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Integrating analytic network process and data envelopment analysis for efficiency measurement of Turkish commercial banks

Abstract

The purpose of this paper is to provide a two-stage multicriteria approach integrating analytic network process (ANP) and data envelopment analysis (DEA) for financial performance evaluation of banks. In the first stage ANP is used and the weights of the criteria for banks' financial performance evaluation are derived. In the second stage data for the criteria, which are the outputs of DEA, have been used to calculate the relative efficiency scores of the banks. The weights obtained in the first stage have been used to construct the assurance region (AR) constraints for the output weights. In order to show the applicability and usefulness of this approach it is applied to the financial performance measurement of 21 Turkish commercial banks. The aim of the application is to determine the relative efficiency scores with and without the weight restrictions and compare the ranking of decision making units (DMUs), in this case the commercial banks. The findings showed that ranking of banks differ and the discriminatory power of DEA model increases with the weight restrictions imposed on the output weights. The ANP-DEA integrated approach provides a methodology for decision makers and/or policy makers to incorporate managerial judgments and preferences into the efficiency measurement framework in which a nonparametric commonly used method, DEA, is employed. There is a lack of research in the literature utilizing ANP in the performance measurement of financial institutions and also integrating ANP with DEA in banking. This study allows the decision makers to evaluate the efficiency of banks, which have a great role in the economy of any country, to rank the banks and also include their preferences in the evaluation process.

Keywords: analytic network process (ANP), data envelopment analysis (DEA), reduced CCR models, assurance regions, banking, financial ratios.
JEL Classification: C67, C44, G21.

Introduction

The banking system plays a crucial role in the economy and economic development of any country. The major component of the banking system is undoubtedly the banks because of their financial intermediation function and deposit liabilities standing for the great part of a country's money supply. The rapidly changing environment, technological advancements and the globalization force the commercial banks to maintain their market share in order to compete with both national and foreign banks. Consequently measuring and evaluating the banks' performance become more critical and essential to regulators, managers, customers and potential investors.

Kumar and Gulati (2008) summarized the reasons why all parties – regulators, customers, managers and stakeholders – involved in the banks' activities bother about the relative efficiency of banks as follows: inefficient banks are riskier and without efficiently functioning banking system, the economy cannot function smoothly and efficiently; only efficient banks can offer better services at reasonable prices and ensure reasonable returns; the efficient banks are better able to compete because of their lower operational costs and can steal business away from less efficient banks.

The focus of our study is to measure the efficiency of 21 Turkish commercial banks by the use of financial ratios as outputs of the data envelopment analysis (DEA). For this purpose we integrated two well-known MCDM approaches, DEA and analytic network process (ANP). While measuring the efficiency of banks the weight restrictions used in assurance region (AR) approach of DEA have been derived from ANP results. By the integrated two-stage approach, the relative efficiency of the banks can be measured through DEA that relies on real and objective data and also the managerial preferences can be incorporated into the measurement process by the use of ANP. As Sarkis and Talluri (2002) pointed out, using such a unifying approach in efficiency analysis allows integrating managerial preferences and data within an analytical approach that helps to evaluate a set of production units, in this study the banks, with the outcome being a ranking of these units.

DEA/AR models with ANP weight restrictions had been studied by some researchers with different applications such as supplier selection (Kuo ve Lin, 2012), project portfolio selection (Sheikhrabori et al., 2012) or monitoring system performance (Talluri and Sarkis, 2002) but not on bank performance. The novelty of this study comes from the fact that the ANP and DEA approaches are integrated in order to measure and evaluate the banks' financial performance for the first time. Another distinguishing feature of this paper is the utilization of financial ratios as outputs of DEA and application of no-input DEA model while integrating ANP results. There exist studies in the literature evaluating banks' performance through other methods such as AHP with the use of financial ratios. For instance, Hunjak and Jakovčević (2001) employed AHP and PROMETHEE to evaluate ten

Crotian banks' performance using both quantity related-financial ratios and quality related criteria. Seçme et al. (2009) also evaluated the financial and non-financial performance of five Turkish commercial banks using ratios for financial performance analysis in the fuzzy AHP-TOPSIS integrated methodology. Also there exist studies comparing the results of ratio analysis and other methods used for efficiency measurement. For instance, Yeh (1996) applied DEA for six Taiwan commercial banks' performance through the 1981-1989 period. The differences in financial performance between banks according to the DEA score classification of 3 score groups by using 12 financial ratios which further arranged into 4 factors as a result of the factor analysis were examined in the study. Despite such studies, there have been only a few papers using the financial ratios as inputs and outputs of DEA instead of dollar values. We have found only five papers which will be further discussed in detail, two of them used no-input model (Al-Shammari and Salimi, 1998; Halkos and Salamouris, 2004) and other two (Mercan et al., 2002; Avkiran, 2011) identified both input and output financial ratios for banks' efficiency measurement. A study by Şakar (2006) also utilized financial ratios, but used five financial ratios as output variables however the inputs of the DEA model had included variables such as branch numbers, number of personnel per branch, share in total assets etc. rather than financial ratios. In our DEA model, some of the 6 output financial ratios used also differ from the ones in those studies.

The remainder of this paper is organized as follows. Next section presents a brief literature review for measuring bank efficiency by using financial ratios and DEA. Section 2 shortly provides the methodological background for ANP and DEA related to our integrated approach. In section 3 we present relevant ANP-DEA literature and describe the proposed methodology for evaluating financial performance of Turkish commercial banks. Section 4 proceeds with the ANP and later then the DEA applications for the observed banks and also provides the efficiency comparisons according to the ownership and size of the banks.

1. Literature review

1.1. Related literature on performance measurement of banks. There have been a great number of studies those have focused on measuring banks' performance using different methods and because of the critical role of banks in the economy there is still a growing need for such studies. Traditional financial performance analysis of firms had relied on the financial statement analysis or ratio analysis. In the early studies such as Tamari (1966), Beaver (1968) and Ohlson (1980) financial ratio analysis had been used to predict failures and bankruptcy. A more recent study of Li et. al. (2001) performed ratio analysis to determine the financial performance of fifteen banks in China using nine financial ratios. As discussed by Al-Shammari and Salimi (1998) ratio analysis has been extensively used for both normative purposes, to compare a ratio to a benchmark such as an industry average, and positive purposes so as to predict future performance and bankruptcy and also to assess the riskiness of a firm. Despite that the use of financial ratios to evaluate bank performance can be helpful, as Halkos and Salamouris (2004) stated the usage of ratios has been criticized by researchers. Kohers et al. (2000) mentioned that the accounting data ignores the current market value of the bank and does not reflect economic value-maximizing behavior. In addition, these financial ratios do not consider the input price and the output mix. In the study of Berger and Humphrey (1997), a survey of 130 papers that apply frontier efficiency analysis, it was emphasized that to evaluate the performance of financial institutions the essential task is to separate those production units that perform well from those that perform poorly, that is to measure the relative efficiency of the production units. They concluded that this can be done by applying frontier efficiency analysis, both parametric and nonparametric approaches, because those methods provide an overall, objectively determined, numerical efficiency value and ranking of the firms that cannot be available with other methods. Frontier efficiency techniques can be used in a variety of ways to assist firms in evaluating whether they are performing better or worse than their peer groups in terms of technology, scale, cost minimization, and revenue and profit maximization (Banker et al., 2010).

As described by Berger and Humphrey (1997) and Kumar and Gulati (2008) frontier efficiency analysis can be performed using both parametric and nonparametric methods. There are basically three parametric and two non-parametric frontier approaches (Berger and Humphrey, 1997). Parametric methods are the stochastic frontier (or economic frontier) approach (SFA), distribution free approach (DFA) and the thick frontier approach (TFA). Bauer et al. (1998) mentioned that both methods have a disadvantage of having to impose on the shape of the frontier by specifying a particular functional form for it. Nonparametric frontier efficiency methods are the data envelopment analysis (DEA) and free disposal hull (FDH). Nonparametric approaches to frontier efficiency measurement have a disadvantage of not allowing for the random errors occurring due to the measurement problems, chance etc. but they impose less on the frontier because do not require specification of a functional form for the frontier. Performance measurement through frontier efficiency analysis can be used to direct management efforts to the areas that most need improvement, to identify attractive targets for mergers and acquisitions, and for many other purposes. Also they can be used within the firm to compare the performance of departments, branches etc. DEA is particularly valuable in this regard because it can be used effectively with smaller sample sizes than SFA (Banker et al., 2010). Parametric or nonparametric, each approach has its particular advantages and disadvantages. Among all of those approaches as mentioned by Kumar and Gulati (2008) and summarized in the results of Berger and Humphrey's survey (1997), DEA has been most commonly used approach, applied in 62 studies of the 122 studies reviewed in the survey employing frontier efficiency analysis for financial institutions. This reflects DEA's significance and relevance in banks' efficiency measurement.

DEA is a linear programming-based nonparametric approach for measuring the relative efficiency of organizational units, called decision making units (DMUs), those produce identical multiple outputs using identical multiple inputs. DMUs can include firms, non-profit organizations, departments or branches of organizations, or even individuals. DEA was first introduced by Charnes-Cooper-Rhodes (1978) based on the Farrell's production frontier (1957). The DEA model (referred to as the CCR model) proposed by Charnes et al. (1978) assumes constant returns to scale (CRS). By removing the constant returns to scale assumption and enabling variable returns to scale (VRS) of production units, Banker et al. (1984) extended the CCR model and this new BCC model was able to decompose technical and scale efficiencies of DMUs.

1.2. DEA applications in banking. As expressed in several studies the first application of DEA in order to measure banks' efficiency was the Sherman and Gold's (1985) study on a US bank's fourteen branches. Several researches and applications have been published in the subsequent years on relative efficiency measurement of banks and bank branches operating in various countries. In the literature most of the studies have been on banks rather than bank branches due to the more availability of the data on institutional level. Survey results of Berger and Humprey (1997) also supported this since most of the studies, approximately the 77% of all, reviewed in the survey were on banks' efficiency measurement. A study in recent years conducted by Kumar and Gulati (2008) measured efficiencies of 27 public sector banks operating in India. Different from other studies they decomposed the overall technical efficiency (OTE) to its components and they also examined the impact of environmental factors on the inter-bank differences in OTE by using logistic regression analysis. In another study by Kumar and Gulati (2010) a two-stage performance evaluation model was proposed and applied to the Indian public sector banks. The outputs of the first stage measuring efficiency were used as the inputs of stage 2, effectiveness measurement. Tsolas (2011) also proposed a two-stage model, to evaluate the performance of thirteen commercial banks listed on the Athens Exchange, using DEA and Tobit regression model in each stage respectively. Hsiao et al. (2011) proposed a fuzzy superefficiency slack-based DEA model in order to evaluate the efficiency of 24 Taiwanese commercial banks and compared the results of the model with the fuzzy BCC outcomes.

There are also numerous studies using DEA for the evaluation of bank branches' efficiency in different countries. For instance Yang (2009) compared the results of five input-oriented BCC-DEA models using different outputs to measure the efficiency of a Canadian bank's branches. Paradi et al. (2011) proposed a two-stage DEA approach by employing CCR and BCC input-oriented models using the three perspectives of production, profitability and intermediation respectively in the first stage. The second stage of the study used a slack-based measurement model to incorporate the efficiency scores of three approaches of the first stage so as to provide an overall DEA score for each branch of a Canadian bank. Most recently, Paradi and Zu (2013) has provided a survey of 80 studies on the DEA efficiency measurement of bank branches covering the 1985-2011 period. They summarized the survey results including the issues such as selection of inputs and outputs, returns to scale assumptions, sample size and objectives of the studies. They determined that most of the studies focused on Canadian bank branches and the number studies has increased over time especially more in the 2001-2005 period.

There have been fewer applications of DEA to measure Turkish banks or bank branches as compared with other countries. We have briefly considered the studies published in refereed academic journals produced on and after 2002, excluding the symposium and conference papers. In the study of Bal and Gölcükcü (2002) a BCC model was employed in order to measure the efficiency of 21 Turkish commercial banks. Isik and Hassan (2002) measured the profit, cost, allocative, technical, pure technical and scale efficiency of Turkish commercial banks operating over the 1988-1996 period. They examined the impact of size, international presence, ownership, control and governance on the efficiency measures and compared the DEA model's results with the results of economic frontier approach. In another study of Isik and Hassan (2003) a two-stage efficiency measurement was carried out by using DEA first and later on the generalized least square and Tobbit multiple regression models to present the differences in efficiency scores according to several variables. Mercan et.al. (2003) aimed at measuring the financial performance of Turkish commercial banks during 1989-1999 by applying DEA that uses the financial ratios as input and output variables. Şakar (2006) studied the banking performance of 11 Turkish commercial banks for the ten quarters between 2003-2005 employing CCR and BCC models in order to determine the effects of variable returns on bank efficiencies and also calculated the Malmquist index for the observed sample of banks. Denizer et.al. (2007) utilized a two-stage DEA, measuring the efficiency of production and the intermediation processes of banks in each stage respectively. They also used a logarithmic regression model to determine the effects of high inflation and volatility of economic growth on the efficiency scores. Ozkan-Gunay and Tektas (2008) applied two DEA models, differing in terms of output variables used, to assess the technical efficiency of private and foreign commercial banks during the 1990-2001 period. Erdem and Erdem (2008) used DEA in order to measure the technical, allocative and economic efficiency of 10 banks trading in Istanbul Stock Exchange for the 1998-2004 period. The calculated economic efficiency scores were used as explanatory variables in capital asset pricing model to determine whether these efficiency scores had effects on the stock price returns of the banks. Fukuyama and Matousek (2011) used a two-stage network model in order to assess the efficiency of Turkish commercial banks over the period of 1991 to 2007 and employed regression analysis to examine the determinants of bank efficiency. Eken and Kale (2011) also applied DEA, both CCR and BCC output oriented models, for efficiency measurement at banks but not on institutional level, they compared the efficiency of 128 bank branches operating in Istanbul and examine the effects of branch size and regional properties on branch efficiency.

Different approaches have been used for selection of input and output variables in the previously mentioned studies in the literature. Favero and Papi (1995) identified five approaches to the input and output specification. These are the production approach, intermediation approach, asset approach, user cost approach and value added approach. They stated that while the first three approaches are related to some functions carried out by banks the remaining two approaches are not related to macroeconomic functions. As discussed in Colwell and Davis (1992) and Berger and Humphrey (1997) the most banking studies do not use national accounts measures but instead they have used either the production or the intermediation approach. According to the production approach, financial institutions are viewed as primarily producing services for account holders. Under this approach the outputs are measured by the number of accounts serviced or transactions processed over a given time period. Inputs in this approach include physical inputs such as capital and labor and their costs but interest costs are not included. On the other hand, according to the intermediation approach banks are considered as intermediators which transform and transfer financial resources from savers to investors. The values of loans and investments are used as output variables and the input of funds and their interest cost should also be included since funds are the main raw material which is transformed in the intermediation process. Consequently operating costs plus interest costs are the relevant cost measure in this approach. Deposits may be either inputs or outputs[1]. Each of the two approaches has advantages and Berger and Humphrey (1997) suggested that the production approach may better suit for the relative efficiency measurement and evaluation of bank branches whereas the intermediation approach may be more appropriate for inter-bank studies because this approach includes interest expenses which constitute a great part of the total costs[2].

After the review of related literature next section will provide a methodological background for the ANP-DEA approach.

2. Methodology background

In this section we present a brief introduction to the methods used in this study: the ANP and DEA.

2.1. The analytic network process (ANP). ANP is the generalization of the AHP, since it allows a network structure including dependence and feedback among the elements of a decision model. The ANP provides a general framework to deal with decisions without the assumptions of the independencies of higher level elements from lower level elements and also the independencies of the elements within the same level. ANP uses a network and influence is the central concept in the method (Saaty, 1999). AHP was proposed by Saaty (1977, 1980) to model subjective decision-making processes based on multiple attributes in a hierarchical system. All decision problems are considered as a hierarchical structure in this method (Tzeng and Huang, 2011). A hierarchy is composed of a goal, levels of elements (criteria, subcriteria and alternatives) and connections between the

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[1] For more detailed discussion on the different approaches for input output specification in DEA see Berger and Humphrey (1997), Favero and Papi (1995) and Colwell and Davis (1992).

[2] In this study we tend to adopt the intermediation approach in our DEA application for cross-bank efficiency measurement and use financial ratios calculated from the monetary values. We included the ratios related to net interest income and non-interest income among the output variables.

elements. These connections are oriented only to elements in lower levels. In a hierarchy connections go only in one direction, that is it has a linear top down structure and since it is authoritarian. It passes the word down only from higher up. Many decision problems cannot be structured hierarchically because they involve the interaction and dependence of higher-level elements on lower-level elements. Therefore, ANP is represented by a network, rather than a hierarchy (Saaty, 2008). Not only does the importance of the criteria determine the importance of the alternatives as in a hierarchy, but also the importance of the alternatives themselves determines the importance of the criteria. A network has clusters of elements, with the elements in one cluster being connected to elements in another cluster (outer dependence) or the same cluster (inner dependence) and it spreads out in all directions and involves cycles between clusters and loops within the same cluster (Saaty and Sodenkamp, 2010; Saaty and Vargas, 2006). The difference between AHP and ANP is the basic structure, a hierarchy in the former and a network in the latter method allowing dependence without the need to define levels.

In the ANP a judgment is provided from the fundamental 1-9 scale of the AHP by answering two types of question with regard to strength of dominance (Saaty, 2004): (1) Given a criterion which of two elements is more dominant with respect to that criterion; (2) Which of two elements influences a third element more with respect to a criterion? Priorities are found in the same way as in the AHP. The priorities derived from pairwise comparison matrices are entered as parts of the columns of a supermatrix. The supermatrix, called as unweighted supermatrix, represents the influence priority of an element on the left of the matrix on an element at the top of the matrix with respect to a control criterion (Saaty, 2005). In the ANP the priorities are obtained from the limiting supermatrix of the problem. To derive the limiting supermatrix it is necessary to raise the powers of the supermatrix in order to derive the steady state probabilities and these probabilities cannot be obtained unless the matrix is column stochastic. To obtain a matrix with all the columns of it sums to one, the unweighted supermatrix is weighted by the cluster matrix. Cluster matrix is constructed by comparing the importance of the clusters. A cluster impacts another cluster when it is linked from it, that is, when at least one node in the source cluster is linked to nodes in the target cluster. The clusters are pairwise compared to establish their importance with respect to each cluster they are linked from and the resulting cluster matrix of numbers is used to weight the corresponding blocks of the original unweighted supermatrix. The weighted supermatrix is found by multiplying all the values in a component in the unweighted supermatrix by the value in the corresponding position in the cluster matrix. This matrix is then raised to powers until it converges, so that all columns are identical, to yield the limit supermatrix (Saaty, 2004; Saaty, 2008; Saaty and Sodenkamp, 2010).

In summary the ANP methodology involves three important steps (Karpak and Topcu, 2010). First is the model construction, that is, determining all the elements that affect the decision and grouping them into clusters in order to obtain the network structure. In the second step the influence relationships and links among those elements are formulated and the pairwise comparisons are performed according to these links. The last step requires the construction of unweighted supermatrix, calculation of the weighted supermatrix and limited supermatrix to obtain the priorities.

Since in the ANP method it is not necessary to assume a hierarchical structure, it is more flexible than AHP for dealing with complex problems that have dependences among the elements in the problem. But ANP applications in the literature have been somewhat limited when compared with AHP, due to its more complex structure relative to AHP and being time consuming (Karpak ve Topcu, 2010). Sipahi and Timor (2010) reviewed 235 AHP and ANP application studies published in the period 2005-2009 and found that a great interest in those applications was in the area of manufacturing, i.e. on supplier selection, supply chain evaluation, facility location selection, system selection or evaluation and strategy evaluation problems.

2.2. The data envelopment analysis (DEA). The three models used in this study, the basic CCR, reduced CCR and assurance region (AR) DEA models will be introduced briefly in this section.

2.2.1. The basic CCR model. DEA was first introduced by Charnes, Cooper and Rhodes (1978) to measure the relative efficiency of homogenous set of decision making units (DMUs) and the initial DEA model referred to as the CCR model. DEA is a data-oriented approach for evaluating the performance of a set of peer entities called DMUs, which convert multiple inputs into multiple outputs (Cooper et al, 2011). In the CCR model measure of the efficiency of any DMU is obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity as shown in the input-oriented CCR model (1) (Charnes et al., 1978). The objective of the model is to derive the weights of inputs and outputs that maximize the efficiency, h_0, of the observed DMU.

$$\text{Maximize } h_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

subject to: $$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \qquad (j = 1, \dots n) \qquad (1)$$

$u_r, v_i \ge 0$ ($r = 1,.., s$; $I = 1,.., m$).

The nonconvex nonlinear formulations in (1) are then transformed into an equivalent ordinary linear programming problem in (2). The change of variables (u, v) to (μ, v) is a result of the Charnes-Cooper transformation (Cooper et al., 2011).

Maximize $$z = \sum_{r=1}^{s} \mu_r y_{r0}$$

subject to: $$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad (j = 1, \dots n) \qquad (2)$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \quad \mu_r, v_i \ge 0 \ (r = 1,..,s;\ i = 1,..,m)$$

Since the introduction of the CCR model in 1978 there has been a speedy and great growth in DEA literature. In the survey of DEA's first 30 years of literature including more than 4000 papers, presented by Emrouznejad et al. (2008), it was pointed out that a significant portion of the published research focused on the DEA application of efficiency measurement in both public and private sector activities. The survey results also indicated that banking, education, health care and hospital efficiency were the most popular application areas. While the basic CCR model allows for measuring the technical efficiency of DMUs and also discriminating efficient DMUs with a score of 1 and the inefficient ones, it does not provide any insights to discriminate among the efficient DMUs and rank these units. A ranking DEA model for efficient DMUs proposed by Andersen and Petersen (1993) is presented in the next section.

2.2.2. A ranking DEA model for efficient DMUs (reduced CCR). Andersen and Petersen (1993) introduced a procedure for ranking efficient DMUs by simply eliminating the test unit for the observed DMU from the constraint set. The basic idea in this approach, also referred to as superefficiency model, is to compare the DMU under evaluation with a linear combination of all other units in the sample, excluding the DMU itself. An efficient DMU may increase its input vector proportionally while staying efficient, and then obtain an efficiency score above one. The superefficiency score reflects the radial distance from the evaluated DMU to the production frontier estimated with that DMU excluded from the sample. This model provides a rating of efficient DMUs and also the same efficiency scores and rating for inefficient DMUs as in the basic CCR model. Following the notation identical with the CCR model (1978), formulation of the ranking DEA model of Andersen and Petersen can be represented by (3). The superefficiency model is also known as reduced CCR model (RCCR).

Maximize $$z = \sum_{r=1}^{s} \mu_r y_{r0}$$

subject to: $$z = \sum_{r=1}^{s} \mu_r y_{r0} - \sum_{i=1}^{m} v_i x_{ij} \le 0$$

($j = 1,\dots n$; excluding the 0^{th} constraint, DMU_0) (3)

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \quad \mu_r, v_i \ge 0 \quad (r = 1,\dots,s;\ i = 1,\dots,m).$$

As stated by Sarkis (1999) the use of ranking DEA model allows for direct inclusion of managerial preferences, i.e. the weight restrictions, by simply adding constraints related to these restrictions as described in assurance region models in the next section.

2.2.3. Assurance region (AR) models for integrating managerial preferences into DEA. There is a large diversity of methods for integrating managerial preferences into the DEA models. Allen et al. (1997) classified the methods into 3 groups as the approaches: (1) using direct restrictions on the weights; (2) adjusting the observed input-output levels; and (3) restricting the virtual inputs and outputs. The first group includes type I and type II assurance region (AR) models introduced by Thompson et al. (1986) and the models with absolute weight restrictions using different methods mentioned in the study. The second group of methods for adjusting the observed input-output data involves the cone-ratio DEA model of Charnes et al. (1990) and Golany's (1988) method of incorporating ordinal relationships without allowing the weights to take a zero value. Finally, Wong and Beasley (1990) presented a method which uses virtual input and output restrictions in DEA[1].

AR models were first presented by Thompson et al. (1986) to evaluate and choose the best site for a high-energy physics laboratory in Texas. AR models were later described in detail and applied to evaluate the efficiency of 83 farms in Kansas in a study of Thompson et al. (1990). While ARI models do not relate the input and output weights, the ARII constraints construct relationships between these weights. We employed ARI constraints since our DEA model for banks efficiency measurement uses no input. The setting of bounds for ARI in practical applications has been either only on expert opinion or expert opinion in conjunction with the price/cost in-

[1] For a detailed comparison of the methods used for weight restrictions in DEA see Allen et al. (1997) and also for the methods discussed see Thompson et al. (1986), Golany (1988), Charnes et al. (1990), Wong and Beasley (1990).

formation (Allen et al., 1997). For instance related to the banking applications of AR constraints, Taylor et al. (1997) used the range of nominal interest rates for the deposits, as one of the two input variables to evaluate the efficiency of thirteen Mexican banks. Thompson et al. (1997) also used weight restrictions which they estimated from the price/cost data distribution of banks provided in federal deposit insurance corporation reports. The efficiency of 100 largest banks in asset size operating in the US was evaluated using these restrictions on the weights of the inputs (total capital employed and total employees) of DEA model.

The process of setting AR is to define upper bound (UB) and lower bound (LB) for each input and output weight. The upper and lower bounds for each weight can help define constraints that relate the weight values of various variables (Sarkis, 2000). Using the lower and upper bounds of input and output weights, additional inequality constraints can be defined and incorporated into the DEA model. The AR constraints relate the weights and their bounds to each other as defined in (4). The generalized AR constraint sets that are derived from LB and UB relations are as in the following form (5a and 5b) (Sarkis, 1999). Similar AR constraints can be added to restrict output weights. The sets of constraints (5a and 5b) will be incorporated into the RCCR model (3) in order to integrate the managerial preferences. The name assurance region comes from these additional constraints which limit the region of weights to some special area. Generally, the DEA efficiency score in the corresponding DEA model is worsened by additions of these constraints and a DMU previously was efficient may subsequently be found to be inefficient after such constraints have been imposed (Cooper et al., 2006). Equation (4) requires a number of $(i(i-1)/2 + 0\ (0-1)/2)$ relations in total to be considered, where i is the number of inputs and o the number of outputs used. Since for each relation two inequality constraints should be added to the RCCR model (3), that makes a total of $(i(I-1)/2 + 0\ (0-1)/2)$ additional constraints incorporated into the linear programming model.

$$\frac{LB_i}{UB_j} \geq \frac{v_i}{v_j} \leq \frac{UB_i}{LB_j} \tag{4}$$

$$v_i \geq \frac{LB_i}{UB_j} v_j \tag{5a}$$

$$v_i \geq \frac{UB_i}{LB_j} v_j \tag{5b}$$

3. Measuring the efficiency of Turkish commercial banks

3.1. Integration of ANP and DEA for bank efficiency measurement. As pointed out before, a limited number of studies have been found that had integrated ANP weights into DEA/AR models and none were in banking and finance. A unifying study on ANP and DEA was first performed by Sarkis (1999) for evaluation of environmentally conscious manufacturing programs. 6 factors including costs, quality, recyclability, waste reduce, waste pack and compliance were used in the ANP model. Costs and quality factors were considered as the inputs and the others as the outputs of the DEA model to evaluate the efficiency of 15 programs. The results of CCR, RCCR and RCCR/AR with weight restrictions obtained through ANP were presented and compared in the study. Findings of the study indicated that managerial preferences, when integrated with the data in DEA model, differ both efficiency scores and ranking of DMUs. Talluri and Sarkis (2002) employed ANP and DEA approaches successively to monitor system performance and included operating costs (the only input of DEA), average work-in-process, average flow-time and yield rate as the performance measures. They evaluated the performance of a sample of 30 DMUs for which the input and output data were randomly generated. Sarkis and Talluri (2002) used ANP and DEA in order to evaluate the performance of the 10 business process improvement (BPI) projects. They constructed the ANP network with 4 clusters of strategic performance measures, each of them containing two operational performance measures. By using the randomly generated data for the inputs and outputs which were the operational performance measures of the ANP model, efficiencies of projects were calculated. Tohumcu and Karasakal (2010) evaluated the performance of 15 R&D projects ongoing in a defense research and development institute. The weights and weight limits were obtained through a questionnaire conducted among six experts from the institute. Lin (2010) used an ANP and fuzzy DEA integrated approach for personnel selection problem and presented a simulated application in the selection of electrical engineer among eight applicants in a Taiwanese electric and machinery company. Kuo et al. (2010) presented a framework to evaluate the performance of 12 mechanic-type green suppliers and accordingly incorporated the ANP weights with DEA evaluations, after determining the dimensions of performance by artificial neural networks. In a more recent study by Kuo and Lin (2012) the ANP-DEA approach was used for supplier selection. Green supplier selection criteria determined in the study were grouped into 4 dimensions including organization structure and manufacturing capability, supplier's implementation capability, quality systems and environmental issues. Using a total of fifteen criteria in these dimensions as the inputs and outputs of DEA, the efficiencies of 42 green suppliers by integrating the ANP weights to determine the bounds for input and output variables were evaluated. Khadivi and Ghomi (2012) integrated ANP weights into DEA to evaluate the site alternatives for solid waste facilities. Sheikhrabori et al. (2012) also applied the ANP and DEA but for the best portfolio selection among a set of fifteen investment proposals in an electronic company.

The integration of ANP and DEA requires a two-stage framework using these methods in each stage respectively. The conceptual flow of the ANP-DEA approach used in this study is displayed in Figure 1.

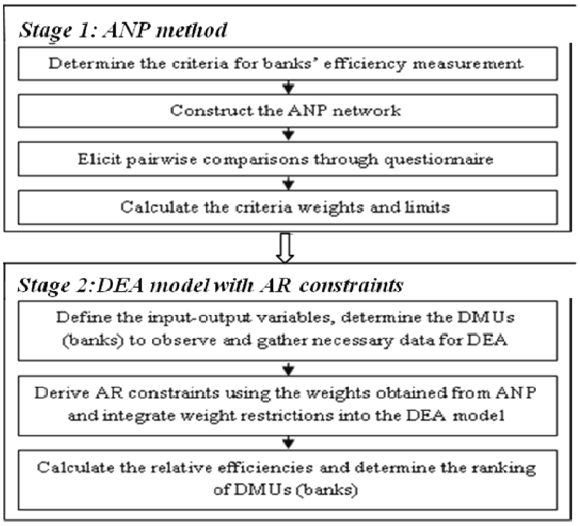


Fig. 1. The ANP-DEA integrated framework for bank efficiency measurement

In stage 1 ANP is utilized in order to obtain the weights of financial performance criteria for the banks. To perform ANP approach first of all the objective and the criteria for evaluating the alternatives according to the objective should be defined. That is the criteria or the nodes in each cluster have to be determined[1]. After the cluster and nodes have been defined the relations and influences among these elements are established and the ANP network is constructed. In the third step of stage 1 the pairwise comparisons have to be performed by the decision maker(s) involving in the process. The evaluations of each decision maker are then incorporated into a supermatrix (one for each decision maker) and later on weighting this matrix with cluster matrix the weighted matrix is calculated and the limit matrix is obtained by taking the powers of weighted supermatrix as described in the previous section. From the limit matrix required criteria weights are derived. Aggregation of weights from the decision makers can be completed as a group decision making effort but we carried out the ANP for each person, as in Sarkis and Talluri (2002), and the minimum and maximum weighting scores for each criterion among decision makers' evaluations will represent the lower and upper bounds that will be used to construct the AR constraints of DEA model in stage 2.

In the second stage, first of all the input-output variables of DEA should be defined. In the first stage we have selected the criteria for ANP which are also applicable for a later efficiency measurement by DEA. Under the intermediation approach, used also in this study, the monetary values reflecting the financial intermediation function of banks such as deposits, loans, interest income and expenses etc. are used as the input and outputs of DEA (Mercan et al., 2003). We did not use solely the monetary values but instead utilized financial ratios calculated through these values for the outputs of DEA and hence incorporated the two approaches of performance measurement, DEA and financial ratios, for banks' efficiency evaluation as in Al-Shammari and Salimi, (1998), Mercan et al. (2003), Halkos and Salamouris (2004), Şakar (2006) and Avkiran (2011). The input and output financial ratios used in these studies are summarized in Table 1.

Table 1. Input-output financial ratios

Authors	Inputs	Outputs
Al-Shammari and Salimi (1998)	No input	Return on investment (Net income/Total assets) Return on equity (Net income/Equity) Earnings per share Credits/Total assets Credits/Deposits Cash and portfolio investment/Deposits
Mercan et al. (2003)	Personnel expenses/Earning assets Total expenses/Total income	Earning assets/Total assets (Equity+ Net profit)/Total liabilities Average ROE

[1] Since these criteria will be the input-output variables of the efficiency measurement in the second stage while we were selecting the criteria we have considered the related literature on input-output specification for DEA discussed in literature review.

Table 1 (cont.). Input-output financial ratios

Authors	Inputs	Outputs
Halkos and Salamouris (2004)	No input	Return difference of interest bearing assets Average ROE Average ROA Profit/Loss per employee Operational expenses/Gross operating profit (loss) Net income/Total assets
Şakar (2006)	Number of branches Number of personnel per branch Share in total assets Share in total loans Share in total deposits	ROA ROE Net interest income/Total assets Net interest income/Total operating income Non-interest income/Total assets
Avkiran (2011)[1]	Reciprocal of capital adequacy ratio Impaired loans/Net interest income Impaired loans/Total assets Impaired loans/Equity Reciprocal of dividends per share Reciprocal of growth rate of assets	Growth rate of earnings per share Return on average equity Post-tax profit/Average total assets Net interest income/Average total assets Price to earnings ratio

However most of the studies had used financial ratios as both input and output variables, Al-Shammari and Salimi (1998) stated, referring to Fernandez-Castro and Smith's (1994) study, that the financial ratios represent the indicators of corporate performance and these ratios may be considered as the outputs of the firms' activities. If the DMUs are operating in similar environments then inputs to the firms can be considered immaterial, as they can be assumed to equal for all, and the performance analysis is then aimed at finding the companies which ensure best financial ratios (outputs) amongst all firms observed. They evaluated the efficiency of 16 banks. Halkos and Salamouris (2004) also used no input in DEA application on Greek banks, number of banks varied between 15 and 18 for the 3 years of observation. Because the DMUs under observation should be homogeneous, we have excluded the development and investment banks and the foreign banks that have few branches operating in Turkey. A foreign bank with negative output data has also been excluded. Since a limited number of DMUs (21 banks) can be observed we have selected only 6 output variables, important financial ratios, for DEA in order to ensure discriminatory results[2] among the DMUs. After specifying the input-output variables of DEA, selecting the DMUs (banks) for efficiency measurement and collecting the input-output data, AR constraints are formulated using the bounds calculated by the aid of ANP. And finally through the use of DEA/AR model which incorporates the managerial preferences into the analysis, efficiencies of banks are calculated and they are ranked.

4. ANP model for evaluating financial performance of Turkish commercial banks

4.1. ANP network and pairwise comparisons. Since the objective of the ANP analysis in this study was to obtain the weights of the financial performance evaluation criteria which will be integrated in the second stage of the framework given in Figure 1, we did not include alternatives in our network. In the network with the objective of financial performance evaluation we defined three clusters and each cluster has two nodes or criteria. The first cluster is related to the banks' asset quality, second one includes criteria pertaining to income and expenditure structure and the third one includes criteria measuring the profitability of banks. The criteria for evaluating financial performance of Turkish commercial banks were selected and later on the ANP network was constructed with the support of academicians studying finance. Network structure is shown in Figure 2.

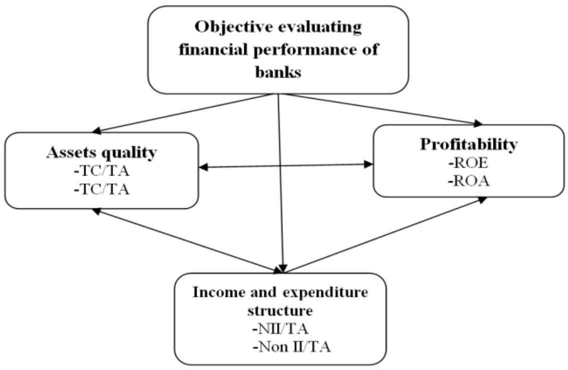
After constructing the network and the interdependency relations, in order to carry out the necessary pairwise comparisons a questionnaire was conducted among five experts. Three of the experts are academicians whose main research field is finance and the other two experts have been working in the Turkish banking industry for at least 15 years. The question asked for objective-clusters relationships, for instance, is "Which of the following group (cluster) of financial ratios is more important in the financial performance evaluation of commercial banks?" The part of the questionnaire related to this question is in Table 2.

Table 2. A part of the questionnaire

Which of the following group (cluster) of financial ratios is more important in the financial performance evaluation of commercial banks?

Assets quality	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Income and exp. structure
Assets quality	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Profitability
Income and exp. structure	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Profitability

[1] One of the three models used for a comparative efficiency measurement had utilized financial ratios as inputs and outputs, the other models had directly used monetary values.
[2] The number of DMUs should be at least three times the total number of inputs plus outputs used (Cooper et al., 2011).



Nodes: Financial ratios in clusters (ratio groups). TC/TA: Total credits/Total assets; TC/TD: Total credits/Total deposits; ROE: Net profit/Equities; ROA: Net profit/Total assets; NII/TA: Net interest income after provisions for credits and other receivables/Total assets; NonII/TA: Non-interet income/Total assets.

Fig. 2. The ANP network for financial performance evaluation of banks

Using the 1-9 scale (Saaty, 1986) as in the AHP, Table 3 shows the pairwise comparison matrix constructed by the judgments of expert 1 for the financial performance measures (clusters of financial ratios) when evaluating their relative importance with respect to the controlling factor (objective).

Table 3. Pairwise comparison matrix for the objective-clusters relationships

CR=0.07721	Assets quality	Inc. exp. structure	Profitability	Weights
Assets quality	1	1/7	1/9	0.05490
Inc. exp. structure	7	1	1/3	0.28974
Profitability	9	3	1	0.65536

4.2. Calculating the criteria weights and limits. Once all the pairwise comparisons are completed the eigenvector, the vector of weights, of each matrix should be computed. Then these weight vectors can be aggregated into the supermatrix. Also the consistency of the pairwise comparison matrices must be checked as in the AHP method. All of these calculations were completed using Super Decisions software for ANP analysis which was available from Creative Decision foundation (http:// superdecisions.com).

In the last column of Table 3 the weights of clusters with respect to the objective is presented. The results show that the profitability is perceived, by this expert, to be the most important financial performance measure (0.65536) and the assets quality is the least important measure (0.05490) for the banks' performance evaluation. The consistency ratio (0.07721) presented in the table indicates the inconsistency is below the acceptable level of 10 percent[1].

To construct the unweighted supermatrix of ANP, a total of 18 pairwise comparisons (adding up to 16 matrices), including node and cluster comparisons, need to be performed by the experts. Three for the objective-clusters of financial performance measures relationship, two for other cluster comparisons, three for objective-nodes relations, and the rest for the node relations. Except for the pairwise comparison matrix for object-clusters relationships, all of these matrices contain two factors since each cluster has only two nodes (or criteria) and thus require making only one pairwise comparison.

Table 4. Unweighted supermatrix

	Objective	Assets quality		Inc. exp. structure		Profitability	
		TC/TA	TC/TD	NII/TA	NonII/TA	NP/E	NP/TA
Objective	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
TC/TA	0.87500	0.00000	0.00000	0.88889	0.10000	0.14286	0.88889
TC/TD	0.12500	0.00000	0.00000	0.11111	0.90000	0.85714	0.11111
NII/TA	0.88889	0.12500	0.88889	0.00000	0.00000	0.00000	0.00000
NonII/TA	0.11111	0.87500	0.11111	0.00000	0.00000	0.00000	0.00000
ROE	0.87500	0.16667	0.83333	0.14286	0.11111	0.00000	0.00000
ROA	0.12500	0.83333	0.16667	0.85714	0.88889	0.00000	0.00000

The next step after building all pairwise comparison matrices and computing the weights is to aggregate them into the initial or unweighted supermatrix shown in Table 4 above. Then we can find the weighted supermatrix presented in Table 6, multiplying the cluster matrix (Table 5) by the initial supermatrix. According to the cluster matrix this expert views the profitability ratios as the most important cluster with respect to the objective of financial performance evaluation of banks.

Table 5. Cluster matrix

	Objective	Assets quality	Inc. exp. structure	Profitability
Objective	0.00000	0.00000	0.00000	0.0000
Assets quality	0.05490	0.00000	0.87500	1.0000
Inc. exp. structure	0.28974	0.88889	0.00000	0.0000
Profitability	0.65536	0.11111	0.12500	0.0000

[1] The consistency ratios calculated for all pairwise comparison matrices were below this level.

Taking the powers of weighted supermatrix, until it converges, the limit supermatrix is obtained (Table 7). The limit supermatrix shows that TC/TA is assessed as the most important financial ratio for financial performance evaluation and NP/E ratio as the least important one by this expert.

Table 6. Weighted supermatrix

	Objective	Assets quality		Inc. exp. structure		Profitability	
		TC/TA	TC/TD	NII/TA	NonII/TA	NP/E	NP/TA
Objective	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
TC/TA	0.04804	0.00000	0.00000	0.77778	0.08750	0.14286	0.88889
TC/TD	0.00686	0.00000	0.00000	0.09722	0.78750	0.85714	0.11111
NII/TA	0.25755	0.11111	0.79012	0.00000	0.00000	0.00000	0.00000
NonII/TA	0.03219	0.77778	0.09877	0.00000	0.00000	0.00000	0.00000
ROE	0.57344	0.01852	0.09259	0.01786	0.01389	0.00000	0.00000
ROA	0.08192	0.09259	0.01852	0.10714	0.11111	0.00000	0.00000

Table 7. Limit supermatrix

	Objective	Assets quality		Inc. exp. structure		Profitability	
		TC/TA	TC/TD	NII/TA	NonII/TA	NP/E	NP/TA
Objective	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
TC/TA	0.24838	0.24838	0.24838	0.24838	0.24838	0.24838	0.24838
TC/TD	0.22531	0.22531	0.22531	0.22531	0.22531	0.22531	0.22531
NII/TA	0.20562	0.20562	0.20562	0.20562	0.20562	0.20562	0.20562
NonII/TA	0.21543	0.21543	0.21543	0.21543	0.21543	0.21543	0.21543
ROE	0.03213	0.03213	0.03213	0.03213	0.03213	0.03213	0.03213
ROA	0.07314	0.07314	0.07314	0.07314	0.07314	0.07314	0.07314

In order to determine the upper and lower bounds of criteria weights ANP analysis need to be performed for the other experts. By completing the pairwise comparisons and later then the weight calculations we derive the results shown in Table 8. The results present the relative weights of each financial ratio with respect to the objective calculated according to the comparisons performed by each expert. According to the results three experts viewed TC/TA ratio as the most important measure of financial performance whereas the other two experts treat the TC/TD and NII/TA ratios respectively. We take the minimum and maximum weights for each criterion among the calculated weights for the five experts, as the lower and upper bounds. These limits which will be used to formulate AR constraints in the next section are in the last two column of the table.

Table 8. Weights and bounds of the criteria

	E1	E2	E3	E4	E5	Lower bound	Upper bound
TC/TA	0.24838	0.42104	0.35158	0.34286	0.17350	0.17350	0.42104
TC/TD	0.22531	0.05264	0.11957	0.11429	0.27933	0.05264	0.27933
NII/TA	0.20562	0.05181	0.36090	0.05714	0.09434	0.05181	0.36090
NonII/TA	0.21543	0.00740	0.04295	0.05714	0.01887	0.00740	0.21543
ROE	0.03213	0.05830	0.10498	0.22500	0.23683	0.03213	0.23683
ROA	0.07314	0.40881	0.02002	0.20357	0.19714	0.02002	0.40881

4.3. Basic DEA and DEA/AR results for Turkish banks. All of the criteria selected for ANP have been used as the outputs of DEA. We have not considered any input variables as in Al-Shammari and Salimi (1998) and Halkos and Salamouris (2004). We have used financial ratios as the performance indicators or the outputs of banks' intermediation process. The data for six financial ratios for the observed set of banks were obtained from Banking Association of Turkey (BAT). BAT reports indicate that by the end of 2011 there have been 48 banks operating in Turkey. One of the banks was taken over by Saving Deposit Insurance Fund agency, 4 of them are participation banks and 13 banks are development and investment banks. In order to obtain data from homogeneous DMUs we have examined only the commercial banks performing similar activities by using similar resources therefore we have excluded the participation banks and the development and investment banks[1]. The 3 state-owned, 11 privately owned banks and the 16 foreign banks constitute the remaining 30 deposit banks. Since we have excluded foreign commercial banks with few branches and banks with negative

[1] Commercial banks operating in Turkey are depository institutions that cannot take part in the leasing and trading real goods for commercial purposes. In contrast, development and investment banks can engage in such activities, but they cannot accept deposits. These non-depository institutions also do not extend small commercial and individual loans (Isık and Hassan, 2002).

output measures[1], our sample includes the data of 21 commercial banks. The data for the financial ratios used in DEA are given in Table 9. Among these 21 banks three banks are state-owned, ten banks are privately owned and the remaining are foreign banks. According to the 2011 reports of BAT, the sector share of state-owned, privately owned and foreign banks by the total assets are 29 percent, 53 percent and 13 percent respectively. The three state-owned, ten privately-owned and eight foreign banks in our sample have a sector share by total assets among the total of 21 banks of 31 percent, 56 and 13 percent respectively while within the whole banking system this percents are 29, 53 and 12. Total assets of 21 banks are worth approximately 94 percent of the Turkish banking sector's assets. That means the banks in our sample represent the Turkish banking sector to a great extent.

Table 9. Financial ratio data for banks

	TC/TA	TC/TD	NII/TA	NonII/TA	NP/E	NP/TA
Bank 1	44.45	63.18	3.14	0.60	1.31	15.94
Bank 2	61.69	84.86	3.58	1.73	2.24	23.67
Bank 3	64.26	94.04	2.78	1.71	1.38	13.19
Bank 4	52.64	91.53	2.76	1.57	1.79	13.64
Bank 5	67.28	119.04	2.85	0.86	0.44	5.83
Bank 6	64.57	101.82	4.71	0.84	1.47	10.14
Bank 7	59.10	93.74	2.95	2.16	0.82	8.07
Bank 8	71.76	101.62	2.62	1.21	0.63	4.28
Bank 9	29.36	47.92	2.55	1.09	0.08	0.45
Bank 10	67.34	112.08	3.48	1.10	0.54	4.91
Bank 11	57.15	99.14	2.99	2.21	2.09	17.47
Bank 12	56.67	93.19	2.45	2.23	1.65	14.88
Bank 13	62.70	106.71	2.64	2.32	1.72	15.88
Bank 14	37.05	49.57	4.55	1.03	0.08	0.60
Bank 15	62.31	111.74	3.86	1.70	2.43	22.12
Bank 16	47.30	102.42	2.04	2.05	0.76	5.94
Bank 17	84.72	102.74	2.72	0.83	0.21	2.22
Bank 18	65.52	103.40	4.46	1.68	1.84	14.89
Bank 19	57.32	104.43	4.18	1.90	1.00	8.61
Bank 20	73.00	133.35	4.40	0.57	0.38	3.35
Bank 21	66.66	92.05	2.86	1.62	0.16	1.05

After the first step of DEA in our framework, the lower and upper bounds (given in Table 8) will be used for the formulation of AR constraints. A total of 30 constraints should be included in the RCCR model. The constraints that should be added for the relation of output 1's weight (as the numerator) to the weight of other outputs are given below as an example to construct ARs.

$$0.27933\mu_1 - 0.17350\,\mu_2 \geq 0,$$

$$-0.05264\mu_1 + 0.42104\mu_2 \geq 0,$$

$$0.36090\mu_1 - 0.17350\,\mu_3 \geq 0,$$

$$-0.05181\mu_1 + 0.42104\mu_3 \geq 0,$$

$$0.21543\mu_1 - 0.17350\,\mu_4 \geq 0,$$

$$-0.00740\mu_1 + 0.42104\mu_4 \geq 0,$$

$$0.23683\mu_1 - 0.17350\,\mu_5 \geq 0,$$

$$-0.03213\mu_1 + 0.42104\mu_5 \geq 0,$$

$$0.40881\mu_1 - 0.17350\,\mu_6 \geq 0,$$

$$-0.02002\mu_1 + 0.42104\mu_6 \geq 0. \tag{6}$$

Following the formulation of AR constraints the CCR, RCCR, CCR/AR and RCCR/AR efficiency scores for banks are calculated, through the EMS software which is available from the web site of Holger Scheel (http://www.holger-scheel.de/ems/). The results of each model are shown in Table 10. The second column of the table shows the results of basic CCR model. According to the CCR results, 9 commercial banks are efficient and have a CCR score of 1. Efficient banks are Bank 2-6-11-13-15-17-18-19 and Bank 20.

The third column of Table 10 shows the RCCR scores for the commercial banks. Using the results of RCCR model, we can discriminate among the efficient nine commercial banks and rank these efficient DMUs. Bank 20 with the highest RCCR score (1.1824) is the most efficient bank among the 21 commercial banks. The efficient banks with the next two highest efficiency scores are Bank 15 (1.1664) and Bank 17 (1.1648). The following RCCR scores, from the highest to lowest, pertain to the Banks 13-18-2-11-6 and 19.

[1] Because the CCR models do not allow negative data and are not translation invariant we could not include DMUs with negative data by making any adjustments.

The fourth and the final columns of the table shows the results of CCR/AR and RCCR/AR results when the weights bounds obtained through ANP and given in Table 8 are integrated in the DEA models in order to derive the AR constraints set. According to these results only three commercial banks seem to be efficient. Among these banks Bank 20 has the highest efficiency score (1.1184) as in the RCCR model, and the next highest scores are the RCCR/AR scores of Bank 17 and Bank 15, that were 1.0851 and 1.0794.

Table 10. DEA scores for the commercial banks

	CCR	RCCR	CCR/AR	RCCR/AR
Bank 1	0.7843	0.7843	0.6885	0.6885
Bank 2	1.0000	1.0702	0.9569	0.9569
Bank 3	0.9450	0.9450	0.9020	0.9020
Bank 4	0.8355	0.8355	0.8060	0.8060
Bank 5	0.9413	0.9413	0.9316	0.9316
Bank 6	1.0000	1.0529	0.9235	0.9235
Bank 7	0.9751	0.9751	0.8247	0.8247
Bank 8	0.9431	0.9431	0.9142	0.9142
Bank 9	0.5981	0.5981	0.4087	0.4087
Bank 10	0.9424	0.9424	0.9099	0.9099
Bank 11	1.0000	1.0580	0.8961	0.8961
Bank 12	0.9591	0.9591	0.8529	0.8529
Bank 13	1.0000	1.0760	0.9472	0.9472
Bank 14	0.9793	0.9793	0.5078	0.5078
Bank 15	1.0000	1.1664	1.0000	1.0794
Bank 16	0.9402	0.9402	0.7631	0.7631
Bank 17	1.0000	1.1648	1.0000	1.0851
Bank 18	1.0000	1.0709	0.9689	0.9689
Bank 19	1.0000	1.0368	0.8545	0.8545
Bank 20	1.0000	1.1824	1.0000	1.1184
Bank 21	0.9462	0.9462	0.8327	0.8327

The other banks (Banks 2-6-11-13-18-19) which were efficient according to the CCR-RCCR scores become inefficient when the weights of the outputs used in DEA have been restricted by the lower and upper bounds calculated through the ANP. That means the managerial preferences when integrated into the DEA alter the DMUs to be efficient or inefficient, the efficiency scores and also the ranking of efficient units. For instance according to RCCR results the first three highest scores were belonging to Bank 20-15 and 17, while the RCCR/AR results differ since the efficient three banks have a ranking of Bank 20-17 and 15. CCR results show that among 3 state-owned banks only one bank is efficient which is found to be inefficient according to CCR/AR model. 3 of the ten privately owned banks have a CCR score of 1, while these CCR-efficient banks tend to be inefficient according to CCR/AR results. 5 banks among the foreign banks are CCR-efficient while only 3 of them are also efficient according to the CCR/AR model. We can summarize that the three banks which have a score over 1 in RCCR/AR model are all foreign commercial banks.

Table 11 shows the descriptive statistics for efficiency scores. The table also shows the mean efficiency scores for subgroups of commercial banks such as state-owned, privately owned and foreign banks; national versus foreign banks and the size groups formed according to the asset size. According to these statistics we can say that the mean RCCR/AR scores are lower than the mean RCCR scores. Among the three groups (state-privately-foreign) the highest mean efficiency score pertains to foreign banks for all DEA models. Although privately owned banks have the second highest mean efficiency scores according to CCR and RCCR, when the managerial preferences are incorporated in the DEA calculations through AR constraints the group with the second highest mean becomes the state-owned banks. When we consider the means calculated according to the nationality variable, national versus foreign banks, we can conclude that the foreign banks have a greater mean efficiency than the national banks (state-owned plus privately owned domestic banks). According to the classification with respect to asset size we have calculated three means for small, medium and large-sized banks. Mean efficiency scores indicate that medium-sized banks are more efficient than the other two groups. By the CCR and RCCR models small-sized banks is the second most efficient bank group while the large-sized banks are ranked as the second most efficient according to CCR/AR and RCCR/AR models.

Table 11. Descriptive statistics for efficiency scores

	CCR	RCCR	CCR/AR	RCCR/AR
Min.	0.5981	0.5981	0.4087	0.4087
Max.	1.0000	1.1824	1.0000	1.1184
Median	0.9751	0.9751	0.9020	0.9020
Mean (21 banks)	0.9424	0.9842	0.8519	0.8653
Mean (state-owned banks)	0.9098	0.9331	0.8491	0.8491
Mean (privately owned banks)	0.9195	0.9381	0.8415	0.8415
Mean (foreign banks)	0.9832	1.0609	0.8659	0.9012
Mean (national banks[1])	0.9172	0.9370	0.8432	0.8432
Mean (small-sized banks[2])	0.9248	0.9490	0.7896	0.7990
Mean (medium-sized banks)	0.9859	1.0613	0.9424	0.9671
Mean (large-sized banks)	0.8947	0.9092	0.8109	0.8109

The authors have also examined the impact of ownership, nationality and size variables on efficiency scores of the observed banks. In order to state whether any statistically significant difference exists on the CCR and CCR/AR efficiency scores according to these variables we have performed nonparametric tests using SPSS software. The results of Mann-Whitney and Kruskal-Wallis tests are presented in Table 12. The last part of the table shows the nonparametric test results for the paired CCR/AR-CCR scores.

Table 12. Nonparametric test results

	Kruskal-Wallis test (ownership)		Mann-Whitney U test (nationality)		Kruskal-Wallis H test (asset size)	
	χ^2	*Significance*	Mann-W. U	*Significance*	*χ^2*	*Significance*
	Kruskal-Wallis test (ownership)		Mann-Whitney U test (nationality)		Kruskal-Wallis H test (asset size)	
CCR	2.763	0.251	30.000	0.097**	4.576	0.101
CCR/AR	0.764	0.683	40.000	0.384	6.933	0.031*
	Kruskal-Wallis Test (ownership)		Mann-Whitney U test (nationality)		Kruskal-Wallis H test (asset size)	
Wilcoxon Test (CCR and CCR/AR efficiency scores)						
		N	Mean rank	Sum of ranks	*Z*	*Significance*
CCR/AR-CCR	(-) ranks	18	9.500	171.000	-3.724	0.000*
	(+) ranks	0	0.000	0.000		
	Ties	3				

Notes: * Significant at the 0.05 level. ** Significant at the 0.10 level.

The results in Table 12 show that both CCR and CCR/AR scores do not differ significantly with respect to ownership structure of the Turkish commercial banks. According to nationality variable only CCR scores are significantly different among domestic and foreign banks at the 0.10 level and mean rank of foreign banks are greater than the domestic ones. There also exist significant differences among CCR/AR scores of the three groups with respect to asset size. The mean rank of medium-sized banks is the highest among the three size groups. Wilcoxon test results indicate that CCR/AR efficiency scores are statistically different from CCR scores (Z = -3.724, p = 0.000). The calculated CCR/AR efficiencies of commercial banks are lower than the CCR efficiencies. This result supports the fact that integration of managerial preferences into DEA prompt to derive significantly different efficiency scores for DMUs.

[1] Include state-owned and privately owned domestic banks.

[2] We have divided commercial banks into 3 groups according to their asset sizes: small-sized banks with an asset size less than 10 billion dollars, medium-sized banks with 10-60 billion dollars and large-sized banks with a total asset greater than $60 billion.

Conclusions

The current study has proposed an integrated approach which uses ANP and DEA successively in each stage for the performance evaluation of Turkish commercial banks. This approach provides several advantages to decision makers. First, since it is a multicriteria decision making framework it can consider multiple performance measures for assessing banks' relative efficiencies. By using ANP it is possible to incorporate the managerial preferences into performance measurement process and provide more realistic weights for the input-output variables of DEA. ANP helps decision makers to structure the decision environment in a more flexible way than AHP since it allows a network to handle interdependencies rather than a strict hierarchy. Employment of assurance region models provides the necessary basis to integrate the weight bounds derived through ANP to the DEA model. The weight restrictions which reflect the preferences of decision makers also enhance the discriminatory power of DEA models. Alternatives of the ANP model may also be compared and evaluated through ANP methodology but a small number of alternatives can be considered because of the necessity of pairwise comparisons. However by the usage of DEA if the data is available for the required number of DMUs a larger set of alternatives can be evaluated and ranked according to their relative efficiencies. Utilization of DEA for alternative evaluation and ANP for only determination of criteria weights reduces the required number of pairwise comparisons. The RCCR models used in this study also allow ranking the efficient DMUs while discriminating efficient and inefficient ones as in the basic CCR model. Proposed ANP-DEA integrated approach let the decision maker to have the advantage of using both ANP and DEA approach in a single framework and while assessing and ranking the DMUS according to their performance also incorporate the managerial judgments into the process. If the managerial judgments remain unchanged for the next time period it will not be necessary to calculate the ANP weights again and only the DEA model will be solved with the actual data set of the period. Solving DEA models have become easier through the aid of available software. From this standpoint the integrated approach enables decision makers to have a straightforward and fast solution procedure for a multicriteria performance evaluation process.

Among the advantages of this approach a few number of practical implications have to be mentioned as in Sarkis (1999). The two-stage approach entails more interaction from the experts since it employs ANP, but this will provide insights about the judgments and preferences of these experts which can further be incorporated into the evaluation process. The second implication is the selection of criteria or the performance measures. It is necessary to determine all the variables to properly measure the performance of observed set of DMUs. Another implication pointed out by Sarkis (1999) was the qualitative factors that should be considered for performance measurement but this is not the case for our study since we aimed at evaluating the financial performance of banks and hence have to use quantitative performance measures as financial ratios. In conclusion besides the fact that this integrated approach require more interaction of experts and may be more time consuming than the traditional DEA models, this interaction provides the managerial preferences that are incorporated into DEA and transforms the model from being solely an efficiency measurement model to a more realistic multiple criteria measurement framework involving preferences.

For decision and/or policy makers, using such an integrated approach provides a meaningful way to incorporate value judgments into evaluation process while considering multiple criteria for performance measurement. Accordingly this approach can be used by banks' executives to evaluate the branch efficiency of a bank by incorporating the related preferences for the criteria used in the performance measurement model. Since the data is not available for bank branches this study aimed at measuring efficiency on institutional level.

A limitation of this approach comes from the fact that the number of DMUs evaluated should be twoor three times of the input and output variables of DEA model. Because of this reason and since there are 21 remaining homogenous DMUs in our sample we could only included a limited number of criteria which were the outputs of DEA model. If the observed sample of DMUs is greater and the data is available for these DMUs, the number of inputs and outputs of DEA model or in other words the criteria in the ANP model may also be increased. By this way it would be possible to include a greater number of factors in the efficiency measurement process and also to incorporate the related preferences of decision makers in a great extent.

The aim of this study was to integrate the ANP and DEA approaches for efficiency measurement of Turkish commercial banks. Therefore, the efficiency scores were computed for only one year. In a further study the variations on efficiency scores over a longer period may be examined.

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