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Impact of Placement Choices and Governance Issues on Credit Risk in Banking: Nonparametric Evidence from an Emerging Market

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This paper is intended to develop some conditional credit risk models through a cursory approach in which any quality deteriorations in banks' cash credit portfolios, measured as unfavourable changes in the ratio of delinquent credits to total credits, are considered to be a signal for an increase in overall credit risk and the weights of credit segments in entire portfolio are used as predictors. In modelling, two separate studies with consolidated and non-consolidated financial statement data covering the time period between March 2003 and March 2009 have been carried out. Our models based on Neural Networks and Multivariate Adaptive Regression Splines provide significant evidence that dynamic structure of credit portfolios are among the important determinants of credit risk. Furthermore, there exist some findings supporting the active role of macroeconomic conditions and our network models yield sound proofs suggesting that corporate governance concerns are influential on credit risk and quality.

Keywords: *Credit quality; credit risk measurement; conditional models; Neural Networks; Multiple Adaptive Regression Splines (MARS)*

JEL Codes*: G11, G21, C14*

Introduction

Banks are confronted with a wide variety of risks that must be delicately handled by them in order to sustain their operations and to have an evident competitive advantage in the industry. These risks, in fact, emanate from some important performance dilemmas shaping the nature and scope of bank decisions. Therefore, the triangle trade-off among profitability, liquidity, and the ability of repaying debts matters much more for banks as compared to non-financial sector firms. In other words, considering the fact that high profitability can be maintained only through generating more revenues, banks must concentrate on investments which yield high returns, but contribute more to the overall risk exposure. However, any investment extension necessitates the allocation of available capital to specified asset classes, which relatively restricts solvency leading to important liquidity problems. These problems may result in the difficulty of repaying bank's debt obligations provided that the bank does not have a prosperous policy for provision-making against expected losses and adequate capital to meet unexpected losses.

A credit transaction is simply defined as transferring wealth via the current provision of commodities, services or purchasing power to individuals or institutions for a certain period of time to enable them to meet their private or commercial needs. Guarantees and pledges as well as cash can be treated as a credit transaction. Whatever is considered to be a credit, banks have to bear a certain degree of risk due to that transaction.

So far, credit portfolios have always constituted a relatively large fraction of total asset portfolio of deposit banks producing a big portion of bank revenues. For instance, it is known that 67 % of total revenues of the American banks came from interests and commissions imposed on the loans given during the late 1990s [1]. Similarly, the ratio of interest revenues to total revenues in the Turkish Banking System from 1988 through 2010 was about 70 % on average. For this reason, effective management of the risks resulting from credit placements (lending transactions) has always been one of the core concerns of banking institutions.

Quality of credit transactions is strongly correlated with both how successfully to estimate the likelihood of repayment of a credit and how effectively to establish harmony among credit culture and organization, lending policies, and credit-related strategies. The reliability of credit risk measurements mainly depends on the extent to which proper risk measurement techniques are designated and measurement applications are kept up-to-date. Moreover, the decisions related to credit transactions must be made in light of relevant legal arrangements and bank's inner dynamics and authorities should regularly monitor and control the risks associated with lending function [2].

The fashion in that lending decisions are taken determines success in balancing liquidity and profitability [3]. Put another way, ascending profitability because of lending more without concentrating on supervision and controlling activities likely leads the bank to a less liquid position and causes diminution in credit quality [4]. Regarding the fact that an illiquid position is undesirable for bank performance and huge credit placements may have a contractionary effect on liquidity, all the decisions to be taken in the process of lending turn out to be more essential and challenging.

Lending process involves a set of tasks carried out to make a healthy analysis, called credit analysis, about whether a loan should be made to a certain applicant and how likely the funds given as loan are going to be repaid by the borrowers [5]. This process resembles the basic methodology of bankruptcy and financial distress prediction studies. Loan application, evaluation of the application, credit pricing, and monitoring of repayment performance constitute the four fundamental phases of a typical lending process [6]. However, the evaluation phase including the task of predicting the likelihood of borrower's default takes place at the heart of the entire process because evasion of wrong lending decisions via successful evaluation helps minimize or fully eliminate some additional costs directly or indirectly attributed to these decisions [7].

Evaluation of loan applications mainly focuses on the analyses to determine applicant's credibility in terms of the five criteria known as 5Cs; applicant's practice of repaying (Character), his financial power to repay (Capacity), his wealth (Capital), short and long term cyclical developments expected possibly to affect the financial position of borrowers (Cyclicality), and the presence of any collateral (Collateral). The past studies have showed that customer selection holds key to reducing credit risk and selection of right applicants to lend might decrease credit risk exposure by 80 % [8].

Since the oversimplifying assumption underlying many of the credit risk models previously proposed and the Asymptotic Single Risk Factor (ASRF) model used by Basel II that credit portfolios are well diversified and no single borrower's behaviour can significantly affect the portfolio quality, challenges prediction accuracies in credit risk assessment, determining the marginal effect of a lending decision on total credit risk exposure comes up as another of essential tasks in risk management [9]. To monitor and control the risk contribution of concentrating on specific credit products, namely concentration risk which results from extreme credit placements to specific sectors or individuals, it is vital to carefully identify homogeneous credit groups making up the entire credit portfolio [10]. At this point, it plays a significant role how the entire credit portfolio is grouped and the way that capital is allocated to those sub-portfolios becomes a critical issue.

Within this context, our paper is focused on detecting any possible relationship between changing structure of credit portfolio and credit quality presenting some nonparametric model proposals developed by using Neural Networks and Multivariate Adaptive Regression Splines (MARS) technique to serve for credit risk projections with a relatively simple approach.

The paper consists of three main sections: The first section includes a broad literature about capital adequacy and credit risk measurement concepts while the second section covers the methodological issues and results of our empirical research. The last section is devoted to the concluding remarks and findings relating to the research hypotheses.

Literature Framework

Banks are purely engaged in so tough a business of managing risks in a way that profitability and liquidity are insured and maintained so as to respect the interests of all related parties and continuously enhance corporate value as a whole. In addition, it is one of the major determinants on economic stabilization how efficiently banks operate because of their financial intermediation role between lenders and borrowers. Put another way, bank failures and any possible financial collapse caused mainly by having inadequate capital in meeting unexpected losses could give way to a systemic crisis that would influence also the industries other than banking [11]. As a matter of fact, the problems observed in the global banking industry especially during the last three decades of the 20th century which led to seriously destructive impacts on almost all economic units were regarded as important symptoms of danger proving the need for urgent redeeming steps to be taken in order to resolve the risk of payment system. The foremost of concrete attempts made to address this issue has been formation of the Basel Committee that is supposed to best serve in building a dynamic environment required to facilitate desired conditions under perfect competition. As the average capital adequacy ratio of the banks operating in such developed countries as Canada, England, and United States of America decreased sharply and hit its historical record of 5 per cent just after the termination of the World War II, the committee was also assigned some duties toward both developing new techniques to be used in supervision of banks and setting their special standards related with capital adequacy [12].

Basel I: First Capital Adequacy Framework

The first Capital Accord, namely Basel I, was designated and published by the Basel Committee in 1988 to satisfy the need for standardization of supervision activities on capital adequacy in big banks operating internationally, but unfortunately couldn't produce what really had been intended since it does not include sufficient arrangements for all the risks to which banks become exposed and ignores possible losses due to operational inefficiency and risks other than credit and market risks already captured. Despite its imperfectness, Basel I brought in a lower limit of 8 % for capital adequacy ratio which is computed through using the elementary formula in Equation 1 and this limit has been taken as a base value by the subsequent capital adequacy convergence, namely Basel II, as well.

$$CAR = \frac{CB}{CRE + MRE} \qquad (1)$$

In the above equation, CAR refers to Capital Adequacy Ratio whilst CB represents Capital Base that is calculated in a certain way proposed in the Accord. Eventually, CRE and MRE are acronyms of Credit Risk Exposure and Market Risk Exposure.

Even though Basel I was considered the first crucial effort to fix banking concerns sticking to capital adequacy subject and revised several times until 1998 to adopt recent shifts in risk management approaches [13], rapidly changing nature of bank operations, rise in variety of financial assets in the wake of developments in secondary markets and derivative instruments, and recognition of new risk concepts such as interest rate risk, operational risk, and liquidity risk after the issuance of Basel I constitute other rationales for why the Accord became unable to cope with the problems [14]. In addition to that, it is another problematic aspect of Basel I that the effect of diversification on portfolio risk is not accounted for [15]. Academicians and practitioners also agreed to the point that Basel I could not adequately manage risk separation among asset classes and failed to deal with the differences in accounting practices across countries. For example, attributing arbitrarily low risk weights to the transactions with the OECD countries regardless of country risk variations among them is considered to be the weakest feature of the Accord. The circumstance that provisions for credit risk were not cared to a required extent by Basel I also challenged its functionality [16].

Basel II: A More Comprehensive Capital Accord

To protect the parties with any stake in banks, especially depositors, against possible costs and losses arising from asymmetric information and moral hazard problems, it is vital that those parties are regularly well informed about the financial position of bank and all the risks it entertains. Moreover, bank managers and staffs must be monitored permanently to be sure enough that they are acting for stakeholders' interest as a matter of corporate governance concept [17]. As supporting this argument, past research showed that high accord with corporate governance principles yields remarkable improvements in financial performance [18]. Resultantly, the Basel Committee has issued eight principles to enhance corporate governance in banks that emphasize such important subjects as required features of the board of directors, corporate goals and their supervision, responsibility culture, compatibility with corporate policies, internal control system and utilization of external auditors' services, human resources policies and their harmony with long-term goals, transparency of management, and impediments before effecting transparency [19]. The committee also requires that all banking risks be managed as to best serve the basic requirements of corporate governance framework.

Considering preponderant concerns about effective implementation of governance rules and previously mentioned deficiencies of Basel I in coping with problems relating risk management practices, the Basel Committee prepared a new Capital Accord known as Basel II in 1999 with an effort to fully cover all the ambiguous matters related to bank operations concentrating particularly on risk management [20]. As a consequence of rising variety of risks that banks confront and along with the announcement of this new Accord, risk management practices in banking are merely targeted to handle banking risks in a more centralized and integrated manner, instead of treating each risk factor individually, rather focusing on banks' capital adequacy for maintaining robustness of banking industry.

Basel II as a new and more comprehensive capital adequacy framework was revised twice in 2001 and 2003, which finally resulted in declaration of its final text in 2004, thereby comprises three pillars; minimum capital requirement, supervision of capital adequacy and market discipline. Apparently, it can be considered a fascinating breakthrough for risk management practices of banks because it has broadened the related framework concerning risk management as well as providing academicians and practitioners with a more detailed and complicated view into capital adequacy phenomenon which was covered also in Basel I, but with a relatively lesser emphasis. Along with the announcement of this latest capital adequacy framework, the most recent trend in risk management practices of banking institutions as a consequence of rising variety of risks that banks are confronted with has been to handle these risks in a more centralized and integrated manner instead of treating each risk factor individually, rather focusing on banks' capital adequacy for maintaining robustness of banking industry. Although it spells no material amendments on the reference figure of minimum capital adequacy and the way of computing proposed in Basel I, maybe the most important of its radical innovations is a more discrete separation and identification of the major risk components affecting banks and their operations. In other words, Basel II has added a new risk concept, called operational risk, and defined total risk as the sum of the three major risk components; credit risk, market risk, and operational risk. Moreover, within scope of the new convergence, the risk profiles of separate asset classes and risk types attributable to them are treated more elaborately. On the other hand, some slight deviation from strict concentration on minimum capital requirement has been observed and instead, the concept of economic capital as a more risk-oriented performance measure has become more considered in assessing optimal capital level that must be realized in the long run [21].

For measuring each risk component, Basel II proposes several alternative techniques with differing degrees of complexity. The standardized approaches available for all three components - standardized approaches for credit and market risks, and basic indicator approach and standardized approach for operational risk - are the simplest options including mandatory and subjective risk weighing procedures. Despite their simplicity and ease of comprehending, their results may be misleading. However, the advanced measurement approaches provided within the Accord - foundation and advanced internal ratings-based approaches for credit risk measurement, advanced measurement approach for market risk, and internal model-based approach for operational risk - allow for the use of more sophisticated risk measurement techniques such as VaR (Value-at-Risk) which is used especially for calculation of market risk exposure, and other user-specific mathematical tools, and produce better results, but may cost much to banks. The Accord also suggests special tests – stress tests and back-testing - to justify the accuracy and reliability of the predictions to be obtained using these advanced methods. Furthermore, the past research showed that the accuracy of risk and capital adequacy estimations could be increased if selecting more sophisticated techniques (22).

The formula depicted by Basel II to use in calculating capital adequacy ratio as including and integrating all three risk components takes the simple form shown in Equation 2:

$$CAR = \frac{CB}{CRE + MRE + ORE} \geq 0{,}08 \qquad (2)$$

In the equation, CAR and CB stand for Capital Adequacy Ratio and Capital Base correspondingly while CRE, MRE, and ORE represent the exposures for credit risk, market risk, and operational risk. The number of 0.08 refers to the proposed minimum level of capital adequacy ratio.

Credit Risk Measurement Approaches in Basel II

Credit risk measurement is regarded as a considerably significant part of risk management procedures defined in Basel II. To measure credit risk accurately, the structure of credit portfolio, characteristics of portfolio components, lending limits, the tools used for purpose of reducing risk, and rating results are the core issues to be finely dealt with. Robustness of measurements are closely related with data reliability and appropriateness of technique employed.

As stated also before, Basel II presents two alternative approaches to be undertaken for measuring credit risk: Standardized Approach and Internal Ratings-Based Approach. The latter is composed of two alternative approaches; namely, the foundation and advanced approaches. Standardized approach with its mandatory and subjective arrangements regarding credit placements to sovereigns, banks, companies and other related parties is easiest to use and interpret [23] whereas advanced internal ratings-based approach in which many statistical and mathematical computation methods can be used is the most difficult one, but with the highest prediction performance. Empirical research suggests that advanced approaches turn out to be more preferable and functional as the size and scope of bank operations expand [24].

The standardized approach suggests computing minimum capital requirements simply by multiplying total value of risk weighted assets with

8 %. Separately, total value of risk weighted assets is calculated as the sum of the products of values of credit portfolio components and their corresponding risk weights to be specifically assigned according to either the arrangements in this approach or the credit rating reports published by prestigious rating agencies, if available. Nevertheless, since the approach uses fixed risk weights for specific credit classes, it fails to sufficiently distinguish between credit components in terms of their risk contributions to the entire credit portfolio. Consequently, it becomes more convenient to use internal approaches more sensitive to differences in risk profiles of banks for such cases that credit portfolios are highly diversified.

Presence of internal ratings-based options in Basel II means banks are allowed to use their own internal credit rating systems as long as they can prove and sustain the reliability and accuracy of these systems. It is also an important condition that internal credit rating systems must be approved and ratified by local supervisory authority. Internal rating-based approaches are more risk-sensitive and can produce more accurate measurement results, but are multi-faceted to apply in comparison to the standardized approach. Put another way, they enhance more realistic capital measurements by lowering the projections about minimum capital requirement that might be estimated relatively higher in case of employing the standardized approach [25].

Loss Definitions and Calculations in Advanced Approaches

Since risks cause banks to suffer losses which are considered to be the core topic also in managing credit risk, the advanced credit risk measurement requires that loss definitions and calculations be made more precisely. Thus, Basel II sets a concrete basis to classify and loss events that suggests losses at first to be categorized as expected (EL) and unexpected losses (UL) and computed separately by using the subsequent two formulas including three fundamental risk parameters; probability of default (PD), exposure at default (EAD), and loss given default (LGD).

$$EL = PD * EAD * LGD \qquad (3)$$

Expected loss (EL) is defined as the average of loss distributions which is likely to happen at any time and it is assumed that with successful provision policies, banks can succeed to cover all expected losses without needing extra funding. Nonetheless, banks must consider the likelihood to encounter some unexpected losses that would lead to huge damages on their financial position. The amount of capital to be needed for meeting unexpected losses is referred to as the standard capital level associated with minimum liquidity level [26]. These unanticipated losses are computed the below equation also including the same three risk parameters.

$$UL = \sigma_{EL} = EAD * LGD * \sqrt{PD * (1 - PD)} \tag{4}$$

PD is, maybe, the most important parameter in measuring minimum capital requirement and represents the probability that borrower will fail to repay the loan. PD estimations should be computed as long-term average of default probabilities. The task to predict PDs is left to banks so that they are allowed to determine PD using their own prediction models only if they can make these models authenticated by the relevant authorities. Furthermore, it is paid attention that banks should develop functional models to derive estimations taking into consideration possible cyclical movements in general economy and provide different risk classifications that will effectively reflect these likely economic scenarios in order to cover risk appetite when trying to overcome moral hazard problem [27].

The parameter of EAD can be defined as the expected amount of credit receivable that would be lost if default event occurred. This amount is a function of the amount of loan already utilized (CEAD) and the portion of currently unutilized loan which would probably be utilized by borrower until the default event [28]. To obtain a good prediction of unutilized loan amount (ULOAN) likely to be utilized, an appropriate loan equivalency factor (LEF) must be assigned using the past data on identical loan transactions and currently unutilized loan amount is multiplied with that factor value. Succinctly, EAD calculations are carried out following the basic process presented in Equation 5:

$$EAD = CEAD + LEF * ULOAN \quad (5)$$

LGD as the last parameter in the equations implies the expression of possible losses to be incurred if borrower defaults as a certain percentage of EAD estimation. This parameter is also very critical to the accuracy of capital adequacy measurements because the value of risk-weighted assets is taken as a core variable in calculating minimum capital requirement and very sensitive to LGD assessments [25].

Following the determination of the risk parameters mentioned above, the next step is to calculate total value of risk-weighted assets and finally to determine minimum capital requirement. In this stage, Basel II brings in a general formula (Equation 6) that enables to reach a final figure representing capital requirement as a matter of Asymptotic Single Risk Factor Model that forms the basis of almost all of the practices in the Accord (25). This model assumes that banks' credit portfolios are well diversified and that there is only one systematic risk factor affecting default probabilities of all credit components [29].

$$K = \left[(LGD) N\left[\frac{1}{\sqrt{1-R}} G(PD) + \sqrt{\tfrac{R}{1-R}}\, G(0{,}999) \right] - PD(LGD) \right] * \left(\frac{1 + (M - 2{,}5) b(PD)}{1 - 1{,}5 b(PD)} \right) \quad (6)$$

In the above equation, N(X) denotes cumulative normal distribution function and G(X) stands for the reverse of cumulative normal distribution function. b(PD) represents maturity adjustment function which has been clearly formulized in Basel II as a function of PD estimations according to the results of the quantitative impact studies performed throughout the world [30] while R is referred to as the assumed correlation coefficient between default events. Different proposals for correlation coefficient estimation in functional forms as a function of estimated default probabilities regarding different credit classes are supplied in the text of

Basel II [31]. Moreover, the letter M in the equation constitutes effective maturity value which can be computed in a fashion similar to that in duration calculation by taking an average of loans' maturities suing collected amounts as weights. In addition, decreasing effects of provisions, guarantees and derivative instruments on credit risk exposure are addressed in detail.

Credit Risk Modeling: Approaches and Practices

Although the use of internally developed models in credit risk measurement is an option allowed by Basel II, it is a very challenging task to create reliable and consistent internal models. Model accuracy is strongly affected by the choices and decisions made on such conceptual modeling issues as assumptions regarding loss distributions, horizon of analysis, modeling approach for loss estimation, probability distributions, use of conditional or unconditional models, and researcher's approach to correlations between loss events [32].

In credit risk modeling, the first step is to select the most appropriate probability function for credit losses that best represents the relationship between targeted PDs and economic capital [33]. The next decision following the determination of proper probability function is about the choice on modeling approach - micro and/or macro modeling alternatives - to employ. Micro models mainly try to establish a separate risk model for each credit transaction or loan whereas macro or portfolio-based models work to produce risk measurements for the entire credit portfolio or sub-portfolios. For the cases where binary analyses based on good-bad credit classification fail, portfolio-based models become more preferable [34]. Then, the researcher must measure credit losses using any of two different conceptual approaches: Default Mode Paradigm and Mark-to-Market Paradigm. Default Mode Paradigm assumes credit losses will appear only if borrower is in default. On the other hand, Mark-to-Market Paradigm approaches such as Discounted Cash Flow Approach and Risk-Neutral Approach suggest that any deterioration in asset's credit quality may be viewed as an omen of degradation and could pave the way to credit losses [35]

Most of currently applied models attempt to identify a suitable probability density function for each case, regarding central tendency measures. However, standard probability density functions may also be preferred even though this alternative likely reduces prediction accuracy in many cases [36]. At this point, it is advisable to keep the reference confidence level so large that the estimation errors could be minimized [37].

Another critical point in credit risk modeling is to decide on whether the model should be conditional or not. The models in which only borrower-related data are included call for unconditional models, but the models that consider the effect of some relevant systematic risk factors such as macroeconomic factors on credit risk are named as conditional models [38]. In fact, the previous empirical findings show that the choice on model conditionality impacts model performance. For instance, Cipollini and Missaglia [39] point out that dynamic factor analyses allowing for the consideration of country risk in risk estimates may positively affect model success.

To analyze the correlations between default events or credit migrations, two main approaches can be undertaken. One of these approaches is the Structural Approach in which a microeconomic model is derived to investigate and quantify the relationships between default events or migrations. The second one is called Reduced-Form Approach that assumes the presence of a functional relationship between default events or credit risk migrations and suggests these factors comprise both some observable variables such as macroeconomic factors and unobservable random risk factors.

Just after handling those methodological issues mentioned before, the modeler should begin to generate estimations relating to LGD changes, expected PD (or change in credit rating), credit spreads, and EAD changes. In estimating LGD changes, any of gross LGD, Bianco LGD and market LGD [40] can be preferred while it is possible to apply actuarial methods or equity-based methods so as to estimate PDs or rating changes. Alternatively, as mentioned before, the reports and relevant figures provided by the professional institutions for these estimates can also be taken as a proxy.

Subsequent to the formation of a proper estimation model, it is vital for the success of any modeling effort to evaluate model performance. The assessment on model accuracy is characterized as a process that is composed of four particular components, which are back-testing, stress tests, sensitivity analysis and the evaluation of the model by an independent authority or agent. In the face of difficulty in using back-testing in credit risk modeling due to insufficient data, if applicable, back-testing helps ascertain the extent to which model estimations are sensitive to any changes in model assumptions and data used. Moreover, a researcher may undertake stress tests and scenario analysis to overcome some model-related uncertainties by observing how the model reacts to unprecedented trends in model parameters, within the context of some predetermined scenarios.

Conventional versus Contemporary Credit Risk Models

Although there are a myriad of credit risk models that have been derived for different purposes using various techniques, the existent models generally employing the VaR phenomenon are divided into two separate groups with respect to the measurement approaches considered in modeling: Portfolio-based models and models towards pricing credits individually. Initial examples of credit risk models were developed with the help of option pricing theories due to unavailability of sufficient internal data, but actuarial methods recently have turned out to be more preferred with the advent of more advanced econometric techniques. In accordance with the research methodology adopted, it is also possible to classify credit risk models as conventional and unconventional, or modern.

Conventional Credit Risk Models

The conventional models merely include risk measurement techniques that emphasize PD - LGD forecasts and default mode paradigm in which any small changes in credibility are ignored and strict classifications in respect of a preset definition of financial distress are being made. Contrary to the conventional models in which some qualitative and quantitative factors in accordance with 5Cs are appraised intuitively by lenders to assess a borrower's credibility, the models based on rating and grading procedures involve the use of certain cardinal econometric methods such as binary logistic regression, discriminant analysis, and profit technique as well as some mathematical methods that are more sophisticated and provide nonparametric solutions, such as Inductive Learning Algorithm, Recursive Partitioning, Chaos Theorem, Neural Networks, Genetic Algorithm and MARS. Furthermore, there also exist in the finance literature some anomalous modeling studies that combined efficiency measurements with credit risk via the use of Data Envelopment Analysis, a special measurement technique conducted for assessment of efficiency, simultaneously with the methods mentioned above [41]. In practice, it is also probable to see few unique models based on judgmental approaches integrated with focus group and brainstorming studies, in which experts' opinions become more important and influential.

Some of the empirical studies that were carried out on credit risk models aimed to explore the superiority of modeling techniques over one another, many of which especially dealt with a performance comparison between parametric and nonparametric model proposals. Most of these studies have led to a preponderant opinion that nonparametric models significantly excel their parametric counterparts in predicting credit risk. As the examples to such studies proposing the supremacy of nonparametric models, Coasts and Fant [42] revealed important results suggesting the predominance of neural networks over discriminant analysis in forecasting corporate financial distress. Sharma, Kamath and Tuluca [43] performed another research to compare the performance of neural networks and linear regression and provided proofs supporting the relative superiority of neural networks. Similarly, Bensic and others [44] reported some convincing results supporting slight dominance of neural networks over logistic regression and decision trees. In addition, [45] presented some relevant findings in their study featuring inductive learning algorithm and probit technique that encourage them to conclude that probit models were outperformed by the models based on inductive learning algorithm.

Even though most of the comparison-oriented studies are with the empirical findings that back up nonparametric model specifications, in the literature are some rare studies destroying the common belief that nonparametric models could perform better. For instance, Altman, Marco and Varetto [46] suggest that neural networks and discriminant analysis can be regarded as equally worthy models while Kaya [47] reports no significant difference between the performances of logistic regression and neural networks.

In the conventional models involving especially corporates, specific financial ratios that are considered to be good measures for such financial performance criteria as liquidity, profitability, efficiency, and financial flexibility, can be included as predictors of credit risk. For example, K & P Default Risk Model created by Koundinya and Puri takes such financial ratios as inputs and puts them into a decision process in order to make a three-level risk categorization – high, moderate, and low - through a judgmental analysis [48].

Contemporary Credit Risk Models

Being characterized as very distinct from the conventional models, modern (or, contemporary) credit risk models can be basically categorized as Structural Approach Models and Reduced Form Models. The structural models developed as based on Black & Scholes Option Pricing Model directly relate a firm's credibility to its net market value. The foremost advocate of this approach is Merton [49] who developed a model in 1974 that is exactly identified with his name. In his model, Merton assumes credit risk to be a European-type call option on borrower's assets with an exercise price equal to the amount of loan borrowed. According to the model, default event could exist at the end of maturity only. If the exercise price exceeds total market value of the assets, the borrower is supposed to be in default. In this manner, the distance to this critical point or situation is computed as a probability figure by a special function derived from the option pricing model, which could be accepted as an approximate measure of the borrower's default risk.

Following the Merton's Model, the next breakthrough, First Passage Models, was carried into effect by Black and Cox [50] in 1976 by relaxing the strict assumption of Merton's Model about the type of call option. They assume an American call option with the suggestion that the default event may exist at any time until the maturity date and state that since bankruptcy costs, interest rate volatility, assurances and priorities given in bond issues, and restrictions relating to interest and dividend payments might have some relative effects on option price, default should be supposed to have occurred at any time when total market value of borrower's assets falls below a certain lower cut-off value which can vary time to time.

Another of the most famed contemporary models belongs to Altman, known with the name of Historical Default Rate Model and concentrates on the performance of the bonds previously issued by borrowers to determine their default probabilities. After the separation of the bonds with respect to their currently assigned ratings, the model is constructed taking into account the rates of the bonds in default and durations left to their maturities. Using the default rates and probabilities computed, a loss projection is made for each bond [6].

The third group of structural models is composed of Factor Models that resemble a typical regression model employing specific risk factors as exogenous explanatory variables over total asset value. In the models of this type, all the factors peculiar to borrower are considered and nonparametric estimation techniques as well as parametric ones can be undertaken in model formation.

From a practical perspective, structural models may become more convenient and preferred because they provide a quantitative view into the subjects relevant to credit risk measurement and help easily produce PD estimations. However, it makes them unattractive and a futile effort that researchers are usually confronted with serious troubles and limitations regarding the application of accuracy tests on these models. Highly volatile credit spreads suspicion about whether bonds are priced truly in the market, and the need for very large horizons to foresee default events are among the other critics against structural models.

Reduced Form Models as another alternative for credit risk modeling ultimately deviate from the structural models as they rely on the assumption that a default event is a random and unexpected phenomenon. These models are also known as Density-Based Measurement Models, developed by Jarrow and Tumbull in 1992 [51]. In establishing a reduced form model, it is assumed that firm's debts consist of only one bond with no interest payments and then, PD and LGD components are separated for calculation purpose. The product of these parameters gives credit spread that is considered to be the cost of default. To separate and calculate PD and LGD, some survival statistics provided by rating agencies may be used.

In addition to structural and reduced form models, there is another category of credit risk models that try to combine pros of the former two, which is called Incomplete Information Models. The pioneer model proposals in this category were provided by Duffie and Lando [52] in 2001, followed by the model proposals of many other researchers. Incomplete information models assume that all relevant information is available to public and that information about firm valuation process, valuation parameters and default frontiers is in blur. Additionally, default event is deemed to be unpredictable.

Nowadays, the credit risk models commonly used in practice depends on the consideration of risks as a whole at portfolio level. Their major focus is on assessing default probabilities of debt instruments in order to understand what portion of credit portfolios constitutes the credits with no chance to collect. Moreover, increases in the variety of off-balance-sheet risks, intense competition in banking industry, volatility of asset values, and technological developments have encouraged market participants and players to discover and use more advanced techniques and systems in credit risk assessment which is one of the crucial functions of financial engineering. Among the contemporary systems of credit risk measurement which are prevalent and robust are Moody's KMV Model, CreditMetrics, CreditRisk+, and CreditPortfolioView.

Recent Revisions in Basel II Regulations and Basel III Declaration

Despite the fact that BASEL II introduces standard and internal rating based credit measurement techniques and encourages the use of advanced techniques in credit risk assessments, some extensive and gradual amendments on it were issued in the course of time to satisfy the needs of rapidly growing banking industries all around the world. In this manner, the Basel Committee issued some revisions on the initial text of BASEL II convergence regarding such matters as modification respective of SMEs' varying risk profiles, more risk sensitivity for retail credits, effective information sharing and collaboration about operational risks, making the convergence more easily understandable, shortening of average maturity to 2,5 years instead of 3 years and allowance for decreasing computed LGD values by at most 5 %, and decreasing the minimum capital base from 90 % to 80 %.

Since the latest global economic crisis had disruptive influences on especially the developed economies, the leading banks of these economies were put upon scenario and stress tests. In accordance with the results of these tests performed, it was noticed that a further radical review on the existing capital adequacy regulations must be done to get rid of any potential problems that those banks could experience during the epochs with substantial economic fluctuations. Resultantly, the Basel Committee has declared several significant changes concerning reference capital adequacy ratios and decided to heighten the existing minimum ratios to some extent. For instance, the minimum Tier I capital ratio is desired to rise by 2,5 % from its old level of 2% while total capital requirement will be kept at 7 % as minimum [53].

Empirical Research

Although the BASEL II Capital Adequacy Convergence has equipped practitioners and academicians with an appreciable amount of information about the ways of assessing credit risk and capital requirements through standard and advanced approaches to credit risk measurement, various difficulties and challenges confronting the users when they employ these approaches in their estimates and calculations make it necessary to search for new techniques and models that are relatively simpler and easily applicable. In our study, it is aimed to develop user-friendly, conventional and conditional credit risk models using nonparametric estimation techniques. By the reason that Turkish Banking Industry is dominated by deposit banks whose main field of activity is to collect funds from depositors and lend them to real persons and enterprises in need of raising funds, the study has been concentrated on domestic and foreign deposit banks operating in Turkey.

Research Purpose

As stated before, assessing judicious default probabilities for credit customers is a task crucial to successful credit risk measurements in which borrowers' credibility and intent are of great importance. Notably in the developing countries such as Turkey, unfortunately, the data needed to construct functional credit risk models are not fully available to the public and the financial statements reported by banks contain inadequate disclosures related with their credit portfolios. Herewith, practitioners and decision makers other than bank staff frequently face hurdles in deriving practicable models. With the hope of closing a deal, we intend to search for effortless model designs that we think would best serve the related parties who are interested in risk estimation practices using a modest methodology in which country risk and credit risk components are being integrated and credit risk is estimated in consideration of banks' credit placement choices regarding customer segments, maturity, and currency type. Nevertheless, our research relies on a restrictive assumption that all the banks within the scope of our study are averagely efficient in their lending practices and apply approximately same covenants and procedures in lending.

In this research, some conditional credit risk models are created using the consolidated and non-consolidated financial statements data of the domestic and foreign banks operating in Turkey and country ratings data provided by OECD. Through the models developed, credit risk is regressed on relative weights of credit groups within the entire cash credit portfolio and periodic country ratings using Neural Networks and MARS, two widely used nonparametric techniques. As a further investigation, the credit risk estimations produced by the models are reprocessed to calculate a representative amount of minimum capital requirement for each bank. Finally, those calculated minimum capital requirement figures are compared to the real figures determined by the independent auditors via some nonparametric tests of correlation.

Selection of Sample Units and Data Collection

As the concentration of our study is on credit risk measurement considering dynamic structure of credit portfolios, it is decided to treat all the domestic and foreign deposit banks, privately owned and state-owned, in the Turkish banking industry as the population of the research. But, due to the economic crises experienced and their impacts on the industry, the total number of deposit banks varied between 31 and 62 from 1988 through 2009. It gradually decreased because of bankruptcies and merger or acquisition events among banks following the most destructive crises lived in 2000 and 2001 and finally reached its lowest level in 2009.

On the other hand, data unavailability problem for some of the banks in the population made it unavoidable to study with a limited number of banks for which all the relevant data are collectible. Thus, the number of the banks included in the sample is only 26 for consolidated analysis, but 38 for non-consolidated one. Owing to the fact that no data are accessible for the periods before December 2002, the horizon of the research has been determined to cover the period between December 2002 and March 2009. As banks' financial statements are published in three-month intervals, 25 periods could be available for every bank. Unfortunately, for some banks, a shorter period of observation is the case on account of absence of relevant financial data and footnotes for certain periods. Besides that, it is another problematic issue altering the quantity of observations available that consolidated financial statements have never been issued for some banks along the entire period which our research is valid for. Eventually, we have 549 immediate observations of 26 banks in case of consolidated analysis and a set of immediate data consisting of 854 observations that belong to 38 banks in case of non-consolidated analysis. Balance sheets, income statements, cash flow statements, and their related footnote disclosures have been obtained and downloaded from the official web site of the Association of Turkish Banks (www.tbb.org.tr). Then, the ratios to be used in the models as predictors have been calculated using the data included in these statements. On the other hand, the series for the explanatory variable representing Turkey's ratings assigned by OECD as a ballpark measure of general economic condition have been generated following the methodology that was previously adopted in a research study on country risk estimation, prepared by Topak and Muzir [54]

Model Variables

As in many of conventional credit risk models, the dependent variable, CREDITRISK, representing default status is a dichotomous variable reflecting whether, or not any deterioration occurs in credit quality, but independent variables mainly composed of specific ratios showing relative importance of the sub-portfolios within the overall cash credit portfolio are continuous. Table 1 lists all the variables included in the models with their labels and short explanations.

Table 1: Model Variables

VARIABLE LABEL	VARIABLE NAME & EXPLANATION
EXP.CREDITS	Export Credits / Total Credits
DISC.CREDITS	Discount Credits / Total Credits
IMP.CREDITS	Import Credits / Total Credits
BUL.CREDITS	Bullion Credits / Total Credits
CARD.CREDITS	Dues from Credit Cards / Total Credits
FINSEC.CREDITS	Credits to Financial Sector / Total Credits
CONS.CREDITS	Consumer Credits / Total Credits
AFF.CREDITS	Credits to Subsidiaries and Affiliates / Total Credits
OVSEA.CREDITS	Overseas Credits / Total Credits
OTHER.CREDITS	Other Non-Specialty Credits / Total Credits
OWNER.CREDITS	Credits to Owners and Members / Total Credits
SPEC.CREDITS	Specialty Credits / Total Credits
SHORT.CREDITS	LOG(Short-Term Credits)
LONG.CREDITS	LOG(Medium and Long Term Credits)
FX.CREDITS	LOG(Credits denominated in foreign currencies)
DC.CREDITS	LOG(Credits denominated in domestic currency)

PUBLIC.CREDITS	LOG(Credits to public sector)
PRIVATE.CREDITS	LOG(Credits to private sector)
COUNTRY.RISK	Changes in country risk measure derived from OECD reports
CREDITRISK	Credit Risk (0: Favorable change in quality of overall credit portfolio 1: Unfavorable change in quality of overall credit portfolio)

As can be seen in Table 1, the dependent variable (CREDITRISK) is a variable with two outcomes that takes the value of 0 whenever no increase in the rate of delinquent loans to total cash credits is observed and the value of 1 if any increase in that ratio occurs. Furthermore, all the independent variables except the variables concerning credit portfolio segmentation according to maturity, sector and currency dimensions, and the one standing for country risk measure comprise such common financial ratios that can be calculated simply by the amount of each type of credit to the total amount of credits granted and are designated with respect to the separation of entire credit portfolio into its sub-portfolios in conformation with the current accounting practices in Turkey so as to incorporate the effect of placement choices into credit risk and quality changes. However, the variables related with credits in terms of maturity and sector dimensions have undergone a typical logarithmic transformation whilst country risk measures have been produced through a conversion process, identical to the one proposed by Topak and Muzir [54], in which the country ratings between 0 and 7 – a lower number refers to a better economic condition – are converted to standard normal distribution scores (Z scores) taking into account both the average rating of all the countries involved and their standard deviation, and then cumulative normal distribution probabilities supposed to infer the riskiness of the country are examined using these corresponding periodic Z scores. And finally, periodical differences in these probabilities have been calculated to establish the data set of country risk variable.

Methodological Issues and Modeling Techniques Employed

To reach robust results and derive more accurate prediction models, Neural Networks and MARS, two nonparametric numerical techniques with no restrictive assumptions about variable distribution and linearity of relationships between dependent and independent variables are preferred as modeling techniques to be undertaken. Also, Kendall's tau-b nonparametric correlation analysis is used to explore the relationships among the model variables in our Neural Network models. All analyses have been carried out on the SPSS V.16 software.

Though nonparametric modeling techniques depend on no assumption regarding variable distribution, an examination on conformity with standard has been conducted via the Kolmogorov – Smirnov Test.

Neural Network Algorithm is an advanced mathematical technique consisting of evenly located data processing units with their own memories that are connected to each other and mimic human brain. The neural networks structures consist of artificial neurons that are called nodes. The simplest neural network structure called perceptron contains only one input and one output layer without any hidden layer. With the addition of hidden layer(s) to this simplest structure, the neural network becomes more complicated and sophisticated, but may provide better solutions to such cases needing more tortuous calculations and examinations. The structures with hidden layers are named as Multilayer Perceptron (MLP) requiring detailed decisions about important model specifications such as optimum number of hidden layers, number of nodes (variables) on each layer, type and coefficient of learning algorithm, sort of activation function, segmentation of available data set as training set, test set, and holdout set, which are supposed to directly affect model prosperity and accuracy.

Our study employs an ordinary supervised feed-forward neural network structure with one hidden layer as well as input and output layers and considers no holdout sample. Therefore, 70 % the data in hand have been included in the training sample while the remaining 30 % in the test sample. Sigmoid (logistic) function has been chosen as the activation function in converting model scores to exact probabilities that help assess group affiliation of observations. On the other hand, the values in the samples are standardized in processing them to establish the final model proposal. In revision of learning coefficients for the purpose of minimizing estimation errors, the gradient descent algorithm has been preferred. Additionally, while the number of nodes on input layer equals the number of explanatory variables, the number of nodes on output layer is assumed to be 2 as the dependent variable is dichotomous. However, the assignment for the number of nodes on hidden layer entails a challenging task that can be accomplished gradually. To determine a proper number of hidden nodes on each trial, the approach that was initially proposed by Masters and Torsun is utilized. In conformity with this approach, for each trial, the number of hidden nodes is accepted to equal the square root of the product of the number of nodes on input and output layers. Reduction in the number of hidden layers is achieved through stepwise elimination of the explanatory variables in such a way that the variables with relatively lower values of importance are excluded to some extent from the model until the total importance percentage of the variables still included will be approximately equal to 95 %. Separately, each trial is continued to result in a better model proposal as long as a satisfactory level is not maintained for the evaluation statistic, the sum of squared errors, but ended once this statistic hits its ever lowest value.

Because no outputs are produced by the Neural Network models to assess the directions of the relationships between independent variables and dependent variable, correlations between the variables have been determined through Kendall's tau-b correlation analysis.

The other nonparametric modeling technique involved is the Multivariate Adaptive Regression Splines (MARS) which assumes no standard distribution and allows for nonlinear relationships. It starts by building a linear regression model and then tries to explore and capture nonlinearities in a functional relationship through investigating basis functions between each independent variable and dependent variable with apposite knots or cut-off points and specific locations for each independent variable at which linearity obviously disappears [55]. The best model is determined by the extent to which the sum of squared errors is reduced or adjusted R2 is increased and according to generalized cross validation statistics betrayed and proposed by Craven and Wabha in 1979 [56].

However, there are such critical decision areas that have significant effect on the performance of MARS models as maximum number of basic functions or knots, speed of learning, and whether to consider interactive relationships between independent variables [57].

Our MARS models have been developed using the MARS software program provided by Salford Systems Company without altering the default specification values set in this program. Put another way, maximum number of basic functions, allowable number of knots, and learning speed have been fixed at 15, 3, and 4, respectively. Both forward and backward cross-validation techniques are concurrently applied.

At the next step, the best cutoff points for classification have been examined and the models have been compared to each other in terms of their accuracy in predicting through ROC analysis, a method applicable to make comparisons between models that try to classify the cases with two or more discrete outcomes. Finally, to illustrate how to use credit risk projections in calculating minimum capital requirement, an unexpected loss amount has been computed as based on corresponding credit risk estimation for each observation separately, using the simple formula given in Equation 4. The computed loss amounts are then compared to the authorized amounts that were previously calculated and officially announced by the independent auditors by Kendall's Tau-b and Spearman's Rho tests in order to argue how successfully the predictions portray the realities.

Research Hypotheses

As previously mentioned, this empirical research is intended both to uncover a possible relationship between the changes in weights of credit segments in overall cash credit portfolios and credit quality and to investigate whether corporate governance issue plays an important role in banks' exposure to credit risk. On these accounts, we are determined to test the hypothesis that credit risk and quality are significantly affected by how well the credit portfolio is diversified through allocation of available funds to credit sub-portfolios. Secondly, the hypothesis that heavy concentration on credit placement to owners and other bank-related members engenders more vulnerability to credit risk will be tested. The third hypothesis to be tested is the common opinion that general condition of an economy is a significant determinant of credit risk. On the other hand, out of the main purpose of this study, we consider an attempt to compare the performance of Neural Network and MARS models arguing if Neural Networks can create a significant difference in predicting credit risk changes when compared to MARS.

Research Findings

Evaluating the results of the consolidated and non-consolidated analyses in a comparative perspective, it can be squarely said that our consolidated data-based models prevailed against the non-consolidated data-based models even though all the models have produced successful results that convince us about their superiority over a simple naïve model. As will be understood from the model finding subsequently presented, no satisfactory evidence has been furnished to conclude that any of the modeling techniques surpasses the other because their performance is almost same. Still, there are slightly evident findings that Neural Network models have done better in the case of consolidate data, but in case of non-consolidated data, MARS models seem to be more eligible.

Distribution Tests and Basic Descriptive Statistics

The results summarized in Tables 2 – 5 show that the data sets don't fit in with either normal or logistic distributions for most of the variables proving the rightness of our decision to employ nonparametric techniques. In the tables, the One-Sample Kolmogorov – Smirnov test statistics are found to be significant even at 99,9 % confidence level for all the variables, which means that the distributions of these variables cannot be assumed to be in conformity with normal and logistic distributions.

Table 2: Normal Distribution Test on Consolidated Data Set

VARIABLE	**N**	**Normal Parameters**		**Most Extreme Differences**			**Kolmogorov-Smirnov Z**	**Asymp. Sig. (2-tailed)**
		Mean	Std. Deviation	Absolute	Positive	Negative		
EXP.CREDITS	549	0,154	0,118	0,130	0,130	-0,095	3,054	0,000
DISC.CREDITS	549	0,008	0,024	0,366	0,258	-0,366	8,584	0,000
IMP.CREDITS	549	0,001	0,005	0,426	0,402	-0,426	9,992	0,000
BUL.CREDITS	549	0,002	0,026	0,463	0,394	-0,463	10,852	0,000
CARD.CREDITS	549	0,057	0,068	0,198	0,198	-0,198	4,650	0,000
FINSEC.CREDITS	549	0,064	0,122	0,300	0,293	-0,300	7,034	0,000
CONS.CREDITS	549	0,117	0,103	0,129	0,109	-0,129	3,020	0,000
AFF.CREDITS	549	0,002	0,010	0,407	0,394	-0,407	9,547	0,000
OVSEA.CREDITS	549	0,031	0,067	0,323	0,254	-0,323	7,569	0,000
OTHER.CREDITS	549	0,422	0,177	0,097	0,038	-0,097	2,281	0,000
OWNER.CREDITS	549	0,030	0,081	0,356	0,303	-0,356	8,351	0,000
SPEC.CREDITS	549	0,028	0,094	0,422	0,422	-0,383	9,891	0,000
SHORT.CREDITS	549	13,855	2,858	0,173	0,147	-0,173	4,042	0,000
LONG.CREDITS	549	13,036	3,478	0,122	0,110	-0,122	2,866	0,000
FX.CREDITS	549	13,226	2,745	0,100	0,087	-0,100	2,346	0,000
DC.CREDITS	549	14,162	2,129	0,090	0,066	-0,090	2,120	0,000
PUBLIC.CREDITS	549	6,313	6,090	0,302	0,302	-0,150	7,071	0,000
PRIVATE.CREDITS	549	14,211	3,254	0,159	0,140	-0,159	3,731	0,000
COUNTRY.RISK	549	-0,029	0,119	0,458	0,293	-0,458	10,733	0,000

Table 3: Logistic Distribution Test on Consolidated Data Set

VARIABLE	N	Mean	Most Extreme Differences			Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)
			Absolute	Positive	Negative		
EXP.CREDITS	549	0,176	0,552	0,552	0,000	10,604	0,000
DISC.CREDITS	549	0,011	0,452	0,452	0,000	9,135	0,000
IMP.CREDITS	549	0,005	5,035	5,035	0,000	48,819	0,000
BUL.CREDITS	549	0,012	3,667	3,667	0,000	41,330	0,000
CARD.CREDITS	549	0,077	0,297	0,297	0,000	6,295	0,000
FINSEC.CREDITS	549	0,076	0,360	0,360	0,000	7,722	0,000
CONS.CREDITS	549	0,132	0,133	0,133	-0,047	3,032	0,000
AFF.CREDITS	549	0,055	3,177	3,177	0,000	39,427	0,000
OVSEA.CREDITS	549	0,044	0,578	0,578	0,000	11,420	0,000
OTHER.CREDITS	549	0,470	0,274	0,192	-0,274	6,360	0,000
OWNER.CREDITS	549	0,029	0,326	0,326	0,000	7,369	0,000
SPEC.CREDITS	549	0,153	3,813	3,813	0,000	42,113	0,000
SHORT.CREDITS	549	0,265	0,226	0,143	-0,226	5,224	0,000
LONG.CREDITS	549	0,206	0,169	0,169	0,000	3,907	0,000
FX.CREDITS	549	0,154	0,212	0,146	-0,212	4,914	0,000
DC.CREDITS	549	0,313	0,241	0,133	-0,241	5,615	0,000
PUBLIC.CREDITS	549	0,114	0,878	0,878	0,000	17,543	0,000
PRIVATE.CREDITS	549	0,381	0,235	0,178	-0,235	5,435	0,000
COUNTRY.RISK	549	0,001	0,200	0,200	-0,184	3,994	0,000

Table 4: Normal Distribution Test on Non-Consolidated Data Set

VARIABLE	N	Normal Parameters		Most Extreme Differences			Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)
		Mean	Std. Deviation	Absolute	Positive	Negative		
EXP.CREDITS	85	0,160	0,151	0,146	0,118	-0,146	4,253	0,000
DISC.CREDITS	85	0,023	0,072	0,373	0,371	-0,373	10,910	0,000
IMP.CREDITS	85	0,001	0,004	0,443	0,443	-0,430	12,940	0,000
BUL.CREDITS	85	0,003	0,035	0,469	0,409	-0,469	13,709	0,000
CARD.CREDITS	85	0,048	0,070	0,248	0,246	-0,248	7,244	0,000

FINSEC.CREDIT	85	0,058	0,127	0,325	0,318	-0,325	9,500	0,000
CONS.CREDITS	85	0,113	0,151	0,226	0,156	-0,226	6,617	0,000
AFF.CREDITS	85	0,00	0,019	0,375	0,345	-0,375	10,945	0,000
OVSEA.CREDIT	85	0,037	0,126	0,385	0,372	-0,385	11,242	0,000
OTHER.CREDIT	85	0,40	0,236	0,045	0,038	-0,045	1,325	0,060
OWNER.CREDI	85	0,04	0,171	0,399	0,364	-0,399	11,650	0,000
SPEC.CREDITS	85	0,029	0,112	0,448	0,448	-0,397	13,089	0,000
SHORT.CREDIT	85	12,69	3,366	0,114	0,112	-0,114	3,318	0,000
LONG.CREDITS	85	10,94	4,950	0,123	0,102	-0,123	3,583	0,000
FX.CREDITS	85	11,63	3,783	0,112	0,089	-0,112	3,284	0,000
DC.CREDITS	85	12,92	2,925	0,079	0,065	-0,079	2,302	0,000
PUBLIC.CREDIT	85	4,401	5,775	0,388	0,388	-0,223	11,344	0,000
PRIVATE.CREDI	85	13,128	3,518	0,098	0,097	-0,098	2,861	0,000
COUNTRY.RISK	85	0,160	0,151	0,146	0,118	-0,146	4,253	0,000

Table 5: Logistic Distribution Test on Non-Consolidated Data Set

VARIABLE	N	Mean	Most Extreme Differences			Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)
			Absolute	Positive	Negative		
EXP.CREDITS	854	0,194	0,179	0,179	-0,019	4,923	0,000
DISC.CREDITS	854	0,039	0,638	0,638	0,000	16,173	0,000
IMP.CREDITS	854	0,006	5,468	5,468	0,000	63,769	0,000
BUL.CREDITS	854	0,017	5,620	5,620	0,000	65,538	0,000
CARD.CREDITS	854	0,084	0,685	0,685	0,000	15,803	0,000
FINSEC.CREDITS	854	0,092	0,755	0,755	0,000	17,926	0,000
CONS.CREDITS	854	0,149	0,342	0,342	0,000	9,174	0,000
AFF.CREDITS	854	0,071	2,228	2,228	0,000	39,363	0,000
OVSEA.CREDITS	854	0,067	0,915	0,915	0,000	21,129	0,000
OTHER.CREDITS	854	0,469	0,212	0,175	-0,212	6,014	0,000
OWNER.CREDITS	854	0,047	0,525	0,525	0,000	14,239	0,000
SPEC.CREDITS	854	0,099	18,530	18,530	0,000	122,915	0,000
SHORT.CREDITS	854	0,281	0,115	0,073	-0,115	3,347	0,000
LONG.CREDITS	854	9,181	0,973	0,973	0,000	27,429	0,000
FX.CREDITS	854	0,142	0,162	0,162	-0,094	4,554	0,000

DC.CREDITS	854	0,288	0,154	0,113	-0,154	4,448	0,000
PUBLIC.CREDITS	854	0,091	0,209	0,209	0,000	5,630	0,000
PRIVATE.CREDITS	854	0,346	0,167	0,143	-0,167	4,835	0,000
COUNTRY.RISK	854	0,001	0,205	0,205	-0,184	5,098	0,000

Results of Neural Network Models

While, in the case of consolidated data, a training sample of 391 observations and a test sample of 158 observations have been used, 653 observations have been included in the training sample and only 251 observations in the test sample for non-consolidated modeling All the data have been standardized before processing them.

It can be clearly observed that the Neural Network model based on consolidated data outperforms the model based on non-consolidated data set. But both models can still be more accurate in comparison to a naïve model so that their overall prediction performance is found to be significant at 99,9 % confidence.

Neural Network Model Based on Consolidated Data

The final neural network model derived using the consolidated data set contains 12 explanatory variables, also including the variable representing country risk changes. The relative importance of these variables in the model and other model outputs are given in Tables 6 – 7 that are accompanied by Table 8 summarizing the results of a correlation analysis. According to the network results, it can be said that concentration on certain credit sub-portfolios, maturity differentiation, sector type to which credits are placed, and the kind of currency in which credits are denominated may affect, to different extents, the level of credit risk. The most and least significant explanatory variables are respectively OWNER.CREDITS and DC.CREDITS with an increasing effect on credit risk. In other words, more concentration on credits to owners and members creates the highest directional effect on credit risk whereas credits in denominated in TL is of relatively lower importance. On the other hand, the only credit segment that is supposed to conversely affect credit risk seems to be credits given for precious metal transactions. In addition, export credits, credit card dues, credits to subsidiaries and affiliates, other non-specialty credits, short-term and long-term credits, credits denominated in foreign currencies, and credits to private sector are all attributed with risk increasing effect. However, the contribution of short term credits to risk formation is much more than that of long-term credits. Similarly, credits in foreign currencies are more accused of increases in credit risk during the analysis period. The underlying reason for that diagnosis may be the fact that TL was mainly appreciated against other currencies within this period.

It is a desirable finding that the country risk variable is found to be significantly effective on risk changes and is expect to proportionally influence a bank's risk exposure, which proves the functionality of conditional models in predicting credit risk.

Table 6: Network Information

Network Information

Input Layer	Covariates	1	*EXP.CREDITS*
		2	*BUL.CREDITS*
		3	*CARD.CREDITS*
		4	*AFF.CREDITS*
		5	*OTHER.CREDITS*
		6	*OWNER.CREDITS*
		7	*SHORT.CREDITS*
		8	*LONG.CREDITS*
		9	*FX.CREDITS*
		10	*DC.CREDITS*

		11	*PRIVATE.CREDITS*
		12	*COUNTRY.RISK*
	Number of Units[a]		12
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		5
	Activation Function		Sigmoid
Output Layer	Dependent Variables	1	CREDITRISK
	Number of Units		2
	Activation Function		Sigmoid
	Error Function		Sum of Squares

a. Excluding the bias unit

Table 7: Model Summary and Variable Importance

Model Summary

Training	Sum of Squares Error	69,622
	Percent Incorrect Predictions	25,3%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	00:00:00,281
Testing	Sum of Squares Error	31,383
	Percent Incorrect Predictions	29,7%

Dependent Variable: KREDİ.RİSKİ

Independent Variable Importance

Variable	Importance	Normalized Importance
EXP.CREDITS	.086	73.[illegible]%
BUL.CREDITS	.111	95.2%
CARD.CREDITS	.082	69.9%
AFF.CREDITS	.064	54.3%
OTHER.CREDITS	.092	78.2%
OWNER.CREDITS	.117	100.0%
SHORT.CREDITS	.102	86.8%
LONG.CREDITS	.064	54.7%
FX.CREDITS	.074	63.2%
DC.CREDITS	.056	48.0%
PRIVATE.CREDITS	.083	70.5%
COUNTRY.RISK	.070	59.9%

Table 8: Kendall's Tau-b Correlation Statistics

VARIABLE	**CORRELATION COEFFICIENT (significance levels in parantheses)**
EXP.CREDITS	0,091 (0,000)
BUL.CREDITS	-0,037 (0,000)
CARD.CREDITS	0,209 (0,004)
AFF.CREDITS	0,034 (0,008)
OTHER.CREDITS	0,257 (0,000)
OWNER.CREDITS	0,085 (0,000)
SHORT.CREDITS	0,389 (0,000)
LONG.CREDITS	0,068 (0,007)
FX.CREDITS	0,086 (0,005)
DC.CREDITS	0,366 (0,009)
PRIVATE.CREDITS	0,489 (0,001)

COUNTRY.RISK	0,327 (0,003)

Neural Network Model Based on Non-Consolidated Data

In the neural network model eventually obtained using the non-consolidated data are 12 variables again also including the country risk variable. Respecting the results given in Tables 9 – 11, it is concluded that all the variables included in the models are significant at 98 % confidence level. Moreover, the most important factor affecting credit risk seems to be maturity choice. Credits with short term maturity make the greatest contribution to risk in direct proportion while long term credits are of second rank in influencing risk exposure, again with a direct proportional effect. Similar to our consolidated model results, export credits and dues from credit cards prove to be the next two variables with considerable impact on credit risk. Additionally, credits denominated in foreign currencies are considered to be instrumental and lead to parallel changes in credit risk, but no evidence could be found to support significance of TL credits. The variable representing credits given to private sector actors appears as an important determinant, which risk exposure is a positive function of. Furthermore, the results also provide supporting evidence to assume that credits to affiliates and owners are among the variables having direct proportional influence. The finding that country risk changes significantly affect credit risk in the same direction can be deemed to be a persuasive proof that conditional models are more appropriate to predict banks' exposure to credit risk. Differently, import credits and credits to public sector parties are included in the network model and risk is considered to be a negative function of these variables.

As can be inferred from the results, it is obvious that Turkish borrowers are inefficient in fulfilling debt covenants especially in case of shorter maturities. Plus, they perform poorly to repay their credit card dues to banks and their inability becomes more apparent in times when general economic condition has weakened. On the other hand, import credits have helped Turkish banks improve their performance during the analysis period whereas export credits make them face increases in credit risk. This situation can be seen as a natural consequence of the dominance of TL in value over other currencies experienced specifically in the covered period. In addition, , our results also show that private sector borrowers, contrary to public sector borrowers, have exhibited explicitly very poor performance in paying their credit debts and more credit placements to public sector have created a relative advantage for the banks since the concentration the credits of this segment have enabled them to reduce their vulnerability to credit risk.

Table 9: Network Information

Network Information

Input Layer	Covariates	1	*EXP.CREDITS*
		2	*IMP.CREDITS*
		3	*BUL.CREDITS*
		4	*CARD.CREDITS*
		5	*AFF.CREDITS*
		6	*OWNER.CREDITS*
		7	*SHORT.CREDITS*
		8	*LONG.CREDITS*
		9	*FX.CREDITS*
		10	*PUBLIC.CREDITS*
		11	*PRIVATE.CREDITS*
		12	*COUNTRY.RISK*
	Number of Units[a]		12
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1

	Number of Units in Hidden Layer 1[a]		5
	Activation Function		Sigmoid
Output Layer	Dependent Variables	1	CREDITRISK
	Number of Units		2
	Activation Function		Sigmoid
	Error Function		Sum of Squares

a. Excluding the bias unit

Table 10: Model Summary and Variable Importance

Training	Sum of Squares Error	98,571
	Percent Incorrect Predictions	22,9%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	00:00:00,219
Testing	Sum of Squares Error	47,801
	Percent Incorrect Predictions	26,3%

Dependent Variable: KREDİ.RİSKİ

Independent Variable Importance

Variable	Importance	Normalized Importance
EXP.CREDITS	,087	56,4%
IMP.CREDITS	,070	45,5%

BUL.CREDITS	,069	44,8%
CARD.CREDITS	,088	56,7%
AFF.CREDITS	,060	38,5%
OWNER.CREDITS	,069	44,4%
SHORT.CREDITS	,155	100,0%
LONG.CREDITS	,132	85,3%
FX.CREDITS	,073	46,9%
PUBLIC.CREDITS	,070	45,5%
PRIVATE.CREDITS	,068	43,7%
COUNTRY.RISK	,060	38,9%

Table 11: Kendall's Tau-b Correlation Statistics

VARIAB LE	**CORRELATION COEFFICIENT (significance levels in parantheses)**
EXP.CREDI	0,163 (0,002)
IMP.CREDIT	-0,187 (0,007)
BUL.CREDI	-0,036 (0,007)
CARD.CRE	0,109 (0,001)
AFF.CREDI	0,101 (0,011)
OWNER.CR	0,072 (0,008)
SHORT.CR	0,149 (0,000)
LONG.CRE	0,040 (0,000)
FX.CREDIT	0,013 (0,007)
PUBLIC.CR	-0,212 (0,006)
PRIVATE.C	0,151 (0,009)
COUNTRY.	0,035 (0,013)

Results of MARS Models

Our MARS models, in general, yield some performance satisfactory enough for us to come to the conclusion that they can be respected as equally worthy models in comparison with the network models. They have achieved approximately the same prediction accuracy even with relatively less number of independent variables. However, the impact of credit segmentation appears to be less substantial while the role of overall economic condition is once more found to be present.

Consolidated data-based MARS model outperforms the one based on non-consolidated MARS model though both of them prove to be prevalent to a naïve model.

MARS Model Based on Consolidated Data

The eventual MARS model based on consolidated financial statements in which only 5 independent variables have been proved to be significant is composed of 10 basis functions that have been derived from these variables. The model results in an adjusted R2 value of 14 %. Table 12 and Table 13 list respectively the variables included in the model in order of relative importance and the regression results containing the basis functions with their significance test statistics and coefficients. In the accompanying table are the basis functions and the regression equation used in calculating group membership probabilities.

Inferring from the information in Table 12, it can be said that the variables found significant are the same as the ones included in the network model, but with two exceptions; specialty credits and discount credits.

Table 12: Relative Variable Importance

Piecewise Cubic Fit on 10 Basis Functions, GCV = 0.22656

Variable	**Importance**	**-gcv**
DC.CREDITS	100.00000	0.23389
SPEC.CREDITS	92.14437	0.23216
PUBLIC.CREDITS	72.21899	0.22843

COUNTRY.RISK	61.68829	0.22682
DISC.CREDITS	46.13420	0.22490

The largest effect on credit risk is caused by the variable standing for credits denominated in TL which is accompanied by, in order, specialty credits (credits provided for project finance, fixed asset acquisition, and commodity purchases), credits to public sector, country risk measure, and discount credits.

Table 13 presents the regression output considering 12 basis functions included in the model and Table 14 gives both the basis function explanations and the model equation (Equation 7). According to the table information, all the basic functions are considered significant at 98 % confidence.

Table 13: Regression Results

MARS Regression: Training Data

N: 549.00	R-SQUARED: 0.15557
MEAN DEP VAR: 0.40073	ADJ R-SQUARED: 0.13987
UNCENTERED R-SQUARED =	R-0 SQUARED: 0.49395

PARAMETER	ESTIMATE	S.E.	T-RATIO	P-VALUE
Constant	-1.59792	0.33239	-4.80732	0.00000
Basis Function 3	36.48980	1.64811	3.93773	0.00009
Basis Function 4	-41.26464	8.31609	-4.96203	0.00000
Basis Function 5	21.39402	4.74171	4.51188	0.00001
Basis Function 6	39.39310	8.14532	4.83628	0.00000
Basis Function 8	0.85826	0.21549	3.98279	0.00008

Basis Function 9	0.01165	0.00482	2.41633	0.01601
Basis Function 10	0.10771	0.01853	5.81284	0.00000
Basis Function 11	0.16586	0.03834	4.32626	0.00002
Basis Function 12	-0.49619	0.13160	-3.77056	0.00018
Basis Function 14	-2.83346	0.86080	-3.29164	0.00106

F-STATISTIC = 9.91133 S.E. OF REGRESSION = 0.45490
P-VALUE = 0.00000 RESIDUAL SUM OF SQUARES = 111.32991
[MDF,NDF] = [10, 538] REGRESSION SUM OF SQUARES = 20.50980

Table 14: Basis Functions and Model Equation

BF3 = max(0, COUNTRY.RISK + 0.0435);
BF4 = max(0, SPEC.CREDITS - 0.067);
BF5 = max(0, SPEC.CREDITS - 0.024);
BF8 = max(0, PUBLIC.CREDITS - 13.8657);
BF9 = max(0, 13.8657 – PUBLIC.CREDITS);
BF10 = max(0, DC.CREDITS - 11.8556);
BF11 = max(0, 11.8556 – DC.CREDITS);
BF12 = max(0, PUBLIC.CREDITS - 13.1713);
BF14 = max(0, DISCOUNT.CREDITS - 3.7334e-010);

$$Y = -1.59755 + 6.48979 * BF3 - 41.2545 * BF4 + 21.3886 * BF5 + 39.3832 * BF6 + 0.858242 * BF8 + 0.0116462 * BF9 + 0.107712 * BF10 + 0.165861 * BF11 - 0.496184 * BF12 - 2.83344 * BF14 \tag{7}$$

The effect of country risk on credit risk level represented by BF3 is direct proportional, which means that credit risk is increased with any upward change in country risk. However, explaining the influence created by specialty credits is not straightforward because it is represented by three basic functions (BF4, BF5 and BF6). This influence is in reverse direction when the variable takes on any value above 6,7 percent, but in direct proportion if it is below that value, until 2,4 %. Any increases within the range of 6,7 – 2,4 % result in risk decreases. Under that lowest value, the influence of the variable becomes extinct.

Considering BF8, BF9, and BF13, it can be concluded that credits to public sector contribute less to risk exposure, a unitary effect of 0,26 as the difference between the coefficients given in BF8 and BF13, provided that the variable is over the cutoff point of 13,865, but decreasing marginal reductions in credit risk is observed if it is between that upper value and 13,171. In other words, upward changes between the values of 13,171 and 13,865 is associated with shrinking risk contributions, On the other hand, a relatively lower risk increases are forecast to occur whenever the value of 13,171 is not exceeded. A similar inference can be made also for credits denominated in TL as BF10 and BF11 suggest that the corresponding variable is expected to cause a rise in risk in case of taking on any value above 11,855, but shrinking rises in case of any upward trend below that cutoff.

Finally, the findings also show that discount credits lead to a decreasing effect in risk as long as it does not fall below 3,73e-10. Nonetheless, no risk change is anticipated below that value.

MARS Model Based on Non-Consolidated Data

Our MARS model derived from the non-consolidated data set contains 8 independent variables and 9 basis functions based on them. Table 15 provides a list of these independent variables ordered in terms of their relative importance. In accordance with the statistics obtained, it can be implied that the most important explanatory variable is dues from credit cards. Secondly, the type of currency in which credits are denominated plays an important role in risk exposure so that the variables denominated in foreign and domestic currencies have been determined to be the significant model parameters following credit cards. Additionally, credits to private sectors is selected as the fourth most significant model variable, followed by the variable referring to country risk level. Other non-specialty credits, short-maturity credits and import credits are among the included variables, but with relatively inferior importance by comparison with the others.

Table 15: Relative Variable Importance

Piecewise Cubic Fit on 9 Basis Functions, GCV = 0.19660

Variable	Importance	-gcv
CARD.CREDITS	100.00000	0.19704
FX.CREDITS	95.55602	0.19667
DC.CREDITS	89.12736	0.19618
PRIVATE.CREDITS	81.14775	0.19561
COUNTRY.RISK	71.46086	0.19499
OTHER.CREDITS	61.79888	0.19445
SHORT.CREDITS	61.62444	0.19444
IMP.CREDITS	55.77682	0.19415

Table 16 containing the regression results introduces some findings about the robustness of the model, its basis functions, and coefficient estimates. It can be primarily interpreted from these findings that the model can be assumed to be statistically adequate with an R2 value of 9,7 % and that all of the basic functions prove to be significant at 99 % confidence level.

Table 16: Regression Results

N: 854.00 R-SQUARED: 0.10661
MEAN DEP VAR: 0.29040 ADJ R-SQUARED: 0.0970
UNCENTERED R-SQUARED = R-0 SQUARED: 0.36605

PARAMETER	ESTIMATE	S.E.	T-RATIO	P-VALUE
Constant	0.76680	0.21516	3.56386	0.00039
Basis Function 1	4.93667	1.03839	4.75417	0.00000
Basis Function 4	60.30600	19.15166	3.14887	0.00170

Basis Function 5	-0.83490	0.24926	-3.34953	0.00085
Basis Function 7	4.66080	1.26428	3.68653	0.00024
Basis Function 9	-0.03513	0.00767	-4.58276	0.00001
Basis Function 10	-0.25376	0.07590	-3.34360	0.00086
Basis Function 12	0.92334	0.23315	3.96036	0.00008
Basis Function 13	-0.03838	0.01294	-2.96658	0.00310
Basis Function 14	+0.06914	0.01712	4.03893	0.00006

F-STATISTIC = 11.19042 S.E. OF REGRESSION = 0.43160
P-VALUE = 0.00000 RESIDUAL SUM OF SQUARES = 157.22030
[MDF,NDF] = [9, 844] REGRESSION SUM OF SQUARES = 18.76096

The statistical expositions pertaining to the basis functions and the derived model equation given in Table 17 provide essential numeric evidence for the nature of the relationships between each independent variable and the dependent variable. According to these expositions, BF1 suggests that credit card dues could cause dramatic upswings in credit risk if the weight of this credit segment in the entire credit portfolio exceeds 19,3 percent. However, below 19,3 percent, no effect is predicted. In addition, other non-specialty are associated with a decreasing effect on credit risk. Furthermore, BF4 representing the effect of import credits implies decreases in risk when the related variable gradually rises up to 0,003, but disappearance of this increase in cases of exceeding that value. On the other hand, in BF7, country risk changes are discovered once more to be effective on credit risk in a fashion that unfavorable country conditions lead to ascending risk profile.

Credits denominated in foreign currencies are held accountable to some extent for risk changes and expected to pave the way to risk reductions while the relevant variable has a rising trend until the value of 16,306. Though, this assumed effect is supposed to perish for all the values over this cutoff. Moreover, credits with shorter maturities are considered to have a reducing impact in the circumstance when the representing variable is assigned any value over 15,274, but no impact below that cutoff value. As another inference from the basis functions, it is possible to state that credits denominated in TL have a direct contribution to credit risk for the cases that the corresponding variable bears any value over 16,656. Yet, the variable is associated with a comparatively lower increasing effect provided that it changes upwardly until reaching the value of 16,656.

Our last determination is about credits to private sector that such credits take a role of increasing credit risk if the variable takes any value above 5,953.

Table 17: Basis Functions and Model Equation

BF1	=	max(0, CARD.CREDITS - 0.193);
BF4	=	max(0, 0.003 – IMP.CREDITS);
BF5	=	max(0, OTHER.CREDITS - 0.675);
BF7	=	max(0, COUNTRY.RISK + 0.0435);
BF9	=	max(0, 16.306 – FX.CREDITS);
BF10	=	max(0, SHORT.CREDITS - 15.274);
BF12	=	max(0, DC.CREDITS - 16.656);
BF13	=	max(0, 16.656 – DC.CREDITS);
BF14	=	max(0, PRIVATE.CREDITS - 5.953);

$$Y = 0.766797 + 4.93667 * BF1 + 60.306 * BF4 - 0.834899 * BF5 + 4.6608 * BF7 - 0.0351314 * BF9 - 0.253763 * BF10 + 0.923338 * BF12 - 0.0383802 * BF13 + 0.0691361 * BF14 \tag{8}$$

Comparison of Model Performances

To determine the best cutoff point of classification for each model and to conduct a comparative analysis on the performance of the network and MARS models, ROC analysis has been utilized. The results of ROC analyses performed are summarized in Table 18 and Table 19.

Table 18: ROC Statistics

DATA	Test Result Variable(s)	Area	Std. Error	Asymptotic Sig.	Asymptotic 95% Confidence Interval	
					Lower Bound	Upper Bound
CONSOLIDATED	NEURAL NETWORK	0,787	0,020	0,000	0,747	0,826
	MARS	0,738	0,021	0,000	0,696	0,779
NON-CONSOLIDATED	NEURAL NETWORK	0,708	0,019	0,000	0,670	0,746
	MARS	0,736	0,022	0,000	0,694	0,780

Table 19: Performance Statistics

DATA	MODEL	NUMBER OF IND. VARIABLES	BEST CUTOFF	TYPE I ERROR	TYPE II ERROR	OVERALL RATE OF CORRECT CLASSIFICATION	ACCURACY t-Value
CONSOLIDATED	NEURAL NETWORK	12	0,455	35,91	19,14	74,13	11,308
	MARS	12 (5)*	0,424	34,55	24,62	71,40	10,028
NON-CONSOLIDATED	NEURAL NETWORK	12	0,373	27,73	27,05	72,68	10,628
	MARS	9 (8)*	0,437	35,00	21,88	72,86	10,713

*Number of basis functions (number of independent variables)
Type I Error: Rate of the observations that are in fact unfavorable, but classified as unfavorable
Type II Error: Rate of the observations that are in fact favorable, but classified as unfavorable
Accuracy t-statistic = (Overall Correct Classification Rate – 0,50)*n1/2 / 0,50

The above tabular information indicates that all the models perform better than a naïve model does since the asymptotic significance probability for all of the models very approximates to 0. On the other hand, the MARS model seems superior to the network model in the case of nonconsolidated data, but inferior in the case of consolidated data. In general, no robust evidence has been obtained to conclude that any of the techniques is more efficient and successful. So, regarding the complexity of network models and the difficulty with transforming them to a functional form, MARS models may pass beyond network models due to their user-friendly and easily understandable structure.

A Further Examination to Use Model Predictions in Calculating Minimum Capital Requirements

With the purpose of assessing the convenience of our model predictions for practical issues, a supplementary attempt has been carried out to test whether the PD predictions that the models produced can be used efficiently in calculating banks' capital requirements and to examine the extent to which these calculations could be accurate. To accomplish that, a minimum capital requirement amount has been calculated for each observation using the unexpected loss formula given in Equation 4 as based on our PD estimations via the models assuming that EAD equals total amount of cash credits and LGD is 100 %, which means full utilization of a credits by borrowers. Then, these amounts have been analyzed in comparison with the officially stated figures through Kendall's Tau-b and Spearman's Rho tests. Table 20 and Table 21 reflect the results of the correlation tests.

As can be inferred from the tabular information, all the correlation coefficients are considered to be significant at 99,9 % confidence. With few exceptions only, there exist strong correlations (bigger than 70 percent) among the actual and calculated capital requirement amounts. These findings are crucial to the aim and scope of our study and support our expectation that it may be practicable to construct simple credit risk models using the publicly available financial statement data of banks.

Table 20: Correlation Statistics for Consolidated Data

			ACTUAL	NEURAL NETWORK	MARS
Kendall's tau_b	ACTUAL	Correlation	1	,688**	,668**
		Sig. (2-	.	0	0
		N	549	549	549
	NEURAL NETWORK	Correlation	,688**	1	,756**
		Sig. (2-	0	.	0
		N	549	549	549
	MARS	Correlation	,668**	,756**	1
		Sig. (2-	0	0	.
		N	549	549	549
Spearman's rho	ACTUAL	Correlation	1	,862**	,842**
		Sig. (2-	.	0	0
		N	549	549	549
	NEURAL NETWORK	Correlation	,862**	1	,898**
		Sig. (2-	0	.	0
		N	549	549	549
	MARS	Correlation	,842**	,898**	1
		Sig. (2-	0	0	.
		N	549	549	549

**. Correlation is significant at the 0.01 level (2-tailed).

Table 21: Correlation Statistics for Non-Consolidated Models

			ACTUAL	NEURAL NETWORK	MARS
Kendall's tau_b	ACTUAL	Correlation Coefficient	1	,668**	,672**
		Sig. (2-tailed)	.	0	0
		N	854	854	854
	NEURAL NETWORK	Correlation Coefficient	,668**	1	,723**
		Sig. (2-	0	.	0

		tailed)			
		N	854	854	854
	MARS	Correlation Coefficient	,672**	,723**	1
		Sig. (2-tailed)	0	0	.
		N	854	854	854
Spearman's rho	ACTUAL	Correlation Coefficient	1	,861**	,851**
		Sig. (2-tailed)	.	0	0
		N	854	854	854
	NEURAL NETWORK	Correlation Coefficient	,861**	1	,868**
		Sig. (2-tailed)	0	.	0
		N	854	854	854
	MARS	Correlation Coefficient	,851**	,868**	1
		Sig. (2-tailed)	0	0	.
		N	854	854	854

**. Correlation is significant at the 0.01 level (2-tailed).

Conclusions

In this paper, some conditional credit models based are introduced that have been constructed using the data that belong to the Turkish Banking Industry and an exactly simple and different methodology in which the quality of cash credit portfolios is measured with the ratio of delinquent credits to total credits and the changes in this ratio are considered as an approximate measure for changes in the banks' credit risk exposure. Financial ratios representing the weights of credit sub-portfolios in the overall portfolio as well as a separate measure of country risk are employed as independent variables to model credit quality changes by Neural Network and MARS algorithms.

The empirical findings show that dynamic structure of credit portfolios in terms of credit segments, length of maturity, and type of currency is one of the determinants of credit risk so that concentration on specific credit sub-portfolios may contribute less or more risk. Moreover, there exists some evidence that overall economic condition of a country may have a great impact on quality of credit portfolios and credit risk to which banks would be exposed. Additionally, especially in our network models, we investigate a parallel relationship between the amount of credits given to bank owners or members and credit risk, which supports the importance of corporate governance issues to risk phenomenon in banking. Similarly, credits utilized by subsidiaries and affiliates are associated with an identical effect on credit risk and quality. Besides, credit cards and short-term credits constitute the most problematic credit portfolios that banks must carefully deal with, merely in developing economies with rapidly changing conditions. The currency in which credits are denominated and the credits given for foreign trade transactions become important risk factors under the circumstances that foreign exchange rates are unsteady and unforeseeable.

Our empirical results provide no convincing proof about the dominance of neural network and MARS techniques to one another. The techniques both have produced comparable prediction performances, anyway better than that of a naïve model. We also obtain some findings suggesting that the PD predictions produced by these models may constitute a precedent and can be taken as input in calculating minimum capital requirement.

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