<u>İSTANBUL BİLGİ UNIVERSITY ★ INSTITUTE OF SOCIAL SCIENCES</u>

CREDIT ASSESSMENT PROCESSES AND BASEL II ACCORD

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ABSTRACT

CREDIT ASSESSMENT PROCESSES AND BASEL II ACCORD

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This study analyses the credit assessment processes of a specific financial institution in Turkey and compares the main drivers of corporate credit approval decisions with the parameters of Moody's rating model for private companies, RiskCalc. The new "International Convergence of Capital Measurement and Capital Standards" or Basel II is expected to bring new applications in terms of credit assessment processes to the banking sector. The latest Banking Sector Development Report by the Banking Regulation and Supervision Agency (BRSA) suggests that Turkish Banks are still in the initial phases of implementation of Basel II, which tries to achieve global financial stability. Its effectiveness is debated especially after the result of the recent turbulence in the financial markets related to the sub-prime mortgage crisis. Basel II –Standard Approach is expected to be applied by the majority of the Turkish banking sector. This approach implies the utilisation of external rating institutions' grades in the credit assessment processes of the financial institutions and requires that each borrower and facility should have a rating prior to the bank entering into a commitment to lend.

To reach the underlined objectives of the study, firstly Basel II framework and its application in Turkey in terms of credit assessment processes are presented. Secondly, in order to model the credit decision data of the financial institution - whether to accept a loan application or not- logit and probit regression models are

introduced. Those models are among the most practiced methods and mentioned in the Basel II framework as the best practices of the banks in their internal credit assessment and credit scoring processes.

Even though not all the parameters for comparison with the model of Moody's could be obtained, the results indicate that qualitative information and/or judgement played an important role in the credit approval decision of the analysed financial institution. This is because the main criteria applied by Moody's, such as debt or leverage ratios, size variables, liquidity ratios were insignificant. Another main criteria, profitability, was only significant in the logit regression. The industry (excluding textile) in which the company operated, played no significant role in the credit decision, which is also not addressed in the model of Moody's as a parameter. The industry binary variable "textile" was significant in both models. Therefore, the models provided a meaningful result about the selectivity of financial institutions to grant credit to the textile industry companies due to the recent difficulties in the sector. Activity ratios, sales growth and audit quality are other parameters utilised by Moody's. Due to inexistence of appropriate data, these measures are not included in this study. It is suggested by Moody's that, the above mentioned ratios and criteria are to be used by the financial institutions. Therefore, with the Basel II implementation, it is expected that those parameters will become a criteria in their rating and credit decision models. Basel II-IRB (internal ratings based) Approach implementation will lead to similar models as those of rating companies to be constructed internally by the financial institutions.

Keywords: Credit Assessment Processes, Basel II, Developing Country, Corporate Loans, , Probit, Logit, Binary Choice Models.

ÖZ

KREDİ DEĞERLENDİRME SÜREÇLERİ VE BASEL II UZLAŞISI

Cihangir, Nuran

Yüksek Lisans, Finansal Ekonomi Bölümü

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Bu çalışma Turkiye'de yerleşik spesifik bir finans kuruluşunun kredi değerlendirme süreçlerini analiz etmekte ve kurumsal kredi kararlarının ana etmenlerini Moody's derecelendirme kuruluşunun özel şirket firmalarına ilişkin model parametreleriyle karşılaştırmaktadır. Yeni "Uluslararası Sermaye Ölçümlenmesi ve Standartları Uzlaşısı" ya da Basel II'nin bankacılık sektörüne kredi değerlendirme süreçleri açısından yeni uygulamalar getireceği öngörülmektedir. Bankacılık Düzenleme ve Denetleme Kurumu'nun en son tarihli Bankacılık Sektörü Gelişim Raporu Türk Bankaları'nın halen Basel II uygulaması konusunda başlangıç aşamasında olduklarını öne sürmektedir, ki Basel II global olarak finansal istikrarın sağlanmasına çalışmaktadır. Verimliliği, özellikle yakın tarihte meydana gelen uluslararası tutsat krizi sonrasında finansal piyasalarda oluşan dalgalanmanın sonucunda tartışılmaktadır. Basel II – Standart Yaklaşım'ın Türk Bankacılık Sektörü'nün çoğunluğu tarafından uygulanması beklenmektedir. Bu yaklaşım dışsal derecelendirme kuruluşlarının ratinglerinin kredi değerlendirme süreçlerinde kullanılmasına yol açacaktır ve her bir kredi borçlusunun ve kredi faaliyetinin banka kredi ilişkisine girmeden önce bir rating derecesi sahibi olmasını gerekli kılmıştır.

Yukarıda belirtilen hedeflere ulaşmak amacıyla, bu çalışmada öncelikle Basel II uzlaşısı ve kredi değerlendirme süreçleri açısından Turkiye'deki uygulaması hakkında bilgi verilmiştir. Buna ek olarak, finansal kurumun kredi karar (kabul ya da red) verisini modellemek amacıyla logit ve probit regresyon modelleri sunulmuştur. Bu modeller en çok kullanılan modeller arasında olup, Basel II'de bankaların içsel kredi değerlendirme ve skorlama süreçlerindeki en iyi uygulamalar arasında bahsedilmektedirler.

Moody's'in modeliyle karşılaştırmak için parametrelere ilişkin verilerin tamamı elde edilememiş olmasına rağmen, sonuçlar kalitatif ve /veya yargısal içerikli bilginin finansal kurumun karar süreçlerinde önemli rol oynadığına işaret etmektedir. Moody's tarafından uygulanan ana kriterler olan, borçluluk ya da finansal kaldıraç oranları, büyüklüğe ilişkin veriler, likidite rasyoları yetersiz açıklayıcılığa sahip değişkenler olarak bulunmuştur. Diğer ana kriter, karlilik oranı, yalnızca logit modelinde yüksek açıklayıcılığa sahiptir. Öte yandan, firmanın içinde bulunduğu sektör (tekstil hariç) değişkeni kredi onay kararında düşük açıklayıcılığa sahiptir, ki Moody's'in modelinde de bir parametre olarak yer almamaktadır. *'Binary'* değişken 'Tekstil' her iki modelde de yüksek açıklayıcılıklı değişkendir. Dolayısıyla, modeller finansal kurumların tekstil sektöründe yer alan firmalara karşı seçici davranması konusunda anlamlı bir sonuca varmıştır, ki tekstil sektörü firmaları yakın zamanlarda çeşitli güçlüklerle karşı karşıya kalmıştır. Faaliyet rasyoları, satış büyüme rakamları ve denetim kalitesi faktörleri Moody's tarafından kullanılmasına rağmen, ilişkin verinin elde edilememesi ya da sağlıklı olmaması nedeniyle bu faktörler calışmaya dahil edilememiştir. Moody's yukarıda bahsedilen rasyo ve kriterlerin finansal kurumlarca kullanılmasını önermektedir. Dolayısıyla, Basel II'nin uygulanmasıyla bu parametrelerin derecelendirme ve kredi karar modellerinde kriter haline gelmesi beklenmektedir. Basel II - İçsel Derecelendirme Yaklaşımı'nın uygulanması, derecelendirme kuruluşlarının benzeri modellerin finansal kurumlar tarafından içsel olarak oluşturulmasına neden olacaktır.

Anahtar Kelimeler: Kredi Değerlendirme Süreçleri, Basel II, Gelişmekte Olan Ülkeler, Kurumsal Krediler, Probit, Logit, Binary Seçim Modelleri.

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LIST OF ABBREVIATIONS

RWA: Risk Weighted Assets

CAR: Capital Adequacy Ratio

OECD: Organisation for Economic Co-operation and Development

IRB: Internal Rating Based Approach

AMA: Advanced Measurement Approach

PIT: Point-in-time Rating System

TTC: Through-the-cycle Rating System

PD: Probability of Default

LGD: Loss-given-default

EAD: Exposure-at-Default

M: Maturity

GPA: Grade Point Average

MCR: Minimum Capital Requirement

SME: Small and Medium Sized Enterprises

SA: Standard Approach

AIG: Basel Committee’s Accord Implementation Group

QIS: Quantitative Impact Study

BRSA: Banking Regulation and Supervision Agency of Turkey

KKB: National Credit Bureau of Turkey (Kredi Kayıt Bürosu)

GDP: Gross Domestic Product

N: Number of observations

μ: Mean (average)

σ: Standard deviation

Min: Minimum value of the observations

Q1: 1st Quartile

Q2: 2nd Quartile (Median)

Q3: 3rd Quartile

Max: Maximum value of the observations

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CHAPTER 1

INTRODUCTION AND REVIEW OF LITERATURE

1.1 Introduction

This study analyses the credit assessment processes of a specific financial institution in Turkey and compares the main drivers of corporate credit approval decisions with the parameters of Moody's rating model for private companies, RiskCalc. The new "International Convergence of Capital Measurement and Capital Standards" or Basel II is expected to bring new applications in terms of credit assessment processes to the banking sector.

To reach the underlined objectives of the study, firstly Basel II framework and its application in Turkey in terms of credit assessment processes are presented. As a consequence of the recent sub-prime mortgage crisis in the USA and spread into other markets, risk management became an even more central topic in finance. Similarly, liberalisation and deregulation of financial markets, globalisation, and ever more complex financial products already made it necessary to have appropriate and enforced regulations. Their aim is to improve risk management practices, and through that, to ensure sound, stable and well functioning financial institutions and markets, and ultimately, prevent the occurrence of financial crisis. With this objective in mind, the new "International Convergence of Capital Measurement and Capital Standards" (or Basel II-accord) has been developed. The accord brings together best practices and emphasises the requirement of a higher capital base in relation to a higher risk portfolio. Currently, its effectiveness is subject to global debate, as it could not prevent the mortgage crisis.

"Credit" or "default" risk is one of the main risks described in the Basel II framework, defined as the probability that the counterparty is not able to appropriately fulfil its loan obligation. As default is costly, financial institutions construct and implement a system to separate "good" from "bad" risk. These risks are then classified in a number of different risk “buckets”, with the credit in each bucket differing in terms of pricing and capital allocation. Those risk buckets are called “rating” and the classification system applied by the institution is named as “rating system”. The new Basel Accord prescribes financial institutions to use either external ratings of rating companies, i.e. standard approach, or internal ratings of the institution, i.e. internal ratings based approach (IRB).

Financial institutions traditionally use the opinion or judgment of internal or external experts to differentiate between risks. Because of the complexity of the data involved, humans have over the years gradually been replaced by statistical models. Yet, because of the remaining limitations of these models, final conclusions are still drawn by experts. In addition, financial institutions have decision making or scoring processes. These are either statistical, expert judgment based or constrained expert-judgment based, depending on the degree of reliance on the expert judgment. Basel II encourages the financial institutions to have one or more statistical based credit assessment models for different credit segments.

Secondly, in order to model the credit decision data of the financial institution - whether to accept a loan application or not- logit and probit regression models are presented. Those models are among the most practiced methods and mentioned in the Basel II framework as the best practices of the banks in their internal credit assessment and credit scoring processes.

Since the rating companies’ ratings will be the basis for Basel II-Standard Approach and similar models as those of the rating companies are being or will be constructed internally by the financial institutions within the Basel II transition process. With the Basel II implementation, it is forecasted that those parameters already used by the rating companies will be utilised by financial institutions in their rating and credit decision models. The study discusses the model used for the empirical research and the parameters estimated by it. The results are compared with the variables of the Moody’s’ private company rating model. In addition, by the quantitative information provided by the institution through an interview, properties of the rating system of the financial institution are analysed. Finally, conclusions and comparisons are drawn regarding the predictive performance of logit and probit regression models.

The first chapter of this thesis focuses on the theoretical developments and statistical methodology in credit and default prediction models. Chapter 2 provides an overview of the Basel II- Accord, its development and its application in credit risk management in Turkey. Chapter 3 introduces the binary choice models. In Chapter 4 the empirical research and the credit assessment process of the analyzed financial institution are described. The data set and (estimated) model parameters are presented, while also the performance of both models is compared. The results are compared with the variables of the Moody's' private company rating model. In addition, characteristics of the rating system of the analysed financial institution are observed. Finally, in Chapter 5 the conclusions are drawn.

1.2 Review of Literature

Theoretical Developments in Modelling and Statistical Methodology

Credit granting decision and default probability estimation has been among the most researched topics in credit modelling starting from the 1930´s.

The studies by Ramser and Foster (1931) [8], Fitzpatrick (1932) [6], Winakor and Smith (1935) [9], and Merwin (1942) [7] were among the first research that predicted the defaults of firms by using financial ratio information. Those studies laid the principals of default prediction research.

During the first research stages of failure prediction (eg. Fitzpatrick, 1932), there were no advanced statistical methods or computers available for the researchers. The financial ratios of failed and non-failed firms were compared and it was concluded that they were poor for the former ones.

In 1963, Myers and Forgy [13] compared scorecards built using regression analysis and discriminant analysis.

Afterwards, Beaver [35] in 1966, realised one of the most significant studies concerning ratio analysis. A fundamental change in research tradition took place when he presented the univariate analysis approach. His objective was to predict the timely payment ability of loans by using likelihoods. Here to, he used for the first time a matched sample of failed and non-failed firms in a univariate discriminant analysis, in order to avoid sample bias. It was concluded that several ratios differed significantly between failed and non-failed firms, especially cash flow/net worth and debt/net worth ratios. Beaver indicated that the differences in some of the most used ratios eg. "debt to net worth" and "cash flow to assets" ratios between failed and viable firms became higher as the time to failure shortened.

Then, Altman [10] extended this analysis into multivariate analysis in 1968. In his model, which is called Z-Score, he used linear combination of ratios and a discriminant function. A set of informative parameters, all powerful in a univariate sense but not perfectly correlated, are used. The data set is composed of 79 defaulted and a similar number of non-defaulted companies. The study, out of the matched sample, predicted 95% of the data correctly. Therefore Altman's Z-Score has gained benchmark status in the academic literature and among accounting and financial analysis textbooks.[1] Until the 1980's, discriminant analysis was the dominant method in failure prediction. After the univariate analysis of Beaver, Altman (1968) pioneered the use of multivariate approach in the context of bankruptcy models. After the Altman study the multivariate approach became dominant in bankruptcy models.

Discriminant analysis tries to derive the linear combination of two or more independent variables that will discriminate best between a priori defined groups, such as failing and viable companies. This is achieved by the statistical decision rule of maximising the between-group variance relative to the within group variance. This relationship is expressed as the ratio of the two.

Discriminant analysis performs very well provided that the variables in every group follow a multivariate normal distribution and the covariance matrices for every group are equal. However, empirical experiments have shown that, especially failing firms violate the normality condition. In addition, the equal group variances condition is also violated. Moreover, multicollinearity among independent variables is often a serious problem, especially when stepwise procedures are employed (Hair et al., 1992 [36]). However, empirical studies have proved that the problems connected with normality assumptions were not weakening its classification capability, but its prediction ability.

The two most frequently used methods in the discriminant models have been the simultaneous (direct) method and the stepwise method. The former is based on model construction by e.g. theoretical grounds, so that the model is ex ante defined and then used in discriminant analysis. When the stepwise method is applied, the procedure selects a subset of variables to produce a good discrimination model using forward selection, backward elimination, or stepwise selection.

[1] e.g., Lovie and Lovie (1986), Casey and Bartczak (1985), Zavgren (1984).

The studies by Deakin (1972)[37], Edminster (1972)[38], Blum (1974) [11], Altman et al. (1977) [39] and El Hennawy and Morris (1983) [40] are representative examples of studies that used a multiple discriminant analysis technique.

Pinches and Mingo [14] and Harmelink [15] applied discriminant analysis in order to assign ratings for the bonds in 1973. In their study, they also made use of accounting data and ratios.

In the following year, Blum [11] analysed the financial ratios concerning profitability and liquidity of 230 companies, half of which is failed and the remaining non-failed. The result of the study demonstrated that 95% of observations, which were related to the period one year prior to default- classified by the model correctly. The prediction power decreased to 70% at the third, fourth and fifth years prior to default.

In addition to the discriminant analysis technique in the 1960's, there were also the time varying decision making models. Those models aimed to avoid unrealistic situations by modelling the applicants' default probability varying over time. The first study on such models was done by Cyert et al. [16]. The following research was by Mehta [17], Bierman and Hausman [18], Long [19], Corcoran [20], Kuelen [21], Srinivasan and Kim [22], and Philosophov et al [23].

In 1962, Cyert et al. [16] by means of a total balance aging procedure built a decision making process to estimate doubtful accounts. In this method, the customers were assumed to move to different credit states through stationary transition matrix. By this model, the loss expectancy rates could be estimated by aging category.

In 1968, Mehta [24] used a sequential process to build a credit extension policy and established a controlling system measuring the policy effectiveness. The system continues with the evaluation of the acceptance and rejection costs alternatives. The alternatives with minimum expected costs were chosen. In 1970, Mehta [17] related the process with a Markov process as suggested by Cyert et al. [16] to include time varying states in order to optimize credit policy. Dynamic relationships, when evaluating alternatives, were taken into account with Markov chains.

In 1970, Bierman and Hausman [18] developed dynamic programming decision rules by using prior probabilities that were assumed to have a beta distribution. The decision was taken by evaluating costs not only including today's loss but also the expected future profit loss.

Myers (1977) [41] has outlined a theoretical model which found out that investors will choose to liquidate if the company's liquidation value exceeds its going-concern value.

Dombolena and Khoury in 1980 [12] further improved the discriminant analysis model by adding the stability measures of the ratios, such as standard deviation of ratios, coefficient of variations and standard error of estimates. Prediction power of the model reached 78% even five years prior to default. Among the others standard deviation was the strongest stability indicator.

The same year Wiginton [28] compared logistic regression and discriminant analysis and concluded that logistic regression performs better than discriminant analysis.

In 1985, Altman, Frydman and Kao [42] introduced the recursive partitioning algorithm.

Altman's study (1986) [4] concluded that a company's probability of failure increases, if it is unprofitable, highly leveraged, and/or suffers cash flow difficulties.

The following year Pantalone and Platt [43] applied logistic regression in their research. In their classification the accuracy ratio was 98% for the failed firms, whereas 92% for the non-defaulted firms.

The beginning of the 1990s was the start of the machine age. Odom and Sharda [44] compared discriminant analysis in 1990 and neural networks while using the explanatory variables in the research of Altman in 1968.

The same year Gilbert et al. [45] showed that a bankruptcy model developed with random sample composed of bankrupted company data is able to distinguish firms that fail from other financially distressed firms through a stepwise logistic regression.

Similarly, the following year Cadden, Coats and Fant made the comparison between the logistic regression and discriminant analysis approaches. After that, in 1992, Tam and Kiang [46] also compared logistic regression and discriminant analysis. In their study they used 18 variables. The following year, Coats and Fant [47] applied Altman's variables (1968) to a panel data. Neural networks produced a improved result in this study.

In 1996, Back, Laitinen, Sere and Wesel [48] did empirical work with 31 variables. In 1998 Kiviluoto [49] modelled by using 6 variables and compared different approaches. The following year Laitinen and Kankaanpaa [50] made a comparison between logistic regression, discriminant analysis, recursive partitioning, survival analysis and neural networks. Only 3 ratios are used in the latter analysis. The neural network provided the best results one year prior to failure, but recursive partitioning performed best two and three years prior to default. The same year, Muller and Ronz [51] applied a semi-parametric generalised partial linear model for the first time, using 24 variables.

Another important study was performed in 1998 by Carling, Jacobson and Roszbach [30]. They used a Tobit model with a variable censoring threshold, in order to observe the effects of survival time. From the distribution of conditional expected durations of loans a distribution of expected profits were calculated. Unlike the credit scoring models, which merely predict default probabilities, it is based on an evaluation of expected profitability. This provided improved insight into the efficiency of current bank lending.

In 2000, McKee and Greenstein [52] applied recursive partitioning, neural networks and discriminant analysis and used 6 ratios as explanatory variables. The same year Cames and Hill [31] used logit, probit, gombit and weibit models and analysed whether the predictive ability is affected by observing the underlying probability distribution of the dependent variable. It was concluded that there was no significant difference between the models.

In 2003 [32] Hayden analysed univariate regression for three different default definitions, two of which are from Basel II and one being a traditional definition. The result demonstrated that there was no significant difference in prediction power when different default definitions are used.

Huyen [33] and Thanh made a study about Vietnam's retail banking market and a stepwise logistic regression is applied as a modelling tool to build a scoring model.

Table 1.1 summarises 31 financial ratios generally used in the respective theoretical & empirical studies.

Table 1.1 Financial ratios found to be well-performing in previous default risk studies

Ratios	Study	
R1 Cash/Current Liabilities	L	E, D
R2 Cash Flow/Current Liabilities	L	E
R3 Cash Flow/Total Assets	L	E-M
R4 Cash Flow/Total Debt	L	Bl, B, D
R5 Cash/Net Sales	L	D
R6 Cash/Total Assets	L	D
R7 Current Assets/Current Liabilities	L	M, B, D, A-HN
R8 Current Assets/Net Sales	L	D
R9 Current Assets/Total Assets	L	D,E-M
R10 Current Liabilities/Equity	L	E
R11 Equity/Fixed Assets	S	F
R12 Equity/Net Sales	S	R-F, E
R13 Inventory/Net Sales	L	E
R14 Long Term Debt/Equity	S	E-M
R15 MV of Equity/Book Value of Debt	S	A, A-H-N
R16 Total Debt/Equity	S	M
R17 Net Income/Total Assets	P	B, D
R18 Net Quick Assets/Inventory	L	Bl
R19 Net Sales/Total Assets	P	R-F, A
R20 Operating Income/Total Assets	P	A, T, A-H-N
R21 EBIT/Total Interest Payments	L	A-H-N
R22 Quick Assets/Current Liabilities	L	D, E-M
R23 Quick Assets/Net Sales	L	D
R24 Quick Assets/Total Assets	L	D, T, E-M
R25 Rate of Return to Common Stock	P	Bl
R26 Retained Earnings/Total Assets	P	A, A-H-N
R27 Return on Stock	P	F, T
R28 Total Debt/Total Assets	S	B, D
R29 Working Capital/Net sales	L	E, D
R30 Working Capital/Equity	L	T
R31 Working Capital/Total Assets	L	W-S,M,B,A,D

Type : L=liquidity, P=profitability, S=solidity

Legend:

A	Altman 1968
A-H-N	Altman, Haldeman, and Narayanan 1977
B	Beaver 1966
Bl	Blum 1974
D	Deakin 1972
E	Edminster 1972
E-M	El Hennawy and Morris 1983
F	Fitzpatrick 1932
M	Merwin 1942
R-F	Ramser and Foster 1931
W-S	Winakor and Smith 1935

CHAPTER 2

THE BASEL II ACCORD AND CREDIT RISK

This chapter consists of a theoretical review of the Basel II framework together with its application in Turkey in terms of credit assessment processes. First of all, a short overview of the Accord's history and objectives are presented and the reasons for its construction are discussed. Then, it is compared with the previous accord, Basel I, and the main factors leading to a new accord are presented. Next, three pillars of Basel II concerning credit risk are discussed. Internal rating models are presented and statistical models and expert judgement based models are compared. Capital requirements in different approaches to capital are discussed. Afterwards, critics to Basel II and its application globally and specifically in Turkey are presented. Finally, the possible effects of Basel II to Turkish Banking Sector and current credit assessment practices of Turkey are evaluated.

2.1 Reasons for new rules of equity

The 1970s financial crisis brought the issue of regulatory supervision of internationally active banks to the fore[2]. As a result of this, the Basel Committee has been created in 1974 by the Central Banks of 10 countries (G-10). This was mainly a response to the failure of the Franklin National Bank in New York and the Herstatt Bank in Germany, that had significant adverse implications for both foreign exchange markets and banks in other countries.[3] Both events demonstrated that the failure of even a moderately sized bank could have implications beyond national boundaries and outside the competence of national supervisory authorities. Thus, armed with the recognition that banks with cross-border operations posed special risks, the Basel

[2] www.bis.org/about/history.

[3] Geoge G. Kaufman, Basel II: The Roar that Moused, 2003, p.2.

Committee has been working to improve bank supervision at the international level.[4] The Committee's members come from Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, the Netherlands, Spain, Sweden, Switzerland, the United Kingdom and the United States. The countries are represented by their Central Bank and also by the authority with formal responsibility for the prudential supervision of banking business where this is not the Central Bank.[5]

The Committee first focused on facilitating and enhancing information sharing and cooperation among banking regulators in major countries, at the same time developing principles for the supervision of internationally active large banks.[6] As losses at some large international banks from loans to less-developed countries mounted in the late 1970's, the Committee became increasingly concerned that the potential failures of one or more of these banks could have serious adverse effects: Those effects would not only impact on the other banks in their own countries, but also on counterparty banks in other countries. The Committee feared that large banks lacked sufficient capital in relation to the risks they were assuming. Another fear was that this capital inadequacy, largely caused the national governments to be reluctant to require higher capital ratios. This practice might put the banks in their own countries at a competitive disadvantage, relative to the ones in other countries.

In the 1980's this concern was particularly directed towards Japanese banks, as a result of financial deregulation. Those banks were rapidly expanding globally, based on valuations of capital that included large amounts of unrealized capital gains from rapid increases in the values of Japanese stocks that they owned. Such gains were not included in the capital valuations of Japanese Banks. However, in most other countries equity ownership by banks were more restrictive and these gains had to be included in the capital valuations. Partially as a result, the Committee began to focus more on developing international regulation that centred on higher and more uniform bank capital standards across countries.[7]

At the beginning of 1990s, many loan takers became insolvent, which resulted in a drastic reduction of equity within the banks. The banking sector became more aware that bank equity should be able to cover unexpected operational and / or

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[4] Smitha Francis, The revised capital accord: The logic, content and potential impact for developing countries, 2006, p. 2.
[5] www.bis.org/bcbs.
[6] Herring and Litan, 1995.
[7] Geoge G. Kaufman, Basel II: The Roar that Moused, 2003, p.3.

international risks. The equity coverage was not sufficient, and this created essential risks for the banks. Some banks could not manage to compensate the big losses resulting from mentioned credit defaults and therefore bankrupted. Moreover, uniform competition rules were needed, since many banks started to operate at international level. [8]

On one hand, the capital requirement can limit the possibility for a bank to provide loans since its provision should be sufficient to cover losses. If this provision is not adequate, this will create a problem of insolvency. Adequately capitalised and well-managed banks are better placed to withstand losses and to provide credit to customers throughout all business cycles. The major challenge has always been to determine how much capital is needed to create a sufficient buffer against future unexpected losses. If capital levels are too low, banks may be unable to absorb high levels of losses and thereby increase the risk of bank failures, which may put depositors' funds at risk. [9]

On the other hand, if the provision amount is too high then banks face with a "Credit Crunch". Numerous banks already faced this "Credit Crunch". [10]. Credit Crunch is defined as a sudden reduction in the availability of loans or credit, which may be due to increased perception of risk, a change in monetary conditions, or even an imposition of credit controls. Such an effect in the financial markets is being currently discussed after the recent mortgage crisis.

Furthermore, as in the case of a bank, a company also needs to have sufficient provision in case of a negative downturn in the economy or negative market conditions. The bank will provide a loan by evaluating the financial situation of a company or the company should be able to repay the loan it obtained from a bank and hence the financial healthiness of the company is important for the bank, too.

Hence, The Basel Committee on Banking Supervision aimed at bringing discipline for borrowers (bank's clients) and lenders (the bank itself) and provide a risk weighted system that reflects the loss history of a specific company or a bank and the type of loan [11] via the new rules of equity. In addition, the Basel Committee on Banking

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[8] Cluse (2005-a), pp.19-24.

[9] www.pwc.com, The challenges of the new capital accord, your money and the new capital accord for the banks, p. 1.

[10] Worldbank (2005), pp.112-113.

[11] Jacobson/ Lindé/Roszbach (2004), p.2.

Supervision ensures the financial stability [12] by reducing the systematic risk, which effects the overall market. Basel Committee develops regulations, standards, codes and rules that may be applicable in both developed and developing countries.[13] This aim is common with those of the other financial organisations such as International Organisations of Securities Commissions and International Association of Insurance Supervisors. Therefore, the Basel Committee on Banking Supervision tries "to arrive at systematically more risk sensitive capital requirements for the stability of the financial system. [14] This is linked to the risk of lending and the right amount of provision. The capital requirement should reduce the risk of non-solvability or the credit risk. This will be done effectively if the bank manages this risk on two levels: It needs to manage both its credit risk (on the bank's level) and on the client's level, this will cover the bank's future losses. [15] Thus, the new rules of equity should create a discipline both for the banks and the clients (debtors).

2.2 Basel I Capital Accord

The Basel I Capital Accord was announced in 1988 and implemented in 1992. It is considered to be a major breakthrough in the international convergence of supervisory regulations concerning capital adequacy. Promoting the soundness and stability of the international banking system and ensuring a level playing field for internationally active banks were its main objectives. Basel I was an important advance that resulted in higher capital levels, more equitable international markets and closer links between banks' capital holdings and the risks they take. [16] Minimum capital requirements for credit risk were imposed, though individual supervisory authorities had discretion to define other types of risks or apply stricter standards. It was initially intended for internationally active banks in G-10 countries, but it was finally accepted as a global standard and adopted by over 100 countries, including places like Tanzania. Therefore, it became a sector standard. The framework defined the components of "regulatory capital" and set the risk weights for four different "classes" of on- and off-balance sheet exposures. The risk weights, which were intentionally kept to a minimum, demonstrated relative credit riskiness across

[12] Feig (2005), pp. 18-19.
[13] Kern (2006-b), p. 79.
[14] Lamy (2006), p. 160.
[15] Kidwell / Blackwell / Whidbee / Peterson (2006), pp. 425-426.
[16] Ben S. Bernanke (15/06/2006)- Modern risk management and banking supervision (Central Bank Article and Speeches), p.1

different types of exposures. Exposures to the same kind of borrowers (such as all balances with other banks or exposures to all corporate borrowers) were subject to the same capital requirement. [17] The minimum ratio of regulatory capital to total risk-weighted assets (RWA) was set at 8%, of which the "core capital" element (a more restrictive definition of eligible capital known as Tier 1 capital) would be at least 4%. The most important amendment to the framework took place in 1996, when after three years of pre-study market risk was also included in the capital adequacy ratio calculation. This was the last revision to the document, although the definition of assets and capital has further evolved over the years parallel with financial innovation.

Even though the Basel I framework helped to "level the playing field" and to stabilize the declining trend in banks' capital adequacy ratios, it had also some drawbacks and they became more and more evident over time. These problems can be summarised as follows:

a) Inadequate risk differentiation in loan categories:

The major criticism to Basel I was that it didn't recognise the potential differences in the creditworthiness and risks that each individual exposure within a class of exposures might pose. For example, weights did not sufficiently differentiate credit risk by counterparty (i.e. financial strength) or loan (e.g. pledged collateral, covenants, maturity) characteristics. Indeed, the capital charge for all corporate exposures was the same without taking into account the rating of the borrower. This implied that banks with the same capital adequacy ratio (CAR) could have very different risk profiles and risk exposures.

b) No weight to any gains from diversification:

Basel I measured credit risk as the sum of the credit risks of the individual asset components and gave no weight to any gains from diversification across correlated assets[18]. Indeed, Basel I is based on the 'building blocks' approach. Therefore; there is no distinction or difference in capital treatment between a well-diversified loan portfolio from one that is very concentrated, even though portfolio theory recognizes the risk reduction benefits from diversification.

[17] www.pwc.com, The challenges of the new capital accord, your money and the new capital accord for the banks, p. 1.
[18] Geoge G. Kaufman, Basel II: The Roar that Moused, 2003, p.4.

c) Inappropriate measurement of sovereign risk:

In Basel I, capital allocation for credit risk is based on the criteria that the counterparty or exposure is within an OECD country or not, the so-called "Club Rule". Lending to OECD governments became more attractive since it required no regulatory capital charge, even though this group included countries with substantially different credit ratings such as Turkey, Mexico and South Korea. Claims to the national government also had a zero risk weight, and this motivated many banks, especially in developing countries, to ignore portfolio diversification rules and lend heavily to their sovereigns.

d) Lack or shortage of emphasis on other risk types:

Basel I is also often criticised due to lack of emphasis on other risk types (e.g. interest rate, operational, business, reputation) and on financial infrastructure issues (e.g. accounting, legal framework). In addition, it is discussed that it did not provide adequate incentives to encourage complementary improvements in banks' risk assessment systems. As a result of this, a high capital adequacy ratio was often over relied upon.

The shortcomings of Basel I meant that regulatory capital ratios were increasingly becoming less meaningful as measures of true capital adequacy, particularly for larger, more complex institutions. In addition, various types of products like securitizations were developed primarily as a form of regulatory capital arbitrage to overcome those rules. Finally, the state of risk measurement and management evolved significantly in the last years, allowing many banks to develop their own sophisticated internal economic capital models to guide business decisions. The of regulatory capital measurement relegated to primarily a legal reporting, compliance and public relations exercise. This had the perverse effect of distancing bank supervisors from the actual risk assessment process and the manner in which those banks were run. In fact, Basel I ratios in many cases formed the sole legal basis for taking supervisory action.

2.3 Basel II Accord

In mid-2004 the Basel Committee members agreed on "International Convergence of Capital Measurement and Capital Standards" (Basel II). This happened after extensive consultations with involved parties and quantitative impact studies. The first draft proposals had been circulated to supervisory authorities between 1999 and

2003.

Basel II has new rules for calculating risk weights and the supervision of financial institutions. The most important difference, from the viewpoint of credit risk, consists in the estimation of minimum capital requirements. The 1988 Accord stated that banks should have minimum CAR of 8%. In Basel II, the estimation is more closely related to rating grades within the bank's lending portfolio .

The main objective of the new framework is to further strengthen the soundness and stability of the international banking system. This is done through the adoption of stronger risk management practices by the banking sector, bringing regulatory capital requirements more in line with (and thus codifying) current good practices in banking. This will be achieved by making credit capital requirements significantly more risk-sensitive and by introducing an operational risk capital charge. The intention is to broadly maintain the aggregate level of capital requirements, but provide incentives to adopt the more advanced risk-sensitive approaches of the revised framework. These changes are implemented by adjusting the definition of RWA (i.e., the denominator of the CAR) while leaving most of the other elements of Basel I untouched, such as the focus on accounting data, the definition of eligible capital, the 8% minimum CAR requirement and the 1996 market risk amendment to the Capital Accord.

For banks adopting the Internal Rating Based Approach (IRB) for credit risk or the Advanced Measurement Approach (AMA) for operational risk, there will be a capital floor following the implementation of the framework as an interim prudential arrangement.

Compared to Basel I, the scope of application is broader and includes, on a fully consolidated basis, all major internationally active banks at every tier within a banking group (i.e. full sub-consolidation), as well as at the level of the group's holding company. Supervisors also need to ensure that individual banks within the group remain adequately capitalized on a stand-alone basis. Consolidation must capture, to the greatest extent possible, all banking and relevant financial activities (both regulated and unregulated) with the exception of insurance. Significant minority investments where control does not exist, as determined by national accounting and/or regulatory practices, will either be deducted from equity or consolidated on a pro-rata basis. However, significant minority and majority investments in commercial entities that exceed certain materiality levels (subject to some national discretion) will be deducted from banks' capital.

Basel II consists of three pillars: minimum capital requirements, supervisory review of capital adequacy and market discipline. These pillars are presented in the following section and summarised in Table 2.1.

Table 2.1 Three Pillars of Basel II

BASEL II CAPITAL ACCORD[19]

1. Minimum Capital Requirements	*2. Supervisory Review of Capital Adequacy*	*3. Market Discipline*
-Sets minimum acceptable capital level	**- Banks must access solvency versus risk profile**	**- Improved disclosure of capital structure**
-Enhanced approach for credit risk	**- Supervisory review of banks' calculations and capital strategies**	**- Improved disclosure of risk measurement practices**
- Public ratings	**- Banks should hold in excess of minimum level of capital**	**- Improved disclosure of risk profile**
- Internal ratings	**- Regulators will intervene at an early stage if capital levels deteriorate**	**-Improved disclosure of capital adequacy**
- Mitigation		
- Explicit treatment of Operational Risk		
- Market Risk framework, capital, definition/ratios are unchanged		

2.3.1 Pillar 1: Minimum Capital Requirements

Pillar 1 sets principles for minimum capital requirements to cover both credit and operational risks. The Committee proposes to allow banks a choice between two broad methodologies for calculating their capital requirements for credit risk.

[19] Mercer Oliver Wyman "The New Rules of the Game- Implications of the New Basel Capital Accord for the European Banking Industries".

2.3.1.1 Credit Risk- Standardised Approach

In the standardised approach banks use the ratings of external rating institutions recognised by the national supervisory authorities in determining their risk weights. At national discretion, a lower risk weight may be applied to banks' exposures to their sovereign (or central bank) denominated and funded in domestic currency. This clause is important for Turkey because the portion of securities issued by the Turkish Republic in bank assets is high.

2.3.1.2 Credit Risk- Internal Ratings Based Approach (IRB)

Rating and rating system

A rating refers to a summary indicator of the risk inherent in an individual credit. Ratings typically embody an assessment of the risk of loss due to failure by a given borrower to pay as promised, based on consideration of relevant counterparty and facility characteristics. A rating system includes a conceptual methodology, management processes and systems that play a role in the assignment of a rating.

The Basel Committee on Banking Supervision describes two different types of rating systems. Respectively, the rating system can be calculated with information from one period (one year) as a "point-in-time" (PIT) rating system or, in line with the Revised Framework, it can be calculated with information from a longer period, that is, a "through-the-cycle" (TTC) rating system. The latter rating system would consider long-run estimations of the probability of defaults (PD).

1. "Point-in-time" (PIT) and "through-the-cycle" (TTC) rating systems

The Revised Framework establishes that a borrower's score must represent the bank's assessment of its ability and willingness to comply with the contract terms despite adverse economic conditions. This means that the bank should not just rely on present estimations of the PD but should also calculate PDs in stress scenarios with bad economic conditions or industry cycle. The PDs that incorporate stress scenarios of the business cycle are named "stressed PDs" and the PDs for a definite period of time are the "unstressed PDs". The unstressed PDs will change with economic conditions while stressed PDs will be relatively stable in economic cycles. The main idea is that stressed PDs are "cyclically neutral" - they move as obligors' particular conditions change but they do not respond to changes in overall economic conditions.

A rating system that remains relatively constant through different business conditions is a "through-the-cycle" (TTC) rating system whilst a rating system that changes period by period is a "point-in-time" (PIT) rating system. Obligors in the same risk category of a PIT rating system would share similar unstressed PDs, and obligors in a risk category of a TTC rating system would share similar stressed PDs. Thus, the characteristics of PDs associated with each risk category are determined by the underlying rating system and the type of information used.

The information needed to forecast the defaults can be aggregate information, which typically includes macroeconomic variables such as GDP growth rates. The other possible variables are exchange rates and interest rates, as well as specific obligor information that includes characteristics of and relevant financial information on obligors. A TTC score should take into consideration specific obligor characteristics plus macroeconomic conditions, but a PIT score would be based mainly on current information on obligors. [20]

In contrast to bank practice, external rating institutions such as Moody's and Fitch rate TTC. They analyse the borrower 's current condition at least partly to obtain an anchor point for determining the severity of the downside scenario. The borrower's projected condition in the event the downside scenario occurs, is the primary determinant of the rating. Only borrowers that are weak at the time of the analysis are rated primarily according to current condition. Under this philosophy, the migration of borrowers' ratings up and down the scale as the overall economic cycle progresses will be muted: Ratings will change mainly for those firms that experience good or bad shocks that affect long-term conditions or financial strategy and for those whose original downside scenario was too optimistic. The agencies' TTC philosophy probably accounts for their considerable emphasis on a borrower's industry and its position within the industry. For many firms, industry supply and demand cycles are as important as or more important than the overall business cycle in determining cash flow. [21]

[20] Veronica Vallés, Central Bank of Argentina, Stability of a "through-the-cycle" rating system during a financial crisis, 2006, p.4-5.
[21] William F. Treacy, Marc S. Carey, Credit Risk Rating at Large U.S. Banks, Federal Reserve Bulletin, 1998, p.899.

2. Main Characteristics of IRB

An important innovation of the Revised Framework is the possibility of using internal rating systems as inputs for capital calculations after they have met minimum requirements set out in the document. The Revised Framework considers that human judgment should be used in the decision to grant loans but highlights the necessity of establishing a formal methodology to rate obligors and to estimate the associated PDs per rating class. Thus, it describes methodologies for banks to construct their IRB systems. Banks may use IRB systems to calculate regulatory capital requirements but also as the basis for internal risk measures. This implies that they will use these risk measures for pricing, managing portfolio exposures and establishing reserves. It is important that IRB systems accurately discriminate between bad and good obligors, in other words those that have higher and lower PD. The accuracy of the estimated PDs and the structure of the rating system would influence capital requirements.

The IRB approach requires reporting an individual score for each obligor and an individual estimated PD. These are the inputs for constructing "risk buckets" or "risk categories".

Obligors that share the same credit quality must be assigned to the same risk bucket. After grouping obligors in risk buckets, a pooled PD of the bucket must be calculated considering that it has to represent the risk of obligors within the group. This is basically a rating system. One important task is to establish the limit scores of risk buckets. The risk buckets' delimitation could be based on a statistical model, on experts' judgment or on both.

The risk measures used to calculate capital requirements are the probability of default (PD), loss-given-default (LGD), exposure at default (EAD) and effective maturity (M). There are two IRB approaches: foundation and advanced. Under both approaches, banks have to provide their own estimates of PD subject to minimum requirements. The Revised Framework specifies that all banks using IRB approaches must estimate a PD for each risk category of the rating system distinguishing between corporate, sovereign and bank exposures.

The Revised Framework highlights that estimated PDs must be a long-run average of one-year PDs for borrowers in each category of the rating system.

There are three fundamental components to calculate the minimum capital requirement according to Basel II, respectively.

a) Probability of Default (PD): the likelihood that an applicant will default in a one year time period.

b) Loss Given Default (LGD): the proportion of the exposure that will be lost if the applicant defaults.

c) Exposure at Default (EAD): The nominal value of a loan granted.

The minimum capital requirement (MCR) estimation is shown in the equation below with respect to Basel II:

$$MCR = 0.08*RW*EAD = 0.08 \ RWA \tag{3.1}$$

Here RW is the risk weight calculated by using PD, LGD and remaining maturity of exposure.

The equation has specific formulas for each asset type. RWA is the risk weighted asset.

$$EL = PD*EAD*LGD \tag{3.2}$$

$$MCL=EAD*LGD*PD-b*EL \tag{3.3}$$

Where EL is the expected loss and b is the proportion of expected loss of loan covered by minimum capital requirement.

There are two approaches to IRB, which are foundation and advanced IRB approaches. They differ primarily in terms of the inputs that are provided by the bank based on its own estimates and those that have been specified by the supervisor. In advanced IRB approach, the bank should provide its own estimates of PD, EAD, LGD and Maturity (M). On the other hand, in foundation IRB approach the bank provides PD based on its internal data, while it makes use of supervisory values set by the Basel Committee or at national discretion.

2.3.1.3 PD Dynamics

Probability of default is one of the most challenging factors that should be estimated while determining the minimum capital requirement. The new accord sets principles in estimating PD. According to Basel II, there are two definitions of default:

a) The bank considers that the obligor is unlikely to pay its credit. There are four main indicators that bank consider the obligor is unlikely to pay the obligation:

• The bank puts the obligation on an non-accrued status

• The bank sells the credit obligation at a material credit related economic loss.

• The bank consents to a distressed restriction of credit obligation.

• The obligor sought or has been placed in bankruptcy.

b) The obligor past due more than 90 days on credit obligation to the bank.

Banks should have a rating system of its obligor with at least 7 grades having meaningful distribution of exposure. One of the grades should be for non-defaulted obligor and one for defaulted only. For each grade there should be one PD estimate common for all individuals in that grade, which is called pooled PD. There are three approaches to estimate pooled PD: historical experience approach, statistical model approach, external mapping approach.

Historical experience approach:

In this approach, PD for the grade is estimated by using the historical observed data default frequencies. In other words, the proportion of defaulted obligors in a specific grade is taken as pooled PD.

Statistical Model Approach

In this approach, firstly predictive statistical models are used to estimate default probabilities of obligors. Then, for each grade the mean or median of PDs are taken as pooled PD.

External Mapping Approach

Through this method, firstly a mapping procedure is established to link internal ratings to external ratings. The pooled PD of external rating is assigned to internal rating by means of the mapping established in the first phase.

Basel II allows the banks to use simple averages of one year default rates while estimating pooled PD.

While establishing the internal rating process, the historical data should be at least 5 years, and the data used to build the model should be representative of the population. Where only limiting data are available or limitations of assumptions of the techniques exist, banks should add the margins of conservatism in their PD estimates to avoid over-optimism. The margin of conservatism is determined according to the error rates of estimates depending on the performance of the models. There should be only one primary technique used to estimate PD, the other methods can be used just for comparison. Therefore, the best model should be taken as the primary model representing the data.

After estimation of PDs, the rating classes need to be built. In this segment the banks are allowed to use the scale of external institutions.

In the PD estimation process, just building the model is not enough. Supervisors need to know not only the application but also the validity of the estimates. Banks should guarantee to the supervisor that the estimates are accurate and robust and the model has good predictive power. For this purpose, a validation process should be built.

The scoring models are built by using a subset of available information. While determining the variables relevant for the estimation of PD, banks should use human judgment. Human judgment is also needed when evaluating and combining the results.

2.3.1.4 Statistical Vs. Expert judgement Based Processes

Rating or credit granting processes of banks and financial institutions can be divided into three out of the observations made in practice: Statistical-based, constrained expert judgement-based and expert judgement-based processes. These categories can be viewed as different points along a continuum defined by the degree of reliance on quantitative techniques. Indeed, scoring models can be considered on the one end of the continuum, and reliance on the personal experience and expertise of loan and credit officers, on the other. [1]

1. Statistical-based processes

When a default probability model or other quantitative tool is the basis for determining a rating or credit decision for counterparties and/or exposures within a certain credit portfolio then, the process is named as a statistical based process. Mentioned models may be developed internally by the Bank, financial institution or by vendors. These models are developed by making use of both quantitative (e.g., financial ratios) and some qualitative but standardised (e.g., industry data, payment history, age, number of employees etc.) factors.

Bank or financial institution first analyses and finds out the financial variables that seem to explain the default case, in order to construct a model. The bank estimates the effect of each of these variables on the payment default by considering the historical data of a sample of loans. The estimated coefficients are then applied to data for living loans to arrive at a score that is indicative of the probability of default; the score is then converted into a rating grade. Similarly, credit decisions of a bank or financial institution can be based on a decision model derived from the data related to past credit decisions. The data, in this case, needs to be similar to those to construct a default model. Since the purpose of a financial institution is to avoid defaults and/or maximize the profit through launched loans, credit decisions should reflect the probability of default of the counterparty or exposure.

2. Constrained expert judgement-based processes

In contrast to a purely mechanical and statistical based process, some financial institutions base their ratings mainly on statistical default and/or credit scoring models or financial analysis. In that case, they make use of objective and quantitative data, but allow the credit analyst to adjust the final rating to an explicitly limited degree, based on judgemental factors. For example, a scorecard determines the rating grade but credit analyst may adjust the final grade up or down by one or two grades or notches based on judgement. Similar application is that, quantitative and judgemental factors are explicitly assigned a maximum number of points, and therefore puts a limit to the effect of judgemental factors on the final rating.

3. Processes based on expert judgement

Some financial institutions are assigning ratings utilising significant judgemental factors, where the relative weight of such elements is not formally limited by the institution. Some of those use no statistical models at all, while some others consider it as a baseline rating that can be over passed by the credit analyst. In all processes based on unconstrained expert judgement, the analyst has unlimited discretion to significantly deviate from statistical model indications in assigning the grade.

Shortcomings of judgemental models

Even though models and human judgement should always be used simultaneously, it is useful to acknowledge that judgemental models alone, from purely subjective to the most elaborate "expert-rule" systems dominate commercial loan analysis. This does not imply that quantitative information is not considered. When several quantitative inputs are analysed, the final judgement of this information is not transparent or easily validated.

Vertical information, i.e. time series information, allows the researcher to at least say whether a company's risk has gone up or down. Cross-sectional analysis is also useful relative values are important. For example, leverage can only be determined to be high if the leverage ratio's average value is known. Given that some of these ratios vary systematically by industry, and also that analysts specialise in a particular industry, these benchmarks are usually taken from peer groups. This allows the analysts to say whether a company has high leverage and is therefore, on this dimension, risky. It is important for a credit analyst to determine the amount of risk relative to the portfolio, as absolute risk is often affected by factors that are too difficult to forecast.

The bottom line is that data are generally presented in a way that facilitates assessing a firm's trend, with a highly selective base for inter-company comparison. The problem is that without a multivariate model, one is often constrained to compare, sequentially, individual ratios, which often leads to ambiguous results. For example, if a firm is rated Aa in liquidity, Baa in profitability, B in leverage, the net result is unclear.

It is generally presumed that given enough time most sufficiently intelligent and experienced analysts would outperform any model. The superiority of quantitative models may exist for cases where it does not pay enough to individually analysed loans, e.g. consumer loans, or when one has complex "option" information (as in a Merton model). However; with financial statements, the situation should be different. For example, quantitative models invariably focus upon a more restricted set of information than it is available to an analyst, which presumably creates an advantage for the analysis.

Certainly, many analysts are better than many models, and some analysts are better than all models. But what we want to know is whether a model developed with a significant numbers of defaults is better than average analyst.

Both humans and models have limitations and biases. These biases include the following: people tend to overestimate the precision of their knowledge (Alpert and Raiffa (1982)); their overconfidence increases with the importance of the task; and finally, they recall information related to their successes more easily than information related to their failures (Barber and Odean (1999)).

Libby (1975) provided empirical evidence in favour of quantitative models vs. judgement as applied to lending. He asked 16 loan officers from small banks and 27 loan officers from large banks to judge which 30 of 60 firms would go bankrupt within three years of the financial statements with which they were presented. The loan officers requested five financial ratios on which to base their judgements. While they were correct 74% of the time, this was inferior to such simple alternatives as the liabilities / assets ratio.

Apart from lending, there are many examples in which models outperformed the experts, including radiology diagnostics (Dawes and Corrigan (1974)).

Paul Meehl (Clinical Versus Statistical Prediction,1954) reviewed evidence that while humans are good at finding important variables, they are not as good at integrating such diverse information sources optimally. Several subsequent reviews corroborate his initial findings (Sawyer (1966)).

Another reason why quantitative models may outperform judgement in default forecasting is that analysis is usually not focused upon a strict default objective. Quantitative models are judged solely on their calibration and power. However, human analysis is focused more deeply on explaining individual assessments.

The final competitive advantage of judgement is to focus upon areas where it adds the most value, as opposed to an undefined and unrestricted scope of analysis. Quantitative models should be support tools, not decision-making tools.

A decision-making process that uses both quantitative information and judgement in a judicious way has the following characteristics:

First, the quantitative information used is not presented as ratios and risk factors, but focuses upon one composite number. When several numbers are relied upon in the final judgement, the aggregation of this information has so many possibilities. Therefore, any one person's summary judgement is basically subjective, not transparent or incomparable between individuals.

Second, judgement is focused on exceptions and present conditions. For example, things known to be 'outside the model', such as knowledge that an export market has recently crashed or that a major competitor recently went out of business, should affect one's outlook as to the future viability of a company.

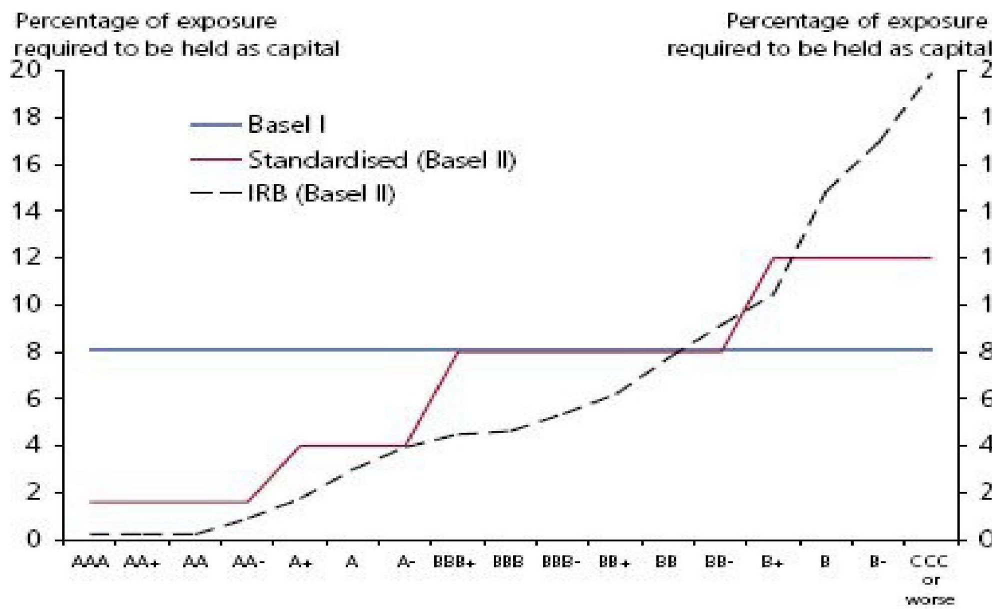
Judgemental models and expert rules systems provide a useful way to integrate information about a company so that more complex refinements of any single score can be made in a disciplined manner. For statistical validation purposes, however, they are ambiguous, and in general inferior to more statistical methods.[22] Judgemental models are unable to handle a large number of applications [3]. However; by the development of classification models and ratio analysis, these models have been replacing the judgemental methods.

2.3.1.5 Capital Requirements Under Different Approaches

Figure 2.1 compares the different approaches to capital requirement. It displays that the better the credit scoring of the entity, the lower the Minimum Capital Requirement (MCR). It also indicates that MCR decreases for the rating classes higher than BB-, regarding Basel I and Basel II (IRB Approach). On the other hand, for the companies rated B+ or below, the MCR increases substantially, especially in IRB approach.

[22] Moody's Rating Methodology-RiskCalcTM for Private companies Moody's Default Model, May 2000, p. 15-17.

Figure 2.1 Capital requirement under Basel I, Standardized and IRB approaches[23]



Easier access to data about corporates will help banks to use the advanced and foundation IRB that require an extensive amount of information about companies in order to calculate their capital requirement. Since a young company or small or medium sized enterprise (SME) is less likely to have historical financial background, it would be more difficult for such a company to calculate capital requirement using IRB.

2.3.2 Pillar 2: Supervisory Review Process

Pillar 2 defines principles for supervisors to ensure adequate capital. Supervisors should expect banks to operate above minimum regulatory capital ratios and should have the ability to require banks to hold capital in excess of the minimum. Banks, on the other hand, should have a process to assess their overall capital adequacy compared to their risk profile and a strategy for maintaining their capital levels. This is due to the fact that there is a relation between capital required and the risk that the bank carries.

Supervisors review and check the rating system and risk management of the banks. They review processes, to ensure that banks have adequate and valid techniques for

[23] Yeh / Twaddle / Frith (2005), p.9

capital requirements. Banks are expected to manage their internal capital. Supervisors should take appropriate supervisory action if they are not satisfied with the results of the risk management processes of the bank.

When supervisors think the validity of the rating process is not adequate, they can take appropriate actions. They should, indeed, seek to intervene at an early stage to prevent capital from falling below the minimum levels required to support the risk characteristics of the bank. In addition, they should require rapid remedial action if capital is not maintained or restored. This pillar is a major concern for most regulators worldwide.

2.3.3 Pillar 3: Market Discipline

Pillar 3 sets principles about banks' disclosure of information related to their risk. It aims to maintain the market discipline by applying pillar 1 and pillar 2. The Basel Committee encourages market discipline by the following: Firstly, by developing sets of disclosure requirements which will allow market participants to assess key pieces of information on the scope of application. Then by; capital risk exposures, risk assessment processes, and therefore the capital adequacy of the institution. According to the new accord, banks should have a disclosure policy and apply a process to assess the appropriateness of the disclosure. For each risk areas banks must describe their risk management objectives and policies. Market discipline should contribute to a safe and sound banking environment.

2.4 Critics to Basel II

Among the most general and large critics about Basel II is that, it is more designed for developed countries and it brings competitive disadvantages for the other countries. Another point is that the same "bad" loan causes more capital requirement in IRB approach than Standard Approach (SA). This may cause those more sophisticated banks using the IRB to try to get rid of assets of less quality. On the other hand, there will be banks using the SA who will launch loans to these borrowers. Those banks have merely no chance to compete with more sophisticated institutions, which will have less capital requirement for the same rated asset. Another concern is that whether the implementation of the new framework would have any adverse impacts on lending to the developing world. With increasing foreign bank entry in the form of takeover of domestic banks, the developing countries may experience less access to international capital due to stricter and more selective procedures for these domestic banks. [24] Moreover, borrowing costs for the countries that have lower ratings are expected to increase.

In addition to these general critics to the framework, following are the critics specific to each of the pillars:

Critics to Pillar 1

The first point discussed is that the loss rates determined by the regulators are subject to large errors so that gaming is still likely. Furthermore, the models used by the banks to generate their internal values are likely to be too complex and opaque for supervisors (and even many banks themselves). This makes it difficult to understand thoroughly the exact situation of the bank. In addition, the capital amounts will be hard to evaluate in terms of its adequacy and compliance with the requirements.

Discussion of Pillar 1 also bypasses a number of important issues concerning the definition and measurement of capital. In particular the following questions should be considered especially: What is capital; is dividing capital into tiers appropriate and, if so, what should be the criteria; role of “subdebt’; what is the relationship between capital and loan loss reserves; and how should loss reserves be determined over the business cycle. [25] Failure to consider these issues greatly weakens the usefulness of the recommendations.

Another point under discussion is that the use of regulator, rather than market-determined risk based capital.

The last controversary point which became more apparent with the recent sub-prime mortgage crisis is the ratings by external rating agencies. External ratings constitute the basis for the Standardised Approach. The ethical side of rating companies’ performance is currently more and more questioned. This is mainly because they are assigning ratings for their clients and the separation between commercial and risk side of their activity is not clear.

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[24] Griffith-Jones Stephany, Spratt Steven, Segoviano Miguel “The onward march of Basel II: Can the interest of developing countries be protected” Institute of Development Studies University of Sussex (2002).

[25] Shadow Financial Regulatory Committee, 2000; Laeven and Majnoni, 2003; and Borio, Furfine, and Lowe, 2001).

Critics to Pillar 2

As stated previously, Pillar 2 indicates that supervisors should take appropriate supervisory action if they are not satisfied with the risk management processes of a bank. In addition, supervisors should have the ability to require banks to hold capital in excess of the minimum. It is argued that it is not highly likely that countries not currently granting regulators such powers will introduce them when adopting Basel II. It is also discussed that the purpose of the sanctions is not to punish the bank per se, but to provide incentives for owners and managers to have higher profitability and a stronger capital position. On the other hand, the framework too much relies on risk assessments made by the banks and gives an intensive role to the supervisors. Supervisors even express that they need assistance in training of their staff especially related to foundations techniques for calculating capital requirements for credit and operational risk.

The other shortcoming is that the supervisory review process cannot discover incorrect data used by the banks but rather focuses on the adequacy of the process used by the bank.

Critics to Pillar 3

It is argued that the requirements for effective market discipline are not discussed in the framework. Rather, it focuses on great detail what information on a bank's financial and risk positions need to be disclosed to the public. [26] Disclosure and transparency is a necessary but not sufficient condition for effective market discipline. Bank stakeholders not at-risk would have little or no incentive to monitor their banks and thus have little, if any, use for the information disclosed about the financial performance of the banks. While market discipline is likely to encourage disclosure, disclosure per se is less likely to encourage market discipline in the absence of significant number of at-risk stakeholders. Because of the fear of substantial economic harm caused by the failure of large banks, governments and bank regulators in almost all countries have tended to avoid failing such institutions. They have protected all depositors and other creditors in a de-facto policy termed "too-big-to-fail". [27] In addition, for developing markets with shallow and illiquid stock markets, with very limited or no subordinated debt facilities, high or full deposit

[26] Lopez (2003).
[27] George G. Kaufman, Basel II: The roar that moused, 2003, p. 9-10.

insurance; talking about market discipline is questionable.

Even though above mentioned critics, Basel II framework is considered to be an important step forward in terms of financial stability of international markets. It both increased the sensitivity and knowledge about risk management by bankers, regulators, analysts and the public in general. It is able to fill some of the shortcomings of Basel I and introduced best practices in the industry and methods of risk management.

2.5 Implementation of Basel II

The framework projected to be implemented in most G-10 countries as of the beginning of 2007, however many EU countries didn't accomplish this process yet.

The latest BIS report on Progress on Basel II implementation dated August- 2007 stated that implementation of the Basel II Framework continues to move forward around the globe. A significant number of countries and banks already implemented the standardised and foundation approaches as of the beginning of 2007. In many other jurisdictions, the necessary infrastructure (legislation, regulation, supervisory guidance, etc) to implement the Framework is either in place or in process, which will allow a growing number of countries to proceed with implementation of Basel II's advanced approaches in 2008 and 2009. This progress is taking place in both Basel Committee member and non-member countries. The Committee's Accord Implementation Group (AIG) and its working groups on validation, operational risk and trading book issues continue to actively share supervisory experiences in Basel II implementation, thereby promoting consistency across jurisdictions.

Supervisors also have made strong progress to coordinate home-host implementation issues at the level of individual banks, particularly for Pillar 1 (minimum capital requirements). The Committee's AIG is now focusing its attention on Pillar 2 (supervisory review process) and it will also begin to work on Pillar 3 (market discipline). Many of the home-host issues that are under review by the AIG are not new but have come to the fore as a result of the rapid globalisation of the banking sector. As indicated by the report, Basel II has served as a catalyst to encourage greater cooperation and communication between jurisdictions and the finance industry.

2.6 Basel Accord in Turkey

Basel I started to be implemented in Turkey in 1989 with a 3 years transition period. In 1996 market risks are included in capital adequacy calculations to Basel I framework. Turkey started to implement this clause as of February 2001, just after the severe financial and economic crisis which hit the financial sector very sharply. Turkey also participated to the 3rd Quantitative Impact Study (QIS) by the Basel Committee in 2003. Afterwards, local QIS studies were realised to estimate the possible impacts of a transition to Basel II, which will lead fundamental changes in the calculation of capital adequacy of banks. As of June 2007, banks started to include operational risk in their capital adequacy ratio calculation.

Additionally, the calculation of rating based loan risk necessitates the real sector companies to prepare financial statements consistent with the international accounting and financial reporting standards. However, a new draft Turkish Commercial Law which was prepared to this end, was not approved by the Parliament. It is also demanded by the representatives of the real sector companies that the said rating implementation to be postponed.

In addition, foreign exchange denominated government securities or receivables from the Turkey of banks will be changed in Basel II. In Basel I, 0% risk weight is applied –as in all OECD countries. However, it shall be weighted depending on the country credit risk. If implemented, this will oblige the banks to allocate more capital for asset items, and accordingly it will effect the monetary and finance policies. The majority of the banks' top managements have also requested the postponement of the implementation of Basel II. Therefore, rating based loan risk measurement, which will be taken as a basis in banks' capital adequacy calculation, is delayed to the beginning of 2009 and rating base accounting shall only be made as an indicator. [28]

The latest QIS Study (QIS-TR2) evaluation report released on July 25th 2007 indicated the following fundamental findings:[29]

- The average capital adequacy ratio of banks participating in the study (31 banks constituting 97% of the sector) decreased from 19.31% to 13.68%, representing a 29.16% drop in ratio. When compared to former QIS studies, QIS-TR2 has a lesser impact on capital adequacy ratio and it is well above

[28] Banking Regulation and Supervision Agency (BRSA) Press Release, July 23th 2007.
[29] BRSA Press Release, July 25th 2007.

the legal minimum, of 8%.

- The main reason for the decrease of the banks' capital adequacy is not the 0% risk weight of FX public securities within their portfolios. The relevant is that Turkey carries a 100% risk weight because of the country rating grade.
- Another reason for the decrease in the capital adequacy ratio is the operational risk, which is recently included in the calculations.
- Similarly to the findings of former QIS studies, it is observed that the positive impact of the retail portfolio on capital adequacy is continuing.
- Contrary to the findings of former QIS studies, it is concluded that the SME portfolios have a positive effect on capital adequacy rather than a negative one. Those portfolios included only the loans and other receivables extended to SMEs and the portfolios which include mostly the loans extended to real sector companies (SMEs and large enterprises).

In parallel with the previously presented critics to Basel II in section 2.4, it is expected that it will bring some negative consequences for Turkey: Foremost due to the fact that Turkey has a low sovereign rating, it will be exposed to higher borrowing costs. In addition, it is expected that there will be a decline in emerging market lending and therefore more selective lending. [30] [31] Finall, overall maturity of lending to Turkish banks may decrease and therefore the volatility due to more frequent renewal of loans. However, the Basel II Accord will bring the best practices for implementation in the sector and therefore improve the solvability and stability of Turkish Banking Sector.

2.6.1 Basel II and Credit Assessment Practices in Turkey

In terms of credit risk assessment practices in Turkey the following points are crucial: Credit rating is a very recent issue in Turkey. Only some internationally active, stock exchange companies or financial institutions have credit ratings by external rating companies like S&P, Moody's or Fitch. From the annual reports of some commercial banks it can be observed that there are developments concerning credit score techniques they applied to their credit portfolios. It is, therefore, expected that the majority of the banks will apply Standard Approach, i.e. ratings of

[30] Survey by Accenture, Mercer Olivier Wyman and SAP Press Release June 2004.
[31] Accenture, Mercer Oliver Wyman, SAP "Reality Check on Basel II" The Banker (2004).

external rating institutions recognised by the national supervisory authorities in determining the risk weights in capital allocation, when the Basel II Accord is started to be implemented.

The Banking Sector Development Report published by BRSA dated 3rd, July 2007 and including banking sector data as of the end of 2006 indicates the followings[32]: The banks comprising 50% of the sector started to implement the strategy and policies for the Basel II transition at single or consolidated basis. 80% of the sector has already founded the related division within the bank and appointed senior management, which will be in charge of Basel II processes, whereas 82% of the banks already employed the head of the implementation team of this process. As of the end of 200672.2% of the banks is largely, 25.9% partially, 1.6% fully compliant to their internal roadmaps in Basel II transition, whereas 0.1% is incompliant. 92% of the banks are more than 50% compliant with credit risk-standard approach requirements, however 73% complied less than 50% of the requirements of IRB approach. When the problems about the Basel II transition are considered, it is seen that the major constraint for the banks is the shortage of PD data (by 29.3%) and LGD and EAD data (27.5%). This is followed by uncertainties in the regulations (24.1%) and technological problems (13.1%). It is understood that most of the banks didn't encounter major problems with budget, qualification of the personnel or the understanding of Basel II. System and infrastructure of 77.1% of the banks are ready to implement the simplified standard approach, 96.5% standard approach, 23.4% IRB and 13% advanced IRB approach of credit risk. Investments of the banks are concentrated on credit risk projects, followed by those focused on market and operational risk.

According to bank representatives, the most important effects of Basel II transition for those banks are plentiful and include issues such as: capital adequacy, data preparation, risk measurement analysis, regulations and supervision, rating systems, legal reporting, provisions, public announcements, reputation, competition structure, reporting systems, profitability, collaterals, limit allocation, portfolio preference, pricing, performance measuring, consolidation and funding costs. Less important effects were expected in terms of human resources and organisational structure.

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[32] BRSA, The Banking Sector Development Report, 3rd, July 2007.

Around 50% of the banking sector projects to implement economic capital allocation, whereas 44.4% has already started to prepare for that. Only 3% of the banks allocated economic capital as of the end of 2006.

In terms of credit risk mitigation techniques, collaterals and guarantees are used by 88% of the banks, whereas insurance is utilised by 24%. About 43.4% of the banks plan to use hedging and 47.9% of those transfer of the risks. On the other hand, 46.7% of the banks does not utilise hedging at all, and 42.4% does not implement risk transfers.

As of December 2006, scorecard models are used by the banks based on rating and scoring or judgement. For corporate and SME's hybrit and parameter forecasting models are implemented.

The six biggest banks, comprising 14% of the sector, stated that they will be able to have the necessary knowledge and data systems infrastructure within 1 year to be able to implement advanced approaches. One bank mentioned 2 years, nine banks 3 years, four banks 4 years and seventeen banks 5 years or more. This implies that the majority of the banks have the necessary infrastructure to use standard approach and they continue to implement their projects for the advanced approaches.

Upto 99% of the banks utilises the credit risk analysis results in decision making processes. Results of the study demonstrated that 74.2% of the credit risk analysis information is used in specifying medium and long term bank-strategies, 68.4% in limit allocations, 56.4% in investment and placement decisions and 43% in performance evaluations. With the improvement of risk management practices parallel with Basel II implementation, it is forecasted that the financial institutions will be able to use rating information in a broader sense.

As indicated above, insufficiency of historical default data constrains the default modelling practices in the banking sector. Recently, banks started to accumulate data intensively. 38% of the banks have data with a history of 4-5 years for PD calculation. 14.2% have data for LGD with a history of 1 year. The same percentage have 5 years' of EAD data. 53.5% of the banks have a portfolio with rating history over the last 4-5 years. 71.6% of the sector started to accumulate rating history data in its credit portfolio and 29.5% for EAD.

78.7% of the banks use credit risk stress tests. Sensitivity and multivariate scenario analysis are utilised by the majority, however historical simulation is not commonly used by the sector. 30% of the banks do not apply stress tests. The majority of the stress tests and back testing is performed by the sector via information technology systems.

Banks comprising 67.5% of the sector have a strategy and policies to evaluate credit concentration and its management. As of end-2006, 27.3% of the banks are in the phase of constructing those policies. 79% of the sector have projects to develop strategy and policies for the assessment of risk and concerning credit risk mitigation techniques. But, only 17% have those strategy and policies already in force. 47% have strategy and policies concerning counterparty risk assessment and its management, whereas 48% plans to develop them.

77.4% of the banks are projecting to utilise internal models to calculate their position exposed to counterparty risk. Only 19.3% already implement such models. Banks use the following methods in order to calculate the value of the over-the-counter derivative positions exposed to risk: more than half of them original exposure method, 43% current exposure method, 3% other methods such as Delta, Vega, Gama values.

According to public disclosure requirements, half of the sector is compliant with SA, only 13% is compliant with IRB in terms of credit risk. In terms of the public disclosure of credit risk mitigations, 52% is in line with Basel II and 20% is not.

Concerning the historical data problems of the banks, another important point is that pooled corporate loan data through a national Credit Bureau is not yet available in Turkey. Such data would provide input for the low default portfolios of the banks. The Credit Bureau in Turkey, named as Kredi Kayıt Bürosu (KKB) A.Ş. was founded in 1995 by the major banks. Its aim is to provide the exchange and dissemination of information among financial institutions for the purpose of monitoring and controlling consumer credit information (including credits cards). KKB created one of the most important and the largest databases of Turkey, the Credit Reference System (CRS). The CRS is an Information Sharing System through which members can share information on personal credit operations.[33] According to a presentation given by Gürsel Kubilay, the chairman of KKB, in May 2007 in the International Credit Risk

[33] www.kkb.com.tr.

and Rating Conference organised by Hacettepe University, KKB started to implement a project –so called Corporate Bureau Project- concerning corporate credit data warehousing. As of October 2004 the system design of the project was completed by KKB and as of April 2007 the user tests started. The projected utilities through the project are the followings:

- Credit decisions of the financial institutions will be based on updated, healthy, extensive and objective information.
- Transparency will increase and credit repayment discipline will be provided.
- Financial institutions will have the possibility to increase their credit volume by keeping the operational costs under control.
- An updated and healthy database service will be provided for Basel II implementation and rating model construction.
- The member institutions and the regulatory authorities will be supported through the statistical reports, which will be produced for different sectors in various fractions.

The corporate database of KKB is composed of 1,238,222 companies, which are 40,139 corporations, 256,942 limited companies, 905,833 sole proprietorships and 35,308 other company types. [34]

All financial institutions are projected by KKB to be included to this system of data sharing. Through the implementation of Corporate Bureau Project, it can be estimated that the financial sector will benefit from the pooled data in its credit risk modeling practices.

In conclusion, while preparing for the implementation of Basel II, the Turkish banking sector has also been reviewing and adjusting its risk assessment processes. Turkish Banks are still in the initial phases of implementation, but on the other hand consider it as a highly important subject. Significant progress has already been made in terms of system and infrastructure. It should be acknowledged that credit rating is a very recent issue in Turkey. Still, only some internationally active, stock exchange listed companies and/or financial institutions have external credit ratings from the major rating companies. On the other hand,

[34] Presentation given by Gürsel Kubilay, the chairman of KKB, the International Credit Risk and Rating Conference, organised by Hacettepe University, May 2007.

almost all Turkish banks utilise credit analysis results in decision making processes. Most banks also use it in specifying medium and long terms strategies, but only to a lesser extent in limit allocations, investment and placement decisions as well as performance evaluations.

CHAPTER 3

VARIABLE SELECTION AND PREDICTION TECHNIQUES

In this study corporate credit decisions -whether to grant or reject a credit- are modelled through an empirical research. Therefore, this chapter focuses on the models most widely used. For this purpose, binary choice models -namely probit and logit models- are among the most widely applied techniques in credit decision modelling. In these models, the dependent variable- whether or not the loan is granted- is binary. For this reason, the regression function can be interpreted as a predicted probability. Such a probability has a non-linear nature and therefore a linear probability model does not provide an optimum probabilistic result. Probit and logit regressions do model this nonlinearity in the probabilities and are, therefore, the preferred methods. Hence; probit and logit regressions are used in our empirical research, which is the subject of the next chapter, Chapter 4.

3.1 Binary Choice Models

In a binary choice model, the dependent variable takes only two possible values. In credit scoring the dependent variable is identified as follows:

$$y = \begin{cases} y_i \text{ if } y_i = 1, \text{ i.e., the firm defaults} \\ y_i \text{ if } y_i = 0, \text{ i.e., the firm non-defaults} \end{cases} \tag{3.1}$$

There are discrete or continuous independent variables; the model is:

$$E\left[Y / X\right] = P\left\{Y = 1 / X\right\} = P\left\{X\beta + \varepsilon > 0 / X\right\} = F\left(X\beta\right) = \pi \tag{3.2}$$

Here F is the cumulative distribution function (inverse link function), β is an unknown parameter vector of the model, and π is the probability that the dependent variable takes the value 1.

In binary response models, since the dependent variable takes only two possible values with probability π, it can be assumed that the distribution of the dependent variable has a Bernoulli probability distribution.

The Bernoulli probability function is:

$$\begin{aligned} f(y/\pi) = \pi^{y}(1-\pi)^{1-y} \qquad & (y = 0,1) \\ & E[y] = \pi \\ & \operatorname{var}[y] = \pi(1-\pi) \end{aligned} \tag{3.3}$$

3.1.1 Maximum likelihood estimation

The logit and probit coefficients, in these models, are estimated using the method of maximum likelihood. This produces efficient (minimum variance) estimators in a wide variety of applications, including regression with a binary dependent variable. The maximum likelihood estimator is consistent and normally distributed in large samples, so that t-statistics and confidence intervals for the coefficients can be constructed.

Regression software for estimating probit and logit models typically uses maximum likelihood estimation (MLE), and it is common to apply MLE in practice.

The likelihood function through the observed data is defined by (3.4):

$$L(x_i) := \prod_{i=1}^{n} \pi(x_i)^{y_i} \left(1-\pi(x_i)\right)^{1-y_i} \tag{3.4}$$

where

$\pi(x_i)$ is the probability that each observation with x_i independent variable vector takes the value 1 as dependent variable.

Generally log-likelihood functions are utilised when MLE is used. This is because it is easier to maximize the natural logarithm of the likelihood function and monotonic transformation does not make any change in the results when calculating the optimum points. The log-likelihood for binary data is defined by (3.5).

$$l(x_i)=\sum_{i=1}^{n}\left\{y_i \ln\left(p_i\left(x_i\right)\right)+\left(1-y_i\right)\ln\left(1-p_i\left(x_i\right)\right)\right\} \quad (3.5)$$

The estimate of unknown parameter $\beta^{\wedge}$ is obtained by solving (3.6).

$$\frac{\partial \ln L(\hat{\beta})}{\partial \beta}=0 \quad (3.6)$$

3.1.2 Goodness of fit measures

Deviance

In regression models for binary dependent variables, the comparison of the predicted and observed models is dependent on the log-likelihood function. The model is called saturated if all independent variables are used in the model. Deviance is a measure of deviation of the model from realized values.

Let logL1 denote the maximum likelihood value of the model of interest (or current model), and let logL0 denote the maximum value of the loglikelihood function when all parameters, except the intercept, are set to zero.

The deviance measure is defined as:

$$y = -2\ln\left(\frac{\log L_1}{\log L_0}\right) \quad (3.7)$$

When models are compared, the deviance is used as a measure to determine which one to choose as a selection criteria. The model with lower deviance will be chosen.

Pearson Chi-Square Goodness of Fit Statistic

Pearson Chi-Square is a simple non-parametric goodness of fit test which measures how well an assumed model predicts the observed data. This statistic proposed by Hosmer and Lemeshow (1980).

The test statistic is:

$$X^2 = \sum_{i=1}^{n} \frac{(observedfrequency - fitted\ frequency)^2}{fitted\ frequency} \tag{3.8}$$

χ^2 is assumed to be chi-square with n – p degrees of freedom.

Unfortunately, like other proposed fit statistics, the Hosmer-Lemeshow statistic does not have good power for detecting particular types of lack of fit (Hosmer et al. 1977). In any case, a large value of a global fit statistic merely indicates some lack of fit but provides no insight about its nature. The approach of comparing the working model to a more complex one is more useful, since it searches for lack of fit of a particular type.

Likelihood Ratio (LR) Statistic

The LR statistic is a goodness of fit test, which depends on a log-likelihood function. The purpose of this test is to compare the models with and without independent variables. The test statistic is:

$$LR = -2\left(\log L_0 - \log L_1\right) \tag{3.9}$$

To test the null hypothesis that all the slope coefficients are simultaneously equal to zero, the equivalent of the F test in the linear regression model is the likelihood ratio (LR) statistic. Given the null hypothesis, the LR statistic follows the X^2 distribution with degrees of freedom equal to the number of explanatory variables .

Pseudo R^2

Pseudo R^2 is the measure of fit using the likelihood function, similar to the R^2 in a linear regression. Pseudo R^2 measures the explained percentage of dependent variables. It can also be called the determination coefficient. Because the MLE maximizes the likelihood function, adding another regressor to a probit or logit model increases the value of the maximized likelihood, just like adding a regressor necessarily reduces the sum of squared residuals in linear regression by Ordinary Least Squares method. This suggests that measuring the quality of fit of a probit model is possible by comparing values of the maximized likelihood function with all regressors to the value of the likelihood .

The formula for this statistic is given by 3.10:

$$pseudoR^2 = 1 - \frac{1}{1 + 2(\log L_1 - \log L_0) / N} \tag{3.10}$$

Where N denotes the number of observations. Pseudo R^2 ranges between 0 and 1. When comparing the models, the model with higher pseudo R^2 will be preferred as it is the determination coefficient.

McFadden's R2

It is an alternative measure of fitness suggested by McFadden (1974) and sometimes referred to as the likelihood ratio index. It is given by the below formula:

$$McFaddenR^2 = 1 - \log L_1 / \log L_0 \tag{3.11}$$

Because the loglikelihood is the sum of log probabilities, it follows that $\log L_0 \leq \log L_1 < 0$, from which both measures take on values in the interval [0,1] only. If all estimated slope coefficients are equal to zero we have $\log L_0 = \log L_1$, such that both R2's are equal to zero. Consequently, the upper limit for this measure is obtained for log L1=0. The upper bound of 1 can be, in theory, attained by McFadden's measure.

3.1.3 Binary logistic regression

Logistic regression is applied when the dependent variable is binary or dichotomous and the independent variables are of any type. Among the first users of logit analysis in the context of financial distress was Ohlson (1980). Logistic regression has advantages because the scores are interpretable in terms of log odds. Therefore, constructed probabilities can be meaningful. Logistic regression is modelled directly as a function, rather than as ratio of two densities. It is a proven method to utilise when combined with feature creation and selection. The disadvantage is that it can over- or under interpret some parameters. [35]

In logistic regression as in the other binary choice models, the dependent variable can take only two possible values and the distribution is assumed to be Bernoulli.

The link function of the logit model is:

$$\eta\left(\pi\left(x\right)\right) = \ln\frac{\pi\left(x\right)}{1-\pi\left(x\right)} = \beta x \tag{3.12}$$

[35] Monsour C., Discrete predictive modelling, Casualty Actuarial Society, Special interest seminar on predictive modelling, Chicago (2004)

The link function in logistic regression is called logit. To predict the unknown parameters the cumulative logistic distribution function is defined as:

$$F(x) = \eta - 1(x) = \Lambda(x) = \frac{1}{1-\exp(-\beta X)} = \pi(x) \tag{3.13}$$

The score vector for logistic regression is:

$$\frac{\partial \ln L(\widehat{\beta})}{\partial \beta} = \sum_{i=1}^{n} x_i (y_i - \Lambda(x_i)) \tag{3.14}$$

By using iterative optimization methods the unknown parameters can be estimated. By Wald test and goodness of fit tests, the significance of the model can be checked. The significant logistic regression model can be applied to predict future values of observations.

Like discriminant analysis, this technique weights the independent variables and assigns a Z score in a form of failure probability to each company in a sample. The advantage of this method is that it does not assume multivariate normality and equal covariance matrices as discriminant analysis does. Logit analysis incorporates non-linear effects, and uses the logistical cumulative function in predicting a bankruptcy. Unlike linear regression there are no assumptions about the linearity between independent and dependent variables and the normality of independent variables before analysing.

3.1.4 Variable Selection in Logistic Regression

Variable selection process is essential because of the following: The main aim of statistical models is to build a parsimonious model that explains the variability in dependent variable. When a model has a lesser number of independent variables, it can be interpreted easier. In addition, the model with multivariate independent variables may give more accurate results within sample observations. On the other hand, when too many variables are employed in a model, it can result in an overparametrisation problem.

Regarding the variable selection process, first, the significance of each coefficient is checked in variable selection process. In binary choice models, Wald statistic can be employed for testing the significance. If the significance $p<0.10$ for any coefficient of the variable with 90% confidence level, it can be concluded that the contribution of the variable to the model is important. Wald statistic has a drawback: if the number of observations is inadequate, the model could be unstable and therefore the Wald statistic would be inappropriate.

After the significance is determined, the insignificant variables are eliminated and models without these variables are compared to the model including those by using G likelihood ratio test. The significance of variables in the new model should also be checked because of the change in the estimated values of coefficients.

Further to the selection of significant variables; if the model includes too many variables, stepwise variable selection method can be used as a variable selection tool.

Stepwise Selection Method

The stepwise selection method is a variable selection tool that is employed to include or exclude a significant variable to the model through the use of decision rules. It is also utilised in linear regression model.

(a) Forwardation

Forward variable selection starts with including only the constant term to the model. In addition, the log-likelihood value of the model is evaluated followed by estimation of log-likelihoods of models for each variable. Finally, by using these estimates, the value of likelihood ratio tests is found:

$$G_j^{(0)} = 2\left(L_j^{\,0} - L_0\right) \qquad \left(j = 1, \ldots p\right) \tag{3.15}$$

where

$G_j^{(0)}$ is the likelihood ratio test and L_j^0 is the log-likelihood of the model with jth independent variable in step 0.

The significance value of G likelihood test is found as:

$$\Pr\left(X_1^{\,2} > G_j^{(0)}\right) \tag{3.16}$$

The most important variable, the variable with smallest significance level, is selected and is included in the model. If the significance level is smaller than α, the process stops.

If the process continues to the next step, the model in step 0 is taken as the reference model and a second “important variable” is selected. The likelihood ratio is estimated for the model with the most important variable versus the model with both the most important variable (of the first model) and the second most important variable. In this step, the significance value is estimated for p − 1 variables and the variable with minimum significance is included into the model. Then, the significance level is compared to the α; if it is smaller than α, it stops. This process continues until all variables that are important by means of alpha criteria are included to the model.

The meaning of α significance value, in this respect, is that it determines the number of independent variables. It is generally recommended to take α between 0.15 and 0.20.

(b) Backwardation

Backwardation starts with including all variables in the model. In the first step, G is estimated for the models with all variables and the variable considered to be deleted. In addition, the significance value is estimated as in the forwardation method. The variable with the maximum significance is deleted. This process continues until all variables with significance estimate above α are deleted from the model.

3.1.5 Binary probit regression

As with binary logistic regression, in binary probit regression the dependent variable can only take two possible values with Bernoulli distribution. Probit regression is a tool for a dichotomous dependent variable. The term “probit” was first used in the 1930’s by Chester Bliss and implies a probability unit. It has the advantages of being easily computable and providing probabilistic results. The disadvantage is that over- and underestimation problems can occur.

The link function for probit regression is,

$$\eta(\pi(x)) = \Phi^{-1}(\pi(x)) = \beta x \tag{3.17}$$

where Φ^{-1} (.) is the inverse standard normal distribution function.

The link function in probit regression is called probit or normit. The cumulative probit function is needed to estimate the unknown parameters. It is identified as:

$$F(x) = \eta^{-1}(x) = \Phi(x) = \pi(x) \tag{3.18}$$

Here Φ(.) is the standard normal distribution function.

The score vector for probit is defined as follows:

$$\frac{\partial \log L(\widehat{\beta})}{\partial \beta} = \sum_{i=1}^{n} x_i \Phi(x_i) \frac{y_i - \Phi(x_i)}{\Phi(x_i)(1-\Phi(x_i))} \tag{3.19}$$

After the significant probit model is formulated, it can also be used for predicting the values of dependent variable.

In both probit and logit regressions the effect of a change in a regressor can be computed in two ways: Firstly, by computing the predicted probability for the initial value of regressors. Secondly, by computing the predicted probability for the new or changed value of the regressors, and taking their difference.

CHAPTER 4

APPLICATION AND RESULTS

In this chapter, the credit assessment process of a financial institution is presented. A specific large Turkish financial institution provided the credit decision data for the empirical research. Since the rating companies' ratings will be the basis for Basel II-Standard Approach and similar models as those of the rating companies are being or will be constructed internally by the financial institutions within the Basel II transition process. With the Basel II implementation, it is forecasted that those parameters already used by the rating companies will be utilised by financial institutions in their rating and credit decision models. The chapter discusses the model used for the empirical research and the parameters estimated by it. The results are compared with the variables of the Moody's' private company rating model. In addition, by the quantitative information provided by the institution through an interview, properties of the rating system of the financial institution are analysed. Finally, conclusions and comparisons are drawn regarding the predictive performance of logit and probit regression models.

4.1 Main considerations of the analysed financial institution in assigning grades

Based on the qualitative information obtained from the financial institution through an interview, the followings are concluded regarding their internal procedures in terms of assigning grades to clients:

The considered financial institution uses last three years` balance sheets, income and cash flow statements of the borrower in its credit approval process. Out of these historical and trend data some financial ratios are calculated by the institution.

The financial institution, then, assigns an internal rating to each of its corporate clients which are already existing or new in its credit assessment process. External ratings are not used.

Figure (4.1) represents the credit assessment and rating system targeted by the studied institution in parallel with Basel II- IRB Approach, though not yet implemented . Because of limited default data available to the institution, PD values are not assigned to each rating category.

The criteria within the rating system of the financial institution are divided into two: qualitative and quantitative. Quantitative factors are defined as those which are in the form of ratios or financial figures, obtained or calculated from the financial statements of the company. Whereas, qualitative factors are those which are complementary to the financial statements of the company. Though most of the qualitative factors used are quantifiable, i.e. can be expressed into numbers, some others are judgemental. The institution attempts to base its process to the extent possible on quantifiable information. It can be concluded that it has a process similar to an expert judgement based process, since the institution allows the credit analyst to adjust the final grade.

Figure 4.1 Rating System Targeted by the Analysed Financial Institution

Time horizon, the expected time interval in which the assigned rating is considered to be valid, is defined as one year. This definition is based on annual financial reporting cycles of the borrower and the institution, frequency of internal review of the rating and uncertainties of projected performance beyond one year –mainly due to cyclicality of the Turkish Economy.

The rating system indicated to be "point-in-time" oriented and therefore the internal rating reflects the assessment of the borrower's condition as of the date of the financial statement and its expected performance within one year, rather than "bottom of the cycle scenario", i.e. its condition under stress. To be able to prove this statistically, one should observe time series default data of the institution. Due to inability to obtain this information, such an analysis could not be made.

Regardless of whether the financial institution assessing rating to borrowers, facilities or both, it assign these ratings based on assessment of the counterparty. The credit risk mitigation techniques are not yet incorporated into the rating process. The institution utilises the rating information for management reporting and limit setting; but not for pricing, compensation and risk adjusted performance measurement purposes.

Table 4.1 Main Sections of the Financial Institution's Internal Rating System

Internal Rating System Main Sections
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QUALITATIVE SECTION
-Operating environment
-Company
-Management
-Semi-financials
QUANTITATIVE SECTION
-Cash flow and liquidity
-Earnings and profitability
-Capital structure

4.2 Data

In this chapter the properties of the data used in the modelling process are analysed. The data was obtained from a financial institution in Turkey, which was used by the institution in its credit assessment and rating processes. It includes all the corporate credit applications, numbered to 532, to the financial institution over the year 2006. 453 of those credit applications were accepted by the institution, whereas 79 of them were rejected. There are 17 independent variables: 2 of them concerns firm-specific characteristics, 7 financial variables or ratios, 8 binary variables about the sector of activity in which the company operates. Table 4.3 presents the breakdown of data in terms of sectors and Table 4.4 demonstrates the sectoral breakdown of rejected companies. The response variable has two categories: 0 means that the credit application of a company is accepted; whereas 1 stands for a rejected credit application.

4.2.1 Variables

The variables used in our modelling process and their corresponding meanings are as follows. Table 4.4 also summarises those variables.

1. AGE:

The number of years the company is operational.

2. EMPLOYEE:

The number of employees of the company.

3. TO:

Turnover or net sales revenue of the company over the last analysed year represented in Turkish Lira (TRY).

Turnover indicates the size of the business of the company. Smaller size implies less diversification and less depth in management, which leads to greater susceptibility to idiosyncratic shocks. Size is also related to “market position”, a common qualitative term used in underwriting. [36]

[36] Moody’s Rating Methodology-RiskCalcTM for Private companies Moody’s Default Model, May 2000, p. 35

4. NETWORTH:

Net worth or total shareholders' equity of the company over the last analysed year represented in TRY. Net worth is also a size factor like turnover.

5. CURRENTR:

Current ratio (current assets / current liabilities) is calculated from the latest balance sheet of the company. It is an indicator of a firms' ability to meet its short term debt obligations. If the current ratio of a company is more than 2, the firm's liquidity level is considered to be satisfactory and therefore, the firm would be expected to meet its short-term obligations without any difficulty. However, in a developing country like Turkey this ratio is in general lower than for the companies operating in developed countries. Therefore, a current ratio of 1.5 or higher is considered to be acceptable by the financial institutions. If the current ratio of a firm is less than 1, one can expect that the company will have problems to fulfil its short-term debt obligations. Liquidity is also an obvious contemporaneous measure of default, since if a firm is in default, its current ratio must be low. [37]

6. SOLVENCYR:

Solvency or debt ratio: (current debts + long term debts) / total assets
Debt ratio is a key measure to firm riskiness and it indicates the percentage of assets that have been financed by borrowing. From a creditors' perspective; the lower the ratio is, the less risky is the firm. It is because high indebtedness can create debt pressure on the company and firms' debt may involve interest rate payments. How much the company finances its current operations or investments by debt or by equity is important to be considered by a financial institution. The repayment schedule of the debts of a company is also important to be analysed at this point. The higher the debt ratio, the smaller the cushion for adverse shocks.

7. PROFITMARG:

Net profit margin (net profit / net sales) of the company over the last analysed period.
The profit margin tells how much profit a company makes for every 1 TRY it generates in revenue. Profit margins vary by industry, but all else being equal, the

[37] Moody's Rating Methodology-RiskCalcTM for Private companies Moody's Default Model, May 2000, p. 36

higher a company's profit margin compared to its competitors, the better. Profit margin is an indicator of effectiveness of the firm in controlling its costs and the extent to which the firm concludes its operations over a given period in profit.

8. SHRETURN:

Shareholders' return or return on equity (ROE) ratio (net profit/shareholders' equity). ROE indicates the profit generated out of the capital invested by the shareholders' of the company. The higher the ratio is, the better is the profit generating capability of the company.
Higher profitability should raise a firm's equity value. It also implies a longer way for revenues to fall or costs to rise before losses occur.[38]

9. TOTALASSETS:

Total assets refers to the sum of current and long-term assets owned by the firm represented in TRY. As turnover, it is a reflection of size risk.

10. AUTOMTV:

Concerns an industry dummy variable and it takes the value "1" if the company is involved in automotive sector and else it takes the value 0.
As the probability of bankruptcy is likely to vary across industry sectors, it is important to include in the model the industry dummies. [39]

11. CHEM:

An industry dummy variable and it takes the value "1" if the company is involved in chemistry sector and else it takes the value 0.

12. CONSTR:

An industry dummy variable and it takes the value "1" if the company is involved in construction sector and else it takes the value 0.

13. ELECTRCL:

An industry dummy variable and it takes the value "1" if the company is involved in electrical and electronical appliances sector and else it takes the value 0.

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[38] Moody's Rating Methodology-RiskCalcTM for Private companies Moody's Default Model, May 2000, p. 32
[39] Clive Lennox (1999), Identifying Failing Companies: A Reevaluation of the Logit, Probit and DA Approaches, p. 351.

14. MACHNRY:

An industry dummy variable and it takes the value "1" if the company is involved in electrical and machinery sector and else it takes the value 0.

15. METAL:

An industry dummy variable and it takes the value "1" if the company is involved in metal sector and else it takes the value 0.

16. SERVICE:

An industry dummy variable and it takes the value "1" if the company is involved in service sector and else it takes the value 0.

17. TEXTILE:

An industry dummy variable and it takes the value "1" if the company is involved in textile sector and else it takes the value 0.

TABLE 4.2 Variable Description

Variable Name	Description
Firm characteristics:	
AGE	Number of years since the company became operational
EMPLOYEE	Number of employees as of the credit assessment period
Financial characteristics:	
TO	Turnover (Net sales of the company) (in TRY)
NETWORTH	Total shareholders' equity (in TRY)
CURRENTR	Current ratio [(current assets)/(current liabilities)]
SOLVENCYR	Solvency ratio [(total debt)/(shareholders' equity)]
PROFITMARG	Net profit margin [(net profit)/(net sales)]
SHRETURN	Shareholders' return [(net profit)/(shareholders' equity)]
TOTALASSETS	Total firm assets (in TRY)
Sector characteristics:	
AUTOMTV	=1 if in automotive industry
CHEM	=1 if in chemicals industry
CONSTR	=1 if in construction industry
ELECTRCL	=1 if in electrical appliances industry
MACHNRY	=1 if in machinery industry
METAL	=1 if in metal industry
SERVICE	=1 if in services sector
TEXTILE	=1 if in textile industry
Credit granting decision (Dependent Variable)	
ACCEPTREJ	=1 if credit is rejected

TABLE 4.3 Breakdown of Companies' Data in terms of Industries

	Industry Sector	Number of Companies	%
1	Automotive	25	4.70%
2	Chemicals	213	40.04%
3	Construction	36	6.77%
4	Electrical Appliances	41	7.71%
5	Machinery	10	1.88%
6	Metal	56	10.53%
7	Service	62	11.65%
8	Textile	89	16.73%
	Total	532	100.00%

TABLE 4.4 Breakdown of Rejected Companies' Data in terms of Industries

	Industry Sector	Number of Companies	%
1	Automotive	2	2.53%
2	Chemicals	30	37.97%
3	Construction	3	3.80%
4	Electrical Appliances	6	7.59%
5	Machinery	1	1.27%
6	Metal	2	2.53%
7	Service	9	11.39%
8	Textile	26	32.91%
	Total	79	100.00%

4.3 Data Diagnostic

Diagnostic of the data is important part of the modelling process. The pre-analysis of the data by making use of descriptive statistics is necessary since it can give some hints about the data. Finding out whether the data complies with the assumptions of the model used or not is important in this process.

The descriptive statistics of the data are presented and analysed in Table 4.5 and the Appendix. The following data anomalies have been noted: Four companies' credit applications have been accepted, even though they had negative shareholders' equity and therefore are technically bankrupt. According to the interview with the institution, the followings are mentioned as possible reasons: The company belongs to a strong group which is expected to support the company in case of insolvency. Another reason can be that the institution wants to closely follow up its credit receivables from the company resulting from previous lending. This can be due to delinquency or negative developments in the company's financial situation. Especially when the company is dependent on lending by the institution, the institution cannot immediately cut its lending, to be able to collect its credit receivables. Another anomaly observed in the data is too high current ratio values for five companies, mainly operating in construction sector. The possible reason indicated by the institution is that those companies are operating in project basis lasting more than one accounting period and their financials are presented in percentage of completion basis. Therefore, revenues earned are recorded as assets until the project is completed. This may create some anomalies in their financial statement values and ratios.

Among those descriptive statistics "mean" or "average" is the central location or arithmetic average of the data. "Average" considered on its own, may not give meaningful information. It becomes more meaningful when it is analysed together with the "standard deviation", which measures the variability or distance from the mean of the data. A low variance indicates that, it demonstrates that mean is more representative for the sample. In our sample, it can be seen that turnover, net worth, number of employees, current ratio, solvency ratio and total assets are highly variable compared to other variables. Therefore; for those, mean is less representative in comparison with the rest of the parameters.

In addition to the mean and the standard deviation there are minimum, maximum, first quartile, second quartile, third quartile values in the data. Minimum and maximum ara the minimum and maximum values observed in a data sample. First quartile or lower quartile cuts off lowest 25% of the data (25th percentile). Second quartile, median or 50th percentile cuts data set in half. Similarly, third quartile or upper quartile cuts off lowest 75% of the data (75th percentile). In our data by checking these statistics, it is observed that the parameters are highly variable.

When the distribution of the data is analysed, firstly it is tested whether the data are normally distributed or not by using skewness and kurtosis. Kurtosis is the degree of peakedness of a distribution. It is a measure of the extent to which observed data fall near the centre of a distribution or in the tails. Standard normal distribution has a kurtosis of zero. Positive kurtosis indicates a "peaked" distribution and negative kurtosis indicates a "flat" distribution. Skewness defines the degree of asymmetry of a distribution. A negative skewness value indicates that the data have a distribution skewed left. A positive skewness value implies a right skewed distribution. A zero skewness value indicates that the data has a symmetric distribution. A normal distribution is charactherised by a skewness value of zero and a kurtosis of three. If kurtosis of a distribution is above three, then it has fat tails which indicates a non-normal distribution.

The skewness and kurtosis statistics are indicated in the Appendix. According to the Figures 1-9; age, current ratio, number of employees, net worth, turnover and total assets variables are right skewed; whereas profit margin, shareholders' return and solvency are left skewed. On the other hand, when the kurtosis value is analysed, it can be seen on the table that all the variables have kurtosis value above three, and therefore have fat-tails.

TABLE 4.5 Descriptive statistics for the data

Spell	Unit	N	μ	σ	min	Q1	Q2	Q3	max
Accepted		**453**							
AGE	years		17.09	11.33	1.00	9.00	15.00	23.00	61.00
EMPLOYEE	number		382.50	935.85	2.00	8,000.00	35.00	80.00	257.00
TO	TRY		442,495,313	1,453,124,250	175,000	17,126,000	73,000,000	268,000,000	20,103,000,000
NETWORTH	TRY		180,688,575	529,529,291	-35,038,000	4,776,500	30,000,000	123,734,000	5,557,000,000
CURRENTR	ratio		20.50	194.93	0.00	1.20	1.57	3.00	4,000.00
SOLVENCYR	percentage		201.28	444.93	-3,286.00	41.22	103.46	240.94	4,476.95
PROFITMARG	percentage		7.13	23.89	-258.08	0.68	2.90	8.00	170.00
SHRETURN	percentage		13.73	28.80	-142.94	2.00	9.65	20.00	282.90
TOTALASSETS	TRY		319,558,724	1,001,587,499	-9,734,819	9,275,000	48,785,000	187,401,000	8,665,000,000
AUTOMTV	binary		0.05	0.22	0	0	0	0	1
CHEM	binary		0.40	0.49	0	0	0	1	1
CONSTR	binary		0.07	0.26	0	0	0	0	1
ELECTRCL	binary		0.08	0.27	0	0	0	0	1
MACHNRY	binary		0.02	0.14	0	0	0	0	1
METAL	binary		0.12	0.32	0	0	0	0	1
SERVICE	binary		0.12	0.32	0	0	0	0	1
TEXTILE	binary		0.14	0.35	0	0	0	0	1
Rejected		**79**							
AGE	years		17.87	11.45	2.00	10.50	15.00	25.00	60.00
EMPLOYEE	number		158.03	295.97	3.00	25.00	52.00	154.00	2,013.00
TO	TRY		68,144,975	155,359,230	170,000	6,736,500	25,000,000	56,082,500	925,295,000
NETWORTH	TRY		14,033,988	51,879,190	-243,000,000	111,000	4,501,000	18,251,423	291,170,000
CURRENTR	ratio		9.71	59.40	0.00	0.60	0.86	1.22	500.00
SOLVENCYR	percentage		27.60	1,494.91	-8,746.64	12.50	96.55	303.55	4,051.77
PROFITMARG	percentage		-33.85	107.06	-800.00	-30.00	-9.82	0.14	107.06

Spell	Unit	N	μ	σ	min	Q1	Q2	Q3	max
SHRETURN	percentage		-60.56	292.66	-2,455.65	-37.96	-15.00	-0.10	334.53
TOTALASSETS	TRY		77,877,283	149,893,942	-76,221,160	4,153,500	24,427,000	78,106,000	904,537,000
AUTOMTV	binary		0.03	0.16	0	0	0	0	1
CHEM	binary		0.38	0.49	0	0	0	1	1
CONSTR	binary		0.04	0.19	0	0	0	0	1
ELECTRCL	binary		0.08	0.27	0	0	0	0	1
MACHNRY	binary		0.01	0.11	0	0	0	0	1
METAL	binary		0.03	0.16	0	0	0	0	1
SERVICE	binary		0.11	0.32	0	0	0	0	1
TEXTILE	binary		0.33	0.47	0	0	0	1	1
Overall		**532**							
AGE	years		17.21	11.34	1.00	9.00	15.00	23.00	61.00
EMPLOYEE	number		349.16	874.51	2.00	31.75	77.50	250.00	8,000.00
TO	TRY		386,905,695	1,348,598,527	170,000	13,294,750	56,937,000	221,550,000	20,103,000,000
NETWORTH	TRY		155,894,390	492,468,942	-243,000,000	3,169,500	21,079,000	98,553,500	5,557,000,000
CURRENTR	ratio		18.90	181.32	0.00	1.05	1.50	2.52	4,000.00
SOLVENCYR	percentage		175.49	707.53	-8,746.64	40.00	101.73	250.00	4,476.95
PROFITMARG	percentage		1.05	48.81	-800.00	0.01	2.01	7.00	170.00
SHRETURN	percentage		2.70	118.27	-2,455.65	0.09	6.88	18.65	334.53
TOTALASSETS	TRY		283,669,938	929,854,212	-76,221,160	8,692,750	43,809,000	163,303,500	8,665,000,000
AUTOMTV	binary		0.05	0.21	0	0	0	0	1
CHEM	binary		0.40	0.49	0	0	0	1	1
CONSTR	binary		0.07	0.25	0	0	0	0	1
ELECTRCL	binary		0.08	0.27	0	0	0	0	1
MACHNRY	binary		0.02	0.14	0	0	0	0	1
METAL	binary		0.11	0.31	0	0	0	0	1
SERVICE	binary		0.12	0.32	0	0	0	0	1
TEXTILE	binary		0.17	0.37	0	0	0	0	1

4.4 Logistic Regression Results

In this study, the logit and probit model coefficients are estimated using the method of maximum likelihood. In both models, initially, 17 variables are analysed each in a univariate model. Those variables were firm-specific factors, e.g. age and number of employees, financial variables including ratios and size figures and the industry in which the company operates as binary variable. Those variables in both logit and probit models are selected through a forward selection algorithm, i.e. a process which includes the variables one by one to the model by taking into account their predictive power.

Univariate logit regression results are summarised in Table 4.6.

TABLE 4.6 Univariate Logit Regression Results

Variable	Constant	Coefficient	p-value
AGE	-1.850	0.006	0.562
EMPLOYEE	-1.563	-8.08E-04	0.049
TO	-1.311	-3.57E-09	0.035
NETWORTH	-1.191	-1.48E-09	0.001
CURRENTR	-1.735	-9.12E-04	0.678
SOLVENCYR	-1.711	-2.67E-04	0.088
PROFITMARG	-1.888	-0.061	0.015
SHRETURN	-1.762	-0.023	0.009
TOTALASSETS	-1.526	-1.73E-09	0.027
AUTOMTV	-1.720	-0.722	0.333
CHEM	-1.707	-0.101	0.685
CONSTR	-1.710	-0.688	0.263
ELECTRCL	-1.745	-0.018	0.967
MACHNRY	-1.739	-0.458	0.666
METAL	-1.645	-1.650	0.023
SERVICE	-1.743	-0.030	0.937
TEXTILE	-1.996	1.110	0.000

The coefficients of the model are shown in Table 4.7:

TABLE 4.7 Logit Regression Model Parameters

Variable	Coefficient	Std. Errors	P-values
constant	-1.549	0.204	0.000
TO	-2.63E-09	1.44E-09	0.067
NETWORTH	-1.45E-08	7.15E-09	0.042
PROFITMARG	-0.047	0.026	0.076
TOTALASSETS	3.39E-09	1.73E-09	0.049
TEXTILE	0.742	0.317	0.019

The regression equation of our model was found as:

$$Z = -1.549 - 2.63E - 09 * TO - 1.45E - 08 * NETWORTH$$
$$-0.047 * PROFITMARG + 3.39E - 09 - TOTALASSETS + 0.742 * TEXTILE$$

Though the dependent variable takes binary values 0 and 1, the regression equation does not provide prediction values of 0 and 1. The regression equation in the form of linear combinations of independent variables gives the log-odds and those log- odds are used to calculate the predicted values of probabilities of default. The parameter coefficients are named as logits of explanatory variables utilised to estimate log-odds. One unit of increase or decrease in a variable with β1 logit is associated with a β1 change in log odds of the dependent variable. It does not directly effect the change in the dependent variable.

The output of logistic regression from Eviews are shown in the Table 4.8.

TABLE 4.8 Logit regression statistics

Dependent Variable: ACCEPTREJ
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 12/10/07 Time: 17:53
Sample (adjusted): 1 532
Included observations: 531 after adjustments
Convergence achieved after 15 iterations
QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.548726	0.203939	-7.594076	0.0000
TEXTILE	0.741621	0.316548	2.342842	0.0191
NETWORTH	-1.45E-08	7.15E-09	-2.034969	0.0419
TOTALASSETS	3.39E-09	1.73E-09	1.966992	0.0492
TO	-2.63E-09	1.44E-09	-1.832475	0.0669
PROFITMARG	-0.046690	0.026269	-1.777378	0.0755

Mean dependent var	0.148776	S.D. dependent var	0.356203
S.E. of regression	0.303171	Akaike info criterion	0.645359
Sum squared resid	48.25398	Schwarz criterion	0.693661
Log likelihood	-165.3428	Hannan-Quinn criter.	0.664264
Restr. log likelihood	-223.3279	Avg. log likelihood	-0.311380
LR statistic (5 df)	115.9702	McFadden R-squared	0.259641
Probability(LR stat)	0.000000		
Obs with Dep=0	452	Total obs	531
Obs with Dep=1	79		

The overall significance of the model is evaluated by the following goodness of fit tests. First the deviance of the model is calculated by the formula given by 3.9. “Likelihood of the current model” indicated in the formula is the same as “log likelihood” given in Table 4.8, and therefore has a value of -165.3428. Likelihood of the saturated model is the “restricted log likelihood” mentioned in the same Table and its value is -223.3279. Hence, deviance is calculated as 0.60124.

As the conventional measure of goodness of fit, R^2, is not particularly meaningful in binary regression models, pseudo-R^2 and McFadden R^2 are used. By the equation 3.12, Pseudo-R^2 of the model is calculated as 0.1792. As shown in the Table 4.8 the value of McFadden R^2 in our model is 0.2596.

To test the null hypothesis that all the slope coefficients are simultaneously equal to zero, the equivalent of the F test in the linear regression model is the likelihood ratio (LR) statistic. Given the null hypothesis, the LR statistic follows the X^2 distribution with degrees of freedom equal to the number of explanatory variables (5 in our model). As indicated in the Table 4.8, LR statistic is 115.9702, whose p-value is 0.000. Therefore, LR statistic indicates that the model is well-fitted.

Table 4.9 Pearson Chi-Square Goodness of Fit for Logit Regression

Dependent Variable: ACCEPTREJ
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 12/10/07 Time: 17:53
Sample (adjusted): 1 532
Included observations: 531 after adjustments
Andrews and Hosmer-Lemeshow Goodness-of-Fit Tests
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	0.0004	53	52.9959	0	0.00413	53	0.00413
2	0.0004	0.0115	53	52.7673	0	0.23275	53	0.23378
3	0.0115	0.0441	51	51.5429	2	1.45711	53	0.20799
4	0.0448	0.0824	52	49.6056	1	3.39437	53	1.80455
5	0.0846	0.1194	51	47.5431	2	5.45690	53	2.44127
6	0.1201	0.1465	47	45.9970	6	7.00304	53	0.16554
7	0.1469	0.1627	46	44.7943	7	8.20568	53	0.20961
8	0.1638	0.1898	44	43.9222	9	9.07779	53	0.00080
9	0.1906	0.2985	39	39.8068	14	13.1932	53	0.06569
10	0.2988	1.0000	16	23.0250	38	30.9750	54	3.73656
		Total	452	452.000	79	79.0000	531	8.86992

H-L Statistic:	8.8699	Prob. Chi-Sq(8)	0.3534
Andrews Statistic:	62.6359	Prob. Chi-Sq(10)	0.0000

Other goodness-of-fit tests are Pearson X^2 type tests, done through Eviews. Table 4.9 demonstrates the results. Two tests were carried out: Hosmer-Lemeshow (1989) and Andrews (1988a, 1988b). The idea is to compare fitted expected values to the actual values by group. The X^2 statistics are reported at the bottom of the table. The p-value for the HL test is large while the value for the Andrews test statistic is small. Therefore, HL test suggests the fit to be not successful, whereas Andrews test indicates a good fit.

In order to decide the effect of the logit regression parameters to the probability of credit rejection decision, the usual method is to calculate the marginal effect at the mean value of the explanatory variables. The mean values of the significant variables TO, NETWORTH, PROFITMARG, TOTALASSETS and TEXTILE are demonstrated in the Table 4.13 and hence the value of Z at the mean was -3.789. From this f(Z), value of logistic function at Z, can be obtained as 0.022. Here "b" stands for the coefficients in the regression equation. The table shows the marginal effects, calculated by multiplying f(Z) by the estimates of the coefficients of the logit regression.

Table 4.10 Logit Estimation Marginal Effect

Variable	Mean	b	Mean x b	f(Z)	bf(Z)
TO	386,905,695	-2.63E-09	-1.02E+00	0.022	-5.79E-11
NETWORTH	155,894,390	-1.45E-08	-2.26E+00	0.022	-3.19E-10
PROFITMARG	1.05	-0.047	-4.94E-02	0.022	-0.001
TOTALASSETS	283,669,938	3.39E-09	9.62E-01	0.022	7.46E-11
TEXTILE	0.17	0.742	1.26E-01	0.022	0.016
Constant	1	-1.549	-1.55E+00		
Total			-3.789		

According to the calculated values in Table 4.10, one-point increase in the TO increases the probability of being rejected by -5.79E-9 percent, which is a very small number. Similarly the effect of NETWORTH and TOTALASSETS to the probability of rejection is very small. Therefore, the variables TO, NETWORTH, TOTALASSETS are insignificant at the 0.1 percent level. However, a one-point increase in the PROFITMARG decreases the credit rejection probability by 0.1%. Similarly, a one-point increase in TEXTILE increases the rejection probability by 1.6%. Thus, PROFITMARG and TEXTILE are significant at the 0.1 percent level.

4.5 Probit Regression Results

Generally both probit and logit models come to the same conclusion, but the interpretation and magnitudes of coefficients are different. Through the forward selection algorithm -as explained in the section 4.2-, the variables in Table 4.12 are chosen. These are the same variables as the ones selected in the logistic regression. The probit regression results are shown in Table 4.11 and Table 4.12.

TABLE 4.11 Univariate Probit Regression Results

Variable	Constant	Coefficient	p-value
AGE	-1.100	0.003	0.565
EMPLOYEE	-0.947	-4.01E-04	0.040
TO	-0.832	-1.53E-09	0.020
NETWORTH	-0.754	-6.82E-09	0.002
CURRENTR	-1.037	-4.40E-04	0.645
SOLVENCYR	-1.023	-1.34E-04	0.178
PROFITMARG	-1.101	-0.019	0.027
SHRETURN	-1.033	-0.007	0.031
TOTALASSETS	-0.927	-8.64E-10	0.015
AUTOMTV	-1.028	-0.376	0.310
CHEM	-1.021	-0.055	0.684
CONSTR	-1.023	-0.360	0.242
ELECTRCL	-1.042	-0.010	0.967
MACHNRY	-1.039	-0.243	0.656
METAL	-0.987	-0.815	0.011
SERVICE	-1.041	-0.016	0.937
TEXTILE	-1.177	0.629	0.000

TABLE 4.12 Probit Regression Model Parameters

Variable	Coefficient	Std. Errors	P-values
constant	-0.927	0.103	0.000
TO	-1.62E-09	7.78E-10	0.037
NETWORTH	-7.78E-09	2.91E-09	0.008
PROFITMARG	-0.017	0.008	0.033
TOTALASSETS	2.08E-09	7.59E-10	0.006
TEXTILE	0.473	0.172	0.006

The calculated Probit model coefficients indicate the effect of the independent variables on the dependent variable. They show the change in the cumulative normal probability of the dependent variable when the independent variable changes by one unit. While logit model expressed log odds, the probit model gives z-scores.

The Z-score equation of the underlying study is found as follows:

$$\Phi^{-1}\left(P\left(Y=1\right)\right) = -0.927 - 1.62E-09 * TO - 7.78E-09 * NETWORTH$$
$$-0.017 * PROFITMARG + 2.08E-09 * TOTALASSETS + 0.473 * TEXTILE$$

The output of the model from Eviews are shown in the Table 4.11.

TABLE 4.13 Probit regression statistics

Dependent Variable: ACCEPTREJ
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 12/10/07 Time: 17:32
Sample (adjusted): 1 532
Included observations: 531 after adjustments
Convergence achieved after 15 iterations
QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.926942	0.103206	-8.981495	0.0000
TEXTILE	0.473002	0.172209	2.746670	0.0060
NETWORTH	-7.78E-09	2.91E-09	-2.673142	0.0075
TOTALASSETS	2.08E-09	7.59E-10	2.748004	0.0060
TO	-1.62E-09	7.78E-10	-2.087309	0.0369
PROFITMARG	-0.016798	0.007864	-2.136100	0.0327

Mean dependent var	0.148776	S.D. dependent var	0.356203
S.E. of regression	0.312049	Akaike info criterion	0.657112
Sum squared resid	51.12163	Schwarz criterion	0.705414
Log likelihood	-168.4631	Hannan-Quinn criter.	0.676016
Restr. log likelihood	-223.3279	Avg. log likelihood	-0.317256
LR statistic (5 df)	109.7295	McFadden R-squared	0.245669
Probability(LR stat)	0.000000		
Obs with Dep=0	452	Total obs	531
Obs with Dep=1	79		

Similar to the logit model, the overall significance of the probit model is evaluated by the following goodness of fit tests. First the deviance of the model is calculated by the formula given by 3.9. Likelihood of the current model is given in Table 4.11 as -168.4631. Likelihood of the saturated model is in the same Table indicated as -223.3279, which are similar to those found for the logit model. Hence, deviance is calculated as 0.56384, which is lower than the logit regression model deviance. Therefore, according to this criteria probit model performed better.

As other goodness of fit measures, by the equation 3.12, Pseudo-R^2 of the model is calculated as 0.1710. As shown in the Table 4.11, the value of McFadden R^2 in our model is 0.245669, which is close to the value calculated for the logit model.

To test the null hypothesis that all the slope coefficients are simultaneously equal to zero, the equivalent of the F test in the linear regression model, is the likelihood ratio (LR) statistic. Given the null hypothesis, the LR statistic follows the X^2 distribution with degrees of freedom equal to the number of explanatory variables (5 in our model). As indicated in the Table 4.11, LR statistic is 109.7295, whose p-value is 0.000. Therefore, LR statistic indicates that the model well-fitted.

Table 4.14 Pearson Chi-Square Goodness of Fit for Probit Regression

Dependent Variable: ACCEPTREJ
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 12/10/07 Time: 17:32
Sample (adjusted): 1 532
Included observations: 531 after adjustments
Andrews and Hosmer-Lemeshow Goodness-of-Fit Tests
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	3.E-05	53	52.9999	0	0.00010	53	0.00010
2	4.E-05	0.0089	53	52.8343	0	0.16570	53	0.16622
3	0.0091	0.0462	51	51.6263	2	1.37372	53	0.29312
4	0.0470	0.0926	52	49.3957	1	3.60426	53	2.01901
5	0.0942	0.1272	50	47.0658	3	5.93421	53	1.63377
6	0.1275	0.1515	47	45.5419	6	7.45807	53	0.33174
7	0.1523	0.1673	46	44.4880	7	8.51199	53	0.31996
8	0.1677	0.1908	45	43.6834	8	9.31663	53	0.22575
9	0.1931	0.3075	34	39.4624	19	13.5376	53	2.96014
10	0.3089	1.0000	21	27.4091	33	26.5909	54	3.04337
		Total	452	454.507	79	76.4932	531	10.9932

H-L Statistic:	10.9932	Prob. Chi-Sq(8)	0.2021
Andrews Statistic:	50.7470	Prob. Chi-Sq(10)	0.0000

Table 4.12 demonstrates the Pearson X^2 type tests of goodness-of-fit, done through Eviews. As in the results of the same tests for logit regression, the p-value for the Hosmer-Lemeshow (HL) test is large while the value for the Andrews test statistic is small. Therefore, HL test suggests that fit is not successful, while Andrew statistic indicates a good fit.

In order to decide the effect of the probit regression parameters to the probability of credit rejection decision, as in the case logit regression, the usual method is to calculate the marginal effect at the mean value of the explanatory variables. The mean values of the significant variables TO, NETWORTH, PROFITMARG, TOTALASSETS and TEXTILE are shown in the Table 4.13 and hence the value of the function Φ at the mean was -2.114. From this f(Z), value of probit function at Z, can be obtained as 0.0172. The table indicates the marginal effects, calculated by multiplying f(Z) by the estimates of the coefficients of the probit regression.

Table 4.15 Probit Estimation Marginal Effect

Variable	Mean	b	Mean x b	f(Z)	bf(Z)
TO	386,905,695	-1.62E-09	-6.27E-01	0.0172	-2.79E-11
NETWORTH	155,894,390	-7.78E-09	-1.21E+00	0.0172	-1.34E-10
PROFITMARG	1.05	-0.017	-1.79E-02	0.0172	0.000
TOTALASSETS	283,669,938	2.08E-09	5.90E-01	0.0172	3.58E-11
TEXTILE	0.17	0.473	8.04E-02	0.0172	0.008
Constant	1	-0.927	-9.27E-01		
Total			-2.114		

According to the calculated marginal effects in the Table 4.13, one-point increase in the TO increases the probability of being rejected by -2.79E-11 percent, which is a very small number. Similarly, this probability is very small for the variables NETWORTH and TOTALASSETS, too. PROFITMARG has no effect to the credit rejection probability. Therefore, the variables TO, NETWORTH, TOTALASSETS, PROFITMARG are insignificant at the 0.1 percent level. However, a one-point increase in TEXTILE increases the rejection probability by 0.8%. Thus, TEXTILE is the only significant variable at the 0.1 percent level.

4.5 Conclusions from Probit and Logit Regression Results

The followings are concluded from the above results concerning both probit and logit models: Even though generally logit and probit analysis yield similar marginal effects, in our study some results they provided were different. From the marginal effects calculated for the probit model, only the binary variable “textile” found to be significant. In the case of logit model, “textile” and profit margin were significant variables. The marginal effect of the variable “textile” to the credit refusal decision probability was larger in logit regression result than that in probit regression. Since, the tails of the logit and probit distributions are different, they can give different results if the sample is unbalanced, with most of the outcomes similar.[40] This is the case in our study, because only 14.85% of the credit applications were rejected.

In addition; all size variables used in the study -namely turnover, net worth and total assets of a company- played no significant role in credit granting decision of the financial institution.

Furthermore, the sector (except textile) in which the firm operated had no significant impact in the credit decision of the financial institution. Concerning textile sector companies, financial institutions indeed became more prudent in their credit granting process after the abolition of import quotas in the textile industry starting from the beginning of 2005. This liberalisation effected the textile companies operating in Turkey negatively and they faced problems to compete especially with Chinese and Indian companies. The models therefore provided a meaningful result about the selectivity of the financial institution to grant credit to textile industry companies.

4.6 Comparison of Probit and Logit Regression Results with the Model Parameters of the Moody's Private Company Rating Model

In this section we will compare our results with the rating model of Moody's for private companies, RiskCalc. Moody's indicates that higher profitability should raise a firm's equity value. It also implies a longer way for revenues to fall or costs to rise before losses occur. The set of profitability measures used by Moody's are EBIT/assets, net income/common equity, net income/assets and operating profit margin. In our study net profit margin is used and it was significant in the logit regression model but not significant in probit regression.

Moody's mentions that, in addition to profitability, leverage is a key measure of firm risk. The higher the leverage, or gearing, the smaller the cushion for adverse shocks. Total liabilities/tangible assets, total debt/total assets, total liabilities/total assets, total debt/net worth, debt service coverage ratio are utilised by Moody's in its rating system. In our empirical research, we used total debt/total assets as a model parameter, however it is found to be insignificant in both probit and logit models.

[40] Introduction to Econometrics, Christopher Dougherty, Oxford Press, pg.291.

Other parameters used by Moody's are size variables. Moody's states that size is related to volatility. Smaller size implies less diversification and less depth in management, which implies greater susceptibility to idiosyncratic shocks. Sales turnover and total assets are utilised by Moody's. In our study, in addition to those, net worth is also included. However, size measures were insignificant in our models.

As stated by Moody's, liquidity is a common variable in most credit decisions. That is, if the company has sufficient current assets, it can pay current liabilities. Current ratio, quick ratio, working capital/total assets, cash/total assets, short term debt/total debt are used by Moody's. In our study, current ratio is used and found to be insignificant.

Activity ratios, e.g. accounts receivables/cost of goods sold, sales/total assets, accounts payable/cost of goods sold, accounts receivables/sales, inventory/cost of goods sold are included in the model of Moody's. However, Moody's indicates that activity ratios have less straightforward relations to risk than other variables. Sales growth and audit quality are other parameters utilised by Moody's. Due to inexistence of appropriate data, these measures are not included in our study.

Several factors, such as industry specific information and management quality, that affect credit are not addressed in the model of Moody's. The major reason for this exclusion indicated by Moody's is that they are too difficult to measure consistently. In our model, we included industry dummies. We found out that only "textile" variable was significant but other industry dummies were insignificant.

Even though not all the parameters to compare with the model of Moody's could be obtained, above results indicate that qualitative information and/or judgement played an important role in the credit assessment and approval process of the analysed financial institution. This is because the main criteria applied by the model of Moody's, such as leverage or debt ratios and liquidity were insignificant. Another main criteria, profitability was only significant in the logit regression.

Finally, Moody's mentions that many ratios are correlates with credit quality. Given these variables' correlations with each other, one has to choose a select subset in order to generate a stable statistical model. The above mentioned ratios used by Moody's were suggested by their univariate power and tested within a multivariate framework on private firm data. Therefore, with the Basel II implementation, it is forecasted that those parameters will be utilised by financial institutions as a criteria in their rating and credit decision models. This is due to the fact that rating companies' rating grades will be the basis for Basel II-Standard Approach. With the implementation of Basel II-IRB Approach, similar models as those of rating companies are being used or will be constructed internally by the financial institutions. Basel II framework states that each borrower and facility must be assigned a rating prior to the bank entering into a commitment to lend, i.e. during the credit approval process. Best practices of the banks, which is the base of Basel II framework, also indicates that credit rating systems typically include both quantitative (e.g. financial ratios) and qualitative but standardised (e.g. industry, payment history/credit report) factors. The modelling technique are mainly discriminant, logit-based, or based on classic credit scoring techniques. [41]

[41] Basel Committee, IRB Consultative Document, 31 May 2001.

CHAPTER 5

CONCLUSION

This study analyses the credit assessment processes of a specific financial institution in Turkey and compares the main drivers of corporate credit approval decisions with the parameters of Moody's rating model for private companies, RiskCalc.

The main findings of the thesis are summarised as follows:

Firstly, the conclusions from the Basel II framework and its application in Turkey in terms of credit assessment processes are the followings: The Basel I and Basel II Accords (Chapter 2) both have as an objective to further strengthen the soundness and stability of the international banking system. Although Basel II is generally considered an important step forward, its effectiveness is globally debated. Currently, because of the recent turbulence in the financial markets related to the sub-prime mortgage crisis, Basel II is scrutinised. While preparing for the implementation of Basel II, the Turkish banking sector has also been reviewing and adjusting its risk assessment processes. The latest BRSA report prepared (end-2006) suggests that Turkish Banks are still in the initial phases of implementation, but on the other hand consider it as a highly important subject. Significant progress has already been made in terms of system and infrastructure. Regarding the Basel Accords, it should be acknowledged that credit rating is a very recent issue in Turkey. Still, only some internationally active, stock exchange listed companies and/or financial institutions have external credit ratings from the major rating companies S&P, Moody's or Fitch. On the other hand, almost all Turkish banks utilise credit risk analysis results in decision making processes. Most banks also use it in specifying medium and long terms strategies, but only to a lesser extent in limit allocations, investment and placement decisions as well as performance evaluations. In general it is expected that the majority of the banks will apply the

Standard Approach (SA). The Basel Accord defines the SA as a system in which ratings of external rating institutions are recognised by the national supervisory authorities in determining the risk weights in capital allocation. Consequently, improvement of risk management practices is expected parallel to the implementation of Basel II. It is forecasted that financial institutions will be able to apply information provided through ratings and credit analysis in a broader sense. Traditionally, -as mentioned above- insufficiency of structural and reliable historical default-data series constrained default-modelling practices in Turkey. Recently banks have started to adjust or improve their IT systems and a pooled data base for corporate loans managed by the National Credit Bureau, as suggested by the Basel Committee, is foreseen.

Secondly, the conclusions from the modelling of credit decision data of the financial institution -whether to accept a loan application are as follows: Logit and probit regression models (Chapter 3) are among the most practiced methods and mentioned in the Basel II framework as the best practices in internal credit approval and credit scoring processes. With the use of such modelling techniques and the help of corporate loan decision data obtained from a major financial institution in Turkey empirical research was executed (Chapter 4). The regression coefficients are estimated using the method of maximum likelihood. Initially, 17 variables are analysed each in a univariate model. Those variables were firm-specific factors (e.g. age and number of employees), financial variables including ratios and size figures as well as a binary variable (the industry in which the company operates). The variables in both multivariate logit and probit models are selected through a forward selection algorithm, i.e. a process which includes the variables one by one to the model in accordance to their predictive power.

- Even though generally logit and probit analysis yield similar marginal effects, in our study some of the results they provided were different. Marginal effects calculated for the logit model indicated that the profit margin and the binary variable “textile” –indicating whether the company is operating in the textile industry or not- are significant. From the marginal effects calculated for the probit model, only the binary variable “textile” found to be significant. The marginal effect of the variable to the credit refusal decision probability was larger in logit regression result than that in probit regression. Since, the tails of the logit and probit distributions are different, they can give different results if the sample is unbalanced, with most of the outcomes similar.[42] This is the case in our study, because only 14.85% of the credit applications were rejected. All size variables used in the study -namely turnover, net worth and total assets of a company- played no significant role in credit granting decision of the financial institution.

- The sector (except textile) in which the firm operated played no role in the credit decision of the financial institution. Concerning textile sector companies, financial institutions indeed became more prudent in their credit granting process after the abolition of import quotas in the textile industry starting from the beginning of 2005. This liberalisation effected the textile companies operating in Turkey negatively and they faced problems to compete especially with Chinese and Indian companies. The models therefore provided a meaningful result about the selectivity of the financial institution to grant credit to textile industry companies.

Thirdly, the comparison of our results with the rating model of Moody's for private companies yielded the following results:

- Even though profitability parameter is used by Moody's, it was significant in the logit regression model but not significant in probit regression in the underlying study. In addition; debt or leverage ratios, size variables, e.g. total assets, net worth turnover and liquidity ratios are part of Moody's rating system. Contrary to that, in the empirical research they are found to be insignificant in both models. Activity ratios are also incorporated by Moody's in its rating model, although Moody's indicates that these have less straightforward relations to risk than other variables. Sales growth and audit quality are other parameters utilised by Moody's. Due to inexistence of appropriate data, these measures are not included in the empirical research.

- Several factors, such as industry specific information and management quality, that affect credit are not addressed in the model of Moody's. The major reason for this exclusion indicated by Moody's is that they are too difficult to measure consistently. In our model, we included industry dummies. We found out that only "textile" variable was significant but other industry dummies were insignificant.

[42] Introduction to Econometrics, Christopher Dougherty, Oxford Press, pg.291.

The above mentioned ratios used by Moody's were suggested by their univariate power and tested within a multivariate framework on private firm data. Moody's mentions that many ratios are correlated with credit quality. Given these variables' correlations with each other, one has to choose a select subset in order to generate a stable statistical model. Therefore, with the Basel II implementation, it is forecasted that those parameters will be used by financial institutions as a criteria in their rating and credit decision models. This is due to the fact that rating companies' ratings will be the basis for Basel II-Standard Approach. With the implementation of Basel II-IRB (internal ratings based) Approach, similar models as those of rating companies have already been used or will be constructed internally by the financial institutions. The Basel II framework states that each borrower and facility must be assigned a rating prior to the bank entering into a commitment to lend, i.e. during the credit approval process. Best practices of the banks, which are the base of Basel II framework, also indicate that credit rating systems typically include both quantitative (e.g. financial ratios) and qualitative but standardised (e.g. industry, payment history/credit report) factors. The modelling techniques are mainly discriminant, logit-based, or based on classic credit scoring techniques. [43]

Furthermore, from the qualitative information provided by the institution through an interview, the rating system and the use of information through the rating are analysed. Firstly it was observed that the institution used an expert judgement based process and rated mainly the current condition of the companies, i.e. point-in-time rating. To be able to prove this statistically, one should observe time series default data of the institution. Due to inability to obtain this information, such an analysis could not be made. This quantitative information suggests a contrary application compared to the Basel II framework, which prescribes the use of statistical default models and through-the-cycle rating system. The latter is a rating philosophy estimating the borrower's condition at the worst point in an economic or industrial cycle. Such a rating system is especially important to assess the companies operating in developing countries with a highly cyclical economy, such as Turkey. In a through-the-cycle rating process the variables should include macroeconomic variables, e.g. GDP growth rates, exchange rates and interest rates. Secondly, the analysed institution used the rating information only for management reporting and limit setting, but not for pricing, compensation and/or risk

[43] Basel Committee, IRB Consultative Document, 31 May 2001.

adjusted performance measurement purposes. As underlined above, this practice should also change over time. In fact, the practices of the financial institution confirm the earlier statements on credit risk management in Turkey, namely that it is still in the early phases.

In conclusion, the models in this study can be used by the financial institution to make a decision whether to grant credit or not. In future studies, as underlined above, in case of availability of a data set including time series of default data, default dynamics can be analysed. With such data the impact of macroeconomic conditions such as the output gap, the yield curve, level of GDP and inflation defaults can be analysed.

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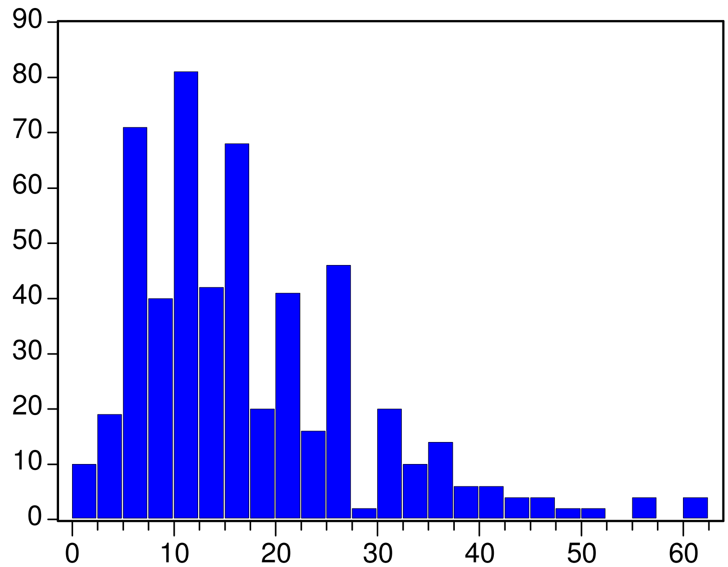
CHAPTER 6

APPENDIX

Figure 6.1 Histogram of the Variable "AGE"



Series: AGE	
Sample 1 533	
Observations 532	
Mean	17.20865
Median	15.00000
Maximum	61.00000
Minimum	1.000000
Std. Dev.	11.34196
Skewness	1.304799
Kurtosis	4.815145
Jarque-Bera	223.9887
Probability	0.000000

Figure 6.2 Histogram of the Variable "CURRENTR"

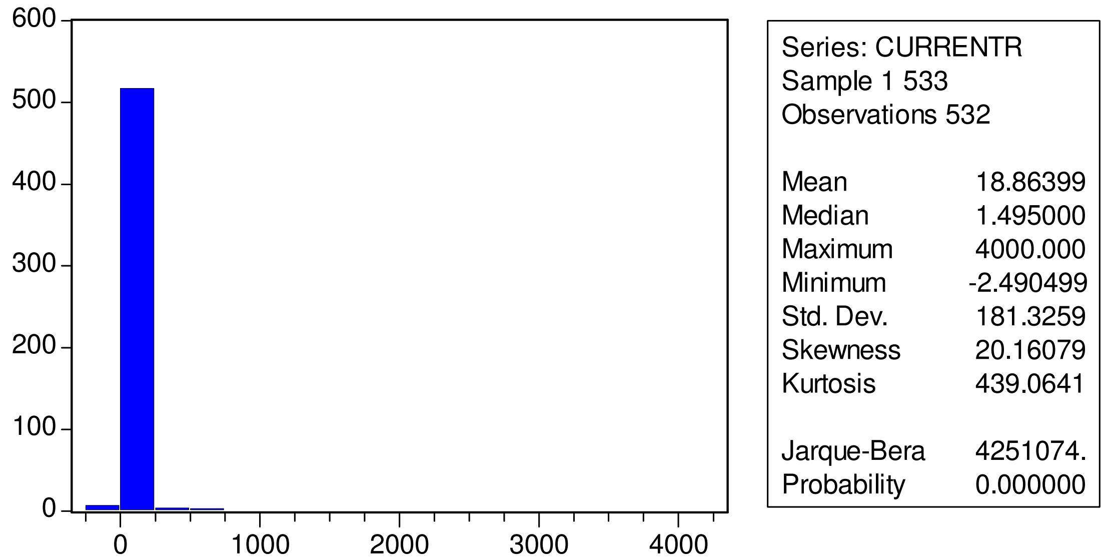


Figure 6.3 Histogram of the Variable "EMPLOYEE"

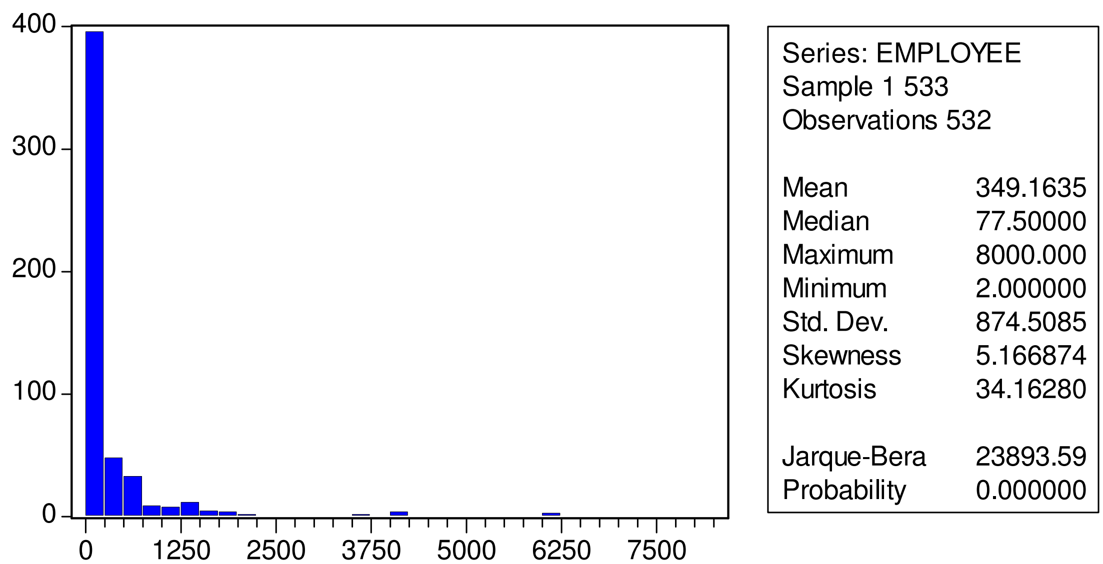
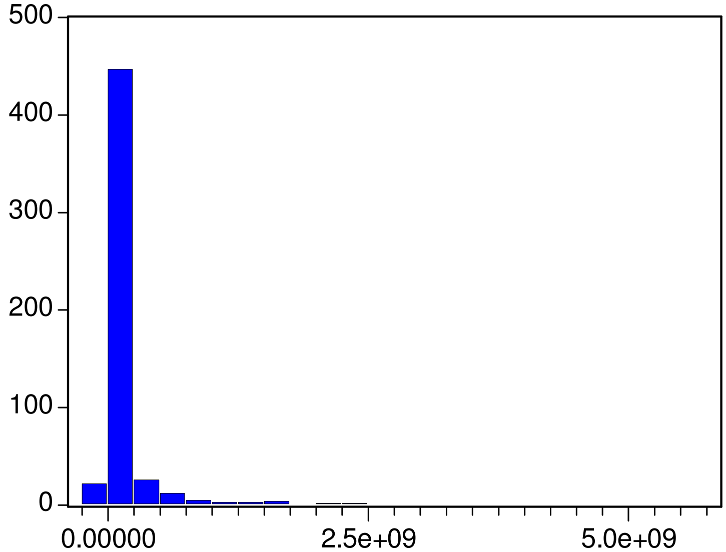


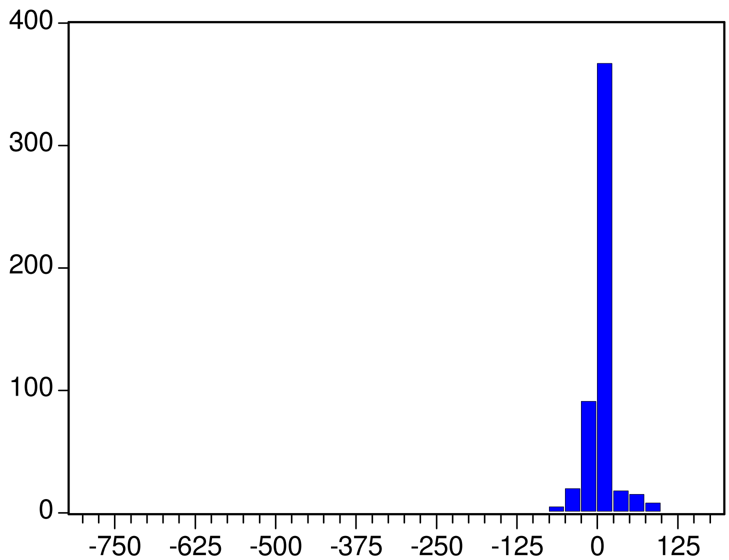
Figure 6.4 Histogram of the Variable “NETWORTH”



Series: NETWORTH
Sample 1 533
Observations 531

Mean	1.56e+08
Median	21079000
Maximum	5.56e+09
Minimum	-2.43e+08
Std. Dev.	4.92e+08
Skewness	6.850305
Kurtosis	62.00963
Jarque-Bera	81195.28
Probability	0.000000

Figure 6.5 Histogram of the Variable “PROFITMARG”



Series: PROFITMARG
Sample 1 533
Observations 532

Mean	1.047703
Median	2.005000
Maximum	170.0000
Minimum	-800.0000
Std. Dev.	48.80780
Skewness	-10.61544
Kurtosis	160.5351
Jarque-Bera	560108.7
Probability	0.000000

Figure 6.6 Histogram of the Variable “SHRETURN”

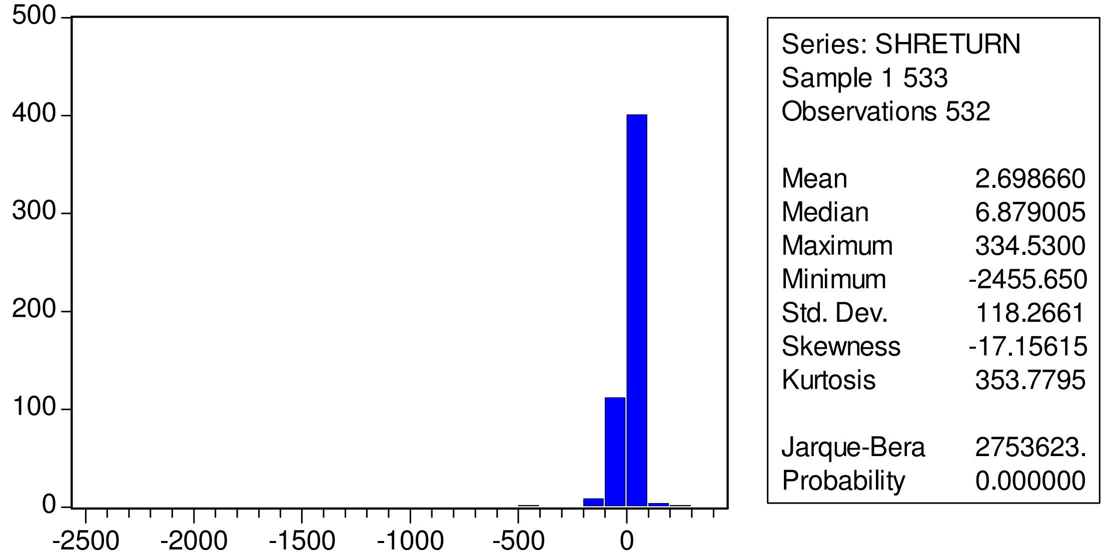


Figure 6.7 Histogram of the Variable “SOLVENCYR”

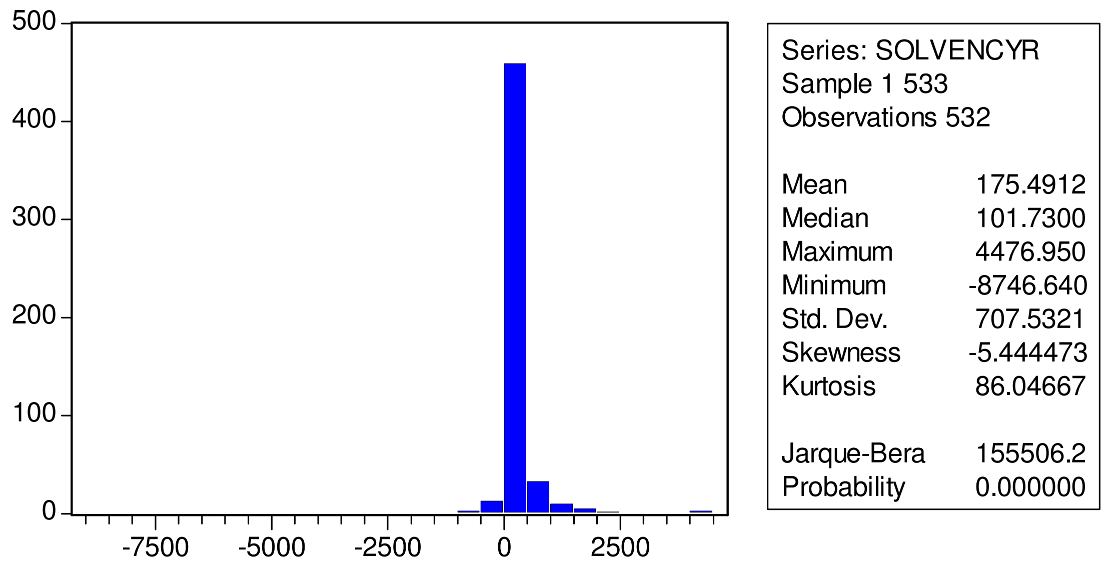


Figure 6.8 Histogram of the Variable "TO"

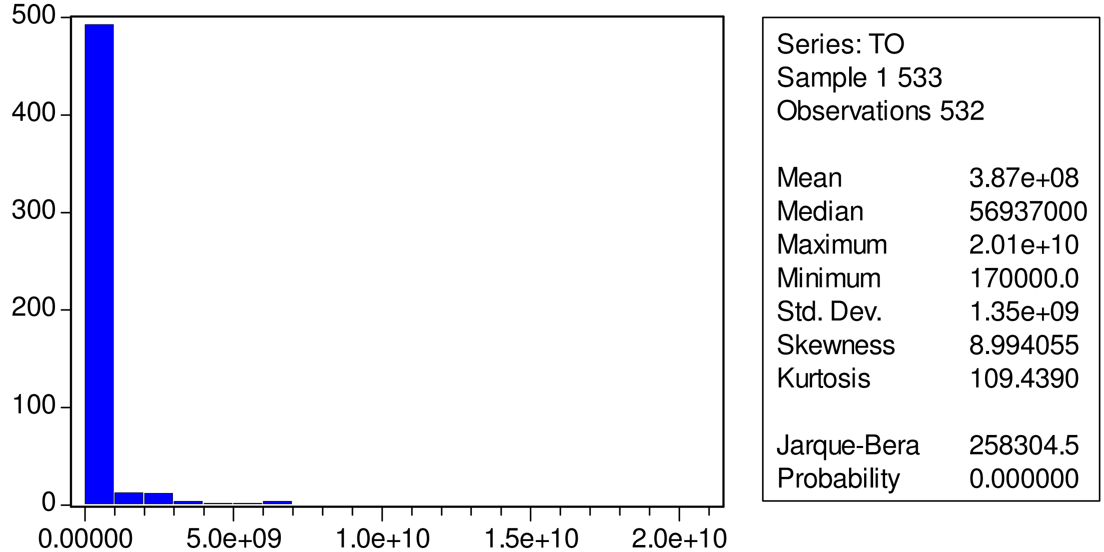


Figure 6.9 Histogram of the Variable "TOTALASSETS"

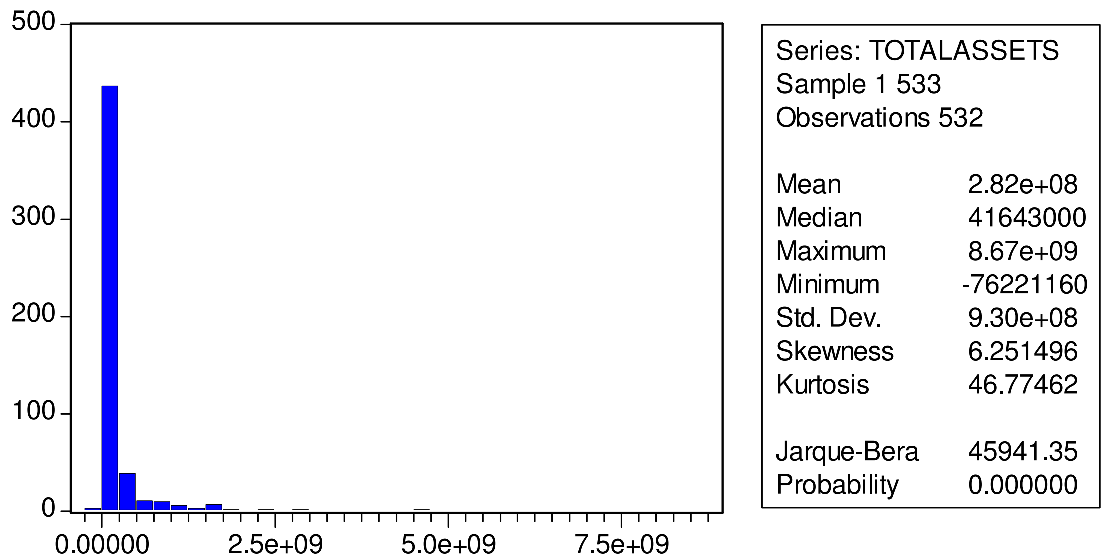
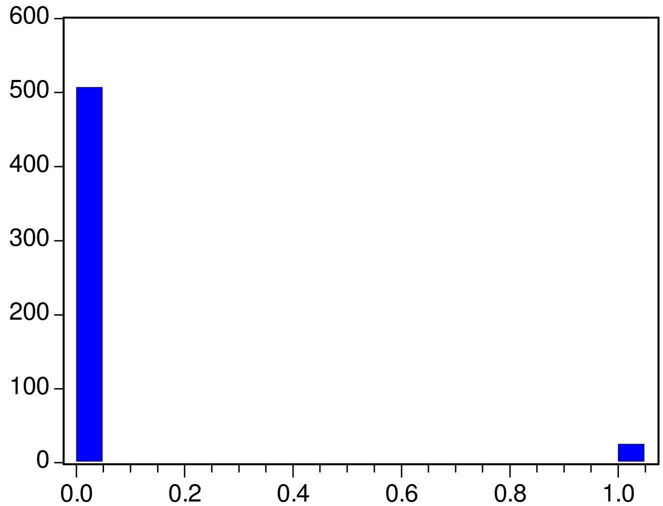
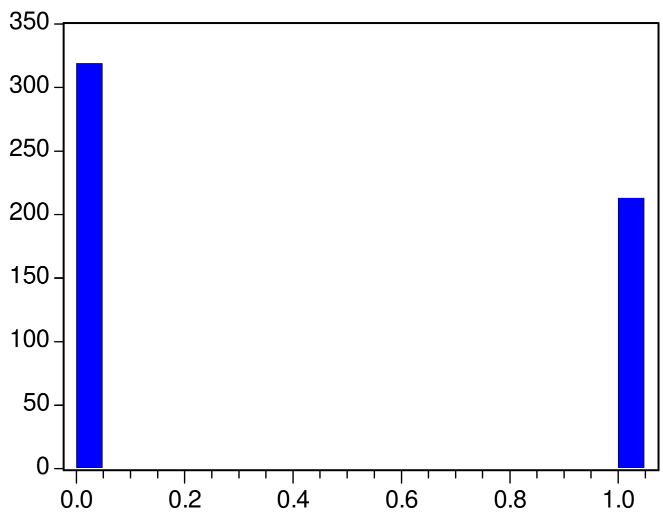


Figure 6.10 Histogram of the Variable "AUTOMTV"



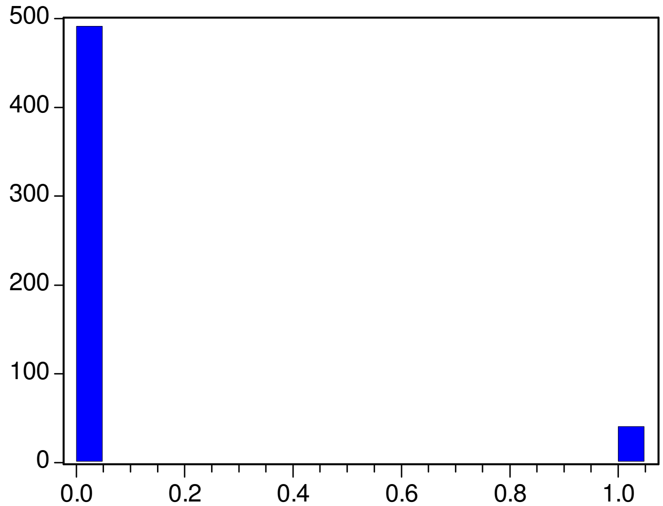
Series: AUTOMTV	
Sample 1 533	
Observations 532	
Mean	0.046992
Median	0.000000
Maximum	1.000000
Minimum	0.000000
Std. Dev.	0.211822
Skewness	4.281274
Kurtosis	19.32931
Jarque-Bera	7535.860
Probability	0.000000

Figure 6.11 Histogram of the Variable "CHEM"



Series: CHEM	
Sample 1 533	
Observations 532	
Mean	0.400376
Median	0.000000
Maximum	1.000000
Minimum	0.000000
Std. Dev.	0.490436
Skewness	0.406650
Kurtosis	1.165364
Jarque-Bera	89.27282
Probability	0.000000

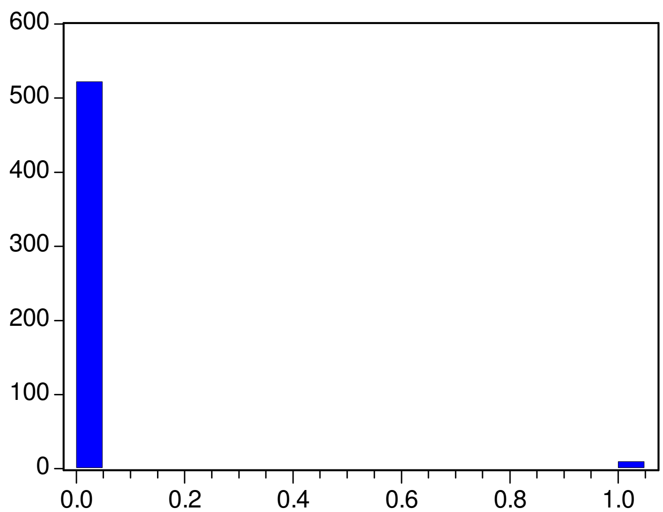
Figure 6.12 Histogram of the Variable "ELECTRCL"



Series: ELECTRCL
Sample 1 533
Observations 532

Mean	0.077068
Median	0.000000
Maximum	1.000000
Minimum	0.000000
Std. Dev.	0.266950
Skewness	3.171610
Kurtosis	11.05911
Jarque-Bera	2331.617
Probability	0.000000

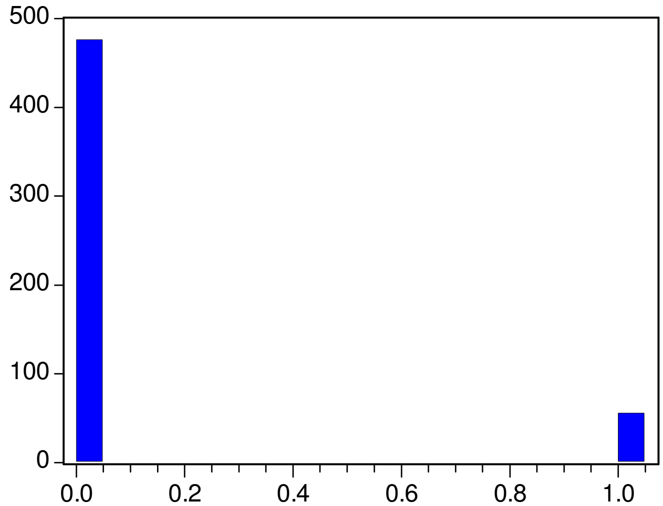
Figure 6.13 Histogram of the Variable "MACHNRY"



Series: MACHNRY
Sample 1 533
Observations 532

Mean	0.018797
Median	0.000000
Maximum	1.000000
Minimum	0.000000
Std. Dev.	0.135935
Skewness	7.086548
Kurtosis	51.21916
Jarque-Bera	55992.20
Probability	0.000000

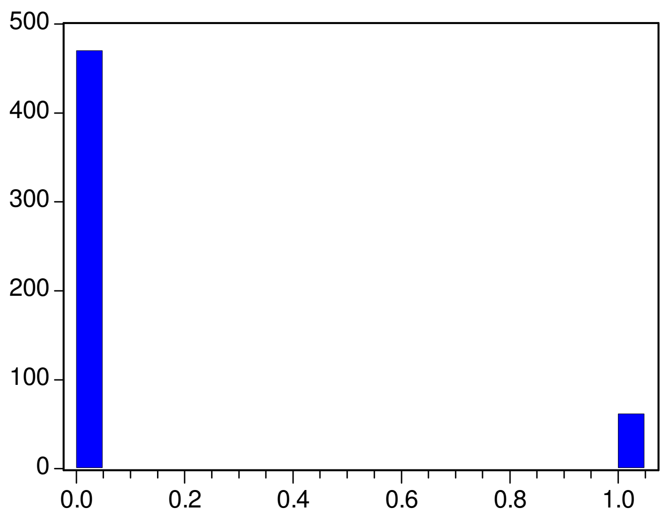
Figure 6.14 Histogram of the Variable "METAL"



Series: METAL
Sample 1 533
Observations 532

Mean	0.105263
Median	0.000000
Maximum	1.000000
Minimum	0.000000
Std. Dev.	0.307181
Skewness	2.572479
Kurtosis	7.617647
Jarque-Bera	1059.417
Probability	0.000000

Figure 6.15 Histogram of the Variable "SERVICE"



Series: SERVICE
Sample 1 533
Observations 532

Mean	0.116541
Median	0.000000
Maximum	1.000000
Minimum	0.000000
Std. Dev.	0.321175
Skewness	2.390096
Kurtosis	6.712560
Jarque-Bera	812.0391
Probability	0.000000

Figure 6.16 Histogram of the Variable "TEXTILE"

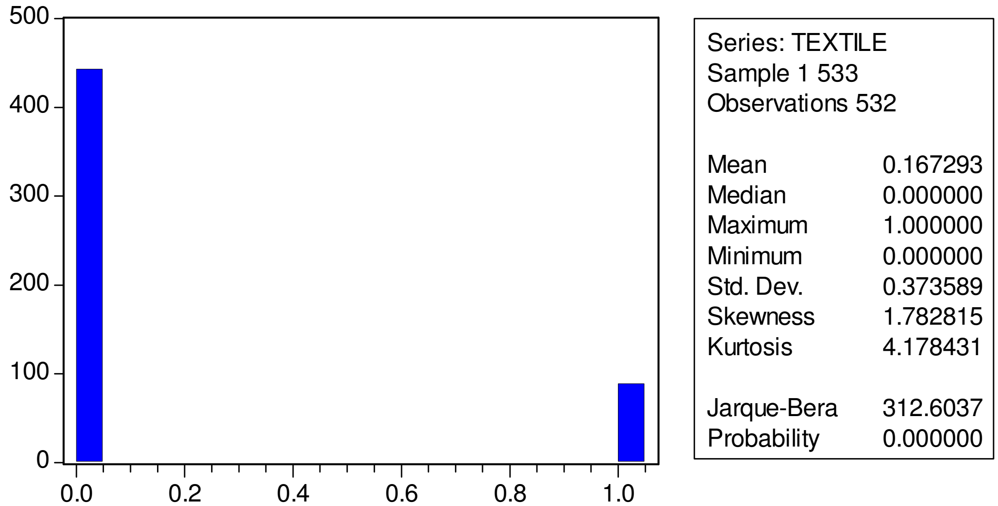


Figure 6.17 Histogram of the Variable "CONST"