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CLASSIFICATION OF DOMESTIC AND FOREIGN COMMERCIAL BANKS IN TURKEY BASED ON FINANCIAL EFFICIENCY: A COMPARISON OF DECISION TREE, LOGISTIC REGRESSION AND DISCRIMINANT ANALYSIS MODELS

TÜRKİYE'DE YERLİ VE YABANCI TİCARET BANKALARININ FİNANSAL ETKİNLİĞE GÖRE SINIFLANDIRILMASI: KARAR AĞACI, LOJİSTİK REGRESYON VE DİSKRİMİNANT ANALİZİ MODELLERİNİN BİR KARŞILAŞTIRMASI

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ABSTRACT

This study compares the data mining (DM) techniques of linear discriminant analysis (LD), logistic regression (LR) and classification and regression tree analysis (CRT), which can be used to develop classification for predicting the group membership of commercial banks into two pre-defined groups, namely domestic and foreign banks. The application of the three techniques is illustrated by comparing the classification models obtained by applying them to selected liquidity, cost-revenue, profitability and activity bank ratios data set. As the results reveal that CRT outperform traditional discriminant analysis and logistic regression techniques in terms of bank classification accuracy and thus provide an effective alternative for implementing bank classification tasks.

ÖZET

Bu çalışmada yerli ve yabancı olarak önceden grup üyeliği belirlenmiş bankaların sınıflandırmasında yaygın olarak kullanılan veri madenciliği tekniklerinden diskriminant, lojistik regresyon ve karar ağacı modelleri karşılaştırılmaktadır. Üç sınıflandırma tekniği, bankalarla ilgili seçilmiş likidite, gelir-gider, karlılık ve faaliyet oranları kullanılarak karşılaştırılmaktadır. Araştırmanın sonuçları, bankaların sınıflandırmasında karar ağacı modelinin geleneksel diskriminant ve lojistik regresyon modellerine üstünlük sağlaya-

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sağlayarak alternatif etkili bir sınıflandırma tekniği olarak kullanılabileceğini göstermektedir.

Logistic Regression and Discriminant Analysis, Data Mining, CRT and Bank Performance
Lojistik Regresyon ve Diskriminant Analizi, Veri Madenciliği, CRT ve Banka Performansı

1. INTRODUCTION

Data mining (DM) also referred to as knowledge discovery in databases (KDD), is systematic approach to find underlying structures and hidden relationships in huge databases. As the term suggests, data mining has an exploratory point of reference: It searches for knowledge buried within difficult patterns of relationships in large amount of data. Data mining has drawn attention from both researchers and practitioners due to its wide applications in important business decisions. The research regarding DM can be classified into two categories: methodologies and technologies. The main methodologies are data visualization, statistical techniques and deductive database (Hair et al., 1998:674-675). The related applications using these methodologies can be summarized as classification, prediction, clustering, summarization, data reduction, dependency modeling and sequential analysis. The technology part of DM consists of techniques such as statistical methods, neural networks, decision trees, genetic algorithms and non-parametric techniques. Among the above-mentioned applications, the classification problems where observations can be assigned to one of several disjoint groups have long played an important role in business decision-making processes. Classification problems can be found in a wide variety of applications such as decision support, financial forecasting, marketing strategy, process control and other related fields (Lee et al., 2006).

The data mining techniques of linear discriminant analysis (LD), logistic regression (LR) and Decision trees (DTs) are among the multivariate techniques used for predicting the predefined class membership of dependent variables (Camdeviren et al., 2007). These techniques have been widely used in bank classification (Harrison and Wood, 1989). In literature, LD, LR and DT techniques are used commonly with the purpose of determining risk factors (Kitsantasa et al., 2007). In recent years DTs has become attractive because they offer a symbolic representation that lends itself to easy interpretation by researchers (Brieman et al., 1984).

Until the 1990s the banking sector in Turkey operated in highly regulated markets, while at the same time, markets on banking services were primarily local in nature. In recent years both developed and developing countries around the world have relaxed restrictions on foreign banking and most of them now permit more foreign banks to embark on more banking-related activities in their domestic markets. This is due to the increasing importance of international trade in goods. Over the last decade, the number of foreign banks has increased in banking sector because of globalization (Kosmidou et al., 2006).

Buch and Golder (2001) describe market entry of foreign banks as a “two-edged sword.” In fact, several authors have addressed the potential benefits of foreign bank entry for the domestic economy (Walter and Gray, 1983). Foreign competition can enhance the efficiency of the domestic banking sector, improve knowledge and technological skills and provide access to foreign savings (Kosmidou et al., 2006).

Despite the substantial structural changes and the importance of the Turkish financial banking sector, the sector remains relatively uninvestigated in literature. It is an interesting research topic to investigate the performance of the commercial banking sector in Turkey, focusing on the performance of domestic banks as opposed to the performance of foreign banks.

The aim of this paper is to identify the distinguishing financial factors characterizing the operation of domestic and foreign banks in Turkey through discriminant analysis, logistic regression and DT techniques comparatively in terms of the results obtained. The factors considered in the analysis cover most important aspects of financial performance; including liquidity, cost-revenue, profitability and activity efficiency. Three appropriate techniques are applied and the effects of certain selected ratios of both domestic and foreign commercial banks examined. We test a hypotheses discussed in prior research, especially for developed countries in the context of the Turkish commercial banking sector. It is typically find out that the foreign banks operating in a developed market are less efficient than domestic banks operating in the same market. We investigate whether this typical pattern also holds in Turkish commercial banking sector.

Several studies have compared the efficiency of foreign versus domestic banks in the same nation or nations. Most of them, which focused on the United States (US) market, employed estimates of either cost or profit efficiency to determine efficiency differences and found foreign banks to be significantly less profit and/or cost efficient than domestic banks (De Young and Noll, 1996; Seth, 1992). Similar results were obtained in studies that examined the Australian and United Kingdom (UK) market (Avkiran, 1997; Sathye, 2001; Kosmidou et al., 2006) and concluded that foreign banks are less efficient than domestic banks in Australia and UK financial market.

Other several studies have examined the European Union (EU) markets. Hasan and Lozano (1998) found out that foreign banks in Spain are about equally as profit efficient as domestic banks. Finally, studies that compared the performance of domestic and foreign banks in both developed and developing countries supported the results of previous studies that foreign banks are disadvantaged compared to the domestic banks in developed countries; however, this is not the case in less developed countries (Demirguc-Kunt and Huizinga, 1999; Claessens et al., 2001).

2. MULTIVARIATE CLASSIFICATION TECHNIQUES

Discriminant analysis, logistic regression and decision tree analysis have widespread application in situations in which the primary objective is to identify the group to which an object belongs.

2.1. Two-Groups Linear Discriminant Analysis

Two-group linear discriminant (LD) analysis is a linear combination of the two or more independent variables that discriminate best between a priori defined groups. Discrimination is achieved by setting weights for each independent variable to maximize the between-group variance to the within-group variance. The linear discriminant function (LDF) is represented by Eq. (1):

$$LDF = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_p x_p \qquad (1)$$

Here, b_0 is constant and b_1 to b_p are the discriminant weights for the p independent variables. The LDF can also be written in standardized form, in which each variable is adjusted by being subtracted from its mean and divided by its standard deviation (Eq. 2):

$$z = \beta_0 + \beta_1 z_1 + \beta_2 z_2 + \cdots + \beta_p z_p \qquad (2)$$

Here, z is the standardized LDF, β_1 to β_p are the standardized coefficients and z_1 to z_p are the standardized variables. The variables that contribute most to the prediction of group membership are the ones with the largest, standardized regression coefficients. The mean of z taken over all observations is zero, because the mean of each variable, when standardized, is zero. Therefore, an object can be classified into one group if its z score is greater than zero and into the other group if its z score is less than zero (Sharma, 1996)

The linear boundary between the two groups can be thought of as a function that is orthogonal to the LDF. Since there are an infinite number of orthogonal surfaces, the most obvious choice is the boundary that is equidistant from the two centroids, namely LD with equal prior probabilities. Alternatively, the boundary can be shifted along the direction of the LDF towards one of the two centroids so that objects of unknown group membership are more likely to be assigned to one group rather than the other. This is called LD with unequal prior probabilities, and is appropriate when it is known, a priori, that there are different proportions of objects in the different groups (Tabachnick and Fidell, 1996).

In theory, standardized LDFs (z scores) can be used to assign objects to groups, although in practice, classification functions are often used instead, especially when there are three or more groups. There will be as many classification functions as groups, and each object will be assigned to the group for which it has the highest classification score. Classification scores are computed according the following equation (Worth and Cronin, 2003):

$$CF_i = w_i + w_{i1}x_1 + w_{i2}x_2 + \cdots + w_{ip}x_p \quad (3)$$

Where the subscript i denotes the respective group; the subscripts 1, 2,…; p denote the p variables; w_i is a constant for the ith group; w_{ij} is the weight for the jth variable in the computation of the classification score for the ith group; x_j is the observed value for the respective object for the jth variable; CF_i is the computed classification score. The weights w_{ij} are derived from the mean values of the p predictors for the ith group and from the pooled within-group variance–covariance matrix, whereas the constants w_i are derived from the mean values of the p predictors for the ith group and from the classification coefficients.

To calculate the probability that a given object belongs to a given group, the Mahalanobis distance is used. This is the distance of the entity from the group centroids in the multidimensional space defined by the predictor variables. The Mahalanobis distance is an appropriate measure of distance when the variables are correlated. If the predictor variables are uncorrelated, it is the same as the Euclidean distance (Sharma, 1996). The calculation of this posterior probability is based not only on the Mahalanobis distance, but also on the prior probabilities.

Canonical discriminant analysis is a variant of LD analysis in which the LDFs are derived in such a way that they are orthogonal (independent). The first function provides the largest contribution to the discrimination between groups; the second function provides second largest and non-overlapping discrimination, and so on. The maximum number of functions will be equal to the number of groups minus one (g-1) or the number of independent variables (p) in the analysis, whichever is smaller.

Linear Discriminant Analysis Assumptions

It is desirable to meet certain assumption for adequate application of LD analysis. The LD has three important assumptions: (1) the independent variables are at least interval or ratio scale variables; (2) the assumption of multivariate normality: the predictor variables have been independently and randomly sampled from a population having a multivariate normal distribution and (3) the assumption of equal variance/covariance matrices. If the assumption of multivariate normality is violated, this does not so much invalidate the classification model as reduce its general predictive power of discriminant function (Hair et al., 1998:259). However, researches should be aware that studies have shown that, although the overall classification error is not effected, the classification error some groups might be overestimated and for other groups it might be underestimated (Lachenbruch, 1967). In contrast, heterogeneity of the variance/covariance matrices is likely to be more important, since objects are more likely to be classified into the group with greatest dispersion (Worth and Cronin, 2003; Hair et al., 1998). Violation of this assumption affects the significance tests and the classification results.

Stepwise Discriminant Analysis

Stepwise discriminant analysis is an alternative method to the full model approach. When a number of potential discriminator variables are known, but there is no suggestion as to which would be the best set of variable for forming the discriminant function. Stepwise linear discriminant (SLD) analysis is a useful technique for selecting the best set of discriminator variables to form the discriminant function. It involves the independent variables into to discriminant function one at a time based on discriminating power. In forward stepwise analysis, all variables are evaluated in the first step to determine which one provides the most significant and unique discrimination between groups. Once this variable has been included in the model, all remaining variables are evaluated to determine which one provides the next best discrimination. The procedure continues until the addition of a new variable does not significantly improve the discrimination between groups (Sharma 1996:264-266).

In the presence of multicolinearity, SLD analysis may or may not be suitable depending on the source of multicolinearity. In the population-based multicolinearity, the pattern of correlation among discriminator variable within sampling error, is the same from sample to sample. In such a case, use of stepwise discriminant analysis is appropriate, as the relationship among variables in a population characteristic and the results will not change from sample to sample. On the other hand, the result of SLD analysis could differ from sample to sample if the pattern of correlation among the independent variables varies across sample. This is called sample-based multicolinearity. In such a case SLD analysis is not an appropriate technique (Sharma, 1996:265).

If stepwise DA is used to estimate the discriminant function, the Mahalanobis D^2 and Rao's V measures are most appropriate (Hair et al., 1998:262). In this study, we used Mahalanobis D^2statistical criteria for SLD analysis. In general, Mahalanobis $D^2$is preferred procedure when the researcher is interested in the maximal use of available information. The Mahalanobis D^2 procedure performs a stepwise discriminant analysis similar to a stepwise regression analysis, designed to develop the best one-variable model, followed best two-variable model, and so forth, until no other variables meet the desired selection criteria (Hair et al., 1998:262).

2.2. Logistic Regression Analysis

When the independent variables are a mixture of categorical and continuous variables, the multivariate normality assumption will not be satisfied. In this case one could use logistic regression analysis as it does not make any assumption about distribution of independent variables. If there are two groups, binary logistic regression (BLR) is used, whereas if there are three or more groups, a choice has to be made between nominal and ordinal logistic regression. Nominal logistic regression is used when there is no natural ordering to the groups, whereas ordinal logistic regression is used when there is an ordering. Logistic regression is discussed further by Hosmer and Lemeshow (1989) and by Dobson (1990).

Logistic Regression Analysis

In logistic regression models, dependent variable is always in categorical form and has two or more levels. Independent variables may be in numerical or categorical form. The BLR model is defined as below (Worth and Cronin, 2003):

$$L = Ln\left(p/1-p\right) = b_0 + b_1x_1 + b_2x_2 + ... + b_px_p \tag{4}$$

Where p/(1-p) is called the odds ratio and Ln(p/1-p) he logit transform of p; x_p is the pth predictor variable; and b_p is the coefficient of the pth predictor variable. In this equation, the logit transform is being used to relate the probabilities of group membership to a linear function of the predictor variables. The parameters of the logistic model (b_0 to b_p) are derived by the method of maximum likelihood (ML). If all observations are independent of one another, the likelihood of obtaining the sample of response values is the geometric sum of the probabilities of obtaining the individual response values. Instead of expressing the likelihood of the model in terms of a geometric sum (product of probabilities), it is customary to take the natural logarithm of the likelihood (the log-likelihood), which then becomes a function of the arithmetic sum of individual probabilities. Thus, algorithms for logistic regression work by maximizing the log-likelihood of a model, which is equivalent to minimizing its negative log-likelihood.

In BLR model, one can directly estimate the probabilities of an objects occurring as in Eq. 5:

$$p = \frac{1}{1+e^{-(b_0+b_1x_1+\cdots+b_px_p)}} \quad \text{and} \quad 1-p = \frac{1}{1+e^{(b_0+b_1x_1+\cdots+b_px_p)}} \tag{5}$$

The BLR model can be manipulated to define a probability for classifying the objects in to the pre-defined groups. The first step is to arrange Eq. 5 to express the probabilities of group membership in terms of independent variables directly. In the second step, the logistic regression coefficients b_1 to b_p; and the constant b_0; are used to define a model for classifying objects into one of the two groups. An object with an equal probability of belonging to the two groups has p=1-p; which means that Ln(p/1-p)=0; and from Eq. (4) that:

$$b_0 + b_1x_1 + \cdots + b_px_p = 0 \tag{6}$$

Therefore, an object can be assigned to fist group or second group according to the following rules:

$$\text{Classify into first group if} \quad b_0 + b_1x_1 + \cdots + b_px_p > 0 \tag{7}$$

$$\text{Classify into second group if} \quad b_0 + b_1x_1 + \cdots + b_px_p < 0 \tag{8}$$

These rules are based on a critical probability (p_c) value (cut-off value) of 0.5. If it is decided to use a different p_c value, the following general rules can be applied:

Classify into first group if $b_0 + b_1 x_1 + \cdots + b_p x_p > L\text{n}(p_c / 1 - p_c)$ (9)

Classify into second group if $b_0 + b_1 x_1 + \cdots + b_p x_p < L\text{n}(p_c / 1 - p_c)$ (10)

Assumptions of Binary Logistic Regression

As mentioned above, logistic regression assumes that a link function (in this case, the logit-transform) can be used to relate the probabilities of group membership to a linear function of the predictor variables. It is also assumed that the observations are independent, but unlike in the case of LD it is not assumed multivariate normal distribution and homogeneity variance.

2.3. Decision Tree Analysis

A decision tree (DT) develops classification systems that predict or classify future observations based on a set of decision rules. It classifies cases into groups or predicts values of a dependent (target) variable based on values of independent variables. The procedure provides validation tools for exploratory and confirmatory classification analysis. The tree consists of a set of decision rules, applied in a sequential manner, until each object has been assigned to a specific group. The first decision rule, applied at the parent node of the tree to the values of all objects along one or more predictor variables, has two possible outcomes: objects are sent either to a terminal node, which assigns a class, or to an intermediate (child) node, which applies another decision rule. Ultimately, all objects are sent to a terminal node and assigned a class. In the simplest type of DT, the splits are binary (each parent node is attached to two child nodes) and the decision rules are univariate (based on a single variable). DTs can be based on continuous or discrete predictor variables, or on a mixture of both.

Decision Tree Algorithms

The existing growing criteria may depend on the growing method, level of measurement of the dependent variable or a combination of the two. Four commonly used algorithms for constructing DTs are the Chi-squared Automatic Interaction Detection (CHAID) algorithm is originally proposed by Kass (1980); the Exhaustive CHAID is by Biggs et al (1991); Classification and Regression Trees (CRT), developed by Breiman et al. (1984); Quick, Unbiased, Efficient Statistical Trees (QUEST), developed and improved by Loh and Shih (1997) and Lim, Loh and Shih (2000).

At each step, CHAID algorithm chooses the independent variable that has the strongest relation with the dependent variable. Categories of each predictor are merged if they are not significantly different with respect to the dependent variable. Exhaustive CHAID, a modification of CHAID, examines all possible splits for each predictor but takes longer to compute. Classification and Regression Trees (CRT), splits the data into segments that are as homogeneous as possible with respect to the dependent variable. A terminal node in which all cases have the same value for the dependent variable is a homogeneous, whereas Quick, Unbiased, Efficient Statistical Tree (QUEST) is a method that is fast and avoids other methods bias in favor of predictors with many categories. QUEST can be used only if the dependent variable is nominal. It is claimed that the CRT algorithm is biased toward selecting predictor variables having more levels, whereas QUEST lacks this bias, and is therefore more appropriate when some predictor variables have few levels and other predictor variables have many levels (Loh and Shih, 1997).

CRT has a number of advantages over other classification methods such as logistic regression or discriminant analysis (Kitsantas et al., 2007). First, it can be used to classify data that involve either categorical or continuous dependent variables; second, it makes no distributional assumptions for the dependent and independent variables and it is not affected by outliers, colinearity, heteroscedasticity, or distributional error structures that affect parametric procedures. Thirdly, it deals effectively with large data sets and the issues of high dimensionality. CRT is a nonparametric classifier that it does not make any assumptions about the distributions of the variables. Thus, CRT analysis can be used when the assumptions of LD and BLR have not been satisfied. CRT analysis, however, is not based on a probabilistic model and thus we cannot describe probabilities associated with predictions derived from a CRT tree (SPSS Inc., 2006).

CRT is quite flexible. It allows unequal misclassification costs in the tree growing process. It also allows specifying the prior probability distribution in a classification problem. You can apply automatic cost-complexity pruning to a CRT tree to obtain a more generalizeable tree (SPSS Inc., 2006).

In CRT algorithm if dependent variable is categorical, there are three splitting criteria available: Gini, Twoing, and ordered Twoing criteria. Gini impurity measure is found that maximize the homogeneity of child nodes with respect to the value of the target variable. In Towing impurity measure, categories of dependent variable are grouped into two subclasses. Splits are found that best separate the two groups. Ordered Twoing is used only when dependent variable is ordinal categorical (SPSS Inc., 2002). The technical details of these homogeneity measures can be found at Brieman et al. (1984).

In this study, the Gini Index was used in the splitting process, while misclassification costs for each class were set to equal values. Cross validation was implemented to evaluate the predictive performance of each classifier. The selections of these criteria were based on the size of the data set (e.g., cross-validation is commonly used for smaller samples).

Splitting Criteria and Impurity Measures and Selecting the Best Tree

If a DT is grown until all terminal nodes are pure, the resulting tree is likely to overfit the data, and will therefore have a lower accuracy of classification when applied to new objects. Stopping rules control if the tree growing process should be stopped or not. The following stopping rules are used in SPSS: (1) if a node has identical values of the dependent variable; the node will not be split. (2) If all cases in a node have identical values for each predictor, the node will not be split. (3) If the current tree depth reaches the user-specified maximum tree depth limit, the tree growing process will stop. (4) If the size of a node is less than the user-specified minimum node size value, the node will not be split. (5) If the split of a node results in a child node whose node size is less than the user-specified minimum child node size, the node will not be split. (6) If for the best split of node t, the improvement is smaller than the user-specified minimum improvement, the node will not be split (SPSS Inc, 2004).

Even when the user applies a stopping rule, the final tree may not be the best tree, for maximizing accuracy of classification while at the same time minimizing complexity. The learning sample (resubstitution) risk decreases as the size of the tree increases. However, the risk generally decreases slowly as the first terminal nodes are removed, until a point is reached when the risk rises rapidly upon removal of additional nodes. This critical point can be used to define the best tree depth. Alternatively, if cross-validation is performed at each step of the pruning process, the cross-validated (CV) risk can be used to identify the best tree in the sequence. Generally, the CV risk falls slowly to a minimum value as terminal nodes are removed, and then rises rapidly as the last few nodes are removed. Thus, the best tree can be defined as the tree closest to the minimum. Alternatively, Breiman et al. (1984) suggested that the best-sized tree (tree depth) can be identified as the smallest tree whose CV risk does not exceed the risk of the minimum CV risk tree plus one standard error of this tree's CV risk. In SPSS with the CRT and QUEST methods, you can avoid over fitting the model by pruning the tree: the tree is grown until stopping criteria are met, and then it is trimmed automatically to the smallest subtree based on the specified maximum difference in risk. The risk value is expressed in standard errors (SPSS Inc., 2002).

2.4. Assessing the Goodness-of-Fit of Classification Models

The goodness-of-fit of a two-group classification model can be assessed in terms of its Cooper statistics, which can be calculated from a 2×2 contingency table (Table 1), using the definitions given in Table 2.

Table 1: A 2*2 Contingency Table

Observed Bank Group	**Predicted Bank Group**		**Marginal Totals**
	Domestic (D)	Foreign (F)	
Domestic (D)	*a*	*b*	*a+b*
Foreign (F)	*c*	*d*	*c+d*
Marginal Totals	*a+c*	*b+d*	*a+b+c+d*

The statistics sensitivity, specificity and concordance are generally of most interest when assessing the performance of a CM, since they provide measures of its ability to detect known domestic banks (sensitivity), foreign banks (specificity) and all banks (accuracy or concordance). The false positive and false negative rates can be calculated from the specificity and sensitivity as shown in Table 2.

Table 2: Definitions of the Cooper Statistics (Cooper et al., 1979)

Statistic	Definition
Sensitivity	The proportion (or percentage) of the domestic banks (banks that give positive results in observed), which the CM predicts to be domestic = $a/(a+b)$
Specificity	The proportion (or percentage) of the foreign banks (banks that give negative results in observed), which the CM predicts to be foreign = $d/(c+d)$
Concordance or accuracy	The proportion (or percentage) of the banks, which the CM classifies correctly = $(a+d)/(a+b+c+d)$
Positive predictivity	The proportion (or percentage) of the banks predicted to be domestic by the CM that give positive results in observed = $a/(a+c)$
Negative predictivity	The proportion (or percentage) of the banks predicted to be foreign by the CM that give negative results in observed =$d/(b+d)$
False positive (over classification) rate	The proportion (or percentage) of the foreign banks that are falsely predicted to be domestic by the CM =$c/(c+d)$= 1-specificity
False negative (uder-classification) rate	The proportion (or percentage) of the domestic banks that are falsely predicted to be foreign by the CM = $b/(a+b)$=1-sensitivity

The other two statistics, the positive and negative predictivity, are of more interest when focusing on the effects of individual banks. These statistics can be thought of as conditional probabilities: if a bank is predicted to be domestic, the positive predictivity gives the probability that it really is domestic; similarly, if a bank is predicted to be foreign, the negative predictivity gives the probability that it really is foreign. Strictly, the Cooper statistics (Cooper et al., 1979) should only be used for two-group CMs. If there are three or more levels of the categorical response, other statistics should be used. An example is the Kappa (κ) statistic, a chance corrected accuracy that takes a value of zero when there is no agreement and a value of one when there is perfect agreement. The κ statistic is defined as follows:

$$\kappa = (O - E)/(1 - E) \tag{11}$$

Where O is the observed and E is the expected accuracy by chance.

3. RESULTS AND DISCUSSION

The data set used in this study involves 18 domestic and 14 foreign commercial banks operating in Turkey in the period of 2002-2006. The reason that only commercial banks are included is to avoid comparison problems between different types of banks (commercial, investment, etc.). Banks have complete annual data for all years in the database.

The variables in this study involve ratios based on the financial statements of banks. Financial market participants and managers of firms have used financial ratio analysis for more than a century. Although most academics and financial analysts were excited about the potential of using these methods, others criticized the usage of financial ratios. However, despite these criticisms financial ratios are still used as a basis to classify a bank's performance. In order to get comparable results with previous studies, which examined the cost and profit efficiency of foreign and domestic banks, we focus on profitability and activity efficiency ratios. However, it has been suggested that a bank may easily increase profitability by taking excessive risks (Golin, 2001). For this reason, in addition to profitability and activity efficiency ratios, liquidity and cost-revenue indicators are also included in the analysis.

Table 3 presents the twelve ratios selected to measure the performance of domestic and foreign banks. Of course, many other ratios could have been used. However, an effort was made to make use of well-known ratios, used in previous bank research, as well as to keep them in a manageable number.

Table 3: Selected Ratios for Comparison of Domestic and Foreign Banks

Ratio Type	**Code**	**Variable (Ratio) Description**
Liquidity	*LA/TA*	Liquid Assets/Total Assets
	LA/STL	Liquid Assets/Short-Term Liabilities
	LA/(D+ROD)	Liquid Assets/(Deposit + Resources Other than Deposit)
Cost-Revenue	*IR/IC*	Interest Revenues/Interest Costs
	IC/TA	Interest Costs/Total Assets
	IR/TR	Interest Revenues/Total Revenues
Profitability	*NP/TA*	Net Profit/Total Assets
	NP/EC	Net Profit/Equity Capital
	PBT/TA	Profit Before Taxes/Total Assets
Activity	*(PE+SB)/TA*	(Personnel Expenses+ Seniority Benefits)/Total Assets
	(PE+SB)/PN	(Personnel Expenses +Seniority Benefits)/Personnel Number*1000 TL
	TOI/TA	Total Operating Income/Total Assets

* TL: Turkish Lira

The analysis of the observed differences between foreign (F) and domestic (D) banks is performed using linear discriminant and logistic regression analysis which is widely used statistical techniques with numerous applications in banking, finance and accounting. In this case, a discriminant and a logistic regression model is developed using as dependent variable the status of the banks (1 for domestic banks and 2 for foreign banks), whereas the independent variables involve the selected financial ratios. In the development of each CM, prior probabilities computed from sample size (unequal prior probabilities) for the two classes (D=1and F=2). When CRT analysis was performed, the Gini index was used as the measure of node homogeneity, maximum tree depth of 7, minimum cases in parent node of 9 and minimum cases in child node size of 3 observations was used as the stopping rules in SPSS 15 version for optimum solution. The best-sized tree in the sequence of optimally pruned trees was identified by applying 10-fold cross-validation pruning and selecting the tree with the minimum cross-validation cost. Finally, Cooper statistics were calculated for the three CMs, using the definitions given in Table 1 and Table 2.

Table 4 presents the descriptive statistics of these ratios using the data set for the period 2002–2006, while Table 5 presents their correlations.

Table 4: Descriptive Statistics of Selected Banking Ratios

Code	Status	n	Min.	Max.	Mean	Std. Dev.	Skew.	Kurt.
LA/TA	D	90	6.89	89.16	42.59	19.64	0.85	0.23
	F	70	19.97	98.47	53.71	22.35	0.43	-1.04
LA/STL	D	90	19.35	14237.32	555.99	2245.60	5.04	25.18
	F	70	40.49	467.87	107.85	62.11	3.26	16.23
LA/(D+ROD)	D	90	8.29	1973.06	125.40	302.28	4.90	25.41
	F	70	29.43	2203.50	122.21	265.57	7.30	56.78
IR/IC	D	90	74.01	22002.66	487.14	2376.14	8.67	78.04
	F	70	19.23	754.29	237.06	144.96	1.57	2.68
IC/TA	D	90	0.08	29.71	9.29	5.30	1.75	4.13
	F	70	1.42	37.91	7.42	6.32	2.56	8.37
IR/TR	D	90	40.21	137.46	81.32	12.75	0.22	4.77
	F	70	10.51	123.07	70.34	19.03	-0.75	2.89
NP/TA	D	90	-63.24	32.21	1.13	9.12	-3.94	30.26
	F	70	-17.61	21.52	1.83	4.85	0.05	7.84
NP/EC	D	90	-178.64	64.85	12.14	27.15	-4.41	28.95
	F	70	-59.14	46.45	8.69	18.03	-1.52	3.82
PBT/TA	D	90	-63.24	19.93	0.21	9.59	-3.79	22.24
	F	70	-17.61	96.82	7.78	16.64	3.38	14.41
(PE+SB)/TA	D	90	0.72	11.98	2.08	1.62	4.37	23.11
	F	70	0.96	10.23	3.02	1.98	2.02	4.75
(PE+SB)/PN	D	90	10.21	81.97	35.79	9.33	0.92	6.17
	F	70	15.07	269.81	82.28	62.43	1.24	0.71
TOI/TA	D	90	2.49	35.72	9.19	5.77	2.99	10.27
	F	70	-0.34	48.23	12.77	9.43	2.23	5.79

D: Domestic Bank and F: Foreign Bank

Different classification models (CMs) were produced by applying three statistical methods (LD, BLR and CRT) to 12 selected banking classification ratios. Strictly, LD is not appropriate, because domestic and foreign banks are not normally distributed (Table 4). The skewness and kurtosis statistics of some independent variables are large (e.g., skew>2, kurtosis>7; Fabrigar et al., 1999). From the Table 4, foreign and domestic banks are not equally dispersed (the standard deviations of bank groups are greatly differ). However, if these conditions are ignored, LD produces a statistically significant ($p<0.000$) discriminant model with a cut-off value 0.247, which is derived from the classification functions for the two groups (Eq. 12 and Eq. 13):

$$CF_D = 2.1 + 0.0002[LA/(D+ROD)] + 0.24[IC/TA] - 0.001[(PE+SB)/PN] + 0.1[TOI/TA] \quad (12)$$

$$CF_F = -3.4 - 0.003[LA/(D+ROD)] + 0.04[IC/TA] + 0.04[(PE+SB)/PN] + 0.2[TOI/TA] \quad (13)$$

Where CF_D, is the classification function for the group of domestic banks and CF_F, is the classification function for the group of foreign banks. Banks are classified as domestic if $CF_D > CF_F$ and as foreign if $CF_F > CF_D$.

To overcome with the effect of multicolinearity among the independent variables stepwise discriminant and logistic regression analysis is used in building discriminant and logistic regression model. Table 6 presents the results of discriminant and logistic regression models. It is founded that four of twelve ratios in logistic and discriminant models effect bank performance significantly, in spite of this seven of them are effective in formation of optimal CRT tree. The DT diagram of CRT model is given in Figure 2. All models are developed on the data set for the period 2002-2006 and four same significant independent variables included in the final logistic and discriminant functions namely LA/(D+ROD), IC/TA, (PE+SB)/PN*1000 TL and TOI/TA (Table 6). This analysis enables the identification of the ratios describing the characteristics of foreign and domestic banks throughout the examined period. LA/(D+ROD) and IC/TA has a negative coefficient in both models indicating that domestic banks are characterized by higher liquidity and interest cost on their assets compared to the foreign banks. On the other hand, (PE+SB)/PN*1000 TL and TOI/TA has a positive coefficient in both models indicating that foreign banks exhibit higher total operating income/total assets and (personnel expenses + seniority benefits)/personnel number*1000 TL compared to the foreign banks.

The three CMs all indicate that for a bank to be characterizing as domestic or foreign bank, it must have a certain threshold. However, the threshold value between foreign and domestic banks differs according to the statistical technique used to develop the CM. Strictly; the most appropriate model is CRT, developed by DT analysis. Since the assumptions of LD and BLR, which produced LD and LR respectively, were violated. However, all three models are reported in this paper to provide a means of comparing the different statistical techniques. The performances of CMs are summarized in Table 7 and Table 8.

Table 7: Classification Results of LD, LR and CRT Models

Build Model	Testing Sample			Validation Sample		
	D-D	F-F	Correct Classification	D-D	F-F	Correct Classification
Discriminant	88 (98.7%)	47 (67.1%)	135 (84.4%)	88 (98.7%)	45 (64.3%)	133 (83.1%)
Logistic	83 (92.2%)	53 (75.7%)	136 (85.0%)	84 (93.3%)	52 (74.3%)	135 (84.4%)
CRT	87 (96.7%)	63 (90.0%)	150 (93.8%)	86 (95.6%)	62 (88.6%)	148 (92.5%)

D: Domestic Bank; F: Foreign Bank

Table 7 summarizes the average correct classification rates of the testing and validation samples for LD, LR and CRT models. The summary of the overall testing (validation) sample classification rates of LD, LR and CRT models are 84.4% (83.1%), 85.0% (84.4%) and 93.8% (92.5%) respectively. The misclassified domestic (foreign) banks for testing sample are 2 (23), 7 (17) and 3 (7) respectively.

Table 5: Correlation Matrix of Independent Variables

	LA/TA	*LA/STL*	*LA/(D+ROD)*	*IR/IC*	*IC/TA*	*IR/TR*	*NP/TA*	*NP/EC*	*PBT/TA*	*(PE+SB)/TA*	*(PE+SB)/PN*
LA/TA	100										
LA/STL	.209	1.00									
LA/(D+ROD)	.398	.142	1.00								
IR/IC	.136	.022	.620	1.00							
IC/TA	.023	.063	.021	-.174	1.00						
IR/TR	-.276	.252	-.367	-.159	-.057	1.00					
NP/TA	.059	-.184	.324	.334	.130	-.429	1.00				
NP/EC	-.025	-.151	.114	.108	.175	-.247	.672	1.00			
PBT/TA	.366	-.324	.160	-.016	.025	-.339	.281	.136	1.00		
(PE+SB)/TA	.173	.204	.084	-.039	.051	-.005	-.501	-.377	-.160	1.00	
(PE+SB)/PN	.529	-.083	.289	-.024	.276	-.507	.188	.001	.414	.319	1.00
TOI/TA	.383	.007	.489	.281	.291	-.484	.335	.196	.136	.445	.489

Table 6: Stepwise Logistic Regression and Discriminant Analysis Results

	Linear Discriminant Analysis				**Logistic Regression Analysis**			
	SM	**CDF**	**SCDF**	***Sig.***	**Score**	***Sig.***	***B***	***Sig.***
Constant		0.578					-2.051	0.006
LA/TA	0.353				10.564	0.001		
LA/STL	-0.115				2.769	0.096		
LA/(D+ROD)	-0.007	-0.002	-0.517	0.001	0.005	0.378	-0.005	0.001
IR/IC	-0.060				0.778	0.044		
IC/TA	-0.208	-1.129	-0.741	0.000	4.073	0.000	-0.319	0.000
IR/TR	-0.304				17.167	0.560		
NP/TA	0.044				0.339	0.358		
NP/EC	-0.060				0.846	0.000		
PBT/TA	0.230				12.210	0.001		
(PE+SB)/TA	0.269				10.238	0.000		
(PE+SB)/PN	0.713	0.025	1.029	0.000	37.631	0.004	0.064	0.000
TOI/TA	0.303	0.047	0.359	0.031	8.432	0.000	0.161	0.003
Model Summary Statistics	(a) Canonical Correlation=61.4%; (b) Wilks' Lamda=0.623 (0.000) (c) Group Centroids: D=-0.682; F=0.877				(a) Nagelkerke R^2 = 58.9% ; (b) -2LogLikelihood *(-2LL)*=126.708 (c) Model Chi-Square = 92.593 (0.000)			

SM: Structure Matrix; CDF: Canonical Discriminant Function; SCDF: Standardized Canonical Discriminant Function.

The validation of discriminant, logistic and CRT model is accomplished by the same method. Although some improvements in the overall classification ratios were seen in the estimation samples, the validation samples were almost identical for LD, LR and CRT models. This leads to the conclusion that all build models have strong empirical support in their validation on samples at approximately same level.

In the case of CRT analysis, all banks predicted to be domestic (ineffective) have a probability of 0.926, which is the same as the positive predictivity associated with CRT (Table 8), and all banks predicted to be foreign (effective) have a probability of 0.045, which is equal to 1-negative predictivity (Table 8). The probability of 0.926 derives from the fact that 94 of the 160 observations are predicted to be domestic (ineffective), of which 87 are actually domestic (true negative) and 3 are foreign (true positive), i.e. p=87/94. The probability of 0.045 derives from the fact that 66 of the 160 observations are predicted to be foreign, of which 63 are actually foreign (true positives) and 3 is a domestic (false positive), i.e. p=3/66. In other words, LD and BLR are advantageous compared to CRT analysis in that they generate a meaningful probability for each bank.

Table 8: Cooper Statistics for LD, LR and CRT Models

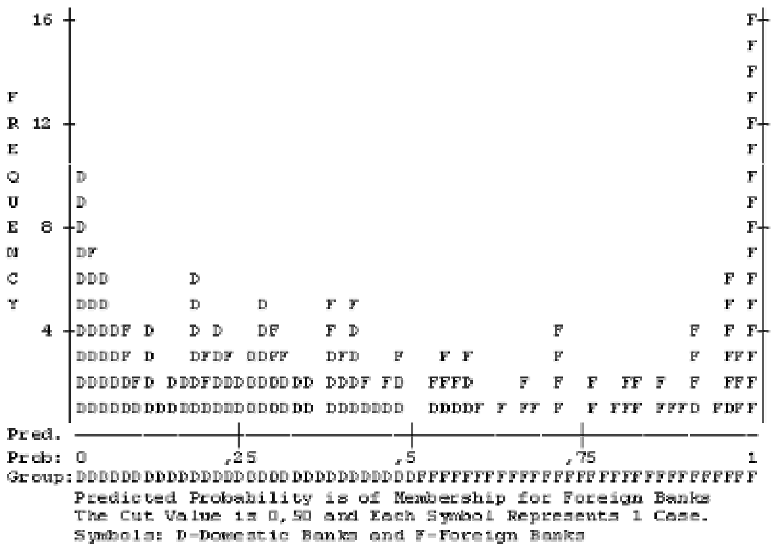
Cooper Statistics (%)	**Build Classification Models**		
	LD	**LR**	**CRT**
Sensitivity	97.8	92.2	96.7
Specificity	67.1	75.7	90.0
Accuracy	84.4	85.0	93.8
Positive Predictivity	79.3	83.0	92.6
Negative Predictivity	95.9	88.3	95.5
False Positive	32.9	24.3	10.0
False Negative	2.2	7.8	3.3

Despite the advantages of LD and BLR, in the case of the data set investigated (Table 4), it turns out that the underlying assumptions of the statistical techniques are not met, which means that CRT analysis is the most appropriate method, and that CRT is the model of choice. The fact that CRT has a sensitivity of 96.7 (Table 8) means that 96.7% of the known observation in the data set of 160 banks are correctly identified, and only 3.3% of the known domestic banks are incorrectly predicted to be foreign (false negative rate, Table 8). However, the price to be paid for the high sensitivity is the high false positive rate of 10%, i.e. 10% of the foreign banks also have a domestic bank performance.

However, the fact that CRT has a high negative predictivity of 95.5% indicates that the model could be useful in the context of a testing strategy in which it is employed for the identification of foreign (effective), but not domestic. The use of CRT could be justified on the basis that even though it only identifies 90% of the known foreign banks in the data set, of those banks it does predict to be foreign, 95.5% of these predictions are correct. Clearly, in the context of a testing strategy, the use of CRT would need to be accompanied by a model for identifying domestic (i.e. a model with a high positive predictivity).

The predicted group probabilities for each domestic and foreign bank are given in Table 11 and Table 12 respectively. In addition, the logistic regression classification results are given in Figure 1. The availability of such probabilities provides a means of overcoming one of the shortcomings of models that employ cut-off values to classify banks.

Figure 1: Observed Groups and Predicted Probabilities of LR Analysis



When banks are predicted to be effective or ineffective, there is no indication of whether the bank is predicted to be near to linear boundary between the foreign and domestics, in which case the prediction may be unreliable, or whether the bank is predicted to be far away from the boundary, in which case the prediction is more likely to be reliable. Probability values overcome this problem, since a bank with a probability of effectiveness close to 0.5 is close to the boundary, whereas banks with probabilities close to 0 or 1 are far way. In Table 11 and Table 12, it can be seen that the probabilities assigned by LD analysis and BLR are different, as would be expected given that they are based on different mathematical algorithms. However, the two methods give the same rank ordering of probabilities, as indicated by the fact that the Spearman rank correlation coefficient is near unity.

Type I And Type II Errors of the Built Models

It is known that, in order to justify the overall bank classification ability of the developed classification models, the prior probability of effective (foreign) and ineffective (domestic) banks, the misclassification probability, and misclassification costs have to be taken into account in order to obtain a model with the smallest expected misclassification costs (Johnson and Wichern, 2002).

Table 9: Type I and Type II Errors of Three Constructed Models

Build Model	Testing Sample		Validation Sample	
	Type I Error	Type II Error	Type I Error	Type II Error
Discriminant (LD)	1.3%	32.9%	1.3%	35.7%
Logistic (LR)	7.8%	24.3%	6.7%	25.7%
CRT	3.3%	10.0%	4.4%	11.4%

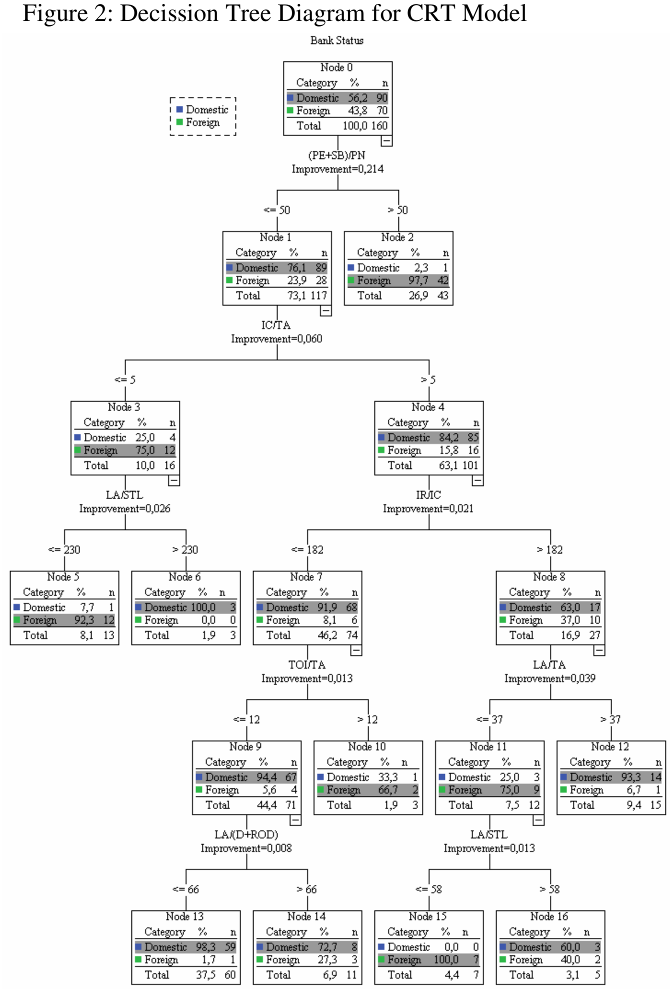
Thus, special attention also needs to be paid to misclassification cost in order to evaluate the bank classification accuracy of the LD, LR and CRT models. It is apparent that the costs associated with Type I errors (a bank being foreign / effective is misclassified as being ineffective / domestic) and Type II errors (a bank being ineffective is misclassified as being effective) are significantly different. In general, the misclassification costs associated with Type II errors are much higher than those associated with Type I errors. The difference can range from five to one up to 20 to one (West, 2000; Lee et al., 2006). Therefore, Type II errors of the three models need to be compared in order to justify the overall bank classification capability. Table 9 summarizes the Type I and Type II errors of the three built models. According to the results from Table 9, CRT has lower Type II errors in comparison with LD and LR models. Hence, we can conclude that CRT not only have higher classification accuracy, but also lower Type II errors and hence can reduce the possible high risks associated with Type II errors.

Evaluation of the Results of CRT Model

The risk complexity measures for building a classification model (Table 10) provides some very extensive information about the specifications used to build the models and the resulting model. Table 10 shows 16 different tree structures for this data set. Complexity of tree structures increases from Tree 1 to Tree 16. The number of terminal nodes is used as a principle complexity indicator. It is considered that risk-complexity measures are balanced and minimum for selection of optimal tree structure. In condition, that it is balanced, predictive accuracy of tree increases. Through the tree structures given in Table 10, the tree numbered 7 balancing the cost of misclassification (resubstitution risk=RS and cross-validation risk=CV), the complexity parameter (a penalty for additional terminal nodes) and the number of terminal nodes, was used in classification. In this tree, it is seen that the RS risk and the CV risk, the complexity parameter values are minimum and in addition to this, the RS risk value is the closest one to CV risk ± 1 standard error boundaries. In the tree structures as including terminal nodes to model, the CV risk got lover values at some points than start to stabilize. On the other hand, as including terminal notes to the tree structure RS risk always goes down but the complexity of the model goes up. Only in optimal tree (Tree 7), the RS risk and CV risk have given the most stable structure. The total number of nodes, terminal notes and tree depth of all possible models is changed between 1-35, 1-18 and 0-7 respectively (Table 10).

The risk and classification tables provide a quick evaluation of how well the model works. The risk estimate of 0.063 indicates that the category predicted by the model (efficient or inefficient) is wrong for 6.3% of the cases. So the risk of misclassifying a bank is approximately 6.3%. The results in the classification table are consistent with the risk estimate. The table shows that the model classifies approximately 93.8% of the banks correctly (Table 7 and Table 10). When the tree structures of other more complex models are obtained (from Tree 8 to Tree 16), overall classification success of banks rose up over 6.2% but no significant variation in classification success of banks was observed (Table 10).

Figure 2: Decission Tree Diagram for CRT Model



The optimal decision tree diagram of domestic and foreign banks is given in Figure 1. Twelve independent variables were specified, but only seven were included in the final model. The variables for IR/TR, NP/TA, NP/EC, PBT/TA and (PE+SB)/TA did not make a significant contribution to the model, so they were automatically dropped from the final model.

Table 10: The Risk Complexity Measures for Building a CRT Model

All Possible Trees	Nodes Number		Tree Depth	Resubstitution		Cross-Validation		Percent Correct
	Total	Terminal		Risk	S. Err.	Risk	Std. Error	
Tree 1	1	1	0	.438	.039	.438	.039	.563
Tree 2	3	2	1	.181	.030	.288	.036	.819
Tree 3	7	4	3	.131	.027	.219	.033	.869
Tree 4	9	5	4	.094	.023	.213	.032	.906
Tree 5	11	6	5	.088	.022	.219	.033	.913
Tree 6	13	7	6	.125	.032	.206	.029	.875
Tree 7*	**17**	**9**	**5**	**.063**	**.019**	**.124**	**.021**	**.938**
Tree 8	19	10	6	.063	.019	.238	.034	.939
Tree 9	21	11	6	.050	.017	.219	.033	.955
Tree 10	23	12	6	.050	.017	.238	.034	.950
Tree 11	25	13	6	.044	.016	.231	.033	.956
Tree 12	27	14	6	.031	.014	.213	.032	.969
Tree 13	29	15	7	.025	.012	.213	.032	.975
Tree 14	31	16	7	.038	.015	.213	.035	.988
Tree 15	33	17	7	.006	.006	.238	.034	.994
Tree 16	35	18	7	.000	.000	.245	.033	100

The tree diagram is a graphic representation of the tree model. This tree diagram shows that using the CRT method, (PE+SB)/PN*100 is the best predictor for bank classification. Both logistic regression and discriminant analysis models have given the same result. For the high (PE+SB)/PN*1000 is the only significant discriminator variable of bank classification. Of the banks in this category, 97.7% (42 banks) have classified as foreign (effective) bank (Figure 2). Since there are no child nodes below it, this is considered a terminal node (Node 2). The details of this result are given in Table 10 and Table 11. For the low (PE+SB)/PN (less than 50), the next best predictor is IC/TA. For low IC/TA (less than 5), the model includes one more predictor for 16 observations: *LA/STL*. Over 92% of those banks (13 banks) less than or equal to 230 have a good performance, while 3 of those over 230 have a bad performance. Since there are no child nodes below these nodes, they are considered as terminal nodes (Node 5 and Node 6).

The tree table (Table 13), as the name suggests, provides most of the essential tree diagram information in the form of a table. For each node, the table displays the number and percentage of cases in each category of the dependent variable. The predicted category for the dependent variable (bank status) is domestic or foreign with more than 50% of cases in that node, since there are only two possible bank statuses. The parent node for each node in the tree, note that node 2 is not the parent node of any node. Since it is a terminal node, it has no child nodes. The split value, the independent variable and its improvement used to split the node is summarized in Table 13.

As a summary, in CRT model four of nine terminal nodes obtained from the optimal tree are predicted as foreign (effective) banks (Nodes 2, 5, 10, 15), and five of them are predicted as domestic (ineffective) banks (Nodes 6, 12, 13, 14, 16) (Figure 2). In this condition, it can be told that in the conditions summarized below the commercial banks performance occur:

Table 11: Classification Results of Domestic Banks

Bank	Year	LD	LR	CRT	P1	P2	P3	N	Bank	Year	LD	LR	CRT	P1	P2	P3	N
Ziraat	02	1	1	1	.98	.99	.98	13	Tekfen	02	1	1	1	.97	.99	.98	13
	03	1	1	1	.92	.96	.98	13		03	1	1	1	.88	.94	.98	13
	04	1	1	1	.78	.83	.98	13		04	1	1	1	.74	.77	.98	13
	05	1	1	1	.75	.80	.98	13		05	1	1	1	.70	.72	.98	13
	06	1	1	1	.77	.83	.98	13		06	1	1	1	.71	.75	.98	13
Halk	02	1	1	2	.99	.99	.67	10	Tekstil	02	1	1	1	.95	.99	.98	13
	03	1	1	1	.94	.98	.98	13		03	1	1	1	.86	.93	.98	13
	04	1	1	1	.88	.94	.98	13		04	1	1	1	.75	.79	.98	13
	05	1	1	1	.81	.88	.98	13		05	1	1	1	.69	.73	.98	13
	06	1	1	1	.79	.85	.98	13		06	1	1	1	.69	.73	.98	13
Vakıflar	02	1	1	1	.94	.98	.98	13	Turkish	02	1	1	1	.95	.99	.73	14
	03	1	1	1	.87	.93	.98	13		03	1	1	1	.84	.91	.73	14
	04	1	1	1	.71	.74	.98	13		04	1	1	1	.82	.90	.73	14
	05	1	1	1	.67	.68	.98	13		05	1	1	1	.69	.64	.73	14
	06	1	1	1	.67	.68	.98	13		06	1	1	1	.75	.82	.73	14
Adabank	02	1	1	1	.93	.98	.73	14	Turkland	02	1	2	1	.59	.58	.60	16
	03	1	1	1	1.0	.99	.73	14		03	1	1	1	.64	.58	.60	16
	04	1	1	1	.75	.80	.93	12		04	1	1	1	.62	.58	.98	13
	05	2	2	2	.75	.90	.98	2		05	1	1	1	.63	.60	.98	13
	06	1	1	1	.75	.83	1.0	6		06	1	1	1	.70	.72	.98	13
Akbank	02	1	1	1	.80	.85	.93	12	TEB	02	1	1	1	.78	.83	.93	12
	03	1	1	1	.71	.69	.93	12		03	1	1	1	.73	.76	.98	13
	04	1	1	1	.64	.60	.93	12		04	1	1	1	.69	.70	.98	13
	05	1	1	1	.64	.62	.93	12		05	1	1	1	.61	.59	.93	12
	06	1	1	1	.66	.66	.98	13		06	1	1	1	.65	.65	.98	13
Alternatif	02	1	1	1	.96	.99	.98	13	Garanti	02	1	1	1	.91	.97	.98	13
	03	1	1	1	.84	.89	.98	13		03	1	1	1	.82	.89	.98	13
	04	1	1	1	.77	.80	.98	13		04	1	1	1	.65	.62	.98	13
	05	1	1	1	.59	.53	.98	13		05	1	2	1	.55	.53	.93	12
	06	1	1	1	.61	.56	.98	13		06	1	1	1	.62	.59	.98	13
Anadolu	02	1	1	1	.92	.97	.98	13	İş	02	1	1	1	.80	.86	.98	13
	03	1	1	1	.88	.94	.98	13		03	1	1	1	.72	.73	.98	13
	04	1	1	1	.76	.81	.98	13		04	1	2	1	.56	.53	.93	12
	05	1	1	1	.73	.77	.98	13		05	1	2	2	.51	.58	.92	5
	06	1	1	1	.67	.67	.98	13		06	1	1	1	.62	.60	.73	14
Oyak	02	1	1	1	.99	.99	.98	13	Yapı	02	1	1	1	.90	.95	.98	13
	03	1	1	1	.90	.96	.98	13	.Kredi	03	1	1	1	.91	.97	.98	13
	04	1	1	1	.83	.89	.98	13		04	1	1	1	.79	.85	.98	13
	05	1	1	1	.71	.73	.98	13		05	1	1	1	.65	.62	.98	13
	06	1	1	1	.77	.83	.98	13		06	1	1	1	.59	.54	.98	13
Şekerbank	02	1	1	1	.98	.99	.98	13	Birleşik	02	2	2	1	.72	.95	.93	12
	03	1	1	1	.91	.96	.98	13	Fon	03	1	1	1	.92	.96	.93	12
	04	1	1	1	.76	.76	.60	16		04	1	1	1	.88	.95	.93	12
	05	1	1	1	.63	.53	.93	12		05	1	1	1	.97	1.0	1.0	6
	06	1	2	1	.57	.55	.93	12		06	1	1	1	.91	.98	1.0	6

Domestic (Ineffective) Bank=1, Foreign (Effective) Bank=2. P1 P2 and P3 are Predicted Group Probabilities for LD, LR and CRT. N=Note Number.

Ineffective risk is less in the foreign banks of which (PE+SB)/PN levels are more than 50.499 (Node 2 in Figure 2 and Table 13).

Ineffective risk is less in the foreign banks of which (PE+SB)/PN levels are less than 50.499 and IC/TA levels less than or equal to 4.677 and LA/STL is less than or equal to 229.835 (Node 5 in Figure 2 and Table 13).

Ineffective risk is less in the foreign banks of which (PE+SB)/PN*1000 levels are less than 50.499 and IC/TA levels greater than 4.677 and IR/IC is less than or equal to 181.962 and TOI/TA is greater than 11.812 (Node 10 in Figure 2 and Table 13).

Table 12: Classification Results of Foreign Banks

Bank	Year	LD	LR	CRT	P1	P2	P3	N	Bank	Year	LD	LR	CRT	P1	P2	P3	N
Arap Türk	02	2	2	2	.78	.94	.98	2	Millennium	02	1	1	1	.24	.69	.60	16
	03	2	2	2	.86	.97	.98	2		03	2	2	2	.57	.70	.92	5
	04	2	2	2	.84	.96	.98	2		04	2	2	2	.54	.67	.98	2
	05	2	2	2	.82	.95	.98	2		05	1	2	2	.53	.55	.98	2
	06	2	2	2	.83	.96	.98	2		06	1	2	2	.53	.53	.98	2
Citibank	02	1	2	2	.51	.71	.98	2	ABN Amro	02	2	2	2	.86	.99	.98	2
	03	2	2	2	.62	.86	.98	2		03	2	2	2	.94	1.0	.98	2
	04	2	2	2	.60	.81	.98	2		04	2	2	2	.98	1.0	.98	2
	05	2	2	2	.65	.86	.98	2		05	2	2	2	.98	1.0	.98	2
	06	2	2	2	.58	.71	.98	2		06	2	2	2	1.0	1.0	.98	2
Deniz	02	1	1	1	.93	.98	.73	14	Banca Di Roma	02	2	2	2	.91	.99	.98	2
	03	1	1	1	.86	.93	.73	14		03	2	2	2	.89	.98	.98	2
	04	1	1	1	.76	.81	.93	12		04	2	2	2	.76	.91	.98	2
	05	1	1	2	.64	.63	.92	5		05	2	2	2	.75	.91	.98	2
	06	1	1	2	.61	.57	1.0	15		06	2	2	2	.83	.95	.98	2
Deutsche	02	2	2	2	.98	1.0	.98	2	Bank Mellat	02	1	2	2	.52	.57	.92	5
	03	2	2	2	.97	1.0	.98	2		03	2	2	2	.52	.65	.92	5
	04	2	2	2	.67	.77	.98	2		04	2	2	2	.51	.59	.92	5
	05	2	2	2	.65	.91	.98	2		05	1	1	2	.60	.60	.92	5
	06	2	2	2	.70	.89	.98	2		06	1	1	2	.56	.52	.92	5
Finans	02	1	1	2	.87	.92	1.0	15	Habib	02	2	2	2	.55	.75	.92	5
	03	1	1	2	.76	.77	.67	10		03	2	2	2	.61	.80	.92	5
	04	1	1	2	.70	.71	1.0	15		04	2	2	2	.63	.83	.92	5
	05	1	1	1	.64	.60	.60	16		05	2	2	2	.67	.83	.98	2
	06	1	1	2	.62	.55	1.0	15		06	2	2	2	.54	.63	.98	2
Fortis	02	1	1	2	.86	.91	.67	10	JP Morgan	02	2	2	2	1.0	1.0	.98	2
	03	1	1	1	.76	.80	.73	14		03	2	2	2	.99	1.0	.98	2
	04	1	1	1	.70	.72	.98	13		04	2	2	2	.99	1.0	.98	2
	05	1	1	2	.65	.82	1.0	15		05	2	2	2	.96	1.0	.98	2
	06	1	2	2	.55	.55	.98	2		06	2	2	2	.87	.98	.98	2
HSBC	02	1	2	2	.59	.55	1.0	15	Societe Generale	02	2	2	2	.96	1.0	.98	2
	03	2	2	2	.65	.87	.92	5		03	2	2	2	.98	1.0	.98	2
	04	2	2	2	.61	.81	.92	5		04	2	2	2	.95	1.0	.98	2
	05	2	2	2	.54	.71	1.0	15		05	2	2	2	.96	1.0	.98	2
	06	2	2	2	.78	.94	.98	2		06	2	2	2	.86	.96	.98	2

Domestic (Ineffective) Bank=1; Foreign (Effective) Bank=2. P1 P2 and P3 are Predicted Group Probabilities for LD, LR and CRT. N=Note Number.

Ineffective risk is more for the domestic banks of which (PE+SB)/PN*1000 levels are less than 50.499 and IC/TA levels is greater than 4.677 and IR/IC is greater than 181.962 and which LA/TA is greater than 36.723 (Node 12 in Figure 2 and Table 13).

Ineffective risk is more for the domestic banks of which (PE+SB)/PN*1000 levels are less than 50.499 and IC/TA levels greater than 4.677 and IR/IC is less than or equal to 181.962 and TOI/TA is less than or equal to11.812 and LA/(D+ROD) levels is less than or equal to 65.985 (Node 13 in Figure 2 and Table 13).

Table 13: Decision Tree Table of Domestic and Foreign Banks (CRT Model)

Node Number	Domestic		Foreign		Total		Predicted Category	Parent Node	Primary Independent Variable		
	n	Percent	n	Percent	n	Percent			Variable	Improvement	Split Values
0	90	56.3	70	43.8	160	100.0	Domestic		-	-	-
1	89	76.1	28	23.9	117	73.1	Domestic	0	*(PE+SB)/PN*	.214	≤50.499
2 (T)	1	2.3	42	97.7	43	26.9	Foreign	0	*(PE+SB)/PN*	.214	>50.499
3	4	25.0	12	75.0	16	10.0	Foreign	1	*IC/TA*	.060	≤4.677
4	85	84.2	16	15.8	101	63.1	Domestic	1	*IC/TA*	.060	>4.677
5 (T)	1	7.7	12	92.3	13	8.1	Foreign	3	*LA/STL*	.026	≤229.835
6 (T)	3	100.0	0	.0	3	1.9	Domestic	3	*LA/STL*	.026	>229.835
7	68	91.9	6	8.1	74	46.3	Domestic	4	*IR/IC*	.021	≤181.961
8	17	63.0	10	37.0	27	16.9	Domestic	4	*IR/IC*	.021	>181.961
9	67	94.4	4	5.6	71	44.4	Domestic	7	*TOI/TA*	.013	≤11.812
10 (T)	1	33.3	2	66.7	3	1.9	Foreign	7	*TOI/TA*	.013	>11.812
11	3	25.0	9	75.0	12	7.5	Foreign	8	*LA/TA*	.039	≤36.723
12 (T)	14	93.3	1	6.7	15	9.4	Domestic	8	*LA/TA*	.039	>36.723
13 (T)	59	98.3	1	1.7	60	37.5	Domestic	9	*LA/(D+ROD)*	.008	≤65.985
14 (T)	8	72.7	3	27.3	11	6.9	Domestic	9	*LA/(D+ROD)*	.008	>65.985
15 (T)	0	.0	7	100.0	7	4.4	Foreign	11	*LA/STL*	.013	≤58.294
16 (T)	3	60.0	2	40.0	5	3.1	Domestic	11	*LA/STL*	.013	>58.294

Growing Method: CRT; Dependent Variable: Bank Status; T: Terminal Node.

Ineffective risk is more for the domestic banks of which (PE+SB)/ PN*1000 levels are less than 50.499 and IC/TA levels greater than 4.677 and IR/IC is less than or equal to 181.962 and TOI/TA is less than or equal to11.812 and LA/(D+ROD) levels is greater than 65.985 (Node 14 in Figure 2 and Table 13).

Ineffective risk is less in the foreign banks of which (PE+SB)/PN*1000 levels are less than 50.499 and IC/TA levels greater than 4.677 and IR/IC is greater than 181.962 and LA/TA is less than or equal to 36.723 and LA/STL is less than or equal to 58.294 (Node 15 in Figure 2 and Table 13).

Ineffective risk is more for the domestic banks of which (PE+SB)/ PN*1000 levels are less than 50.499 and IC/TA levels greater than 4.677 and IR/IC is greater than 181.962, LA/TA is less than or equal to 36.723 and LA/STL is greater than 58.294 (Node 16 in Figure 2 and Table 13).

4. CONCLUSION

This paper identifies the unique financial factors of domestic and foreign banks in Turkey through discriminant, logistic regression and DT analysis comparatively in terms of the results obtained. Twelve financial ratios were employed for this purpose, covering most aspects of banking financial performance. The factors considered in the analysis cover all aspects of financial performance including liquidity, cost-revenue, profitability and activity efficiency. We test the hypothesis discussed in prior research, especially for developed countries in the context of the Turkish banking sector. It is typically find out that the foreign banks operating in a developed market are less efficient than domestic banks operating in the same market. We search whether this typical pattern also holds in Turkish commercial banking sector.

The obtained results show that the foreign banks exhibit higher overall performance compared to the domestic banks operating in the Turkey. Especially, domestic banks are characterized by higher liquidity and interest cost on their assets compared to the foreign banks. From the other point of view, foreign banks exhibit higher total operating income/total assets and (personnel expenses + seniority benefits)/personnel number*1000 TL compared to the foreign banks. As mentioned earlier that similar results have also been reported in previous studies on commercial banks efficiency for less developed countries (Demirguc-Kunt and Huizinga, 1999; Claessens et al., 2001). The financial indicators of NP/TA, NP/EC, PBT/TA and (PE+SB)/TA are not statistically significant in all LD, LR and CRT models.

The results of this study do not support in general the home advantage hypothesis under which domestic banks are generally more efficient than foreign banks for developed and developing countries. In contrast, it supports in the hypothesis under which foreign banks are generally more efficient than domestic banks for less developed countries.

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