tend to be more efficient because there is less competition and higher profit margins for the remaining firms. Savings banks, which focus on taking in deposits and making loans to consumers and small businesses, tend to be more efficient than commercial banks, which offer a wider range of financial products and services. This is because savings banks have a more focused business model and can often operate with lower overhead costs.

Data

For the purpose of this paper we obtained data from the Federal Deposit Insurance Corporation for USA banks in years 2010-2016. Firstly, the data was balanced to 2,199 banks for each of the 6 years. Then, for the Data Envelopment Analysis and the Malmquist Index, we split the banks based on their assets to two categories: small banks with assets value up to 100,000\$ and large banks with assets value higher than 100,000\$. Finally, for the Stochastic Frontier Analysis the data were parameterised on the basis of the median.

Table 1: Mean bank efficiencies for each year

	Year	2012	2013	2014	2015	2016
	CRS	0.88	0.86	0.87	0.89	0.88
SB	VRS	0.90	0.89	0.90	0.91	0.91
	Scale	0.97	0.97	0.97	0.98	0.97
LB	CRS	0.84	0.85	0.85	0.86	0.86
	VRS	0.86	0.87	0.87	0.88	0.88
	Scale	0.98	0.98	0.98	0.98	0.98

SB = Small Banks, LB = Large BanksSource: FDIC (2010 - 2016)

Table 2: Productivity change of banks for years 2012-2016

	Productivity Change	Technical Change	Efficiency Change	Scale Change
Small Banks	1.05	1.02	1.01	1.00
Large Banks	1.05	1.02	1.02	1.00

Source: FDIC (2010 - 2016)

Empirical Model

Firstly, for the Cobb Douglas model the equation was formatted as:

$$logY_{it} = b_0 + b1logxl_{it} + b2logxE_{it} + b3logxD_{it} + b4logxL_{it} + u_{it}$$

 $i=1,...,2,199$
 $t=1,...,6$

where Y is the sum of loans, investments, and non-interest income, xl are the liabilities, xE the total equity capital and xD the deposits of banks.

Then, for the Translog function after configured the output and the inputs based on their median, the equation was formatted as:

$$logY_{it} = b_0 + b1logxl_{it} + b2logxE_{it} + b3logxD_{it} + b4logxL_{it} + \frac{1}{2}xl_{it} * xl_{it} + \frac{1}{2}logxl_{it}^2 + \frac{1}{2}logxE_{it}^2 + \frac{1}{2}logxD_{it}^2 + logxL_{it} * l$$

$$i=1,...,2,199$$

 $t=1,...,6$

Furthermore, for the estimation of which elements affect the inefficiency of the banks the OLS regression was formatted as:

$$Y_{it} = C_{it} + N3_{it} + N9_{it} + LIQ_{it} + ROA_{it} + u_{it}$$

 $i=1,...,2,199$
 $t=1,...,6$

where Y is the inefficiency of each bank, C is the bank's capital adequacy (Chortareas et al. 2012) defined as the ratio of the sum of Tier 1 (core) capital plus Tier 2 Risk-based capital divided by bank's total assets, N3(NPLS3) is the bank's asset quality which is defined as the ratio of total assets past due 30 through 89 days and still accruing interest to the bank's total assets, N9(NPLS9) defined as the ratio of total assets past due 90 or more days and still accruing interest to the bank's total assets, ROA is the return on assets and LIQ represents banks' liquidity (Chortareas et al. 2012; Andriakopoulos and Kounetas, 2022) is defined as the ratio of loans and lease financing receivables of the institution, including unearned income to total deposits.

Finally, the last two models estimate the effect of the Herfindahl Index on the inefficiency of the banks and the difference between saving banks and commercial banks to the inefficiency formatted as:

$$Y_{it} = b_0 + HHI_{it} + u_{it}$$

$$i=1,...,2,199$$

 $t=1,...,6$

where Y is the inefficiency of each bank and HHI is the Herfindahl Index.

$$Y_{it} = b_0 + COM_i + u_{it}$$

$$\substack{i=1,...,2,199\\t=1,...,6}$$

where Y is the inefficiency of each banks and COM is a dummy variable with value 1 if the bank is a commercial bank and 0 if it is a savings bank.

Empirical Results

Using the Likedhood Ratio test we come to a conclusion that Translog fits our data better. Even so, below are the tables of Cobb Douglas and Translog with their coefficients respectively

Table 3: Cobb Douglas Regression

Y	Estimate	Std. Error	z value	$\Pr(> \mathbf{z})$
(Intercept)	9,60E+03***	1,74E+02	552.267	<.00
$\log(xl)$	8,20E+03***	$3{,}76\mathrm{E}{+}01$	2.183.291	<.00
$\log(xE)$	1,35E+03***	$2{,}73E{+}01$	493.835	<.00
$\log(\mathrm{xD})$	1,04E+02***	$1,\!68\mathrm{E}{+01}$	61.852	<.00
$\log(\mathrm{xL})$	$5,\!80\mathrm{E}{+}02^{***}$	$2,\!53\mathrm{E}{+}01$	228.738	<.00
sigmaSq	2,47E+02***	$6{,}15\mathrm{E}{+}00$	402.408	<.00
gamma	9,59E+03***	$1{,}13E{+}01$	8.463.120	<.00
time	3,85E+02***	$1{,}17E{+}01$	328.145	<.00
$\operatorname{sigmaSqU}$	2,37E+02***	$6{,}14\mathrm{E}{+}00$	386.336	<.00
$\operatorname{sigmaSqV}$	1,01E+01***	1,39E-01	729.472	<.00
sigma	1,57E+03***	1,95E+01	804.816	<.00
sigmaU	1,54E+03***	1,99E+01	772.672	<.00
sigmaV	$3{,}18E+02***$	$2{,}18E+00$	1.458.945	<.00
lambdaSq	2,34E+05***	$6{,}77\mathrm{E}{+}03$	346.333	<.00
lambda	4.84E+04***	$6,\!99\mathrm{E}\!+\!02$	692.667	<.00

*** p<0.01, ** p<0.05, * p<0.1

Source: FDIC(2010-2016)

Table 4: Translog Production Function

Y	Estimate	Std. Error	z value	$\Pr(>\! \mathrm{z})$
(Intercept)	1,20E+03***	$2{,}16E{+}01$	553.307	< 2.2e-16
$\log(\text{xl_star})$	8,69E+03***	$3{,}40\mathrm{E}{+}01$	2.557.014	< 2.2 e-16
$\log(xE_star)$	1,43E+03***	$2,\!84\mathrm{E}{+}01$	503.209	< 2.2 e-16
$\log(\text{xD_star})$	-2,08E+02***	$1,\!67\mathrm{E}{+01}$	-124.810	< 2.2 e-16
xL_star	2,70E+02***	$1,\!28\mathrm{E}{+}01$	211.294	< 2.2e-16
xL_star * xL_star	-1,10E+01***	7,22E-01	-152.548	< 2.2 e-16
$(0.5 * \log(xl_star)\hat{2})$	-1,07E+03***	$1{,}73E{+}02$	-61.909	5,98E-07
$(0.5 * \log(xE_star)\hat{2})$	$9{,}44\mathrm{E}{+}01$	$8{,}72E{+}01$	10.817	0.279372
$(0.5 * \log(xD_star)\hat{2})$	-5,72E+01 **	$2{,}49E{+}01$	-2.2978	0.021574
$(\log(xl_star) * \log(xE_star))$	$4{,}31E{+}02***$	$1{,}10E{+}02$	39.201	8,85E-02
$(\log(xl_star) * \log(xD_star))$	4,27E+02***	$5{,}52\mathrm{E}{+}01$	77.383	1,01E-11
$(\log(xE_star) * \log(xD_star))$	-1,39E+02***	$4{,}29\mathrm{E}{+}01$	-32.430	0.001183
$(\log(xL_star) * \log(xD_star))$	-3,77E+02***	$3{,}56\mathrm{E}{+}01$	-105.825	< 2.2 e-16
$(\log(xL_star) * \log(xE_star))$	-4,86E+02***	$6{,}74\mathrm{E}{+}01$	-72.101	$5,\!59\text{E-}10$
$(\log(xL_star) * \log(xl_star))$	$4{,}34E{+}02***$	$7{,}36\mathrm{E}{+}01$	58.908	3,84E-06
sigmaSq	$3{,}11E+02***$	$1{,}02E{+}01$	303.100	< 2.2 e-16
gamma	9,65E+03***	$1{,}34\mathrm{E}{+}01$	7.197.748	< 2.2 e-16
sigmaSqU	$3{,}00E+02***$	$1{,}03E{+}01$	291.554	< 2.2 e-16
$\operatorname{sigmaSqV}$	$1,\!09E+01***$	1,48E-01	737.308	< 2.2 e-16
sigma	1,76E+03***	2,91E+01	606.200	< 2.2e-16
sigmaU	1,73E+03***	2,97E+01	583.109	< 2.2e-16
sigmaV	$3{,}30E{+}02***$	$2{,}24E{+}00$	1.474.615	< 2.2 e-16
lambdaSq	2,75E+05***	$1,\!09\mathrm{E}{+}04$	252.389	< 2.2 e-16
lambda	5,25E+04***	$1{,}04\mathrm{E}{+}03$	504.779	< 2.2 e-16
varU	$1{,}09E{+}02$	_	_	-
$\mathrm{sd}\mathrm{U}$	$1,\!04\mathrm{E}{+03}$	_	-	-
gammaVar	9,09E+03	_	-	

*** p<0.01, ** p<0.05, * p<0.1

Source: FDIC(2010-2016)

It is noticable that an increase of NPLS3 by 1 unit will result in an ineffeciency increase of 0.91 units. Liquidity also increases inefficiency by 0.46 units. Finally an increase on NPLS9 or CAP will result in a inefficiency decrease by 0.11 and 0.07 units respectively.

Table 5: OLS regression for the inefficiency

Inefficiency	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	0.019809***	0.001041	19.038	<2e-16
CAP	-0.078779***	0.002366	-33.299	< 2e-16
NPLS3	0.910805***	0.058563	15.553	< 2e-16
NPLS9	-0.113101	0.092091	-1.228	0.219
LIQ	$0.459925I^{***}$	0.002430	189.299	<2e-16
ROA	0.022167***	0.001075	20.628	<2e-16

*** p<0.01, ** p<0.05, * p<0.1

Source: FDIC(2010-2016)

In Table 6, we can see that a less concentrated market means more inefficiency. An increase on the Herfindahl Index will decrease inefficiency by 0.03 units.

Table 6: OLS regression for the effect of Herfindahl Index on efficiency

Inefficiency	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	0.1578935***	0.0007905	199.739	< 2e-16
HHI	-0.0373608***	0.0131230	-2.847	0.00442

*** p<0.01, ** p<0.05, * p<0.1

Source: FDIC(2010-2016)

In Table 7, it is noticable that commercial banks are more inefficient than savings banks by 0.02 units.

Table 7: OLS regression (commercial banks)

	Estimate	Std. Error	t	value	$\Pr(> t)$
(Intercept)	0.135911	0.001931		70.37	< 2e-16
COM	0.023376	0.002051		11.39	< 2e-16

*** p<0.01, ** p<0.05, * p<0.1

Source: FDIC(2010-2016)

In Figure 1 we can see that as years go by, banks tend to find ways to become even more efficient with the advance of technology and the new ideas that are created in the field.

Inefficiency change through years 2011-2016

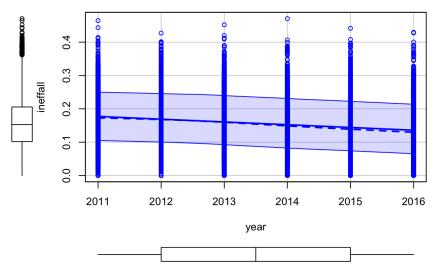


Figure 1. Inefficiency of banks throughout the years

Conclusion

It is generally believed that small banks tend to be more efficient than large banks due to their smaller size and ability to make decisions more quickly. This is because they have fewer layers of management and bureaucracy, which allows them to be more nimble and responsive to the needs of their customers.

Furthermore, markets that are more concentrated, with fewer players, tend to be more efficient as well. This is because there is less competition, which can lead to higher profit margins for the remaining firms.

Savings banks, which focus on taking in deposits and making loans to consumers and small businesses, tend to be more efficient than commercial banks, which offer a wider range of financial products and services. This is because savings banks have a more focused business model and can often operate with lower overhead costs.

Overall, it seems that small banks, concentrated markets, and savings banks tend to be more efficient than their larger, more diversified counterparts.

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