Predicting business failures using the rough set theory approach: The case of the Turkish banks

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***Abstract*—** Predicting business failures before they actually take place is very important in order to be able to take necessary preventative measures. Such predictions are especially important in the banking sector that plays a key role in any economy. This paper focused on the Turkish banking sector, and after reviewing a number of quantitative tools, selected to apply the Rough Set Theory (RST) approach to analyze the failures of banks during the 1995-2007 period. The data for the financial ratio analysis for the 41 banks investigated from the publicly available sources. The results showed that early warning systems based on statistical models can effectively be used to predict bank failures. In this study, low capital ratios were found to be important variables in discriminating between failed and successful banks in Turkey. Also low and medium assets quality and profitability ratios were the leading indicators in predicting potential failures. The overall results showed that RST model is a promising alternative to the conventional methods for failure prediction.

***Keywords*—**Bank failure, financial ratios, prediction, rough set theory.

I. Introduction

The banking sector, because it plays a key role in any economy, is highly regulated. Such control is especially important in transition economies since the banking infrastructure and the needed legal framework is not well established yet. Thus, mismanagement of financial and human resources and sometimes corruption lead to bank failures leading to economic crisis. Examples of such bank failures include: Chile, Argentina, and Mexico (1980s); Thailand, Malaysia, Korea, Philippines, and Indonesia (1997); Russia (1998); and Turkey (1994, 2000, and 2001).

Key reasons for the collapse of a particular bank include poor banking practices, insufficient revenue diversification, inadequate capital, inability to assess credit risk, and lending to connected enterprises. The resulting nonperforming loans typically lead to crises that require government intervention. This might take in the form of creating new regulatory agencies and/or new laws. In some cases, public money is injected into the failing as a short-term solution. In other cases, the failing banks are liquidated and closed, merged with other banks or sold to other domestic or foreign banks.

The main goal of government regulatory agencies is to create a safe banking system that the investors could trust. Therefore, they are very much interested in establishing an "early warning system" that they can use to predict potential bank failures and prevent bankruptcies. Such models could use publicly available data and hence minimize the need for on-site examinations. Such analysis has a long history dating back to 1960s. For example, one of the early researchers on this topic, Altman proposed that firms with certain financial structures have a higher probability of failure within the next period than firms with opposite characteristics [1]. He used multivariate discriminant analysis to predict failing banks using five key financial ratios. Many other predictions techniques were introduced and tested with real data in later years.

The Rough Set Theory (RST) was introduced by Pawlak as one of those techniques that can be used in determining potential success/failure of a particular business [2]. The main objective of this study is to apply this theory to the Turkish banking sector for the 1995-2007 period to find out whether many of those bank failures could have been predicted using the publicly available financial data for these banks. Thirty six key ratios were used for the analysis.

This paper is organized as follows: Section 2 will be devoted to a literature review on bank failure models. Section 3 will provide a brief overview of RST. In section 4, an overview of the Turkish banking industry with special reference to reasons for the failure of certain firms and current regulatory system will be provided. Section 5 will introduce the methodology used and Section 6 will be devoted to the discussion of the empirical findings. The paper will be completed with a discussion of the conclusions and suggestions for further research.

II. Literature Review: Bank Failure Prediction Models

Academic researchers have devoted a great deal of time and effort in bank failure prediction models since late 1960s. Most of the earlier models were built using classical statistical techniques, such as multivariate discriminant analysis [3],

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logit regression [4], factor analysis [5], simultaneous-equations model [6], and Cox proportional hazards model [7]. Later studies have also used neural networks [8], split-population survival-time model [9], Bayesian belief networks [10], and isotonic separation [11].

Other types of models that combine non-parametric approaches with the discriminant or logit analysis for bank failure prediction have also been introduced. Tam and Kiang introduced neural network approach to perform discriminant analysis, as a promising method of evaluating bank conditions [12]. Jo and Han suggested an integrated model approach for bankruptcy prediction [13]. After comparing the discriminant analysis and two artificial intelligence models, neural network and case-based forecasting, the researchers concluded that the integrated models produced higher prediction accuracy than individual models. Alam stated that fuzzy clustering algorithm and self-organizing neural networks approaches provide valuable information to identify potentially failing banks [14]. Kolari used both parametric logit analysis and the nonparametric trait approach to develop computer-based early warning systems to identify large bank failures, and conclude that this system provides valuable information about the future viability of large banks [15]. Lam and Moy combined several discriminant methods, and performed simulation analysis to enhance the accuracy of classification results for classification problems in discriminant analysis [16].

Most of the above-mentioned models predict likely bank failures using financial ratios, instead of accounting variables. These financial ratios are usually constructed based on publicly available data that commercial banks are required to report to regulatory authorities on a regular basis. Given the importance of the subject, extensive research has been devoted to the design and identification of such financial ratios in the last three decades. As a result, a large set of financial ratios has been identified and applied in regulatory practices. These financial ratios are believed to be more effective explanatory variables than the raw accounting data in predicting and explaining bank failures.

Most of the financial ratios used in existing research can be classified into the categories of the CAMEL rating framework used by Federal Deposit Insurance Corporation (FDIC) of the United States. CAMEL is an acronym for the five major characteristics of a bank's financial and operational conditions: Capital adequacy, Asset quality, Management quality, Earnings ability, and Liquidity position. FDIC developed the CAMEL rating system in the early 1970s to assist in their scheduling of on-site bank examinations [17].

"Capital adequacy" is a measure of the level and quality of a bank's capital base while "asset quality" measures the level of risk of a bank's assets. "Management quality" is a measure of the quality of a bank's officers and the efficiency of its management structure. "Earnings ability" is used as a measure of the performance of a bank and the stability of its earnings stream. "Liquidity position" measures a bank's ability to meet unforeseen deposit outflow in a short time. One or more of these general characteristics could have an impact on a bank's profitability and eventual failure [18].

Although many of the models discussed above provided satisfactory ability to discriminate between healthy and potentially risky (candidates for bankruptcy) businesses, they also had their limitations. These limitations were often due to the unrealistic assumption of statistical hypotheses. The use of confusing language of communication with the decision makers also added to the problem [19]. As was mentioned earlier, this study uses the Rough Set Theory (RST) as an analytical tool to assess potential bank failures in Turkey.

III. BASIC CONCEPTS OF THE ROUGH SET THEORY (RST)

The Rough Set theory (RST), which proposed by Pawlak, has attracted the attention of many researchers and practitioners all over the world during the last decade. This has led to many scholarly contributions in its further development and applications [19]-[23]. It has found applications in a number of different fields [2]. For example, in pharmacology, the analysis of relationships between the chemical structure and the antimicrobial activity of drugs [24] has been successfully investigated. It was also used in several market research applications [2], [20]. Several researchers have also used for the banking industry in risk evaluation [2], [25], [26].

The RST can be approached as an extension of the classical set theory, for use when representing incomplete knowledge. RS can be considered sets with fuzzy boundaries, that is, sets that cannot be precisely characterized using the available set of attributes. The basic concept here is the notion of approximation space. Intuitively, a RS is a set or a subset of objects that cannot be expressed exactly by employing available knowledge [27].

The RS method accepts both quantitative and qualitative variables by deriving a number of decision rules (deterministic and non-deterministic sorting rules) or if… then rules. First, a range of minimal subsets of independent attributes is constructed. A subset of attributes is called a minimal subset if this subset has the same sorting quality as the whole set of attributes. Then, the core of attributes is defined as the intersection of all minimal subsets. Next, a reduced decision table is constructed, in which the redundant attributes are eliminated. Finally, on the basis of this decision table, the set of sorting rules, the sorting algorithm, is derived and firms are classified by matching their description to the set of sorting rules [28], [29].

A given RS has a lower and an upper approximation in terms of classes of indiscernible in terms of classes of indiscernible objects. Thus, one can argue that a rough set is a collection of objects that cannot be precisely characterized in terms of the values of the set of attributes, while its lower and upper approximations can. The lower approximation consists of all objects which certainly belong to the set. The upper approximation contains objects which possibly belong to the set and can be possibly classified as elements of that set using the set of attributes in the table [27].

The most important step in RS approach is the generation of decision rules which are then used to assign new objects to a decision class by comparing the condition part of one of the decision rule to the description of the object [27]. This process is sometimes referred to as knowledge reduction. Here one needs to introduce two key concepts, the core and the reduct.

The reduct is a subset of attributes which by itself can fully characterize the knowledge in the database. The reduct of an information system may not be unique. The set of attributes which is common to all reducts is called the core. The core is the set of attributes which is possessed by every legitimate reduct, and therefore consists of attributes which cannot be removed from the information system without causing collapse of the equivalence class structure. In other words, the core is the intersection of all reducts. Thus, the core is the most important subset of attributes and none of its elements can be removed without affecting the classification power of attributes. Complexity of computing all reducts in an information system is rather high. However, in many applications, one does not need to compute all reducts, but only some of them, satisfying specific requirements.

The solution procedure involves representing the objects in the form of an information table. The rows of the table are labeled by objects, whereas columns are labeled by attributes (or criteria). The entries of the table are attribute values (evaluations). An information table where the set of attributes is split into condition and decision attributes is called decision table [30]. Each decision rule is characterized by the strength of its suggestion. In other words, when applying the approximate rules, the strength of relationships is calculated for each possible decision class separately. Procedures for generating decision rules from a decision table operate on inductive learning principles [5].

A number of algorithms are available both for discretization and reduct computation [31]. In Rosetta software, three algorithms (genetic, Johnson's, and Holte's) are available for reduct computation [32]. Johnson's algorithm uses a simple greedy algorithm to compute single reducts only, however genetic algorithm is an implementation of a genetic algorithm for computing minimal hitting sets. In general, the genetic algorithm computes more reducts than the Johnson's algorithm More details about the Rosetta system and the different algorithms available can be found elsewhere [31], [32].

IV. TURKISH BANKING SECTOR

The pre-1980 Turkish banking sector can be characterized as a system with highly regulated and restricted interest rates, high intermediation costs, and strictly controlled foreign exchange operations. As the structure of the economy changed with the introduction of the Stabilization Program in 1980, several financial and trade liberalization programs were activated. The banks were allowed to fix credit and deposit rates and borrow directly from international financial institutions. The foreign exchange regime was also liberalized. In addition, uniform accounting principles were introduced, external auditing became mandatory.

The 1985 Banking Law established the Istanbul Stock Exchange and the Capital Markets Board. The inter-bank money markets were established and regular auctions of T bills and government bonds started. Several banks expanded their operations to the overseas markets by establishing subsidiaries and branches in Europe and the United States. The expansionary fiscal policies after the 1980s and the loose monetary policies in the early 1990s resulted in high inflation and public sector borrowing. The government relied on domestic borrowing by issuing short-term debt at high interest rates. Investing in government securities by opening foreign exchange positions became a main tool for private commercial banks.

Many international and domestic events affected the Turkish economy in a negative manner during the early 1990s. The Gulf War, the collapse of the Soviet Union, conflicts in the Middle East and the Balkans and perhaps the signing of the Customs Union agreement with the European Union contributed to an unstable economic and political environment in Turkey. Growing balance of payments account deficits applied pressure on the exchange rates resulting in a 60 percent devaluation in 1994 [33]. The overnight interest rates that reached to the 1000 percent level resulted in massive withdrawal from bank deposits. Banks faced severe liquidity problems and three banks were taken over by the regulatory agency. An IMF-supported stabilization program was introduced to overcome the crisis [34].

After the above crisis, the government found it much harder to raise money on international debt markets and hence it had to rely on domestic banks for its borrowings. It attracted the interests of the domestic by issuing bills and bonds with high interest rates [35]. Banks however, could not pursue the strategy of investing in government securities and creating foreign exchange (FX) positions for long. Net FX positions which were restricted to 50 percent of a bank's capital until July 1998 were reduced to 30 percent of the capital base by the end of 1998. It was further lowered in 1999 to 20 percent. These changes and other changes related to bank deposits increased the operational costs for banks and hence reduced profits [33].

Five banks that were having problems were taken over by the Saving Deposit Insurance Fund (SDIF) at the end of 1999. To avoid further failures, a new regulatory body, the Board of Bank Regulation and Supervision Agency (BRSA), was established in September 2000. The main goal of this new agency was bank supervision by addressing issues such as capital requirements open positions in foreign exchange [36]. Meanwhile, the government started privatization efforts for four large state banks. Nevertheless, another banking crisis in November 2000 due to a combination of exchange rate and interest rate shocks resulted in the failure of three more banks. In response, the IMF rapidly released a $10 million credit in December 2000. However, these efforts could not prevent the currency crisis of February 2001 with 30 percent devaluation in the Turkish Lira [37].

The above crises once again showed the structural weaknesses and the fragility of the banking system. During the 1997-2002 period, 20 banks were transferred to the SDIF [39]. In 2001, the Banking Sector Restructuring Program was announced as to eliminate structural weaknesses, to ensure transparency and to enhance confidence in the banking sector [38].

V. THE METHODOLOGY

As was mentioned earlier, under the liberalized banking system during the 1980s, the number of banks in Turkey reached to 41 in 1995. A number of domestic and international events in early 1990s caused economic hardships for the country and also for the banking industry. As a result, the first bank failure (Turk Ticaret Bankasi) took place in 1997. Further failures took place until 2003, and the total number of banks declined to 29. There have been no more bankruptcies between 2004 and 2007. Could these bank failures be prevented if the government regulators had some early warning systems?

The main objective of this study was to investigate whether the failures in the Turkish banking system during 1995-2007 period could have been predicted in advance. The rough set theory (RST) was used as an analytical tool. The data used was obtained from the web site of the Banks Association of Turkey. This site is publicly accessible and provides detailed ratios of all of the Turkish banks [35]. The files on this site are presented in two sections; ratios between years of 1988-2000, and the ratios between years of 2001-2006. For 1988-2000, 49 ratios are defined and reported. After the economic crisis of 2001, these ratios were redefined and increased to 60. For the 2001-2006 time period, the information on failed banks has been removed and only ratio information on banks in activity has been given.

The key financial ratios for the commercial banks under investigation were examined under 5 groups (Table I) where the ratios in each group were compared for the same years. This was to ensure that the banks in each group were influenced by the same macroeconomic, political, and legal environment. For each group, the year of failure is denoted as year (t). It is argued that potential failure signals might have been given one (t-1) or two (t-2) years before the actual failure. Thus, financial ratios were analyzed for a three-year period for each group. For example, all 41 banks were included in group I. Of these, Turk Ticaret Bank failed in 1997. Thus, 1997 was year (t) for group I banks while 1996 was (t-1) and 1995 was (t-2). Consequently, ratio analysis was completed for these three years for group I banks.

Group II consisted of 40 banks after removing the single failed bank (Ticaret Bank) from the list. One of these banks failed in 1998 (year t). Thus, the ratios for the years 1998, 1997, and 1996 were examined for Group II. Likewise, Group III consisted of 39 banks (33-healthy, 6-failed) and the ratio analysis was conducted for 1999, 1998, and 1997. After removing the 6 failed banks, Group IV consisted of 33 banks. For these, the ratio analysis was conducted for the years 2000, 1999, and 1998. Four banks failed in 2000. As a result, Group V consisted of 29 banks of which 8 failed in 2001. The ratio analysis for this final group was conducted for the years 2001, 2000, and 1999. Table I is provided for decision attributes, where "1" indicates a healthy bank and "0" indicates a failed bank.

Table I. Privately-owned commercial banks in Turkey from 1995 to 2001

Code	Privately-owned Commercial Banks	G-I	G-II	G-III	G-IV	G-V
a1	Adabank A.S.	1	1	1	1	1
a2	Akbank T.A.S.	1	1	1	1	1
a3	Alternatif Bank A.S.	1	1	1	1	1
a4	Anadolubank A.S.	1	1	1	1	1
a5	Birlesik Turk Korfez Bankası A.S.	1	1	1	1	1
a6	Denizbank A.S.	1	1	1	1	1
a7	Fiba Bank A.S.	1	1	1	1	1
a8	Finans Bank A.S.	1	1	1	1	1
a9	Koçbank A.S.	1	1	1	1	1
a10	MNG Bank A.S.	1	1	1	1	1
a11	Oyak Bank A.S.	1	1	1	1	1
a12	Pamukbank T.A.S.	1	1	1	1	1
a13	Sekerbank T.A.S.	1	1	1	1	1
a14	Tekstil Bankası A.S.	1	1	1	1	1
a15	Turkish Bank A.S.	1	1	1	1	1
a16	Turk Dis Ticaret Bankası A.S.	1	1	1	1	1
a17	Turk Ekonomi Bankası A.S.	1	1	1	1	1
a18	Turkiye Garanti Bankası A.S.	1	1	1	1	1
a19	Turkiye Imar Bankası T.A.S.	1	1	1	1	1
a20	Turkiye Is Bankası A.S.	1	1	1	1	1
a21	Yapı ve Kredi Bankası A.S.	1	1	1	1	1

1: Healthy, 0: Failed

Code	Banks Under the Department Insurance Fund	G-I	G-II	G-III	G-IV	G-V
a22	Turk Ticaret Bankası A.S. (Jan 6, 1997)					
a23	Bank Ekspres A.S. (Dec 12, 1998)	1	0	-	-	-
a24	Interbank (Jan 7, 1999)	1	1	0	-	-
a25	Turkiye Tutunculer Bankası Yasarbank A.S. (Dec 21,1999)	1	1	0	-	-
a26	Egebank A.S. (Dec 21, 1999)	1	1	0	-	-
a27	Yurt Ticaret ve Kredi Bankası A.S. (Dec 21, 1999)	1	1	0	-	-
a28	Sumerbank A.S. (Dec 21, 1999)	1	1	0	-	-
a29	Eskisehir Bankası T.A.S. (Dec 21, 1999)	1	1	0	-	-
a30	Demirbank T.A.S. (Dec 6, 2000)	1	1	1	0	-
a31	Etibank A.S. (Oct 27, 2000)	1	1	1	0	-
a32	Bank Kapital Turk A.S. (Oct 27, 2000)	1	1	1	0	-
a33	Kibris Kredi Bankasi (Sep 27,2000)	1	1	1	0	-
a34	Bayindirbank A.S. (July 9,2001)	1	1	1	1	0
a35	Ege Giyim Sanayicileri Bankası A.S. (July 9, 2001)	1	1	1	1	0
a36	Iktisat Bankasi T.A.S. (Mar 15, 2001)	1	1	1	1	0
a37	Milli Aydin Bankası T.A.S. (July 9, 2001)	1	1	1	1	0
a38	Sitebank A.S. (July 9, 2001)	1	1	1	1	0
a39	Toprakbank A.S. (Nov 30,2001)	1	1	1	1	0
a40	Kentbank A.S. (July 9, 2001)	1	1	1	1	0
a41	Ulusal Bank T.A.S. (Feb 28, 2001)	1	1	1	1	0

1: Healthy, 0: Failed

The Banks Association of Turkey provides data on 49 variables on its Web site [35]. For the purposes of this study, six categories of financial data were relevant. These categories were as follows: Capital ratios; Assets quality; Liquidity; Profitability; Income-Expenditure structure; and Activity ratios. Overall, a total of 36 variables were relevant for the purposes of this study and were selected (Table II). These variables were chosen to create condition attributes of the information table used in the study.

Table II. Financial Ratios Investigated

Ratio	Var	Definitions
Capital Ratios (%)	cr1	Standard Capital Ratio (*This was the ratio which was calculated by the banks according to the Decree no.23388 that was published by the Under secretariat of the Treasury.)*
	cr2	(Shareholders' Equity +T. Income)/Total Assets
	cr3	(Shareholders' Equity + T. Income)/(Deposits + Non-deposit Funds)
	cr4	Net Working Capital/Total Assets
	cr5	(Shareholders' Equity+ Total Income)/(T. Assets + Contingencies and Commitments)
	cr6	Fx Position/Shareholders' Equity
Assets Quality (%)	aq1	Total Loans/Total Assets
	aq2	Non Performing Loans/Total Loans
	aq3	Permanent Assets/Total Assets
	aq4	Fx Assets/Fx Liabilities
Liquidity (%)	li1	Liquid Assets/Total Assets
	li2	Liquid Assets /(Deposits + Non-deposit Funds)
	li3	Fx Liquid Assets/Fx Liabilities
Profitability (%)	pr1	Net Income(Loss)/Average T. Assets
	pr2	Net Income(Loss)/Average T. Assets
	pr3	Net Income(Loss)/Average Share-in Capital
	pr4	Income Before Tax / Average Total Assets
	pr5	Provision for Loan Losses/Total Loans
	pr6	Provision for Loan Losses / Total Assets
Income-Expenditure Structure (%)	ie 1	Net Interest Income After Provision/Average T. Assets
	ie 2	Interest Income/Interest Expenses
	ie 3	Non-Interest Income /Non-Interest Expenses
	ie 4	Total Income / Total Expenditure
	ie 5	Interest Income/Average Profitable Assets
	ie 6	Interest Expenses/Average Non-Profitable Assets
	ie 7	Interest Expenses/Average Profitable Assets
	ie 8	Interest Income/Total Income
	ie 9	Non-Interest Income /Total Income
	ie 10	Interest Expenses/Total Expenses
	ie 11	Non-Interest Expenses/Total Expenses
Activity Ratios (%)	ar1	(Salaries and Emp'ee Benefits +Reserve for Retirement)/T. Assets
	ar2	(Salary and Emp'ee Bene.+ Res. for Retire.)/No. of Pers. (Bil. TL)
	ar3	Reserve for Seniority Pay/No. of Personnel (Billion TL)
	ar4	Operational Expenses/Total Assets
	ar5	Provisions except Provisions for Income Tax/Total Income
	ar6	Provisions including Provisions for Income Tax/Total Income

The first step of the analysis involves recoding the quantitative ratios (continuous variables) into categorical variables using quartiles (-∞, 0.25]-low, (0.25, 0.50]-medium, (0.50, 0.75]-high and (0.75, ∞)-very high) with corresponding numeric values of 1, 2, 3 and 4. The recoding is done by dividing the original domain into subintervals since such analysis is very useful in drawing general conclusions from the ratios in terms of dependencies, reducts, and decision rules [19]. In fact, the original domain can be divided into different number of subintervals using different approaches (such as the use of medians and geometric means), but in literature, generally quartiles were used for this purpose. This recoding is a requirement of the RST, but the Rosetta software does not do that automatically. So the user recodes the domain manually. Thus, in this study, the information tables were created by recoding the original data into four subintervals based on the quartiles for the actual ratios (for the current year (year t), and for years (t-1) and (t-2) for the whole sample. The subintervals were assigned codes 1 through 4 where the highest code (code 4) was reserved for the best subinterval (e.g. highest assets quality).

In the second step, the recoded 36 condition attributes (Table II) and decisions attributes belong to each group (Table I) are examined individually for each year by using the ROSETTA GUI Version 1.4.41 software [32]. For each group, the condition attributes that affect the decision attributes for years (t-2), (t-1), and (t) were examined under the same economic, political, and legal conditions. Overall, 14 different information tables were organized for examination. Johnson's algorithms produced better solutions in reduction process than the genetic algorithms for the data used in this paper.

VI. EMPIRICAL RESULTS

As was previously mentioned, many different approaches have been used by researchers to predict business failures and bankruptcies. The RST has been used for the same purpose in many fields during the last decade. For example, the unfavorable changes in financial ratios of banks due to economic conditions they are experiencing may give danger signals for the future failure outcomes. If these signals are recognized correctly, perhaps remedies could be found. The main research question of this study was as follows: Were the attributes that ensure discrimination between the banks in the bankruptcy/failure) year (year t) the same signals in year (t-1) or year (t-2)?

The information in Table III is used here as a way of illustrating the notation used in the remaining tables in this paper. RST classifies banks according to decision conditions. After using Johnson's algorithm for reduct computation, seven decision rules were established for the year 1995 and the results were shown (Table III). The first column shows the number of rules obtained from Johnson's algorithm, columns 2-5 show same attributes of banks whose codes were defined in Table I and Table II. The values on the second through the fifth columns are the codes for common attributes. In the sixth column for the year 1995, D represents decision which shows whether the banks failed (with corresponding number 0) or not failed (with the corresponding number 1) and in the seventh column of Table III, S represents strength which shows the number of the banks that have the same attributes. For example, in 1995, rule 1 indicates that there were 7 banks with very high cr1 ratio (code 4) and rule 2 indicates that there were 8 banks with medium cr1 ratio (code 3). The remaining rows in this table and in Tables IV, V, and VI can be interpreted in a similar fashion.

If one can recognize of danger signals 1 year or 2 years before the actual failure, perhaps necessary actions can be taken to avoid the failure. For example, when the ratios of the Turk Ticaret Bank that failed on Jan 6, 1997 and ratios of other 40 banks are examined together for years 1995, 1996 and 1997, the low capital ratios of this bank gave danger signals. For the year 1995, cr1-low and ie8-medium and in 1996, li2-medium and pr6-medium indicate that the economical indicators are in low level. In 1997, when the bank failed, cr5 and pr2 were in low level (Table III). The decision rules on the Bank Express that failed on Dec 12, 1998 are given in Table IV. When the ratios of Bank Express and of 39 banks that were active in 1998 are examined together, it is seen that capital ratios are the attributes that ensure discrimination.

Table III. Decision rules for Turk Ticaret Bank

Year 1995						
Rule	ca1	ca2	ca4	ie8	D	S
1	4				1	7
2	2				1	8
3	3				1	8
4		4			1	7
5		2			1	8
6			1		1	7
7	1			2	0	1

Year 1996								
Rule	ca1	ca2	ca4	ca5	li3	pr6	D	S
1	2						1	8
2	4						1	5
3	3						1	10
4			2				1	8
5			3				1	8
6		2					1	8
7				2			1	8
8					2	2	0	1

Year 1997								
Rule	ca1	ca2	ca4	ca5	aq2	pr2	D	S
1	4						1	8
2	2						1	8
3	3						1	8
4					3		1	8
5		2					1	8
6		4					1	8
7			2				1	7
8				1		1	0	1

Table IV. Decision rules for Bank Ekspres

Year 1996							
Rule	ca1	ca2	ca4	ca5	aq3	D	S
1	2					1	6
2	4					1	7
3	3					1	8
4		3				1	8
5		4				1	7
6		2				1	8
7			3			1	8
8				3		1	8
9		1			2	0	1

Year 1997						
Rule	ca1	ca2	ca4	pr5	D	S
1	4				1	8
2	3				1	9
3	2				1	7
4		3			1	8
5		4			1	8
6			1	2	0	1

Year 1998							
Rule	ca1	ca2	ca4	ca5	ca6	D	S
1		2				1	8
2		3				1	8
3	4					1	8
4	2					1	8
5	3					1	8
6				4		1	8
7			3			1	7
8	1				2	0	1

In 1999, the year when the commercial banks in Turkey faced with economical crises for the first time resulted in collective failures experienced. 6 banks failed in 1999. An examination of Table 5 indicates that the capital ratios and profitability ratios for total 39 banks (33-healthy, 6-failed) were low in year t-2 (1997) and year t-1 (1998). Low capital ratios ensured discrimination between banks in great extent in 1999.

Table V. Decision rules for Group III

Year 1997											
Rule	ca1	ca2	ca4	ca6	aq1	aq3	li3	pr5	pr6	D	S
1	4									1	8
2	3									1	9
3						4				1	9
4			3							1	10
5							3			1	10
6		4								1	9
7					3					1	9
8				3						1	9
9									3	1	6
10								1		1	11
11	1		1							0	1
12	1		2							0	3
13		1							2	0	3
14	1							3		0	1
15		2						2		0	1

Year 1998											
Rule	ca1	ca2	ca4	aq1	aq3	li1	li2	pr3	ac3	D	S
1	4									1	9
2	3									1	9
3			3							1	10
4					3					1	10
5				2						1	9
6								3		1	10
7		4								1	9
8				3			1			0	3
9	2								1	0	1
10		1				1				0	3
11			1			1				0	4

Year 1999								
Rule	ca1	ca2	ca3	ca4	ca6	aq1	pr3	D	S
1	4							1	8
2	3							1	9
3	2							1	9
4			3					1	10
5		2						1	10
6					4			1	10
7				3				1	9
8			1		1			0	6
9						2	1	0	1
10				1	1			0	6

Four more banks failed in 2000. When one examines Table VI, it is seen that capital ratios ensured discrimination between the banks that bankrupted and the banks that continued their activities and additionally, assets quality ratios were also the attributes that caused discrimination. While in 1998 the attributes causing the discrimination were low and medium, in 1999, they improved slightly as medium and high but in 2000, they again decreased to low and medium levels.

Table VI. Decision Rules for Group IV

Year 1998									
Rule	ca1	ca2	ca4	ca6	aq2	aq3	aq4	D	S
1	4							1	7
2	2							1	8
3		3						1	7
4		4						1	8
5			2					1	9
6			3					1	8
7				3				1	7
8			1			2		0	2
9		2					2	0	1
10			1		1			0	1

Year 1999										
Rule	ca1	ca2	ca3	ca4	ca6	aq2	li4	aq5	D	S
1		2							1	7
2		4							1	7
3			3						1	8
4	3								1	8
5	2								1	8
6				3					1	7
7						4			1	7
8					2				1	7
9						3		2	0	1
10			1				2		0	1
11					3			2	0	2

Year 2000										
Rule	ca1	ca4	ca5	ca6	aq1	aq3	pr1	pr2	D	S
1	4								1	7
2	3								1	8
3	2								1	8
4					2				1	8
5				4					1	7
6				2					1	7
7			3						1	7
8						3		1	0	1
9		2					1		0	1
10					2			1	0	2

In 2001, Turkey experienced a major economic crisis pulling all economic indicators down. One of the sectors greatly affected from that economical crisis was the finance and banking sector. In 2001, many companies went bankrupt including 8 commercial banks. The economic crisis of 2001 was not due to the result of a major change of that year. It was the result of final explosion of the economic disorder that continued for years.

Table VII. Decision rules for Group V

Year 1999													
Rule	ca1	ca2	ca3	ca4	ca6	aq2	aq3	pr1	pr3	ie7	ac6	D	S
1					3							1	7
2							4					1	7
3	3											1	7
4								3				1	7
5		3		4								1	2
6									3			1	8
7						2						1	7
8		2								3		0	1
9	2										2	0	3
10	2									3		0	2
11	1									3		0	1
12	1				2							0	2
13	1			2								0	1
14	2		1									0	1

Year 2000									
Rule	ca1	ca2	ca4	ca6	aq4	pr1	pr2	D	S
1	4							1	7
2	3							1	7
3							3	1	7
4					3			1	8
5						3		1	7
6			4					1	7
7		2		1				0	1
8	1							0	7

When ratios of 29 banks (21-healthy, 8-failed) are examined for 1999 and 2000 years, it is seen that assets quality, profitability, income-expenditure structure and activity ratios were effective in addition to capital ratios (as ratios of failed banks were removed from the list, ratios information of 2001 year could not be obtained). Table VII indicates that many ratios in the banking sector began to change in a negative manner in years of 1999 and 2000 indicating that danger was about to appear. After the crisis, as indicated before, there were major measures taken in the banking sector including the creation and reporting of additional ratios (ratios increasing from 49 to 60) to predict potential failures in advance. As a result, from 2001 until today, only 2 banks failed and other banks have continued their activities.

VII. CONCLUSIONS

Banking industry, because of the key role it plays in any country's economy, is highly regulated all around the world. In spite of this, bank failures are not uncommon both in the developed and developing countries. Given the potentially high cost of a failed banking enterprise to the economy, all measures must be taken to prevent bankruptcies. Frequent on-site visits by the government regulators might be one solution. However, such visits are costly and impractical. An alternative might be to create statistical models that would use publicly available data about individual banks and create an early warning system. The types of models used by researchers during the last decades have been reviewed earlier. One such model is based on RST.

In this study, the Turkish banking system was used as a case analysis to determine whether RST can be applied in discriminating between failing banks and successful banks. The result was that, this technique provides strong results in explaining bank failures in Turkey. The 1995-2007 period was used for the analysis using 46 financial variables from publicly available data sources provided by the Bank Association of Turkey. The major conclusions of this study are:

- Early warning systems based on statistical models can effectively be used to predict whether a particular bank is giving negative signals one or two years before the actual failure.
- The RST is a powerful analytical tool that can point out potential business failures before the actual outcomes so that policy-makers can take necessary measures.
- In the Turkish case, the low capital ratios were found to be important variables in discriminating between successful banks and those that failed.
- Low and medium assets quality and profitability ratios were the leading indicators in predicting future failures.
- One limitation of this study is that, due to the economic crisis and removal of information of failed banks in the year 2001, decision rules examined only for the years 1999 and 2000 for Group V.

This study utilized the RST as a tool in the direction of creating an early warning system to avoid bank failures. The results were very promising. In the second stage of this project, the researchers will aim at comparing the prediction power of these models with selected other models that are commonly used for the same purpose. In order to predict future failures of banks, statistical techniques such as discriminant analysis, logistic regression or fuzzy clustering, were left for future studies.

REFERENCES

[1] E. I. Altman, "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy," *J of Finance*, vol. 4, pp. 589–609, 1968.

[2] Z. Pawlak, "Rough Set Approach to Knowledge-Based Decision Support," *European J of Oper Res*, vol. 99, pp. 48-57, 1997.

[3] S. W. Looney, J. W. Wansley, and W. R. Lane, "An examination of misclassification with bank failure prediction models," *J of Eco and Bus*, vol. 41, pp. 327–336, 1989.

[4] J.B. Thomson, "Predicting bank failures in the 1980s," *Economic Review*," Q: I, pp. 9–20, 1991.

[5] R. G. West, "A factor-analytic approach to bank condition," *J of Banking and Finance*, vol. 9, pp. 254–266, 1985.

[6] A. Demirgue-Kent, "Modeling large commercial-bank failures: A simultaneous equation analysis," Working paper 8905, Federal Reserve Bank of Cleveland: Cleveland, OH, 1989.

[7] G. Whalen, "A proportional hazards model of bank failure: An examination of its usefulness as an early warning tool," *Economic Review*, Federal Reserve Bank of Cleveland, vol. 27, pp. 21–31, 1991.

[8] P. Swicegood, and J. A. Clark, "Off-site monitoring systems for predicting bank underperformance: A comparison of neural networks, discriminant analysis, and professional human judgment," *Int J of Intelligent Syss in Acc, Finance & Management*, vol. 10, no. 3, pp. 169–186, 2001.

[9] R. Cole, and J. Gunther, "Separating the likelihood and timing of bank failure," *J of Banking and Finance*, vol. 19, no: 6, pp. 1073–1089, 1995.

[10] S. Sarkar, and R. S. Sriram, "Bayesian models for early warning of bank failures," *Management Science*, vol. 47, no: 11, pp. 1457–1475, 2001.

[11] Y. U. Ryu, and W. T. Yue, "Firm bankruptcy prediction: Experimental comparison of isotonic separation and other classification approaches," *IEEE Trans. on Sys, Man, and Cybernetics*, Part A, vol. 35, no: 5, pp. 727–737, 2005.

[12] K.Y. Tam, M.Y. Kiang, "Managerial applications of neural networks: The case of bank failure predictions," *Management Science*, vol. 38, no: 7, 1992.

[13] H. Jo, I. Han, "Integration of case-based forecasting, neural network, and discriminant analysis for bankruptcy prediction," *Expert Systems with Applications*, vol. 11, pp. 415– 422, 1996.

[14] P. Alam, L.K. Booth, T. Thordason, "The use of fuzzy clustering algorithm and self-organizing neural networks for identifying potentially failing banks: An experimental study," *Expert Systems with Applications*, vol. 18, pp. 185–199, 2000.

[15] J. Kolari, D. Glennon, H. Shin, M. Caputo, "Predicting large us commercial bank failures," *J of Eco & Bus*, vol. 54, pp. 361–387, 2002.

[16] K.F. Lam, and J.W. Moy, "Combining discriminant methods in solving classification problems in two-group discriminant analysis," European J of Operational Research 138, 294–301. 2002.

[17] Federal Reserve Bank of San Francisco, "Using CAMELS Ratings to Monitor Bank Conditions**,"** http://www.frbsf.org/econrsrch/wklyltr/wklyltr99/el99-19.html, June 11, 1999.

[18] Zhao, H. et al., Effects of feature construction on classification performance: ., Expert Systems with Applications (2008),

[19] Dimitras A.I.; Slowinski R.; Susmage R.; Zopounidis C., Business Failure Prediction Using Rough Sets, *European J of Oper Res*, vol. 144, no: 2, pp. 263–280,1999.

[20] W. Ziarko, and J. Katzberg, *Control Algorithms Acquisition, Analysis and Reduction: Machine Learning Approach*, Knowledge-Based Systems Diagnosis, Supervision and Control, Plenum Press, Oxford, pp. 167-178, 1989.

[21] Z. Pawlak, *Rough Sets; Theoretical Aspects of Reasoning about Data*, Kluwer Academic Publishers, Dordrecht, 1991

[22] R. Slowinski, "Rough Set Approach to Decision Analysis," *AI Expert Magazine*, vol. 10, no: 3, pp. 18-25, 1995.

[23] Z. Pawlak, and R. Slowinski, "Rough set approach to multiattribute decision analysis," *European J of Oper Res*, vol. 72, pp. 443-459, 1994.

[24] J. Krysifiski, "Application of the rough sets theory to the analysis of structure-activity-relationships of antimicrobial pyridinium compounds," *Die Pharmazie*, vol. 50, pp. 593-597, 1995.

[25] R. Stowifiski, C. Zopounidis, "Working Paper: Applications of the rough set approach to evaluation of bankruptcy risk," *Decision Support System Laboratory*, Technical University of Crete, Chania, pp. 93-08, 1993.

[26] R. Stowifiski, C. Zopounidis, *Rough Set Sorting of Firms According to Bankruptcy Risk*, in: M. Paruccini (ed.), Applying Multiple Criteria Aid for Decision to Environmental Management, Kluwer, Dordrecht, Netherlands, pp. 339-357, 1994,.

[27] Z. Díaz, M.J. Segovia, J. Fernández, and E.M. Pozo, "Machine learning and statistical techniques: an application to the prediction of insolvency in Spanish non-life insurance companies," The *Int J of Digital Acc Res*, vol. 5, no: 9, pp. 1-45, 2005.

[28] S. Balcaen, H. Ooghe, "Alternative methodologies in studies on business failure: Do they produce better results than the classic statistical methods?" vol. 16, 2004. Available: *Vlerick Leuven Gent Management School Working Paper Series.*

[29] R. Slowinski, and C. Zopounidis, "Application of the rough set approach to evaluation of bankruptcy risk", *Int J of Intelligent Systems in Accounting, Finance and Management*, vol. 4, pp. 27-41, 1995.

[30] S. Greco, B.Matarazzo, R. Slowinski, "Rough approximation of a preference relation by dominance relations," *European J of Oper Res*, vol. 117, pp. 63-83, 1999.

[31] T. R.; Hvidsten, M. S. Bjanger, J. Komorowski, *Fault Diagnosis in Rotating Machinery Using Rough Sets and Rosetta: Extended Abstract.*

[32] A. Øhrni Rosetta, Technical Reference Manual, 1999. Avaliable: http://www.idi.ntnu.no/_aleks/rosetta

[33] Central Bank of the Republic of Turkey, *Monetary Policy Report,* November 2002.

[34] IMF, Turkey: Selected Issues and Statistical Appendix, Country Report No. 00/14, Int. Monetary Fund, Washington, DC, 2000.
[35] Banks Association of Turkey, Avaliable: http://www.tbb.org.tr/english/bulten/yillik/2000/ratios.xls.
[36] Banking Regulation and Supervision Agency (BRSA). Towards a sound Turkish banking sector. May 2001. Avaliable: http:// bddk.org.tr.
[37] Banks Association of Turkey, Banks in Turkey, Various issues from 1990 to 2003.
[38] Bank Capital Strengthening Program. February 2002a, Available: http://bddk.org.tr.
[39] Banking Sector Restructuring Program-Progress Report (V), November 2002b. Available: http://bddk.org.tr

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