Efficiency and Productivity in Turkish Banks:

A Bootstrap DEA Approach

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Abstract

As a result of financial liberalization, deregulation and globalization processes, financial institutions in developing countries encounter increasing competition and greater volatility to external shocks. This introduces inherent fragility into banking systems of those countries. In such an environment, the efficiency and productivity of the most essential players of financial markets, namely banks, have been crucial in maintaining the stability of not only financial markets, but also overall economy. On this basis, this paper, by using DEA (Data Envelopment Analysis) technique and Malmquist Productivity Index, addresses the impacts of 2007 global financial crisis on the efficiency and productivity of Turkish banks, throughout the 2003-2010 interval which covers both pre and post crisis periods. Moreover, two-stage, fixed effects panel data regression has been used to analyze the determinants of DEA efficiency scores. However, because of the existence of inherent dependency among the DEA efficiency scores, the basic assumption of regression analysis, namely, independence within the sample is violated. This paper improves upon the existing DEA literature by applying bootstrapping method to efficiency and productivity scores of banks to overcome the dependency problem and to be able to make valid statistical inferences based on those estimates.

Key words: *Efficiency, Productivity, Data Envelopment Analysis, Malmquist Productivity Index, Bootstrapping, Turkish Banks*

1. INTRODUCTION

In the last decade, Turkish economy has undergone a transformation period consisting series of reforms to pass from a centralized economy to a well-integrated market economy. Undoubtedly, one of the most crucial steps of the reform process has been the establishment of an effective and solid financial system. However, the liberalization of prices, the liberalization of circulation of goods, services, capital, the deregulation of financial systems and globalization introduced inherent fragility into the banking systems of developing countries.

2007 global financial crisis that has initiated from USA and spread throughout European countries hit, however, not only developing countries but also developed countries. The crisis has also been experienced by the Turkish banking sector.

In such a crisis environment, the efficiency and productivity of banks have gain particular importance in the evaluation of performance of overall economy. Since efficient banks are better able to diversify their activities and channel funds effectively, they provide greater stability for the economy. Therefore, the efficiency of the banking system is studied not only by the academic world but also by market decision makers and participants around the world during last three decades. A large number of papers have been published in which the efficiency of banking system both in the developed and developing countries has been examined in detail.

Motivated by those developments, this study presents an empirical analysis of the relative efficiency and productivity of Turkish banking system before and after the 2007 global financial crisis by using a rich panel data set observed during 2003-2010 periods. The methods used to assess relative efficiency and productivity are Data Envelopment Analysis (DEA) and Malmquist Productivity Index (MPI)[1]. The study improves upon the traditional DEA and productivity literature by employing a procedure called *bootstrapping* that permits to estimate bias corrected efficiency scores and productivity indices. In contrast to the econometric approaches which argue that DEA techniques are non-statistical and that statistical noise caused by DEA-estimators may introduce bias, bootstrap is seen as the only way of assessing statistical properties (i.e. bias, variance, confidence interval) of the efficiency estimators that come from some data generating process. So, through the bootstrapping, a researcher will be able to make statistical inferences based on those DEA-

[1] Hereafter DEA is used as an abbreviation for Data Envelopment Analysis and MPI is used as an abbreviation for Malmquist Productivity Index.

estimators. Finally, fixed effects panel data regression analysis has been used to analyze the determinants of DEA efficiency scores.

The organization of the paper is as follows: The next chapter is devoted to the survey of DEA and MPI literature. Chapter 3 explains the methodology used in this study to measure bank efficiency and productivity. Chapter 4 provides the information on the data used and describes the main variables employed in the efficiency model and in the regression. Chapter 5 discusses empirical results of the analysis. Finally, Chapter 6 concludes.

2. LITERATURE SURVEY

In the literature, there are two empirical ways to measure efficiency: *non parametric programming* introduced by Charnes et al. (1978) and *parametric stochastic frontier technique* introduced by Aigner et al. (1977). The most popular non parametric technique is *Data Envelopment Analysis (DEA)* and the most popular parametric technique is *Stochastic Frontier Analysis (SFA)*. The fundamental difference between both techniques is that the non parametric techniques involve use of linear programming methods to construct a non-parametric piece-wise frontier whereas parametric techniques postulate a parametric frontier, based on a behavioral maximization hypothesis and assume that maximizing behavior is present and that it is exhibited by the most efficient firms in the sample. However, as argued by Leaven (1997), often there do not exist any *a priori* grounds for making this assumption.

In fact, there is no consensus in the literature to use either DEA or SFA in the measurement of efficiency. The main advantage of DEA over SFA is that DEA can be used even when conventional cost and profit functions that depend on optimizing reactions to prices cannot be justified (Leaven, 1997). Another advantage of DEA, as pointed out by Amoda and Dyson (2006), is that if the specific functional form chosen for the stochastic production frontier does not represent the actual technology, the specification bias may lead to misleading efficiency measurements. On the contrary, since DEA involves the use of linear programming methods to construct a non-parametric piece-wise frontier over the data, efficiency measures that are calculated relative to this frontier will not carry a specification bias and hence will be more accurate.

As pointed by Schmidt (1986), opponents of DEA claim that DEA estimates give only an upper bound to efficiency measures, it does not assume statistical noise, which means that all the the error term in the estimation is attributed to inefficiency and so tend to underestimate efficiency scores and efficiency scores generated by DEA are not very robust and are highly sensitive to sample selection, that's to say DEA efficiency scores are dependent on each other due to the nature of the estimation technique which is based on the construction of best practice frontier from the sample in hand to assess relative performance.

However, to remove those anomalies inherent in DEA estimators and to be able to make statistical inferences based on DEA estimates, in their challenging studies Simar and Wilson (1993, 1998, 2000) developed various measures based on the idea of *bootstrapping* initially proposed by Efron (1979). Moreover, Wilson (2008) developed a distinguished software package called *Frontier Efficiency Analysis with R* (FEAR) that incorporates the idea of bootstrapping to compute not only DEA estimates of technical, allocative and overall efficiency while assuming either variable, non-increasing or constant returns to scale but also MPIs and scale efficiency measures. In their papers, Xue and Harker (1999) and Casu and Molyneux (2003) also use bootstrapping to overcome the inherent dependency of DEA efficiency scores. Based on those challenging works, this paper uses DEA and employs bootstrapping method in the measurement of efficiency and productivity.

The major reasons to prefer DEA over SFA in this paper are that as mentioned above, DEA does not assume a priori production frontier to be maximized for the unobserved population and it does not need to measure output prices which are not available for transaction services and fee-based outputs and which are probably distorted by regulations and other market imperfections. Moreover, employing bootstrapping technique in the measurement of efficiency and productivity enables to eliminate the critiques toward DEA by allowing us to make statistical inferences based on DEA estimates. Hence, considering the structure of the market and the data in hand, it seems that DEA is more appropriate for the assessment of the efficiency of Turkish banks. The details of the DEA technique would be explained in the methodology section of the paper.

In the DEA literature, determination of choice variables, namely bank inputs and outputs deserves particular attention because it significantly affects the results. There are two different approaches that dominate DEA literature: *production and intermediation approach.*

Under the *production approach*, pioneered by Benston (1965), a financial institution is defined as a producer of services for account holders, that is, they perform transactions on deposit accounts and process documents such as loans. Hence, according to this approach, the number of accounts or its related transactions is the best measure for output, while the number of employees and physical capital are considered as inputs (Sufian, 2009).

In the *intermediation approach*, however, banks are regarded as intermediators that accumulate deposits and other funds and transfer such funds to loans and other interest income producing assets. In this approach, banks' total loans and securities are assumed as outputs whereas deposits along with physical capital and labor are assumed as inputs. Moreover, under this approach, in contrast to the production approach, monetary values of accounts are used as choice variables.

More recently, there are several studies employing *mixed approach* in terms of the definition of bank inputs and outputs. In the mixed approach, banks are regarded as enterprises providing intermediation services and meanwhile engaging in production. Thus, under this approach measurement of inputs and outputs do not comply with either of the two previously mentioned approaches.

In the light of those approaches, this paper, regards banks as financial institutions trying to maximize profit through competition in the deposits and loan markets. On this basis, some leading indicator ratios regarding profitability, income, loans and deposits are used as bank inputs and outputs. In this approach, since a bank is regarded as a competitor, that's to say, producer of loans and deposits in the market, the study complies with the production approach. However, the data used in this study are not represented in terms of *account numbers* as in the production approach, but in terms of *monetary values* as in the intermediation approach. On the other hand, by using monetary values to form ratios the study diverges from intermediation approach, either. Therefore, the inputs and outputs used in this study should be classified under the *mixed approach*.

There are number of papers aiming to measure efficiency of Turkish banks by using DEA technique. One of the preceding papers for Turkey in this field is prepared by Zaim (1995). The paper investigates the effects of financial liberalization on the Turkish banking sector in the period of 1981-1990 by using DEA and finds out that differences in bank efficiency scores are eliminated during liberalization. Similarly, Işık and Hassan (2002, 2003) by using MPI and variable returns to scale (VRS) input oriented DEA approach examine the efficiency of commercial banks in Turkey during 1981-1990 period and conclude that after deregulation all forms of Turkish banks have recorded significant productivity gains driven mostly by efficiency increases rather than technical progress.

Cingi and Tarım (2000) studies the efficiency of Turkish banking sector between 1989 and 1996 by employing various bank indicator ratios in DEA approach, namely mixed approach, and shows that there is high degree of concentration in the sector and the inefficiency of public banks could be attributed to scale inefficiencies. More recently, Aras and Kurt (2007) use constant returns to scale (CRS) DEA to analyze the efficiency of banks operating in Turkey in the period of 1992-2003. In their analysis, they use mixed approach in the determination of bank inputs and outputs. They also take into account bank risk factors in measuring the efficiency and find out that banks transferred to Savings Deposit Insurance Fund (SDIF) had extreme loan growth and low efficiency scores and they had been carrying out high risk before transferred.

Besides the studies examining the Turkish banking system, there are also several studies that examine the efficiency of various developed and developing countries. Laeven (1997) uses DEA and introduces risk measure to fully take into account bank performance in order to analyze bank efficiency in East Asian banks during the pre-crisis period (1992-96). Casu and Molyneux (2000) investigates whether the productive efficiency of European banking systems has improved and converged towards a common European frontier between 1993 and 1997, following the process of EU legislative harmonisation. They use DEA and Tobit regression afterwards to analyze the determinants of European bank efficiency. To remove inherent dependency problem of DEA efficiency scores they apply bootstrapping technique before running Tobit regression.

Favero and Papi (1995) for Italy, Saha and Ravisankari (1999) for India, Vujcic and Jemric (2001) for transition economies in Europe, Sufian (2009) for Malaysia by using DEA and MPI, Howcroft and Ataullah (2006) for India and Pakistan by using output oriented DEA and MPI, Rezitis (2006) for Greece by using output oriented DEA, MPI and Tobit regression, Andries (2010) by comparing the results of SFA and DEA methods on Central and Eastern European countries during 2004-2008, Sing and Munisamy (2008) for Asia Pacific banks, Matthews (2011) for Chinese banks are the other remarkable studies in this literature.

In the studies discussed so far, different input and output combinations are used in the calculation of bank efficiency. Table below summarizes those combinations used in the banking literature.

Table 1: Studies on the Efficiency of Banking

Author	Observation Period	Inputs	Outputs	Method	Approach
Favero Papi	1991	Labor Capital Loanable Funds	Loans Securities Non-interest Income	DEA 2-Stage Regression	Intermediation Asset
Isık Hassan	1981-1990	Labor Capital Loanable Funds (deposit+non-deposit)	Short Term Loans Long Term Loans Off-Balance Sheet Items Other Earning Assets	DEA	Intermediation
Zaim Ertuğrul	1981-1990	Number of Employees Total Interest Expenses Amortisation Costs Other Costs	Volume of Short and Long Term TL Deposits Volume of Short and Long Term TL Loans	DEA	Value Added
Rezitis	1982-1997	Labor Capital Expenses Deposits	Loans Investment Assets	DEA 2-Stage Regression	Intermediation
Cingi Tarım	1989-1996	Various Ratios	Various Ratios	DEA	Production
Saha Ravishankar	1991-1995	Number of Branches Number of Staff Establishment Expenditure Non-establishment Expenditure	Deposits Advances Investments Total Income	DEA	Production
Jackson Fethi İnal	1992-1996	Number of Employees Non-Labor Operating Expenses	Loans Deposits	DEA	Value Added
Laeven	1992-1996	Interest Expense Labor Expense Other Operating Expense	Loans Securities	DEA 2-Stage Regression	Intermediation
Aras Kurt	1992-2003	Various Ratios	Various Ratios	DEA	Mixed
Casu Molyneux	1993-1997	Total Costs Total Deposits	Loans Other Earning Assets	DEA 2-Stage Regression Bootstrap	Intermediation
Thangavelu Findlay	1994-2008	Personnel Expenses Book Value of Fixed Assets Loanable Funds	Loans Non-interest Income	DEA 2-Stage Regression	Intermediation
Vujcic Jemric	1995-2000	Fixed Assets Number of Employees Deposits	Loans Short Term Securities	DEA	Operating Intermediation
Çolak Altan	1999-2000	Various Ratios	Various Ratios	DEA	Production
Sufian	2001-2004	Deposits Labor Fixed Assets	Loans Total Income	DEA	Intermediation
Andries	2004-2008	Deposits Fixed Assets Operational Expenses	Loans Total Investments Other Incomes	SFA DEA	Intermediation
Singh Singh Munisamy	2006	Deposits Assets	Loans Interest Income	DEA	Intermediation

3. METHODOLOGY

3.1. DEA Technique

In a simple production technology, there exist two main variables, namely inputs and outputs. On this basis, a multi-input and multi-output production technology involving N number of inputs and M number of outputs could be defined as follows:

(3.1.1) $$T = \left\{ (x, y) \in R_{+}^{M+N} : x \text{ can produce } y \right\}$$

where $x = (x_1, ..., x_N) \in R_{+}^{N}$ represents vector of inputs and $y = (y_1, ..., y_M) \in R_{+}^{M}$ represents the vector of outputs. Intuitively, production set T consists of all combinations of inputs and outputs such that x can produce y.

Production technology could equivalently be represented by output set (also known as production possibility set) which is defined as:

(3.1.2) $$P(x) = \left\{ y \in R_{+}^{M} : (x, y) \in T \right\}$$

Given the notation presented above, we now move onto the definition of output distance function which is very useful tool in describing the technology in such a way that it enables us to measure efficiency and productivity in a reliable manner. Distance function is simply based on radial contractions and expansions. Malmquist (1953) and Shephard (1953) introduced this notion, independently in their own studies. The advantage of using distance functions is that it allows defining multi input and multi output production technology without the need to specify a behavioral objective such as cost minimization or profit maximization (Coelli et al., 2005). A researcher could either use input or output distance functions depending on the objective of the analysis. Particularly, input distance function concentrates on the idea of minimal proportional contraction of the input vector, given the output vector whereas output distance function concentrates on the idea of maximal proportional expansion of the output vector, given the input vector. In this paper, since banks are regarded as decision making units trying to maximize their profits (i.e. outputs) given the funds available (i.e. inputs), it would be more appropriate to use output oriented DEA. Hence, given the input vector, one can define the output distance function as follows:

(3.1.3) $$D_O(x, y) = \min \left\{ \mu : (y/\mu) \in P(x) \right\}$$

where $0 \le D_O(x, y) \le 1$.[2] Choice of orientation to calculate the efficiency is not the end of the story. Since it is possible to have firms that are efficient both technically and allocatively but that are not operating at an optimal scale, one should also be careful in choosing the appropriate returns to scale technology that will be applied in the analysis.

Efficiency could either be estimated assuming constant returns to scale (CRS), variable returns to scale (VRS) or non increasing returns to scale (NIRS) technology[3]. However, the CRS assumption holds when all banks are operating at an optimal scale, but this becomes very unrealistic when imperfect competition, government regulations, constraints on finance etc. are considered. Moreover, assuming CRS, when not all banks are operating at an optimal scale would result in technical efficiency measures confounded by scale efficiencies (Coelli et al., 2005). Hence, in such cases, it would be more appropriate to assume VRS yielding technical efficiency estimates that are free of scale efficiency effects.

Another advantage of VRS specification over the CRS is that this approach forms a convex hull of intersecting planes that envelope the data points more closely than the CRS and NIRS conical hull. Moreover, the more developed banking system is, the more likely it is that the banks face non-constant returns to scale (McAllister and McManus, 1993 and Wheelock and Wilson, 1995).In terms of banking, some papers use CRS approach with the motivation of being more conservative in the measurement of bank efficiency scores, because efficiency scores obtained under CRS assumption would certainly be smaller than scores obtained under VRS assumption. However, when we estimate efficiency scores under two approaches we observe that the scores are very close to each other. Therefore, for the reasons explained above, in this paper we assume VRS for the Turkish banking sector[4].

Based on the notation explained so far and the discussion above, the DEA model that is used in this paper could be formulated as follows:

Assume that there exist $k = 1,...K$ observations in the sample. Hence, given our data set, for VRS specification, an output set that holds for every period and for all observations can be constructed in the following way:

[2] Efficiency scores could either be estimated by using Shephard or Farrell distance functions. Since Farrell distance functions are nothing more than the inverse of Shephard distance functions, a researcher could use any one of them. In this study, efficiency scores are calculated in terms of Shephard distance functions.
[3] For graphical representation and detailed discussion of the issue see Diler (2009).
[4] Large number of papers aiming to measure bank efficiency in the literature adopts VRS assumption. For the detailed discussion of the issue, see McAllister and McManus (1993), Wheelock and Wilson, (1995), Sufian (2009), Molyneux and Casu (2000).

$$(3.1.4) \qquad P(x) = \left\{ y \in R_+^M : \sum_{k=1}^{K} z_k y_{km} \geq y_m \right.^{5} \qquad m = 1,...M$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq x_n \qquad n = 1,...N$$

$$z_k \geq 0 \qquad k = 1,...K$$

$$\left. \sum_{k=1}^{K} z_k = 1 \right\}^{6}$$

where z_k 's stand for the intensity variables (weights) assigned to each observation while constructing the production set. Thus, given the production set and constraints specified above, the fractional programming problem that should be solved by DEA (i.e. **output oriented VRS DEA model**) for each k, would be as follows:

$$(3.1.5) \qquad D_O(x, y) = \min_{\mu,z} \left\{ \mu : \sum_{k=1}^{K} z_k y_{km} \geq y_m / \mu \right. \qquad m = 1,...M$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq x_n \qquad n = 1,...N$$

$$z_k \geq 0 \qquad k = 1,...K$$

$$\left. \sum_{k=1}^{K} z_k = 1 \right\}$$

[5] It is the direct consequence of strong disposability of outputs. For a detailed discussion see Fare and Grosskopf (1998-2000).

[6] Convexity constraint that imposes the VRS assumption . It ensures that an inefficient firm is only benchmarked against firms of a similar size. That's, the projected point for that firm on the DEA frontier is a convex combination of observed firms.

However, the software used in the analysis is designed to solve only linear programming problems. So, the algorithm transforms the fractional programming problem in (3.1.5) to the linear programming problem as follows[7]:

(3.1.6)[8]

$$\theta_k^* = (D_O(x,y))^{-1} = \max_{\theta,z}\left\{ \theta : \sum_{k=1}^{K} z_k y_{km} \geq \theta y_m \qquad m = 1,\ldots M \right.$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq x_n \qquad n = 1,\ldots N$$

$$z_k \geq 0 \qquad k = 1,\ldots K$$

$$\left. \sum_{k=1}^{K} z_k = 1 \right\}$$

By taking the inverse of efficiency score obtained from (3.1.6.), the algorithm returns the output oriented Shephard distance function, namely $D_o(x,y)$ which lies between zero and one, for each bank.

[7] The fractional programming problem in (3.1.5) and the linear programming problem in (3.1.6) are trivially identical. However, (3.1.5) is transformed into (3.1.6) through $\theta = 1/\mu$, to make it linear.

[8] The linear programming model discussed here is originally developed by Charnes, Cooper and Rhodes (1978, 1979) and is known as CCR model. This model measures the efficiency under CRS assumption. Based on this study, Banker et al. (1984) extended the CCR model by relaxing the CRS assumption. The resulting "BCC" model uses VRS assumption. In this paper, we assume VRS in the linear programming problem to be solved for each bank to obtain efficiency scores. For the transition of linear programming problem from the CCR model to the linear programming model based on Shephard distance function see Banker, Charnes and Cooper (1984).

3.2. Bootstrapping

More recently, in their 1998 and 2000 papers, for multi-input and multi-output model, Simar and Wilson suggested the use of bootstrapping technique which was originally developed by Efron (1979) in order to be able to assess statistical properties of non-parametric efficiency estimates derived from some unobservable data generating process, to remove inherent dependency among efficiency scores and eventually to obtain bias corrected DEA efficiency scores.

To begin with, suppose a data generating process (DGP), φ generating a random sample of:

(3.2.1.) $$S = \{ (x_k, y_k) : k = 1,...K \}$$

By some method *M*, this sample defines estimators of T and $P(x)$ discussed in the previous section, namely $\hat{T}$ and $\hat{P(x)}$. Given those, for k*th* observation, the output oriented technical efficiency score at point (x_k, y_k) can be calculated as follows:

(3.2.2) $$\hat{\theta}_k = \max\{\theta : \theta y \in \hat{P(x)} \}$$

which is the estimator of the true but unobserved population efficiency score θ_k. The problem is that sampling distributions of $\hat{T}$ and $\hat{P(x)}$ could not be inferred because φ is unknown and the complexity of *M* makes it almost impossible to determine it. However, bootstrapping technique which is based on the idea that there exists a consistent estimator of , φ namely $\hat{\varphi}$, enables us to obtain consistent estimators of T and $P(x)$, even though φ is unknown.

Now, suppose that, given the sample S, by using our knowledge, we can produce a consistent estimator of φ namely, $\hat{\varphi}$. Then, consider another sample S^* which is generated by $\hat{\varphi}$ through random resamplings with replacement from S. Formally,

(3.2.3) $$S^* = \{ (x_k^*, y_k^*) : k = 1,...K \}$$

Similar to S, by some method *M*, this pseudo sample also defines corresponding estimators of T and P(x) that are $\hat{T}^*$ and $\hat{P(x)}^*$ respectively. Thus, for any pair of (x_k^*, y_k^*), the corresponding output oriented technical efficiency score is given by:

(3.2.4) $$\hat{\theta}_k^* = \max\left\{\theta : \theta y \in \hat{P}(x)^* \right\}$$

Expression (3.2.4) could equivalently be defined as a linear programming problem:

(3.2.5) $$\hat{\theta}_k^* = \max_{\theta,z} \left\{ \theta : \sum_{k=1}^{K} z_k y_{km}^* \geq \theta y_m \qquad m = 1,...M \right.$$

$$\sum_{k=1}^{K} z_k x_{kn}^* \leq x_n \qquad n = 1,...N$$

$$z_k \geq 0 \qquad k = 1,...K$$

$$\left. \sum_{k=1}^{K} z_k = 1 \right\}$$

In this case, however, since the underlying DGP, $\hat{\varphi}$ is already known, the sampling distributions of the estimators $\hat{T}^*$ and $\hat{P}(x)^*$ are completely known, although it may be difficult to estimate analytically. Nevertheless, the sampling distributions could easily be approximated by Monte Carlo methods. The steps of the approximation can be summarized as follows:

1. Use $\hat{\varphi}$ to generate B number of pseudo samples such that S_b^*, where $b = 1,...B$.
2. Apply M to each of those samples and obtain the estimators $\hat{\mathrm{T}}_{b*}$ and $\hat{\mathrm{P}(\mathrm{x})}_{b*}$ for b = 1,…,B.
3. Obtain $\hat{\theta}_{kb}^*$ for each k, where $k = 1,...K$ and $b = 1,...B$.

This procedure allows us to estimate the empirical density function of $\{\hat{\theta}_{kb}^*\}_{b=1}^{B}$ which is nothing more than the Monte Carlo approximation of the distribution of $\hat{\theta}_{kb}^*$ conditional on $\hat{\varphi}$. Intuitively, by repeatedly simulating or mimicking the DGP through resampling with replacement and through applying the original estimator to each simulated sample, we could approximate the sampling distributions of the original estimator.

Given the assumption[9] that $\hat{\varphi}$ is a consistent estimator of φ, the bootstrap method concludes that the known bootstrap distributions obtained by the procedure described above

[9] See Hall (1992).

will mimic the original unknown sampling distributions of the estimators of interest (Simar and Wilson, 1998)[10]. More formally,

(3.2.6) $$\left(\hat{\theta}_k^* - \hat{\theta}_k\right) \mid \hat{\varphi} \;\sim\; \left(\hat{\theta}_k - \theta_k\right) \mid \varphi$$

That's to say, *within the true world*, $\hat{\theta}_k$ is an estimator of θ_k based on the sample S, generated from some DGP, φ whereas, *in the bootstrap world*, $\hat{\theta}_k^*$ is an estimator of $\hat{\theta}_k$ based on the sample S^* generated from $\hat{\varphi}$. On this basis, we can estimate:

(3.2.7) $$bias_{\varphi,k} = E_{\varphi}\left(\hat{\theta}_k\right) - \theta_k$$

by using its bootstrap estimate given by:

(3.2.8) $$bias_{\hat{\varphi},k} = E_{\hat{\varphi}}\left(\hat{\theta}_k^*\right) - \hat{\theta}_k$$

which could be approximated by Monte Carlo realizations $\hat{\theta}_{kb}^*$:

(3.2.9) $$bi\hat{a}s_k = \frac{1}{B}\sum_{b=1}^{B}\hat{\theta}_{kb}^* - \hat{\theta}_k = \bar{\theta}_k^* - \hat{\theta}_k \qquad \text{for } b = 1,...B$$

Thus, bias corrected estimator of $\hat{\theta}_k$ is given by:

(3.2.10) $$\tilde{\theta}_k = \hat{\theta}_k - bi\hat{a}s_k = 2\hat{\theta}_k - \bar{\theta}_k^*$$

The standard error of $\hat{\theta}_k$ can be estimated by:

(3.2.11) $$s\hat{e} = \left\{ \frac{1}{B-1}\sum_{b=1}^{B}\left(\hat{\theta}_{kb}^* - \bar{\theta}_k^*\right)^2 \right\}^{1/2}$$

The confidence interval for θ_k for some values a_α and b_α given by:

(3.2.12) $$Prob\left\{-b_\alpha \le \left(\hat{\theta}_k - \theta_k\right) \le -a_\alpha \right\} = 1-\alpha$$

can easily be calculated by using its bootstrap estimate for some bootstrap values a_α^* and b_α^* ,which is given by:

[10] For more detailed discussion and derivations, see Simar and Wilson (1998, 2000).

$$\text{(3.2.13)} \qquad Prob\left\{-b_\alpha^* \le \left(\hat{\theta}_{kb}^* - \hat{\theta}_k\right) \le -a_\alpha^* \;\middle|\; S^* \right\} = 1-\alpha \qquad \text{for } b = 1,\ldots B$$

substituting a_α^* and b_α^*, for a_α and b_α in (3.2.12), combined with (3.2.13) leads to the bootstrap approximation:

$$\text{(3.2.14)} \qquad Prob\left\{-b_\alpha^* \le \left(\hat{\theta}_k - \theta_k\right) \le -a_\alpha^* \;\middle|\; S^* \right\} \approx 1-\alpha$$

Therefore,

$$\text{(3.2.15)} \qquad \hat{\theta}_k + a_\alpha^* \le \theta_k \le \hat{\theta}_k + b_\alpha^*$$

3.3. Malmquist Productivity Index

Malmquist Productivity Index (MPI) is the total factor productivity index that measures the change in total productivity of the factors between the two time periods by calculating the ratio between the distance from each point observed in the respective technology. There exists input and output oriented MPI introduced by Caves et al. (1982) which are composed of Shephard (1970) input and output distance functions discussed in the previous section[11]. Following Fare et al. (1994b), output oriented MPI used in this study based on output distance functions is defined as[12]:

$$\text{(3.3.1)} \qquad M_O\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \left[\frac{D_{O,CRS}^t\left(x^{t+1}, y^{t+1}\right)}{D_{O,CRS}^t\left(x^t, y^t\right)} \times \frac{D_{O,CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{O,CRS}^{t+1}\left(x^t, y^t\right)}\right]^{1/2}$$

A value of M_o greater than 1 indicates improvement in productivity whereas a value less than 1 indicates deterioration from time t to t+1. We must note that equation (3.3.1) is actually geometric mean of two indices. The first one is evaluated in relation to the technology of time t, and the second one relative to the technology of period t+1. Therefore,

[11] In this section to conserve space, output oriented MPI is discussed. Input oriented MPI involves a straightforward translation of the notation explained in this section.

[12] $D_0^{t+1}(x^t, y^t)$, for example, measures the distance of bank at time t relative to the frontier at time t+1. Thus, the superscript on the distance function denotes the reference technology whereas superscripts on inputs and outputs denote the time period under consideration.

MPI can be decomposed into two different components, namely efficiency change (MEFFCH) and technical change (MTECH) defined as follows[13]:

(3.3.2) $$MEFFCH_t^{t+1} = \frac{D_{O,CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{O,CRS}^{t}\left(x^{t}, y^{t}\right)}$$

(3.3.3) $$MTECH_t^{t+1} = \left[\frac{D_{O,CRS}^{t}\left(x^{t+1}, y^{t+1}\right)}{D_{0,CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D_{O,CRS}^{t}\left(x^{t}, y^{t}\right)}{D_{O,CRS}^{t+1}\left(x^{t}, y^{t}\right)} \right]^{1/2}$$

Equation (3.3.1) combined with (3.3.2) and (3.3.3), together imply that:

(3.3.4) $$M_t^{t+1} = MEFFCH_t^{t+1} \times MTECH_t^{t+1}$$

The first component measures the change in technical efficiency between time t and t+1, and hence whether the production is getting closer to the best practice frontier for all observations in the sample (Taskin and Zaim, 1997). The second component shows the shift in frontier between time t and t+1. Overall, index values greater than one indicates improvement in productivity whereas values less than one indicates deterioration in productivity.

However, Fare et al. (1994) further decomposed (3.3.4) as pure efficiency change and scale efficiency change defined by:

(3.3.5) $$PUREEFFCH_t^{t+1} = \frac{D_{O,VRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{O,VRS}^{t}\left(x^{t}, y^{t}\right)}$$

(3.3.6) $$SCALEEFFCH_t^{t+1} = \frac{D_{O,CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right) / D_{O,VRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{0,CRS}^{t}\left(x^{t}, y^{t}\right) / D_{O,VRS}^{t}\left(x^{t}, y^{t}\right)}$$

Hence, (3.3.5) and (3.3.6) combined with (3.3.4) implies that,

(3.3.7) $$M_t^{t+1} = PUREEFFCH_t^{t+1} \times SCALEEFFCH_t^{t+1} \times MTECH_t^{t+1}$$

The advantage of using MPI is that unlike alternative indices, it does not require any information on prices of inputs or outputs. The estimation of MPI requires the estimation of

[13] For graphical representation and derivation of MPI components, see Diler (2009).

four different output distance functions explained in the previous section. However, similar to DEA estimators, MPI is also obtained by non parametric DGP based on the estimation of true but unobserved best practice frontier and this introduces dependency and bias to MPI, as well. Hence, to remove this bias, based on their 1998 paper, Simar and Wilson (1999) suggested applying bootstrapping technique to MPI. The procedure is similar to the one explained for DEA estimators[14]. In this context, bootstrapping technique provides confidence intervals for MPI that enable us to assess whether productivity changes as measured by the MPI are significant in a statistical sense. If it is significant, then the results imply a real change in productivity, otherwise it should be considered as nothing more than a trick of sampling noise. Therefore, in this paper bootstrapped, namely bias corrected, MPI obtained through 2000 random resamplings is used to evaluate bank productivity.

4. DATA

The data used in this study are taken from The Bank Association of Turkey, which is a rich source for balance sheet and profit & loss account data for individual banks. The data is on 22 Turkish commercial deposit banks[15] for the years 2003-2010.

Given the data set, banks are divided into five groups as public banks, private 1 banks, private 2 banks, private 3 banks and private 4 banks, according to their scale and size, placing the largest private banks into private 1 group and smallest banks into private 4 group[16].

The coverage of data is quite good. In terms of bank loans and deposits, the coverage of the total commercial banking system by our sample is about 90,8% for loans and 94,4% for deposits. In terms of number of commercial banks, the coverage by our sample is 68,8%.

Table-2 below summarizes the data used in this study. According to the data, during 2003-2010 period, Turkish banking sector experienced extreme loan growth (728,3%). Public banks and small scale private banks (private 4), were the banks that had the largest loan growth among other groups.

[14] For theory and methodology of estimating and bootstrapping MPI, see Simar and Wilson (1999).

[15] In DEA analysis, working with a sample including similar decision making units in terms of scale, size and ownership is essential for the sake of the analysis. Since incentives for managers to efficiently allocate resources might differ under different ownership arrangements, this study eliminates 8 foreign owned deposit banks in total of 32 commercial deposit banks. Also, one bank transferred to SDIF (Saving Deposit Insurance Fund) and one bank which should be considered as an outlier in terms of its inputs and outputs are eliminated from the analysis to obtain a homogeneous sample. Hence, we are left with 22 commercial banks.

[16] Banking groups could be seen in Table 3 in the next section.

Moreover, net profit and total assets of the banking sector[17] increased sharply during this period. Also, it is important to note that although private 4 banks were the banks that had extreme loan growth, their net profit growth was the smallest among the others. During this period, however, non performing loans increased by 157,6%. This indicates that in overall, while experiencing growth, Turkish banking sector had also incurred risks, but growth of nonperforming loans were relatively moderate when compared to the loan, asset and net profit growth rates. Also, we observe conservative growth rates in noninterest expenses and securities during 2003-2010.

In 2003-2004 and 2007-2008 periods we observe decrease in net profits of the banking sector. Following the crisis, in 2009-2010 net interest income and noninterest expenses also decreased. Also, it is important to note that soon after the 2007 crisis, total equity of the banking sector increased by 28,9% from 2007 to 2008. The idea was that increased equity could serve as a buffer against crisis.

[17] In this study, banking sector corresponds to 22 commercial banks. Therefore, total amounts regarding the banking sector were the totals of those 22 commercial banks that cover more than 90% of the total banking sector in terms of loans and deposits.

Table 2: Summary Statistics for 22 Commercial Banks (2003-2010)

(Million TL)	2003	2004	2005	2006	2007	2008	2009	2010	Growth (%) (2003-2010)
NON PERFORMING LOANS									
PUBLIC	3.531	1.601	1.516	1.405	1.424	1.856	2.523	2.613	-26,0
PRIVATE 1	3.055	3.264	4.151	5.110	6.230	7.743	11.490	9.753	219,2
PRIVATE 2	344	489	712	886	1.428	2.445	4.810	4.746	1.279,9
PRIVATE 3	188	194	361	406	387	723	1.176	1.118	494,6
PRIVATE 4	28	27	27	28	51	106	211	181	547,4
TOTAL	**7.146**	**5.575**	**6.767**	**7.835**	**9.519**	**12.872**	**20.210**	**18.410**	**157,6**
SECURITIES									
PUBLIC	40.813	53.225	54.164	58.839	59.188	73.920	88.724	92.678	127,1
PRIVATE 1	47.412	52.636	68.952	83.330	84.560	95.912	143.475	157.709	232,6
PRIVATE 2	6.968	7.115	8.721	9.186	12.581	14.213	17.284	22.512	223,1
PRIVATE 3	2.457	2.489	2.595	3.254	2.456	4.162	5.014	5.046	105,4
PRIVATE 4	399	388	439	479	1.717	2.145	2.128	2.086	422,8
TOTAL	**98.049**	**115.853**	**134.872**	**155.089**	**160.502**	**190.352**	**256.626**	**280.030**	**185,6**
DEPOSITS									
PUBLIC	47.353	64.397	72.094	84.961	96.644	120.569	139.265	173.965	267,4
PRIVATE 1	76.245	90.284	125.625	159.549	182.850	236.645	264.663	312.199	309,5
PRIVATE 2	16.297	22.101	27.648	39.152	47.366	57.358	62.723	74.608	357,8
PRIVATE 3	5.315	6.037	6.926	10.156	11.816	15.650	16.124	18.180	242,0
PRIVATE 4	785	772	996	1.407	1.835	2.808	3.201	3.435	337,3
TOTAL	**145.995**	**183.591**	**233.290**	**295.225**	**340.512**	**433.030**	**485.976**	**582.386**	**298,9**
NET PROFIT									
PUBLIC	1.558	2.058	2.334	2.964	3.482	3.153	5.142	5.723	267,2
PRIVATE 1	2.443	2.672	641	5.055	7.752	6.760	10.667	12.201	399,4
PRIVATE 2	628	679	1.256	1.584	1.544	1.339	1.936	2.049	226,2
PRIVATE 3	132	160	221	205	467	378	423	422	218,6
PRIVATE 4	22	17	18	20	23	26	50	45	98,9
TOTAL	**4.785**	**5.585**	**4.471**	**9.827**	**13.268**	**11.656**	**18.219**	**20.440**	**327,2**
NET INTEREST INCOME									
PUBLIC	4.854	4.974	3.783	4.771	5.342	5.953	8.562	7.957	63,9
PRIVATE 1	3.142	7.843	9.230	10.307	12.544	14.317	20.724	19.252	512,7
PRIVATE 2	1.399	2.221	2.919	3.399	4.454	5.836	7.338	6.794	385,5
PRIVATE 3	227	586	706	808	1.219	1.527	1.609	1.325	483,1
PRIVATE 4	94	78	76	77	124	196	235	211	124,0
TOTAL	**9.717**	**15.703**	**16.714**	**19.363**	**23.684**	**27.829**	**38.468**	**35.539**	**265,7**
NON INTEREST EXPENSES									
PUBLIC	3.917	3.362	2.375	3.034	3.192	4.468	4.588	4.727	20,7
PRIVATE 1	8.101	9.776	13.308	12.027	14.575	18.261	20.565	19.030	134,9
PRIVATE 2	2.278	3.113	3.276	4.275	5.585	8.315	9.406	8.956	293,2
PRIVATE 3	699	841	999	1.271	1.570	1.968	1.947	1.747	149,9
PRIVATE 4	113	121	114	140	157	290	322	393	248,3
TOTAL	**15.108**	**17.212**	**20.072**	**20.746**	**25.080**	**33.302**	**36.827**	**34.852**	**130,7**
LOANS									
PUBLIC	7.386	12.864	19.523	28.289	38.689	54.954	67.191	99.564	1.248,1
PRIVATE 1	36.035	53.259	82.215	122.384	156.222	203.801	205.190	273.729	659,6
PRIVATE 2	11.221	19.150	28.596	41.722	53.780	63.748	65.670	83.225	641,7
PRIVATE 3	2.657	4.124	5.241	8.017	11.055	12.265	13.508	17.372	553,9
PRIVATE 4	322	486	725	1.079	1.530	2.025	2.499	3.376	949,5
TOTAL	**57.620**	**89.883**	**136.301**	**201.491**	**261.276**	**336.793**	**354.057**	**477.266**	**728,3**
ASSETS									
PUBLIC	66.016	82.704	92.103	107.241	121.389	155.734	185.594	224.448	240,0
PRIVATE 1	120.988	148.518	208.814	268.804	309.205	388.536	444.230	528.425	336,8
PRIVATE 2	26.644	37.466	50.138	68.467	83.610	103.756	106.324	132.181	396,1
PRIVATE 3	7.733	9.516	11.165	17.646	18.922	23.631	23.564	29.052	275,7
PRIVATE 4	1.490	1.720	2.031	2.664	4.490	6.124	6.994	7.832	425,6
TOTAL	**222.872**	**279.924**	**364.251**	**464.822**	**537.615**	**677.782**	**766.706**	**921.938**	**313,7**
EQUITY									
PUBLIC	8.401	8.056	8.993	10.359	11.601	11.650	16.114	20.903	148,8
PRIVATE 1	17.792	23.688	25.869	28.977	38.218	42.651	56.648	69.930	293,0
PRIVATE 2	3.903	5.013	6.137	7.310	9.934	11.982	14.312	16.872	332,3
PRIVATE 3	798	1.084	1.339	1.746	2.539	3.106	3.635	4.050	407,6
PRIVATE 4	252	301	316	372	565	883	1.091	1.129	347,8
TOTAL	**31.146**	**38.142**	**42.654**	**48.764**	**62.857**	**70.271**	**91.801**	**112.883**	**262,4**

As discussed in the previous section, in the literature, there is no consensus regarding inputs and outputs that should be used in the efficiency analysis of banks. For the reasons explained previously, this study adopts *mixed approach* and uses 8 ratios (5 inputs and 3 outputs) to measure bank efficiency[18]. The inputs used for each bank are:

- ✓ Securities / Total Assets
- ✓ Deposits / Total Assets
- ✓ Non Performing Loans (Gross) / Total (Cash) Loans[19]
- ✓ Total Loans / Total Assets[20]
- ✓ Non Interest Expense / Total (Average) Assets

The outputs used are:

- ✓ Return on Average Assets (ROA): Net Profit (Loss) / Total (Average) Assets
- ✓ Return on Average Equity (ROE): Net Profit (Loss) / Total (Average) Equity
- ✓ Net Interest Income / Total Income

To further investigate the determinants of bank efficiency we follow the so called Two-Step approach, as suggested by Coelli et al. (1998). Using the efficiency measures derived from the DEA as the dependent variable, we then estimate the following fixed effect regression model:

$$\hat{\theta}_k^* = b0 + b1ROA + b2LNTA + b3LOANSTA + b4NPLTA(-1)$$

$$+ b5CAR + b6DLNRGDP + b7NIM + b8INF + b9LNDEP + ei$$

where:

ROA: Return on average assets

LNTA: Logarithm of total assets

LOANSTA = Total Loans / Total Assets

NPLTA(-1): Non Performing Loans (Gross) / Total (Cash) Loans with one period lag

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18 Similar output and input combinations have been used in studies of Charnes (1990), Çolak and Altan (2002), Cingi and Tarim (2000) and Aras and Kurt (2007).

19 Since this ratio is considered to be bad (undesirable) output i.e. output that is tried to be minimized by banks, it is regarded as an output in this study. See Pasuphaty (2002) for more detailed discussion of the issue.

20 Although in terms of intermediation and production approaches loans are regarded as output of a bank, the ratio of total loans to total assets are regarded as input in this study. The reason is that this ratio is regarded as an indicator of asset management and quality from the view point of the bank management. The concern of the bank management is not the production of loans, but careful placements of loans. So, when a bank extends its credits it would incur more risks and since bank wants to minimize the risk incurred, the ratio is classified as an input.

CAR: Capital adequacy ratio

DLNRGDP: Logarithm difference of real GDP

NIM: Net interest margin i.e. spread between deposit and loan rates

INF: Inflation (% change in CPI, annually)

LNDEP: Logarithm of total deposits

5. EMPIRICAL RESULTS

To obtain empirical results, output oriented DEA model under the assumption of VRS and output oriented MPI is used as formulated in methodology described in section 3. All the computational work is done by software package *Frontier Efficiency Analysis with R (FEAR) 1.11* developed by Wilson (2008)[21]. What distinguishes FEAR from the alternative software packages like DEAP or STATA is that it permits to estimate not only non parametric DEA estimates of technical, allocative, scale and overall efficiency (while assuming either CRS, NIRS or VRS) and MPIs but also it permits to estimate bootstrapped (i.e. bias corrected) efficiency scores which eventually enables us to do statistical inference based on those findings. In the first sub section of this part, bootstrapped efficiency scores of banks are discussed. The second sub section is devoted to the bootstrapped Malmquist index scores of banks. Finally, in the last sub section, results of two-stage regression analysis are discussed.

5.1. DEA Efficiency Scores of Banks

Based on the previously mentioned data, DEA efficiency scores are estimated for each bank, for the period 2003-2010. On this basis, as explained in the data section, banks are grouped into 5 as public, private 1, private 2, private 3 and private 4 banks according to their ownership status and size, with private 4 being the bank group comprised of the smallest scale private banks.

Table 3 below summarizes the results and compares DEA efficiency scores with bootstrapped DEA efficiency scores of banks.

[21] For further discussion on FEAR, see FEAR 1.11 Command Reference or User Guide, Wilson (2008)

Table 3: Comparison of DEA and Bootstrap Efficiency Scores, 2003-2010

Banka Kodu	2003	2003*	2004	2004*	2005	2005*	2006	2006*	2007	2007*	2008	2008*	2009	2009*	2010	2010*
B1	1,000	0,789	1,000	0,697	1,000	0,808	1,000	0,796	1,000	0,903	1,000	0,943	1,000	0,824	1,000	0,763
B2	1,000	0,732	1,000	0,708	0,657	0,587	0,792	0,719	0,871	0,827	0,971	0,946	1,000	0,849	1,000	0,768
PUBLIC	*1,000*	*0,760*	*1,000*	*0,703*	*0,811*	*0,689*	*0,890*	*0,757*	*0,933*	*0,864*	*0,986*	*0,944*	*1,000*	*0,837*	*1,000*	*0,765*
B3	0,725	0,632	1,000	0,799	0,833	0,756	1,000	0,907	1,000	0,904	1,000	0,940	0,975	0,909	0,840	0,762
B4	1,000	0,644	1,000	0,707	1,000	0,806	1,000	0,858	1,000	0,930	1,000	0,939	1,000	0,912	1,000	0,772
B5	1,000	0,646	0,744	0,676	0,853	0,791	0,860	0,791	1,000	0,899	1,000	0,942	1,000	0,894	1,000	0,839
B6	0,478	0,414	0,739	0,672	0,898	0,817	0,834	0,776	0,744	0,704	0,790	0,769	0,859	0,806	0,876	0,808
B7	0,280	0,238	0,443	0,405	0,677	0,639	0,759	0,699	0,686	0,661	0,953	0,926	0,870	0,820	1,000	0,886
PRIVATE 1	*0,627*	*0,482*	*0,754*	*0,636*	*0,845*	*0,759*	*0,885*	*0,803*	*0,874*	*0,812*	*0,945*	*0,900*	*0,939*	*0,867*	*0,940*	*0,812*
B8	1,000	0,631	1,000	0,711	0,955	0,858	1,000	0,839	0,894	0,850	1,000	0,941	0,770	0,715	0,907	0,821
B9	1,000	0,636	0,662	0,587	0,809	0,749	0,952	0,880	0,900	0,865	0,901	0,876	0,685	0,642	0,765	0,717
B10	0,847	0,711	1,000	0,752	1,000	0,811	0,974	0,894	0,899	0,854	0,745	0,724	1,000	0,823	1,000	0,852
B11	0,901	0,764	1,000	0,748	1,000	0,797	1,000	0,803	1,000	0,928	0,901	0,878	0,876	0,817	1,000	0,893
B12	1,000	0,650	1,000	0,706	1,000	0,803	1,000	0,797	1,000	0,900	1,000	0,939	1,000	0,904	1,000	0,908
B13	0,775	0,666	0,901	0,803	0,938	0,841	0,998	0,909	0,862	0,826	1,000	0,940	1,000	0,819	1,000	0,852
PRIVATE 2	*0,916*	*0,675*	*0,917*	*0,714*	*0,948*	*0,809*	*0,987*	*0,853*	*0,924*	*0,870*	*0,920*	*0,879*	*0,879*	*0,782*	*0,941*	*0,838*
B14	1,000	0,745	1,000	0,862	0,950	0,877	0,747	0,692	0,904	0,869	0,964	0,940	0,884	0,832	0,804	0,747
B15	1,000	0,836	0,787	0,717	1,000	0,805	1,000	0,828	1,000	0,897	1,000	0,957	0,800	0,748	1,000	0,767
B16	1,000	0,637	1,000	0,700	0,757	0,684	1,000	0,812	1,000	0,901	1,000	0,939	1,000	0,898	0,913	0,836
B17	0,549	0,486	0,374	0,335	0,782	0,709	1,000	0,795	1,000	0,899	1,000	0,940	1,000	0,920	0,691	0,631
B18	1,000	0,619	1,000	0,703	0,749	0,669	0,840	0,763	1,000	0,896	1,000	0,940	1,000	0,822	1,000	0,748
PRIVATE 3	*0,887*	*0,654*	*0,783*	*0,633*	*0,841*	*0,745*	*0,911*	*0,776*	*0,980*	*0,892*	*0,993*	*0,943*	*0,933*	*0,842*	*0,873*	*0,743*
B19	1,000	0,628	1,000	0,714	1,000	0,812	1,000	0,803	1,000	0,897	1,000	0,941	1,000	0,820	1,000	0,759
B20	1,000	0,652	1,000	0,701	1,000	0,800	1,000	0,801	1,000	0,901	1,000	0,941	1,000	0,816	1,000	0,759
B21	0,767	0,662	0,714	0,640	0,747	0,691	0,422	0,394	0,840	0,814	1,000	0,940	0,907	0,847	0,616	0,577
B22	0,700	0,601	0,731	0,658	0,633	0,582	0,702	0,648	1,000	0,900	1,000	0,940	0,401	0,371	0,347	0,315
PRIVATE 4	*0,856*	*0,635*	*0,850*	*0,678*	*0,829*	*0,715*	*0,738*	*0,636*	*0,957*	*0,877*	*1,000*	*0,941*	*0,776*	*0,677*	*0,680*	*0,569*
BANKING SECTOR	**0,831**	**0,620**	**0,841**	**0,669**	**0,865**	**0,754**	**0,888**	**0,772**	**0,932**	**0,862**	**0,962**	**0,915**	**0,895**	**0,798**	**0,877**	**0,748**

(*) Bootstrapped DEA efficicency scores.

The banks with an efficiency score of 1,000 are regarded as efficient banks whereas banks with efficiency scores below 1 are regarded as inefficient by an amount below 1. The group efficiency scores equals to geometric means of efficiency scores of banks within that group.

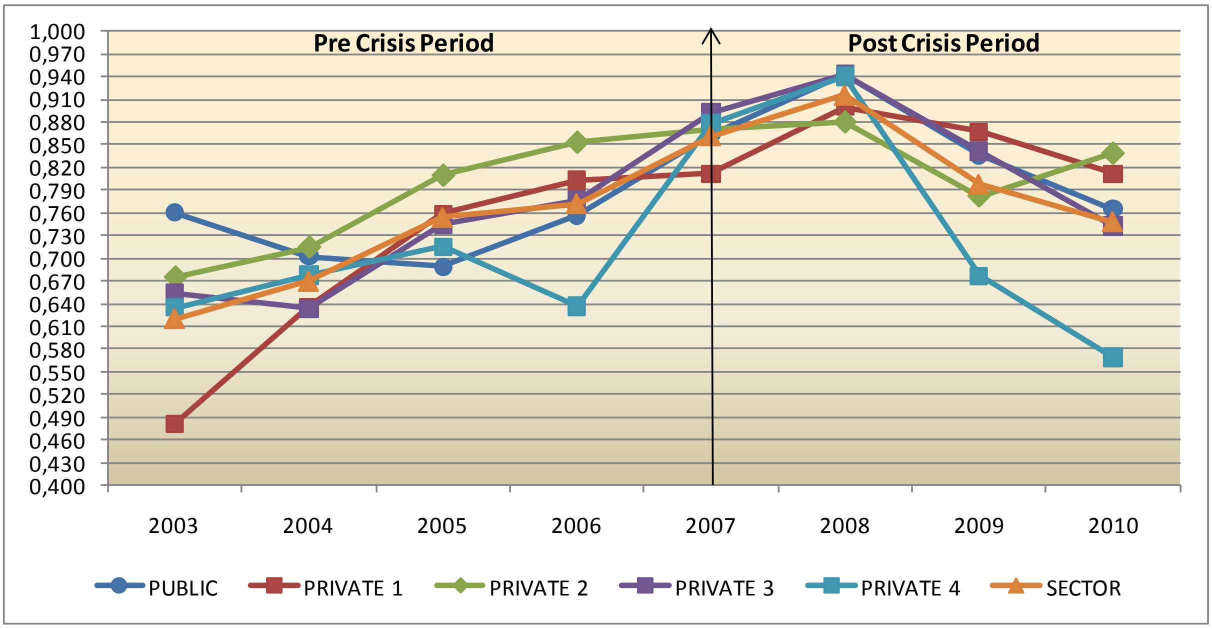
Comparison of DEA efficiency scores with bootstrapped efficiency scores show that banks which are indicated as inefficient by the ordinary DEA procedure are actually more inefficient than it is thought to be due to the bias inherent in ordinary DEA scores. So, DEA efficiency scores tend to overestimate the actual efficiency of banks.

During the period under study, bootstrapped efficiency scores vary between 0,5 and 0,9 for the bank groups and 0,6 and 0,9 for the banking sector. The following Figure-1 together with the Table-3 above allows us to follow the trend in bank groups during 2003-2010.

As it is seen from the Figure-1, in terms of the evaluation of DEA scores, performance of Turkish banks could be studied by dividing the time period under consideration into two: 2003-2008 period (upward trend) and 2008-2010 period (downward trend).

In the 2003-2008 period, Turkish banking sector efficiency score has improved from 0,62 to 0,92, but decreased to 0,75 thereafter.

Figure 1: Evaluation of Bootstrapped Bank Efficiency Scores, 2003-2010



It is observed that during 2003-2008, efficiency scores of bank groups had increased gradually and uninterruptedly, except public and private 4 banks[22]. In contrast to the other banking groups, public banks had suffered during 2003-2005 period, but caught the increasing trend thereafter. As it could be seen in the figure above, another exception to the general upward trend is the decline in efficiency scores of private 4 banks from 2005 to 2006. Moreover, in contrast to the other bank groups, it is the only bank that experienced sharp decline in efficiency score in this period.

After the year 2008, however, all bank groups experienced declines in their efficiency scores. The main reason of the decline during 2008-2010 period is the global financial crisis which was initiated by the USA economy in September 2007 and which extended through the most of European economies thereafter. According to the results, impacts of global financial crisis began to be experienced by the Turkish banking sector 2008 onwards. The sharpest decline was observed in private 4 banks (0,3 units). Other sharp declines were experienced by public and private 3 banks, respectively. It is known that in crisis periods, depending on the reduced GDP growth which is accompanied by lower household incomes, the probability of credits to default increases. So, by increasing loans especially in those periods, banks would obviously incur more risks than normal times. So, keeping pre-crisis loan growth rates in

[22] Also, private 3 banks encountered decline in their efficiency scores from 2003 to 2004, however the decline is ignorable.

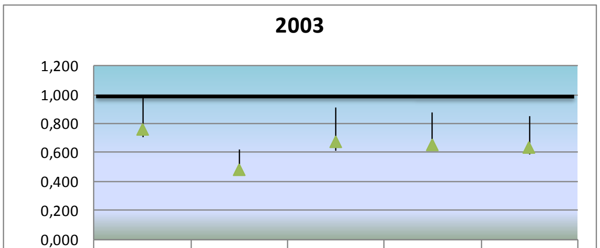
crisis periods would be riskier for banks and decrease efficiency. Our finding is supported by the fact that from 2008 to 2009, the largest loan growth rates are observed in private 4 (23,4%), public (22,3%) and private 3 banks (10,1%), meanwhile, according to the Figure-1, the banks that suffer most in terms of efficiency are private 4, public and private 3 banks, respectively. Also it is important to note that not only largest loan growth rates but also the largest rates in nonperforming loans are also observed by private 4 banks (99%) in this period. On the contrary, private 1 and private 2 banks decreased both their loan growth rates and loan shares in the market in crisis period, so they experienced relatively smoother and milder decline in their efficiency scores.

Private 2 banks is an exception to 2008-2010 period. In contrast to other bank groups, private 2 banks improved their efficiency from 2009 to 2010. The reason of this performance could be attributed to the relatively conservative approach of private 2 banks. That's to say, while other bank groups, especially private 4 banks, continue to grow in the market by increasing their deposits and loans further, private 2 banks seems to decrease their deposit and loan growth rates. Those decreases in deposit and loan growth rates were accompanied by sharp decline in NPLRs which finally brought improvement in efficiency scores. So, it could be concluded that, in the crisis environment, decreased deposit and loan growth rates could serve as a buffer against crisis.

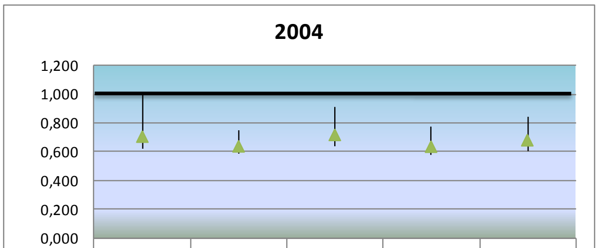
An advantage of bootstrapping is that, as mentioned earlier, it predicts the efficiency scores within a given confidence interval which enables us to do statistical inferences. More specifically, bootstrapping allows assessing whether the efficiency scores obtained are statistically significant. If it is significant, then the results explained above show real efficiency level of the banks, otherwise it should be considered as nothing more than a trick of sampling noise. Hence, if the efficiency score obtained by DEA falls into the confidence interval, then one can infer that efficiency score is statistically significant and efficiency score could be used in statistical analysis. On this basis, Figure-2 below shows confidence interval widths for bias corrected (bootstrapped) efficiency scores of bank groups[23]. According to the figures, all banks are below the efficiency level of 1,00 during 2003-2010.

[23] Upper and lower bounds of confidence intervals and bias corrected efficiency scores for bank groups are obtained through calculating geometric means of confidence intervals and efficiency scores of banks for each group.

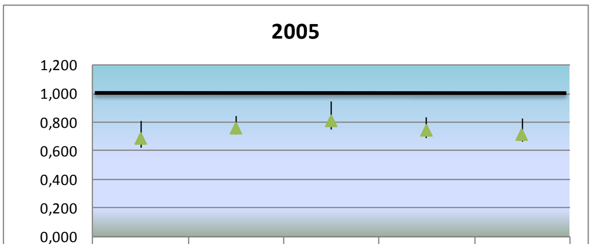
Figure 2: Confidence Intervals for Bias Corrected Efficiency Scores[24]



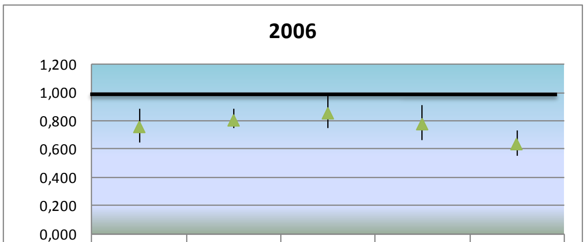
	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	0,992	0,622	0,908	0,879	0,849
lb	0,709	0,440	0,614	0,612	0,582
deabc	0,760	0,482	0,675	0,654	0,635



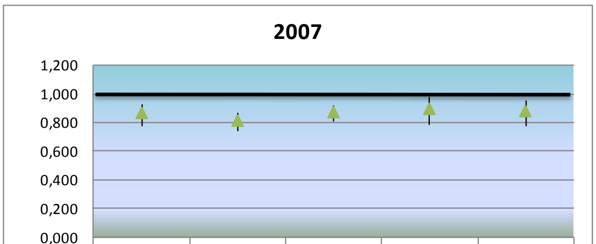
	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	0,994	0,749	0,912	0,778	0,845
lb	0,619	0,584	0,638	0,579	0,603
deabc	0,703	0,636	0,714	0,633	0,678



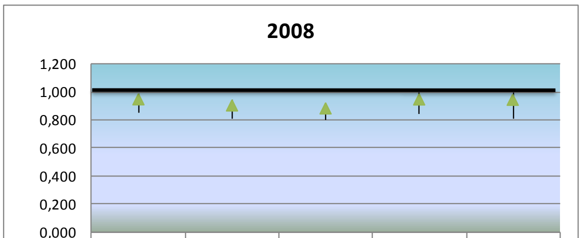
	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	0,806	0,840	0,942	0,836	0,824
lb	0,622	0,714	0,745	0,688	0,661
deabc	0,689	0,759	0,809	0,745	0,715



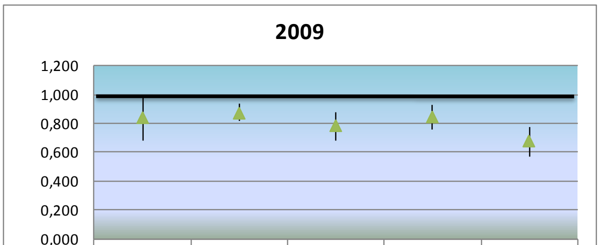
	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	0,885	0,881	0,982	0,906	0,734
lb	0,645	0,749	0,744	0,666	0,552
deabc	0,757	0,803	0,853	0,776	0,636



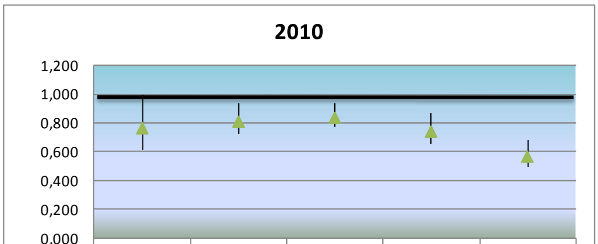
	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	0,931	0,872	0,922	0,977	0,954
lb	0,770	0,737	0,808	0,783	0,774
deabc	0,864	0,812	0,870	0,892	0,877



	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	0,984	0,943	0,918	0,992	0,999
lb	0,854	0,805	0,795	0,840	0,805
deabc	0,944	0,900	0,879	0,943	0,941



	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	0,995	0,935	0,876	0,929	0,773
lb	0,676	0,813	0,682	0,753	0,566
deabc	0,837	0,867	0,782	0,842	0,677



	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	0,994	0,935	0,935	0,868	0,676
lb	0,610	0,726	0,777	0,653	0,489
deabc	0,765	0,812	0,838	0,743	0,569

[24] In the figures, ub stands for upper bound of the confidence interval whereas lb stands for lower bound and deabc denotes the bias corrected (bootstrapped) DEA efficiency score.

First figure suggests that, efficiency scores of all bank groups are within confidence interval and vary between 0,6 and 0,8 range, except private 1 banks which should be considered as significantly more inefficient than other bank groups in 2003. In other words, efficiency differences between private 1 banks and other bank groups are significant in a statistical sense in 2003. The most efficient bank group in this period was public banks.

However, by the year 2005 banks efficiency scores began to converge each other and come closer to the fully efficient level of 1,00. From 2003 to 2005, efficiency of all private bank groups improved whereas efficiency of public banks deteriorated. In contrast to the 2003, the most efficient bank group became private 2 and private 1 banks, respectively and the least efficient bank group became public banks.

In 2006, all bank groups' efficiency scores increased compared to the 2005. Performances of Turkish banks continued to increase until 2008 and reached top levels in the year 2008. Also it is important to note that confidence intervals became narrower compared to the previous years in this period. This means increase in accuracy of our estimation and assessments based on those estimations. In this period, bank efficiency scores vary between 0,8 and 1,0. Public banks and private 3 banks became the most efficient banks in 2008.

However, in 2009, we observe decreases in bank efficiency scores due to the impacts of global financial crisis occurred in September, 2007. Banks began to diverge from each other in terms of efficiency. Moreover, efficiency range fell to 0,6 - 1,00 interval. The largest decrease in efficiency was observed in private 4 banks. Based on the confidence intervals, figure suggests that in this period, performance of private 4 banks are significantly lower than other bank groups.

In 2010, private 4 banks deteriorated further. All bank groups efficiency scores decreased, except private 2 banks in this period.

5.2. Malmquist Productivity Index of Banks

The output oriented bootstrapped Malmquist productivity index (MPI) with its components, namely technical change and efficiency change which is also composed of pure and scale efficiency changes, is estimated for all bank groups in the sample over the period 2003-2010 through 2000 random resamplings. Bank by bank results are displayed in appendix B.

Table-4 below summarizes MPI scores[25] and its components for bank groups and the following Figure-3 shows the *cumulative* MPI scores[26] obtained for each group of bank and allows us to assess the productivity changes over 2003-2010. It is important to note that Table-4 shows one period change in productivity from time t to t+1 whereas Figure-3 shows the cumulative change in the productivity over the period under consideration. As noted earlier, a value greater than unity indicates improvement in that component whereas a value less than unity indicates deterioration.

On this basis, as table and figure suggest, during 2003-2010, we observe significant deteriorations in MPI scores from 2007 to 2008. This fact is supported by the global financial crisis initiated on September, 2007. From 2008 to 2009, however, we observe improvements. 2009 improvements are followed by small scale and ignorable deteriorations in MPI scores in 2010.

According to Table-4, from 2003 to 2004, bank groups that experienced improvements in their productivity, i.e. bank groups that have MPI greater than unity are private 1 and public banks[27]. Private 1 banks' improvement could largely be attributed to the efficiency change whereas technical change is responsible for the improvement in productivity of public banks. In other words, from 2003 to 2004 private banks came closer to the best practice frontier while public banks managed to shift their production frontier further away. In banking literature, this implies that in this period private 1 banks managed to use their existing funding sources (inputs) in more profitable instruments (outputs), on the other hand public banks expand their intermediation activities further. Especially, restructuring reforms implemented soon after the 2001 crisis in Turkey to remove the inefficiencies inherent to public banks were

[25] MPI score for each group of bank is obtained by calculating geometric mean of MPI scores of banks within that group.

[26] In the calculation of cumulative MPI, for each group of bank, MPI in 2003 is assumed to be 1,00 and the MPI in 2004 is estimated by multiplying 1,00 with MPI score for that group in 2004 and MPI in 2005 is estimated by multiplying MPI score of 2004 obtained in the previous step with that of 2005 and so on.

[27] Private 3 bank groups' productivity improvement is negligible, namely it's 1,001.

responsible for the high performance of public banks in this period. In overall, sector's productivity has increased from 2003 to 2004.

Table 4: MPI and Its Components for Bank Groups, 2003-2010

MPI (2003-2004)	malm	eff	tech	pure.eff	scale
PUBLIC	1.121	0.950	1.180	1.000	0.950
PRIVATE 1	1.435	1.404	1.022	1.202	1.167
PRIVATE 2	0.956	1.013	0.944	1.002	1.011
PRIVATE 3	1.001	0.910	1.100	0.883	1.031
PRIVATE 4	0.874	1.002	0.873	0.993	1.009
SECTOR	1.058	1.056	1.001	1.013	1.043

MPI (2004-2005)	malm	eff	tech	pure.eff	scale
PUBLIC	0.970	0.861	1.127	0.811	1.062
PRIVATE 1	1.107	0.999	1.108	1.121	0.891
PRIVATE 2	1.340	0.996	1.346	1.033	0.964
PRIVATE 3	1.124	1.002	1.121	1.075	0.933
PRIVATE 4	0.986	0.911	1.082	0.976	0.934
SECTOR	1.132	0.969	1.168	1.028	0.943

MPI (2005-2006)	malm	eff	tech	pure.eff	scale
PUBLIC	1.101	1.099	1.002	1.098	1.002
PRIVATE 1	1.054	1.167	0.903	1.047	1.114
PRIVATE 2	0.988	1.053	0.938	1.042	1.010
PRIVATE 3	1.022	1.098	0.931	1.083	1.014
PRIVATE 4	0.743	0.927	0.801	0.889	1.043
SECTOR	0.969	1.067	0.907	1.027	1.039

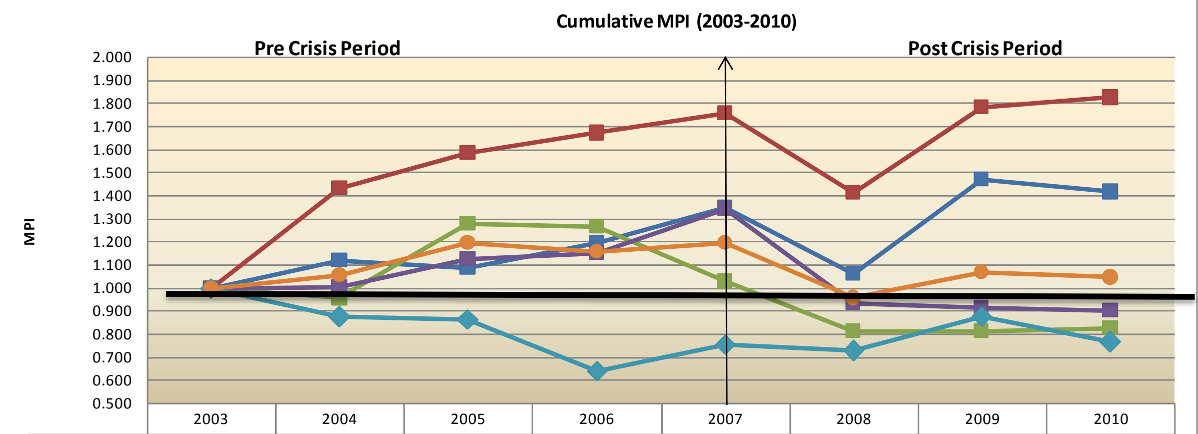
MPI (2006-2007)	malm	eff	tech	pure.eff	scale
PUBLIC	1.126	1.047	1.075	1.049	0.998
PRIVATE 1	1.052	0.980	1.074	0.987	0.993
PRIVATE 2	0.812	0.927	0.875	0.936	0.991
PRIVATE 3	1.170	1.152	1.015	1.076	1.071
PRIVATE 4	1.181	1.259	0.938	1.298	0.970
SECTOR	1.032	1.055	0.979	1.049	1.006

MPI (2007-2008)	malm	eff	tech	pure.eff	scale
PUBLIC	0.789	1.058	0.745	1.056	1.002
PRIVATE 1	0.804	1.101	0.730	1.081	1.018
PRIVATE 2	0.793	1.020	0.777	0.995	1.025
PRIVATE 3	0.694	0.993	0.699	1.013	0.980
PRIVATE 4	0.961	1.006	0.956	1.045	0.963
SECTOR	0.799	1.032	0.774	1.033	1.000

MPI (2008-2009)	malm	eff	tech	pure.eff	scale
PUBLIC	1.384	1.015	1.364	1.015	1.001
PRIVATE 1	1.261	0.997	1.265	0.994	1.003
PRIVATE 2	0.996	0.943	1.057	0.956	0.986
PRIVATE 3	0.981	0.941	1.042	0.940	1.001
PRIVATE 4	1.206	0.883	1.366	0.776	1.138
SECTOR	1.117	0.949	1.177	0.930	1.021

MPI (2009-2010)	malm	eff	tech	pure.eff	scale
PUBLIC	0.963	1.000	0.963	1.000	1.000
PRIVATE 1	1.024	1.005	1.020	1.002	1.003
PRIVATE 2	1.019	1.024	0.995	1.070	0.957
PRIVATE 3	0.986	0.915	1.077	0.935	0.978
PRIVATE 4	0.872	0.840	1.038	0.876	0.959
SECTOR	0.979	0.957	1.024	0.980	0.976

Figure 3: Cumulative MPI Scores, 2003-2010



	2003	2004	2005	2006	2007	2008	2009	2010
PUBLIC	1.000	1.121	1.087	1.197	1.347	1.062	1.471	1.417
PRIVATE 1	1.000	1.435	1.588	1.673	1.761	1.415	1.784	1.827
PRIVATE 2	1.000	0.956	1.281	1.265	1.027	0.814	0.811	0.827
PRIVATE 3	1.000	1.001	1.125	1.150	1.346	0.934	0.916	0.903
PRIVATE 4	1.000	0.874	0.862	0.641	0.757	0.727	0.877	0.765
SECTOR	1.000	1.058	1.197	1.160	1.197	0.956	1.068	1.046

From 2004 to 2005, except private 4 banks, all private bank groups experienced improvements in their productivity which is attributed to the technical change rather than efficiency change. This finding is supported by the fact that following the 2001 Turkish banking crisis which had long lasting effects on banks up to 2003, intermediation activities had gained pace once again. After then, private banks began to expand their intermediation activities and hence improved their performances based on the restored financial stability.

In 2005-2006 period, banking sector encountered negligible decrease in productivity which stem from the sharp deterioration in productivity of private 4 banks as suggested by the figure. Although both efficiency and technical change scores of private 4 banks was below unity in this period, the reason of worsening in productivity could largely be attributed to the deterioration in technical change. Furthermore, in this period, loan, deposit and asset shares of private 4 banks in the market decreased whereas shares of other private bank groups increased. So, it could be argued that other private bank groups expanded at the expense of the private 4 banks in this period. On the contrary, from 2006 to 2007, we observe deterioration only in the productivity of private 2 banks. However, both private 4 and private 2 banks productivity scores were below the sector's average, but in overall sector's productivity improved.

In contrast to the previous years, from 2007 to 2008, depending on the global financial crisis, we observe sharp deteriorations in productivity of all bank groups as suggested by the Figure-3. According to the Table-4, the reason of decline is the worsening in technical change rather than efficiency change. This implies large contractions in best practice frontiers of banking groups. In banking terms, this means reduction in intermediation activities of banks due to the uncertainty and financial instability created by the global financial crisis. On the other hand, we observe that efficiency change component is above unity in this period. The reason is that since best practice frontier contracted, banks are getting closer to the frontier.

Soon after the crisis, from 2008 to 2009, we observe improvements in sector-wide, with negligible deteriorations in productivity of private 2 and private 3 banks. The reason of improvements is the advance in technical change. So, by considering the reason of worsening in the previous period, it could be argued that technical change rather than efficiency change is more responsive to financial crisis. Also, base year effect seems to dominate in this period and banks' productivity scores has improved in 2009 compared to 2008 which is the year hit most severely by the crisis. According to the figure, private 1 and public banks' productivity scores are above the sector average whereas other bank groups' performances are below the sector in 2009.

Finally, from 2009 to 2010, we observe that the base year effect had eliminated and banks began experience small decreases in their productivity in 2010 compared to 2009.

Also, it is important to note that, as suggested by the Figure-3, from 2003 to 2007 public, private 2 and private 3 banks converge to each other in terms of productivity whereas private 1 and private 4 banks diverge from the rest. That's to say, productivity of private 1 banks are seem to outperform the rest whereas productivity of private 4 banks fall behind. However, private banks began to diverge from each other by the year 2007. The reason may be the differentiation in banking products among bank groups. Introduction of new products i.e. derivatives, advantageous and competitive consumer credits could help that bank group to perform better. Finally, in 2010, it is observed that private 1 and public banks diverge from the rest and surpass other bank groups and private bank groups converge to each other once again in terms of cumulative MPI calculated over 2003-2010.

Similar to the bootstrapped efficiency scores, bootstrapped MPIs are also predicted within a confidence interval which allows us to do statistical inferences based on those estimates. Figure-4 below depicts the confidence interval widths for bias corrected (bootstrapped) MPIs of bank groups. As seen from the figure, the rigidity of estimated confidence intervals shows the accuracy of the estimation.

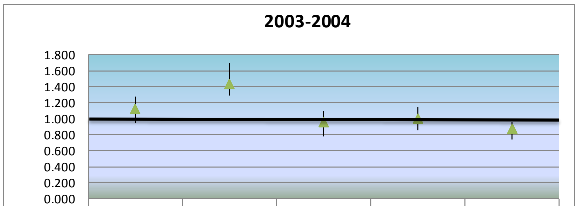
According to the figure, from 2003 to 2004, public and private 1 banks encountered improvements whereas other bank groups encountered deterioration in their productivity scores. Bootstrapping enables us to conclude that those bank groups' productivity scores were also significantly different from public and private 1 banks in a statistical sense.

From 2004 to 2005, the only bank groups that we observe deterioration in their productivity scores are the public and private 4 banks. However, the deterioration is ignorable. Moreover, bank groups' productivity scores began to converge each other, with private 2 banks being an exception due to its high productivity score. From 2005 to 2006, the convergence trend among bank groups in terms of productivity became more apparent. The only exception to the trend in this period is the private 4 banks whose productivity score is significantly lower than the rest.

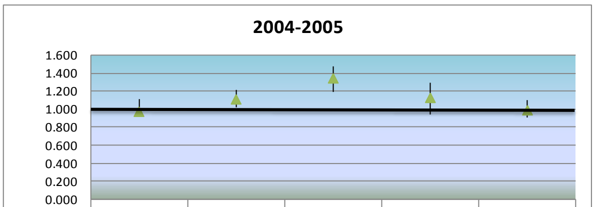
During 2007-2008 and 2008-2009 periods, trend toward convergence was broken down and due to the impacts of global financial crisis on the banking sector; we observe divergence among bank productivity scores. More specifically, from 2007 to 2008, all bank groups experienced deterioration in their productivity scores as seen from the Figure-4.

Soon after the crisis, from 2009 to 2010, similar to what we observe in bank efficiency scores, a gradual recovery of banking sector is detected. Public and private 4 banks are the only bank groups that experienced deterioration in their productivity scores. Moreover, convergence trend observed in the pre crisis period is attained again in this period.

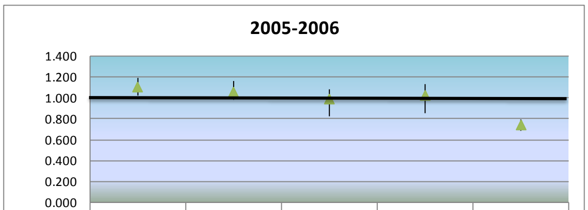
Figure-4: Confidence Intervals for Bias Corrected MPIs[28]



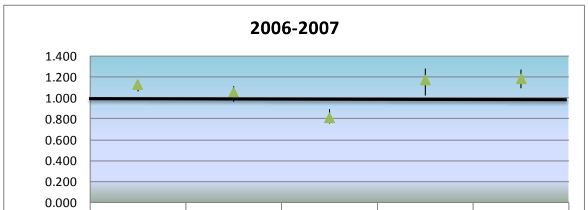
	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	1.275	1.698	1.095	1.150	0.955
lb	0.939	1.290	0.779	0.855	0.741
MPI(bc)	1.121	1.435	0.956	1.001	0.874



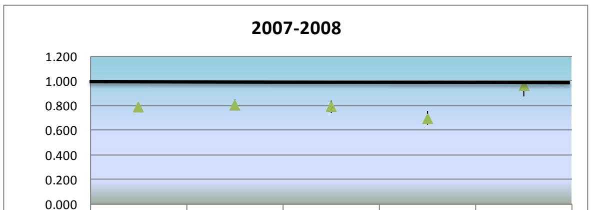
	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	1.107	1.213	1.481	1.293	1.097
lb	0.918	1.022	1.187	0.942	0.909
MPI(bc)	0.970	1.107	1.340	1.124	0.986



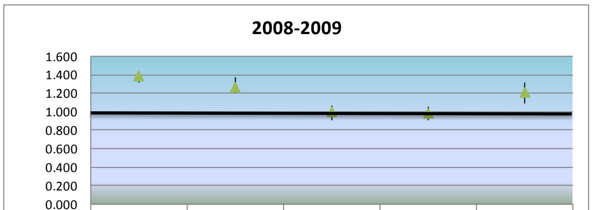
	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	1.190	1.167	1.080	1.132	0.795
lb	1.019	0.978	0.821	0.853	0.683
MPI(bc)	1.101	1.054	0.988	1.022	0.743



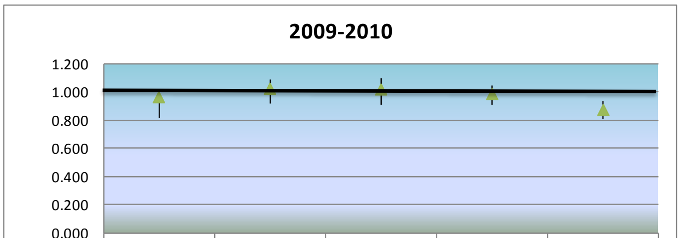
	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	1.173	1.109	0.889	1.279	1.270
lb	1.060	0.963	0.758	1.025	1.088
MPI(bc)	1.126	1.052	0.812	1.170	1.181



	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	0.820	0.849	0.843	0.761	1.007
lb	0.772	0.767	0.741	0.646	0.876
MPI(bc)	0.789	0.804	0.793	0.694	0.961



	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	1.406	1.375	1.068	1.058	1.314
lb	1.311	1.200	0.910	0.909	1.084
MPI(bc)	1.384	1.261	0.996	0.981	1.206



	PUBLIC	PRIVATE 1	PRIVATE 2	PRIVATE 3	PRIVATE 4
ub	1.001	1.091	1.098	1.046	0.933
lb	0.820	0.919	0.911	0.909	0.805
MPI(bc)	0.963	1.024	1.019	0.986	0.872

[28] In the following figures, ub stands for upper bound of the confidence interval whereas lb stands for lower bound and MPI(bc) stands for the bias corrected (bootstrapped) MPIs.

5.3. Two-Stage Regression Analysis

Based on Laeven (1997), Coelli et al. (1998), Sufian (2009) and McDonald (2009) to explain the variation in changes in output efficiencies through time a two-stage ordinary least squares (OLS) regression model is specified as a fixed effects model:

$$\hat{\theta}_k^* = b0 + b1ROA + b2LNTA + b3LOANSTA + b4NPLTA(-1)$$
$$+ b5CAR + b6DLNRGDP + b7NIM + b8INF + b9LNDEP + ei$$

In the regression, return on assets (ROA) is used as a proxy for bank profitability, logarithm of total loans (LNTA) is used as a proxy of bank size to capture the possible cost advantages associated with size, namely, economies of scale. The ratio of loans to total assets (LOANSTA) is used as an indicator for bank liquidity which is an indication of bank's ability to meet its customers' day-to-day cash needs and respond to sudden cash withdrawals. The ratio of nonperforming loans to total assets with one period lag (NPLTA(-1)) is used as an indicator of risk in case banks extend their loans. Since the ratio is expected to have impacts on banks' balance sheet with a time lag we take the ratio with a one period lag. Capital adequacy ratio (CAR) is used as a proxy for capital adequacy and a cushion against future losses. Logarithm of real gross domestic product growth (DLNRGDP) and inflation (INF) are employed as a proxy for economic conditions. Logarithm of deposits (LNDEP) is used as a proxy of market share. On the other hand, dependent variable is assumed to be the bootstrapped bank efficiency scores obtained in the first step, in the previous section. This is why regression analysis is called "two-stage" in the literature.

Annual panel data from 2003 to 2010, for 22 commercial banks is used in the regression. Regression is run by assuming fixed effects model, instead of random effects model. The advantage of fixed effects model is that it imposes time independent bank specific effects that are possibly correlated with regressors whereas random effect model assumes no fixed, individual effects for banks. In other words, fixed effect models controls for the unobserved heterogeneity in the sample when this heterogeneity is constant over time and correlated with independent variables. In fixed effects model time independent bank specific effects can be removed from the data through differencing, for example, taking the first difference will remove any time invariant components of the model. So, to take into account the impacts of bank specific effects, we use fixed effects model. Also, Hausman test to see whether the bank specific effects are correlated with other regressors is conducted. Hausman test suggests that our data set supports fixed effects model. Table below summarizes OLS regression results. (see appendix A for more detailed regression results).

Table 5: Two-Stage Regression Analysis

	Coefficient	Std. Error	t-Statistics	Prob.
C	1,153	0.158160	7,289	0.0000
ROA	1,831	0.594996	3,078	0.0026
LNTA	-0,133	0.031347	-4,226	0.0000
LOANSTA	-0,143	0.038402	-3,733	0.0003
NPLTA(-1)	-1,106	0.426295	-2,594	0.0106
CAR	-0,084	0.072124	-1,159	0.2486
DLNRGDPSA	-1,311	0.200330	-6,545	0.0000
NIM	-0,062	0.007385	-8,370	0.0000
INF	-0,006	0.003175	-1,729	0.0863
LNDEP	0,143	0.032955	4,351	0.0000

According to the regression results, CAR and INF are insignificant whereas the rest of the variables are significant in a statistical sense. So, the effects of those variables are ignorable in the evaluation of DEA efficiency scores.

The results suggest that ROA has the largest impact in the determination of DEA efficiency scores. Following this variable, DLNRGDP and NPLTA(-1) have the largest impacts on the efficiency scores among other variables. That’s to say, 1 unit increase in ROA, i.e. profitability, increases efficiency score by 1,8 units. This implies that more profitable banks tend to exhibit higher efficiency. Also, banks reporting higher profitability ratios are usually preferred by clients and attract the larger share of deposits and it would be easier for those banks to find funding sources in international markets. Such conditions would obviously create a favorable environment for profitable banks to be more efficient in terms of intermediation activities.

It is expected that the demand for financial services tends to grow as economies expand and households become wealthier. However, it is observed that DLNRGDP is statistically significant and has negative sign. Hence, a 1 unit increase in DLNRGDP, decreases efficiency score by 1,3 units. The explanation could be that during the period under consideration, Turkey experienced volatile growth rates, ranging from 6,2% annual growth in 2001 to 9,4% in 2004, falling into a recession with growth rate of -4,8% in 2009 before covering to 9% in 2010, annually. Therefore, the volatile economic growth could have resulted in banks to suffer from lower demand for their financial services, increased loan defaults, and thus lower output.

Another factor which could explain Turkish banks' efficiency is non performing loans to total assets ratio. It is observed that a 1 unit increase in NPLTA(-1) decreases efficiency by 1,1 units, as expected. This implies that higher the amount of loan defaults lower the efficiency for that bank. So, banks should carefully monitor the counter party before extending its loans.

LNTA is statistically significant and has negative sign. So, one could argue that the larger the size of a bank, the more inefficient the bank would be. So, economies of scale argument does not hold for the Turkish banks. The possible explanation could be that Turkish banks are already in the decreasing returns to scale portion of their long run average cost curve.

LOANSTA is also statistically significant and has negative sign. The finding implies that the banks with higher loans to asset ratio tend to have lower efficiency scores. This finding could also be supported by the previous findings on LNTA and NPLTA(-1). That's to say, as banks extend their loans, due to the decreasing returns to scale their efficiency would decrease, moreover, if banks do not monitor their customers carefully while increasing loans, they would probably suffer from the loan defaults and hence nonperforming loans. Bearing in mind that, ROA is positively related with efficiency, it could be argued that banks could increase their efficiency by investing various instruments, and by decreasing their concentration into relatively riskier loans, especially in crisis times. Furthermore, Figure-1 and Figure-3 combined with Table-2 also suggests that the banks which decrease their loan growth rates during crisis periods suffer less and so have greater efficiency and productivity scores.

LNDEP is statistically significant and has positive sign, suggesting that the more efficient banks are associated by larger market share. The possible explanation could be that banks could increase their efficiency by obtaining funds from market and so by increasing their deposit share, and then investing those funds to profitable instruments, other than risky loans in risky periods.

NIM, namely, spread between loan and deposit rates is statistically significant and has negative sign. There is no a priori expectation for the sign of this variable, it could either be positive or negative depending on the balance sheet position and the amount of interest sensitive assets and liabilities of the banking sector. For Turkish banks, it is observed that as spread increases, efficiency decreases.

6. CONCLUSION

A linear programming technique called Data Envelopment Analysis (DEA) and Malmquist Productivity Index (MPI) is used to estimate the efficiency and productivity of 22 commercial deposit banks in Turkey for the years 2003-2010.

In the estimation of efficiency, output oriented VRS DEA model is used. Inputs and outputs are determined according to the mixed approach in banking literature. The inputs used are the ratio of securities to total assets, the ratio of deposits to total assets, the ratio of nonperforming loans (gross) to total (cash) loans, the ratio of total loans to total assets and the ratio of non interest expense to total (average) assets. The outputs used are the ratio of net interest income to total income, return on (average) assets and return on (average) equity.

We then extend the established literature on the estimation of DEA efficiency scores by recognizing the problem of the inherent dependency of DEA efficiency scores when used in the regression analysis or when used to make statistical inferences. To overcome the dependency problem, we follow the approach suggested by Simar and Wilson (1998, 2000) and apply a bootstrapping technique to our DEA efficiency scores. Bootstrapping allows us to assess the statistical significance of the efficiency scores obtained. Results reveal that our estimates are statistically significant and could be used in statistical inference making, i.e. in the regression analysis.

It is observed that except public and private 4 banks, efficiency scores of all bank groups had increased uninterruptedly and gradually up to 2008. And bank groups' efficiency scores began to converge each other, with private 4 banks being an exception due to the lower efficiency scores during this period. However, due to the impacts of 2007 global financial crisis, all bank groups' efficiency scores decreased 2008 onwards, with private 4 banks having the poorest performance. Banks' efficiency scores began to diverge from each other in 2010 compared to 2008. Also, it is observed that the bank groups that continued to keep pre-crisis loan growth rates are the banks that suffer most in crisis period.

To measure the change in total factor productivity between two time periods, output oriented MPI is used. Bootstrapping technique is also applied to the MPI to get unbiased productivity scores. The advantage of MPI is that unlike alternative productivity indices, MPI does not require any information of prices of inputs and outputs. It is observed that productivity of all bank groups, except private 4 banks, increased continuously during 2003-2007, cumulatively. During this period, private 1 group banks became the best performer whereas private 4 banks became the worst performer among all bank groups. As in the case in efficiency, our findings on productivity are also supported by the 2007 global financial crisis. Sharp decreases in productivity scores of all bank groups are observed 2007 onwards. The best performers of post-crisis periods became public and private 1 banks that have productivity scores above the sector's average. Also, it is found that technical change i.e. shift of production frontier further away rather than efficiency change i.e. getting closer to the production frontier is more responsive to the financial crisis and is the main determinant of bank productivity.

Finally, to analyze the determinants of bootstrapped DEA efficiency scores obtained in the first stage of the analysis, a two-stage fixed effects regression model is estimated. The model controls for bank heterogeneity and endogeneity issues by adopting the two-stage ordinary least square estimation of fixed effects. In the regression, annual panel data set for 22 commercial banks, during 2003-2010 is used. It is found that return on assets has the largest positive impact on the efficiency whereas GDP growth and the ratio of nonperforming loans to total assets have the largest negative impact on efficiency scores, respectively.

To sum up, this study observes that during 2003-2008, efficiency and productivity of Turkish banking sector had improved gradually and uninterruptedly, however in 2008-2009 sudden decreases in efficiency and productivity are detected. From 2009 to 2010, we, however, observe gradual recovery. Our findings are strongly supported by the September, 2007 global financial crisis that was also experienced in Turkey. In overall, it can be concluded that by the end of 2010, the impacts of crisis on Turkish banking sector have been eliminated.

APPENDIX A

Two-Stage Regression Results

Dependent Variable: DEA
Method: Panel EGLS (Cross-section weights)

Sample (adjusted): 2004 2010
Periods included: 7
Cross-sections included: 22
Total panel (balanced) observations: 154
Linear estimation after one-step weighting matrix
White cross-section standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.152867	0.158160	7.289246	0.0000
ROA	1.831185	0.594996	3.077644	0.0026
LNTA	-0.132482	0.031347	-4.226245	0.0000
LOANSTA	-0.143336	0.038402	-3.732504	0.0003
NPLTA(-1)	-1.105745	0.426295	-2.593846	0.0106
CAR	-0.083616	0.072124	-1.159343	0.2486
DLNRGDPSA	-1.311146	0.200330	-6.544938	0.0000
NIM	-0.061812	0.007385	-8.370306	0.0000
INF	-0.005489	0.003175	-1.728893	0.0863
LNDEP	0.143402	0.032955	4.351479	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.666057	Mean dependent var	1.198761
Adjusted R-squared	0.584607	S.D. dependent var	0.643462
S.E. of regression	0.089723	Sum squared resid	0.990177
F-statistic	8.177534	Durbin-Watson stat	2.148322
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.529470	Mean dependent var	0.796668
Sum squared resid	1.068311	Durbin-Watson stat	1.949412

APPENDIX B

Comparison of Bootstrapped Malmquist Productivity Index, 2003 - 2010

	2003-2004							2004-2005						
Banka Kodu (*)	mpi	mpi lb	mpi ub	eff	tech	pure.eff	scale	mpi	mpi lb	mpi ub	eff	tech	pure.eff	scale
B1	1,194	0,895	1,354	1,000	1,194	1,000	1,000	1,158	1,068	1,390	1,000	1,158	1,000	1,000
B2	1,052	0,986	1,200	0,902	1,166	1,000	0,902	0,812	0,788	0,882	0,741	1,096	0,657	1,127
PUBLIC (**)	1,121	0,939	1,275	0,950	1,180	1,000	0,950	0,970	0,918	1,107	0,861	1,127	0,811	1,062
B3	1,976	1,763	2,172	1,515	1,304	1,380	1,098	0,791	0,739	0,951	0,809	0,979	0,833	0,970
B4	0,897	0,864	1,192	1,000	0,897	1,000	1,000	1,157	1,023	1,307	1,000	1,157	1,000	1,000
B5	1,515	1,391	1,850	1,296	1,169	0,744	1,742	1,202	1,141	1,254	1,020	1,179	1,147	0,889
B6	1,419	1,240	1,563	1,631	0,870	1,544	1,056	1,242	1,153	1,335	1,128	1,101	1,216	0,928
B7	1,596	1,359	1,883	1,701	0,938	1,585	1,073	1,216	1,120	1,262	1,072	1,134	1,527	0,702
PRIVATE 1	1,435	1,290	1,698	1,404	1,022	1,202	1,167	1,107	1,022	1,213	0,999	1,108	1,121	0,891
B8	0,691	0,607	0,916	1,000	0,691	1,000	1,000	1,211	1,050	1,410	0,897	1,350	0,955	0,939
B9	0,578	0,478	0,663	0,662	0,873	0,662	0,999	1,121	1,053	1,204	1,052	1,065	1,221	0,862
B10	1,293	1,162	1,352	1,209	1,070	1,181	1,024	2,036	1,865	2,199	1,000	2,036	1,000	1,000
B11	1,203	0,808	1,300	1,115	1,079	1,110	1,004	1,254	1,150	1,379	1,000	1,254	1,000	1,000
B12	1,117	0,869	1,275	1,000	1,117	1,000	1,000	1,352	1,165	1,559	1,000	1,352	1,000	1,000
B13	1,099	0,943	1,270	1,209	0,909	1,162	1,041	1,238	1,015	1,317	1,035	1,196	1,042	0,993
PRIVATE 2	0,956	0,779	1,095	1,013	0,944	1,002	1,011	1,340	1,187	1,481	0,996	1,346	1,033	0,964
B14	0,979	0,908	1,216	0,957	1,023	1,000	0,957	0,627	0,462	0,681	0,661	0,949	0,950	0,696
B15	0,655	0,523	0,739	0,683	0,959	0,787	0,867	2,207	1,640	2,559	1,465	1,507	1,270	1,153
B16	1,149	0,981	1,333	1,000	1,149	1,000	1,000	0,693	0,596	0,886	0,676	1,025	0,757	0,893
B17	0,792	0,631	0,940	0,708	1,119	0,680	1,041	2,432	2,285	2,667	2,083	1,168	2,095	0,994
B18	1,725	1,548	1,785	1,349	1,279	1,000	1,349	0,769	0,721	0,877	0,742	1,037	0,749	0,990
PRIVATE 3	1,001	0,855	1,150	0,910	1,100	0,883	1,031	1,124	0,942	1,293	1,002	1,121	1,075	0,933
B19	0,923	0,846	0,957	1,000	0,923	1,000	1,000	0,837	0,818	0,877	1,000	0,837	1,000	1,000
B20	0,746	0,556	0,903	1,000	0,746	1,000	1,000	1,042	0,929	1,301	1,000	1,042	1,000	1,000
B21	0,895	0,803	0,948	0,948	0,943	0,931	1,019	1,212	1,075	1,307	0,967	1,253	1,046	0,925
B22	0,950	0,799	1,016	1,063	0,894	1,044	1,018	0,894	0,837	0,971	0,712	1,256	0,866	0,822
PRIVATE 4	0,874	0,741	0,955	1,002	0,873	0,993	1,009	0,986	0,909	1,097	0,911	1,082	0,976	0,934
SECTOR	1,058	0,899	1,210	1,056	1,001	1,013	1,043	1,132	1,013	1,266	0,969	1,168	1,028	0,943

	2005-2006							2006-2007						
Banka Kodu (*)	mpi	mpi lb	mpi ub	eff	tech	pure.eff	scale	mpi	mpi lb	mpi ub	eff	tech	pure.eff	scale
B1	1,036	0,994	1,069	1,000	1,036	1,000	1,000	1,077	1,069	1,091	1,000	1,077	1,000	1,000
B2	1,170	1,045	1,325	1,209	0,968	1,205	1,003	1,177	1,052	1,261	1,096	1,073	1,100	0,996
PUBLIC (**)	1,101	1,019	1,190	1,099	1,002	1,098	1,002	1,126	1,060	1,173	1,047	1,075	1,049	0,998
B3	1,150	1,104	1,249	1,237	0,930	1,200	1,031	1,008	0,931	1,063	0,964	1,045	1,000	0,964
B4	0,837	0,774	0,913	1,000	0,837	1,000	1,000	1,008	0,973	1,059	1,000	1,008	1,000	1,000
B5	1,042	0,959	1,134	1,132	0,920	1,008	1,123	1,531	1,238	1,581	1,171	1,307	1,163	1,007
B6	0,844	0,817	0,923	0,999	0,845	0,929	1,076	0,937	0,866	1,000	0,933	1,004	0,893	1,045
B7	1,532	1,337	1,808	1,547	0,991	1,121	1,380	0,885	0,851	0,942	0,858	1,032	0,904	0,949
PRIVATE 1	1,054	0,978	1,167	1,167	0,903	1,047	1,114	1,052	0,963	1,109	0,980	1,074	0,987	0,993
B8	0,918	0,740	0,991	1,115	0,823	1,047	1,065	0,729	0,671	0,830	0,893	0,817	0,894	0,999
B9	1,099	1,052	1,169	1,304	0,843	1,177	1,107	0,883	0,832	0,896	0,834	1,060	0,945	0,882
B10	0,483	0,408	0,557	0,882	0,547	0,974	0,906	0,749	0,708	0,779	1,009	0,742	0,923	1,094
B11	1,252	0,930	1,403	1,000	1,252	1,000	1,000	0,762	0,704	0,928	1,000	0,762	1,000	1,000
B12	1,339	1,064	1,423	1,000	1,339	1,000	1,000	0,928	0,860	1,009	1,000	0,928	1,000	1,000
B13	1,137	0,973	1,232	1,061	1,072	1,064	0,997	0,840	0,792	0,909	0,847	0,992	0,864	0,981
PRIVATE 2	0,988	0,821	1,080	1,053	0,938	1,042	1,010	0,812	0,758	0,889	0,927	0,875	0,936	0,991
B14	0,779	0,737	0,860	0,834	0,934	0,786	1,061	1,381	1,325	1,498	1,496	0,923	1,210	1,236
B15	0,842	0,658	1,021	1,000	0,842	1,000	1,000	0,983	0,812	1,133	1,000	0,983	1,000	1,000
B16	1,228	1,115	1,312	1,479	0,830	1,321	1,120	0,940	0,843	1,042	1,000	0,940	1,000	1,000
B17	1,375	0,914	1,489	1,151	1,195	1,278	0,901	1,419	1,153	1,513	1,132	1,254	1,000	1,132
B18	1,007	0,913	1,082	1,125	0,895	1,121	1,004	1,210	1,083	1,279	1,199	1,010	1,191	1,006
PRIVATE 3	1,022	0,853	1,132	1,098	0,931	1,083	1,014	1,170	1,025	1,279	1,152	1,015	1,076	1,071
B19	0,828	0,799	0,867	1,000	0,828	1,000	1,000	0,784	0,722	0,836	1,000	0,784	1,000	1,000
B20	0,747	0,666	0,788	1,000	0,747	1,000	1,000	0,892	0,786	0,952	1,000	0,892	1,000	1,000
B21	0,427	0,382	0,448	0,537	0,795	0,565	0,951	2,303	2,269	2,453	2,159	1,067	1,992	1,084
B22	1,153	1,069	1,310	1,377	0,837	1,108	1,243	1,208	1,087	1,334	1,164	1,038	1,425	0,817
PRIVATE 4	0,743	0,683	0,795	0,927	0,801	0,889	1,043	1,181	1,088	1,270	1,259	0,938	1,298	0,970
SECTOR	0,969	0,850	1,060	1,067	0,907	1,027	1,039	1,032	0,944	1,111	1,055	0,979	1,049	1,006

	2007-2008							2008-2009						
Banka Kodu (*)	mpi	mpi lb	mpi ub	eff	tech	pure.eff	scale	mpi	mpi lb	mpi ub	eff	tech	pure.eff	scale
B1	0,788	0,781	0,806	1,000	0,788	1,000	1,000	1,314	1,308	1,317	1,000	1,314	1,000	1,000
B2	0,789	0,763	0,835	1,120	0,704	1,115	1,004	1,458	1,314	1,501	1,031	1,415	1,029	1,001
PUBLIC (**)	0,789	0,772	0,820	1,058	0,745	1,056	1,002	1,384	1,311	1,406	1,015	1,364	1,015	1,001
B3	0,775	0,723	0,803	0,974	0,795	1,000	0,974	1,296	1,225	1,345	1,019	1,271	0,975	1,045
B4	0,770	0,743	0,803	1,000	0,770	1,000	1,000	1,419	1,355	1,607	1,000	1,419	1,000	1,000
B5	0,583	0,561	0,647	1,000	0,583	1,000	1,000	1,211	1,147	1,396	1,000	1,211	1,000	1,000
B6	0,857	0,812	0,907	1,057	0,811	1,061	0,996	1,318	1,254	1,385	1,082	1,218	1,088	0,994
B7	1,125	1,085	1,168	1,568	0,717	1,389	1,129	1,087	1,042	1,178	0,891	1,220	0,913	0,976
PRIVATE 1	0,804	0,767	0,849	1,101	0,730	1,081	1,018	1,261	1,200	1,375	0,997	1,265	0,994	1,003
B8	0,768	0,721	0,797	1,120	0,686	1,119	1,001	0,784	0,723	0,855	0,762	1,029	0,770	0,990
B9	1,130	1,094	1,196	1,176	0,961	1,002	1,174	0,876	0,836	0,914	0,687	1,275	0,760	0,904
B10	0,588	0,562	0,631	0,833	0,706	0,829	1,005	1,414	1,289	1,497	1,347	1,049	1,342	1,004
B11	0,666	0,625	0,724	0,856	0,779	0,901	0,949	1,127	1,056	1,222	0,995	1,133	0,972	1,024
B12	0,688	0,633	0,739	1,000	0,688	1,000	1,000	0,764	0,734	0,824	1,000	0,764	1,000	1,000
B13	1,060	0,946	1,112	1,200	0,883	1,160	1,035	1,170	0,943	1,262	1,000	1,170	1,000	1,000
PRIVATE 2	0,793	0,741	0,843	1,020	0,777	0,995	1,025	0,996	0,910	1,068	0,943	1,057	0,956	0,986
B14	0,844	0,796	0,866	1,015	0,831	1,067	0,951	1,066	1,012	1,097	0,920	1,159	0,917	1,004
B15	0,650	0,592	0,734	0,950	0,684	1,000	0,950	0,784	0,727	0,830	0,804	0,975	0,800	1,005
B16	0,778	0,721	0,847	1,000	0,778	1,000	1,000	1,100	0,968	1,197	1,000	1,100	1,000	1,000
B17	0,531	0,502	0,612	1,000	0,531	1,000	1,000	0,916	0,875	1,057	0,998	0,918	1,000	0,998
B18	0,711	0,661	0,773	1,000	0,711	1,000	1,000	1,078	0,993	1,151	1,000	1,078	1,000	1,000
PRIVATE 3	0,694	0,646	0,761	0,993	0,699	1,013	0,980	0,981	0,909	1,058	0,941	1,042	0,940	1,001
B19	1,329	1,249	1,345	1,000	1,329	1,000	1,000	2,320	2,218	2,550	1,000	2,320	1,000	1,000
B20	0,791	0,686	0,872	1,000	0,791	1,000	1,000	1,001	0,736	1,062	1,000	1,001	1,000	1,000
B21	1,169	1,026	1,213	1,311	0,892	1,191	1,101	0,810	0,778	0,901	0,899	0,901	0,907	0,991
B22	0,695	0,670	0,724	0,780	0,891	1,000	0,780	1,126	1,085	1,221	0,677	1,662	0,401	1,690
PRIVATE 4	0,961	0,876	1,007	1,006	0,956	1,045	0,963	1,206	1,084	1,314	0,883	1,366	0,776	1,138
SECTOR	0,799	0,749	0,850	1,032	0,774	1,033	1,000	1,117	1,034	1,202	0,949	1,177	0,930	1,021

	2009-2010						
Banka Kodu (*)	mpi	mpi lb	mpi ub	eff	tech	pure.eff	scale
B1	0,882	0,738	0,908	1,000	0,882	1,000	1,000
B2	1,052	0,912	1,103	1,000	1,052	1,000	1,000
PUBLIC (**)	0,963	0,820	1,001	1,000	0,963	1,000	1,000
B3	0,972	0,927	1,039	0,844	1,151	0,861	0,981
B4	0,996	0,880	1,072	1,000	0,996	1,000	1,000
B5	1,000	0,914	1,059	1,000	1,000	1,000	1,000
B6	0,983	0,914	1,039	1,023	0,961	1,020	1,003
B7	1,183	0,960	1,262	1,184	0,999	1,150	1,030
PRIVATE 1	1,024	0,919	1,091	1,005	1,020	1,002	1,003
B8	1,070	0,881	1,147	1,051	1,018	1,178	0,892
B9	1,244	1,178	1,364	1,045	1,191	1,118	0,935
B10	1,100	1,028	1,177	1,000	1,100	1,000	1,000
B11	1,097	0,991	1,162	1,175	0,934	1,142	1,029
B12	0,853	0,736	0,909	0,896	0,952	1,000	0,896
B13	0,817	0,736	0,903	1,000	0,817	1,000	1,000
PRIVATE 2	1,019	0,911	1,098	1,024	0,995	1,070	0,957
B14	0,984	0,945	1,055	0,945	1,041	0,909	1,039
B15	1,408	1,321	1,462	1,309	1,075	1,249	1,048
B16	0,974	0,923	1,050	0,787	1,237	0,913	0,862
B17	0,683	0,610	0,750	0,660	1,036	0,691	0,955
B18	1,011	0,881	1,033	1,000	1,011	1,000	1,000
PRIVATE 3	0,986	0,909	1,046	0,915	1,077	0,935	0,978
B19	0,973	0,969	1,007	1,000	0,973	1,000	1,000
B20	1,038	0,878	1,148	1,000	1,038	1,000	1,000
B21	0,701	0,652	0,741	0,612	1,145	0,679	0,901
B22	0,817	0,758	0,885	0,813	1,005	0,865	0,940
PRIVATE 4	0,872	0,805	0,933	0,840	1,038	0,876	0,959
SECTOR	0,979	0,884	1,044	0,957	1,024	0,980	0,976

(*)"mpi ub" stands for upper bound of the confidence interval for MPI score whereas mpi lb stands for lower bound and eff, tech, pure.eff and scale show the efficiency, technical, pure efficiency and scale efficiency changes, respectively.

(**)MPI score for each group of bank is obtained by calculating geometric mean of MPI scores of banks within that group.

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