Efficiency Dynamics and Structural Characteristics of the Largest Commercial Banks in Turkey[1]

Çınar Y.

Recent developments in Turkish economy have forced banks to account for expenses and loan losses while increasing their loan supply to become more profitable. In this context, this study evaluates the efficiency dynamics of the largest Turkish commercial banks, by focusing on their lending decisions and profit generating behaviors. Clustering methodology is used for grouping banks in terms of structural similarities. DEA Window Analysis method is applied in efficiency analyses. The results mainly indicate that, efficiency level in the sector improved during the study period in general. It was not dramatically affected by the global crisis (in 2008), as well. Individually, banks exhibit different efficiency patterns relative to each other. Foreign banks outperform the others with respect to the efficiency models including only interest expenses and revenues. However, large-scale Turkish banks improve their efficiencies, when we consider non-interest returns in addition to interest gains. This conclusion implies that, non-interest revenues earned from diversified financial services have a crucial role in bank management. Results also show that, risk-taking behavior was more beneficial than conservative strategies in our analysis period.

Keywords: efficiency; Turkish banking sector; Data Envelopment Window Analysis; cluster analysis.

1. Introduction

Between the years 2004 and 2009, which is also selected as the analysis period in this study, Turkish financial system can generally be characterized by falling interest rates, low inflation and capital inflow, in parallel with the rising economic activity.

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Çınar Y. – Ankara University, Faculty of Political Sciences, Cebeci, 06590, Ankara, Turkey. E-mail: Yetkin.Cinar@politics.ankara.edu.tr

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These developments have led to a rapid growth in banking sector, but have incurred lower profit margins and more competitive pressure for the banks. Moreover, thanks to the positive effects of the reforms achieved in Turkish banking sector in early 2000's, the strength of shareholders' equity of the banks was preserved and currency risk remained limited (e.g. see [4; 41]). Thus, having a more healthy structure banks had to account for expenses and loan losses while trying to increase their loan supply and earnings. Therefore, detecting efficiency trends of these operations became more crucial for all stakeholders. In this context, this study provides a quarterly (dynamic) efficiency analysis on the largest Turkish commercial banks with respect to their loan operations and profit generating behaviors.

For this aim, the study begins with analyzing «ten largest commercial banks» which control vast majority of the Turkish banking sector. Testing for the homogeneity of this initial sample it is shown that, two of the state-owned banks have significantly different structural characteristics among others. Hence, thereafter only well-grouped eight banks remained to be taken into account. Different efficiency models associated with loan operations and profit generating behaviors of the banks have been constructed. Then, dynamic efficiency patterns have been evaluated via Data Envelopment Window Analysis method which had been first proposed by Charnes et al. [17]. Finally, obtained efficiency trends have been discussed not only in terms of banks' ownership, but also according to their structural characteristics.

In this framework, the rest of the paper is organized as follows. Chapter 2 gives a brief literature review on banking efficiency studies. This chapter also highlights the main scope and general formulation of this research. Chapter 3 introduces the formal methodology used. Chapter 4 presents and discusses the results of the empirical application. Chapter 5 concludes.

2. Banking performance and efficiency studies: main issues, primary aim and scope of the research

A great number of researches have been devoted to banking sector performance analyses [26]. One approach to explore performance is to analyze the ratios between the financial statement table items. These ratios show different financial dimensions of a bank's performance and have generally been measured by the internationally accepted ratio-based «CAMEL» methodology [27]. In this methodology, ratios related to capital adequacy, asset quality, management, earnings, liquidity are obtained from banks' financial statements. Then, a combined evaluation on these different aspects provides an overall picture of the global performance (or financial soundness) of banking. Since they usually contradict each other (e.g. liquidity versus profit) a proper methodology is required to aggregate them. Accordingly, Multicriteria Decision Making (MCDM) approach and its methods provide powerful tools. Thanassoulis et al. [39], Yeh [43], Aleskerov et al. [7] and Secme et al. [37] can be counted as examples of that kind of studies.

A second approach is the «efficiency analysis» in which inputs and outputs of a production function are defined and weights of them are derived by means of an optimizing calculation. Based on that, units can be classified into two groups: efficient and inefficient. In these analyses both parametric and non-parametric methodologies are used. Non-parametric Data Envelopment Analysis (DEA) first introduced by Charnes et al. [16] and parametric Stochastic Frontier Approach (SFA) proposed by Aigner et al. [2] are most widely used methodologies to assess the relative efficiencies of decision making units (DMUs). In DEA units are assumed to be similar in terms of goods and services they produce. Only in this case, the method yields a single dimensionless «relative» efficiency measure for each unit, without a priori assumption of some formal analytic production function [40, p. 91; 19].

There are many banking efficiency studies within the international literature. However, there is a considerable disagreement on a globally used methodology for assessing bank efficiency (e.g., see [12; 26]). Differences in selection of the sampling, determining the analysis period or method modeling (SFA, regression analysis or DEA) affect the results (e.g., see [14, p. 896]). Results are also influenced by different assumptions made on the production process of banks, i.e. selection of inputs and outputs of the production function. In order to define the bank production process, there are different approaches, namely the «intermediation», «production», «value-added» or «operating» etc.

Efficiency in Turkish banking sector was also studied in Zaim [46], Yolalan [44], Jackson, et al. [31], Isık and Hassan [29], Mercan et al. [40], Ozkan-Gunay and Tektas [33], Chambers and Çifter [15], Denizer et al. [21], Abbasoğlu et al. [1], Isık [30], Aysan and Ceylan [9; 10], Matousek et al. [32], Aydın et al. [8], among others. Studies of late 1990s and early 2000s focused mainly on the effects of liberalization in Turkish banking. They generally show that, liberalization increased the level of efficiency, with the exception of the financial crises occurred in Turkey in 1994 and in 2001. Recent works have focused on the post-crisis or post-regulation era after 2001. Most of them highlighted the effects of scale and ownership characteristics on efficiency.

Some basic findings of these studies can be reviewed briefly as follows: Isık [30] by using DEA based Malmquist Total Factor Productivity (TFP) change index have found foreign banks more efficient than domestic banks. Abbasoğlu et al. [1] have analyzed the efficiency of commercial banks for 2001–2005 by constructing a cost frontier. They found that large banks had higher efficiency, however the least efficient foreign banks were more profitable compared to the domestic banks. Aysan and Ceyhan [9] have used DEA and TFP index and found that total efficiency increased over the period 1990–2006. They also mentioned that state-owned banks became the most efficient banks after 2001, replacing foreign banks. Aysan and Ceylan [10] have showed that the restructuring process after the 2001 crises results in efficiency improvement of banks. Matousek et al. [32] have analyzed the efficiency of Turkish banking system for 2000–2005 by applying SFA. Their results suggested that state-owned banks were more efficient than Turkish private banks.

It can be observed that, efficiency studies on Turkish banks have also produced different empirical results due to the issues mentioned above. Hence, the results of a particular implementation should be interpreted with respect to its framework and suppositions. In this context, the primary aim of this research is to evaluate relative efficiency dynamics of the main banks in the sector. The secondary aim is to investigate possible links between the structural characteristics and the efficiency patterns.

In this framework, potential contributions of this article to the recent literature can be summarized as follows: First, regarding with the recent developments in Turkish banking sector, this study focuses on loan activities and profit generation behaviors of banks in efficiency analyses. The study is also a new approach in Turkish banking efficiency measurement, as it evaluates only the largest banks by grouping them according to their structural characteristics (ratios). Moreover, it is one of the few attempts which provide efficiency analysis in quarterly time periods in Turkish banking. In this respect, Chambers and Çifter [15] and Aydın et al. [8] may be given as other examples. They have used original version(s) of DEA and performed contemporaneous (cross-section) analyses each including only observations from one quarter. Differently, our study implements a sequential time periods' analysis by using DEA Window methodology. This method not only provides a closer examination of dynamic efficiency trends and stability, but also helps us to deal with small number of units.

In the light of above considerations, detailed formulation of the research is described in the following two sections.

2.1. Selecting the initial sample and testing the structural homogeneity

This article applies a DEA based methodology to evaluate the «relative» efficiency dynamics of the largest banks in Turkey. As suggested by Yeh [43] and others, DEA seems most meaningful when it is applied to observation sets of units providing similar services and using similar resources. Therefore, it is a valuable effort to take the homogeneity requirement into consideration, i.e. to select the most similar units (banks) before constructing DEA models. It is widely accepted that homogeneity may decrease within large data sets. In this respect, e.g. Sarkis [35, p. 306] states that: «utilizing homogeneity can ideally be provided through the use of small samples which contain units having similar characteristics». In this case, fewer numbers of units may decrease the discrimination power of classical DEA models. However, performing a dynamic analysis using DEA Window methodology can overcome this difficulty.

This approach is particularly useful when a highly concentrated banking sector is being analyzed. Since ten-bank concentration ratio was about 87% (by total assets) in Turkish banking sector by the end of the analysis period, this article selects «ten largest commercial banks» as an initial sample. Only commercial banks are selected, because they differ significantly from investment banks in terms of their operations that also consist of accepting deposits and structure of their credit portfolio. Existing empirical banking studies in the global literature also support these suggestions. Reporting that large banks and small banks may employ different production technologies and management strategies, many studies take into account only the larger or smaller banks or both of them within different groups [3, p. 316–317; 25; 43].

Previous studies have also shown that, factors such as ownership status and institution-specific (structural) characteristics of banks may influence efficiency, although these banks operate in the same environment and/or at similar scales. It is mentioned that commercial banks are not perfectly homogenous within themselves, i.e. they may still have structural differences [5; 6; 40; 43]. Therefore, a better treatment of this issue may be to find out structural similarities or differences within the initial sample by using a clustering methodology at the first step of the analysis. Further, monitoring efficiencies by taking into account the banks' structural characteristics can give a clearer perspective to the researcher. For this purpose, in our study a hierarchical clustering method (Ward's method) is used, as it does not require a priori assumption about the number of homogenous groups. After that, possible links between the banks' efficiency trends and structural characteristics is explored.

2.2. Determining the important factors and detecting dynamic efficiency trends

In banking efficiency studies, first of all, there is a need for making an assumption for the bank production process. In this respect, widely used approaches are labeled as «production» and «intermediation». The former assumes banks as producers of various services (loans and deposits) for their customers by using labor and capital as inputs. The latter views banks as financial intermediaries transferring funds from depositors to lenders for profit. Berger and Humphrey [13] argue that neither of them is perfect. They point out when evaluating financial firms as a whole the intermediation approach is more proper, but the production assumption may be more appropriate when evaluating bank branches. Resulting from the similar arguments, intermediation approach is accepted as the one favored in the literature [26, p. 191].

This study employs variants of intermediation approach. Moreover, in the light of recent developments in Turkish banking, it is decided to focus on the loan activities and profit generating behaviors of banks for the efficiency analysis. Detected trends in Turkish banking after 2003 revealed that banks have mainly concentrated on their credit management abilities while increasing their loan supply to maintain their profits and growth (e.g. see [4, p. 35–38; 41]). The winning strategy in such a competitive environment turned out to be successful on finding less risky borrowers while increasing loans and returns gained from them. This dilemma highlights the relative importance of reducing the credit risk[2]. It is especially so, when banks are faced with lower interest (profit) margins in the financial market. Under such an environment, the emphasis on bank management is expected to be on making sound lending decisions [28, p. 415; 43, p. 983] or diversification of the earnings.

The other important issue in dynamic efficiency evaluation is to deal with time series or panel data. It is reported in Asmild et al. [18, p. 81] that, contemporaneous analyses each including only observations from one time period could be an ideal approach to this issue. That is, however problematic when comparing a small number of DMUs in existence of large number of periods. In such cases, inter-temporal or sequential efficiency analyses can be useful. Inter-temporal analysis compares each DMU with the whole data set over all time periods. But, e.g. comparing a bank in 2004 with the one in 2009 could render relative results meaningless due to the change of technology employed in the market [42, p. 312]. Therefore, sequential analysis in which each DMU is compared only with alternative subsets of panel data would be a better approach. For this purpose, DEA Window Analysis is utilized in this paper. This method is an extension of the original/static version of DEA which is typically applied to cross-section data to analyze relative efficiency. DEA Window assesses the performance of DMUs over time by treating them as different units in each time period. Doing so, the performance of a unit in a particular period is contrasted with its performance in other periods in addition to the performance of other units. Then, it provides an increase in the number of data points. Therefore, for evaluating the banking industries which usually exhibit oligopolistic structures with a few large participants controlling about 90% of the market (as in Turkey), this method might be a proper choice [18; 28; 42; 45].

In the following chapter, the methodology will be explained in formal terms and in details.

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[2] Throughout this paper the credit risk is measured by non-performing loans over total loans ratio.

3. Methodology

3.1. Cluster analysis

A class of techniques used to classify units into relative groups by looking at the similarity between them is known as «Cluster analysis». A cluster is a group of relatively homogeneous observations or units (DMUs). Units in a cluster are similar to each other and dissimilar to units in other clusters based on selected characteristics (criteria). Thus, it provides a simple profile of DMUs and of similar/partitioned groups.

Cluster analysis begins with a basic multicriteria data matrix (or its normalized form) where n Decision Making Units (DMUs) $A_1 \ldots A_n$ are evaluated in terms of m criteria $X_1 \ldots X_m$. Then resulting matrix $X = (x_{ij})_{n\times m}$ can be given as

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}, \quad (1)$$

where x_{ij} are the ratings (e.g. financial ratios) of each alternative A_i (banks) with respect to each criterion X_j (characteristics). By using (1) one can cluster DMUs in accordance with their similarities. For this aim, any valid metric may be used as a measure of similarity between pairs of units. The choice of which clusters to merge or split is determined by a linkage criterion, which may be a function of the pair wise distances between units. At the next stage, a clustering method or algorithm, i.e. the procedure for combining clusters is executed [34, p. 10].

In cluster analysis, grouping can be achieved by either hierarchically or non-hierarchically partitioning the samples. In the non-hierarchical method a position in the measurement is taken as central place and distance is measured from such central point. Since identifying a right central position is difficult and this procedure requires a pre-assumption for number of clusters, non-hierarchical methods are less popular. Hierarchical clustering uses an algorithm that starts with each unit in a separate cluster and combines clusters until only one is left. This procedure creates a hierarchy of clusters which may be represented in a tree structure called a «dendrogram». This structure helps one to see the relationship among observations. The root of the tree consists of a single cluster containing all observations, and the leaves correspond to individual units. The branching-type nature of the dendrogram gives an idea of how great the distance was between units or groups that are clustered in a particular step, using a 0 to 25 scale along the top of the chart. The bigger the distances before two clusters are joined, the bigger the difference in these clusters [Ibid, p. 119–125].

This study utilizes one of the most often used hierarchical clustering methods known as «Ward's minimum variance» by which clusters are merged so as to reduce the variability within a cluster [Ibid, p. 129–135]. This method looks at cluster analysis as an analysis of variance problem, instead of using distance metrics or measures. It involves an algorithm, which starts out with all sample units in k clusters of size 1 each and continues until all the observations are included into one cluster. For this aim, an index formulation called the (minimum) sum-of-squares index, or variance is defined as

$$SS = \sum_c \sum_i \sum_j \left| X_{ijc} - \bar{x}_{cj} \right|^2. \quad (2)$$

where X_{ijc} denote the value for criteria j in observation i belonging to cluster c. Here, summing over all criteria, and all of the units within each cluster, it compares the individual units for each criterion against the cluster means for that criterion ($\bar{x}_{cj}$). When the SS is small, then this suggests data are close to their cluster means, implying that having a cluster of similar units. Ward's method follows a series of clustering steps. At each step the pair of sample units that yield the minimum SS will form a cluster. Clusters or units are combined in such a way and the algorithm stops when all sample units are combined into a single large cluster of size k and a dendrogram is constructed.

3.2. Data Envelopment Window analysis

Data Envelopment Analysis (DEA) is a multi-factor productivity model for measuring the relative efficiencies of a homogenous set of $DMUs$, originally in a static manner. DEA was first introduced by Charnes et al. [16] and Banker et al. [11]. As a time dependent version of the method, «DEA Window analysis» was also proposed by Charnes et al. [17]. This model captures the variations of efficiency in multiple time periods. It assesses the performance of a DMU over time by choosing a «window» of w observations for each DMU and treating these as if they represented w «different» DMUs. Hence, in the analysis, a total of $n \times w$ units are evaluated and w different scores for each DMU are created. DEA Window analysis works on the principle of moving averages, i.e. by moving the window by one period and repeating the analysis, efficiency trends across the w observations for a DMU within the same data set can be detected [45].

Formally, consider n DMUs which produce k outputs by using m inputs and which are observed in T periods $(t = 1,...,T)$. The sample thus has $n \times T$ observations, and an observation i in period t, DMU_i^t has an m-dimensional input vector $\mathbf{x}_i^t = (x_i^{1t},...,x_i^{mt})$ and k-dimensional output vector $\mathbf{y}_i^t = (y_i^{1t},...,y_i^{kt})$. The window starting at time $s\,(1 \le s \le T)$ and with the width w $(1 \le w \le T - s)$ is denoted by sw and has $n \times w$ observations. Then, similar to (1), the matrices of inputs and outputs are denoted as follows [18, p. 70]:

$$X_{sw} = \begin{bmatrix} x_1^s & x_2^s & \dots & x_n^s \\ x_1^{s+1} & x_2^{s+1} & \dots & x_n^{s+1} \\ \dots & \dots & \dots & \dots \\ x_1^{s+w} & x_2^{s+w} & \dots & x_n^{s+w} \end{bmatrix}, \; Y_{sw} = \begin{bmatrix} y_1^s & y_2^s & \dots & y_n^s \\ y_1^{s+1} & y_2^{s+1} & \dots & y_n^{s+1} \\ \dots & \dots & \dots & \dots \\ y_1^{s+w} & y_2^{s+w} & \dots & y_n^{s+w} \end{bmatrix}. \quad (3)$$

The efficiency ratings for i-th DMU in the whole time period t, beginning at s-th period and the windows with the width of w, *i.e.* the optimal score for Φ_i^{swt}, can be obtained by the following model:

$$Min\,\Phi_j^{swt}, \tag{4}$$

$$s.t. \quad Y_{sw}\lambda \geq \mathbf{y}_j^t, \tag{5}$$

$$X_{sw}\lambda \leq \Phi\mathbf{x}_j^t, \tag{6}$$

$$\lambda_i \geq 0, \quad (i = 1,\ldots, n \times w). \tag{7}$$

Here λ is a vector of weights assigned to each DMUs. The assumptions made on this vector determine the shape of the efficient frontier (envelopment) and the production return to scale. The model with the constraints $\lambda \geq 0, e^T\lambda = 1, e^T = [1, 1,\ldots,1]_{n\times 1}$ defines Variable Return to Scale (VRS) (convexity) assumption which is first made by Banker et al. [11][3]. The above problem is run n times to compute the relative efficiency scores for each of the DMUs.

4. Empirical application and the results

4.1. Data and sample selection: clustering the banks

Using the framework described above, this study analyzes dynamic efficiencies on the sequentially overlapped frontiers formed by the largest commercial banks in Turkey. In Turkish banking sector, there are 45 banks, 32 of them are commercial banks. However, these banks are still different in many aspects and there is a large distinction in their sizes. Some of the commercial banks have only a few numbers of branches and seem to be dealing only with information gathering. Thus, it makes little sense to compare them with the biggest ones (for similar arguments see e.g. [42, p. 312; 43, p. 982]). In order to ensure homogeneity in data sampling, first with respect to the size criterion ten largest commercial banks have been included in the sample initially. All of them have assets above 10 Billion USD and they control 86,3% of total bank assets by the end of the analysis period. This sample set also exhibits a balanced distribution in terms of its members' ownership characteristics: It consists of 3 state-owned, 4 private (Turkish) and 3 foreign banks. The majority of the other 22 banks have total assets lower than 2 Billion USD [41].

Financial data (ratios) of the selected banks over the 22 quarters in between 4th quarter of 2003 and 1st quarter of 2009 have been obtained from the database released by the Banks Association of Turkey (BAT). The banks included in the initial sample are given in Table 1 in an alphabetical order. This table also shows the banks' ownership characteristics and some indicators of size.

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[3] It is stated in Stavárek [38] that VRS assumption is more suitable for banking efficiency studies.

Table 1.

Banks included in the analysis

Banks	Abbreviation	Ownership structure*	Share by total assets, %**	№ of branches
AkBank	AKBNK	Turkish Private	11,7	875
DenizBank	DENIZ	Foreign	2,8	399
FinansBank	FINBN	Foreign	3,8	459
INGBank	INGBN	Foreign	2,2	374
T.C.ZiraatBankası	ZRBNK	State-owned	15,0	1279
T.GarantiBankası	GARAN	Turkish Private	13,1	728
T.HalkBankası	HALKB	State-owned	7,3	638
T.ISBankası	ISBNK	Turkish Private	13,6	1051
T.VakıflarBankası	VAKBN	State-owned	7,8	526
YapıKrediBankası	YKBNK	Turkish Private	9,0	856

* Banking Regulation and Supervision Agency (BRSA) classification. ** As of March 2009.

It is stated by Mercan et al. [40, p. 193] that some banks on their balance sheets may indicate a high share of loans and deposits, some may rely heavily on funds borrowed from abroad or have a relatively high security stock in their total assets, vis-a-vis other banks. In addition, the operations as well as financial statements of state banks may be affected from special duties assigned to them or from being somehow market makers. In Aleskerov et al. [5] and Aleskerov et al. [6], it was shown that Turkish banks exhibit heterogeneous «bank-specific» (structural) characteristics. Hence, testing for the homogeneity in the sample to avoid institution-specific (structural) differences and grouping the banks with almost similar portfolios is a valuable effort.

For this purpose, the ratios used in Aleskerov et al. [6] and commonly accepted bank-specific factors reviewed in Fethi and Pasiouras [26, p. 192] have been considered. Then, proxies for five major structural characteristics of the banks have been derived from the «banking sector ratios» released by BAT. These are associated with asset, liabilities, earnings, liquidity and capital structures of the banks. Table 2 shows the selected variables.

Here it is assumed that the values of these ratios have no required or expected direction, instead, their specific levels are treated as the indicators of bank management strategies. For example it is assumed that, a relatively high ASTSTR ratio of a bank implies that it prefers lending to households or firms rather than investing in financial securities. Higher LIASTR indicates a financing structure relying on borrowing from other banks (or abroad) rather than deposits. Moreover, this can be interpreted as having prevailing borrowing facilities, while a lower value of LIASTR may imply a superior deposit collecting capability. When LQAST is high, it is considered as the bank is risk-averse in its lending and investing decisions. That is, the bank prefers to preserve liquidity in its asset composition. EARNSTR is taken to show the weight of interest income over total income. It is also an indicator of diversity in the banks' earning composition, i.e. interest vs. non-interest earnings. Capital to Risky Assets ratio is selected as an indicator for capital structure[4].

Table 2.

Financial ratios used for clustering

Variable	Abbreviation	Representative Structure
Total Loans/Financial Assets (net)	ASTSTR	Asset Structure
Borrowed Loans/Total Deposits	LIASTR	Liabilities Structure
Liquid Assets/Total Assets	LQAST	Liquidity
Interest Income (net)/Total Income (net)	EARNSTR	Earning Structure
Capital/Risky Assets	CAPSTR	Risky Assets ratio or Capital Structure

Since we have a large scale panel data (22 periods and 8 banks), dynamic clustering analysis methods such as the one proposed and utilized for banking in Aleskerov et al. [5, 6] and Aleskerov et al. [24] could have been used. It is remained as an extension of this study since we execute a dynamic analysis methodology (DEA Window) for efficiency analysis[5] Instead, in our case structural variables are considered as control variables which show institution specific differences. Thus, in this clustering analysis stage, a classical method has been implemented on a 10×5 data matrix consisting of the mean values of the ratios over the analysis period for all banks. In order to make the ratios more equally contribute to the similarities among banks, all of them have been standardized to z scores, with a mean of 0 and a standard deviation of 1. The dendrogram plot diagram generated via Ward's method on the standardized matrix is presented on Fig. 1.

The analysis has been repeated with four variables by excluding CAPSTR which has very high negative correlations with the most discriminating variables ASTSTR and LIASTR. Also various clustering methods (e.g. between group homogeneity, within group clustering) have been implemented. Slight differences on the levels of cluster distances have been observed and the clustering scheme shown in Fig. 1 remained unchanged. In any case, the two state-owned banks labeled by ZRBNK and HALKB have been very far grouped from the others. This implies that they have considerably different institution-specific characteristics (ratios). Another remarkable point was the inclusion of VAKBN to Private Turkish Banks' group[6]. Each time, foreign banks (DENIZ, FINBN and INGBN) were grouped together.

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[4] More generally used Capital/Total Assets ratio (capital adequacy) is not preferred in our case, because it is observed that, on average, the banks have very similar scores with respect to this variable.

[5] Normally, the variation of structural variables (ratios of stock variables) in time is lower than the changes in performance aspects (flow variables) which are used in DEA models.

[6] This result may be due to the continuing privatization process of this bank in the analysis period.

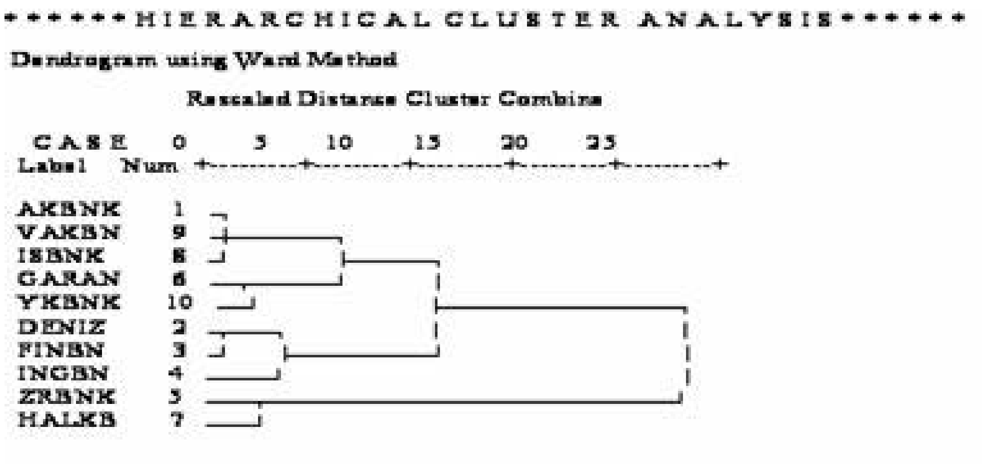


Fig. 1. Cluster analysis results for ten largest banks on structural variables

In order to provide more substantial explanations for this clustering scheme, Fig. 2 is constructed. For this illustration, the ratios have been normalized with the mean of zero and the values have been averaged within the groups obtained in cluster analysis

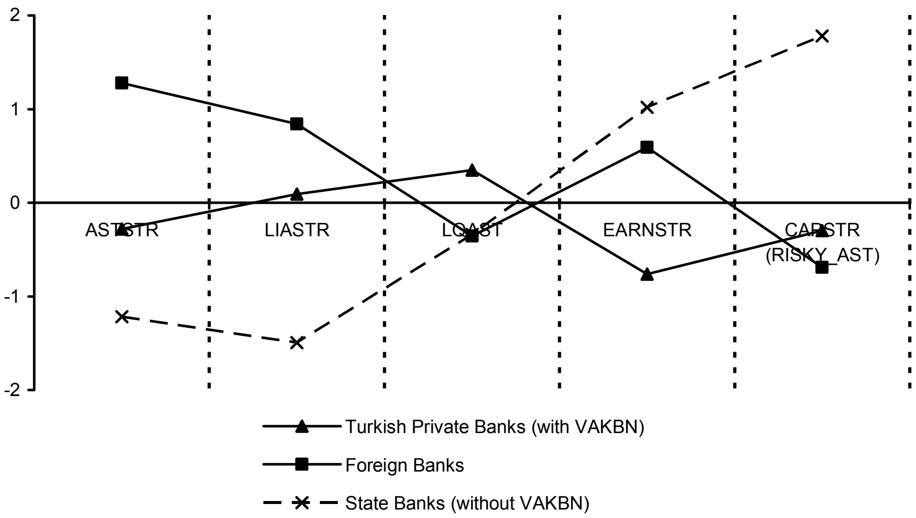


Fig. 2. Structural characteristics of bank groups or clusters

It can be seen from Fig. 2 that, the two state-owned banks ZRBNK and HALKB are heavily discriminated from the others with respect to ASTSTR, LIASTR and CAPSTR. When we ignore EARNSTR and LQAST, the least discriminating variables. So it seems reasonable to treat these two banks as outliers. Then, we omit them from the initial sample to ensure validity of further analysis results. Hereafter, eight banks will be considered as the final sample, assuming that they could be measured on the same frontier(s).

Figure 2 also shows that, there are still structural differences between remaining two groups. Regarding with them, the most discriminating variables turn out to be ASTSTR and EARNSTR. These banks have similar characteristics with respect to LQAST and CAPSTR. Clearly, foreign banks' group can be characterized by higher ratios in terms of ASTSTR, LIASTR and EARNSTR and lower values for LQAST and CAPSTR. That means, on average major share in their funds has been devoted to the borrowed loans. In other words, their borrowing capabilities could be better than the Turkish private banks' group within the analysis period. Moreover, the results imply that foreign banks have preferred lending to households or firms rather than investing in financial securities.

4.2. Dynamic efficiency trends: DEA models

In the light of considerations about recent developments in Turkish banking (given in Introduction and in Chapter 2.2), different DEA models have been created with a focus on loan operations and profit generated behaviors of the banks. They coincide with some variants of the intermediation approach adopted in a number of recent efficiency studies [26, p. 191]. As a result, the following models are constructed:

Model 1: This DEA model has been developed and used to measure the efficiency of loan operations of the banks by choosing «non-performing loans (CRDLOSS)» and «interest expenses (INTCOST)» as inputs and «interest revenues (INTREV)» as output, following Hartman and Storbeck [28]. The authors call this model as «loan efficiency». This model aims to measure the technical efficiency by focusing on lending decisions of a bank, i.e. it shows a relative performance measure on the basis of loan productivity of banks. In other words, this model evaluates relative efficiency of a bank for a given INTREV, minimization of INTCOST and CRDLOSS. It is assumed that the attained interest revenues (expenses) are a function of the amount the management of the bank has decided to lend (collect) as well as the price the bank has charged for its loans (deposits). By selecting revenues and expenses rather than the amounts of loans or deposits, the model includes decision variables related with prices and amounts together, but consisting of fewer variables [Ibid, p. 415]. Thus, this approach has an advantage to obtain larger differences between efficiency scores attained by the banks in the sample.

Model 2: This model is constructed to obtain overall profit efficiencies by adding «non-interest expenses» and «non-interest revenues» to «interest expenses» and «interest revenues» respectively. It is a variant of the models proposed in Berger and Humphey [13] and Drake et al. [23], among others. In these studies it is stated that a competitive and thus efficient firm would minimize its costs (COST) for its total revenue (REV) to maximize profits. Drake et al. [23] call this model as «profit-oriented (or operating) approach». They define revenue components (e.g. interest income, non-interest income, etc.) as outputs and cost components (e.g. personnel expenses, interest expenses, etc.) as inputs. They also state that this approach can be more appropriate in capturing the diversity of strategic responses by financial firms in the face of dynamic changes in competitive and environmental conditions. In our case, the effect of earning structure diversity on efficiency is interpreted by comparing the results of

Model 1 with Model 2. By computing total expenses and total revenues in an additive form, the same number of the variables will have been used in both models to ensure a proper comparison.

Model 3: As an alternative to previous ones, Model 3 has been formed by including the amounts of loans and deposits similar to the classical intermediation approach [22; 42; 45]. Table 3 shows the variables used in all DEA models.

Table 3.

DEA models

	Inputs*	Output(s)*
Model 1	Interest expenses non-performing loans	Interest revenues
Model 2	Interest + non-interest expenses non-performing loans	Interest + non-interest revenues
Model 3	Deposits Interest + non-interest expenses non-performing loans	Loans Interest + non-interest revenues

* Following Yolalan [44] all input and output variables are defined as the ratios of total assets. Computed ratios from flow over stock variables (e.g. expenses/total assets) are adjusted from quarterly basis to annual basis, using a formal methodology offered by BRSA.

In all models, a unique commonly used variable is the «non-performing loans». It is a proxy for credit risk or loan quality. There is an extensive debate in the literature about inclusion of this variable in the models (see [22], review on this subject). Most of the researchers state that the incorporation of credit losses is vitally important in studies of banking efficiency, so its omission may distort the derived efficiency results.

In order to employ DEA Window analysis on the models shown in Table 3, required input-output matrices have been prepared in the format given in (3). The window width of four periods (quarters) has been selected in order to minimize the problem of unfair comparisons and make the seasonal affects observable. By 22 quarters with a width of four quarters (a year), 19 windows (22 − 4 +1) have been generated. This means the observations are compared within a year time span. All calculations of the formulations given in (4–7) have been performed by using the program «EMS» provided by Scheel (2000). Only pure technical efficiencies (under VRS assumption) have been calculated and reported.

Figure 3 shows the results for technical efficiencies according to Model 1. Figure 4 presents the results for Model 2. In both figures windows representation is used. It shows moving averages of the efficiency scores in a year sequence.

Figure 3 indicates that, the largest foreign banks (relatively «middle-scaled» banks) are stronger than the largest Turkish private banks by means of their interest revenue generating functions. On the other hand, when we consider non-interest returns in addition to interest gains (as in Model 2); relatively large-scale Turkish private banks (see Table 1) improve their efficiencies. Even foreign banks are loosing their superior positions, especially in the last four windows. This result can be seen by comparing Fig. 3 with Fig. 4. In both models it can be easily seen that the efficiency level of Turkish banking has generally improved over time.

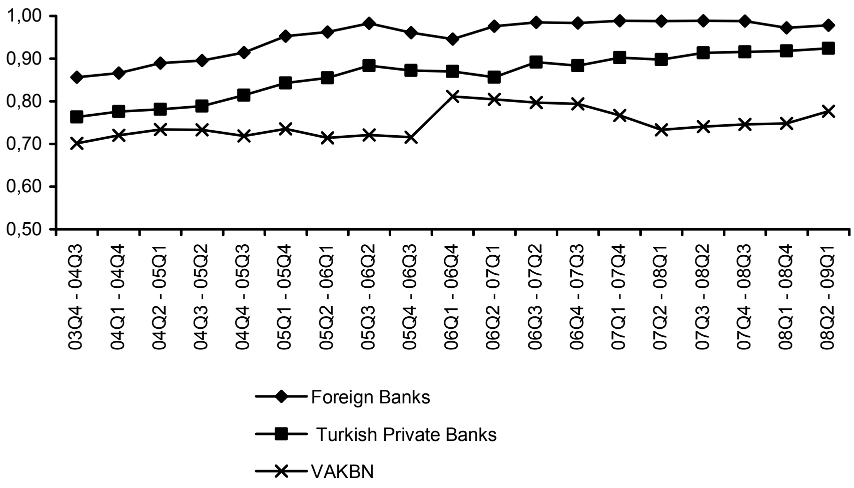


Fig. 3. Efficiency trends: Model 1

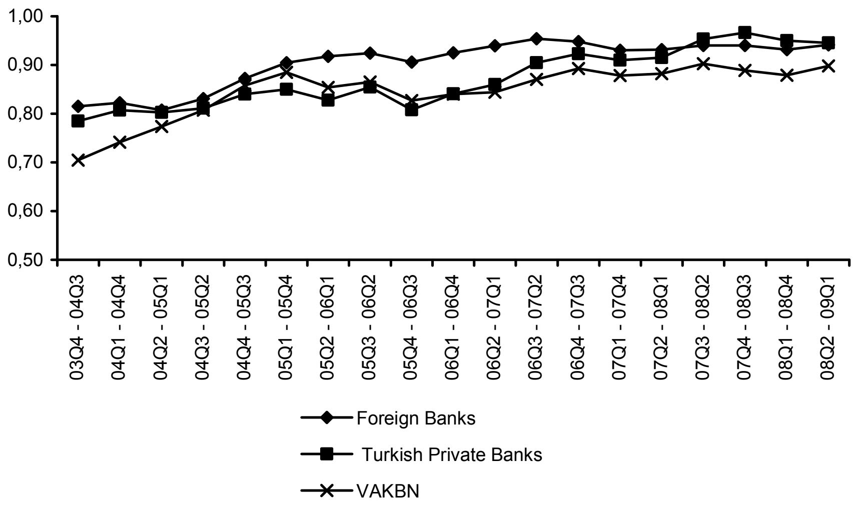


Fig. 4. Efficiency trends: Model 2

Table 4 shows means and variances of efficiency scores obtained by all banks across all windows. In this table, the banks are grouped in «weak» and «strong» categories by comparing the mean efficiency of a bank with the mean efficiency of the sample. Moreover, by comparing individual variances with the mean variance of the sample across all windows, the stability is determined and it is labeled as: «consistent» – «inconsistent». Then, a categorical rating scale is constructed as follows:

A = Strong – Consistent,
B = Strong – Inconsistent,
C = Weak – Consistent,
D = Weak – Inconsistent.

Table 4.

DEA Window analysis results

Across windows (W1–W19)		Mean efficiency, %			Difference, %			Variance, %			Category (Rating)		
		Models			Models			Models			Models		
BANKS	Ownership Structure*	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
AKBNK	TUR	96	98	99	–5	–2	–2	0,06	0,03	0,01	**A**	**A**	**A**
DENIZ	FOR	91	84	96	23	18	3	0,54	0,44	0,06	**B**	**D**	**B**
FINBN	FOR	96	92	99	13	18	0	0,29	0,39	0,01	**B**	**B**	**A**
INGBN	FOR	98	95	100	1	2	–2	0,03	0,19	0,00	**A**	**A**	**A**
GARAN	TUR	88	90	95	23	21	3	0,81	0,72	0,21	**B**	**B**	**B**
ISBNK	TUR	85	93	97	12	18	–2	0,22	0,30	0,03	**D**	**B**	**B**
VAKBN	ST	75	85	87	7	19	5	0,11	0,30	0,05	**C**	**D**	**D**
YKBNK	TUR	75	68	87	34	27	–8	1,46	1,89	0,67	**D**	**D**	**D**
	SAMPLE	**88**	**89**	**95**	**14**	**15**	**0**	**0,19**	**0,26**	**0,03**			

* TUR = Turkish Private Bank, FOR = Foreign Bank, ST = State-Owned Bank, SAMPLE = Eight Banks.

The results first indicate that, except VAKBN, neither of the banks is weak and consistent (in category C). This implies that generally stronger banks are more consistent or weaker banks are inconsistent. This result is in accordance with the assertions of Charnes et al. [17, p. 106] which state that generally more performance yields more consistency.

In Model 1, all foreign banks are categorized as «strong», even one of them (INGBN) is rated as «consistent» (this bank is assigned in category A). Performance patterns of the Turkish banks are more heterogeneous. For example, while AKBNK and GARAN are «strong» performers (rated in categories A and B respectively), YKBNK and ISBNK are weak. Another implication is that, foreign banks having higher ASTSTR and LIASTR ratios (see Fig. 2) outperform the others in Model 1 with a more stable pattern. With respect to observed trends in Model 2, the large-scale/multi-branch Turkish private banks (AKBNK, GARAN, ISBNK) and VAKBN improve their efficiencies, when we consider the «non-interest» expenses and revenues in addition to the interest returns. Finally with respect to Model 3, totally higher and more stable efficiency scores are obtained compared with the results according to Model 1 and Model 2. It is expected, because the banks weight additional input and output (the amounts of deposits and loans) so as to reach higher efficiency scores in this model.

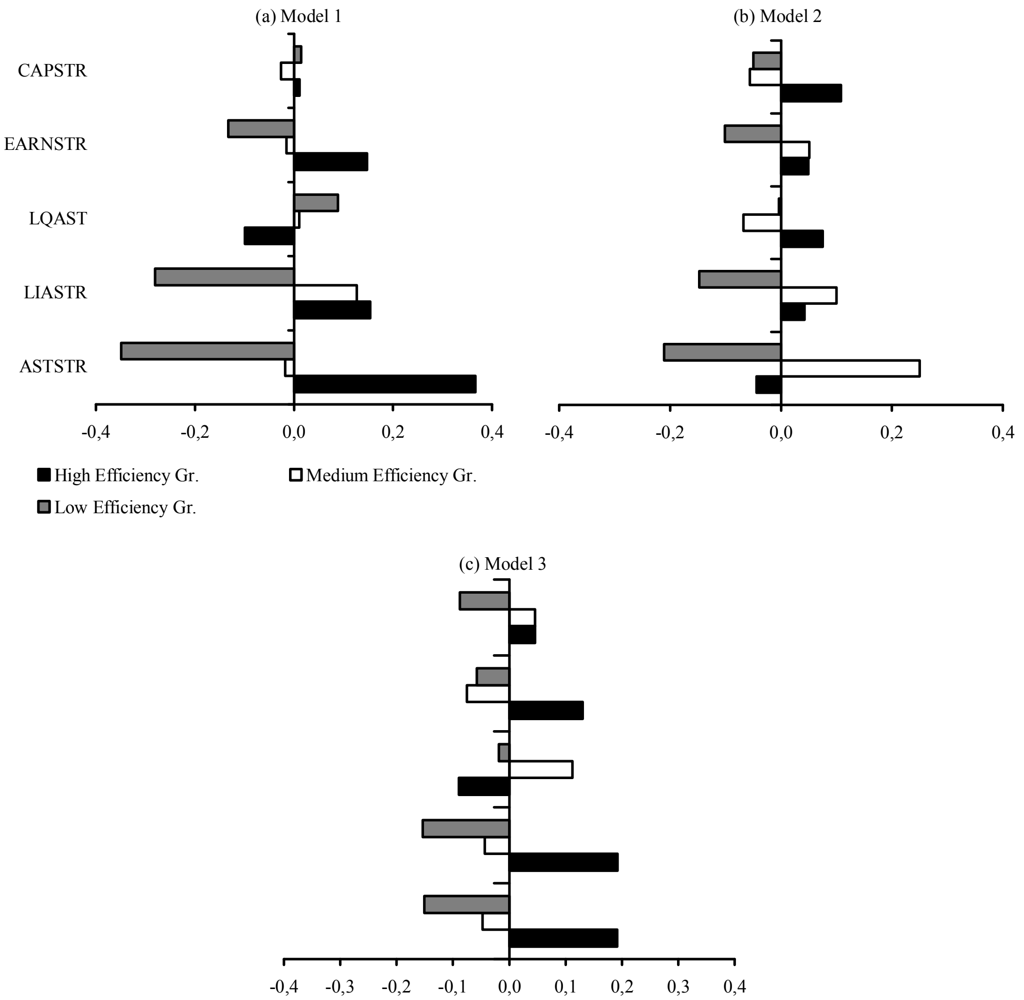
The correlations between the efficiency scores and the input-output variables have also been computed. According to the results, CRDLOSS is positively and significantly correlated with the efficiency scores. That is, efficient banks assigned higher weights to CRDLOSS rather than INTCOST or (total) COST within DEA optimization. Keeping in mind that in DEA optimization banks tend to put higher virtual weights to the variable which they are relatively advantageous; these results imply that inefficient banks are not successful mainly in terms of credit losses. In other words, inefficient units should improve themselves preferably in terms of managing CRDLOSS.

4.3. Peer group analysis: links between efficiency and structural characteristic

In order to observe the links between efficiency trends and structural characteristics of the banks more accurately, a peer group analysis has been designed, as in Yeh [43]. For this aim, 176 observations (efficiency scores of 8 banks in 22 periods) have been ranked and divided into three equal parts indicating the highest, medium and the lowest efficiency groups, respectively. Then corresponding values on the structural characteristics of observations have been averaged within each group. Since it is easier to observe the links between efficiency groups and their characteristics in plot form, values of the characteristics have been standardized with a mean of zero for all groups. The results are illustrated in Fig. 5 which shows the relative magnitudes in plot diagrams within a range between −0,40 to +0,40 for each of the three models. Correlations between efficiency scores and the structural variables have also been computed and shown just below Fig. 5.

It can be easily seen from Fig. 5 (a) that in Model 1, the banks in the highest efficiency group significantly have higher ASTSTR, LIASTR and EARNSTR ratios than those in the lowest efficiency group. On the other hand, the results are almost the opposite in terms of LQAST. The distinction between the highest and the lowest efficiency groups in Model 1 is more remarkable by means of ASTSTR. These links are similar but weaken with respect to efficiency scores in Model 2 and Model 3. These results are shown in Fig. 5 (b) and Fig. 5 (c), respectively. All assertions can also be read from the corresponding correlations.

The implications from peer group analysis coincide with the arguments derived from cluster analysis results. When considering of the models all together, the most discriminating variable turn out to be ASTSTR; next one is LIASTR and then EARNSTR. In all models efficiency groups are closer in terms of LQSTR and CAPSTR. Hence, in relative magnitudes the results support the assertion that management strategies of the efficient banks have been focused on lending decisions rather than conservative policies such as liquidity preserving etc. In general, the largest foreign banks used these strategies, thus became efficient.



CORRELATIONS

Structure	Efficiency Scores – Model 1	Efficiency Scores – Model 2	Efficiency Scores – Model 3
ASTSTR	0,525(**)	0,168(**)	0,323(**)
LIASTR	0,448(**)	0,378(**)	0,363(**)
LQAST	−0,240(**)	0,096	−0,164(*)
EARN	0,443 (**)	0,191(*)	0,364(**)
CAPSTR	−0,174 (*)	0,157(*)	−0,014

(*) Correlations are significant at 0,05 level (N = 176); (**) Correlations are significant at 0,01 level (N = 176).

Fig. 5. Efficiency scores vs. structural characteristics

5. Conclusion

The primary aim of this paper was to evaluate the efficiency dynamics of the largest Turkish commercial banks between the years 2004 and 2009, in a quarterly basis. Regarding with the recent developments in Turkish Banking Sector and Turkish economy, the study has been focused on the banks' loan operations and revenue (profit) generating behaviors. The banks were grouped with respect to their structural similarities. In this way, efficiency trends were not only discussed in terms of ownership status, but also according to their structural characteristics. This approach provides us the capability of assessing the consequences of particular managerial decisions in a closer view.

Results first indicate that, efficiency level of the Turkish largest banks have generally improved over time. In this study it is also found that, efficiencies have not dramatically decreased during the last global crisis.

Individually, banks exhibit different efficiency trends relative to each other. The largest foreign banks' group outperforms the largest Turkish private banks' group in terms of efficiency in loan operations and by means of intermediation function. In these two models, efficiency has been evaluated basically by interest expenses and revenues. However, large-scale/multi-branch Turkish banks improve their efficiency scores and converged to the efficient frontier, when we consider non-interest earnings together with interest returns. This conclusion indicates that, in a more competitive environment non-interest revenues earned from diversified financial services may have a crucial role in bank management strategies.

The results of the peer group analysis also support these implications. According to the findings from the models associated with loan operations and intermediary function; strategies such as having larger borrowing facilities, investing more funds in loans and making high utilization of assets have made banks relatively more efficient. However, these implications loose their strength when we include non-interest earnings and non-interest expenses into the model.

Overall, our results confirm general implications of other studies which state that Turkish banking sector has reached a healthy structure in recent years. Thanks to increasing competition and positive effects of banking sector reforms (regulations) achieved in early 2000's, banks – in a safe manner – have focused on their intermediation function. In this period banks have focused on credit functions while preserving their liquidity and capital, and thus they became efficient. In addition, this study highlights the links between structural characteristics and efficiency levels of the largest banks. This analysis mainly implies that the most efficient banks over the analysis period were aggressive in their loan applications. Furthermore, they were the best performers in lending decisions. These results also support the general suggestion that, during a booming period, risk-taking behavior is more beneficial than conservative strategies provided that credit losses are not increasing.

Findings of this paper should be updated in the new era, after 2008 crisis; in order to investigate the most recent evolutions (after booming period) in the Turkish banking sector. Moreover, repeating the efficiency analysis via parametric methodologies such as SFA and analyzing a sample of smaller banks would be valuable extensions of this study.

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