

Technical and Scale Efficiency of Banks in Georgia. Using Data Envelopment Analysis (DEA)

Metin MERCAN *

Abstract

This paper uses data envelopment analysis (DEA) to analyze the efficiency of the Georgian commercial banks from 2011 to 2018 years. Paper analyses the scale and technical efficiency of banks. The results show that banks efficiencies are not much changed in sample years, average efficiency is 0.67 while scale efficiency is 0.877. The results also reveal the input excess and output shortfalls. Banks in Georgia has highly input excess compared to results in other findings.

Keywords: banks and Georgia, DEA, efficiency

JEL: G21, C24, C67

Introduction

Banks are the most well-known financial institutions, and their productivity is critical for an economy. As a result, factors that influence bank productivity should be examined closely. In recent years, the Georgian banking industry had undergone significant restructuring. Foreign banks acquisitions, internationalization of competition and deregulation are all important economic effect on bank development in Georgia. Banks in Georgia has also seen significant advancements in modernizing their delivery networks, which provide new products and platforms such as internet banking in addition to conventional branches and ATMs.

The aim of this paper is to examine the efficiency of banks in Georgia. Georgia is an emerging country with liberalized financial markets and open borders for international banks. Despite the fact there have been a variety of research in developed countries. But there is scarce research in post-soviet countries like Georgia. I unfortunately could not find any literatures and research about Georgian banks efficiency. To the best of the author 'knowledge, this is the first study in the literature that measure efficiency of Georgian banks.

Literature

There are numerous studies focusing on the efficiency of financial institutions have employed by the concept of DEA. These research studies determine meaningful and useful findings which may help for financial institutions management or branch manager. DEA has been widely used in the case of banking efficiency. The efficiency of banking institutions has been measured by managers and researcher using financial ratios. When multiple input and outputs are included, this practice is not able provide a general efficiency score (Siriopoulos and Tziogkidis, 2010). Farrell(1957) approached this issue by employing a frontier model based on the production possibilities curve to assess the productive efficiency of agriculture in America. Charnes et al (1978) applied thenon-parametric linear programming, data envelopment analysis (DEA), to appraise efficiency score of non-profit and governmental organization for the first time. Other methods addressed this task is the parametric stochastic frontier approach (SFA)introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and Van denBroeck (1977).

* PhD, Faculty of Business and Technologies, International Black Sea University, Tbilisi, Georgia.

Email: mmercan@ibsu.edu.ge

Ariff and Can (2008) study cost and profit efficiency of 29 Chinese banks from 1995 to 2004 by the DEA approach. They determine that private and medium sized banks are the most efficient. Kwan, Halkos and Salamous (2004) use similar methodology for Greek banking system and find that large and private banks are more efficient in terms of general and profit. Staub et al. (2010) study cost, technical and allocative efficiencies for Brazilian banks, using data envelopment analysis. By using three different panel data specification to analyze the indications of bank efficiency scores, they find that non-performing loans is an important determinant of efficiency level besides market share.

On the other studies, Rammohan and Ray (2004) focus on the efficiency of public, private and foreign banks. These studies concluded that public sector banks were more efficient banks than private banks; Mahesh and Rajeev (2009) and Das et al. (2005) showed that private banks were efficient in Indian banking sector.

Berger et al. (2009) estimated the profit efficiency of Chinese banks from 1994 to 2003 and determined that the big four state banks are the least efficient, while foreign banks are the most efficient and minority foreign ownership will likely improve efficiency. Chen et al. (2005) correlate the cost efficiency of the four largest banks and two smaller size for the period 1993–2000 in Chinese banks, finding that the big four and smaller joint-equity banks are all cost-efficient, comparing to medium-sized joint-equity banks. Stanícková and Skokan (2012) conducted a research in Czech Republic banking sector and detect banks are highly efficient over time. Stavárek and Repková (2011) find similar results that efficiency increased in the period 2000–2010 and they also show that the largest banks perform significantly worse than medium-sized and small banks. In another study, Isik and Hassan (2002) examine cost and profit efficiencies of Turkish banks and find that score of efficiency decreased over time after financial liberalization, but they also conclude private and foreign banks are more efficient.

The majority of DEA studies are done by using US data, European sectors and especially Former Soviet Union countries have been neglected. Lack of studies in Transition countries analyzing banking efficiency conducting Data Envelopment Analysis gives an opportunity for this research. However, some interesting studies are found for Eastern European and Former Soviet Transition countries as well. Merten and Urga (2001) analyze the efficiency of commercial banks in Ukraine, concluding that small banks are more efficient in term of cost, in contrast less efficient in terms of profit comparing to large banks which present significant scale diseconomies. Kraft and Tirtiroglu (1998) examine the Croatian banking sector applying parametric method (SFA) and determine that old banks are more efficient than new private banks.

Methodology

The choosing appropriate methodology for building an efficient frontier for best-practice banks is a longstanding discussion. The existing methodologies used in order to calculate efficiency of banking institutions can be divided into the stochastic efficiency frontier (SFA), distribution free approach (DFA) and linear programming methods (Data Envelopment Analysis). Berger et al. (1993) shows key discussion points and compare these methods in the banking sector. In the present study I use the data envelopment analysis (DEA) technique, is by far most used technique, which is presented by Charnes et al (1978). DEA is a classical, non-parametric technique based on linear programming, employing the comparative assessment of decision making units (DMU). A significant advantage of DEA is that it works particularly well with the smallest observation, and does not require any specific functional form on the data to assess the efficiency score. However, a disadvantage of DEA is that data is free of measurement error and algorithm cannot take negative values. Data Envelopment Analysis is an easy technique to deal with multiple outputs and assign the conclusion of cost, technical and scale efficiencies without knowledge of input prizes. This is the main factor to use DEA in the study.

DEA uses linear programming for measuring efficiency against best –observed performance to the developed frontier (Charnes et al., 1978). It is a technique implemented for assessing the relative performance of a set of firms that uses a variety of inputs to produce variety of outputs. The best-practice frontier for Decision making units is constructed to conclude which DMUs efficiently use the resources available to generate outputs. Each DMU is given an efficiency score that ranges from 0 to 1. The most efficient DMUs are rated to score of one, while the less efficient DMUs have scores between zero and one.

Analysis of DEA can carry out by using input oriented or output-oriented model. An input-oriented DEA determine the proportion of reduction of inputs to be efficient unit while keeping its current level of output constant. In contrast, an output-oriented model indicates the increasing and decreasing level of output at the same time keeping its input level constant. Moreover, there is the option to implement by assuming either constant return to scale (CRS) introduced by Charnes, Cooper and Rhodes(CCR) (1978), or variable return to scale (VRS), introduced by Bankers, Charnes and Cooper (BBC) in 1984. A Constant Return to Scale means that a change in the amounts of inputs leads to a similar change in the amounts of the outputs. However, a Variable Return to Scale includes both increasing and decreasing return to scale. The following is an input—oriented DEA method presented for m outputs, n inputs and k firms:

$$Min \theta_0 - \varepsilon \left(\sum_{i=1}^n e_{i0} + \sum_{j=1}^m d_{j0} \right) \quad (1)$$

Subject to

$$\sum_{r=1}^k \lambda_r x_{ir} + e_{i0} = \theta_0 x_{i0}, \quad i=1,2,\dots,n$$

$$\sum_{r=1}^k \lambda_r x_{jr} - d_{j0} = y_{j0}, \quad j = 1,2, \dots, m$$

$$e_{i0}, d_{j0}, \lambda_r \geq 0, \quad \text{for all } i, j, r$$

Where θ_0 = the efficiency score for firm 0,

x_{i0} = amount of input i used by DMU₀,

y_{j0} = amount of output j produced by DMU₀,

e_{i0} = the amount of excess input i for firm ₀,

d_{j0} = the amount of deficit output j for firm ₀,

n = the number of inputs,

m = the number of outputs.

The above model involving 1-4, which is known as envelopment form of CCR model that was developed by Charnes et al. (1978) and based on Farrell's input-oriented TE measure in the literature under the assumption of constant-returns-to-scale (CRS) (Cook and Zhu 2005).

Banker et al. (1984) suggested to use variable return to scale that compose overall technical efficiency (OTE) into product of two components Pure Technical efficiency (PTE) and Scale Efficiency (SE). Technical efficiency is to measure the ability of managers to utilize firms' resource in terms of optimal output that can be produced from given inputs or optimal combination of inputs to reach a given level of output. The second is scale efficiency (SE) and refers to exercise scale economics by achieving at a point where the production frontier demonstrate CRS. CCR model estimates the global efficiency of DMU. This efficiency consists of technical and scale efficiency. On the other hand, BBC model considers the variation of efficiency with respect to the scale efficiency and measure pure technical efficiency.

Data and Variables

The published consolidated financial statements of Georgian commercial banks, which operate through the time periods ending December 31 of 2011-2018, have been analyzed. There are two fundamentally debated approaches employed to determine bank efficiency: the production approach, the transaction approach and the intermediation approach. Berger and Humphrey (1997) reveal that neither of these two approaches is appropriate because they cannot capture the dual role of financial institutions as providing services and transactions. Different studies offer different approaches for selecting inputs and outputs of banks. The production approach is pioneered by Benston (1965) and assumes that banks produce loans, deposit and several of banks assets, using labor and capital as inputs. The intermediation approach is proposed by Sealey and Lindley (1977) and views banks as financial intermediaries that use purchased funds, capital, labor, interest and non-interest expense to transform these funds into loans and other assets. Berger and Humphrey show that neither of these two approaches is perfect. They indicate that production approach is good for examining the efficiency of branches of units whereas intermediation approach is more covenants for evaluating bank level activity.

The most challenging task is to select the inputs and outputs to measure the efficiency level. There is no consensus on the models (Casu and Girardone, 2004). In this paper, following the most recent studies, I use the intermediation approach by selecting input variables are capital (measured fixed asset), personnel expense and purchased funds (measured as the sum of deposits). The output used for calculating efficiency scores are loans and other earning assets. This is a classical model under the intermediation approach used in most studies. The strong and significant correlation between inputs and outputs is an important task that DEA model shows a robustness result of efficiency score. Only positive and significant correlations for variables are valid for DEA. In addition, strong correlation between inputs and outputs validate the results, low correlation may indicate that this variable does not fit the model. Therefore, correlation matrix is very much essential to constitute appropriate inputs and outputs. Table 1 gives the Pearson correlation matrix (with their significance levels attached in asterisk). As can be seen in Table 1, there is a positive and significant correlation between inputs and outputs at 5% level of significance. Henceforth, the variables in this study are consistent.

Table 1. Pearson Correlation Matrix

Output/Input	Fixed assets	Purchased Funds	Personnel Expenses
Net loans	0.8668* (.000)	0.9846* (.000)	0.9489* (.000)
Other earning assets	0.9285* (.000)	0.9592* (.000)	0.8800* (.000)

**Correlation is significant at the 0.05 level.

Empirical Result

Using Data Envelopment Analysis, I compute allocative, technological, pure technological, and scale productivity for Georgian banks. I compare the individual bank productivity in terms of their combined frontier. Efficiency results are indicated in table 2 Mean efficiency result is lower in 2011 to 2017 and after results are increasing in the last two years. The average productivity found in study is smaller than found in previous studies like Poland (Grigorian and Manole,2002)

Average TE varies from 0.58(2013) to 0.77 (2011), with an overall mean of 0.67 for entire sample year, while equivalent estimates for SE are 0.83(2015) ,0.92 (2011,2011) and overall mean 0. 877.As a result, technological efficiency of banks from 2011 to2018 decreased by 5 percent and size efficiency decreased also by 6.5 percent. When loan loss provision is taken into consideration, however, the average mean technological performance rises by 1.2 percent. As a consequence, correcting for credit risk tends to have an impact on performance of efficiency scores.

During the study period of 2011-2018, efficiency scores in TE, PTE and SE are changing from year to another year, mostly did not increase but rather declined on average. Table 2 shows that efficiency (TE) finally increase to 0.72 compared to previous years like 0.58(2013) and 0.64(2014). Changes in technical productivity is 24 % in 2018.

Table 2. Average Efficiency of Georgian Banks

Year	TE	PTE	SE
2011	0.77	0.83	0.92
2012	0.69	0.76	0.92
2013	0.58	0.68	0.85
2014	0.64	0.77	0.84
2015	0.63	0.77	0.83
2016	0.65	0.74	0.89
2017	0.75	0.85	0.91
2018	0.72	0.84	0.86
Mean	0.67	0.78	0.87

TE: Technical efficiency, PTE: Pure Technical Efficiency SE: Scale Efficiency

This result indicate that banks are reorganized well in previous year to 2018 and had already additional cost in technologies and human capital, and began to be efficient in later years.

The reason cause of Georgian banks 'inefficiency in earlier years of sample in this paper, is fast growth of loans and increased incidence of the non-performing loans issues. The composition of assets changed dramatically over the time frame under consideration.

Table 3. Average Input Excesses and Output Deficits

Year	Capital	Purchased funds	Personnel Expenses	Net Loans	Other earning assets
2011	-23.83%	-30.80%	-24.51%	16.46%	3.57%
2012	-45.57%	-31.33%	-31.01%	0.00%	0.00%
2013	-42.15%	-53.07%	-47.21%	0.54%	30.05%
2014	-37.81%	-39.28%	-40.88%	0.00%	70.73%
2015	-41.78%	-39.47%	-39.29%	0.00%	56.09%
2016	-42.27%	-40.13%	-36.65%	0.00%	28.48%
2017	-27.92%	-37.72%	-27.63%	0.00%	5.86%
2018	-30.98%	-31.88%	-33.01%	0.00%	37.96%

Technical efficiency be further divided into pure technical efficiency and scale efficiency. After removing the scale, it can be noted that significant increase in technical efficiency.

Comparing Scale Returns

According to their scale efficiency, banks are divided into three categories: increasing return to scale (IRS), constant return to scale (CRS), and declining return to scale (DRS). IRS represents a proportionally greater change in output as a result of a change in input, while CRS signifies a proportionally equal change and DRS indicates a proportionally smaller change in output as a result of a change in input. Table 4 shows the numbers of banks in these three groups. There is a higher number of banks 11(2014), 11 (2015) and 10 (2016) in the category of DRS than number of banks 0(2014), 11(2015) and 2(2016) in the category of IRS. The number of banks in CRS is also higher in all year than number of banks in CRS.

Table 4. Number of Banks in Each Category of Scale Returns

Year	IRS	DRS	CRS	Total
2011	5	9	4	18
2012	5	7	5	17
2013	0	6	12	18
2014	0	11	8	19
2015	0	11	7	18
2016	2	10	5	17
2017	0	9	8	17
2018	0	9	9	18

IRS: Increasing Return to Scale, DRS: Decreasing Return to Scale
CRS: Constant Return to Scale

Causes of Technical Inefficiencies

Table 3 clearly shows that the bank's inputs excess is dominated in all years. In 2011, the highest inputs excess in capital was -45,57 percent, while the lowest was -22,83 percent. As seen in table, the inputs excess decreased in 2017 and 2018. The highest excess input in personal expense is in -47.21 percent (2013), while the lowest is -24.51 percent (2011). The highest excess input in capital was -45 percent (2012), the minimum was -23.83 percent (2011).

The output deficit of Georgian banks is also depicted in Table 3 in all years except 2011, the output deficit in other earning assets has been far greater than the output deficit in net loans. In the observed years, the net loan deficit was just 16.46 percent (2011) and 0.54 percent (2013). These findings outlined the reasons why Georgia banks were inefficient in the study years examined. The other earning asset is the main causes of banks' inefficiency in terms of output deficit.

Conclusion

In this paper, I calculate the technical and scale efficiency of Georgian banks over the years from 2011 to 2018. I measured banks' efficiency by using input-oriented data envelopment analysis (DEA) and get the results with variable return to scales. Since this period coincided with the rapid growth of foreign controlled banks in Georgia, therefore this time period used in the paper provided us opportunity to assess the extent of and shifts in the efficiency improvements of the banks.

Since 2011, results in the paper discovered that Georgian banks have steadily improved their performance and efficiency, but the result also shows that banks used excess inputs. The findings of this study should create a basis for more research and a starting point for further research, including other methodology like profit and cost efficiency. The results also provide good validations and information for banks' policy and bank regulators in Georgia.

References

- Aiger, D., Lovell C.A.K., Schmit, P. *Formulation and estimation of stochastic frontier production function models*. Journal of Economics, Volume 6, Issue 1, 1977, paged 21-37. [https://doi.org/10.1016/0304-4076\(77\)90052-5](https://doi.org/10.1016/0304-4076(77)90052-5).
- Ariff, M. and Can, L. (2008). *Cost and Profit Efficiency of Chinese Banks: A non-parametric Analysis*. China Economic Review 19 (2): 260-273. DOI: 10.1016/j.chieco.2007.04.001
- Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manage. Sci.* 30, 1078–1092
- Berger, A.N., Humphrey, D.B., 1997. Efficiency of financial institutions: international survey and directions for future research. *Eur. J. Operat. Res.* 98, 175–212 [https://doi.org/10.1016/S0377-2217\(96\)00342-6](https://doi.org/10.1016/S0377-2217(96)00342-6)
- Berger, A.N.; I. Hasan; and M. Zhou. 2009. *Bank Ownership and Efficiency in China: What Will Happen in the World's Largest Nation?*. Journal of Banking & Finance 33, no. 1: 113–130
- Casu, B., Girardone, C., 2004. Financial conglomeration: efficiency, productivity and strategic drive. *Appl. Financ. Econ.* 14, 687–696
- Charnes, A.; W.W. Cooper; and E. Rhodes. 1978. *Measuring the Efficiency of Decision Making Units*. European Journal of Operational Research 2, no. 6: 429–444 [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
- Charnes, A.; W.W. Cooper; and E. Rhodes. 1978. *Measuring the Efficiency of Decision Making Units*. European Journal of Operational Research 2, no. 6: 429–444. [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
- Cook, W.D., and J. Zhu. 2005. "Allocation of Shared Costs Among Decision Making Units: A DEA Approach." *Computers & Operations Research* 32, no. 8: 2171–2178
- Farrell, M.J. 1957. *The Measurement of Productive Efficiency*. Journal of the Royal Statistical Society (A, General) 120, no. 3: 253–281. <https://doi.org/10.2307/2343100>
- Grigorian, D., and V. Manole. 2002. "Determinants of Commercial Bank Performance in Transition: An Application of Data Envelopment Analysis." Policy Research Working Paper no. 2850, World Bank, Washington, D.C
- Halkos, G.E., Salamouris, D.S., 2004. *Efficiency measurement of the Greek commercial banks with the use of financial ratios: a data envelopment analysis approach*. *Manage. Account. Res.* 15, 201–224. <http://dx.doi.org/10.1287/mnsc.30.9.1078>
- Isik, I., and M.K. Hassan. 2002. *Technical, Scale and Allocative Efficiencies of Turkish Banking Industry*. Journal of Banking & Finance 26, no. 4: 719–766 [https://doi.org/10.1016/S0378-4266\(01\)00167-4](https://doi.org/10.1016/S0378-4266(01)00167-4)

- Kraft E., Tırtıroğlu D. *Bank Efficiency in Croatia: A Stochastic-Frontier Analysis*. Journal of Comparative Economics, Volume 26, Issue 2, 1998, Pages 282-300. <https://doi.org/10.1006/jcec.1998.1517>.
- Mahesh H P., Rajeev M. *Banking Sector Reforms and NPA: A Study of Indian Commercial Bank*. Working paper.
- Meeusen, W. and Van den Broeck, J., (1977). *Efficiency estimation from Cobb-Douglas production functions with composed error*. International Economic Review, 18, 435-444.
- Merten A, Urga G. Efficiency, Scale and Scope Economies in the Ukrainian Banking Sector in, 2001- 1998, 1-21.
- Mohan, T.T. Ram and Ray, Subhash C. *Productivity Growth and Efficiency in Indian Banking: A Comparison of Public, Private, and Foreign Banks*. (2004). *Economics Working Papers*. 200427. https://opencommons.uconn.edu/econ_wpapers/200427
- Roberta B. Staub, Geraldo da Silva e Souza, Benjamin M. Tabak. *Evolution of bank efficiency in Brazil: A DEA approach*. European Journal of Operational Research, Volume 202, Issue 1, 2010, Pages 204-213. <https://doi.org/10.1016/j.ejor.2009.04.025>.
- Sealey, C.W., Jr. and Lindley, J.T. (1977). INPUTS, OUTPUTS, AND A THEORY OF PRODUCTION AND COST AT DEPOSITORY FINANCIAL INSTITUTIONS. The Journal of Finance, 32: 1251-1266. <https://doi.org/10.1111/j.1540-6261.1977.tb03324.x>
- Siriopoulos, C., Tziogkidis, P. *How do Greek banking institutions react after significant events? — A DEA approach*. Omega, Volume 38, Issue 5, 2010, Pages 294-308 <https://doi.org/10.1016/j.omega.2009.06.001>.
- Staníčková M., Skokan K. *Evaluation of Visegrad Countries Efficiency in Comparison with Austria and Germany by Selected Data Envelopment Analysis Models*. Proceedings of the 4th WSEAS World Multiconference on Applied Economics, Business and Development (AEBD'12). Recent Researches in Business and Economics, Pages 168-173.
- Stavarek, Daniel & Repkova, Iveta, 2011. *Estimation of the competitive conditions in the Czech banking sector*. MPRA Paper 30720, University Library of Munich, Germany. <https://ideas.repec.org/p/pramprapa/30720.html>