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DOCTORAL THESIS

Philosophy of Doctorate (PhD)

MICRO FINANCIAL CREDIT RISK METRICS: A PROPOSED MODEL FOR BANKRUPTCY AND ITS ESTIMATION

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DECLARATION

I hereby declare that this doctoral thesis titled as "**Micro Financial Credit Risk Metrics: A Proposed Model for Bankruptcy and Its Estimation**" has been written by myself without applying the help that can be contrary to academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honour.

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ABSTRACT

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Micro Financial Credit Risk Metrics: A Proposed Model for Bankruptcy and Its Estimation

Şaban ÇELİK

Dokuz Eylül University

Graduate School of Social Sciences

Department of Business Administration

Business Administration Program

The main purpose of this thesis is to propose a theoretical model that incorporates the dynamics of the firms for bankruptcy process. The proposed model has an aim to overcome weaknesses of the previously developed models. The most important feature of the proposed model is that it changes the way of approaching the problem for predicting bankruptcy. The power of the model comes from linking the main dynamics of the firm to value addition and dilution processes. The linkages between the dynamics of the firms and the bankruptcy process are set in a sense that the model brings a wider perspective. Empirical investigation of proposed model is conducted on manufacturing firms listed in Istanbul Stock Exchange (ISE) for the period from 2007 to 2011. The analyses are carried out within the structure of cross-sectional framework. Empirical results of proposed model indicate that the estimated models give promising results in case of one and two years before the final condition of the firms. Estimated models perform over 90% correct classifications for 2010 and 2011. In terms of practical implication, it is claimed that the proposed model will be benefited by all stakeholders as a general road map in financial environment.

Keywords: Micro Credit Risk Metric, Modeling, Bankruptcy, Financial Distress

ÖZET

Doktora Tezi

Mikro Finansal Kredi Risk Ölçütleri: İflas için Önerilen bir Model ve Tahminlemesi

Şaban ÇELİK

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Bu tezin ana amacı, iflas süreci için firma dinamiklerini içeren bir kuramsal model önermektir. Önerilen modelin amacı daha önceden geliştirilen modellerin eksikliklerini gidermektir. Bu modelin en önemli özelliği, iflas sorununa yaklaşım biçimini değiştirmiş olmasıdır. Modelin gücü, firma temel dinamiklerinin değer katma ve kaybetme süreçleri ile ilişkilendirmesinden gelir. Firma dinamikleri ile iflas süreci ilişkileri, modelin daha geniş bir bakış açısı getirecek şekilde oluşturulmuştur. Modelin görgül incelemeleri, 2007-2011 yılların arasında İstanbul Menkul Kıymetler Borsası'nda işlem gören üretim sektörü firmaları üzerinde gerçekleştirilmiştir. Analizler, yatay-kesit araştırma yapısında uygulanmıştır. Modelin görgül analiz sonuçları göstermiştir ki firmaların en son durumundan önceki iki yıl için elde edilen sonuçlar umut vermektedir. Tahminlenen modeller, 2010 ve 2011 yılları için %90'dan daha fazla doğru sınıflama performansı göstermiştir. Uygulama sonuçları açısından, finansal piyasalarda tüm paydaşların genel bir yol haritası olarak önerilen modelden faydalanacağı iddia edilmektedir.

Anahtar Kelimeler: Mikro Finansal Kredi Risk Ölçütü, Modelleme, İflas, Finansal Sıkıntı.

MICRO FINANCIAL CREDIT RISK METRICS: A PROPOSED MODEL FOR BANKRUPTCY AND ITS ESTIMATION

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CHAPTER TWO

A PROPOSED MODEL FOR BANKRUPTCY

CHAPTER THREE

ESTIMATION OF THE PROPOSED MODEL

ABBREVIATION

GMI	Governance Metrics International
LTCM	Long Term Capital Management
AIES	Artificially Intelligent Expert Systems
SSCI	Social Science Citation Index
SCI	Science Citation Index
MDA	Multivariate Discriminant Model
NN	Neural Networks
RPDT	Recursive Partitioning Decision Trees
GE	Genetic Algorithm
OP	Overall Performance Accuracy
USA	United State of America
UK	United Kingdom
CUSUM	Cumulative Sum Partial Adjustment
ZPP	Zero-Price Probability Model
QRA	(binary) Quantile Regression Approach
RPDT	Recursive Partitioning Decision Trees
MCDA	Multi-Criteria Decisions Aid
CBR	Case Based Reasoning
RS	Rough Set
PDA	Preference Disaggregation Analysis
DT	Decision Trees
SMO	Sequential Minimal Optimization
DEA	Data Envelop Analysis
SOM	Self-Organizing Map
NAIC	National Association of Insurance Commissioners
IRIS	Insurance Regulatory Information System
CSR	Corporate Social Responsibility
WACC	Weighted Average Cost of Capital

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INTRODUCTION

Default modeling is a general term used for several interrelated field of risk management. Bond defaults, credit (loan) defaults, firm defaults, country defaults are examples of this kind. The scope and reason of existence of present thesis is to mainly focus on firm default.

The models developed in the research area of predicting bankruptcy can be divided into two main categories. The first category contains a model that has some theoretical background and implications. This category is defined as theory based model in the context of the thesis. The second category, on the other hand, includes a statistical justification of selecting and/or classifying. This category is defined as Non-Theory based Models. The second category can be also divided into two sub categories. These are statistical based models and artificial intelligent models (AIES).

The evaluation of any model can be judged by several ways. First of all, time dimension is the primary step to judge a model. That is, a model should be effective in the long run. Most of the statistical based models fail in this step. Altman (1968; 1977), the well-know contributor of this field, proposed two models for predicting bankruptcy. These are called Z-Score Model and ZETA Model. Both models contain different variables whereas both models are using for the same purpose. The main reason is that such way of constructing models (not relying on a theoretical framework) is subject to time effect in which the data are collected. The second step is about sample characteristics. When we construct a model depending mainly upon sample characteristics, then it is logical to expect that the model will be needed to modify. This is the case for almost all Statistical based Models and AIES based Models. The third step is about the structure of the model. If another construct (factor) or variable is added to the model, then the marginal contribution of the mentioned variable should be negligible. However, it is the case for almost all models in which different variables were used. The fourth step is about how the models reflect financial health of the firms. This requires a deep understanding of financial theory of the firm. Statistical based Models and AIES based Models are all failed in this step whereas theoretical models do not reflect all the dynamics regarding to financial health of the firms. The fifth step is about sector or country specification. Most of the models do contain different set of variables depending upon sector or country. The last but not least, the models should be flexible to reflect life cycle of the firms. This means that all firms are not at the same level of their life. Some may be at growing stage or some may be at mature stage. Therefore, their dynamics are different to the bankruptcy process. There is no model available to mention this feature of the firms.

The main purpose of the thesis is to propose a theoretical model that incorporates the dynamics of the firms with bankruptcy process. The proposed model has an aim to overcome all of these weaknesses. The most important feature of the proposed model is that it changed the way of approaching the problem for predicting bankruptcy. The power of the model comes from linking the main dynamics of the firm to the bankruptcy process. The linkages between the dynamics of the firms and the bankruptcy process are set in a sense that the model brings a wider perspective.

Researchers have used different sets of variables in predicting bankruptcy. Financial ratios are the oldest and most applied variables in this manner. The early studies used financial ratios extensively. In addition, trend variables, statistical variables and dummy variables are employed to increase efficiency of predictions. The primary aim of the models developed in literature is to predict overall performance of the model and so called type 1 classifying failed firms as non-failed, and type 2 errors classifying non-failed firms as failed. The overall performances show the model’s ability to differentiate bankrupt and non-bankrupt firms.

In the context of present study, the main testable proposition is about how to differentiate distress and non-distress firms within the scope of the model. In order to perform the required tests, univariate and multivariate statistical analyses are conducted. In the context of univariate analysis, parametric and non-parametric independent sample tests are applied depending upon the normality test of the variables. In the context of multivariate analysis, multivariate logistic regressions are conducted for the purpose of determining the variable that affect the probability of belonging the specified sample.

The analysis is conducted on manufacturing firms listed in Istanbul Stock Exchange (ISE) for the period from 2007 to 2011. The analyses are carried out within the structure of cross-sectional framework. The data including financial statements and their footnotes, stock prices, special reports, annual reports, etc. are derived mainly from the websites of ISE, Public Disclosure Platform (PDP), Capital Markets Board of Turkey and the sample firms.

Evaluation processes of estimated models are carried out at four stages. The first stage gives an examination of overall accuracy of classification, Type I and Type II Error rates. The second stage examines significance of coefficients of the estimated models. The third stage evaluates signs of coefficients of the estimated model with respect to the proposed model. Finally at the last stage, the overall model fit is analyzed. Empirical results of proposed model indicate that the estimated models give promising results in case of one and two years before the final condition of the firms. Estimated models perform over 90% correct classifications for 2010 and 2011.

The main contribution of the thesis is to introduce a conceptual model that incorporates the firm dynamics with value addition and dilution process of the firms. Therefore, the proposed model can be estimated with different methodologies and data in all over the World. In terms of practical implication, it claims that the proposed model will be benefited by all stakeholders as a general road map in financial environment.

The stakeholders that can benefit from the proposed model can be executives, investors, creditors, auditors and all other market participants. Executives can benefit from the model in a way to construct a well-functioning corporate governance mechanism for their firms. Initial condition for having such mechanism requires understanding the linkages among corporate governance, risk, cost of capital and value generation process. The proposed model shows a clear picture of these linkages. Investors can benefit from the model for evaluating their investments in a sense that how much required return they can expect. If the firms (their investments) are run in risky environment, then the proposed model gives a road map for evaluating the mechanism (return performance). Essentially, investors may understand the linkages among the risk and their investments. Creditors can benefit from the model by evaluating the methodology by which they rate the firm. The proposed model is a new challenge for creditors to re-think how to rate the firms.

Auditors and all other market participants can have an opportunity to benchmark their existed methods with the propositions of the model for their operations. For example, if a firm is audited in such a way that the auditing report does not show the realm for the firm, then market participant may suspect by consulting the structure of the model.

CHAPTER ONE

MICRO CREDIT RISK METRICS

1.1. INTRODUCTION TO DEFAULT MODELING

Default modeling is a general term used for several interrelated field of risk management. Bond defaults, credit (loan) defaults, firm defaults, country defaults are examples of this kind. The scope and reason of existence of present thesis is to mainly focus on firm default. Default modeling is more specifically used as credit risk modeling. Therefore, both terms will be used interchangeably.

Credit risk modeling has become an important field of research since 1960s whereas the importance of evaluating firm creditability dates back to the beginning of trading. Academic literature shows that the late of 1960s can be a structural break between quantitative and qualitative research in the field of credit risk modeling. Despite the methodological differences, the basic purpose of evaluating firm credibility and default probability remains the same. The role of credit risk modeling becomes a critical stage in the risk management systems at financial institutions (Lopez and Saidenberg, 2000: 152).

In contemporary financial environment, rating the bonds, firms or countries plays a vital role for firms' executives, investors, politicians, regulators, fund providers, financial institutions and intermediates. In such an important field, there are some rating firms actively providing financial advice for their creditworthiness. Standard & Poor's Rating Services, Moody's Investor Services and Fitch Ratings are those well-known institutions in this area. Credit ratings and the changes in these rates are paid attention and watched carefully (Chan et al., 2010: 3478). The reason of having such importance in rating is that corporate governance advice constitutes a considerably high market value. Daines et al.,(2010: 439) stated that

> *"RiskMetrics / Institutional Shareholder Services (ISS),the largest advisor, claims over 1,700 institutional clients managing $26 trillion in assets, including 24 of the top 25 mutual funds, 25 of the top 25 asset managers, and 17 of the top 25 public pension funds. ISS was sold in 2007 to RiskMetrics, a firm that has since gone public, for an estimated $550 million. Governance Metrics International (GMI) advises clients managing $15 trillion"*

Corporate executives have numerous tasks to accomplish whereas the task of maintain firms' operation and solvency is one of the most critical ones. Platt and Platt (2011: 1139) pointed out that this role becomes more crucial following 2008 and counts financial crisis which left so many companies either petitioning bankruptcy courts for protection or forcing the selloff of significant assets to repay creditors.

Detecting firm default and developing early warning systems of impending financial crisis are important not only to sector players in developed countries but also developing countries. Altman (1984: 171) underlined the fact that even non-capitalist nations are obliged to consider individual firm performance assessment. In addition to this obligatory situation, smaller nations are more vulnerable to financial panics coming out from defaults of individual enterprises.

Default (failure) is defined in many different contexts depending upon specific interest or condition of the firms. A general definition is stated that '*failure is the situation that a firm cannot pay lenders, preferred stock shareholders, suppliers, etc., or a bill is overdrawn, or the firm is bankrupt according to law*' (Dimitrias et al., 1996: 487). The way of defining default may vary whereas this does not change the reality that the firms no more continue their operations. Another related concept is default risk which refers '*a probability that counterparty's intrinsic credit quality deteriorates such that contractual agreements cannot be honored within a given time horizon'* (Baestaens, 1999: 233). The term 'intrinsic' imply the presence of credit enhancement in the form of collateral or guarantees.

Defaults constitute high costs to all stakeholders. Beaver (1968: 179) demonstrates that stock market price of the firm decreases as it approaches to bankruptcy. Therefore, prediction of default (bankruptcy) is inevitable to prevent possible costs occurring as a result of default. In the last two decade, corporate world witnessed some major bankruptcies such as WorldCom, Enron and LTCM (Long Term Capital Management). All of these defaults produces significant loses and brings high costs to all related parties. Basel II and other related regulations are aiming to minimize credit risk for this reason.

Predicting bankruptcy is a long standing research interest in financial literature. The models that are intended to predict bankruptcy are playing an important role in two ways: (i) developing model may predict bankruptcy and work as an 'early warning system'. In this case, the decisions regarding to merger and acquisition, liquidation or reorganization are some to work for (Casey et al., 1986: 150) and (ii) these models may help to evaluate firm at the investment point of view (Dimitrias et al., 1996: 488).

Maclachian (1999: 92) pointed out the benefits of improved credit risk modeling as follows: (a*) traditional bank products contain many covenants that mirror embedded credit derivatives.* Modeling the value of the credit derivative improves understanding of bank risks and the efficient design of debt contracts. (b) *bank regulators wish to move towards an internal models approach for allocating regulatory capital to credit risk.* A prerequisite of value at risk credit portfolio models is the ability to accurately price credit risk and (c) *improved modeling of credit risk has significant benefits in related fields of finance, such as the measurement of interest rate duration on default-risky instruments, and improved modeling of optimal capital structures in the presence of bankruptcy costs.*

The models developed in the research area of predicting bankruptcy can be divided into two main categories. The first category contains a model that has some theoretical background and implications. This category is defined as theory based model in the context of the thesis. The second category, on the other hand, includes a statistical justification of selecting and/or classifying. This category is defined as Non-Theory based Models. The second category can be also divided into two sub categories. These are statistical based models and artificial intelligent models.

Researchers have used different sets of variables in predicting bankruptcy. Financial ratios are the oldest and most applied variables in this manner. The early studies used financial ratios extensively. In addition, trend variables, statistical variables and dummy variables are employed to increase efficiency of predictions. The primary aim of the models developed in literature is to predict overall performance of the model and so called type 1 and type 2 errors. The overall performances show the model's ability to differentiate bankrupt and non-bankrupt firms. Type 1 error also called credit mistake shows *instances whereby a credit was granted to a counterparty that subsequently defaulted*. Type 2 error also called commercial mistake shows *instances whereby a credit was refused to a counterparty* *that subsequently survived* (Baestaens, 1999: 225). Researchers claimed that Type 1 errors are more costly than those of Type 2 errors. Therefore, models that provide low Type 1 error are more appealing than the others.

The main purpose of the thesis is to propose a theoretical model that incorporates the dynamics of the firms with bankruptcy process. There are several researchers pointed out the need of such attempts explicitly. The previously developed theoretical models have some disadvantages to be a reliable road map to follow. Balance Sheet Decomposition (Entropy) Theory, Gambler's Ruin Theory, Cash Management Theory, Failing Company Model and Contingent Claim Models are those of theoretical attempts to predict bankruptcy. None of these models are able to explain the whole picture about the dynamics of the firms and bankruptcy process. The following quotes support this claim:

- *Detailed reading of the literature provides no coherent theory underpinning the use of financial ratio analysis and only very tenuous guidance on the appropriate measures in different situations* (Taffler, 1982: 344).

- *The inference would therefore seem to be that the underlying causes of corporate bankruptcy are many and various, and any market agent interested in trying to forecast which companies are vulnerable will have a wide information set on which to base his predictions. This will comprise macro-economic lead indicators, industry specific information, and measures of diversification and quality of management, as well as financial ratios relating to a particular company* (El Hennawy and Morris, 1983: 209)

- *In the absence of such a conceptual foundation, there is little reason to expect a sustainable correlation between independent variables and the event to be predicted* (Blum, 1974a: 3).

- *Ratios included in bankruptcy prediction models are based on a type of ad hoc pragmatism rather than a sound theoretical work* (Aziz et al., 1988: 419)

- *A unifying theory of business failure has not been developed, in spite of a few notable efforts such as Wilcox's (1971) ruin model and Scapens et al. (1981) catastrophic theory*[1] *approaches* (Dimitrias et al., 1996: 487).

[1] These models will be explained in details in forthcoming section whereas catastrophic theory approach of Scapens et al. (1981) is ignored for the fact that this approach is difficult to empirically test. In fact, there is no empirical article that used this approach to predict bankruptcy in the pool of study's extensive literature review.

- *Thus, after 30 years of research on this topic, there is no generally accepted model for bankruptcy prediction that has its basis in a causal specification of underlying economic determinants. Clearly, research convergence will be necessary for this situation to improve* (McKee and Lensberg, 2002: 437)

The evaluation of any model can be judged by several ways. First of all, time dimension is the primary step to judge a model. That is, a model should be effective in the long run. Most of the statistical based models fail in this step. Altman (1968; 1977), the well-know contributor of this field, proposed two models for predicting bankruptcy. These are called Z-Score Model and ZETA model. Both models contain different variables whereas both models are using for the same purpose. The main reason is that such way of constructing models (not relying on a theoretical framework) is subject to time effect in which the data are collected. The second step is about sample characteristics. When we construct a model depending mainly upon sample characteristics, then it is logical to expect that the model will be needed to modify. This is the case for almost all Statistical based Models and AIES based Models. The third step is about structure of the model. If another construct (factor) or variable is added to the model, then the marginal contribution of the mentioned variable should be negligible. However, it is the case for almost all models in which different variables were used. The fourth step is about how the models reflect financial health of the firms. This requires a deep understanding of financial theory of the firm. Statistical based Models and AIES based Models are all failed in this step whereas theoretical models do not reflect all the dynamics regarding to financial health of the firms. The fifth step is about sector or country specification. Most of the models do contain different set of variables depending upon sector or country. The last but not least, the models should be flexible to reflect life cycle of the firms. This means that all firms are not at the same level of their life. Some may be at growing stage or some may be at mature stage. Therefore, their dynamics are different to the bankruptcy process. There is no model available to mention this feature of the firms.

Keasey and Watson (1991: 90) suggested the following questions that should be addressed for evaluating the predictive models:

- *Are the statistical models capturing the dimensions of financial health which are important to the decision context?*
- *Do they work better than other techniques?*
- *Do they work consistently over time?*
- *Can the model be improved upon?*

Keasey and Watson (1991: 90) also pointed out that statistical models do not constitute an explanatory theory of failure or distress. Rather they summarize (via statistical aggregation) information contained in a firm's financial statements, to determine whether or not the firm's financial profile most resemble the financial profile of previously failed (distressed) or non-failed (non-distressed) firms. On the other hand, theoretical based models are mixed in their structure. Some of these models have been rooted from a different field of science. Gambler's Ruin Theory is basically a statistical framework or Balanced Sheet Decomposition Theory is a framework about entropy concept that is a term coming from thermodynamics in the Science of Physics. The other mentioned theoretical models approach the problem in narrow scope. Therefore, the model proposed in the context of thesis is aimed to be successful under the obstacles regarding to model evaluation.

1.2. LITERATURE REVIEW

Literature review is conducted on the studies that have a specific or general purpose in dealing with credit risk metrics. The present thesis classifies articles within five categories: (i) the first category includes articles that propose a theoretical model about credit risk metrics; (ii) the second category includes articles that propose a statistical model; (iii) the third category includes articles that propose an artificially intelligent model; (iv) the fourth category includes articles that review the related literature and (v) the fifth category includes articles that are not belong to the first four categories whereas they are dealing with the details or a part of discussion regarding to credit risk metrics. The studies other than academic articles constitute a different source of knowledge. Therefore, it was not intended to cite lecture notes, working papers, etc. except giving some academic books as an example written on the concepts.

The method of conducting literature review has both structural and non-structural way of selecting the appropriate articles to interpret in the context of the thesis. At the side of having a structural literature review, it is meant that the way of selecting articles apply some systematic path. The systematic path followed here can be summarized as:

- Journal based selection: The article should be published in a journal that should be indexed by Social Science Citation Index (SSCI) or Science Citation Index (SCI).
- Database based selection: The article should be published in a journal that should be available in the databases covering the field of business, economics and finance.
- Scope based selection (firm default): The article should be mentioning firms default rather than credit (loan) default, bond default or country default.

At the side of non-structural way of selecting the appropriate articles, it is meant that the way of selecting articles apply some subjective judgments. The way followed in subjective judgment in the context of thesis is to read every single article acquiring by structural review and carefully examining their references which are deserved to be an appropriate source for the thesis. As a result of this process, the last available article that has some particular interest in credit risk metrics is evaluated. However, since evaluation of the articles is well-structured, some articles are ignored to be mentioned here. One of the possible reasons is that an article may not document the findings of empirical investigations in proper way in which there is no way out to understand the results. In such and similar cases, some articles had to be ignored whereas the ratio of ignored article to mentioned articles is negligible.

Starting with evaluating review articles of credit risk metrics is providing possibly very useful help to approach the literature. Table 1 documents nineteen articles conducted on credit risk metrics. Column one indicates the reference of the article. The first article was conducted in 1984 while the last one was 2009. Second column depicts review methodology of the articles whether it has a structural or non-structural path. The only study that used a structural path is the one written by Dimitrias et al. (1996: 489) who restricted his study only to: (a) journal articles presenting models and (b) pertaining to industrial and retail application. Column three shows the size of the reviews that reflect the number of references. However, it should be noted that the real number of core articles written on credit risk metrics are much less than those of presented in Table 1. The reason the number of all references underlined is to show the deepness of the concept. Column four shows the time period in which review is conducted whereas most of the mentioned articles do not reported this point. Column five demonstrates the models that are reviewed. As depicted, there is a clear independence between contingent claim models and the others. The logical reason behind this picture is that contingent claim models are more prone to bond default. However, the reason of covering contingent claim models is the possibility of applying on firm default.

In the light of these reviewed articles, the structure of review process of the thesis covers all types of models with no time, sector or country limitation. As a result, ninety two (92) empirical articles and eleven (11) theoretical articles are chosen to evaluate in addition to nineteen reviewed articles.

Table 1: Literature Review Studies

References	Review Methodology		Size	Time	Model		
Author (date)	Structural	Non-Structural	Number of Studies Reviewed	Time Period Reviewed	Theory Based	Statistic Based	AIES Based
Taffler (1984)		√	59	NM	-	MDA	-
Altman (1984)		√	50	NM	-	MDA	-
Barnes (1987)		√	98	NM	-	-	-
Keasey and Watson (1991)		√	78	NM	-	-	-
BarNiv and McDonald (1992)		√	76	NM	-	Univariate MDA LOGIT NonPar. DA	RPDT
Dimitrias et al. (1996)	√		158	32-94	Gambler's Ruin	Univariate MDA LPM LOGIT PROBIT HAZARD	RPDT MCDA
Altman and Saunders (1998)		√	52	78-98	-	MDA	-
Maclachlan (1999)		√	43	NM	Contingent Claim	-	-
Bohn (2000)		√	49	NM	Contingent Claim	-	-
Crouhy et al. (2000)		√	22	NM	Contingent Claim	-	-
Kao (2000)		√	91	NM	Contingent Claim	MDA HAZARD	RPDT NN
Jarrow and Turnbull (2000)		√	109	NM	Contingent Claim	-	-
Gordy (2000)		√	11	NM	Contingent Claim	-	-
Uhrig-Homburg (2002)		√	58	NM	Contingent Claim	-	-
Bakshi et al. (2006)		√	48	NM	Contingent Claim	-	-
Aziz and Dar (2006)		√	78	NM	Contingent Claim CMT BSDM Gambler's Ruin	Univariate MDA LPM LOGIT PROBIT CUSUM Par.Adj.	RPDT CBR NN GA RS
Agarwal et al. (2007)		√	68	85-10	-	MDA	-
Capuano et al. (2009)		√	67	NM	Contingent Claim	-	-
Lee et al. (2009)		√	83	NM	Contingent Claim	-	-

Note: AIES: Artificially Intelligent Expert Systems; NM: Not Mentioned; MDA: Multivariate Discriminant Analysis; Non.Par.DA: Non-parametric Discriminant Analysis; RPDT: Recursive Partitioning Decision Trees; LPM: Linear Probabilistic Model; MCDA: Multi-Criteria Decisions Aid; CMT: Cash Management Theory; CUSUM Par.Adj.: Cumulative Sum Partial Adjustment; CBR: Case Based Reasoning; NN: Neural Networks; GA: Generic Algorithm; RS: Rough Set.

1.2.1. Framework of Micro Credit Risk Metrics

Framework of micro credit risk metrics is structured into three categories. The first category includes Theory based Models. These models are developed and/or proposed as a conceptual framework in predicting defaults. In this case, conceptual framework determines which constructs (factors) and/or variables are appropriate in predicting bankruptcy. The second category contains Statistical based Models. These models are developed as a result of statistical examination of firms' data. The main argument proposed here is that the best available discriminating or classifying variables are assumed to be the predictors of defaults without relying on a theoretical justification. Third category involves Artificially Intelligent Models. These models are resemble to Statistical based Models in the sense that they do not relying on a theoretical foundations. In a dissimilar way, these types of models apply different sets of algorithms (neural networks, decision tress etc.) to classify or differentiate the bankrupt and non-bankrupt firms.

1.2.1.1. Conceptual Framework of Micro Credit Risk Metrics

Conceptual framework of credit risk metrics as stated involves three categories. Table 2 and Graph 1 depict the number of articles written on these models. Theory based Models, Statistic based Models and AIES based Models are studied in 11, 83 and 31 articles respectively. These numbers are not mutual exclusive. In some articles, two types of models or even three types of models are mentioned. Therefore, they were counted independently. The number of treatments, on the other hand, show that how many models are estimated in the article. Naturally, some papers documents findings for more than one models. As a result, the numbers of treatments for Theory based Models, Statistic based Models and AIES based Models are 15, 128 and 50 articles respectively.

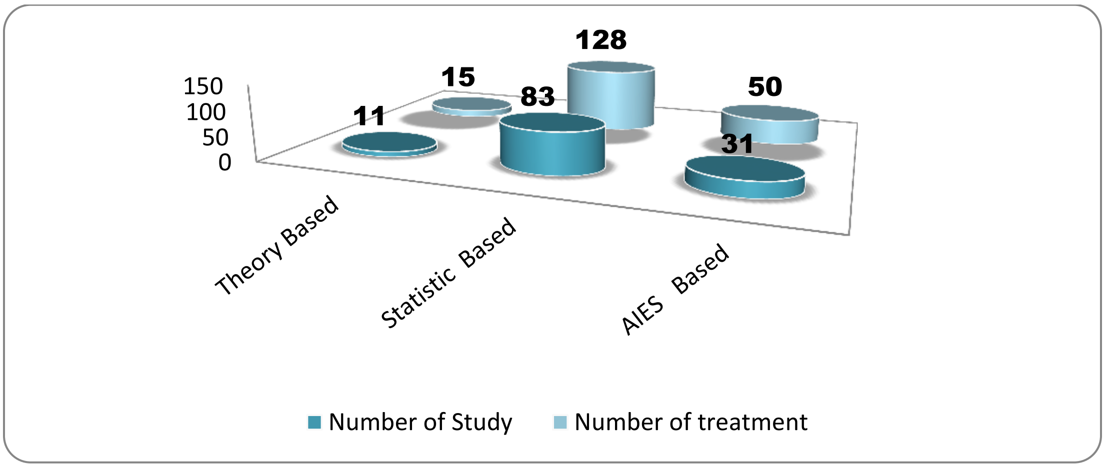
Table 2: Types of Models

		Number of Studies	Number of Treatments
Models	Theory Based	11	15
	Statistic Based	83	128
	AIES Based	31	50
	TOTAL	**125**	**193**

Note: AIES: Artificially Intelligent Expert Systems

The numbers of articles and the treatments conducted show that Theory based Models are much less studied than Statistic and AIES based Models. The inference can be derived from this statistic is that either (i) developing a conceptual framework is difficult than applying some statistical discrimination or classification methods or (ii) the proposed theoretical models are not good enough to replicate or extend. However, (ii) can be falsified by the fact that articles that apply statistical or AIES based models do not mention or follow a theoretical model. Therefore, is it safe to state that developing a conceptual framework may contribute the existed literature. The numbers of studies that follow Statistical based Models are higher than the others for the fact that applying a Statistical based Model is relatively easier than the other two types of the models.

Graph 1: Types of Models



Note: AIES: Artificially Intelligent Expert Systems

Theory based Models include five (5) different justifications as depicted in Table 3 and Graph 2. These are Gambler's Ruin Theory, Failing Company Model, Balanced Sheet Decomposition Model, Cash Management Theory and Contingent Claim Model. The number of studies and treatments shows that Contingent Claim Model was the most examined one among these attempts. In addition to this statistic, it should be noted that there is a relatively high volume of articles written on Contingent Claim Model in the context of bond defaults. The studies mentioned here is that they are focusing on firm default.

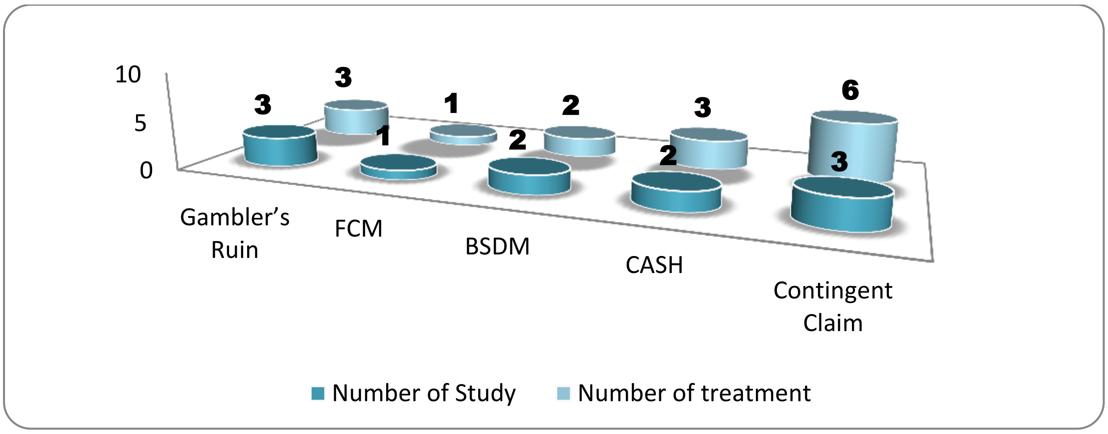
Table 3: Theory based Models

		Number of Studies	Number of Treatments
Theory based Models	Gambler's Ruin	3	3
	FCM	1	1
	BSDM	2	2
	CMT (CASH)	2	3
	Contingent Claim	3	6
	TOTAL	**11**	**15**

Note: FCM: Failing Company Model; BSDM: Balanced Sheet Decomposition Model; CMT: Cash Management Theory

These five models have somehow different source of construction. Gambler's Ruin Theory is probabilistic argument in statistic and mathematics. Balance Sheet Decomposition Model is relying on the concept of entropy which is coming from laws of thermodynamics in physics. Failing Company Model is a model that is proposed in Law. Contingent Claim Model is an application of Option Pricing Model in default (Black and Sholes, 1973). Cash Management Theory may be considered the only model that reflects a part of financial management.

Graph 2: Theory based Models



Note: FCM: Failing Company Model; BSDM: Balanced Sheet Decomposition Model; CMT: Cash Management Theory

Statistical based Models involve a lot of different applications in discriminating and classifying firms into default and non-default firms. Table 4 and Graph 3 demonstrate related statistics about the articles written on the concepts and treatments applied within the mentioned articles. The common argument coming from Statistical based Models is that they do not rely on a theoretical justification in selecting the variables into models. However, there were some attempts in conducting factor analysis in order to derive how many factors can explain all the variables. The way of applying factor analysis in mentioned articles does not constitute or lead a theoretical framework.

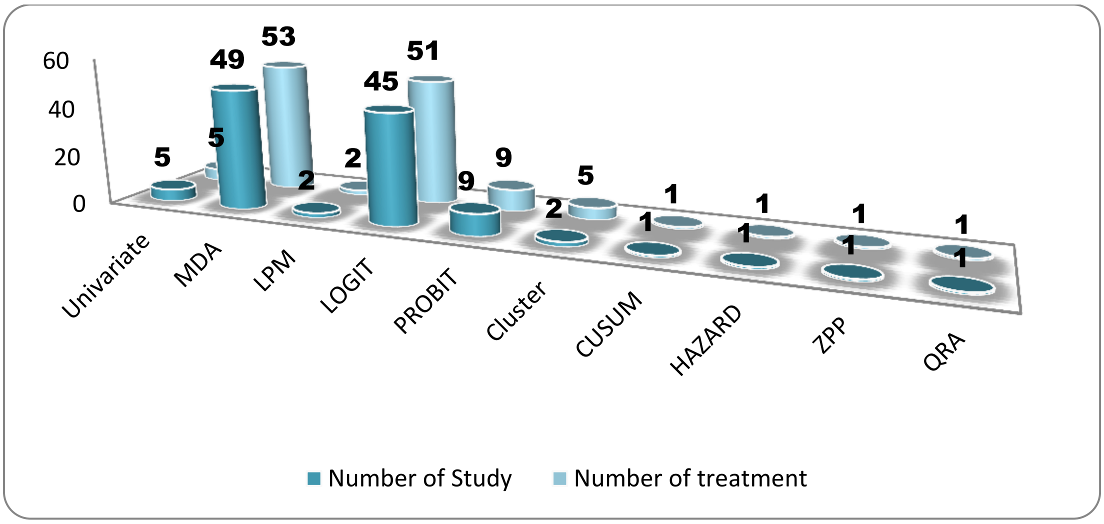
Table 4: Statistical based Models

		Number of Studies	Number of Treatments
Statistic based Models	Univariate	4	4
	MDA	49	53
	LPM	2	2
	LOGIT	45	51
	PROBIT	9	9
	Cluster	2	5
	CUSUM	1	1
	HAZARD	1	1
	ZPP	1	1
	QRA	1	1
	TOTAL	**115**	**128**

Note: MDA: Multivariate Discriminant Analysis; LPM: Linear Probabilistic Model; CUSUM Par.Adj.: Cumulative Sum Partial Adjustment; ZPP: Zero-Price Probability Model; QRA: (binary) Quantile Regression Approach.

The most obvious inference coming out from these statistics is that Multivariate Discriminant Model (MDA), LOGIT Model and PROBIT Model are far away from the other applications. One reason can be stated that MDA is the first conducted in Altman (1968) which shows how Altman Z-Score is derived. In addition, LOGIT Model is proposed as a good alternative to MDA in terms of its assumptions flexibility. Despite the fact that all of these models have a common aim that is classifying or discriminating firms into default or non-default, they have somehow different features and assumptions. Another interesting point that arises in conducting these statistical models is that different sets of variables or even sometimes different constructs (factors) were used in predicting bankruptcy. This is the most important weakness of this type of applications. Among the other types of models, Statistical based Models are rather easy to replicate. This allows researcher to conduct one of these statistical methods in different samples, sectors and countries.

Graph 3: Statistical based Models



Note: MDA: Multivariate Discriminant Analysis; LPM: Linear Probabilistic Model; CUSUM Par.Adj.: Cumulative Sum Partial Adjustment; ZPP: Zero-Price Probability Model; QRA: (binary) Quantile Regression Approach. .

The Artificially Intelligent Expert Systems (AIES) Models includes so many methods of classifying or discriminating firms into bankrupt or non-bankrupt. The common goal in these attempts is that these models apply an algorithm in predicting defaults. Neural Networks (NN), Recursive Partitioning Decision Trees (RPDT), Genetic Algorithm (GE) are well known and applied methods among others. The process of deriving variables in classifying firms is carried out in so called training sample rather than relying on a theoretical foundations. In evaluation of these models, it is observed that there is a considerable amount of efforts spent to outline the methods proposed in prediction whereas there is no satisfactory emphasis to explain why and how the variables used. This situation does not allow researchers to develop a better conceptual framework rather it leads them to focus on more complicated classification or discrimination techniques. As a result, the aim of the mentioned (some) articles in this type of applications, turns out to be applying a different technique for increasing the efficiency of the proposed model instead of developing a better conceptual model. This is the most important weakness of this type of applications in terms of conceptualization.

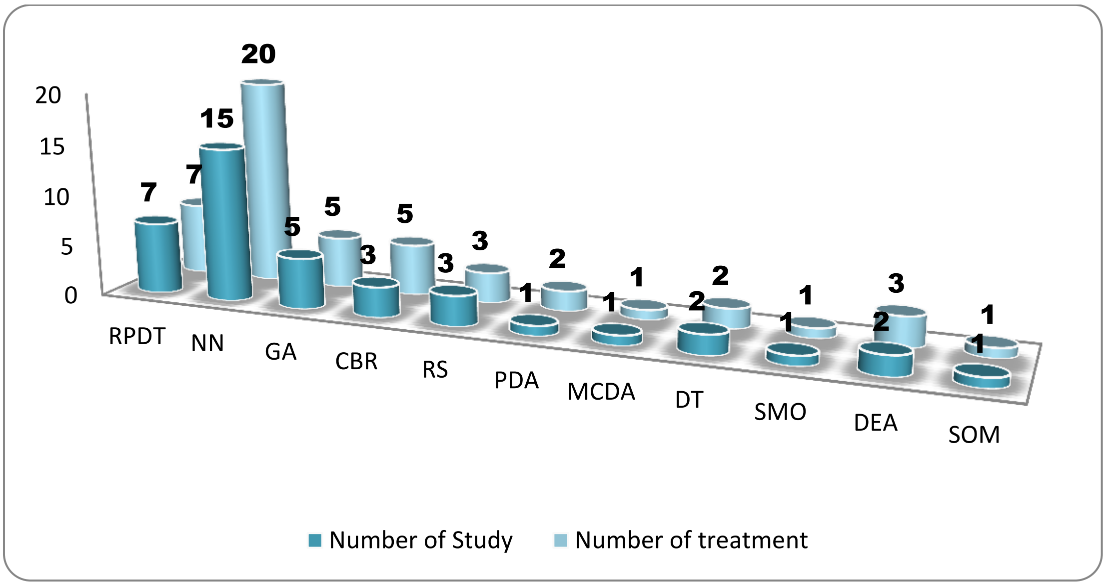
Table 5: AIES Based Models

		Number of Study	**Number of Treatment**
AIES Based Models	RPDT	7	7
	NN	15	20
	GA	5	5
	CBR	3	5
	RS	3	3
	PDA	1	2
	MCDA	1	1
	DT	2	2
	SMO	1	1
	DEA	2	3
	SOM	1	1
	TOTAL	**41**	**50**

Note: AIES: Artificially Intelligent Expert Systems; RPDT: Recursive Partitioning Decision Trees; MCDA: Multi-Criteria Decisions Aid; CBR: Case Based Reasoning; NN: Neural Networks; GA: Generic Algorithm; RS: Rough Set; PDA: Preference Disaggregation Analysis; DT: Decision Trees; SMO: Sequential Minimal Optimization; DEA: Data Envelop Analysis; SOM: Self-Organizing Map.

On the side of empirical justification, the algorithms developed and used in prediction are derived among the variables. This way of deriving variables used in the models may lead another problem namely sample bias indicating that there can be a different set of variables for another sample or another time period or another country.

Graph 4: AIES based Models



Note: AIES: Artificially Intelligent Expert Systems; RPDT: Recursive Partitioning Decision Trees; MCDA: Multi-Criteria Decisions Aid; CBR: Case Based Reasoning; NN: Neural Networks; GA: Generic Algorithm; RS: Rough Set; PDA: Preference Disaggregation Analysis; DT: Decision Trees; SMO: Sequential Minimal Optimization; DEA: Data Envelop Analysis; SOM: Self-Organizing Map.

1.2.1.2. Country Based Review of Micro Credit Risk Metrics

Country based review is examined in all empirical articles (92). USA has the highest proportion by having 52 studies that contain 90 treatments. UK is the second country in terms of numbers of papers and treatments. Korea and Greece are two countries that follow USA and UK.

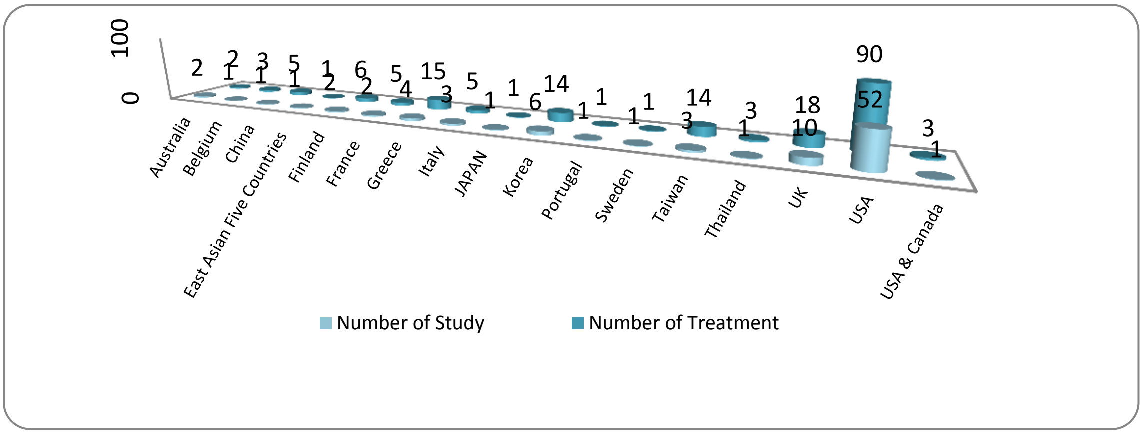
Table 6: Country based Review

Country	Australia	Belgium	China	East Asian Five Countries	Finland	France	Greece	Italy	JAPAN	Korea	Portugal	Sweden	Taiwan	Thailand	UK	USA	USA & Canada	TOTAL
Number of Studies	2	1	1	1	2	2	4	3	1	6	1	1	3	1	10	52	1	**92**
Number of Treatments	2	3	5	1	6	5	15	5	1	14	1	1	14	3	18	90	3	**187**

Note: East Asian Five Countries: Indonesia, Korea, Malaysia, Philippines, and Thailand; USA & Canada: the study uses data from both countries.

Evaluations of the models are documented at three stages: (i) Overall performance of the model (this is stated as Overall Performance Accuracy (OPS)); (ii) Type I error of the models and (iii) Type II error of the models. Overall performance of the models shows how successful the models predict bankrupt and non-bankrupt firms. Type I error shows the ratio of classified failed firms as non-failed. Type II error, on the other hand, indicates the ratio of classified non-failed firms as failed.

Graph 5: Country based Review



Note: East Asian Five Countries: Indonesia, Korea, Malaysia, Philippines, and Thailand; USA & Canada: the study uses data from both countries.

Table 7 presents these three indicators of the models among countries. It should be stated that some articles do not report one of these indicators. Therefore, they denoted as Not Available (NA). Comparison of the statistics depicted in Table 7 is difficult to interpret for the fact that the numbers of studies are not equal and quite limited for some countries. There is one treatment available for three countries; two treatments for one country and three treatments for three countries and so on. In this manner, it is not logical to compare overall performance of the models among countries whereas it is useful to see how results are distributed. It is also useful to show that the results for USA, UK, Taiwan, Korea, and Greece are getting more reliable results as the numbers of treatments increase. It is safe to state that the OPA for the models applied in USA is the most realistic findings among the countries due to high volume of treatments conducted.

Table 7: Evaluations of Models among Countries

Country	Number of treatment	OPA (mean)	Number of treatment	Type I Error (%) (mean)	Number of treatment	Type II Error (%) (mean)
Australia	2	88,45	2	11,95	2	11,2
Belgium	3	71	NA	NA	NA	NA
China	5	88,67	NA	NA	NA	NA
East Asian Five Countries	1	77,5	NA	NA	NA	NA
Finland	6	81,42	6	17,98	6	19,18
France	5	81,94	NA	NA	NA	NA
Greece	15	91,94	15	6,31	15	8,82
Italy	5	91,18	1	16	1	16
JAPAN	1	94,4	1	2,8	1	8,3
Korea	14	77,07	2	47,15	2	19,5
Portugal	1	95	NA	NA	NA	NA
Sweden	1	84	NA	NA	NA	NA
Taiwan	10	80,54	8	29,66	8	18,29
Thailand	3	67,97	NA	NA	NA	NA
UK	15	89,68	17	11,46	17	13,08
USA	85	87,24	63	16,29	62	11,41
USA & Canada	3	86	3	39,33	3	4

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPS; Overall Performance Accuracy; East Asian Five Countries: Indonesia, Korea, Malaysia, Philippines, and Thailand; USA & Canada: the study uses data from both countries.

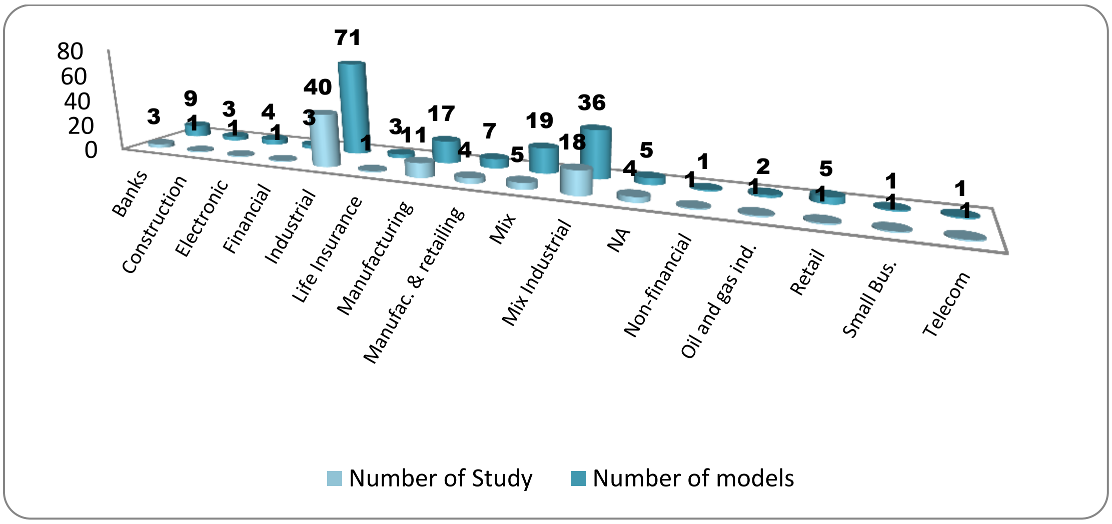
1.2.1.3. Sector Based Review of Micro Credit Risk Metrics

Sector based review is depicted in Table 8 and Graph 6. The names of the sectors are coded as researchers reported. In this respect, mix industrial and industrial sectors are coded differently. Manufacturing and Industrial firms are more prone to study whereas there are several studies written on banks, financial and life insurance sectors. Some researchers do not report which sectors they studied. Therefore, their articles are coded as Not Available (NA) in terms of sector. Industrial, manufacturing and mix industrial sectors constitute the highest share in this category.

Table 8: Sector based Review

sector	Banks	Construction	Electronic	Financial	Industrial	Life Insurance	Manufacturing	Manufac. & retailing	Mix	Mix Industrial	NA	Non-financial	Oil and gas ind.	Retail	Small Bus.	Telecom
Number of Study	3	1	1	1	40	1	11	4	5	18	4	1	1	1	1	1
Number of models	9	3	4	3	71	3	17	7	19	36	5	1	2	5	1	1

Graph 6: Sector based Review



Evaluations of the models are depicted in Table 9 in terms of OPA, Type I error and Type II error. As a general consequence of the results, the numbers of studies shows how much the reported findings are reliable. In this sense, sectors that are studied more can be interpreted whereas the sectors that are studied less should be interpreted with caution. OPA's of the models conducted in Industrial, manufacturing, mix and mix industrial sectors are structured between 80% and 90%. Type I errors of these sectors are structured between 14% and 22%. Type II errors of these sectors are structured between 2% and 13%. These findings shows that Type I errors, classifying bankrupt firms as non-bankrupt, are reasonable high. Even at the minimum level of Type I error, 14 out 100 firms are misclassified.

Table 9: Evaluations of Models among Sectors

sector	Number of treatment	OPA (mean)	Number of treatment	Type I Error (%) (mean)	Number of treatment	Type II Error (%) (mean)
Banks	9	84,22	8	12,45	8	12,7
Construction	3	71	NA	NA	NA	NA
Electronic	NA	NA	4	41,59	4	21,85
Financial	3	67,97	NA	NA	NA	NA
Industrial	63	87,53	43	17,27	43	10,64
Life Insurance	3	89,9	3	11,9	3	8,3
Manufacturing	17	82,22	12	21,24	12	13,84
Manufacturing and retailing	7	81,61	6	16,63	6	15,72
Mix	20	85,79	4	2,75	4	2,25
Mix Industrial	36	86,16	30	14,63	29	13,39
NA	5	90,94	4	6,2	4	11,08
Non-financial	1	92	NA	NA	NA	NA
Oil and gas ind.	2	85,5	2	11,5	2	19,5
Retail	5	91,22	NA	NA	NA	NA
Small Bus.	1	93	1	15	1	0
Telecom	1	97,4	1	4,29	1	0

Note: NA treatments are excluded

1.2.1.4. Time Based Review of Micro Credit Risk Metrics

The time based review shows the historical perspective for the types of the models being used to predict bankruptcies. Table 10 indicates the numbers of studies being studied through the time. Four periods are determined from 1966 to 2011. The historical stream for Theory based Models shows stable pattern in studying bankruptcy. There are 5, 2, 1 and 3 studies written on bankruptcy prediction in the periods of 1966-1980, 1981-1990, 1991-2000 and 2001-2011 respectively. Theoretical studies are much less than those of Statistical based Models and AIES based Models.

Statistical based Models have been studied more extensively since 1980s. There are more than 30 studies that involve a statistical based model in the last three periods. MDA is one of the most popular statistical tools in predicting bankruptcy. LOGIT Models are repeatedly used another statistical tool that shows a high usage especially in the period of 2001-2011. There are some Statistical based Models that used rarely in bankruptcy prediction such as CUSUM, HAZARD, ZPP and QRA Models.

AIES based Models, on the other hand, have become popular since 1990s. Despite the fact that there are only two studies published in the period of 1966-1990, researchers have reported forty studies since 1991. RPDT is the first AIES based Model that applied in bankruptcy prediction among the articles analyzed. In addition to RPTD, NN, GA and CBR are the other AIES based Models that have been used repeatedly.

The most concrete inference coming out from the results depicted in Table 10 is that AIES based Models are proposed for handling a more complex structure of bankruptcy. It is clear from the published studies that researchers have paid more and more attention on the algorithms for detecting differences between bankrupt and non-bankrupt firms rather than focusing on a different conceptualization for bankruptcy process.

Table 10: Time based Review

		1966-1980		1981-1990		1991-2000		2001-2011	
		Number of Studies	Number of Treatments	Number of Studies	Number of Treatments	Number of Studies	Number of Treatments	Number of Studies	Number of Treatments
Theory Based	Gambler's Ruin	3	3	0	0	0	0	0	0
	FCM	1	1	0	0	0	0	0	0
	BSDM	1	1	1	1	0	0	0	0
	CASH	0	0	1	2	1	1	0	0
	Contingent Claim	0	0	0	0	0	0	3	6
	TOTAL	**5**	**5**	**2**	**3**	**1**	**1**	**3**	**6**
Statistic Based	Univariate	2	2	1	1	0	0	1	1
	MDA	10	12	16	18	14	14	9	9
	LPM	1	1	0	0	1	1	0	0
	LOGIT	1	1	13	15	12	14	19	21
	PROBIT	0	0	3	3	3	3	3	3
	Cluster	0	0	0	0	1	2	1	3
	CUSUM	0	0	0	0	1	1	0	0
	HAZARD	0	0	0	0	0	0	1	1
	ZPP	0	0	0	0	0	0	1	1
	QRA	0	0	0	0	0	0	1	1
	TOTAL	**14**	**16**	**33**	**37**	**32**	**35**	**36**	**40**
AIES Based	RPDT	0	0	2	2	3	3	2	2
	NN	0	0	0	0	7	9	8	11
	GA	0	0	0	0	2	2	3	3
	CBR	0	0	0	0	1	1	2	4
	RS	0	0	0	0	1	1	2	2
	PDA	0	0	0	0	1	2	0	0
	MCDA	0	0	0	0	0	0	1	1
	DT	0	0	0	0	0	0	2	2
	SMO	0	0	0	0	0	0	1	1
	DEA	0	0	0	0	0	0	3	3
	SOM	0	0	0	0	0	0	1	1
	TOTAL	**0**	**0**	**2**	**2**	**15**	**18**	**25**	**30**

Note: FCM: Failing Company Model; BSDM: Balanced Sheet Decomposition Model; CMT: Cash Management Theory MDA: Multivariate Discriminant Analysis; LPM: Linear Probabilistic Model; CUSUM Par.Adj.: Cumulative Sum Partial Adjustment; ZPP: Zero-Price Probability Model; QRA: (binary) Quantile Regression Approach; AIES: Artificially Intelligent Expert Systems; RPDT: Recursive Partitioning Decision Trees; MCDA: Multi-Criteria Decisions Aid; CBR: Case Based Reasoning; NN: Neural Networks; GA: Generic Algorithm; RS: Rough Set; PDA: Preference Disaggregation Analysis; DT: Decision Trees; SMO: Sequential Minimal Optimization; DEA: Data Envelop Analysis; SOM: Self-Organizing Map.

1.2.1.5. Variables Based Review of Micro Credit Risk Metrics

Variables based review documents the variables used in the models to predict bankruptcy. Table 11 demonstrates the author (s), numbers of variables analyzed, numbers of variables used in the models and numbers of factors mentioned. Researchers follow the procedures of selecting the variables by at least three ways. The first method is that they arbitrary and subjectively decide the variables used in the models. In this manner, they apply some statistical techniques to determine what discriminating variables for prediction are. The second method is that they decide arbitrary and subjectively some factors (constructs). This follows to select appropriate variables for each factor. In this manner, some researchers apply factor analysis to diminish the numbers of variables into several factors. Then they define each factors with the variables contained. The third method is that researchers determine the variables based on the proposed theoretical model. In this case, factors are predetermined whereas variables are arbitrary and subjectively chosen.

Studies that apply factor structure in predicting bankruptcies can be a starting point to the conceptualization of bankruptcy process. However, the way researchers approach the problem is limited to document antecedents of bankruptcy predictions. In most cases, researchers tried to derive factor structure of bankruptcy from financial statements of the firms. However, antecedents of bankruptcy process are not all available in financial statements. Financial statements are presenting the last outcomes of firm operations. What affects these outcomes is the critical justification of bankruptcy process. For this reason, the factors those are derived and frequently used in the studies cannot able to describe the whole process of bankruptcy. This weakness of factor structure is realized by some researchers who process different type of factors whereas the dynamics of bankruptcy process are not examined and proposed with the risk that firms encountered, environment that firms operated, and management that firms executed. This is one of the primary reasons in developing and proposing a conceptual model for bankruptcy process which is explained in chapter two.

Studies that do not apply factor structure have a purpose of discriminating or classifying the firms into bankrupt and non-bankrupt firms. These studies can be preliminaries attempts even before proposing a factor structure of bankruptcy process.

Table 11: Variables based Review

Author (date)	Number of Variables analyzed	Number of Variables used in the model	Number of factor mentioned
Beaver (1966)	30	6	6
Beaver (1968)	5	5	NM
Altman (1968)	9	5	NM
Meyer and Pifer (1970)	12	12	NM
Edmister (1972)	7	7	NM
Deakin (1972)	14	14	4
Wilcox (1973)	3	3	NM
Blum (1974)	12	12	3
Wilkox (1976)	2	2	NM
Altman et al. (1977)	7	7	7
Moyer (1977)	8	8	NM
Santomero and Vinso (1977)	2	2	NM
Norton and Smith (1979)	32	23	NM
Sharma and Mahajan (1980)	11	2	4
Ohlson (1980)	8	8	NM
Dambolena and Khoury (1980)	19	19	4
Taffler (1982)	32	3	3
Tsffler (1983)	4	4	NM
Booth (1983)	2	2	NM
El Hennawy and Morris (1983)	8	8	NM
Takahashi, et al. (1984)	6	6	NM
Casey and Bartczak (1984)	3	3	NM
Appetiti (1984)	32	2	6
Izan (1984)	10	5	NM
Mensah (1984)	32	32	NM
Micha (1984)	7	7	NM
zmijewski (1984)	3	3	NM
Casey and Bartczak (1985)	6	6	NM
Gentry, et al. (1985)	8	8	NM
Frydman et al. (1985)	21	21	NM
Zavgren (1985)	7	7	7
Lo (1986)	6	6	NM
Peel, et al. (1986)	9	9	NM
Lau (1987)	10	10	3
Gombola, et al. (1987)	24	9	6
Aziz, et al. (1988)	17	17	NM
Messeir and Hansen (1988)	10	10	NM
Dambolena and Shulman (1988)	5	5	NM
Aziz and Lawson (1989)	16	16	NM
Keasey and McGuinness (1990)	16	16	NM
Skogsvik (1990)	20	20	NM
Keasey, et al. (1990)	16	16	NM
Gilbert, et al. (1990)	14	3	NM
BarNiv and Hershbarger (1990)	31	8	6
Platt and Platt (1990)	28	7	8

Note: NM: Not Mentioned.

Table 11: Variables based Review (cont.)

Author (date)	Number of Variables analyzed	Number of Variables used in the model	Number of factor mentioned
Theodossiou (1991)	13	5	NM
Tam and Kiang (1992)	19	19	NM
Coats and Fant (1993)	5	5	NM
Ward (1994)	8	8	NM
Altman et al. (1994)	8	8	NM
Johnsen and Melicher (1994)	13	13	NM
Back et al. (1996)	31	31	3
Begley, et al. (1996)	13	13	NM
Jo et al. (1997)	32	32	3
Pompe and Feelders (1997)	10	10	NM
Latinen and Latinen (1998)	12	12	NM
Varetto (1998)	8	8	NM
Yang et al. (1999)	5	5	NM
Dimitras et al. (1999)	28	12	NM
Kahya and Theodossiou (1999)	27	27	8
Sung et al. (1999)	32	32	4
Lennox (1999)	7	7	NM
Zopounidis and Doumpos (1999)	12	12	NM
Zhang, et al. (1999)	6	6	NM
Beynon and Peel (2001)	11	11	5
Lin and Piesse (2004)	10	10	7
Shumway (2001)	13	13	NM
Reynolds, et al. (2002)	12	12	NM
Park and Han (2002)	28	28	10
McKee and Lensberg (2002)	12	12	NM
Shin and Lee (2002)	9	9	NM
Doumpos, et al. (2002)	11	11	NM
Brochman and Turtle (2003)	10	10	NM
Foreman (2003)	8	8	NM
Claessens, et al. (2003)	10	10	NM
Koh and Low (2004)	6	6	NM
Charitou, et al. (2004)	32	32	4
Shin, et al. (2005)	10	10	NM
Tseng and Lin (2005)	3	3	NM
Hu and Ansell (2007)	8	8	NM
Benos and Papanastasopoulos (2007)	10	10	NM
Li and Sun (2008)	20	20	5
Sueyoshi and Goto (2009)	9	9	NM
Premachandra et al. (2009)	7	7	2
Min and Yeong (2009)	27	27	NM
Lin (2009)	20	20	NM
Chen and Du (2009)	32	32	NM
Bhimani, et al. (2010)	32	32	NM
Su and Huang (2010)	32	32	NM
Li and Miu (2010)	6	6	NM
Jardin and Severin (2011)	10	10	NM
Premachandra et al. (2011)	7	7	NM

Note: NM: Not Mentioned.

Developing a factor (constructs) structure of bankruptcy process involves a critical step. This is the step of extracting factor. There are three alternative techniques of extracting factors proposed in the studies. The first and the most applied technique is the criteria of selecting factor on subjective based selection. In this manner, researchers decide the factors by a prior knowledge of their expertise. However, the linkages among the factors proposed and the relationship with bankruptcy process are not well structured. Therefore, each proposed factor structure can be beaten by another version of others. In such cases, it is argued that proposed factor structure has some default in its structure. The second technique of extracting factors is factor analysis. (Explanatory) Factor analysis is a statistical technique to diminish the numbers of variables into conceptually similar set of variables. In using factor analysis, researchers are assumed to have no knowledge on factor structures. As a result, conceptually similar sets of variables are defined by researchers. It should be underlined the fact that factor analysis application on financial variables is totally based an incorrect justification. The reason is that financial variables are calculated for a known specific purpose such as a variable that shows profitability, solvency or cash flow. Applying factor analysis may distribute the variables into factors whereas spurious correlations can affect an incorrect distribution of variables into factors. That is why applying factor analysis and deriving a factor structure does not have only theoretically weaknesses but also statistical errors. Third technique of extracting factors is relying on constructs of a proposed model. In this case, researchers determine the appropriate variables for each constructs and predict bankruptcy.

Among the techniques of extracting factors, model based selection have some advantages over others in terms of reflecting the dynamics of bankruptcy on a theoretical ground. Table 12 lists the studies that propose a factor structure in bankruptcy predictions. The numbers of factors are varying from two to ten. Each of these factors may or may not common in the studies.

Table 12: Variables based Review

Author (date)	Numbers of factors mentioned	Technique of extracting factors
Beaver (1966)	6	subjective based selection
Deakin (1972)	4	subjective based selection
Blum (1974)	3	model constructs
Altman et al. (1977)	7	subjective based selection
Sharma and Mahajan (1980)	4	subjective based selection
Dambolena and Khoury (1980)	4	subjective based selection
Taffler (1982)	3	factor analysis
Appetiti (1984)	6	subjective based selection
Zavgren (1985)	7	subjective based selection
Lau (1987)	3	subjective based selection
Gombola, et al. (1987)	6	subjective based selection
BarNiv and Hershbarger (1990)	6	subjective based selection
Platt and Platt (1990)	8	subjective based selection
Back et al. (1996)	3	factor analysis
Jo et al. (1997)	3	subjective based selection
Kahya and Theodossiou (1999)	8	subjective based selection
Sung et al. (1999)	4	subjective based selection
Beynon and Peel (2001)	5	subjective based selection
Lin and Piesse (2004)	7	subjective based selection
Park and Han (2002)	10	model constructs
Charitou, et al. (2004)	4	subjective based selection
Li and Sun (2008)	5	subjective based selection
Premachandra et al. (2009)	2	subjective based selection

Researchers have used several factors and variables in predicting bankruptcy. The classification of the factors and variables contained is demonstrated through Table 13 to Table 25. The first column of these tables indicates the name of the factor; the second column indicates the code of the variables in the context of the thesis; the third column indicates the formula of variable and the fourth column of the variable indicates the numbers of variable usage in the studies analyzed. The reason of coding variables is that there are more variables than reported in these tables. The presented variables are based on the numbers of usage in the studies whereas some variables and accordingly some factors are rarely used and indicated a specific factor. Therefore, the numbers of usage is not set to an equal number among factors. Since researchers did not define each formula used, some formulas are reported without a name. In addition, some researchers did not classify the variables into a factor. This is done by justification of variables and their purpose of calculation.

Cash flow is one of the most frequently used concepts in predicting bankruptcy. Despite the fact that the underlining rational of using cash flow is not explicitly explained by the researchers, the importance of the concept can be best explained that the cash flow contains a lot of elements (signals) to the stakeholders. Table 13 presents applications of the cash flow factor and related variables. The most frequently used variables that are contained in cash flow factor are depicted. The number of usage of given variables is set to five (5) for presenting here. As it is depicted, cash flow from operations and adjusted cash flow are two main features of the cash flow factors. These two dimensions are relating to total assets, total liabilities, current liabilities and sales. In total, thirteen (13) variables are coded in the context of cash flow factor.

Table 13: Cash Flow Factor

Factor	code	Variables used in the models	Formula	number of usage
Cash Flow	CF1	Cash flow to total debt	Cash Flow from Operations / Total Liabilities	20
	CF2	Cash flow to total assets	Cash Flow from Operations / Total Assets	12
	CF3	Adjusted Cash Flow	Adjusted Cash Flow	10
	CF4		Cash Flow from Operations / Current Liabilities	6
	CF5		Cash Flow from Operations / Sales	5

Profitability is one of another the most frequently concepts in predicting bankruptcy. The rationale behind the concept can be explained by its role in performance whereas it is common to indicate that profitability is not as effective as cash flow in signaling. Profitability figures are mostly accounting based and hence, can be misleading in shorter terms. Table 14 presents six (6) variables regarding to profitability.

Table 14: Profitability Factor

Factor	code	Variables used in the models	Formula	number of usage
Profitability	PR1	Net Income to total assets	Net Income / Total Assets	35
	PR2	return on assets	Earnings Before Interest & Taxes / Total Assets	33
	PR3		Retained Earnings / Total Assets	24
	PR4	Net income to book value of equity	Net income / Total Equity	18
	PR5		Net Income / Sales	12
	PR6	Operating Income to Sales	Earnings Before Interest & Taxes / Sales	10

Solvency (short-term) is another most frequently used construct in predicting bankruptcy. In most studies, solvency is not separated into short-term and long-term. Short-term solvency sometimes refers to liquidity. In terms of numbers of variables being used in predicting bankruptcy, short-term solvency is primarily used in many studies. As depicted in Table 15, the first seven variables are used more in ten studies.

Table 15: Solvency (Short-Term) Factor

Factor	code	Variables used in the models	Formula	number of usage
Solvency (Short-Term)	SS1	Current ratio	Current Assets / Current Liabilities	34
	SS2	Net working capital to total assets	Net Working Capital / Total Assets	34
	SS3	Acid Test Ratio	Quick Assets / Current Liabilities	23
	SS4	Current assets to total assets	Current Assets / Total Assets	13
	SS5	Cash to current liabilities	Cash / Current Liabilities	12
	SS6	Cash to total assets	Cash / Total Assets	11
	SS7		Quick Assets / Total Assets	10
	SS8		Current Liabilities / Total Assets	9
	SS9	Net working capital to sales	Net Working Capital / Sales	7
	SS10		Net Working Capital / Total Equity	5
	SS11		Current Liabilities / Total Equity	5
	SS12		Current Liabilities / Total Liabilities	5

Long-term solvency is another part of solvency indicating long term condition of firms' ability to pay their debt obligations. Therefore, it is crucial to take this construct into account in predicting bankruptcy. As depicted in Table 16, the first four variables are used in more than ten studies.

Table 16: Solvency (Long-Term) Factor

Factor	code	Variables used in the models	Formula	number of usage
Solvency (Long-Term)	SL1	Total Liabilities to total assets	Total Liabilities / Total Assets	31
	SL2	Times Interest Earned	Earnings Before Interest & Taxes / Total Interest Payments	14
	SL3	Stockholders' equity to total assets	Total Equity / Total Asset	14
	SL4		Total Liabilities / Total Equity	12
	SL5	equity to debt ratio	Total Equity / Total Liabilities	8
	SL6		Total Equity / Fixed Assets	6
	SL7	Fixed assets to total assets	Fixed assets / Total Assets	5

Asset utilization is another construct used in predicting bankruptcy. Measuring the efficiency of the assets is playing an important role in performance evaluation. Therefore, variables regarding to asset utilization show a valuable signals. The numbers of usage is set four (4) for presenting a variable contained in the construct. Especially, sales to total assets is used in twenty-four (24) studies.

Table 17: Asset Utilization Factor

Factor	code	Variables used in the models	Formula	number of usage
Asset Utilization	AU1	Sales to total assets	Sales / Total Assets	24
	AU2	Inventory to sales	Inventory / Sales	6
	AU3	Stockholders' equity turnover ratio	Sales / Total Equity	5
	AU4	Receivables turnover ratio	Sales / Receivables	5
	AU5		Sales / Net Working Capital	4
	AU6	Inventories turnover ratio	Cost of Goods Sold / Inventory	4

Researchers figured out that the trend of some specific variables should be taken into account for the fact that their volatility (or simply trend) may capture the difference between bankrupt and non-bankrupt firms. It is the reason behind using the variables depicted in Table 18 in the context of predicting bankruptcy. The number of usage is set to three (3) studies for growth (trend) construct.

Table 18: Growth (Trend) Factor

Factor	code	Variables used in the models	Formula	number of usage
Growth (Trend)	GR1	Growth rate of sales	Growth Rate of Sales	7
	GR2	Growth rate of total assets	Total Asset Growth	6
	GR3	Growth rate of net income	Net Income Growth	6
	GR4	Owner's Equity Growth	Total Equity Growth	4
	GR5	Tangible Fixed Asset Growth	Growth Rate of Property, Plant, and Equipment	3

Another widely used variables set is that of Market Value factor. The main argument behind using these types of variables is that the impact of market is not transmitted to financial statements properly due to accounting standards and regulations. In order to get rid of this obstacle, some researchers have proposed to use the variables depicted in Table 19. Especially the first two variables in market value factor are used in ten studies.

Table 19: Market Value Factor

Factor	code	Variables used in the models	Formula	number of usage
Market Value	MV1		Total Assets	10
	MV2		Market Value of Equity / Total Assets	10
	MV3		Market Value of Equity / Book Value of Equity	6
	MV4	MVE to total liabilities	Market Value of Equity / Total Liabilities	5
	MV5	earnings per share	Earnings per Share	5
	MV6		Market Value of Equity / (preferred stock liquidating value + market value of equity + long-term debt + capitalized leases)	4
	MV7		log (Total Assets / GNP Price Level Index)	4
	MV8		Sales (£; $ 000)	3

The decomposition measures that are depicted in Table 20 are used in the context of applying Balanced Sheet Decomposition Theory. Therefore, these variables are outcome of calculating several figures in financial statements.

Table 20: Decomposition Measure

Factor	code	Variables used in the models	Formula	number of usage
Decomposition Measures	DM1	New Decomposition Measures on the Liability Size, Two Components	New Decomposition Measures on the Liability Size, Two Components	3
	DM2	New Decomposition Measures on the Liability Size, Four Components	New Decomposition Measures on the Liability Size, Four Components	3
	DM3	New Decomposition Measures on the Assets Size, Four Components	New Decomposition Measures on the Assets Size, Four Components	3

Some researchers have proposed different set of constructs as well. Competitive Advantage of the Firms is one of them. These variables depicted in Table 21 are proposed for the reason that non-financial indicators of the firms are also playing an important role in predicting bankruptcy. Despite the fact that the number of usage is quite limited in literature, the idea behind using such type of variables may contribute a direction of conceptualizing bankruptcy prediction.

Table 21: Competitive Advantage of Firms Factor

Factor	code	Variables used in the models	Formula	number of usage
Competitive advantage of firms	CA1	Personnel and staff hiring policy	Personnel and Staff Hiring Policy	1
	CA2	Technology development and quality innovation	Technology Development and Quality Innovation	1
	CA3	Pricing competitive advantage	Pricing Competitive Advantage	1
	CA4	International competitive advantage	International Competitive Advantage	1
	CA5	Firm’s market position	Firm’s market position	1
	CA6	Special competitive advantage	Special competitive advantage	1

Reliability factor is another construct representing non-financial indicators of the firms. The variables depicted in Table 22 are those of reliability construct. In evaluation of variables of this construct, it is realized that the measurability of the variables are difficult to carry out. Therefore, scale based metric is proposed to measure mentioned characteristics.

Table 22: Reliability Factor

Factor	code	Variables used in the models	Formula	number of usage
Reliabilities	RL1	Past payment record (trade)	Past Payment Record (trade)	1
	RL2	Industry reputation	Industry Reputation	1

Management capacity factor shows the first time how management ability is taken into account in predicting bankruptcy. Despite the limited number of usage of this construct and measurability problem of these variables, the approach they bring over may contribute the conceptualization of bankruptcy prediction. The major innovation here is that the proposed construct shows that there are some effects in management that directly affect firm's overall performance. As mentioned earlier, financial statements are lag variables showing activities at least for three months in quarterly announced, and 12 months in annually announced. Therefore, these non-financial characteristics may allow the researchers and stakeholders to concentrate on the ability of management itself. As depicted in Table 23, some variables are measured through proposed scales and some used as they are.

Table 23: Management Capacity Factor

Factor	code	Variables used in the models	Formula	number of usage
Management capacity	MC1	Quality of management	Qualitative (scale)	1
	MC2	Relationship between Labor and Capital	Qualitative (scale)	1
	MC3	Working Conditions and Welfare Facilities	Qualitative (scale)	1
	MC4	Director resignations over the financial year, as a proportion of the total number of directors recorded in office at the financial year end	Director resignations over the financial year, as a proportion of the total number of directors recorded in office at the financial year end	1
	MC5	Director appointments over the financial year, as a proportion of the total number of directors recorded in office at the financial year end.	Director appointments over the financial year, as a proportion of the total number of directors recorded in office at the financial year end.	1
	MC6	The change in directors' beneficial shareholdings in the issued equity capital of the company between accounting financial year ends	The change in directors' beneficial shareholdings in the issued equity capital of the company between accounting financial year ends	1
	MC7	The time lag between a company's accounting financial year end and the date the annual accounts were actually published.	The time lag between a company's accounting financial year end and the date the annual accounts were actually published.	1
	MC8	The change in the time lag in publishing accounts	The change in the time lag in publishing accounts	1
	MC9	Manager's work experience	Manager's work experience	1
	MC10	The proportion of collateralized shares by the board of directors	The proportion of collateralized shares by the board of directors	1
	MC11	shares by the board of directors	shares by the board of directors	1
	MC12	Insider holding ratio	Insider holding ratio	1

The construct and related variables depicted in Table 24 are a very special case in bankruptcy prediction of insurance sector. During the 1970s the National Association of Insurance Commissioners (NAIC) in USA developed the Insurance Regulatory Information System (IRIS) in which the variables depicted in Table 14 are included (BarNiv and Hershbarger, 1990). Therefore, this type of the construct proposed by a regulatory body may help researchers and / or practitioners to better understanding the sector itself.

Table 24: Insurance Regulatory Information System ratios

Factor	code	Variables used in the models	Formula	number of usage
Insurance Regulatory Information System ratios	IR1	Real Estate to Capital & Surplus	Real Estate to Capital and Surplus	1
	IR2	Investments in Affiliate to Capital & Surplus	Investments in Affiliate to Capital and Surplus	1
	IR3	Change in Product Mix	Change in Product Mix	1
	IR4	Change in Reserving Ratio	Change in Reserving Ratio	1

Some researchers have used statistical variables that are either calculated based on a theoretical model or based on simply a statistical indicator in predicting bankruptcy. As depicted in Table 25, these variables are not used frequently in the studies analyzed. In evaluating the importance of these variables in predicting bankruptcy, it is noted that some variables are representing market impact such as market premium and riskless rate.

Table 25: Statistical Variables

Factor	code	Variables used in the models	Formula	number of usage
Statistical Variables	SV1	Default spread	Default spread	2
	SV2	Sigma	Sigma	1
	SV3	market premium	market premium	1
	SV4	Asset volatility	Asset volatility	1
	SV5	Riskless rate	Riskless rate	1
	SV6	The five years correlation coefficient between government debt and total sales	The five years correlation coefficient between government debt and total sales	1

The last type of variables used can be categorized into dummy factor due to their role in estimating the models. Dummy type variables are extremely important in term of evaluating the structure of model. One of the main reasons behind using a dummy in this context is that the model proposed is not flexible to be applied in all firms. That is why a dummy is needed to account a structural difference among the firms. For example, the industry dummy is sign showing that industrial effects are present. In case of having a dummy for dividend shows that there are differences between firms paying dividends and not paying dividends. Most importantly, the proposed model is not capable of capturing such differences. At statistical point view, there is usual way of using a dummy in order to increase efficiency of the given model whereas at the theoretical ground point view there is a call for extending the model parameters.

Table 26: Dummies

Factor	code	Variables used in the models	Formula	**number of usage**
Dummies	DM1	number of years company has been operating since incorporation date	number of years company has been operating since incorporation date	4
	DM2	dummy	One if total liabilities exceeds total assets, zero otherwise	2
	DM3	dummy	One if net income was negative for the last two years, zero otherwise	2
	DM4	dummy	1 if one of the firm's loan agreements contains 3 or more restrictive terms and the loan's interest is above the prime rate	1
	DM5	dummy	1 if no dividend is being paid currently	1
	DM6	dummy	1 if the firm liquidates its operating assets in the period and there is no decreasing trend of earnings flow	1
	DM7	dummy	1 if dividend payments are omitted or reduced more than 40% in the period	1
	DM8	Number of days between account year end and the date the annual report and accounts were filed at company registry.	number of days between account year end and the date the annual report and accounts were filed at company registry.	1
	DM9	coded 1 if changed auditor in previous three years,	coded 1 if changed auditor in previous three years,	1
	DM10	coded 1 if company auditor is a Big6 auditor,	coded 1 if company auditor is a Big6 auditor,	1
	DM11	dummy	Industry dummy for quarrying and construction	1
	DM12	dummy	Industry dummy for distribution	1
	DM13	Industry effects	1 if company i operates in industry j;	1
	DM14	dummy	identifying firms that are affiliated with a business group and where the ultimate owner has at least 20% of the voting rights	1
	DM15	dummy	identifying firms that are owned by a bank or by a business group that also owns a bank	1
	DM16	dummy	indicating Anglo-Saxon legal origin	1
	DM17	dummy	indicating German legal origin	1

1.2.1.6. Findings Based Review of Micro Credit Risk Metrics

Findings based review documents the overall performance of the models used in predicting bankruptcy in the line with type I and type II errors. In the context of the thesis, there are 13, 119, 50 treatments conducted in the framework of theory based, statistical based and AIES based models respectively. Despite the fact that the dispersion among the numbers of treatments, it still useful to evaluate the findings. Overall performance of Theory based models account 83,96 % of correct predictions; Statistical based models account 85,73 % of correct predictions and AIES based models account 85,82 % of correct prediction. It is not intended to compare these statistic among the different type of the models due to the dispersion among the numbers of treatments made whereas statistical based and AIES based models seem to outperform that of theory based models in terms of overall performance.

Average rate of Type I error and type II error show that statistical based and AIES based models are better than theory based models. However, the findings should be interpreted with a caution that there is a very high dispersion in the numbers of treatments. There is another reason that statistical and AIES based models are derived based on the findings reported in Table 27. In the other words, the variables sets are rotated in statistical justification in order to increase the overall performance of the models or decrease the error rates. However, there is no chance to use another type of variables that are not related to theory. Even though some studies use both application including theory based and one of the other models, their results are reported independently due to the small numbers of treatments.

Table 27: Findings based Review

		Number of treatment	OPA (mean)	Number of treatment	Type I Error (%) (mean)	Number of treatment	Type II Error (%) (mean)
Models	Theory Based	13	83.96	11	28.22	11	17.17
	Statistic Based	118	85.73	90	15.66	89	11.99
	AIES Based	50	85.82	23	13.05	13	12.37

Note: NA treatments are excluded; OPA: Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems.

More specifically, the type of theory based models is evaluated in terms of findings as depicted in Table 28. Since the numbers of studies are quite limited, it is hard to compare the models among themselves. Having this difficulty in mind, it is noted that Gambler's Ruin Model performs best in terms of OPA whereas researchers have not reported type I and II errors in their papers. On the other side, Cash Management Theory Models have produced the worst results in OPA. Another interesting point coming out is that Contingent Claim Models have produced the worst type I error which is an important weakness in model evaluation.

Table 28: Findings based Review on Theory based Models

		Number of treatment	OPA (mean)	Number of treatment	Type I Error (%) (mean)	Number of treatment	Type II Error (%) (mean)
Theory Based Models	Gambler's Ruin	3	95.06	NA	NA	NA	NA
	FCM	1	88.6	1	15	1	10
	BSDM	2	85.1	2	10.5	2	8.5
	CASH	3	68.18	3	22.82	3	33.82
	Contingent Claim	4	85.75	5	41.13	5	12.09

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; FCM: Failing Company Model; BSDM: Balanced Sheet Decomposition Model; CMT: Cash Management Theory.

Findings based review on the types of statistical based models is depicted in Table 29. As mentioned earlier, it is rather safe to interpret the findings of frequently used techniques. In this manner, MDA, LOGIT and PROBIT models show 87,56 %, 86,38 % and 87,33 % of success in OPA. Additionally, these three models outperform the others in terms of OPA. The highest type I error is produced by LOGIT model with a rate of 16,87 % among these highly used three models. The lowest Type I error is reported by MDA with a rate of 12,55 %. The statistics regarding to the others are open to debate due to the limited number of treatments.

Table 29: Findings based Review on Statistical based Models

		Number of treatment	OPA (mean)	Number of treatment	Type I Error (%) (mean)	Number of treatment	Type II Error (%) (mean)
Statistical Based Models	Univariate	4	79.26	4	25.55	3	22.31
	MDA	50	87.56	38	12.55	38	10.11
	LPM	2	86.33	2	3.28	2	11.11
	LOGIT	47	86.38	35	16.87	35	12.79
	PROBIT	8	87.33	7	15.45	7	10.38
	Cluster	5	65.26	2	36.45	2	24.55
	CUSUM	1	82.5	1	18	1	17
	HAZARD	NA	NA	NA	NA	NA	NA
	ZPP	NA	NA	1	34.76	1	18.84
	QRA	1	88	NA	NA	NA	NA

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; MDA: Multivariate Discriminant Analysis; LPM: Linear Probabilistic Model; CUSUM Par.Adj.: Cumulative Sum Partial Adjustment; ZPP: Zero-Price Probability Model; QRA: (binary) Quantile Regression Approach.

Findings based review on the types of AIES based models is demonstrated in Table 30. NN, RPDT, GA and CBR are the types that are used at least in five treatments. Therefore, it is useful to mention their overall performance and type I and II errors. As depicted, NN models were used in twenty treatments in which 85,36 % of OPA, 8,82 % of type I error and 13,21 % type II error are reported. RPDT models were used in seven treatments in which 84,6 % of OPA, 21,3 % of type I error and 12,4 % type II error are reported. GA models were used in five treatments in which 85,42 % of OPA, 15,13 % of type I error and 7 % type II error are reported. CBR models were used in five treatments in which 87,34 % of OPA is reported whereas the statistics regarding to type I and II errors were not reported by researchers.

Table 30: Findings based Review on AIES based Models

		Number of treatment	OPA (mean)	Number of treatment	Type I Error (%) (mean)	Number of treatment	Type II Error (%) (mean)
AIES Based Models	RPDT	7	84.6	4	21.3	4	12.4
	NN	20	85.36	8	8.82	8	13.21
	GA	5	85.42	2	15.13	2	7
	CBR	5	87.34	NA	NA	NA	NA
	RS	3	85.4	3	14.17	3	14.8
	PDA	2	81.58	2	13.16	2	23.69
	MCDA	1	99.5	1	0	1	1
	DT	2	85.75	1	4	1	6
	SMO	1	90.24	NA	NA	NA	NA
	DEA	3	88.17	2	20.71	2	8.2
	SOM	1	82.73	NA	NA	NA	NA

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; RPDT: Recursive Partitioning Decision Trees; MCDA: Multi-Criteria Decisions Aid; CBR: Case Based Reasoning; NN: Neural Networks; GA: Generic Algorithm; RS: Rough Set; PDA: Preference Disaggregation Analysis; DA: Data Mining; SMO: Sequential Minimal Optimization; DEA: Data Envelop Analysis; SOM: Self-Organizing Map.

1.2.2. Theory-based Models

Theory based Models include five (5) different justifications that are Gambler's Ruin Theory, Failing Company Model, Balanced Sheet Decomposition Model, Cash Management Theory and Contingent Claim Model. These previously developed theoretical models have some disadvantages to be a reliable road map to follow. None of these models are able to explain the whole picture about the dynamics of the firms and bankruptcy process. In this section, these models will be reviewed in brief for the fact that there might be several extensions from the initial models. Especially, this is the case for contingent claim models which have numerous extensions. Therefore, the primary purpose here is to show the fundamentals of the models proposed.

1.2.2.1. Balance Sheet Decomposition (Entropy) Measure

Balance Sheet Decomposition Measure is a tool developed for examining the changes in the financial statements. The most frequent application is conducted on balance sheet items. That is why this measure is called balance sheet decomposition. The logic behind the measure is a concept so called entropy. Entropy is first introduced by German physician Rudolf Clauses in the context of law of the conservation of energy. Clauses defined measurement of energy as a function of temperature and heat in a closed system and gave Greek name of entropy which means transformation due to its similarity to energy (in German it is energie). This is also known as second law of thermodynamics. At the beginning, Clauses believed that entropy will be following the law of the energy conservation whereas he realized that the amount of entropy in a closed system is getting higher. He interpreted this observation that universe will be ending as a result of heat death due to the fact that universe is a closed system (no energy can be transferred from somewhere else). The popularity of concept of entropy is getting higher by its application in information theory which is developed by Shannon (1948). Shannon used the concept of entropy as an indicator of uncertainty in information. In several other fields, entropy is used whereas its role in finance is popularized by Theil (1969). Theil (1969) showed how to use entropy concept in analysis of financial statements. Following Theil (1969), several studies conduct balance sheet decomposition measure in bankruptcy prediction (Moyer, 1977; Booth, 1983; Lev, 1973).

Lev (1973: 56) claimed that '*a major characteristic of all living organisms is homeostasis- an equilibrium maintained by a self-regulatory mechanism'*. This implies that when such equilibrium disturbed, forces are set in motion to restore it. In case of homeostasis, it is believed that optimal (equilibrium) relationship among the various inputs and outputs are determined and efforts are made to maintain them against disturbances. Therefore, there should be existing optimal relationship between (e.g.) labor and capital inputs, inventory and sales, cash and short-term securities, debt and equity capital. This logic can be best interpreted through the concept of entropy in financial point of view.

Decomposition measures are proposed to demonstrate the changes in financial statements. Despite the fact that ‘common size statements’ have been suggested to figure out these changes, Lev (1973: 56) pointed out that ‘*such an analysis is inefficient if it examines all financial statement items for the various periods’*. Decomposition measures are claimed to be efficient and convenient device for identifying (a) *whether a significant change in financial statement constructs has occurred* and (b) *where most of the change is located* (Lev, 1973: 56).

Financial statements can be seen as decomposition of some aggregate figures such as total assets, total liabilities or total sales. Therefore, these measure the changes in the composition of these aggregate figures between financial statement dates. In case of applying decomposition measures, standardized financial statements are required for the analysis (Booth, 1983: 67).

Balance Sheet Decomposition Measure can be formulated as follows (Theil, 1969: 463; Lev, 1973: 57; Moyer, 1977: 15; Booth, 1983: 70):

$$\sum_{i=1}^{2} \sum_{j=1}^{2} q_{ij} \log_e \frac{q_{ij}}{p_{ij}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

Where

q_{11}= current assets as a fraction of twice total assets.

q_{21}= long-term assets as a fraction of twice total assets.

q_{12} = current liabilities as a fraction of twice total assets.

q_{22}= long-term liabilities plus total equites as a fraction of twice total assets.

p_{11}, p_{21}, p_{12}, p_{22} are the corresponding fractions in the previous consecutive year.

The assets, Equities and Liabilities Decomposition Measures can be formulated as follows (Theil, 1969: 463; Lev, 1973: 57; Moyer, 1977: 15; Booth, 1983: 70):

$$\sum_{i=1}^{n} q_i \log_e \frac{q_i}{p_i} \quad \ldots\ldots(2)$$

Where

i: a subset of the appropriate total, be it total assets, liabilities or equities.

n: the number of subsets of each total.

q_i: the fraction subsets 'i' is of the appropriate total in one year.

p_i: the corresponding fraction in the previous consecutive year.

It is proposed that deconposition measures tend to be higher for failing firms than non-failing firms (Moyer, 1977: 15). The reason behind using logarithm operator in (1) and (2) is that the choice is based on the important mathematical property of additivity that allows the user to disaggregate and compute weighted averages of decomposition measures (Lev, 1973: 58). The purpose of decomposition analysis that differs from conventional ratio analysis is that decomposition measures are related to yield a summary economic indicator especially from different categories such as net income and total assets (Lev, 1973: 62).

Table 31 summarizes the empirical investigations that use decomposition measures conducted on bankruptcy predictions. As it is depicted, decomposition measures are used via multiple discriminant analysis with additional variables such as cash flow variables. However, it is claimed that decomposition measures play an important role in discriminating the failing and non-failing firms. The interesting argument coming from the studies depicted in Table 31 is that both studies reported that the models they used report 85 % of overall performance accuracy.

Table 31: Studies for Balance Sheet Decomposition Model

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Moyer (1977)	USA	NA	65-75	48(23F/25NF)/111	Mix	BSDM	MDA	-	85,19	3,00	5,00
Booth (1983)	Australia	Industrial	64-79	34(17F/17NF)/16	Mix	BSDM	MDA	-	85,00	18,00	12,00

Note: NA (not available); Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; BSDM: Balance Sheet Decomposition Model; Multivariate Discriminant Analysis; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms.

1.2.2.2. Gambler's Ruin Theory

Application of Gambler Ruin Approach is proposed by Wilcox (1971). Wilcox (1971) realized that the luck of conceptual framework in predicting bankruptcy lead disappointing results in applying statistical based classification techniques such as Altman (1968) (Z-Score) Model. Gambler Ruin Approach is assumed to be a conceptual framework in estimating default probability. Wilcox (1971: 390) formulates this probability as follows:

Suppose a system can exist in only one of the finite number, *N*, of states S_j, *j=0,1,2,…, N-1,* at any time *t*. Suppose further that the probability of being in state S_j is completely defined by the state S_i of the system at the previous time *t-k,* where *k* is a constant for all *t*. *N* is allowed to increase without bound, but remain countable infinite. This is Markov process. Define $P(S_j|S_i)$ as the probability of S_j at time *t* given S_i at time *t-k*.

Let

$P(S_0|S_0)=1$

$P(S_j|S_i,\ i=j-1,\ i\neq 0)=p$

$P(S_j|S_i,\ i=j+1)=1-p$

And all other $P(S_j|S_i)=0$

This specification of a one-dimensional random walk which has an absorbing barrier at one end and no barrier at the other hand – the classic gambler's ruin model. Let $q=1-p$. Then, according to random walk theory, the probability of the system starting at the state S_z and ultimately visiting state S_0 and thus being ruined or failing is:

$$P(ultimate\ \ failure)=\begin{cases}1,\ if\ \ p\leq q\\(q/p)^z,\ otherwise\end{cases} \qquad \text{………………………(3)}$$

This is a classical probability problem which is adopted to default probability of firms by Wilcox (1971) as follows:

Suppose there exists a firm of wealth *C*, which every year plays a game which nets it a gain or loss of constant size $\pm\sigma$, where the probability of gain equals *p*, and a loss *q*. Suppose $p > q$. Then the probability of this firm's ultimate failure is:

$$P(ultimate \ \ failure) = (q/p)^{c/\sigma} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Where the number of losses *z* the firm can take in a row before being ruined is c/σ. Therefore, q/p, c and σ should be estimated. In estimating these parameters, Wilcox (1973: 164) provides the following treatment:

N and q/p can be estimated through accounting data. N is estimated as the adjusted cash position dividend σ which is the estimated size of the interval between adjacent states in each term. Using this notation, $(p-q)\sigma$ is the average drift-rate per period along the sequence of states in cash terms. $(p-q)\sigma$ is estimated as the mean adjusted cash flow. Since $q = 1-p$, $q/p = [(1-(p-q))/(1+(p-q))]$. Thus, doing some algebraic manipulation, if *'x'* represent the mean adjusted cash flow dividend by σ, $q/p = [(1-x)/(1+x)]$. The following formulas are proposed for calculating mentioned terms:

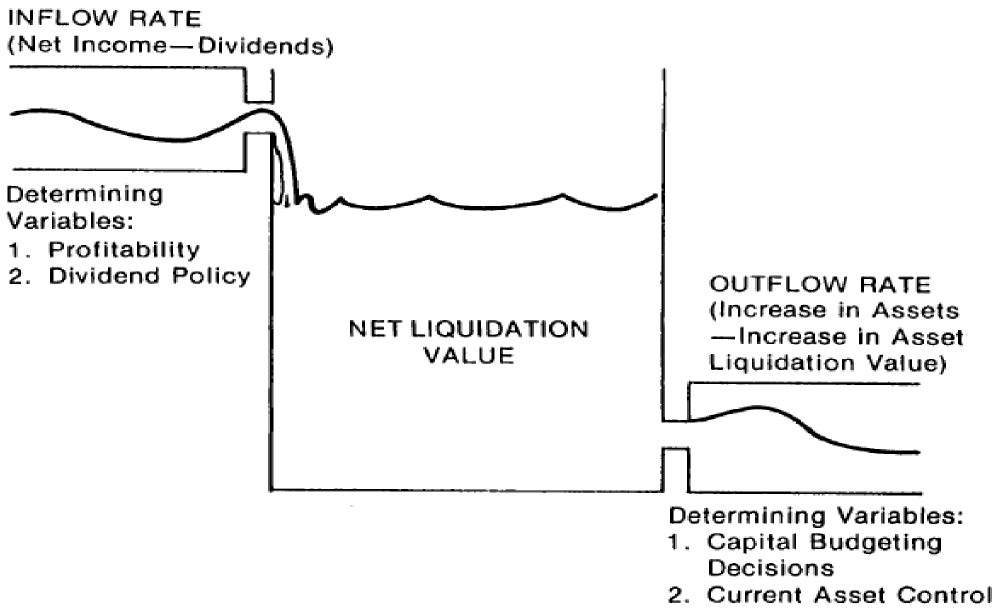
$$adjusted \ \ cash \ \ flow = Net\,Income - Dividends - (0{,}3)\begin{pmatrix} period\ to\ period \\ increase\ in\ current \\ assets\,other\ \ than\ \ cash \end{pmatrix} - (0{,}5)\begin{pmatrix} period\ to\ period \\ increase\ in \\ longterm\ \ assets \end{pmatrix} + \begin{pmatrix} stock\ \ issued\ \ in \\ merger\ \ and\ \ acquisition \end{pmatrix} \ \ldots..(5)$$

$$adjusted\ cash\ position = cash + (0{,}7)\begin{pmatrix} current\ assets \\ other\ than\ cash \end{pmatrix} + (0{,}5)\begin{pmatrix} longterm \\ assets \end{pmatrix} - (1)(Liabilities) \quad \ldots..(6)$$

$$\sigma = \sqrt{\begin{pmatrix} mean\ adj. \\ Cash\ flow \end{pmatrix}^2 + \begin{pmatrix} statistical\ var. \\ of\ adj.\ cash\ flow \end{pmatrix}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

The mean adjusted cash flow is simply the statistical mean over a number of observations of the adjusted cash flow. Wilcox (1971, 1973, 1976) proposes net liquidation value as a basic variables in Gambler Ruin Approach.

Figure 1: Variables in Gambler Ruin Approach

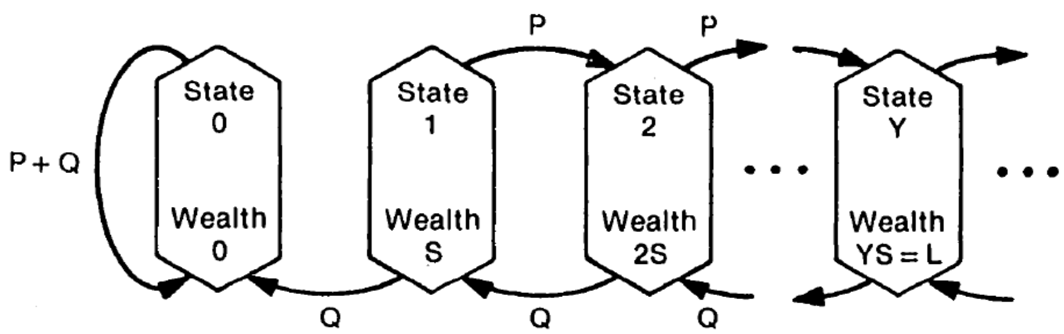


Source: Wilcox (1976:35)

Figure 1 demonstrates the conceptual framework behind Gambler Ruin Approach. According to Wilcox (1973), net liquidation value is, in the language of system dynamics, a level fed by liquidity inflow rate and drained by a liquidity outflow rate. The inflow rate is governed by profitability and management's dividend policy. This inflow rate is defined as the difference between net income and dividend. The liquidity outflow rate is governed by management's capital budgeting policy and the interaction of sales fluctuations with current control procedures. This outflow rate is defined as the increase each period in the book value of assets less the increase in liquidation value of those assets. Creditors tend to assert their claims when net liquidation value becomes negative. This often precipitates bankruptcy. A continuing management process and strategic position imply in statistical terms a 'stable process'. Given this stable process, the future probability of the net liquidation value being reduced to zero is determined by (i) *the current net liquidation or current wealth,* (ii) *the average adjusted cash flow and* (iii) *the variability of the adjusted cash flow.*

The critical question Gambler Ruin Approach is trying to answer is that *'how much net liquidation value and average adjusted cash flow are required to achieve a given degree of safety?'* This means that what cash or borrowing reserves should be held and how much asset growth can we afford given our expected profitability and dividends? Wilcox (1976) underlines the concept called *'size of the bet'* in answering these questions. This is the adjusted cash flow at risk each year. The meaning of size of the bet (labeled as *S*) and its role in determining risk can be seen most clearly in the classic gambler's ruin model as depicted in figure 2.

Figure 2: Classic Gambler Ruin Model



Source: Wilcox (1976: 37)

Despite the intuitive appealing of the model, Wilcox (1976: 38) figures out some cautions in applying to estimate the default probability.

> *"First, the ratio of average adjusted cash flow to the size of the bet and the ratio of net liquidation value at a point in time to the size of the bet are subject to evolution as management process and strategic position change. Second, the probability distribution of adjusted cash flow is distributed over more than two possible outcomes. Third, the parameters estimated are fundamental indicators of relative financial risk (as it is well illustrated by data when taken for five years)."*

Table 32 summarizes the empirical investigations that use Gambler Ruin Approach conducted on bankruptcy predictions. Wilcox (1973,1976) conducted the model in two studies in which OPA is 94% whereas the error rates were not reported (calculated) in the papers. The other study is conducted by Santomero and Vinso (1977) for evaluating the cross-section risk of the banking industry on the ground of similar treatment of Gambler Ruin Approach whereas the classification is carried out through multivariate discriminant analysis which reported 97 % of OPA. However, these authors did not report the error rates for evaluation.

Table 32: Studies for Gambler Ruin Model

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Wilcox (1973)	USA	Industrial	49-71	64(32F/32NF)/NA	FR	Gambler's Ruin	-	-	94,00	NA	NA
Wilkox (1976)	USA	Industrial	49-71	52(26F/26NF)/NA	FR	Gambler's Ruin	-	-	94,00	NA	NA
Santomero and Vinso (1977)	USA	Banks	65-74	NA (NAF/NANF)/ NA	FR	Gambler's Ruin	MDA	-	97,19	NA	NA

Note: NA (not available); Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; Multivariate Discriminant Analysis; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio.

1.2.2.3. Cash Management Theory

Cash management theory considers the short term management of corporate cash balances proposed by Laitinen and Laitinen (1998) as a theoretical framework which can be connected with the failure process of the firms. Cash management is referring to the process of managing cash inflow and outflow. Therefore, it is the reason that the failure of cash management can be defined as an imbalance between cash inflow and cash outflow which (may) lead to failure (by means of inability of the firm to pay its financial obligations).

As Beaver (1966: 71) defined the situations of bankruptcy, bond defaults, an overdrawn bank account and nonpayment of a preferred stock dividend as operationally default for the firms. Laitinen and Laitinen (1998: 894) claimed that '*all these events are originated in cash management function of a firm having failed the cash balance requirements'*. For this reasons, the linkage between failure of the firms and their cash management behavior is evaluated in the context of cash management theory.

Laitinen and Laitinen (1998) use Baumal (1952) and Tobin (1956) cash inventory management framework in testing cash management arguments for default and non-default firms. Baumal-Tobin cash inventory management framework is simply described as follows (Laitinen and Laitinen, 1998: 896):

Let

Lump sum (fixed) cost = *a*

Variable cost = *b*

Interest rate = *i*

Total volume of transactions to cash needed to finance the difference between (periodic and instantaneous) in a fixed period *t* = *S*

This amount is invested as a secondary asset at the beginning of the period and will be transferred to cash in equal parts A during the period. This leads to average cash balance of A/2 and to the opportunity cost of A/2.

The number of transaction during the period t = S/A (N)

The fixed transaction cost = a (S/A)

Variable cost = bS

Total cost of cash management = opportunity cost + transaction cost

$$= i(A/2) + a(S/A) + bS \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

The size of transferred volume A minimizing total costs can be found taking the first derivative of (8) with respect to A, setting this equal to zero and solving for the optimal A^a as follows:

$$= i(A/2) + a(S/A) + bS$$

$$0 = i/2 - aSA^{-2}$$

$$A^a = \left(\frac{2aS}{i}\right)^{0,5} = \left(\frac{aN}{i}\right)^{0,5} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Equation (9) is commonly used in finding optimal cash balance. Laitinen and Laitinen (1998: 896) point out that '*this equation gives 0,5 elasticity of optimal cash balance with respect to the rate of fixed costs, to the volume of transactions, and to the number of transactions as well as -0,5 for the elasticity with respect to the rate of interest*.' In this framework, Laitinen and Laitinen (1998) assume that the actual cash balance of a firm in period t is a multiplicative function of *S* and *i* assuming that *a* is a constant as follows:

$$\ln M(t) = \ln D + e_S \ln S(t) + e_i \ln i(t) + u(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

Where

D is a scale constant; t refers to the period; u(t) a random variable;

In the context of predicting default, cash management approach relies on the fact that cash management behaviors become peculiar in case of financial distress. The first argument is that the firms have a shortage of cash and as a result, very low degrees of freedom with the cash balance. In this case, the range between upper level and lower level of cash balance is small. Therefore, this range can be a factor in discriminating the firms in terms of financial distress. This means that small portion of cash are varying with respect to factors *S(t)* and *i(t).* Consequently, the absolute values of the elasticities of *M(t)* with respect to *S(t) (es)* and to *i(t) (ei)* would be lower than for a healthy firm. In this situation, when *M(t)* is close to lower level of cash balance, firms are assumed to be in financial distress rather than having efficient cash management behavior. When this is the case, the firm cannot react to an increase in *S(t)* by an appropriate increase in *M(t).* In the same way, an increase in i(t) may only lead to a very small, if any, decrease in *M(t)* because *M(t)* is close to lower level of cash balance (Laitinen and Laitinen, 1998).

In estimating equation (10), where *M (t)* is the actual cash balance in period *t*; *S(t)* is the volume of transactions; *i(t)* is the opportunity cost; *es* and *ei* are the elasticities of cash balance with respect to *S* and *i*, respectively, *u(t)* the error term with standard autoregressive properties, and *D* the scale constant. Variables in Equation (10) are *M* (actual cash balance) was measured by cash on hand and in bank, *S* (volume of transactions) by net sales, and *i* by interest expenses per interest-bearing debt multiplied by 100 (opportunity cost).

The empirical test of cash management theory proposed by Laitinen and Laitinen (1998) produce poor classification accuracy as depicted in Table 33. The authors suggest that cash management information should be used with other data sets. However, this does not change the reality that cash management behaviors are varying depending upon financial health of the firms. This variation, however, is not sufficient to be indicative for predicting default. The second study in context of cash management behavior is the one conducted by Casey and Bartczak (1984) in which cash flow measures are used in prediction rather than cash balance frameworks. This study produces mix results in applying different set of variables.

Table 33: Studies for Cash Management Model

REFERENCES	SAMPLE – DATA – VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Casey and Bartczak (1984)	USA	Mix Industrial	71-82	290(60F/230NF)/NA	FR	CASH	MDA	-	86,00	17,00	13,00
Casey and Bartczak (1984)	USA	Mix Industrial	71-82	290(60F/230NF)/NA	FR	CASH	Univariate	-	60,00	10,00	47,00
Latinen and Latinen (1998)	Finland	Mix Industrial	86-91	82(41F/41NF)/NA	CF	CASH	LOGIT	-	58,54	41,46	41,46

Note: Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; Multivariate Discriminant Analysis; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; CF: Cash Flow Measures;

1.2.2.4. Failing Company Model

At the practical point of view, one may ask how judicial systems approach the case of bankruptcy. Failing Company Model (FCM) (Blum, 1974a) is the only solid argument developed for the failing firms under the name of Failing Company Doctrine (Blum, 1974b) which is formulated originally by Supreme Court in USA in merger of International Shoe with the W. H. McElwain Company on May 11, 1921. As Blum (1974a) indicates that FCM is one of the possible defenses to a merger prosecution for preventing antitrust laws. This is the case *'when one of two merging companies is failing and the failing company receives no offer to merge from a company with which a merger would have been legal. The FCM was constructed to aid in assessing the probability of business failure, where failure is defined in accordance with the meaning courts have imputed to it in the context of this antitrust defense.*' (Blum, 1974a: 1). The logic and reason behind the doctrine is to sustain continuousness of the competition and to prevent all stakeholders from the likely harm caused by allowing a failing and presumably weak but still intact firm to merge with a competitor.

Theoretical foundation of FCM is based on a theory of the various ways impending failure might be symptomized by accounting data. '*A theory of symptoms of failure focuses on how the behavior of fundamental economic variables would be expected to be portrayed in financial statement*' (Blum, 1974a: 3). However, there is no underlining explanation behind what so called *'theory of symptoms'* in Blum (1974a; 1974b). This is, in fact, what Blum (1974b) describes for variables selected to estimate of FCM. He underlined the fact that there is no conceptual foundation among the variables used to estimate. Therefore, he assumed that there is a little reason to expect a sustainable correlation between independent variables and the event to be predicted.

Despite the fact that Blum (1974b) does not follow a conceptual framework for variables selected to estimate FCM, He mainly focuses on the cash flow and profitability concepts and proposes the following linkages. Other things being equal, one would expect that probability of failure is more likely (Blum, 1974b: 4):

1. the smaller the reservoir (a larger reservoir would be a better buffer against uncertainties),
2. the smaller the inflow of resources from operations in both the short- and long-run,
3. the larger the claims on the resources by creditors,
4. the greater the outflow of resources required by the operation of the business,
5. the more highly variable are earnings and claims against resources, represented both by outflows to maintain current operations and by obligations to creditors (the less variable are inflows and outflows, the more likely that future events can be predicted), or
6. the more "failure-prone" the industry locations of a firm's business activities are expected to be (certain industries at specified times- such as automobile manufacturing in the early twentieth century or prefabricated home construction in the early 1960s-are characterized by a higher frequency of failures than other industries-such as automobile or steel manufacturing in the 1960s).

Table 34: Failing Company Model

I. Liquidity	A: Short Run Liquidity	Flow	1. The Quick Flow Ratio[a]
		Position	2. Net Quick Assets / Inventory
	B: Long Run Liquidity	Flow	3. Cash Flow / Total Liabilities
		Position	4. Net Worth at Fair Market Value / Total Liabilities[b] 5. Net Worth at Book Value / Total Liabilities
II. Profitability			6. Rate of Return to common stockholders who invest for a minimum of three years[c]
III. Variability			7. Standard Deviation of net Income over a period
			8. Trend breaks for Net Income[d]
			9. Slope for net Income[e]
			10-12. Standard Deviation, Trend Breaks and Slope of the Ratio, net quick assets to inventory; (variables 10,11,12 are only used at the first and second year before failure)

Note: Blum (1974: 16) [a] Cash + Notes Receivable +Market Securities + (Annual Sales /12)/(Cost of Goods Sold – Depreciation Expense + Selling and Administrative Expense + Interest)/12; [b] Fair market value was measured by the harmonic mean of the bounds to the range of stock prices during a year. The implicit weighting system of the harmonic mean is inverse to the size of the observation (reciprocal of the arithmetic average of reciprocal). Thus speculative upsurge in market value will not be as influential as in the case of the arithmetic mean; [c] The market rate of return accrues to a common stockholder who bought his shares at an average price at beginning of given time span (e.g., from the fifth to the first year before failure) and sold them at an average price during the last year of the span. The rate of return is based on the stockholder’s gain or loss and cash dividend received, all adjusted for temporal location by present value analysis. The internal rate of return to an investor and all variables using net worth at fair market value were adjusted for capital changes. To compare entities more nearly similar, shares issued in mergers or offered to the public were added to prior totals of shares outstanding, adjusted for stock splits and dividends; [d] A trend break is defined as any performance by a variable loss favorable in one year than in the preceding year, such as a decline in income from $10000 to $1000 from year three to year four before failure; [e] Slope of a trend line fitted to the group of observations by the method of least square.

FCM is constructed on three factors: (i) Liquidity, (ii) Profitability and (iii) variability. These are assumed to be common denominators in the cash flow framework. The *"quick flow"* ratio relates reservoir size and resource inflow to resource outflow. Net quick assets/inventory indicates the relationship of both current liabilities (short- term resource claims) and inventory (relatively illiquid component of the reservoir) to the highly liquid quick assets (cash and equivalents, plus accounts and notes receivable). Cash flow/total liabilities relates resource inflow to total claims; both of the net worth measures relate reservoir size to total claims. The profitability measure, rate of return to common stockholders, reflects all of the elements of the cash-flow framework. The last six variables indicate variability and trend of resource inflow (net income) and of the short-term liquidity indicator and net quick assets/inventory (Blum, 1974a: 4).

The variables set depicted in Table 34 are used to discriminate the failing and non-failing firms through Multivariate Discriminant Analysis (MDA). The constructs (factors) and related variables are assumed to be the appropriate discriminators in predicting bankruptcy. The results show that 88,6 % of overall performance accuracy is achieved whereas the error rates become 15 % for type I and 10% for type II. Despite the fact that it is difficult to evaluate a model based on a single study, FCM contains some defects in its formulation. Firstly, there is no theoretical framework behind the constructs and related variables. This may lead many different alternatives for the variables set. Secondly, profitability, liquidity and variations of these factors are assumed to be the only indicator for default without mentioning the linkages among them. This may lead a weakness in the development of the model. If another construct is added to the model, there should not be a major increase in the efficiency of the model. However, there is no such attempt to test in empirical investigation carried out.

Table 35: Studies for Failing Company Model

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Blum (1974)	USA	Industrial	54-68	140(70F/70NF)/ 62	FR	FCM	MDA	-	88,60	15,00	10,00

Note: Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; MDA: Multivariate Discriminant Analysis; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; FCM: Failing Company Model.

1.2.2.5. Contingent Claim Models

Contingent claim as a term is a claim whose value depends on the value of another asset. In this respect, options are contingent claim on assets such as equities or commodities. *'In contrast to most quantitative credit models that rely on financial ratios to assess credit risk, some approaches extract default probabilities directly from traded price/spread data in the equity and bond markets'* (Kao, 2000: 56).

Contingent claim based modeling credit risk has resulted in many model variations, but all the models have three basic building blocks: '*the interest rate process, the default (or rating-transition) process, and the asset-recovery process'*. The last but not least element is that of correlations among these three processes. *'Despite its theoretical importance to a pricing model, specifying realistic correlations is difficult because of limited empirical data'* (Kao, 2000: 57).

Despite the fact that contingent claim based modeling can be structured within mainly three different blocks, these are further partitioned in many different ways. The following routes are examples of this feature (Kao, 2000: 57).

- *How the default risk is determined.*
  - *It may be derived from (i) the company's financial fundamentals or rating, (ii) a firm-value process and associated capital structure, (iii) a risk measure implied in credit spreads and market prices, or (iv) macroeconomic state variables.*
- *How the default intensity and recovery rate are defined. They may be endogenous or exogenous to the processes.*
- *How a process is presented. A process may involve continuous time or discrete time, be deterministic or stochastic, or incorporate diffusion or jump diffusion.*
- *How the elements of a process are implemented. The method may be a lattice (e.g., binomial), finite differencing, or simulated implementation.*

In related literature, these types of models are categorized into two main streams: Structural Form Models and Reduced Form Models[2]. Structural Form is also called the firm value based model due to its relation to capital structure of the

[2] The terms Structural and Reduced Form are coming from time series econometrics whereas the meanings are completely different. In the sense of econometrics, structural equation expresses the endogenous variable as being dependent on the current realization of another endogenous variable. Reduced-form equation expressing the value of a variable in terms of its own lags, lags of other endogenous variables, current and past values of exogenous variables and disturbance terms (Enders, 2004: 5).

firms. The main difference between Structural and Reduced From Model is the type of input variables used. Structural approach uses company-specific variables in the line with market based variables in way of treating debts as a contingent claim (option) in the firm's value. Structural approach tries to specify firm value process. Default risk is derived from the linkages between firm value and debt. On the other hand, Reduced Form Modeling ignores firm valuation and deal directly with market information. Default risk is derived from what is implied in market prices, credit spreads or rating transitions (Kao, 2000: 58).

The structural (firm-value approach) to credit-risk pricing was developed on the classic Black and Scholes (1973) option-pricing theory, according to which a defaultable debt is a contingent claim on the value of the company. As formulized by Merton (1974a) and extended by Black and Cox (1976) and Geske (1977), Structural Form assumes the debt of firm as a defaultable bond which can be viewed as a default-free bond minus a European put on the market value of the company. Since then, firm's equity represents a call option linked to the firm's value; a defaultable bondholder is essentially a writer of a compound option (Kao, 2000: 58).

The obvious critic regarding to Structural Form is focusing on difficulties in measuring firm value, especially if the companies are not quoted or thinly traded in stock exchanges. The problem becomes more crucial if underlying assets for the firm do not exist or unobservable (intangible). Kao (2000: 60) pointed out that *'Applicability of the structural approach to other areas, such as municipal bonds and sovereign debt, remains questionable. Moreover, the model requires numerous input data, including debt structures and contractual terms. Because most companies carry multiple liability claims, the structural model, in theory, should evaluate all debts simultaneously. As a result, the model is often considered computationally burdensome.'*

Reduced Form Modeling does not take the company's financial fundamentals into consideration and deals directly with market prices or spreads. The first attempt in this type of modeling area include Duffie and Singleton(1995), Jarrow and Turnbull (1995), Jarrow, Lando, and Turnbull (1997), and Lando (1994). In this approach, default risk is not related to company parameters as it is the case in Structural Form. In case of Reduced Form, the price of spread of a defaultable bond is directly related to a risk-free bond through default and recovery rates that are defined exogenously. Credit term structure under this approach is taken directly from market data rather than derived from a company's financial fundamentals or macroeconomic factors. This way of modeling is considered mathematically more tractable whereas it is less intuitive than the Structural Form in terms of corporate credit fundamentals (Kao, 2000: 60).

Reduced Form Modeling is directly linked to traded debt instruments and their market data. Therefore, there is a certain difficulty in applying this approach on private debt and commercial loans. Kao (2000: 61) highlights this weakness that *'most of the models exclusively use aggregate market or sector data about default rates, the default term curve, the rating-transition matrix, and the recovery rate. Thus, company-specific risk is not evaluated directly and financial fundamentals are essentially ignored. Like the structural pricing approach, the reduced-form model lacks extensive empirical study, especially for individual corporate bonds.'*

Despite the fact that both types of models have important pitfalls, Bohn (2000: 55) stated that *'while reduced-form models are likely to fit better any particular set of credit spread data (including data full of noise) than structural models, they break the link between the economics of firm behavior and the event of default. Reduced-form models take the economics out of the risky debt valuation problem.'*

In the context of the thesis, reduced form models are excluded to mention for the fact that they have no linkage with firm fundamentals. Therefore, the first form of structural model is briefly evaluated. The Black-Scholes (BS) (1973) and Merton (1974a) contingent claims model is used to value the liabilities and equity of a firm. Under this theory the equity of a firm is considered a European call option on the value of the firm. The conventional assumptions of the contingent claims literature are as follow:

(A.l) Capital markets are perfect, with no transaction costs or taxes and equal access to information.

(A.2) Trading is continuous.

(A.3) The value of the firm, V, follows a Wiener process.

(A.4) The instantaneous mean and variance of return on firm value are constant.

(AS) The term structure of interest rates is nonstochastic (the instantaneous interest rate is a known function of time).

(A.6) Management acts to maximize shareholder wealth.

(A.7) The absolute priority rule is applied in bankruptcy states.

(A.8) No new securities besides common equity can be issued when debt is outstanding.

(A.9) The firm can sell assets at market value at any time in order to make cash payments.

Under these assumptions, the value of equity, is a function of the underlying firm value, the instantaneous standard deviation of firm value, the face value of the debt (the exercise price), the time remaining until maturity of the debt, and the risk free rate of return (Trussel, 1997: 200).

Recall that equity holders have the residual claim on a firm's assets while being subject to limited liability. Merton (1974b) recognized that equity in a firm is equivalent to a long position in a call option on the firm's assets, and used this correspondence to derive the market value and volatility of the firm's underlying assets. More precisely, Merton used the Black and Scholes (1973) framework to solve for the asset value and volatility implied by the option price and the option price volatility. The asset value and the asset volatility can then be combined into a risk measure called distance to default that is directly related to the credit worthiness of the equity issuing firm.

At the heart of the Merton (1974b) model, there is a modified version of the Black–Scholes formula linking the market value of equity and the market value of assets as follows (Byström and Kwon, 2007: 510):

$$V_E = V_A N(d_1) - e^{-r(T-t)} D N(d_2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(11)$$

where

$N(.)$: the cumulative normal distribution

V_E : Market value of the firm's equity

V_A : Market value of the firm's assets

D : Total amount of the firm's debt

$T - t$: Time of maturity of the firm's debt

r : risk free interest rate

$$d_1 = \frac{\ln(V_A / D) + \left(r + \frac{1}{2}\sigma_A^2\right)(T-t)}{\sigma_A \sqrt{T-t}}$$

$$d_2 = d_1 - \sigma_A \sqrt{T-t}$$

Moreover, the linkage between the equity and asset volatility is decomposed as follows:

$$\sigma_E = \frac{V_A}{V_E} N(d_1)\sigma_A \quad \text{...(12)}$$

Where σ_E and σ_A are volatilities of the firm's equity and asset returns respectively. Solving non-linear system of equation (11) and (12) gives V_A and σ_A and the distance to default which is expressed as follows:

$$\gamma = \frac{\ln(V_A / D) + \left(r - \frac{1}{2}\sigma_A^2\right)(T-t)}{\sigma_A \sqrt{T-t}} \quad \text{...(13)}$$

This is simply the number of standard deviations that the firm value is from threshold point and the smaller the value of γ the larger the probability that the firm will default on its debt.

The primary concern of giving empirical examples related to Contingent Claim Approach is that the studies should be directly (or somehow) dealing with firm's default. As mentioned, these types of models are mainly working on traded debt instruments. Table 36 provides the summary of three empirical studies conducted through Structural Form Modeling. However, since there are many different forms of Structural Form Models, author uses different versions. Brochman and Turtle (2003), Benos and Papanastasopoulos (2007) and Su and Huang (2010) have commonly reported poor performance of the models they used in predicting firm's default. In addition, Brochman and Turtle (2003) did not report the Type I and Type II errors; Su and Huang (2010) did not report OPA.

However, Brochman and Turtle (2003: 511) claimed that implied failure probabilities dominate Z-scores (Altman, 1968) in most cases (85 % OPA against 75 % OPA). Benos and Papanastasopoulos (2007: 47) pointed out a very important concluding remarks regarding to their empirical investigation that '*financial ratios and accounting variables contain significant and incremental information; thus the risk neutral distance to default metric does not reflect all available information regarding the credit quality of a firm.'* Su and Huang (2010) tried to explain why their empirical investigation gives high Type I and Type II errors by underlying the fact that the prediction of non-failed firms should be more examined further than that of failed firms.

Table 36: Studies for Contingent Claim Models

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Brochman and Turtle (2003)	USA	Industrial	89-89	NA(NA-F/NA-NF)/NA	Mix	Contingent Claim	-	-	85,00	NA	NA
Benos and Papanastasopoulos (2007)	USA & Canada	Industrial	01-02	100(27F/73NF)/ NA	Mix	Contingent Claim	-	-	89,00	21,00	7,00
Benos and Papanastasopoulos (2007)	USA & Canada	Industrial	01-02	100(27F/73NF)/ NA	Mix	Contingent Claim	-	-	85,00	43,00	4,00
Benos and Papanastasopoulos (2007)	USA & Canada	Industrial	01-02	100(27F/73NF)/ NA	Mix	Contingent Claim	-	-	84,00	54,00	1,00
Su and Huang (2010)	Taiwan	Electronic	07-08	124(24F/100NF)/ NA	Mix	Contingent Claim	-	-	NA	42,83	22,48
Su and Huang (2010)	Taiwan	Electronic	07-08	124(24F/100NF)/ NA	Mix	Contingent Claim	-	-	NA	45,08	25,97

Note: Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms;

1.2.3. Non-Theory-based Models

Non-Theory based Models contain two categories: Statistical based Models and Artificially Intelligent based Models. Standard procedures of these two types of models involve examination of firms' data through various statistical and algorithm search in order to find patterns. The main argument proposed here is that the best available discriminating or classifying variables are assumed to be the predictors of defaults without relying on a theoretical justification. These models do not rely on a theoretical foundation when selecting the variables for prediction. The difference between these two types of models is that artificially intelligent models apply different sets of algorithms (neural networks, decision tress etc.) to classify or differentiate the bankrupt and non-bankrupt firms.

1.2.3.1. Statistical Based Models

Statistical based Models involve a lot of different applications in discriminating and classifying firms into default and non-default firms. Statistical based Models are proposed mainly to discriminate firms into default and non-default groups. In this process, scholars tried to decrease the numbers of variables used into the models via reducing the dimensionality without relying on any theoretical framework. Some of these applications were used more frequently than the others. Therefore, this section reviews the models relatively in details than those of relatively less applied. Univariate analysis was the first technique to differentiate the variables in bankruptcy prediction. This is a special reason behind starting with univariate analysis to review. Multiple Discriminant, Logit and Probit analysis are the applications that are used more frequently than the others. Linear Probabilistic Model, Cumulative Sum Partial Adjustment Model, Zero-Price Probability Model and Quantile Regression Approach are the other applications that are rarely used in bankruptcy prediction. The details of methodological aspects of these applications are ignored due to space limitations and scope of the thesis.

1.2.3.1.1. Univariate Analysis

The initial attempts to analyze financial ratios in the context of firm default are the studies of Beaver (1966; 1968) in which univariate analysis is conducted. The term univariate is used for the fact that the failure status of the firms are determined based on a single ratio. Beaver (1966; 1968) conduct his analysis on thirty ratios and called his analysis as the dichotomous classification test which aims to predict the failure status of a firm, based solely upon a knowledge of the financial ratios. Descriptive examination of ratios is carried out before conducting the test. This descriptive analysis is called profile analysis. In contrast to the profile analysis, univariate analysis is used as a predictive test.

Beaver (1966: 83) claimed that *the classification test is an intuitively appealing approach. It closely resembles the decision-making situation facing many users of ratios*. It is given an example that a bank's lending decision can be viewed as a dichotomous choice of accepting or rejecting a loan application. In this case, the object of the ratio analysis would be to classify firms as acceptable or not. However, the ultimate decision is not ending to accept or reject the proposal. The bank must also decide how much to loan and at what rate to loan, if the firm is classified as acceptable. As illustrated, the example does show the parallel between certain kinds of decisions and the classification test. The test proposed by Beaver (1966) also provides a convenient sifting device for selecting the six ratios that may serve as a focus for analyzing firm default.

Beaver (1966: 84) did not report analytical description of the test he proposed, instead, he qualitatively explain the methods applied as follows:

> *The classification test makes a dichotomous prediction-that is, a firm is either failed or non-failed. In order to make the predictions, the data are arrayed (i.e., each ratio is arranged in ascending order). The array of a given ratio is visually inspected to find an optimal cutoff point-a point that will minimize the per cent of incorrect predictions. If a firm's ratio is below (or above, as in the case of the total debt to total-assets ratio) the cutoff point, the firm is classified as failed. If the firm's ratio is above (or below, for the total debt to total-assets ratio) the critical value, the firm is classified as non-failed.*

Empirical studies carried out through univariate analysis are not many. Two treatments are carried by Beaver (1966; 1968) in which he reported 87% OPA. This result seems to be very promising whereas the critics are centered on the heart of analysis. In case of univariate analysis, naturally, the multidimensional effects among variables are totally ignored. This means that interrelations of two ratios are not taken into account when the classification is made. This creates a serious problem.

Casey and Bartczak (1984) uses three cash flow based ratios in classifying default firms by univariate analysis and reported that 60% OPA which is not promising or even worse ever. However, their study is an example of showing that how much multivariate effect may change the results. In applying multiple discriminant analysis, they reported much better results in terms of OPA (86%).

The study of Hu and Ansell (2007) shows an empirical investigation so called Bayesian probability in predicting default firms which is also suggested by Beaver (1966). However, Beaver (1966) did not empirically evaluate this technique. Hu and Ansell (2007) use the technique primarily suggested in the form of univariate analysis, in way of containing more than one variable. Despite this difference, the result reported in this section. Hu and Ansell (2007) reported almost 91% OPA for the sample they analyzed. The weakness part in Bayesian probability analysis in this context is that the ratios do influence the results so that it is mainly sample dependent. When they work with a different set of sample, they may see that the different value of ratios will produce different probabilities.

Table 37: Studies for Univariate Analysis

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Beaver (1966)	USA	Mix Industrial	54-64	158(66F/92NF)/ NA	FR	-	Univariate	-	87,00	22,00	5,00
Beaver (1968)	USA	Mix Industrial	54-64	158(79F/79NF)/ NA	FR	-	Univariate	-	87,00	22,00	NA
Casey and Bartczak (1984)	USA	Mix Industrial	71-82	290(60F/230NF)/NA	FR	CASH	Univariate	-	60,00	10,00	47,00
Hu and Ansell (2007)	USA	Retail	94-02	246(51F/195NF)/ NA	Mix	-	Univariate	-	91,06	NA	NA

Note: Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio;

1.2.3.1.2. Multiple Discriminant Analysis

Discriminant analysis that can be applied in the form of liner and quadratic is a multivariate statistical technique. The technique is used extensively in a large number of studies for predicting firm default. This multivariate technique differentiates firms by independent variables which characterize each group membership. Two-group or multi-group differentiation can be estimated. In case of two group populations (default and non-default firms), it is assumed that the *'independent variables are distributed within each group according to a multivariate normal distribution with different means but equal dispersion matrices.'* The main aim of the technique is *'to obtain the linear (or quadratic) combination of the independent variables that maximizes the variance between the populations relative to within group variance'* (Dimitras, et al., 1996: 498). Discriminant (linear) function can take the following form:

$$Z_i = a_0 + a_1 x_{i1} + a_2 x_{i2} + a_3 x_{i3} + ... + a_n x_{in} \text{ ....(14)}$$

where Z_i is the Z-score for firm *i* and $x_{i1}, x_{i2}, ..., x_{in}$ are the *n* independent variables for firm *i*.

A cut-off score (a threshold that divided firms into groups) is calculated according to '*the a-priori probabilities of group membership'* and '*the costs of misclassification*.' Based on its Z-score and the cut-off score, a firm is classified to the default or the non-default group. If the assumption of equality of dispersion matrices is not satisfied, then quadratic discriminant analysis instead of linear ones may be advantageous (Dimitras, et al., 1996: 499).

Multivariate Discriminant Analysis (MDA) is a statistical technique used to '*classify an observation into one of several a priori groupings dependent upon the observation's individual characteristics'* (Altman, 1968:591). Altman (1968) applied MDA in his groundbreaking article in which firms were classified into bankrupt or non-bankrupt groups. In case of MDA, the primary stage is to define the groups.

After the groups are established, data are collected for the objects in the groups; MDA then attempts to derive a linear combination of these characteristics which "best" discriminates between the groups. Altman (1968) used linear form of MDA in his article in 1968 whereas he proposed a different version of discriminant function which is derived in the form of quadratic MDA in his ZETA model (Altman, et al., 1977).

Altman so called Z-score model is depicted as follows:

$$Z = 0.021X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \quad (15)$$

where, X_1:Working Capital / Total Assets; X_2: Retained Earnings / Total Assets; X_3 : EBIT / Total Asset; X_4: Market Value Equity / Total Asset and X_5: Sales / Total Asset

Altman (1968), derived (15) based on 33 manufacturing firms failed in the period 1946-1965 matched by industry and asset size to 33 non-failed firms. The rational behind using these ratios is related to their popularity and potential relevancy rather than a sound theoretical background. Altman, et al. (1977) proposed a different discriminant model for the same problem in which the model is derived by using quadratic MDA (so called ZETA Model). In this model, variables are EBIT / Total Assets, Standard Error of Estimate of EBIT/TA (normalized), EBIT / Total Interest Payments, Retained Earnings / Total Assets, Current Assets / Current Liabilities, Common Equity / Total Capital and Total Assets. In deriving this study, a sample of 53 manufacturing and retailing firms that went bankrupt in the period of 1969-1975 was selected. The default firms were matched by industry group and year of data to 58 non-bankrupt firms.

Eisenbeis (1977) summarized 7 main problems in the application of MDA: (i) *violation of the assumption of multivariate normal distribution of the variables;* (ii) *use of linear instead of quadratic discriminant functions when the group dispersions are unequal;* (iii) *unsuitable interpretation of the role of the independent variables;*

(iv) *reduction in dimensionality;* (v) *group definition;* (vi) *inappropriate choice of a priori probabilities and/or costs of misclassifications;* (vii) *problems in estimating classification error rates to assess the performance of the models.*

Strictly speaking, what a z-score model asks is '*does this firm have a financial profile more similar to the failed group of firms from which the model was developed or the solvent set?*' As such, it is descriptive in nature. The z-score model is made up of a number of fairly conventional financial ratios measuring important and distinct facets of a firm's financial profile, synthesized into a single index. The model is multivariate, as are a firm's set of accounts, and is doing little more than reflecting and condensing the information they provide in a succinct and clear manner (Agarwal and Taffler, 2007: 297).

The z-score is primarily a readily interpretable communication device, using the principle that the whole is worth more than the sum of the parts. Its power comes from considering the different aspects of economic information in a firm's set of accounts simultaneously, rather than one at a time, as with conventional ratio analysis. The technique quantifies the degree of corporate risk in an independent, unbiased and objective manner. This is something that is difficult to do using judgment alone. Clearly, to be of value, a z-score model must demonstrate true ex ante predictive ability (Agarwal and Taffler, 2007: 297).

Z-score models are also commonly censured for their perceived lack of theory. For example, Gambling (1985: 420) entertainingly complains that (Agarwal and Taffler, 2007: 298):

> *'… this rather interesting work (z-scores) … provides no theory to explain insolvency. This means it provides no pathology of organizational disease … Indeed, it is as if medical research came up with a conclusion that the cause of dying is death … This profile of ratios is the corporate equivalent of … ''We'd better send for his people, sister'', whether the symptoms arise from cancer of the liver or from gunshot wounds.'*

Despite usefulness of Z-score like models in practice, the critics are centered on lack of theory behind. As Gambling (1985) and Agarwal and Taffler (2007) among others, mentioned, lack of theory is not a little issue that can be skipped. The reason is simply proved by Altman by which he introduces a different discriminant models in two papers. The point here is that there might be a different model can be derived, if someone works on a different set of samples and different time periods which are the case in the studies depicted in Table 38.

Some scholars realized this important weakness and hence follow a theoretical road map before conducting MDA for classifying firms into default and non-default groups. These theoretical frameworks are those explained in above section such as Gambler's Ruin Theory, Failing Company Model, Balanced Sheet Decomposition Model, and Cash Management Theory. However, as explained, these theoretical frameworks have their own pitfalls which create a different source of weaknesses.

Table 38: Studies for Multiple Discriminant Analysis

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Altman (1968)	USA	Manufacturing	46-65	66(33F/33NF)/25	FR	-	MDA	-	95,00	6,00	3,00
Edmister (1972)	USA	Small Bus.	54-69	82(42F/42NF)/ NA	FR	-	MDA	-	93,00	15,00	0,00
Deakin (1972)	USA	NA	64-70	68(34F/34NF)/ NA	FR	-	MDA	-	87,00	14,00	13,00
Blum (1974)	USA	Industrial	54-68	140(70F/70NF)/ 62	FR	FCM	MDA	-	88,60	15,00	10,00
Altman et al. (1977)	USA	Manufacturing and retailing	69-75	111(53F/58NF)/111	FR	-	MDA	-	92,80	3,80	10,30
Moyer (1977)	USA	NA	65-75	48(23F/25NF)/111	FR	-	MDA	-	88,10	5,00	18,00
Moyer (1977)	USA	NA	65-75	48(23F/25NF)/111	Mix	BSDM	MDA	-	85,19	3,00	5,00
Santomero and Vinso (1977)	USA	Banks	65-74	NA (NAF/NANF)/ NA	FR	Gambler's Ruin	MDA	-	97,19	NA	NA
Norton and Smith (1979)	USA	Industrial	71-75	51 (23F/28NF)/ NA	FR	-	MDA	-	93,00	14,80	0,00
Norton and Smith (1979)	USA	Industrial	71-75	50 (22F/28NF)/ NA	FR	-	MDA	-	93,00	11,10	3,30
Sharma and Mahajan (1980)	USA	Industrial	70-76	72(36F/36NF)/ 72	FR	-	MDA	-	91,67	NA	NA
Dambolena and Khoury (1980)	USA	Industrial	69-75	46 (23F/23NF)/ 46	FR	-	MDA	-	94,40	11,00	0,00
Taffler (1982)	UK	Industrial	68-73	68(23F/45NF)/43	FR	-	MDA	-	98,50	1,00	0,00
Tsffler (1983)	UK	Industrial	69-76	92(46F/46NF)/46	FR	-	MDA	-	97,80	4,30	0,00
Booth (1983)	Australia	Industrial	64-79	34(17F/17NF)/16	Mix	BSDM	MDA	-	85,00	18,00	12,00
El Hennawy and Morris (1983)	UK	Mix Industrial	60-71	44(22F/22NF)/44	Mix	-	MDA	-	98,00	5,00	0,00
Takahashi, et al. (1984)	JAPAN	NA	61-77	72 (36F/40NF)/ 48	FR	-	MDA	-	94,40	2,80	8,30
Casey and Bartczak (1984)	USA	Mix Industrial	71-82	290(60F/230NF)/NA	FR	CASH	MDA	-	86,00	17,00	13,00
Appetiti (1984)	Italy	Manufacturing	78-80	50 (25F/25NF)/ NA	MIX	-	MDA	-	84,00	16,00	16,00
Izan (1984)	Australia	Industrial	63-79	99 (51F/48NF)/ 10	FR	-	MDA	-	91,90	5,90	10,40

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; FCM: Failing Company Model; BSDM: Balanced Sheet Decomposition Model; CMT: Cash Management Theory; MDA: Multivariate Discriminant Analysis. Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio;

Table 38: Studies for Multiple Discriminant Analysis (cont.)

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Mensah (1984)	USA	Manufacturing	72-80	84 (42F/42NF)/ NA	FR	-	MDA	-	88,00	19,04	4,70
Mensah (1984)	USA	Manufacturing	72-80	62 (31F/31NF)/ NA	FR	-	MDA	-	85,50	16,13	13,01
Micha (1984)	France	Industrial	75-80	83 (NAF/NANF)/ 264	MIX	-	MDA	-	81,30	NA	NA
Casey and Bartczak (1985)	USA	Industrial	71-82	290 (60F/230NF)/ NA	FR	-	MDA	-	87,00	13,00	13,00
Frydman et al. (1985)	USA	Manufacturing and retailing	71-82	200(58F/142NF)/NA	FR	-	MDA	-	72,00	9,00	19,00
Lo (1986)	USA	Industrial	75-83	76 (38F/38NF)/ NA	FR	-	MDA	-	NA	NA	NA
Gombola, et al. (1987)	USA	Manufacturing and retailing	70-82	154(77F/77NF)/NA	FR	-	MDA	-	89,00	NA	NA
Aziz, et al. (1988)	USA	Mix Industrial	71-82	98(49F/49NF)/NA	FR	-	MDA	-	88,80	NA	NA
BarNiv and Hershbarger (1990)	USA	Life Insurance	75-85	56 (28F/28NF)/ 62	FR	-	MDA	-	89,30	14,30	7,10
BarNiv and Hershbarger (1990)	USA	Life Insurance	75-85	56 (28F/28NF)/ 62	FR	-	MDA	-	89,30	10,70	10,70
Tam and Kiang (1992)	USA	Banks	85-87	118 (59F/59NF)/ NA	FR	-	MDA	-	89,00	0,00	22,00
Coats and Fant (1993)	USA	Mix Industrial	70-89	141(47F/94NF)/141	FR	-	MDA	-	87,90	36,20	0,00
Altman et al. (1994)	Italy	Industrial	85-92	1108(404F/404NF)/300	FR	-	MDA	-	92,80	NA	NA
Back et al. (1996)	Finland	Mix Industrial	86-89	74(37F/37NF)/NA	FR	-	MDA	-	85,14	13,51	16,22
Begley, et al. (1996)	USA	Industrial	80-89	1365 (65F/1300NF)/ NA	FR	-	MDA	-	78,40	21,50	21,60
Jo et al. (1997)	Korea	Mix Industrial	91-93	544(272F/272NF)/482	FR	-	MDA	-	82,22	NA	NA
Pompe and Feelders (1997)	Belgium	Construction	88-94	288(144F/144NF)/288	FR	-	MDA	-	70,00	NA	NA
Varetto (1998)	Italy	Industrial	82-95	3840(1920F/1920NF)/898	FR	-	MDA	-	95,10	NA	NA
Yang et al. (1999)	USA	Oil and gas ind.	84-89	84(25F/59NF)/ 38	FR	-	MDA	-	87,00	13,00	12,00
Dimitras et al. (1999)	Greece	Mix Industrial	86-93	80(40F/40NF)/ 38	FR	-	MDA	-	90,00	7,50	12,50

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; FCM: Failing Company Model; BSDM: Balanced Sheet Decomposition Model; CMT: Cash Management Theory; MDA: Multivariate Discriminant Analysis. Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio;

Table 38: Studies for Multiple Discriminant Analysis (cont.)

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Kahya and Theodossiou (1999)	USA	Manufacturing and retailing	74-91	189(72F/117NF)/NA	FR	-	MDA	-	77,80	31,00	17,00
Sung et al. (1999)	Korea	Manufacturing	91-97	78(29F/49NF)/ 78	FR	-	MDA	-	82,10	31,00	10,20
Lennox (1999)	UK	Industrial	87-96	6418 OBS(90F/6326NF)/3288OBS	FR	-	MDA	-	NA	13,33	30,38
Zopounidis and Doumpos (1999)	Greece	Mix Industrial	86-93	80(40F/40NF)/ 38	FR	-	MDA	-	90,00	12,50	7,50
Beynon and Peel (2001)	UK	Manufacturing	NA	60(30F/30NF)/ 30	Mix	-	MDA	-	78,30	16,70	26,70
Shumway (2001)	USA	Industrial	62-92	3482(300F/3182NF)/ NA	FR	-	MDA	-	NA	NA	NA
Doumpos, et al. (2002)	Greece	Mix	96-97	200(100F/100NF)/ 1211	FR	-	MDA	-	94,50	7,00	4,00
Brochman and Turtle (2003)	USA	Industrial	89-89	NA(NA-F/NA-NF)/NA	Mix	-	MDA	-	74,50	NA	NA
Li and Sun (2008)	China	Mix	00-05	270(135F/135NF)/ NA	FR	-	MDA	-	87,04	NA	NA
Sueyoshi and Goto (2009)	USA	Industrial	91-04	1081(130F/951NF)/ NA	FR	-	MDA	-	94,80	4,00	0,40
Min and Yeong (2009)	Korea	Mix	01.Nis	508(254F/254NF)/ NA	FR	-	MDA	-	70,20	NA	NA
Lin (2009)	Taiwan	Industrial	98-05	254(96F/158NF)/ NA	FR	-	MDA	-	84,30	18,70	13,80
Jardin and Severin (2011)	France	Mix	95-03	880(440F/440NF)/ NA	FR	-	MDA	-	81,93	NA	NA

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; FCM: Failing Company Model; BSDM: Balanced Sheet Decomposition Model; CASH: Cash Management Theory; MDA: Multivariate Discriminant Analysis. Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; OBS: Observation Based Sample.

1.2.3.1.3. Logit Model

Despite the fact that MDA is one of the most applied statistical methods to classify firms into predetermined groups and estimate the associated probabilities of default, it has some assumptions that scholars worth mentioning to overcame. In doing this, logit analysis was chosen to avoid some fairly well known problems associated with MDA. Ohlson (1980: 112), one of the first scholar who applied logit model in case of firm default, stated some of these problems: (i) *There are certain statistical requirements imposed on the distributional properties of the predictors for MDA.* It is assumed in case of MDA that the variance-covariance matrices of the predictors should be the same for both groups (failed and non-failed firms); moreover, a requirement of normally distributed predictors certainly mitigates against the use of dummy independent variables, and (ii) *The output of the application of an MDA model is a score which has little intuitive interpretation, since it is basically an ordinal ranking (discriminatory) device.* For decision problems such that a misclassification structure is an inadequate description of the payoff partition, the score is not directly relevant. If, however, prior probabilistic of the two groups are specified, then it is possible to derive posterior probabilities of failure.

Conducting logit analysis, essentially avoids all of the problems discussed with respect to MDA. The fundamental estimation problem can be reduced simply to the following statement: *given that a firm belongs to some prespecified population, what is the probability that the firm fails within some prespecified time period?* No assumptions have to be made regarding prior probabilities of bankruptcy and/or the distribution of predictors. These are the major advantages. The statistical significance of the different predictors are obtained from asymptotic (large sample) theory (Ohlson, 1980: 112).

Logit analysis (logistic regression) is in many ways the natural complement of ordinary linear regression whenever the regressand is not a continuous variable but a state which may or may not hold, or a category in a given classification (Cramer, 2003: 1). If dependent variable takes the form of two outcomes, then it is called binary logistic regression. This regression equation can be depicted as follows (Gujurati, 2004: 596):

$$L_i = In\left(\frac{P_i}{1-P_i}\right) = Z_i \qquad \text{………………………(16)}$$
$$= \beta_1 + \beta_2 X_i$$

Where

$$P_i = E(Y = 1|X_i) = \frac{1}{1+e^{-(\beta_1+\beta_2 X_i)}} = \frac{1}{1+e^{-(Z_i)}} = \frac{e^z}{1+e^z} \text{ ……………………..(17)}$$

Hence, the probability of $1-P_i$ can be computed as;

$$1-P_i = \frac{1}{1+e^{Z_i}} \text{ ……………………………………..(18)}$$

Therefore, the odds ratio can be written as follows;

$$\frac{P_i}{1-P_i} = \frac{1+e^{Z_i}}{1+e^{-Z_i}} = e^{Z_I} \text{ ....(19)}$$

The estimation of parameters of Logit Model is carried out by the Maximum Likelihood Method. Since the data are micro, individual level, in the case of many studies depicted in Table 39, it is not possibly to conduct Ordinary Least Squares Method. Specification of dependent variable is binary as a default or non-default. It is assumed that there are several a priory selected independent variables to affect this probability.

As stated, logit analysis was first proposed for the prediction of business failure by Ohlson (1980). Ohlson selected 105 industrial firms failed in the period 1970-1976. All firms had to have been traded on the stock exchange during the three years before failure. The non-failed firms were selected at random. The goal was to construct three models able to predict firm failure up to three years prior to actual failure.

The main purpose of using logit analysis is to obtain better classification accuracy. Zavgren (1985) applied logistic function and use measures of entropy to assess the uncertainty of unexpected failure. Keasey and McGuinness (1990) developed their models with relevant variables in their application of UK firms. Keasey et al. (1990) extended binary logit model to a multi-logit model to classify firms according to the time. In this case, the aim was to classify firms into more than two groups and predict the default.

Results of logit analysis, however, are not far away from MDA as expected. While logit analysis seems preferable to MDA, because of the limitations of MDA, comparative studies between the two methods have not proved higher classification accuracy for studies depicted in Table 39.

Table 39: Studies for Logit Analysis

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Ohlson (1980)	USA	Industrial	70-76	2163 (105F/2058NF)/ NA	FR	-	LOGIT	-	96,12	NA	NA
Casey and Bartczak (1985)	USA	Industrial	71-82	290 (60F/230NF)/ NA	FR	-	LOGIT	-	88,00	37,00	6,00
Zavgren (1985)	USA	Mix Industrial	72-78	90(45F/45NF)/32	FR	-	LOGIT	-	90,00	NA	NA
Lo (1986)	USA	Industrial	75-83	76 (38F/38NF)/ NA	FR	-	LOGIT	-	NA	NA	NA
Peel, et al. (1986)	UK	Industrial	74-82	78 (34F/44NF)/ 24	FR	-	LOGIT	-	96,69	5,88	0,00
Lau (1987)	USA	Industrial	72-75	400 (350S0/20S1/15S2/10S3/5S4)/ 400	MIX	-	LOGIT	-	96,00	NA	NA
Aziz, et al. (1988)	USA	Mix Industrial	71-82	98(49F/49NF)/NA	FR	-	LOGIT	-	91,80	14,30	2,10
Dambolena and Shulman (1988)	USA	Industrial	77-80	50 (25F/25NF)/ 50	FR	-	LOGIT	-	92,00	2,00	14,00
Dambolena and Shulman (1988)	USA	Industrial	77-80	50 (25F/25NF)/ 50	FR	-	LOGIT	-	89,00	4,00	18,00
Aziz and Lawson (1989)	USA	Industrial	73-82	NA (NAF/NANF)/ 93	FR	-	LOGIT	-	91,80	14,30	2,10
Keasey and McGuinness (1990)	UK	Mix Industrial	76-84	86(43F/43NF)/30	FR	-	LOGIT	-	86,00	14,00	14,00
Keasey, et al. (1990)	USA	Industrial	76-86	80 (40F/40NF)/ 24	FR	-	LOGIT	-	86,00	14,00	14,00
Gilbert, et al. (1990)	USA	Industrial	72-83	260 (52F/208NF)/ 120	FR	-	LOGIT	-	88,50	32,70	6,20
Gilbert, et al. (1990)	USA	Industrial	72-83	260 (52F/208NF)/ 120	FR	-	LOGIT	-	81,90	69,20	5,30
BarNiv and Hershbarger (1990)	USA	Life Insurance	75-85	56 (28F/28NF)/ 62	FR	-	LOGIT	-	91,10	10,70	7,10
Platt and Platt (1990)	USA	Mix Industrial	72-86	114(57F/57NF)/114	FR	-	LOGIT	-	90,00	7,00	14,00
Theodossiou (1991)	Greece	Mix Industrial	80-84	363(54F/309NF)/138	FR	-	LOGIT	-	94,52	3,56	7,41
Tam and Kiang (1992)	USA	Banks	85-87	118 (59F/59NF)/ NA	FR	-	LOGIT	-	92,30	8,50	6,80

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; CASH: Cash Management Theory; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; S0: Financial Stability; S1: Omitting or Reducing Dividend Payment; S2: Technical Default and Default on Loan Agreement; S3: Protection under Chapter X or XI of the Bankruptcy Act; S4:Bankruptcy and Liquidation.

Table 39: Studies for Logit Analysis (cont.)

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Ward (1994)	USA	Non-financial	84-88	227(S0164/S122/S223/S318)/158	FR	-	LOGIT	-	92,00	NA	NA
Johnsen and Melicher (1994)	USA	Industrial	70-83	405 (112F/293NF)/ NA	FR	-	LOGIT	-	97,00	5,40	1,70
Back et al. (1996)	Finland	Mix Industrial	86-89	74(37F/37NF)/NA	FR	-	LOGIT	-	86,49	13,51	13,51
Begley, et al. (1996)	USA	Industrial	80-89	1365 (65F/1300NF)/ NA	FR	-	LOGIT	-	84,42	29,20	14,90
Latinen and Latinen (1998)	Finland	Mix Industrial	86-91	82(41F/41NF)/NA	Mix	-	LOGIT	-	80,49	17,07	21,95
Latinen and Latinen (1998)	Finland	Mix Industrial	86-91	82(41F/41NF)/NA	CF	CASH	LOGIT	-	58,54	41,46	41,46
Latinen and Latinen (1998)	Finland	Mix Industrial	86-91	82(41F/41NF)/NA	Mix	-	LOGIT	-	80,49	17,07	21,95
Dimitras et al. (1999)	Greece	Mix Industrial	86-93	80(40F/40NF)/ 38	FR	-	LOGIT	-	90,00	2,50	2,50
Kahya and Theodossiou (1999)	USA	Manufacturing and retailing	74-91	189(72F/117NF)/NA	FR	-	LOGIT	-	77,20	33,00	16,00
Lennox (1999)	UK	Industrial	87-95	6417 OBS(90F/6326NF)/3288OBS	FR	-	LOGIT	-	NA	6,67	30,29
Zopounidis and Doumpos (1999)	Greece	Mix Industrial	86-93	80(40F/40NF)/ 38	FR	-	LOGIT	-	90,00	7,50	12,50
Zhang, et al. (1999)	USA	Manufacturing	80-91	35(15F/20NF)/ NA	FR	-	LOGIT	-	77,27	18,18	27,27
Beynon and Peel (2001)	UK	Manufacturing	NA	60(30F/30NF)/ 30	Mix	-	LOGIT	-	80,00	16,70	23,30
Lin and Piesse (2004)	UK	Industrial	85-94	77(32F/45NF)/ 77	Mix	-	LOGIT	-	87,00	12,50	13,33
Shumway (2001)	USA	Industrial	62-92	3482(300F/3182NF)/ NA	FR	-	LOGIT	-	NA	NA	NA
Reynolds, et al. (2002)	Thailand	Financial	93-96	91(66F/35NF)/ NA	FR	-	LOGIT	-	67,90	NA	NA
Reynolds, et al. (2002)	Thailand	Financial	93-96	91(66F/35NF)/ NA	FR	-	LOGIT	-	67,60	NA	NA
Doumpos, et al. (2002)	Greece	Mix	96-97	200(100F/100NF)/ 1211	FR	-	LOGIT	-	98,00	2,00	2,00

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; CASH: Cash Management Theory; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; OBS: Observation Based Sample; S0: Healthy; S1: Forty Percent Reduction in Dividend; S2:Loan Default; S3:Default.

Table 39: Studies for Logit Analysis (cont.)

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Foreman (2003)	USA	Telecom	99-01	77(14F/63NF)/ NA	Mix	-	LOGIT	-	97,40	4,29	0,00
Claessens, et al. (2003)	East Asian Five Countries	Industrial	96-98	727(644FD/83B)/ NA	Mix	-	LOGIT	-	77,50	NA	NA
Koh and Low (2004)	USA	Industrial	80-87	100(50GC/50NGC)/ NA	FR	-	LOGIT	-	94,00	6,00	6,00
Charitou, et al. (2004)	UK	Industrial	88-97	102(51F/51NF)/ NA	FR	-	LOGIT	-	93,75	8,33	4,17
Charitou, et al. (2004)	UK	Industrial	88-97	102(51F/51NF)/ NA	FR	-	LOGIT	-	85,56	15,56	13,33
Tseng and Lin (2005)	UK	Industrial	85-94	77(32F/45NF)/ NA	FR	-	LOGIT	-	93,20	NA	NA
Hu and Ansell (2007)	USA	Retail	94-02	246(51F/195NF)/ NA	Mix	-	LOGIT	-	91,87	NA	NA
Li and Sun (2008)	China	Mix	00-05	270(135F/135NF)/ NA	FR	-	LOGIT	-	87,93	NA	NA
Premachandra et al. (2009)	USA	Industrial	91-04	1583(50F/1533NF)/ NA	FR	-	LOGIT	-	67,00	30,70	36,00
Min and Yeong (2009)	Korea	Mix	01.Nis	508(254F/254NF)/ NA	FR	-	LOGIT	-	71,20	NA	NA
Lin (2009)	Taiwan	Industrial	98-05	254(96F/158NF)/ NA	FR	-	LOGIT	-	86,40	21,98	8,28
Bhimani, et al. (2010)	Portugal	Mix	97-03	31025(1700F/29325NF)/NA	Mix	-	LOGIT	-	95,00	NA	NA
Su and Huang (2010)	Taiwan	Electronic	07-08	124(24F/100NF)/ NA	Mix	-	LOGIT	-	NA	43,70	20,09
Li and Miu (2010)	USA	Industrial	96-06	500(127F/373NF)/ NA	FR	-	LOGIT	-	81,75	NA	NA
Jardin and Severin (2011)	France	Mix	95-03	880(440F/440NF)/ NA	FR	-	LOGIT	-	81,14	NA	NA

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; CASH: Cash Management Theory; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; GC: going concern; NGC: Non-going concern.

1.2.3.1.4. Probit Model

Probit models are similar to the logit analysis. The main difference between them is that using cumulative standard normal distribution function for the calculation of probability in case of probit analysis, instead of logit function.

Zmijewski (1984) examines two potential biases in firm default literature caused by sample selection and data collection procedures by using probit analysis. These two biases defined in Zmijewski (1984) as choice-based sample bias and sample selection bias. The first is resulting from choosing firms based on dependent variables (default and non-default firms). Second results when only observations with complete data are used to estimate the model and incomplete data observations occur non-randomly. Both biases result in asymptotically biased parameter and probability estimates (Zmijewski, 1984: 77).

Gentry, et al. (1985) used a probit model to generate coefficients from the funds flow components and used these to predict the probability of failure or non-failure of the 66 industrial firms. Overall performance of the model estimated is 83,30 % (OPA). Type I and Type II errors are 21,20 % and 12,10 % respectively.

Skogsvik (1990) apply probit analysis to empirically test current cost accounting ratios regarding the ability to predict business failure for a sample of Swedish industrial companies. The reason behind using probit analysis used instead of MDA is that some assumptions were not satisfied by the data analyzed ((i) The distribution of the independent variables is multivariate normal in each group; and (ii) The group dispersion (variance-covariance) matrices are equal in the groups.)

Theodossiou (1991), Zopounidis and Doumpos (1999) and Doumpos, et al. (2002), applied probit analysis in the line with logit for developing a reliable failure prediction model for manufacturing firms in Greece.

Table 40: Studies for Probit Analysis

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
zmijewski (1984)	USA	Mix Industrial	72-78	840(40F/800NF)/ 841	FR	-	PROBIT	-	97,70	37,50	0,05
Gentry, et al. (1985)	USA	Industrial	79-81	66 (33F/33NF)/ NA	FR	-	PROBIT	-	83,30	21,20	12,10
Skogsvik (1990)	Sweden	Mix Industrial	66-80	379(51F/328NF)/NA	FR	-	PROBIT	-	84,00	NA	NA
Theodossiou (1991)	Greece	Mix Industrial	80-84	363(54F/309NF)/138	FR	-	PROBIT	-	93,71	5,18	7,41
Lennox (1999)	UK	Industrial	87-94	6416 OBS(90F/6326NF)/3288OBS	FR	-	PROBIT	-	NA	6,67	30,29
Zopounidis and Doumpos (1999)	Greece	Mix Industrial	86-93	80(40F/40NF)/ 38	FR	-	PROBIT	-	87,50	12,50	12,50
Reynolds, et al. (2002)	Thailand	Financial	93-96	91(66F/35NF)/ NA	FR	-	PROBIT	-	68,40	NA	NA
Doumpos, et al. (2002)	Greece	Mix	96-97	200(100F/100NF)/ 1211	FR	-	PROBIT	-	98,00	2,00	2,00
Lin (2009)	Taiwan	Industrial	98-05	254(96F/158NF)/ NA	FR	-	PROBIT	-	86,02	23,08	8,28

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; OBS: Observation Based Sample

1.2.3.1.5. Other Statistical Based Model

This section review several studies in which relatively rare used statistical methods applied to classify and predict firm default. Meyer and Pifer (1970) and Theodossiou (1991) made their investigation through Liner Probability Model in the line with the other techniques they employed. The linear probability analysis can be described as a regression model in which the dependent variable is dichotomous and takes the value of one for default firms and the value of zero for non-default firms. The model's regressors include financial variables with explanatory power with respect to failure.

Meyer and Pifer (1970) conducted their analysis on bank's failure by reporting 80% overall performance accuracy in sample of 30 default and 30 non-default banks. The holdout sample (test sample) consists of 18 banks. Theodossiou (1991) made the analysis on Greek firms on the unequal samples of 54 default and 309 non-default firms. Holdout sample contains 138 firms. In both studies, financial variables were used to predict default probabilities.

Tam and Kiang (1992) applied cluster analysis in which k Nearest Neighbor Algorithm is used which is a nonparametric method for classifying observations into one or several groups based on one or more quantitative variables along with Neural Networks and Decision Trees methods. They used bank data to estimate the failure whereas the results are not promising in terms of overall performance accuracy and Type I and II errors. Chen and Du (2009) conducted cluster analysis on Taiwanian firms in line with Neural Networks which does not produce promising overall performance accuracy in several treatments.

Kahya and Theodossiou (1999) stressed an important feature of financial variables used in distress models that is modeling distress model for multi-period analysis. This requires dealing with serial correlation problem and stationary of explanatory financial variables. Kahya and Theodossiou (1999: 323) applied a time series cumulative sum model for AMEX and NYSE manufacturing and retailing firms. They claimed that the model they proposed has *the ability to distinguish between changes in the financial variables of a firm that are the result of serial correlation and changes that are the result of permanent shifts in the mean structure* *of the variables due to financial distress.* In addition, their results show that time series cumulative sum model outperform that of Logit and Probit counterparts.

Shumway (2001) proposed a different technique to resolve the problems of single period model which is called hazard model. Hazard model allows scholars to incorporate time effect in line with other financial variables. Shumway (2001: 101) claimed that '*about half of the accounting ratios that have been used in previous models are not statistically significant'* when time effect taken into consideration. In addition to accounting based variables, Shumway (2001) realized that market size, past stock returns, and idiosyncratic returns variability are all strongly related to bankruptcy.

Su and Huang (2010) suggested that contingent claim based model has contained some drawbacks. This occurs as a result of measurability of asset value and market risk. In addition to this, the equity and asset values are non-negative in trading markets. However, Su and Huang (2010) claimed that *the loss for firms such as Lehman Brothers Corp. should be unlimited and the equity book value must turn out to be negative in accounting if the firms do not declare bankruptcy.* Under these circumstances, so called Zero-probability Model proposed by Fantazzini et al. (2008) is conducted by Su and Huang (2010) to predict firm default based on the input variables such as equity and bond prices. The results of this attempt in practice are disappointing by producing high error rates for the model.

Li and Miu (2010) used information for both accounting-ratio-based z-score and market-based distance-to-default (DD) statistics in a regression so called Bivariate Quantile Regression Model in which both the z-score and DD are used as explanatory variables. Quantile Regression is method to estimate model for conditional median function (it is mean function in Ordinary Regression).

Table 41: Studies for Other Statistical Based Model

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Meyer and Pifer (1970)	USA	Banks	48-65	60(30F/30NF)/18	FR	-	LPM	-	80,00	3,00	0,00
Theodossiou (1991)	Greece	Mix Industrial	80-84	363(54F/309NF)/138	FR	-	LPM	-	92,66	3,56	11,11
Tam and Kiang (1992)	USA	Banks	85-87	118 (59F/59NF)/ NA	FR	-	Cluster	-	59,50	37,30	23,70
Tam and Kiang (1992)	USA	Banks	85-87	118 (59F/59NF)/ NA	FR	-	Cluster	-	59,50	35,60	25,40
Kahya and Theodossiou (1999)	USA	Manufacturing and retailing	74-91	189(72F/117NF)/NA	FR	-	CUSUM	-	82,50	18,00	17,00
Shumway (2001)	USA	Industrial	62-92	3482(300F/3182NF)/ NA	FR	-	HAZARD	-	NA	NA	NA
Chen and Du (2009)	Taiwan	Industrial	99-06	68(34F/34NF)/ NA	Mix	-	Cluster	-	78,75	NA	NA
Chen and Du (2009)	Taiwan	Industrial	99-06	68(34F/34NF)/ NA	Mix	-	Cluster	-	67,86	NA	NA
Chen and Du (2009)	Taiwan	Industrial	99-06	68(34F/34NF)/ NA	Mix	-	Cluster	-	60,71	NA	NA
Su and Huang (2010)	Taiwan	Electronic	07-08	124(24F/100NF)/ NA	Mix	-	ZPP	-	NA	34,76	18,84
Li and Miu (2010)	USA	Industrial	96-06	500(127F/373NF)/ NA	FR	-	QRA	-	88,00	NA	NA

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; LPM: Linear Probabilistic Model; CUSUM Par.Adj.: Cumulative Sum Partial Adjustment; ZPP: Zero-Price Probability Model; QRA: (binary) Quantile Regression Approach.

1.2.3.2. Artificially Intelligent Models

This section reviews the applications that are considered within the category of artificially intelligent models. Recursive Partitioning Decision Trees, Case Based Reasoning, Neural Networks, Genetic Algorithms are reviewed relatively more in detail than the others due to their pioneering role in bankruptcy prediction. Multi-Criteria Decisions Aid, Rough Set, Preference Disaggregation Analysis, Decisions Trees, Sequential Minimal Optimization, Data Envelop Analysis and Self-Organizing Map are the other applications used in bankruptcy prediction whereas methodological details are not mentioned due to place limitation and scope of thesis.

1.2.3.2.1. Recursive Partitioned Decision Trees

The recursive partitioning decision trees (also known as recursive partitioning algorithm) is a non-parametric classification technique (Frydman, et al., 1985). The method starts with the sample of firms, their financial characteristics, the actual group classification, the prior probabilities and the misclassification costs. A binary classification tree is built, where a rule is associated to any node. These are, usually, univariate rules; that is a certain financial characteristic and a cut-off point that minimize the cost of misclassification for the rest of the firms. The risk of misclassification in any node t, R(t), is calculated as follows (Dimitrias et al., 1996: 505):

$$R(t) = (C_{21} + C_{12}) P_1 P_2 \frac{1}{p(t)} \frac{n_2(t)}{N_2} \frac{n_1(t)}{N_1} \quad \text{...(20)}$$

where;

N_1, N_2 : The total number of firms in each group (failed and non-failed firms)

$n_1(t), n_2(t)$: The total number of firms in each group on node t

C_{21} : Cost of misclassifying a firm in group 1 while it is in group 2

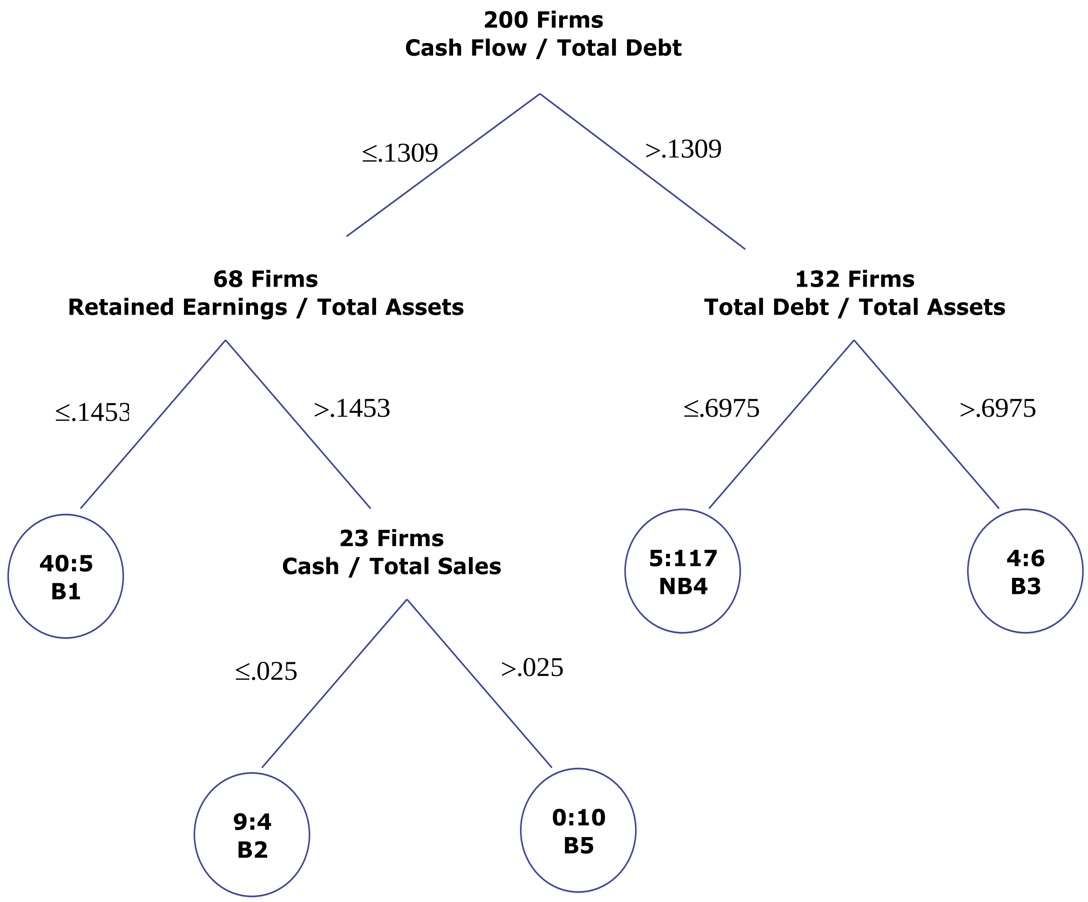
C_{12} : Cost of misclassifying a firm in group 2 while it is in group 1

P_1, P_2 : Prior probabilities of a firm to be a member of group 1 or group 2

$p(t)$: Probability of classifying a firm on node *t*.

After the classification tree is constructed, the risk of the final nodes and the risk for the entire tree are calculated. For the classification of any new object (firm), the object descends the tree and falls into a final node that identifies the group membership for the specific firm and the associated probability (Dimitrias et al., 1996: 505).

Figure 3: Recursive Partitioning Algorithm



Source: Frydman et al. (1985: 272). Classification tree based on financial data on 200 firms, prior probabilities of bankrupt and nonbankrupt groups (P1, P2) = (0.02, 0.98), and misclassification costs C12 = 50, C21 = 1. The firms with the value of the partitioning variable higher than the cutoff value go right. The terminal nodes are circled. The leftmost terminal node has 45 firms of which 40 are group 1 and five are group 2 firms. This is a group 1 (bankrupt) node which is denoted by letter B in the circle. The group 2 terminal nodes are denoted by letters NB. The numbers following the letters B and NB can be ignored in this section. This tree misclassifies five bankrupt and 15 nonbankrupt firms. Its resubstitution risk R(T) = 0.19.

Frydman et al. (1985) applied recursive partitioning decision trees algorithm in case of bankruptcy prediction and compared the results with multiple discriminant analysis. Figure 3 depicts a representative scheme of the technique conducted by Frydman et al. (1985). As noted, this algorithm successively classifies firms into two groups by 80% (OPA). In this case, Type I and II errors are 5% and 15% respectively. On the other hand, results coming from conducting MDA show 72% OPA, 9% Type I error and 19% Type II error (see Table 38).

Table 42 gives results of empirical investigations of Messeir and Hansen (1988), Tam and Kiang (1992), Pompe and Feelders (1997), Sung et al. (1999), Beynon and Peel (2001) and Hu and Ansell (2007) in using recursive partitioning decision trees for bankruptcy predictions. There is an important stage of developing prediction model. The first step is to train variables on the data which is called training sample. The second step is to test the selected variables or algorithm on the different set of data which called test sample or holdout sample. In case of applying artificially intelligent model in general, recursive partitioning algorithm in particular, there is always a difference between the performances of the selected variables among these two samples. The reported statistics in Table 42 are representing holdout sample statistics for one year before bankruptcy. Despite reporting the most successful statistics of this technique, it is seen that the results are mixed. On the other hand, this technique and others as well diminish the number of variables in prediction considerably. Hu and Ansell (2007) started with 170 measures and then reduce this number to just 5 measures based on the technique algorithm.

Table 42: Studies for Recursive Partitioning Decision Trees

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Frydman et al. (1985)	USA	Manufacturing and retailing	71-82	200(58F/142NF)/NA	FR	-	-	RPDT	80,00	5,00	15,00
Messeir and Hansen (1988)	USA	NA	75-76	32(16F/16NF)/16	FR	-	-	RPDT	100,00	NA	NA
Tam and Kiang (1992)	USA	Banks	85-87	118 (59F/59NF)/ NA	FR	-	-	RPDT	92,30	10,20	5,10
Pompe and Feelders (1997)	Belgium	Construction	88-94	288(144F/144NF)/288	FR	-	-	RPDT	70,00	NA	NA
Sung et al. (1999)	Korea	Manufacturing	91-97	78(29F/49NF)/ 78	FR	-	-	RPDT	65,50	63,30	19,50
Beynon and Peel (2001)	UK	Manufacturing	NA	60(30F/30NF)/ 30	Mix	-	-	RPDT	91,70	6,70	10,00
Hu and Ansell (2007)	USA	Retail	94-02	246(51F/195NF)/ NA	Mix	-	-	RPDT	92,68	NA	NA

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; RPDT: Recursive Partitioning Decision Trees.

1.2.3.2.2. Case Based Reasoning

Case-based reasoning (CBR) is a methodology for problem solving and decision-making in complex and changing business environments. Many CBR algorithms are derivatives of the k-nearest neighbor (k-NN) method, which has a similarity function to generate classification from stored cases. Several studies have shown that k-NN performance is highly sensitive to the definition of its similarity function. Many k-NN methods have been proposed to reduce this sensitivity by using various distance functions with feature weights (Park and Han, 2002: 1).

In business forecasting, managers often use the outcome of past analogous cases to predict the outcome of the current one. They (1) observe significant attributes in describing a case, (2) identify past cases similar in these attributes to the current case, and (3) predict the outcome of the current case based on those of the analogous cases identified through some mental simulation and adjustment. This process of forecasting can be termed forecasting-by-analogy. This process takes the following steps (Jo et al., 1997: 98):

(i) Identifying key attributes in identifying similar cases to predict the target variable;
(ii) accessing similarity and retrieving analogous cases;
(iii) generating a forecast through combining the similar cases selected.

For selecting key attributes the following model is calculated (Jo et al., 1997: 98):

$$Max\ Z = \frac{\sum_{j=1}^{m} p_{tj} x_j}{\sqrt{\sum_{j=1}^{m} \sum_{l=1}^{m} p_{jl} x_j x_l}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(21)$$

Where; m is the number of all independent (explanatory) attributes; p_{tj} is the correlation between the dependent (target) attribute and explanatory attribute *j*; p_{jl} is the correlation between explanatory attributes *j* and *l*; The variable x_j represents attribute *j* and has a binary value of 0 or 1; In the solution, if variable x_j is 1, then attribute *j* is selected; otherwise it is left out.

For selecting similarity measure the following Euclidean metric model is calculated (Jo et al., 1997: 99):

$$d_{ab} = \left[\sum_{j=1}^{m} w_j \left| x_{aj} - x_{bj} \right|^r \right]^{\frac{1}{r}} \text{..........}(22)$$

where d_{ab} the weighted distance measure between case *a* and *b*. Inter case similarity can be derived from the distance measure by equation (22). Jo et al. (1997: 99) used the modified exponential decay function to transfer distance into similarity which reflects the nonlinearity decreasing attribute. The equation takes the following forms:

$$s_{ab} = e^{-d_{ab}} \quad , \forall d_{ab} \text{..........}(23)$$

For generating a forecast by combining useful cases, the expected target value (TV) of the target case is calculated in the following form (Jo et al., 1997: 99):

$$\begin{aligned} E\left(TV_t \middle| \{S_{tb}\}_{t=1,n}\right) &= \sum_{b=1}^{n} P\left(TV_k = TV_b \middle| \{S_{tb}\}_{t=1,n}\right) TV_b \\ &= \sum_{b=1}^{n} \left(\frac{s_{tb}}{\sum_{t=1}^{n} S_{ti}} \right) TV_b \end{aligned} \text{..........}(24)$$

where *n* is the number of cases selected to generate the overall prediction; S_{tb} is the similarity between the new target case *t* and the base case *b*; and TV_b is the predicting (target) value of base *b*.

In the model, the similarity ratio (i.e. similarity of each base case with the new target case over the sum of the similarities of all the cases) is used as the case's weight in the combining process. Thus, the combined prediction (predicted target value) on the target value of the current case (TV_t) is represented as a linear combination of the target values of base cases, weighted in proportion to their relative similarities to the current case. The last step is to determine how many analogies should be combined to generate the system's prediction. This step is carried out in the following form (Jo et al., 1997: 99):

$$Max \;\; SF = \frac{\sum_{b=1}^{n} S_{tb} Z_b}{\left(\sum_{b=1}^{n} \sum_{q=1}^{n} S_{bq} z_b z_q \right)} \text{..(25)}$$

$$\begin{aligned} subject\ to\,(s.t.) \qquad & (s_{tb} - s_{tq}) x (z_b - z_q) \geq 0 \qquad \forall b \wedge a \\ & z_b = 0 \vee 1, \\ & 0 \leq \gamma \leq 0.5 \end{aligned}$$

where n is the number of cases selected to combine; s_{tb} is the similarity between the target case *t* and base case *b*; s_{bq} is the similarity between base *b* and base *q*; The variable z_b represents case *b* and has a binary value 0 or 1; In the solution, if variable z_b is 1, then base case *b* is selected; otherwise it is left out; The parameter γ is estimated in terms of cross-validation using the cases in the data set; The constraint $(s_{tb} - s_{tq}) x (z_b - z_q) \geq 0$ requires that a similar case always has priority over less similar ones in combination. The system combines the target values of the set of cases maximizing this function value.

Jo et al. (1997) compare three techniques for predicting defaults: Discriminant analysis, case based reasoning and neural networks. In case of case based reasoning, equal size of default and non-default firms were investigated. The performance of the technique (depicted in Table 43) is around 84% overall accuracy. However, the errors statistics were not reported in any studies in which case based reasoning is used as prediction technique.

Table 43: Studies for Case Based Reasoning

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Jo et al. (1997)	Korea	Mix Industrial	91-93	544(272F/272NF)/482	FR	-	-	CBR	83,79	NA	NA
Park and Han (2002)	Korea	Manufacturing	95-98	2144(1072F/1072NF)/ 320	Mix	-	-	CBR	84,52	NA	NA
Li and Sun (2008)	China	Mix	00-05	270(135F/135NF)/ NA	FR	-	-	CBR	90,30	NA	NA
Li and Sun (2008)	China	Mix	00-05	270(135F/135NF)/ NA	FR	-	-	CBR	90,07	NA	NA
Li and Sun (2008)	China	Mix	00-05	270(135F/135NF)/ NA	FR	-	-	CBR	88,00	NA	NA

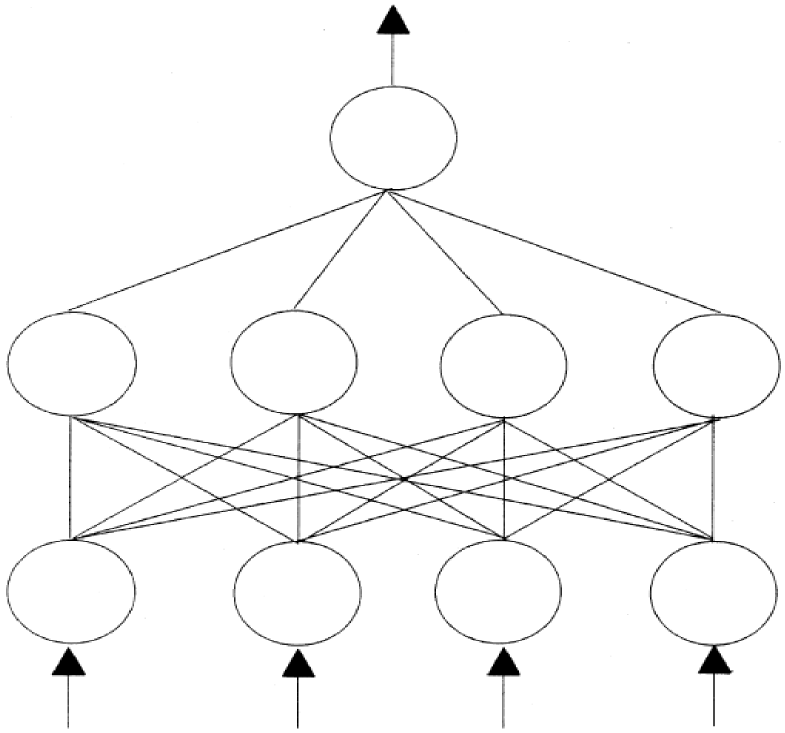
Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; CBR: Case Based Reasoning.

1.2.3.2.3. Neural Networks

Neural networks (usually referring to artificial) are non-parametric modeling technique which may perform any complex functions mapping with arbitrarily determined accuracy. Figure 4 depicts a representative demonstration of a neural network structure. There are three main elements taken place in a structure. These are *input layers* (in case of bankruptcy predictions, financial variables are input variables), *hidden layers* that identify the pattern in the data and *output layer* where the network produces the model solution. Each circle is called a *node* which receives an input signal from other nodes or external inputs and then after processing the signals locally through *a transfer function*, it outputs a transformed signal to other nodes or final result. The architecture of a neural network contains the number layers, the number of nodes and the connections among these nodes. The well-known type of a neural network is called *multi-layer perceptron* in which all nodes are designed and formulated in a *feed-forward* manner. That is the process of transformation of signals is starting from inputs nodes to output nodes. The figure 4 represents a multi-layer perceptron with one hidden layer and one output node (Zhang, et al., 1999; Tam and Kiang, 1992; Jo et al., 1997; Koh and Low, 2004; Charitou, et al., 2004; Lin, 2009).

In applying a neural network, the required estimation is carried out for weights of connections which contain relevant information for the outcome. These weights are determined as a result of a training algorithm. The training phase is a critical part in the use of neural networks. In usual application of neural networks in bankruptcy prediction, scholars divided their samples arbitrary into training and test samples. The types of training can be divided into two forms: supervised and non-supervised. The difference is that the network training is a supervised one in that the desired or target response of the network for each input pattern is always known a priori which is the case in bankruptcy prediction.

Figure 4: Multi-layer Perceptron



Source: Zhang et al., (1985: 18)

The process of activating a neural networks starts with introducing patterns to the input layers. The activation values of the input nodes are weighted and accumulated at each node in the hidden layer. The weighted sum is transferred by an appropriate transfer function into the node's activation value. It then becomes an input into the nodes in the output layer. Finally an output value is obtained to match the desired value. The aim of training is to minimize the differences between the ANN output values and the known target values for all training patterns (Zhang et al., 1985: 17).

Numerically, the process takes the following forms (Zhang, et al., 1999; Tam and Kiang, 1992; Jo et al., 1997; Koh and Low, 2004; Charitou, et al., 2004; Lin, 2009):

Let $x_1, x_2, ..., x_n$ be an n-vector of inputs (predictive variables), *y* be the output from the network, $w_{1,} w_2, ..., w_n$ be the matrices of linking weights from input to hidden layer and from hidden to output layer, respectively. Then a multilayer network takes a nonlinear model of the following form:

$$y = f_2\left(w_2 f_1\left(w_1 x\right)\right) \qquad (26)$$

where f_1 and f_2 are the transfer functions for hidden node and output node respectively. The common type of these functions in literature is that of the sigmoid function:

$$f_1\left(x\right) = f_2\left(x\right) = \left(1 + e^{-x}\right)^{-1} \qquad (27)$$

In the training sample, weight matrices in (26) in a way that an overall error measure such as the mean squared errors (MSE) or sum of squared errors (SSE) is minimized. MSE is defined as:

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\left(a_j - y_j\right)^2 \qquad (28)$$

where a_j and y_j represent the target value and network output for the *j*th training pattern respectively, and *N* is the number of training patterns. At this point of view, network training is an unconstrained nonlinear minimization problem. The most popular algorithm for training is the well-known *backpropagation* (Zhang, et al., 1999; Tam and Kiang, 1992). Tam and Kiang (1992) gives a description of this algorithm.

Scholars (Zhang, et al., 1999; Tam and Kiang, 1992; Jo et al., 1997; Koh and Low, 2004; Charitou, et al., 2004; Lin, 2009) generally claim that neural networks have advantages over standard statistical tools such as MDA and Logit Analysis applied in bankruptcy predictions in terms of having fewer assumptions. In terms of reporting overall performance accuracy (see table 44), it is not well clear that neural networks performs much better than those of its counter parts such as MDA and Logit.

Table 44: Studies for Neural Networks

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Tam and Kiang (1992)	USA	Banks	85-87	118 (59F/59NF)/ NA	FR	-	-	NN	92,00	5,00	11,00
Tam and Kiang (1992)	USA	Banks	85-87	118 (59F/59NF)/ NA	FR	-	-	NN	96,20	0,00	7,60
Coats and Fant (1993)	USA	Mix Industrial	70-89	141(47F/94NF)/141	FR	-	-	NN	95,00	10,60	2,10
Altman et al. (1994)	Italy	Industrial	85-92	1108(404F/404NF)/300	FR	-	-	NN	91,80	NA	NA
Jo et al. (1997)	Korea	Mix Industrial	91-93	544(272F/272NF)/482	FR	-	-	NN	81,52	NA	NA
Pompe and Feelders (1997)	Belgium	Construction	88-94	288(144F/144NF)/288	FR	-	-	NN	73,00	NA	NA
Yang et al. (1999)	USA	Oil and gas ind.	84-89	84(25F/59NF)/ 38	FR	-	-	NN	84,00	10,00	27,00
Zhang, et al. (1999)	USA	Manufacturing	80-91	176(88F/88NF)/ 44	FR	-	-	NN	88,64	NA	NA
Zhang, et al. (1999)	USA	Manufacturing	80-91	35(15F/20NF)/ NA	FR	-	-	NN	79,55	31,82	9,09
Koh and Low (2004)	USA	Industrial	80-87	100(47GC/53NGC)/ NA	FR	-	-	NN	91,00	6,00	12,00
Charitou, et al. (2004)	UK	Industrial	88-97	102(51F/51NF)/ NA	FR	-	-	NN	95,83	0,00	8,33
Shin, et al. (2005)	Korea	Manufacturing	96-99	2320(1160F/1160NF)/ NA	FR	-	-	NN	74,60	NA	NA
Shin, et al. (2005)	Korea	Manufacturing	96-99	2320(1160F/1160NF)/ NA	FR	-	-	NN	71,70	NA	NA
Hu and Ansell (2007)	USA	Retail	94-02	246(51F/195NF)/ NA	Mix	-	-	NN	90,24	NA	NA
Min and Yeong (2009)	Korea	Mix	01.Nis	508(254F/254NF)/ NA	FR	-	-	NN	78,10	NA	NA
Lin (2009)	Taiwan	Industrial	98-05	254(96F/158NF)/ NA	FR	-	-	NN	82,14	7,14	28,57
Chen and Du (2009)	Taiwan	Industrial	99-06	68(34F/34NF)/ NA	Mix	-	-	NN	90,74	NA	NA
Chen and Du (2009)	Taiwan	Industrial	99-06	68(34F/34NF)/ NA	Mix	-	-	NN	86,11	NA	NA
Chen and Du (2009)	Taiwan	Industrial	99-06	68(34F/34NF)/ NA	Mix	-	-	NN	82,41	NA	NA
Jardin and Severin (2011)	France	Mix	95-03	880(440F/440NF)/ NA	FR	-	-	NN	82,61	NA	NA

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; NN: Neural Networks; GC: Going Concern; NGC: Non-going Concern.

1.2.3.2.4. Genetic Algorithms

Genetic Algorithms (GA) are belonging to a special branch of Artificial Intelligence so called *Machine* or *Automatic Learning*. This branch comprises a rather broad spectrum of methodologies, such as *neural networks*, *pattern recognition* and *GA* (Varetto, 1998: 1422). GAs are stochastic search techniques that can search large and complicated spaces on the ideas from natural genetics and evolutionary principle. GAs are particularly suitable for multi-parameter optimization problems with an objective function subject to numerous hard and soft constraints (Shin and Lee, 2002: 3). GAs[3] use some type of fitness measure to evaluate the performance of each individual in a population. Fitness is typically determined from the objective function for some optimization problem, e.g., the number of correctly classified cases in a set of bankrupt and non-bankrupt firms (McKee and Lensberg, 2002: 439). Several scholars applied GA in predicting default (Varetto, 1998; Shin and Lee, 2002; McKee and Lensberg, 2002 among others).

GAs are distinct from many conventional search algorithms in the following ways (Karr, 1995; Shin and Lee, 2002: 3):

i. GAs consider not a single point but many points in the search space simultaneously reducing the chance of converging to local optima;

ii. GAs work directly with strings of characters representing the parameter set, not the parameters themselves;

iii. GAs use probabilistic rules, not deterministic rules, to guide their search.

GAs are used to derive a set of rules in predicting bankruptcy. The crucial stage is the step in which these rules are derived. Despite the fact that many experimental studies reported the usefulness of neural networks in classification studies, there is a major drawback in building and using a model in which '*the user cannot readily comprehend the final rules that NN models acquire'* (Shin and Lee, 2002). The primary advantage of GAs is that it is capable of extracting rules that are easy to understand for users like expert systems.

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[3] Genetic programming differs by using a subset of some programming language to represent the individual behavior rules (McKee and Lensberg, 2002:439).

In applying GAs, thresholds (cutoffs) levels for variables are determined. In case of having two variables such as quick ratio and a debt ratio, the final rule of the GA returns as follows (Shin and Lee, 2002: 4):

IF [debt ratio >1.50 and quick ratio <0.35] THEN Dangerous

However, in many cases, the simplistic rule like the above example is insufficient to model relationships among financial variables. Shin and Lee (2002) provide a structure that contains five conditions using ‘AND’ relations as follows:

IF [the VAR1 is GREATER THAN OR EQUAL TO (LESS THAN) C1,
AND the VAR2 is GREATER THAN OR EQUAL TO (LESS THAN) C2,
AND.....,
AND the VAR5 is GREATER THAN OR EQUAL TO (LESS THAN) C5]
THEN Prediction is Dangerous

If all of the five conditions are satisfied, then the model will produce ‘dangerous’ signal for an evaluated company. C1 to C5 denote the cutoff values which are found through genetic search process[4]. The cutoff values range from 0 to 1, and represent the percentage of the data source’s range. This allows the rules to refer to any data source, regardless of the values it takes on. Output of Shin and Lee (2002) study is depicted in Table 45.

[4] For the details of this algorithm, refers to references in Varetto, 1998; Shin and Lee, 2002; McKee and Lensberg, 2002.

Table 45: An Example of Rule Generations of Genetic Algorithms

Rule number	Description
Rule 1	IF Net income to stockholder's equity is less than 0.426 AND Liquidity ratio is less than 0.847 AND Current liability to total assets is less than 0.520 AND Stockholders' equity to total assets is less than 0.595 AND Financial expenses to sales is less than 0.665, THEN Dangerous
Rule 2	IF Net income to stockholder's equity is less than 0.520 AND Quick ratio is less than 0.697 AND Stockholders' equity to total assets is less than 0.590 AND Financial expenses to sales is less than 0.503, THEN Dangerous
Rule 3	IF Net income to stockholder's equity is less than 0.426 AND Liquidity ratio is less than 0.560 AND Retained earnings to total assets is greater than or equal to 0.082 AND Stockholders' equity to total assets is less than 0.590 AND Financial expenses to sales is less than 0.590, THEN Dangerous
Rule 4	IF Net income to stockholder's equity is less than 0.560 AND Quick ratio is less than 0.697 AND Retained earnings to total assets greater than or equal to 0.130 AND Stockholders' equity to total assets is less than 0.577 AND Financial expenses to sales is less than 0.515, THEN Dangerous
Rule 5	IF Net income to stockholder's equity is less than 0.560 AND Quick ratio is less than 0.697 AND Retained earnings to total assets is greater than or equal to 0.082 AND Stockholders' equity to total assets is less than 0.590 AND Financial expenses to sales is less than 0.520, THEN Dangerous

Source: Shin and Lee (2002:6)

Shin and Lee (2002) reported more than one rule as a result of GAs they applied. The logic behind their actions is that each of these rules produces high level of performance accuracy. The one reported in Table 45 shows that almost 80% OPA is achieved by conducting GAs in predicting bankruptcy. Similarly, McKee and Lensberg (2002) and Min and Jeong (2009) reported OPAs close to 80%. On the other hand, Back et al. (1996) and Varetto (1998) produce better OPAs which are higher than 90%. The justification of GAs can be hidden at the process of inputting the variables to the systems. The primarily scholars conduct some types of classical statistical tools (such as factor analysis or t-test univariate test) in order to decrease the dimensionality of the variables. This shows that pre-stage of conducting GAs requires a good knowledge of financial expertise.

Table 46: Studies for Genetic Algorithms

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	**Country**	**Firm Type**	**Years**	**ES/TS**	**Inde.Var.**	Theory Based	Statistic Based	AIES Based	**OPA**	**Type I Error (%)**	**Type II Error (%)**
Back et al. (1996)	Finland	Mix Industrial	86-89	74(37F/37NF)/NA	FR	-	-	GA	97,30	5,26	0,00
Varetto (1998)	Italy	Industrial	82-95	3840(1920F/1920NF)/898	FR	-	-	GA	92,18	NA	NA
McKee and Lensberg (2002)	USA	Mix Industrial	91-97	291(146F/150NF)/ 141	FR	-	-	GA	80,60	25,00	14,00
Shin and Lee (2002)	Korea	Manufacturing	95-97	528(264F/264NF)/ 52	FR	-	-	GA	79,70	NA	NA
Min and Jeong (2009)	Korea	Mix	01.Nis	508(254F/254NF)/ NA	FR	-	-	GA	77,30	NA	NA

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; GA: Genetic Algorithms.

1.2.3.2.5. Others Artificially Intelligent Models

Artificially Intelligent Techniques are not limited to models mentioned in the previous sections. In this section, results of the other types of techniques are shortly reviewed whereas the methodological details are ignored for the place limitations and scope of the thesis. Some of these methods are Multi-Criteria Decisions Aid (MCDA), Rough Set (RS), Preference Disaggregation Analysis (PDA), Decisions Trees (DT), Sequential Minimal Optimization (SMO), Data Envelop Analysis (DEA) and Self-Organizing Map (SOM). Table 47 reports key features and findings of the studies that contain one of these techniques. The primary difference of these studies is that they are all conducted in last 13 years. Therefore, these techniques are not specifically designed to be implemented for bankruptcy predictions. Instead, they are used to predict bankruptcy as a tool. This may led to a safe critic that there are still rooms to train these techniques due to the limited number of treatments.

Dimitras et al. (1999), Zopounidis and Doumpos (1999) and Doumpos, et al. (2002) conducted their treatments via RS, PDA and MCDA respectively on Greek firms within different time period and samples. Dimitras et al. (1999) reported 97,5% OPA for the technique conducted whereas this result is an outcome of their so called learning sample accuracy. The test sample in which the derived variables and set of algorithm applied gives disappointing results (around 70% of OPA which is not reported in Table 47). Zopounidis and Doumpos (1999) reported 100% and 63% OPA for the technique applied. In sum, the test sample statistics are much worse than the training (learning) sample statistics. Despite the fact that this is not a general conclusion for all artificially intelligent technique, it is safe to state that non-linear characteristics of these techniques create such inconsistency especially for those studies that never mentioned a theoretical background for the variables used in prediction.

McKee and Lensberg (2002), Koh and Low (2004), Hu and Ansell (2007), Sueyoshi and Goto (2009), Premachandra et al. (2009) and Premachandra et al. (2011) conducted their treatments via RS, DT, SMO, DEA, DEA and DEA respectively on US firms within different time period and samples. McKee and Lensberg (2002) give the results of RS application in bankruptcy prediction which is not promising. Koh and Low (2004) applied DT for prediction and/or classification by dividing observations into mutually exclusive and exhaustive subgroups. DT as a technique gives 95% OPA. Hu and Ansell (2007) by applying SMO reached around 90% OPA. Sueyoshi and Goto (2009), Premachandra et al. (2009) and Premachandra et al. (2011) applied DEA which is well-applied technique in operation research literature for bankruptcy prediction. They reported 95%, 77% and 92% OPA respectively.

Beynon and Peel (2001) conduct their treatment on UK firms by which RS is used as a technique to predict bankruptcy. They reported 91% OPA for their treatment. Min and Yeong (2009) conduct their treatment on Korean firms by which DT is used as a technique to predict bankruptcy. They reported 76% OPA for their treatment. Jardin and Severin (2011) conduct their treatment on French firms by which SOM is used as a technique to predict bankruptcy. They reported 82% OPA for their treatment.

Table 47: Studies for Others Artificially Intelligent Models

REFERENCES	SAMPLE – DATA - VARIABLE					MODEL			FINDINGS		
Author (date)	Country	Firm Type	Years	ES/TS	Inde.Var.	Theory Based	Statistic Based	AIES Based	OPA	Type I Error (%)	Type II Error (%)
Dimitras et al. (1999)	Greece	Mix Industrial	86-93	80(40F/40NF)/ 38	FR	-	-	RS	97,50	2,50	2,50
Zopounidis and Doumpos (1999)	Greece	Mix Industrial	86-93	80(40F/40NF)/ 38	FR	-	-	PDA	100,00	0,00	0,00
Zopounidis and Doumpos (1999)	Greece	Mix Industrial	86-93	80(40F/40NF)/ 38	FR	-	-	PDA	63,16	26,32	47,37
Beynon and Peel (2001)	UK	Manufacturing	NA	60(30F/30NF)/ 30	Mix	-	-	RS	91,70	13,30	3,30
McKee and Lensberg (2002)	USA	Mix Industrial	91-97	291(146F/150NF)/ 141	FR	-	-	RS	67,00	26,70	38,60
Doumpos, et al. (2002)	Greece	Mix	96-97	200(100F/100NF)/ 1211	FR	-	-	MCDA	99,50	0,00	1,00
Koh and Low (2004)	USA	Industrial	80-87	100(47GC/53NGC)/ NA	FR	-	-	DT	95,00	4,00	6,00
Hu and Ansell (2007)	USA	Retail	94-02	246(51F/195NF)/ NA	Mix	-	-	SMO	90,24	NA	NA
Sueyoshi and Goto (2009)	USA	Industrial	91-04	1081(130F/951NF)/ NA	FR	-	-	DEA	95,50	18,00	0,40
Premachandra et al. (2009)	USA	Industrial	91-04	1583(50F/1533NF)/ NA	FR	-	-	DEA	77,00	23,42	16,00
Min and Yeong (2009)	Korea	Mix	01-04	508(254F/254NF)/ NA	FR	-	-	DT	76,50	NA	NA
Jardin and Severin (2011)	France	Mix	95-03	880(440F/440NF)/ NA	FR	-	-	SOM	82,73	NA	NA
Premachandra et al. (2011)	USA	Industrial	91-04	951(50F/901NF)/ NA	FR	-	-	DEA	92,00	NA	NA

Note: NA (not available) treatments are excluded; Type I Error (%): classifying failed firms as non-failed; Type II Error (%): classifying non-failed firms as failed; OPA: Overall Performance Accuracy; AIES: Artificially Intelligent Expert Systems; Inde.Var.; Independent Variables; ES: Estimation Sample; TS: Test Sample; F: Failed firms; NF: Non-failed firms; FR: Financial Ratio; MCDA: Multi-Criteria Decisions Aid; RS: Rough Set; PDA: Preference Disaggregation Analysis; DT: Decisions Trees; SMO: Sequential Minimal Optimization; DEA: Data Envelop Analysis; SOM: Self-Organizing Map; GC: Going Concern; NGC: Non-going Concern.

CHAPTER TWO

A PROPOSED MODEL FOR BANKRUPTCY

2.1. INTRODUCTION

The purpose of this chapter is to introduce a conceptual model for bankruptcy process. In the first chapter, an extensive literature review is given on the related literature in which the models are categorized into two main blocks: Theory based Models and Non-Theory based Models. In addition, Non-Theory based Models are divided into two sub-categories as Statistical based Models and Artificially Intelligent based Models. In this typology, the proposed model can be seen as competing one with those of Theory based Models due to lack of any theoretical (conceptual) framework behind Non-Theory based Models. However, it is claimed that the proposed model overcome the pitfalls of existed Theory based Models and can be a *'new'* road map for all Non-Theory based Models to be replicated.

In the first chapter, it was stressed that how a model should be judged in case of predicting bankruptcy. The qualification of model is standardized as follows:

- The evaluation of any model can be judged by several ways. First of all, time dimension is the primary step to judge a model. That is, a model should be effective in the long run. Most of the statistical based models fail in this step. Altman (1968; 1977), the well-know contributor of this field, proposed two models for predicting bankruptcy. These are called Z-Score Model and ZETA model. Both models contain different variables whereas both models are using for the same purpose. The main reason is that such way of constructing models (not relying on a theoretical framework) is subject to time effect in which the data are collected.
- The second step is about sample characteristics. When we construct a model depending mainly upon sample characteristics, then it is logical to expect that the model will be needed to modify. This is the case for almost all Statistical based Models and AIES based Models.

- The third step is about structure of the model. If another construct (factor) or variable is added to the model, then the marginal contribution of the mentioned variable should be negligible. However, it is the case for almost all models in which different variables were used.
- The fourth step is about how the models reflect financial health of the firms. This requires a deep understanding of financial theory of the firm. Statistical based Models and AIES based Models are all failed in this step whereas theoretical models do not reflect all the dynamics regarding to financial health of the firms.
- The fifth step is about sector or country specification. Most of the models do contain different set of variables depending upon sector or country.
- The last but not least, the models should be flexible to reflect life cycle of the firms. This means that all firms are not at the same level of their life. Some may be at growing stage or some may be at mature stage. Therefore, their dynamics are different to the bankruptcy process. There is no model available to mention this feature of the firms.

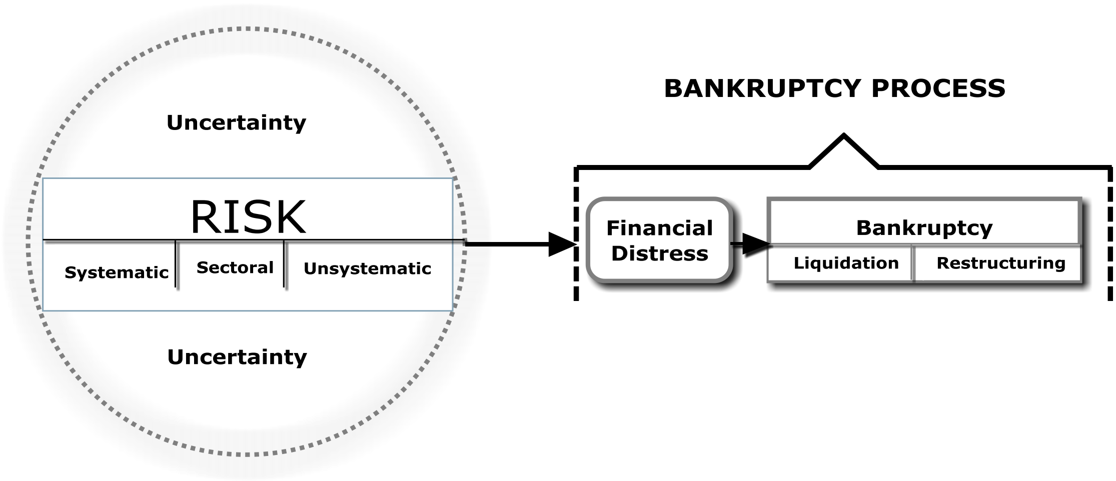
The proposed model has an aim to overcome all of these weaknesses. The power of the model comes from linking the main dynamics of the firm to the bankruptcy process. The linkages between the dynamics of the firms and the bankruptcy process are set in a sense that the model brings a wider perspective. However, the most important feature of the proposed model is that it changed the way of approaching the problem for predicting bankruptcy (will be mentioned in details in the forthcoming section). On the side of Non-Theory based Models, the direct linkage is usually made between the symptoms of failures and prediction of failure pragmatically without explaining why these symptoms exist in a conceptual framework. On the side of Theory based Models, two of five models (Gambler's Ruin Theory and Balanced Sheet Decomposition Model) are developed based on statistical concepts that are gambler ruin problem and entropy. The Failing Company Model of these types is developed in the context of the US law system. Cash Management Theory and Contingent Claim Model are very limited in terms of their scope.

2.2. MODEL CONSTRUCTS

The proposed model in the full form is depicted in Figure 8. However, it is very useful to begin with its core dynamic which is a totally different approach than any other justification in literature. The basic idea underlined that the risk (*a countable part of uncertainty* (Knight, 1921: 209)) affects the bankruptcy process. Since risk is defined as measureable part of uncertainty, uncertainty is showed with a dash circle in Figure 5. The classification of risk is structured as systematic, sectoral and unsystematic. This classification eliminates every single undefined symptom that might be considered as a default predictor. In other words, each symptom should be carefully taken into account if it is a really risk factor. This classification is well-documented in financial literature in different context especially in related literature of asset pricing (Çelik, 2009).

Bankruptcy process is defined as a process constituted by two sub-processes which are process of financial distress and a process of bankruptcy formation. This distinction is another contribution of the proposed model when compared with the studies in related literature. Despite the fact that financial distress is well studied, it is not structured in bankruptcy prediction literature as it is depicted in Figure 5. This is crucial for the fact that bankruptcy is not a single point in time rather it is a process as defined. The structure of this process contains another two processes as well. Therefore, which process is going to be predicted become an interesting question. Even tough bankruptcy is defined as process in some studies, the empirical inquiries in many studies treated the bankruptcy as a point in time by aiming to classify firms into two groups: bankrupt or non-bankrupt.

Figure 5: Risk-Bankruptcy Process



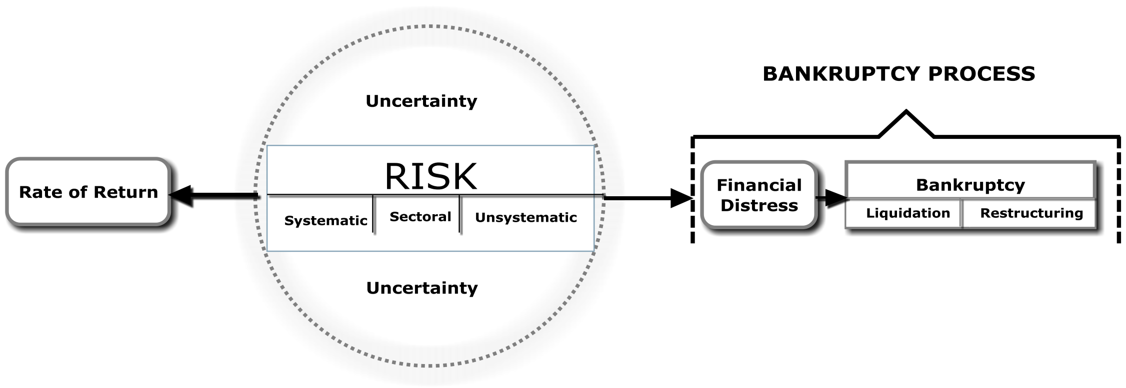
The process of bankruptcy formation takes at least two forms: liquidation[5] and restructuring[6]. These two forms and other types of outcomes such as merger and acquisition because of financial distress are natural results of increasing impact of risk factors. In the first chapter, it was documented that considerable amount of studies follow the procedures to discriminate default and non-default firms. For this reason, those firms that merged or acquired due to financial distress were not considered within the samples analyzed. This creates another version of '*survivorship bias*'[7] in literature of bankruptcy prediction. Despite the fact that some studies tried to classify firm into more than two groups such as default, insolvent and non-failed firms (Jones and Hensher, 2004); State 0: financial stability, State 1: omitting or reducing dividend payments, State 2: technical default and default on loan payments, State 3: protection under Chapter X or XI of the Bankruptcy Act and State 4: bankruptcy and liquidation

[5] Liquidation means termination of the firm as a going concern, and it involves selling off the assets of the firm. The proceeds, net of selling costs, are distributed to creditors in order of established priority (Ross, et al.,2004: 595).
[6] Reorganization is the option of keeping the firm a going concern; it often involves issuing new securities to replace old securities (Ross, et al.,2004: 595).
[7] *Survivorship bias* is term used in studies on mutual funds for referring to a recurring problem in the performance of mutual funds. Brown, Goetzmann, Ibbotson and Ross (1992) claim that this bias can be serious in mutual fund performance studies for the fact that its presence may falsely indicate a persistency in the predictability of excess returns.

(Lau, 1987), it is not sufficient to escape from survivorship bias in given methodology and perspective.

In its core dynamic of the proposed model, it is clearly stressed that risk (factors) should be identified instead of searching among various symptoms to predict financial distress and/or bankruptcy. The determinations of these risk factors will be elaborated in forthcoming sections.

Figure 6: Return-Risk-Bankruptcy Process



Instead of searching for the risk factors[8] initially as it has been done in related literature, it is proposed that it should be approaching firms in a wider perspective[9]. Therefore, a question is arising that what makes a firm to survive and maintain its operations on the contrary of going bankrupt. This can be called *value additivity* which is assumed to be represented (measured) by the term *rate of return.* It is logical to expect that continuous positive rate of return will make every stakeholders happy. The common factor in this equilibrium (trade off) as it is depicted in Figure 6 is the risk factors. The construct of rate of return is playing an extremely crucial role in proposed model. The main reason behind this importance is that rate of return (value additivity) is

[8] It should be underlined the fact that symptoms are not defined and categorized as risk factors in literature. This perspective is totally new.
[9] This perspective can be best describe as looking at the forest from the top instead of looking at some trees on the bottom in order to understand how deep the forest is.

main concern for all stakeholders. If rate of return for a firm is continuously becoming negative, then the firm is starting to have a serious distress. It is not surprised that there is a huge literature written on linkage between the risk factors and rate of return (Çelik, 2009; 2012). However, it is very surprising that there are only three studies mentioning the concept of rate of return in predicting the bankruptcy in literature reviewed in chapter one. Despite the fact that Beaver (1968), one of the first scholars who used financial variables to predict bankruptcy, proposed to use rate of return in prediction, Blum (1974a) and Back, et al. (1996) are the other two studies using the rate of return in analysis. Blum (1974a) consciously used the rate of return as a variable in Failing Company Model whereas Back, et al. (1996) used it without mentioning its linkage with bankruptcy process. Despite the fact that theoretical linkage between risk and return is well documented in literature, conceptual reasoning is going to be given in the forthcoming section.

Figure 7: Cost of Capital-Return-Risk-Bankruptcy Process

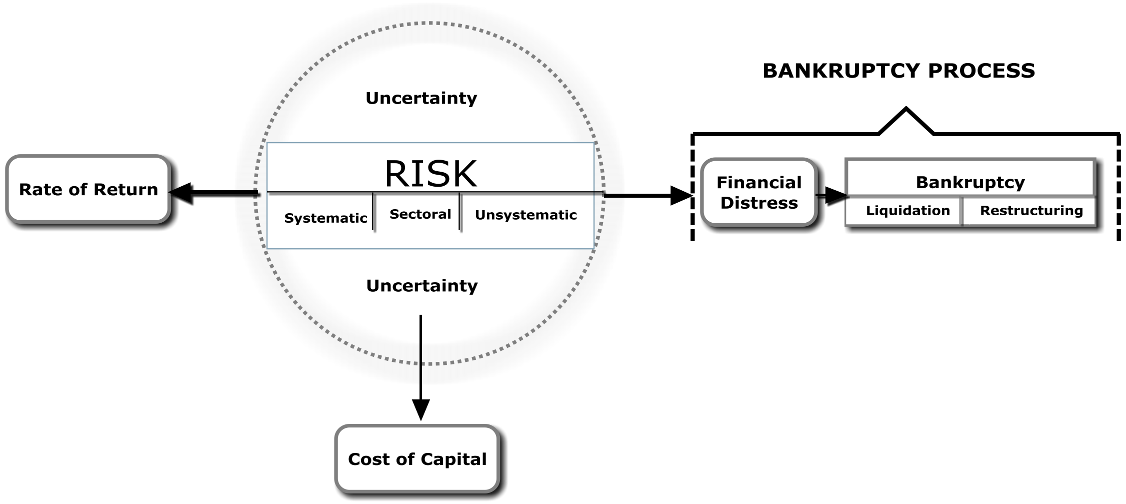


Figure 7 shows another construct that is crucially related to risk-return-bankruptcy process: *Cost of Capital.* Cost of capital is one of the primary concerns of firms in their all operations. Every single project is evaluated in terms of cost of capital.

The proposition proposed here is that the risk determines cost of capital. High risk will require high cost of capital which leads the positive relation between high cost of capital and the probability of bankruptcy process. This inference will be shown in a more formal demonstration in forthcoming section. However, it is very surprising that there is no single study that attempts to underline the linkage between cost of capital and bankruptcy process despite its obvious reality. This reality, in fact, comes from real world application. For example, some firms that are rated AAA have low cost of capital than those of having BBB. The proposed model introduces cost of capital first time here as an important construct in return-risk-bankruptcy process.

Figure 8: Proposed Model

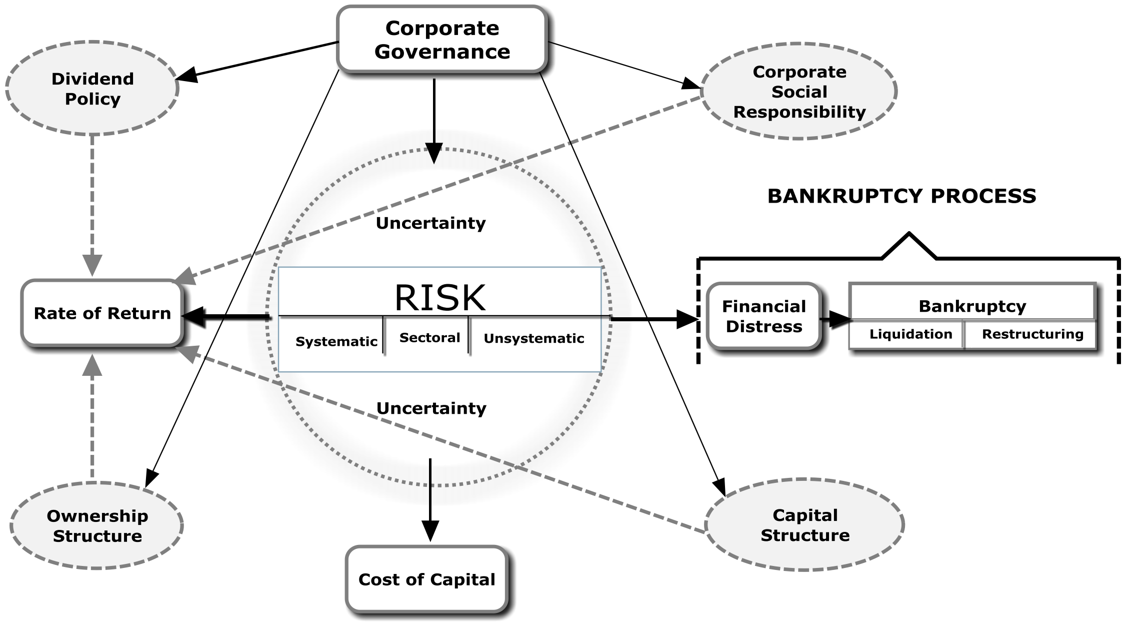


Figure 8 demonstrates the proposed model in the full form. As depicted, the last crucial construct is *Corporate Governance.* Corporate governance has two roles in proposed model. The first role is that it has direct impact on the level of risk (mainly on unsystematic). The second role is that it has direct priority to determine the policies about dividend, capital structure, ownership structure and corporate social responsibility. These sub-constructs are assumed to be effective variables that affect rate of return in a market where perfect capital market assumptions[10] are violated. For example, for deriving Sharpe-Lintner Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), it is needed several other assumptions as well in addition to perfect capital market assumptions (Çelik, 2009). If these assumptions are satisfied, then there is no need these sub-constructs to be proposed. The simplest argument to show why these sub-constructs are needed within the model is that the proposed model does not require any kind of unrealistic assumptions. In addition, these sub-constructs are shown with a dashed line to be linked to rate of return due to the possibility of having different impact in different type of market such as perfect capital market. The dash line represents their certainty level meaning that they may not be active in all different type of markets. Park and Han (2002) clearly emphasize the role of corporate governance under the construct of management capacity in predicting bankruptcy. The relevancy of corporate governance and these sub-constructs will be elaborated in more details in forthcoming sections.

Dividend policy is used in several studies in predicting bankruptcy. Sung et al. (1999) used ratio of Dividends / Net Income within the construct of profitability in their analysis. Lin (2009) used the same ratio in predicting bankruptcy without linking it to any conceptual construct. Jo, et al. (1997) used the ratio of Dividend / Total Equity within the construct of profitability in their analysis. Gentry, et al. (1985), Gombola, et al. (1987) and Aziz and Lawson (1989) used dividend in the form of absolute value in their analysis. Besides these studies, dividend policy was treated as a state variable and used as a dummy in their models. For example, Lo (1986) took dividend policy within two variables: 1 if no dividend is being paid currently and 0 otherwise; and 1 if dividend payments are omitted or reduced more than 40% in the period. All of these studies show that dividend policy have a discriminating role in predicting bankruptcy whereas they did not propose a conceptual linkage with bankruptcy process. The proposed model shows how dividend policy takes place within the dynamics of the firms and bankruptcy process.

[10] Some of these assumptions are as following: (i) All assets are perfectly divisible and priced in a perfectly competitive market; (ii)Asset markets are frictionless and information is costless and simultaneously available to all investors; (iii) There are no market imperfections such as taxes, regulations or restrictions.

Capital structure is one of the most used financial position in predicting bankruptcy in related literature given in chapter one. This position is measured by ratio of Total Liabilities / Total Equity in twelve (12) and Total Liabilities / Total Assets in thirty four (34) studies reviewed under the construct of long-term solvency. As it is the case for dividend policy, capital structure decision may become irrelevance under certain assumptions regarding to market condition. Since the proposed model does not pose any kind of assumptions regarding to market conditions, capital structure is assumed to be an effective variable in explaining rate of return. Therefore, it is assumed to have a linkage with bankruptcy process.

Ownership structure is another construct proposed to be an important variable in relation with rate of return. In related literature, Claessens, et al. (2003) emphasized ownership structure in predicting bankruptcy by two variables: (i) identifying firms that are affiliated with a business group and where the ultimate owner has at least 20% of the voting rights, and (ii) identifying firms that are owned by a bank or by a business group that also owns a bank. However, the role of ownership structure is assumed to be an effective variable in explaining rate of return rather than directly linking with bankruptcy.

Corporate social responsibility (CSR) as a construct is perhaps the most surprising one among others. The rationale behind the role of CSR has a groundbreaking idea. In many financial textbook nowadays, it is believed that the primary goal of firms' management is to maximize shareholders' wealth whereas it is no longer true that the role of other stakeholders can be ignored. It is proposed first time here that the primary goal of firms' management is to maximize stakeholders' wealth. Despite the fact that the importance of CSR has not been recognized yet in the last two decades, firms are becoming more eager to promote themselves as more friendly to environment, recycling or energy savers. All of these arguments are quite solid that nobody can escape to ignore the importance of CRS in explaining rate of return.

2.2.1. Corporate Governance Construct

This section describes corporate governance construct and its related sub-constructs which are capital structure, dividend policy, ownership structure and corporate social responsibility. The main argument brought over here is to explain their direct or indirect linkages with bankruptcy process within the structure of proposed model. The primary reason of starting with corporate governance is that the impact flow of decisions is coming first from managing authorities to other sub-divisions of the organizations. Decisions regarding to capital structure, dividend policy, ownership structure and corporate social responsibility are determined by managing authorities first, then they are affected by the environment in which firms operate. This impact flow has not been recognized clearly. Therefore, empirical inquiries conducted on the cause-effect relationship are sometimes giving misleading and/or mix results. Scholars have derived their inferences mainly on various assumptions in order to gain mathematically sound arguments.

Decisions about capital structure, dividend policy and ownership structure have been analyzed in related literature of predicting bankruptcy whereas the role of these decisions was taken a place as a symptom rather than given within a conceptual framework. Corporate social responsibility has not been even mentioned in this context. The problematic idea, however, here is that these symptoms were treated as discriminating factors in predicting bankruptcy without underlining their rationale behind. The proposed model gives a solution to this problem by linking the dynamics of the firms with bankruptcy process. The innovative idea developed within the proposed model is that it changes the way of approaching the problem of predicting bankruptcy. Instead of searching for discriminating symptoms pragmatically, the model gives the linkages between the dynamics of the firms and bankruptcy process. The following sections give relatively detailed explanations regarding to rationale behind using these constructs with the proposed model.

2.2.1.1. Corporate Governance

One may think that what linkages between corporate governance and bankruptcy process are due to very limited number of studies mentioning these linkages in an extensive literature review taken place in chapter one. The possible reason is that scholars behaved pragmatically to search for discriminating variables in predicting bankruptcy. This section describes how important corporate governance is in the process of all firms' operations generally and bankruptcy process particularly.

The term *governance* should be clearly defined in order to understand its role within structure of proposed model. Governance is defined as *'the structure and function of a corporation in relation to its stakeholders generally, and its shareholders specifically'* (Banks, 2004:3). The importance of corporate governance around the world rises significantly due to its possible impact on all stakeholders. Banks (2004: 3) summarizes this process as follows:

> *'Privatizations, pension deregulation, free capital movement, and market integration are creating a greater equity investment culture around the world. This phenomenon, together with an increase in the frequency and severity of corporate problems, has moved governance back into the limelight. Public focus is strong because governance failures can now impact a very large number of stakeholders: institutional and retail shareholders (the original and primary focus of most governance initiatives), retirees and pensioners, employees, bank creditors, clients, suppliers, regulators and broad communities. There is heightened realization that good governance is effective in protecting stakeholders, while poor governance puts all parties at risk. Governance failures can lead to a broad range of problems, from temporary reputational damage to insolvency. Events of recent years have demonstrated that even small governance problems can turn into much larger ones if left unchecked. They must therefore be resolved forcefully: any delay can damage a firm's reputation, market share and shareholder value.'*

Banks (2004) underlines two facts: (i) the first one is about the impact of corporate governance on stakeholders and (ii) the second one is about the risk that may take place if corporate governance is not effectively designed.

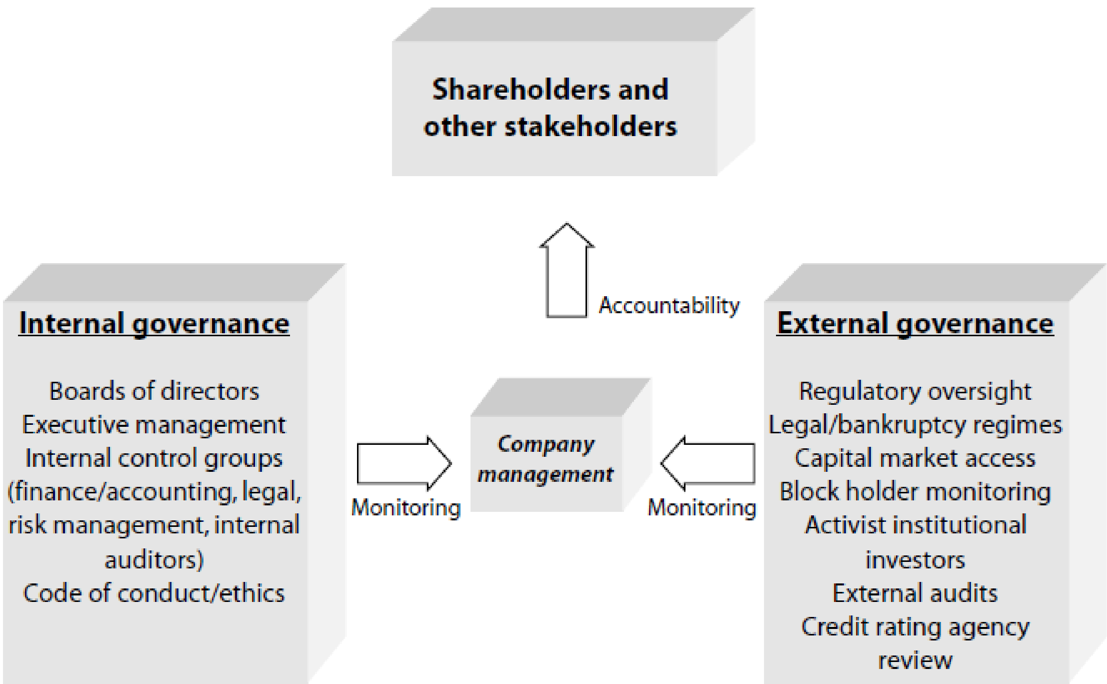
There are many examples that show how corporate governance affects the firms' operations around the world. Some of these are Enron, Tyco, Andersen, and WorldCom from USA; Swissair from Switzerland; Kirch Media from Germany; Daiwa Bank and Sumitomo Corporation from Japan and many others (see Banks (2004) for an extensive list).

Governance assumes various forms in modern corporate systems. These elements of governance are centered on both internal and external mechanisms. Internal governance is based on specific mechanisms and actions taken by individual firms to enforce control and accountability. These can vary by company, industry, and country, but broadly speaking include (Banks, 2004: 24): *(i) establishing a capable and unbiased board of directors; (ii) creating appropriate responsibilities and norms within the ranks of executive management; (iii) developing independent control groups, including finance/accounting, legal, risk management and internal audit; (iv) creating and promulgating a code of conduct*[11]. Supplementing internal governance processes are external forces that establish overarching frameworks which define, or operate with, internal mechanisms. Again, although specific external elements vary by country and economic system (depending on law, custom, and behavior), key forces include (Banks, 2004:25): *(i) establishing appropriate regulatory oversight; (ii) creating proper legal and bankruptcy regimes; (iii) ensuring efficient capital markets access; (iv) encouraging corporate control activities (such as mergers and buyouts); (v) permitting block holder monitoring of corporate activities; (vi) encouraging the participation of activist institutional investors; (vii) requiring thorough and comprehensive external audits; and (viii) facilitating credit rating agency reviews.*

[11] This is also known as code of ethic.

Figure 9[12] depicts internal and external governance mechanisms. There are two important features presented here: the first one is about monitoring company management and the second one is about accountability to the all stakeholders.

Figure 9: Internal and External Governance Mechanisms



Source: Banks (2004: 25)

In the structure of proposed model, it is claimed that governance mechanisms play a crucial role in protecting stakeholders that is mainly related to maximizing the stakeholders wealth (this is an effect flow over risk to rate of return) and minimizing risk (this is an effect flow over risk to bankruptcy process). Banks (2004: 103) support these claims of the proposed model as follows:

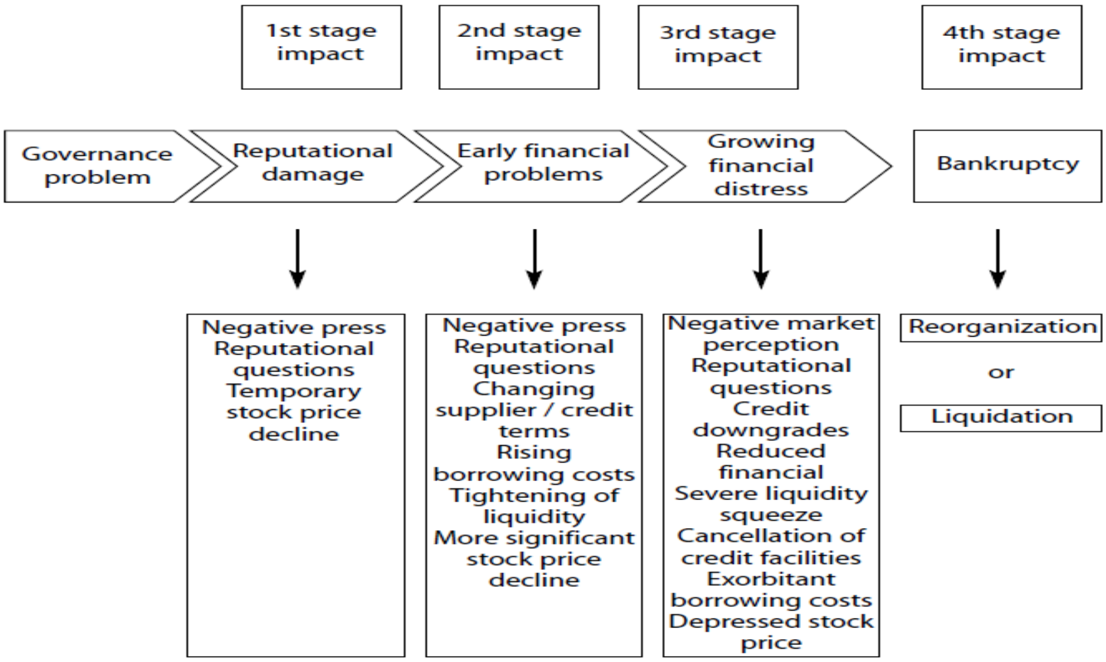
[12] The detailed descriptions of each element in Figure 9 are ignored for the space limitation and scope of the thesis. Interested readers may consult Banks (2004).

'Internal and external governance mechanisms exist to protect stakeholders, and in practice often work as intended. Occasionally, however, they break down as a result of some flaw, such as a failure within the board of directors or the executive suite, ineffective internal controls or corporate policies, and inadequate regulations. Any of these might lead to a corporate problem. In some cases several shortcomings might appear at the same time, increasing the possibility of a more extreme outcome, such as an excessively large and unexpected loss, a liquidity crisis, financial distress, or even bankruptcy.'

Figure 10 depicts how corporate governance problem affect bankruptcy process in a well understating framework. This framework does support the way of approaching and treating bankruptcy process as it is structured within the proposed model. As depicted, corporate governance problem may lead reputational damage at the first stage in which negative press, reputational questions and temporary stock price decline are observed. Then after, early financial problems take place at stage two in which negative press, reputational questions, changing supplier / credit terms, rising borrowing costs, tightening the liquidity and more significant stock price decline are observed. These two stages lead growing financial distress at the stage three in which negative market perception, reputational questions, credit downgrades, reduced financial sources, severe liquidity squeeze, cancellation of credit facilities, exorbitant borrowing costs and depressed stock price are observed. Bankruptcy process takes place at final stage in which liquidation and restructuring (reorganization) are observed.

There are many supporting ideas given in Figure 10 for proposed model. Firstly, as it is claimed, the cost of capital is directly affected and bankruptcy process is the last stage after having a process of financial distress. However, the proposed model assumes that corporate governance problems may increase the risk so that costs of capital and bankruptcy process are affected. It is realized that all these indicators shows how the constructs of the proposed model are affected. It is starting with a corporate governance problem; then (since risk is increased) stock prices are starting to fluctuate (to be depressed) which affects the rate of return; then (since risk is increased) cost of capital is increased and then (since risk is increased) financial distress takes place.

Figure 10: The Impact of Governance Problem on Corporate Operations



Source: Banks (2004: 149)

There are some empirical researches that treat corporate governance as an important construct (Peel, et al., 1986; Park and Han, 2002, McKee and Lensberg, 2002, Chen and Du, 2009). The important fact regarding to measuring corporate governance construct is that there are some difficulties in dealing with (e.g.) quality of management. Therefore, some authors use qualitative based research design in which a scale is developed to measure quality of management (Park and Han, 2002). Others use several variable indicating the role and action of corporate management. Table 23 gives the full list of variables used to predict bankruptcy process based on variables of corporate governance.

Corporate governance construct is claimed to be related to those of sub-constructs such as capital structure, dividend policy, ownership structure, corporate social responsibility. The primary reason behind this linkage is the decisions that are taken for determining policies regarding to these sub-constructs. The following sections give the second step of impact of these sub-constructs on rate of return.

2.2.1.2. Capital Structure

Capital structure decision, *the specific mixture of long-term debt and equity the firm uses to finance its operations* (Ross, et al., 2004: 38), is one of the primary decisions taken by firm management. Therefore, related literature on capital structure is quite extensive and well studied. However, the focus of the corporate structure in the context of present study is its possible impact on rate of return (value additivity).

Modigliani and Miller (1958) (MM) proposed that capital structure decision does not affect firm value under the assumption of perfect market in which taxes and bankruptcy costs are ignored. When taxes are taken into consideration, the firm value and debt ratio have a linear relationship in way that firm value increases as debt ratio increases. When both taxes and bankruptcy costs are taken into account (this is called static theory), since an increase in debt ratio will bring tax advantages, weighted average cost of capital of the firm will decrease and firm value will increase. However, high level of debt ratio will create a problem so called bankruptcy risk which imposes an increase on weighted average cost of capital. Therefore, this increase on weighted average cost of capital will lead a decrease in firm value. The following illustrations give a detailed description of MM propositions and static theory.

Under the assumption of perfect market in which taxes and bankruptcy costs are ignored, the following propositions are derived:

MM Proposition I: *The value of the firm is independent of the firm's capital structure*.

MM Proposition II: *A firm's cost of equity capital is a positive linear function of the firm's capital structure.*

In other way of stating Proposition I is that the value of the firm levered (V_L) is equal to the value of the firm unlevered (V_U) which implies that (i) a firm capital structure is irrelevant and (ii) a firm's weighted average cost of capital (WACC) is the same no matter what mixture of debt and equity is used to finance the firm.

WACC is cost that represents all sources of finance for the firm's operations. It is calculated as follows:

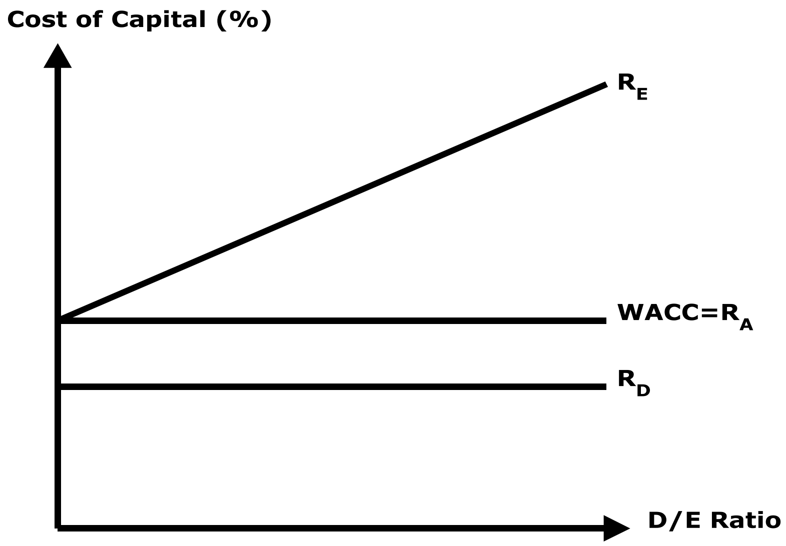
$R_A = [D/(E+D)] \text{ X } R_D + [E/(E+D)] \text{ X } R_E$

where; R_A is WACC; R_D is the cost of debt; and D/E is the debt-equity ratio. If R_E is left alone, then R_E becomes;

$R_E = R_A + (R_A - R_D) \text{ X } (D/E)$ .... (29)

In the light of equation (29), proposition II implies that (i) the cost of equity rises as the firm increases its use of debt financing and (ii) the risk of the equity depends on two things: the riskiness of the firm's operations (business risk) and the degree of financial leverage (financial risk). Business risk determines R_A; financial risk determined by D/E.

Figure 11: MM Proposition I and II with No Taxes



Source: Ross, et al. (2004: 576)

Under the assumption of perfect market in which taxes are taken into account and bankruptcy costs are ignored, propositions I and II are modified as follows:

MM Proposition I with taxes: the value of the firm levered (V_L) is equal to the value of the firm unlevered (V_U) plus the present value of the interest tax shield:

$V_L = V_U + T_C$ X D ....(30)

where; T_C is the corporate tax rate and D is the amount of debt.

Implications of proposition I with taxes are that (i) Debt financing is highly advantageous, and, in the extreme, a firm's optimal capital structure is 100 percent debt; (ii) A firm's weighted average cost of capital (WACC) decreases as the firm relies more heavily on debt financing.

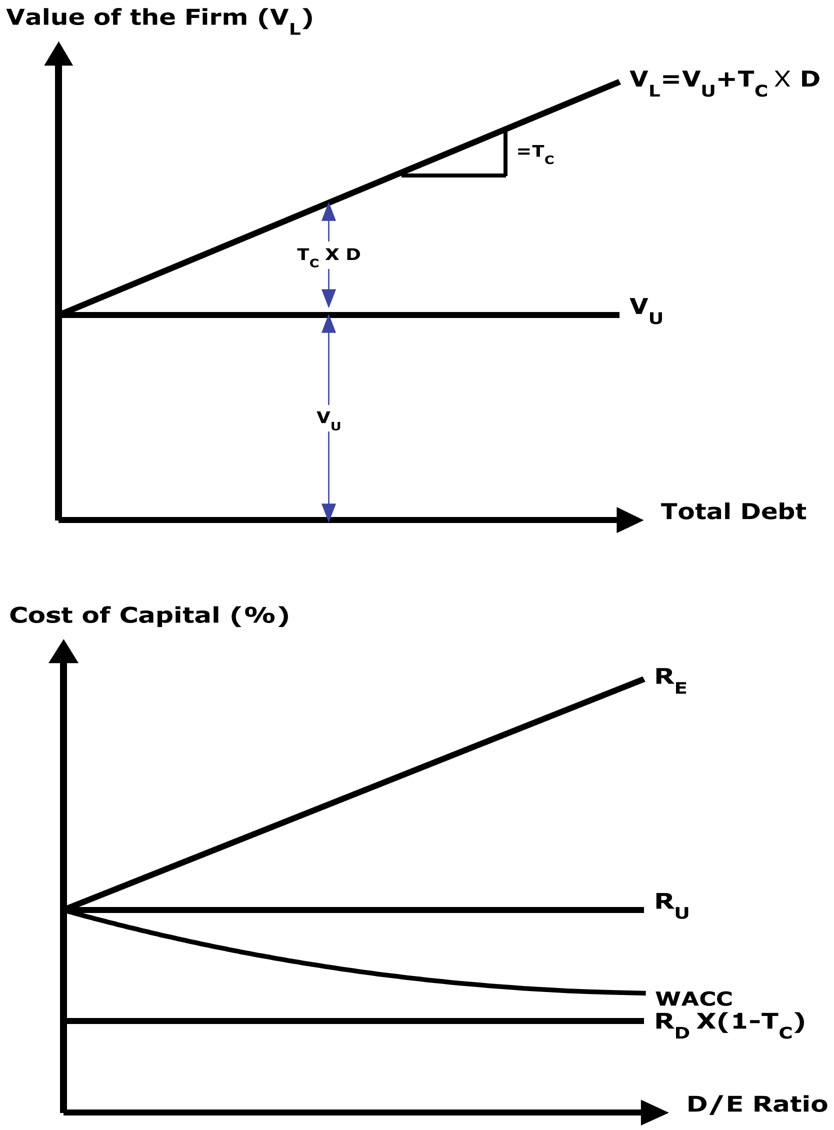
MM Proposition II with taxes: The cost of equity R_E becomes;

$R_E = R_U + (R_U - R_D)$ X (D/E) X $(1\text{-}T_C)$... (31)

where, R_U is the unlevered cost of capital, that is, the cost of capital for the firm if it has no debt.

Unlike the case with Proposition I, the general implications of Proposition II are the same whether there are taxes or not. In sum, the value of the firm increases as total debt increases because of the interest tax shield. This is depicted in Figure 12.

Figure 12: MM Proposition I and II with Taxes

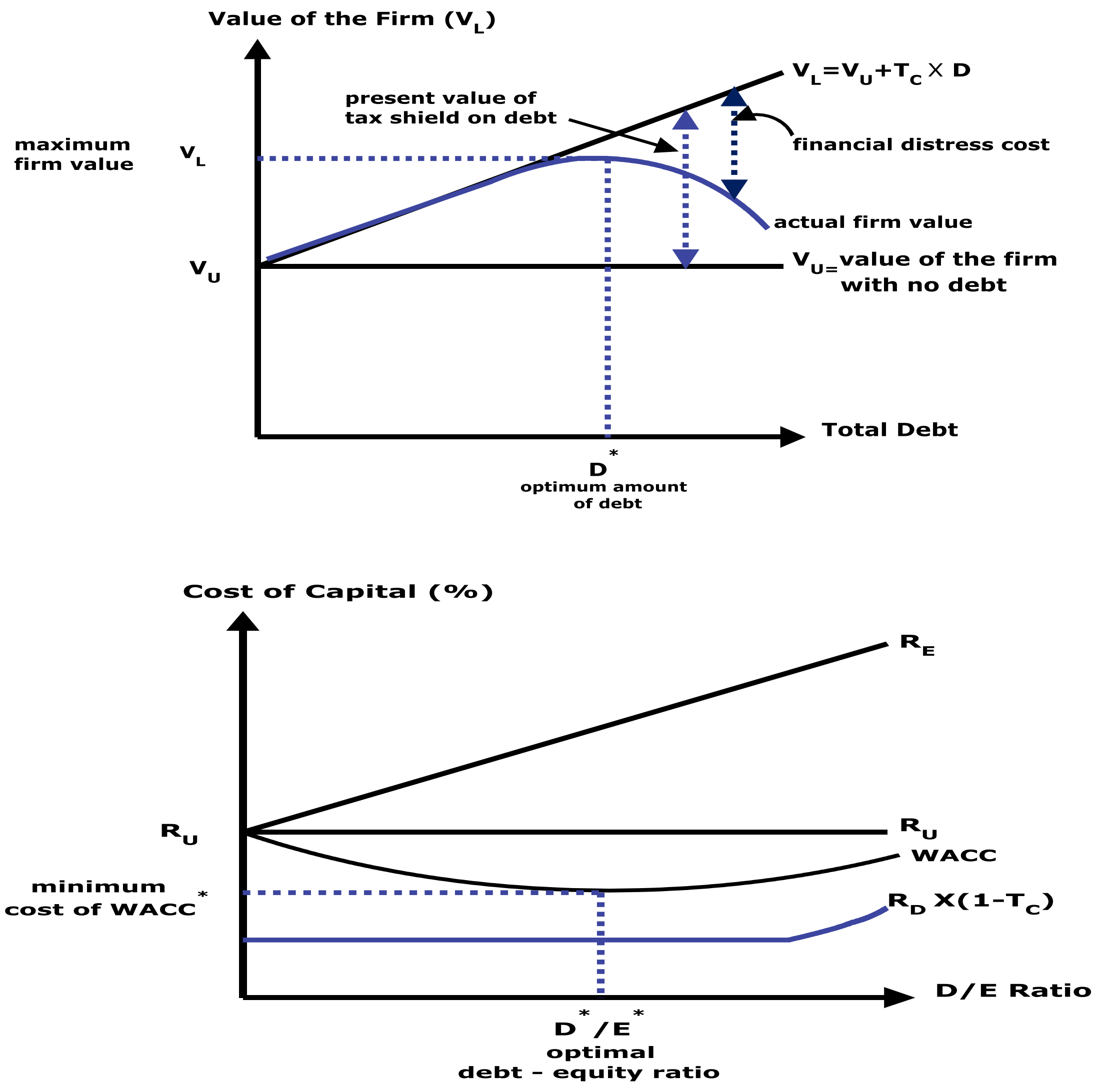


Source: Ross, et al. (2004: 581-583)

Figure 12 depicts two relationships: the first one is the one between firm value and total debt and the second one is the one between cost of capital and D/E ratio. As depicted in the first one, there is an increasing trend observed by an amount of slope which is equal to tax shield. In the second one, WACC has an decreasing trend as D/E Ratio is becoming higher.

Figure 13 illustrates the static theory, which implies that (i) the gain from the tax shield on debt is offset by financial distress costs. An optimal capital structure exists that just balances the additional gain from leverage against the added financial distress cost. (ii), the WACC falls initially because of the tax advantage of debt. Beyond the point D* /E*, it begins to rise because of financial distress costs.

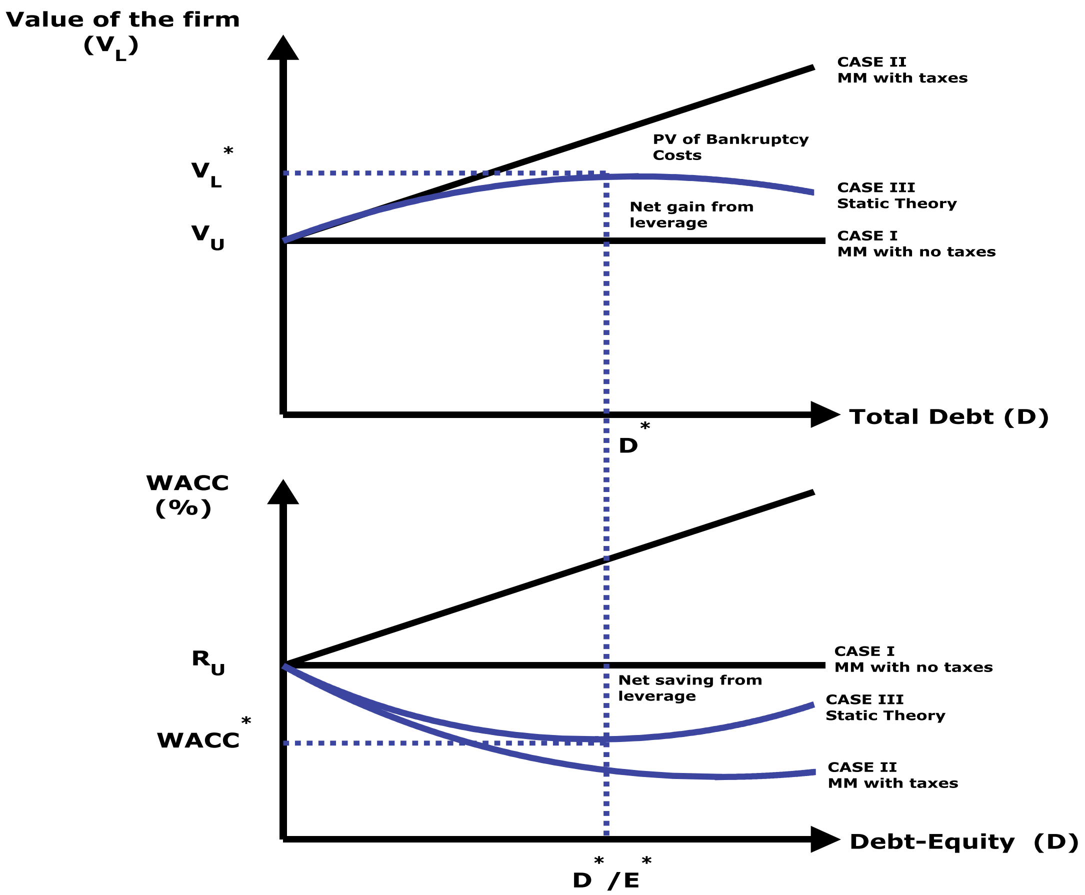
Figure 13: Static Theory of Capital Structure



Source: Ross, et al. (2004: 587-588)

Figure 14 gives a summary of all three cases in one. The first case is MM with no taxes which implies that *with no taxes or bankruptcy costs, the value of the firm and its weighted average cost of capital are not affected by capital structures*.; the second case is MM with taxes which implies that *with corporate taxes and no bankruptcy costs, the value of the firm increases and the weighted average cost of capital decreases as the amount of debt goes up* and the third one is static theory which implies that *with corporate taxes and bankruptcy costs, the value of the firm, V_L, reaches a maximum at D*, the point representing the optimal amount of borrowing. At the same time, the weighted average cost of capital, WACC, is minimized at D*/E** (Ross, et al., 2004: 589).

Figure 14: MM Proposition I – II and Static Theory



Source: Ross, et al. (2004: 589)

Empirical researches devoted to explore the linkage between capital structure and rate of return (firm value) produce several important facts. Bhandari (1988) reported a positive relationship between average common stock return and financial leverage (debt/equity). This relationship is claimed to be statistically significant when beta, systematic risk indicator, and firm size are controlled within the model. In their important studies in which Three Factor Model is introduced, Fama and French (1992; 1993; 1996) observed that the relationship between beta and stock return disappeared within the period of 1963 and 1990 in USA. This observation is supported by a three factor model in which book value /market value ratio and the company's size measured by its market capitalization are taken into model in the role of sorting factor of portfolio construction. These portfolios returns were used as factors addition to beta. Financial leverage is assumed to be absorbed by the ratio of book value /market value which becomes an important sorting factor in predicting stock returns.

Barbee, Mukherji and Raines (1996) document some evidence that sales/price and debt/equity ratios are more predictive variables than those of book value / market value and firm size in their study conducted in South Korea. In the same vein, Mukherji, Dhatt and Kim (1997) reported an interesting relationship between financial leverage and stock return. They claimed that common stock returns of small firms that have high financial leverage are higher than those of other firms. Durukan and Mandacı (2003) investigated the role of beta, market value / book value, debt / equity, firm size, price-earnings ratio and sales / price ratio on common stock returns of manufacturing firms in Turkey and reported that debt/equity ratio is not statistically significant study. Çelik, Mandacı and Çağlı (2009) introduced a factor model for explaining cross sectional common stock returns for manufacturing firms in Turkey. They examined the role of beta, debt-to-equity ratio, market-to-book ratio, ownership concentration, foreign investor ratio, and dividend payments in their model. They found that variations in the common stock returns are best explained by the variations in the variables, namely market-to-book ratio, ownership concentration, and dividend payments.

2.2.1.3. Dividend Policy

Dividend policy had been a controversy issue in financial literature in terms of its linkage with firm value. There are three different views on how relationship exists between firm value and dividend policy. The first view is that an increase in dividend payout increases firm value. This is mainly related to the desire for current income and related factors. Despite the fact that this is the oldest belief among others, there is argument so called signaling effect (Allen, Bernardo and Welch, 2000) proposed to encourage high dividend payout. This means that well-managed companies want to signal their worth for having a high proportion of demanding institutions among their stockholders. They believed that they can achieve this goal by paying high dividends. Therefore, those shareholders who pay tax do not object to these high dividends as long as the effect is to encourage institutional investors who are prepared to put the time and effort into monitoring the management (Brealey and Meyers, 2003).The second view which is totally against to the first one is that an increase in dividend payout decreases firm value. This is mainly related to tax effects for individual investors and new issues costs. Since investors are not eager to pay high taxes, it is expected that the low payout firms will be more attractive than others which eventually increase the value of the firm. The third view which is located between the first two views is that dividend policy is irrelevant. This is related to the homemade dividend argument which means that *the tailored dividend policy created by individual investors who undo corporate dividend policy by reinvesting dividends or selling shares of stock* (Ross, et al. (2004: 611). This view is a result of Miller and Modigliani (1961) who proposed that dividend policy is irrelevant in a world without taxes, transaction costs, or other market imperfections.

Empirical studies that analyze the possible relationship between rate of return (firm value) and dividend policy document mix results. Black and Scholes (1974) claimed that the best way of exploring the impact of dividend policy on common stock prices (equivalently rate of return) is to test the impact of dividend yield on rate of return of common stock. Conceptually, returns from common stock are composed of two parts. The first part is coming from price differentials so called capital gain. The second part is coming from dividends distributed. Therefore, dividend yield and growth of dividend payout become important determinants in explaining common stock returns

(Ünlü, Bayrakdaroğlu and Ege, 2009). Ang and Liu (2007) point out that the possible relationship between dividend yields and expected stock return is coming from Gordon growth model (Gordon, 1962).

There are many studies that examine the linkages between dividend yields and stock returns. Among others, Blume (1980) and Keim (1985) observed a non-linear relationship between long-term dividend yields and stock returns. However, Keim (1985) underlined the fact that this relationship disappear when the January Effect is taken into consideration. Fama and French (1988) figure out that dividend yields explained 25% variation in stock return in the study conducted in New York Stock Exchange for fourtyfive-year period. In the same vein, Campbell and Shiller (1988) found that there is a positive relationship between dividend yields and stock returns. Lewellen (2004) realized that dividend yield is the most important variable that explains stock returns in the study conducted for investigating the impact of financial ratios on stock returns within the period of 1946-2000. Campbell and Yogo (2006) claimed that the previously conducted methodologies were incorrect and examined the relationship among dividend yields, Price-Earnings ratio and stock return in way of proposing a new methodology. They observed that dividend yields have an explanatory power on stock return on annual data in the study that is conducted on both annual and monthly data. Nagayasu (2007) examined the impact of dividend yields on stock return by conducted panel data analysis and found a statistically significant relationship.

Aydoğan and Güney (1997) claimed that high stock returns are observed after the months in which high dividend yields were achieved in their study conducted in Istanbul Stock Exchange for evaluating predictive ability of dividend yields on stock returns. Ünlü, Bayrakdaroğlu and Ege (2009) analyzed the linkage between Indices of ISE100 and S&P500 and dividend yields of these indices instead of stock based examination. They found that dividend yields of indices have a predictive ability on indices return and claim that dividend yields can be decision criteria to invest on common stocks.

2.2.1.4. Ownership Structure

Ownership structure is another sub-construct that is assumed to affect stock return within the proposed model. This effect, however, is not dictated to be true in all form of market structure such as perfect market. There is no assumption presumed regarding to market structure in which firms operate. It is for this reason that there is a possible relationship between firm value and ownership structure which can be linked to agency theory. Agency theory is referring to explaining the relationship between principals (shareholders) and agent (executives) which basically focus on conflict of interest (agency problem) and reconciliation of principals and agents. However, overcoming these problems bring cost to the firms in two forms: (i) indirect cost of agency problem such as a lost opportunities that management does not take for not bearing its risk; (ii) direct costs of agency problem are unnecessary expenditures and monitoring expenditures for the executives.

The basic idea behind the sub-construct of ownership structure is that executives are supposed to act in best of shareholders. However, it is not the case for the reasons mentioned above. How this situation can be evaluated is directly related to ownership structure. If the ownership structure is composed of few shareholders who may easily affect the executives, then they can make them sure to act in the best of themselves. However, if the other case is present, then the control of the firm may be dispersed among many shareholders who may not able to affect the executives.

Acoording to Shleifer and Vishny (1997), increased centralization of ownership will increase ability of shareholders to control executives which lead to an advantage to raise firm value. Morck, Shleifer and Vishny (1988) document that there is no meaningful relationship between ownership intensity and firm value. However, Hiraki, Inoue, Ito, Kuroki and Masuda (2003) in their study in Japan and Gorton and Schmid (2000) in their study in Germany found out a positive relationship between firm value and ownership intensity. Mandacı and Gümüş (2010) figure out a positive and statistically significant relationship between firm value and ownership intensity in their study conducted on 203 manufacturing firm in Istanbul Stock Exchange.

Çelik, Mandacı, Masood and Aktan (2009) investigate the linkages between the investors' characteristics and stock returns. They found that there is positive linear relationship between realized mean return and risk when stocks sorted based on percentage of foreign investors' allocations in their study conducted on manufacturing firms traded in Istanbul Stock Exchange within the period of 2002:01 and 2008:06 based on monthly data.

2.2.1.5. Corporate Social Responsibility

Corporate social responsibility (CSR) is the last sub-construct that is assumed to be an important decision to affect stock returns. As noted earlier, the reason behind of underlining the importance of CSR is that the paradigm change in determining goals of firms' management. Previously and still, there is a strong belief that the primary goal of firms' management is to maximize shareholders' wealth whereas it is no longer true that the role of other stakeholders can be ignored. It is proposed first time within the proposed model that the primary goal of firms' management is to maximize stakeholders' wealth. Despite the fact that the importance of CSR has not been recognized yet in the last two decades, firms are becoming more eager to promote themselves as more friendly to environment, recycling or energy savers. All of these arguments are quite solid that nobody can escape to ignore the importance of CRS in explaining rate of return.

Most theorizing on the relationship between corporate social/environmental performances (CSP) and corporate financial performance (CFP) assumes that the current evidence is too fractured or too variable to draw any generalizable conclusions (Orliztky, Schmidt and Rynes, 2003). Orliztky, Schmidt and Rynes, (2003) conducted a meta-analysis of 52 studies (which represent the population of prior quantitative inquiry) yielding a total sample size of 33,878 observations. The meta-analytic findings suggest that corporate virtue in the form of social responsibility and, to a lesser extent, environmental responsibility is likely to pay off, although the operationalizations of CSP and CFP also moderate the positive association.

The Domini 400 Social Index (DS400) is a float-adjusted, market capitalization-weighted, common stock index of U.S. equities. Launched by KLD in May 1990, the DS400 is the first benchmark index constructed using environmental, social and governance (ESG) factors. It is a widely recognized benchmark for measuring the impact of social and environmental screening on investment portfolios. DS400 holds at approximately 250 S&P 500 companies, 100 additional large and mid cap companies chosen for sector diversification, and 50 smaller companies with exemplary social and environmental records. Companies engaged beyond specific levels of involvement in certain industries are not eligible for the Index. These include: Tobacco, alcohol, gambling, firearms, military weapons and nuclear power (FactSet Research Systems and Standard & Poor’s, 2009:2).

KLD selects companies for the DS400 that have positive environmental, social and governance (ESG) performance. KLD recognizes that many companies will have some ESG concerns and gives careful consideration to how companies address the risks and opportunities they face in the context of their sector or industry and relative to their peers. The ESG performance evaluation is based on overall company performance using the following indicators:

Table 48: Social Responsibility Indicators

Environment	Social	Governance
Alternative Energy	Community Relations	Accounting
Climate Change	Workforce Diversity	Executive Compensation
Liabilities	Employee Relations	Political Accountability
Management Systems	Human Rights	Transparency
Regulatory Problems	Product Quality and Innovation	Ownership

Source: FactSet Research Systems and Standard & Poor’s (2009: 3).

2.2.2. Risk

The proposed model assumes that risks affect the bankruptcy process. If a firm operates within a high risk (micro or macro) environment, then it is logical to expect that this firm exposure to high risk which may lead eventually to financial distress and default. The critical point in this logical framework is that how to make a taxonomy for risk to measure its impact on rate of return (value additivity) and bankruptcy process.

Starting to distinguish between two related and some time misused concepts of risk and uncertainty may be beneficial to introduce taxonomy for risk within the structure of proposed model. Risk and uncertainty are two concepts for describing the environment in which the action takes place. Therefore, the critical justification is the measurability of these concepts in the context of risk management.

"If you cannot measure it....your knowledge is of a meager and unsatisfactory kind." This is a quotation by Lord Kelvin chiseled in stone on the social science building at Chicago. It is true that measurement is inevitable feature of contemporary social sciences but how accurate we can measure. Knight sarcastically interpreted the quotation above to mean *"Oh, well, If you cannot measure, measure anyhow."* Knight[13] (1921: 209) was the first to distinguish between risk and uncertainty (Çelik, 2009: 28):

> *"Uncertainty must be taken in a sense radically distinct from the familiar notion of risk, from which it has never been properly separated. [...] It will appear that a measurable uncertainty or risk proper [...] is so far different from an immeasurable one that is not in effect an uncertainty at all."*

He applies the notion of risk to those unknown events for which 'objective probabilities' can be assigned. Uncertainty, on the other hand, Knight applies to events for which such probabilities cannot be assigned, or for which it would not make sense to assign them. Keynes takes a similar view (1936–37: 213–14):

[13] Frank Knight (1885–1962), in his classic *Risk, Uncertainty and Profit* (1921: 226) reasoned why risk and uncertainty should be differed :"[Any given] instance....is so entirely unique that there are no others or not a sufficient number to make it possible to tabulate enough like it to form a basis for any inference of value about any real probability in the case we are interested in." (cited in Bernstein (1996: 219)).

"By 'uncertain' knowledge, let me explain, I do not mean merely to distinguish what is known for certain from what is only probable. The game of roulette is not subject, in this sense, to uncertainty; [...] The sense in which I am using the term is that in which the prospect of a European war is uncertain, or the price of copper and the rate of interest twenty years hence, or the obsolescence of a new invention. [...] About these matters, there is no scientific basis on which to form any calculable probability whatever. We simply do not know. "

It should be figured out that both Knight and Keynes were objectivists[14]. They emphasized that risk and uncertainty are different concepts whereas they were not successfully giving an operational definition of risk. Knight (1921: 226) prefers his own terminology to clarify what is meant by risk and uncertainty as follows:

"To preserve the distinction...between the measurable uncertainty and an immeasurable one we may use the term 'risk' to designate the former and the term 'uncertainty' for the latter."

Despite the fact that this distinction continues to be a debate among economists, it is clear and common manner to use risk and uncertainty interchangeably as one term due to its usefulness in finance. Even Markowitz did not define the term risk explicitly but suggested a metric how to measure it in his groundbreaking paper 'portfolio selection' in 1952. Markowitz (1952: 77) proposes the following rule:

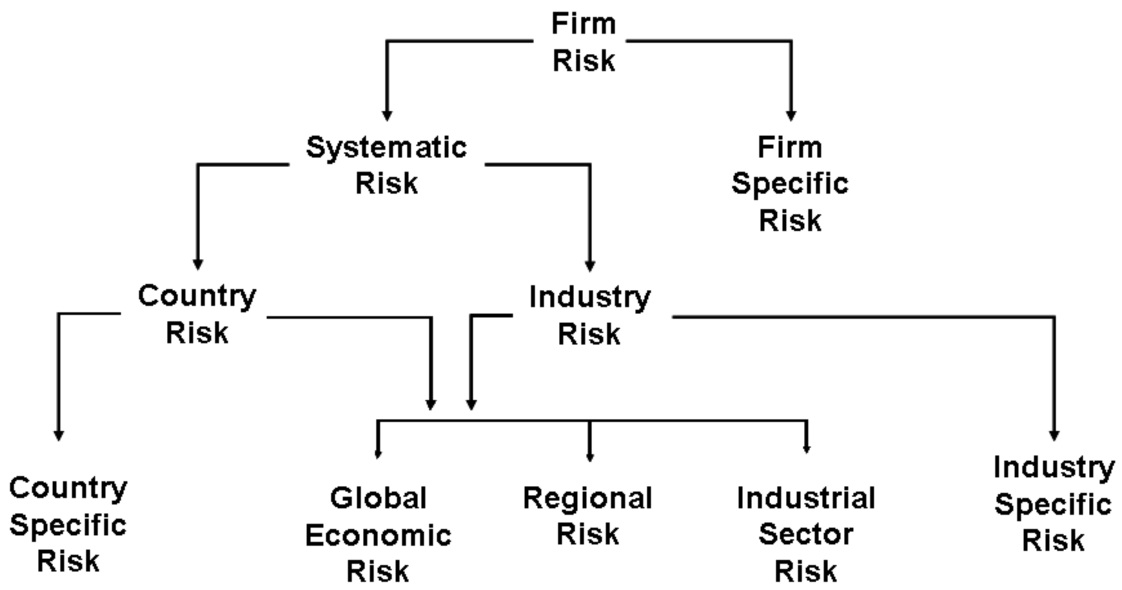
"That the investor does (or should) consider expected return a desirable thing variance of return an undesirable thing."

[14] To comprehend risk we should look at two streams flowing through the 20th century. One is subjective probability. The other one is operationalism. Holton (2004) reviewed the literature and concluded that according to objective interpretations, probabilities are real. We may discover them by logic or estimate them through statistical analysis. According to subjective interpretations that probabilities are human beliefs. They are not intrinsic to nature. Individuals specify them to characterize their own uncertainty.

In the context of portfolio theory (Markowitz, 1952;1959) and Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), risk is classified as systematic and unsystematic components despite the fact that there are various types of risk and their definitions (see Moosa (2007: 13) for such a list). Systematic risk is mainly defined as the risk that affects all firms in the market so that it is not diversably through portfolio construction. Systematic risk is also defined as market risk and non-diversably risk. Uncertainties about general economic conditions, such as *GDP, interest rates, or inflation, are examples of systematic risks* (Ross, et al., 2004: 426). Unsystematic risk, on the other hand, is defined as the risk that is unique to individual firm. Unsystematic risk is also defined as firm specific risk and diversably risk. *The announcement of an oil strike by a company* is given as an example for unsystematic risk (Ross, et al., 2004: 426). However, the definitions of systematic and unsystematic risk will be reformulated within the proposed model.

There are some specifications for the taxonomy of risk. Two of them will be simply introduced. The first one is taxonomy of Moody's which is called Moody's KMV GCorr. This taxonomy is depicted in Figure 15. The first level of the structure divides between firm specific and systematic risk. The firm's systematic risk is assumed to be captured by a single composite factor. This factor is constructed uniquely for each firm based upon the firm's exposure to countries and industries. The composite factor is constructed as a weighted sum of the country and industry factors at the second level of the structure. Since the country and industry factors at the second level of the structure are correlated with each other, their risk can also be decomposed into systematic and idiosyncratic components. The systematic component of the risk is captured by the basic factors in the third and last level of the structure. There are three types of basic factors: (i) global economic factors, (ii) regional economic factors, and (iii) industrial sector factors. The countries' and industries' idiosyncratic risk components are captured by the country and industry specific factors.

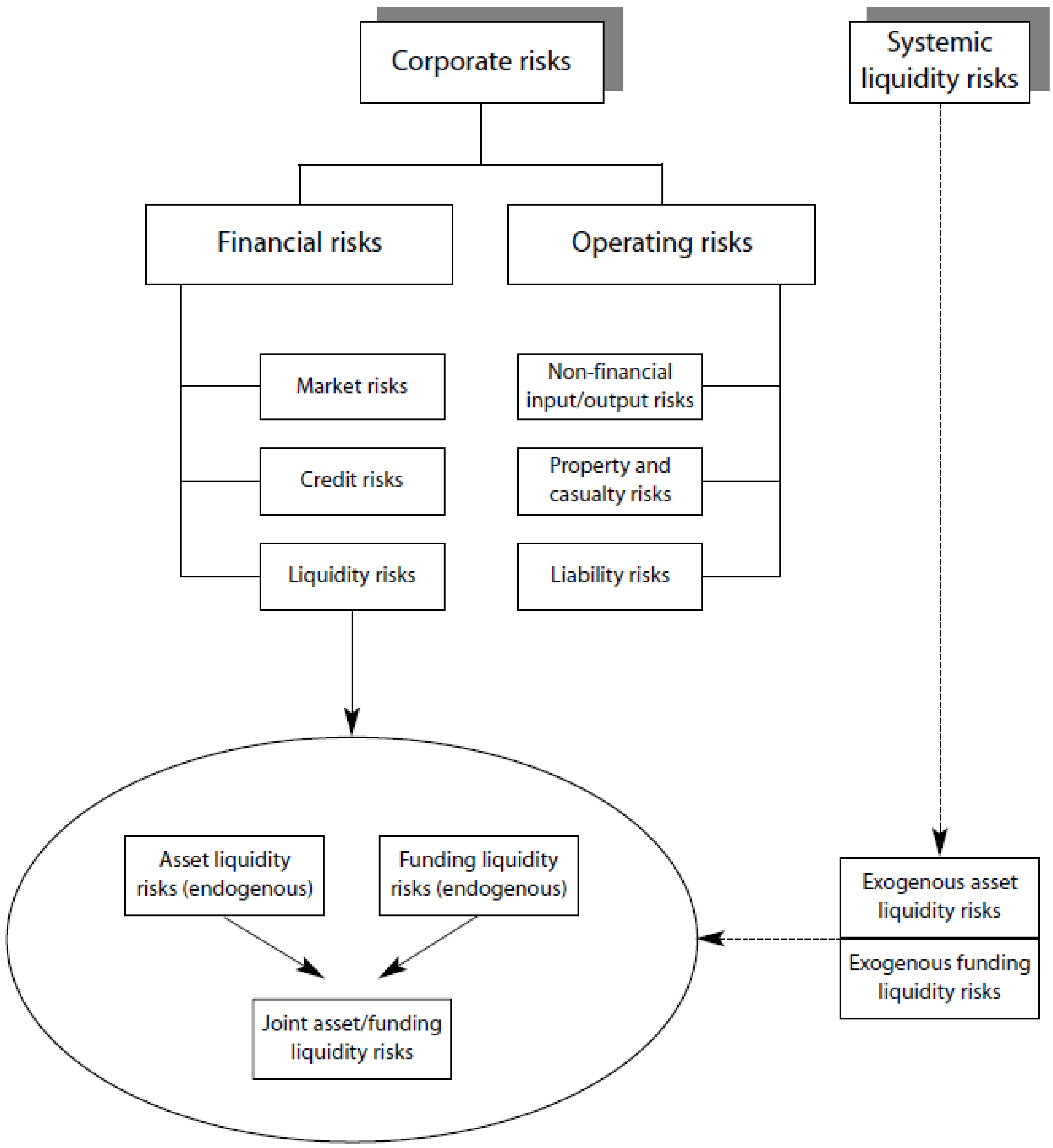
Figure 15: The First Risk Taxonomy



Source: Levy (2008: 15) from Moody's Investor Service and Oricchio (2011: 76).

The second taxonomy for risk is proposed by Banks (2005) depicted in Figure 16. Banks divided corporate risk within two broad categories such as financial risk and operating risk (sometimes called business risk). In order to capture systematic risk, it is proposed that systematic liquidity risk will contain this factor. Additionally, financial and operation risk are further divided into three categories. Financial risk is assumed to be composed of market risk, credit risk and liquidity risks. Operating risk, on the other hand, consists of non-financial input/output risk, property and casualty risk and liability risk. Besides, liquidity risk are assumed to be related to asset liquidity and funding liquidity components for both endogenous (firm based) and exogenous (market based) characteristics.

Figure 16: The Second Risk Taxonomy

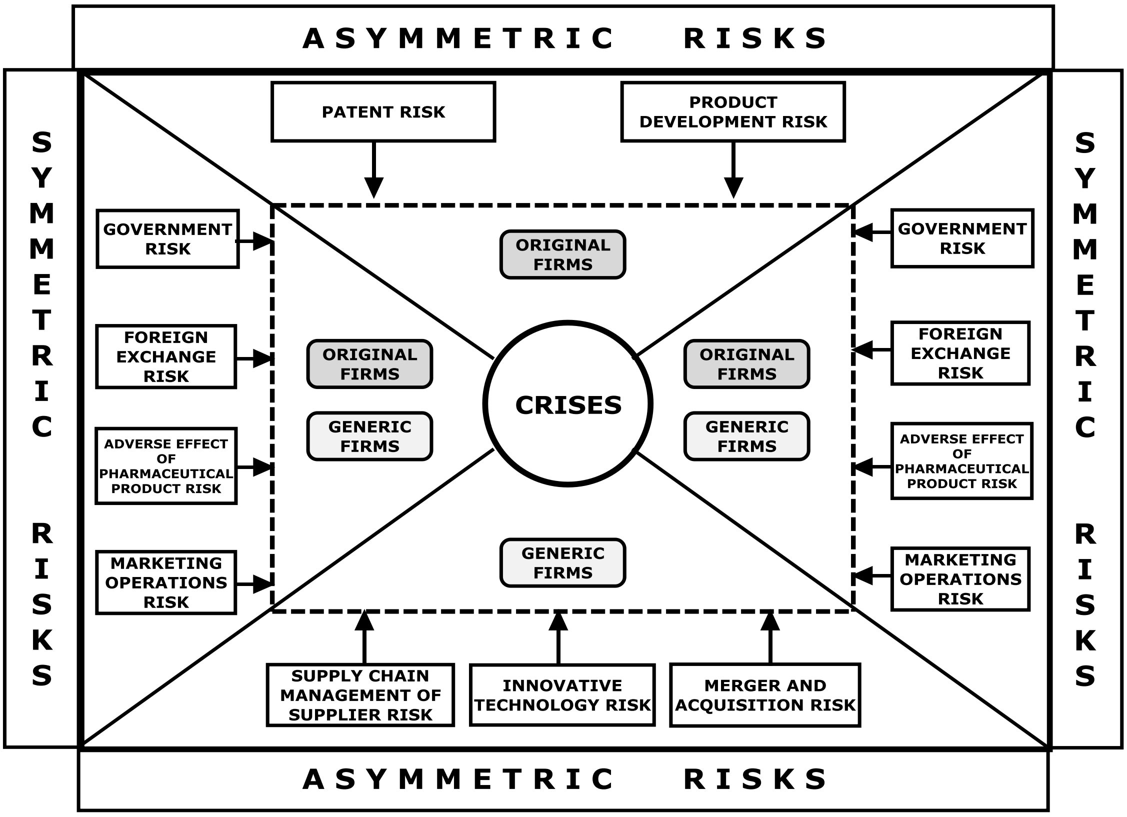


Source: Banks (2005: 7)

The proposed model categorizes risk into three main categories: systematic risk, sectoral risk and unsystematic risk. As it is a similar view proposed within Moody's taxonomy, this categorization will help to measure firm, industry and market specific risk better than the one proposed by Banks (2005). However, the configuration of systematic, sectoral and non-systematic risk components will be mentioned and reformulated within the proposed model.

General taxonomy of risk constructs may be quite different if a specific sector is analyzed. Akgöl (2010) proposed a risk-crises model for pharmaceutical industry as depicted in Figure 17. She argued that crisis management literature focuses mainly on the facts in the crisis stage or after crisis stage. Consequently, she claimed that risk was not explicitly examined pre-crisis stage in the context of crisis management. Deriving the risk factors of pharmaceutical industry, she classifies risks into symmetric and asymmetric risks that affect firms which have characteristics of being original firms and generic firms. Original firms are those of producing and developing drugs with their production and know-how facilities. Generic firms, on the other hand, are those that re-produce the previously introduced products. Therefore, author claimed that there are different risks that affect these two types firms and categorized these risks into asymmetric risks. By using the term symmetric risk instead of systematic risk is a reason of the structure of their model. Since there are two types of firms, risks that are presented on the left and right side of their model appear symmetrical. In fact, these symmetrical risk factors can be also called systematic risks that affect all firms in pharmaceutical industry. One important caution is that these asymmetric and symmetric risk factors are derived through developing a scale to measure each risk factor. Therefore, the main characteristic of these risk factors is to be perceived by market practitioners.

Figure 17: Risk-Crisis Model of Pharmaceutical Industry in Turkey



Source: Akgöl (2010: 102).

In the structure of proposed model, three types of risks are introduced as taxonomy: systematic risks, sectoral risks and unsystematic risks. The conceptualization of these risk classes can be made in the following sections whereas the most important issue is to derive and measure the correct risks within each class. As it is the case on Risk-Crises Model of Akgöl (2012), there might be a quite different taxonomy for specific sector. The problem of deriving and measuring risk factors for three classes are mainly related to the possibly association among themselves. Therefore, Moody's decomposes sector risk into systematic and non-systematic components. This problem is mainly an empirical issue rather than conceptualization. Therefore, systematic, sectoral and unsystematic risk factors will be mainly evaluated in terms of their measurability in practice.

2.2.2.1. Systematic Risk

Systematic risk is a term defined as market wide impact on all firms. It should be noted that this term is commonly used in the context of portfolio theory in way to describe non-diversely component of risk through diversification. In the context of proposed model, systematic risk is similarly defined as the risk that affects all firms. Extensive literature written on portfolio theory and asset pricing witnessed a well-known measure for systematic risk so called beta coefficient. Beta is assumed to capture all systematic risks under the assumptions[15] of CAPM.

CAPM is the most popular model of the determination of expected returns on securities and other financial assets. It is considered to be an "asset pricing" model since, for a given exogenous expected payoff, the asset price can be backed out once the expected return is determined. Additionally, the expected return derived within the CAPM or any other asset pricing model may be used to discount future cash flows. These discounted cash flows then are added to determine an asset's price. In more formal way, CAPM is depicted as follows (Sharpe, 1964; Lintner, 1965):

$$E[R_X] = r_f + \left[\frac{COV[R_X, R_M]}{VAR[R_M]}\right]\left[E[R_M] - r_f\right] \quad \text{...}(32)$$

Where;

$$\frac{COV[R_X, R_M]}{VAR[R_M]} = \beta_X$$

CAPM states that expected return ($E[R_X]$) of an asset is equal to risk free rate (r_f) plus asset's risk premium ($\beta_X \left(E[R_M] - r_f\right)$). ($E[R_M]$ is the expected return of hypothetical market portfolio return which consists of all assets). β_X is beta coefficient.

[15] For assumptions and derivation of CAPM, see Çelik (2009) and references therein.

Total risk of any individual asset can be partitioning into two parts – systematic risk, which is a measure of how the assets co-varies with the economy and unsystematic risk, which is independent of the economy (Copeland, Weston and Shastri, 2005):

Total risk = systematic risk + unsystematic risk ....(33)

Mathematical precision can be attached to the equation (33) by noting that empirically the returns on any asset is a linear function of market return plus a random error term $\tilde{\varepsilon}_i$ which is independent of the market:

$$\tilde{R}_i = \alpha_i + \beta_i \tilde{R}_M + \tilde{\varepsilon}_i \qquad (34)$$

Equation (34) contains three terms: a constant, α_i which has no variance; a constant times a random variable, $\beta_i \tilde{R}_M$; and a second random variable, $\tilde{\varepsilon}_i$ which has zero covariance with $\tilde{R}_M$. Using expected value operators, the following relationship is obtained:

$$\sigma_i^2 = \beta_i^2 \sigma_M^2 + \sigma_\varepsilon^2 \qquad (35)$$

The variance is total risk. It can be partitioned into systematic risk, $\beta_i^2 \sigma_M^2$ and unsystematic risk, σ_ε^2. This turns out that β_i in the simple linear relationship between individual asset return and market return is exactly the same as β_X in the CAPM[16].

[16] One proof is available in Copeland, Weston and Shastri (2005: 153).

There is a very important fact coming out from discussion of beta that there is only one systematic risk. This fact is related to assumptions behind CAPM and the contradicting issue so called Efficient Market Hypothesis (Fama, 1969). Argument of efficient market hypothesis is stated that all available and non-available information are priced in a way that there is no possibility to predict future return in the full form market efficiency. If this the case, covariant of individual security with that of hypothetical market portfolio return is assumed to capture all systematic risks within one measure such as the impact of GDP, inflation, interest rate etc. However, many scholars extend CAPM in way to capture other types of systematic risks as well. One example is Arbitrage Pricing Theory of Ross (1976) and Intertemporal CAMP of Merton (1973). Therefore, it is safe to state that there might be more than one systematic risk as long as the risk should satisfy the definition that describe what should a systematic risk be. Despite the fact that there is a technical difficulty of measuring the impact of more than one systematic risk on asset return due to possible correlation among them, there might be more than one systematic risk in practice at least conceptually.

One important observation is that there is no systematic risk measures among variables used to estimate bankruptcy predictions in reviewed literature taken place in chapter one. The main reason behind this observation is that the innovative approach of the proposed model that aims to link the dynamics of firms to the bankruptcy process. Since it is started to assume that the risks affect the bankruptcy process, then it is logical to figure out what are those risks. However, this argument is mainly ignored in literature.

2.2.2.2. Sectoral Risk

There are certain differences among industries in terms of their size, history, sensitivity to business cycle. Therefore, once systematic impact of overall economy is taken into consideration, it is necessary to determine the impact of industrial differences into account in case of predicting rate of return and bankruptcy process. *Clearly, the cigarette industry is largely independent of business cycle. Demand for cigarette does not seem affected by the state of the macroeconomy in any meaningful way. This is not surprising. Cigarette consumption is determined largely by habits that it not be given up in hard times* (Bodie, Kane, Markus, 2008: 586). In practice, differences among industries can be observed on the financial figures of the firms belonging to different industries. Examination of the biotechnology industry may show that there are high rates of investment, high rates of return on investment and low dividend payout ratios whereas these figures are different for public utility industry as having lower rates of return, lower investment rates and higher dividend payout ratios (Bodie, Kane, Markus, 2008). The characteristics of an industry should be necessarily taken into account in predicting bankruptcy whereas the way of treating it may be empirically difficult. As it is the case of Risk-Crises Model of Akgöl (2010), when focusing on a certain industry, there might be some industrial factors playing a role of a systematic factor that affects all firms within the industry while some others may affect some portion of these firms. That is why Moody's splits industrial effect into two components as industry specific risk and industry systematic risk.

In the taxonomy of risk proposed, sector (industry) effect is separately defined as the impact of sectoral risk on rate of return and bankruptcy process. Each sector contains its own dynamics that may affect the firms' operations. This reality is realized by some scholars who take industry effect into their model to predict bankruptcy (El Hennawy and Morris, 1983, Lennox, 1999). El Hennawy and Morris (1983) takes industry effect into account by two variables: Industry dummy for quarrying and construction and Industry dummy for distribution. In the same vein, Lennox (1999) use a dummy variable of 1 if company i operates in industry j in order to measure the impact of industrial effect on bankruptcy process.

2.2.2.3. Unsystematic Risk

In the context of unsystematic risk taxonomy, it is proposed that unsystematic risk should be treated differently than that of portfolio theory approach. There are commonly used two terms used to describe unsystematic risks for the firms: Business risk, *the riskiness of the firm's stock if it uses no debt* and financial risk, *which is the additional risk placed on the common stockholders as a result of the firm's decision to use debt.* Business risk is treated as firm unsystematic risk which is *a function of the uncertainty inherent in projections of a firm's return on invested capital* (ROIC), defined as follows (Ehrhardt and Brigham, 2007: 476):

$$ROIC = \frac{NOPAT}{Capital} = \frac{EBIT(1-T)}{Capital} = \frac{\begin{pmatrix} Net\ Inocme\ to \\ common\ stockholders \end{pmatrix} + \begin{pmatrix} After-tax \\ Interest\ payments \end{pmatrix}}{Capital} \quad ..(36)$$

where; ROIC: return on invested capital; NOPAT: net operating profit after taxes and capital; T: Tax rate; EBIT: Earnings before Interest and Taxes. Business risk can be measured by the standard deviation of its ROIC.

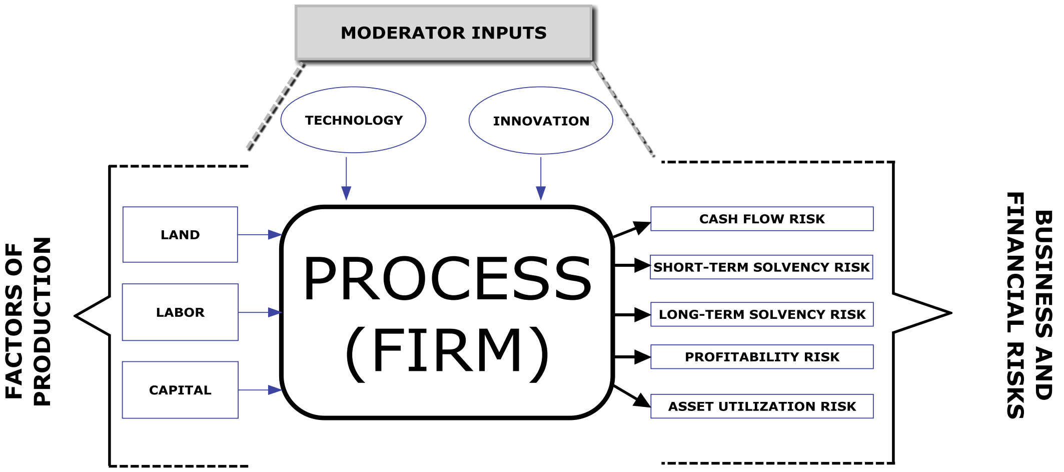
On the other hand, financial risk is the additional risk placed on the common stockholders as a result of the decision to finance with debt. Conceptually, stockholders face a certain amount of risk that is inherent in a firm's operations which is its business risk. If a firm uses debt (financial leverage), this concentrates the business risk on common stockholders. Thus, the use of debt, or financial leverage, concentrates the firm's business risk on its stockholders. This concentration of business risk occurs because debtholders, who receive fixed interest payments, bear none of the business risk (Ehrhardt and Brigham, 2007: 477).

Despite the usefulness of business and financial risk taxonomy, there are clear pitfalls in measuring these kinds of risks. The first problem is that by definition, financial and business risks do not reflect all aspects of unsystematic risks. For example, equation (36) does not tell where business risk comes from. In addition, definition of financial risk has a conceptual weakness that described in section of capital structure.

There is no consensus on the amount of debt that creates a financial risk. All of these reasons require a different way of approaching to unsystematic risks in terms of measurability.

Figure 18 shows a general framework of firm (which can be treated as a process), its inputs and possible measurements of its unsystematic risks (financial and business risks). As depicted, initial factors of productions are mainly accepted as Land, Labor and Capital whereas despite different views on the role of technology and innovation, it is assumed that these two other inputs have a moderator role in the process. By having a moderator role means that technology and innovation affect the direction and/or strength of the relation. This view is not primary issue of the thesis. However, the way of measuring the riskiness (unsystematic) of the process can be measured through cash flow risk, short-term solvency risk, long-term solvency risk, profitability risk and asset utilization risk that may well represents and better measures financial and business riskiness of the firms. However, it should be noted that there might be different measures that can be proposed for specific sector such as banking and insurance. The measures proposed in Figure 18 are more suitable for manufacturing industry. The existed literature that is aimed to predict bankruptcy uses this taxonomy as reviewed extensively in chapter one.

Figure 18: Unsystematic Risk Taxonomy



2.2.3. Rate of Return

The concept of rate of return is a representation of value added of firms' operations. The proposed model can be seen as a balanced model between value addition which is measured by rate of return and value dilution which is measured by bankruptcy process. If firm has continuous value dilution, then it is safe to state that the firm will be struggling with many problems which eventually lead to a financial distress and/or default. This is where the proposed model makes its crucial linkage that ties rate of return with bankruptcy process through the impact of risks. Risk component is playing a role of wind that changes the equilibrium between value additivity and value dilution.

Figure 19: Value added and Dilution Balance

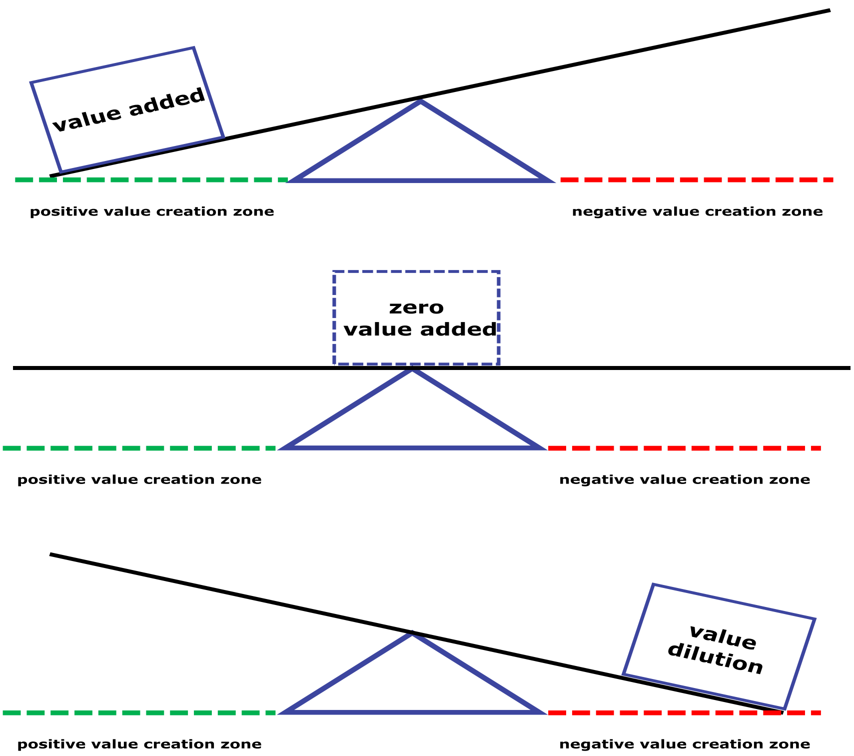


Figure 19 illustrates value added and value dilution balance. There are three alternatives in which value added takes form. In the first alternative, there is a creation of value produced by firm that leads the firm to stay in positive value creation zone. In the second alternative, there is no (zero) value produced by firm that makes no changes that lead firm to stay in neither positive and negative value creation zone. In the third alternative, there is negative value produced by firm that leads the firm to stay in negative value creation zone.

The framework of value added and value dilution process should be measured in order to evaluate overall condition of the firm. There are three types of metrics proposed for measuring value creation: Accounting (based) rate of return, economic (based) rate of return and market (based) rate of return. These three metrics are different in the sense that their calculations are affected by different factors. Accounting rate of return is a figure derived from financial statements without taking risk and expectation into account. Economic rate of return is a figure that account rate of return in way to incorporate risk into account whereas it does not take expectations into consideration. Market rate of return is a figure that is assumed to incorporate both risk and expectation into account whereas it does contain heuristic biases.

Despite the fact that measuring rate of return is primarily an empirical issue, it is very useful to underline the differences among the metrics proposed to measure. In all three types, there are advantages and disadvantages in properly measuring rate of return that firms generate. Each of these advantages and disadvantages does not change the reality that value creation should be appropriately measured for monitoring and controlling overall condition of the firms. The following sections give a rather short description for each metric and the examples developed to be representative for each one.

2.2.3.1. Accounting Rate of Return

The first type of metric that is proposed to measure rate of return is the one calculated based on accounting profit which is reported through income statements under the framework of accounting standards. Since accounting profit is open to be manipulated through accounting standards, there is a possibility of reporting high or low accounting figures depending upon management consideration. There are at least two reasons available to report high or low accounting profit. The first reason is that accounting standards are flexible[17] to manipulate and the existence of agency problem. Depending upon conflicts of interests between shareholders and executives, accounting figures can be reported in the best interest of executives. For instance, executives' compensations may be linked to positive profits. The second reason is that recognition principle of income and costs. Accounting profit is calculated over accrual based income and costs which may not reflect the impact of time value of money and risk whereas economic profit is calculated on cash based figure. The primary difference between accounting profit and economic profit more specifically is that accounting profit does not take cost of equity into account despite the fact that accounting profit by definition is the difference between income and cost.

Accounting based performance measures focus on the past, transactions-oriented, highly dependent on the choice of measurement method, conservatively biased, ignore some economic values and value changes that accountants feel cannot be measured accurately and objectively, ignore the cost of equity capital, ignore risk and changes in risk (Merchant and Sandino, 2009; Çelik and Aslanertik, 2011). In many different studies, it was stated that accounting based performance measures such as net profit, return on investment and return on equity are inadequate measures of financial performance especially in evaluating the goal of achieving value creation for shareholders (Rappaport 1986; Biddle, Bowen, Wallace, 1997; Çelik and Aslanertik, 2011).

[17] Accounting standards can be simply dividend two main branches: principle and rule based accounting. Accounting standards of USA which is Generally Accepted Accounting Principles (GAAP) is an example of rule based accounting standards. Accounting standards of England and continent Europe is an example of principle based accounting standards.

2.2.3.2. Economic Rate of Return

The second type of metric that is proposed to measure rate of return is the one so called economic profit. The most popular metric for measuring economic profit[18] is Stern Stewart's Economic Value Added (EVA). EVA is the financial performance measure that most accurately reflects a corporation's true profit (Stewart, 1991). EVA is the difference between a company's net operating income after taxes and its cost of capital of both equity and debt (Stewart, 1994). EVA accepts the assumption that the primary financial objective of any business is to maximize the wealth of its shareholders. Returns over and above the cost of capital increase shareholder wealth, while returns below the cost of capital erode shareholder wealth (Çelik and Aslanertik, 2011).

Another closely related metric is that of Market value added (MVA) which is the difference between the equity market valuation of a company and the sum of the adjusted book value of debt and equity invested in the company. This is a measure of the value generated by managers for shareholders. Because it captures both valuation – the degree of wealth enrichment for the shareholders and performance i.e. the market assessment of how effectively a firm's managers have used the scarce resources under their control - as well as how effectively management has positioned the company on the long term (Ehrbar, 1998). MVA is said to be a more effective investment tool than other measures such as market value of equity, book/price ratio and price/earnings ratio (Yook and McCabe, 2001). Some empirical studies in literature supports the idea that EVA is superior to all other traditional accounting measures (Grant,1996; Lehn & Makhija, 1997; O'Byrne, 1996; Uyemura, Kantor, & Pettit,1996; Walbert, 1994), while some others proved the opposite (Biddle et al., 1997; Chen & Dodd, 2001; Clinton & Chen, 1998; Ray, 2001). Grant (1996) focused on the MVA/CAPITAL and EVA/CAPITAL ratios to adjust for firm size. The study concludes that EVA has a significant impact on the market-value-added of a firm and this wealth effect stems from the company's positive residual return on capital (Çelik and Aslanertik, 2011).

[18] Economic profit is also defined as residual income.

2.2.3.3. Market Rate of Return

The third type of metric that is proposed to measure rate of return is the one coming from market. However, this metric can be only used for listed companies. Market rate of return as stated is assumed to incorporate both risk and expectation into account whereas it does contain heuristic biases. This statement does contain two important concepts at the same time. The first important concept is Efficient Market Hypothesis as previously discussed. If market is (a full-form) efficient then it is said for the market to reflect all available (and non-available-insider trading) information which does contain expectations as well. Market does also adjust prices depending upon perceived risks for the given stock. The second term just comes in here that price adjustments may not fully be rational since investors take many irrational decisions (heuristics). Therefore, the war between neo-classical finance and behavioral finance start to describe how prices adjust information whether correctly or not (Çelik, 2009). As a result, the statement that market based return does contain risk and expectation is not fully agreed among two streams of financial thoughts[19].

Market capitalization (Shares outstanding x share price), Tobin Q (market value of assets / replacement cost of asset), Market value/book value and Price - Earnings ratio (Price/ (earning per share) are commonly used metrics for measuring market rate of return. Tobin Q is a metric often used as a measure of the real value created by a firm's management. The higher the Q, the more value is added. The estimation of the replacement cost of assets is fairly difficult. One approximation was proposed by Lindenberg and Ross (1981) in which the numerator is the sum of the book value of debt (adjusted for age), market value of common equity, and book value of preferred stock, less net short-term assets. The denominator is total assets plus an adjustment for inflation on the firm's equity capital. These calculations can be quite complex with respect to the debt adjustment and the inflation adjustment (Çelik and Aslanertik, 2011).

[19] Shefrin (2005) clarifies this point by giving the following example: An example of the confusion can be found in a side-by-side debate conducted on the pages of The Wall Street Journal on December 28, 2000. The Journal published two opinion pieces: "Are Markets Efficient?: Yes, Even if They Make Errors" by Burton G. Malkiel, and "No, Arbitrage Is Inherently Risky" by Andrei Shleifer. A key difficulty with that debate was that the two authors did not subscribe to a shared definition of market efficiency. Shleifer focused on the mispricing of particular securities, whereas Malkiel focused on the absence of abnormal profits being earned by those he took to be informed investors.

2.2.4. Cost of Capital

Cost of capital is one of the primary concerns for all parties getting involved in business transactions. By definition, cost of capital is the minimum rate of return that demander of funds must achieved to satisfy suppliers of funds (stockholders or bondholders). The proposed model assumes that the risk increases cost of capital. This claim will be shown in several form of calculating cost of three types of sources: cost of debt, cost of preferred stock and cost of equity (Table 49). Before moving on these derivations, it is useful to mention the descriptions of several terms regarding to cost of capital: weighted average cost of capital, cost of capital of a project, embedded cost of capital and marginal cost of capital.

Weighted average cost of capital (WACC) is referring to *the firm's overall cost of capital that is the cost of capital for all of the firm's projects past and present*. Project cost of capital is a minimum *rate of return for a specific project*. While WACC is used in performance evaluation techniques, project cost of capital is used in capital budgeting applications for individual projects. Generally, *a project's cost of capital is determined by first starting with the firm's overall cost of capital and then tailoring this value to reflect the project's relative riskines*s. The marginal cost of capital is the rate of return for raising additional capital which is used in capital budgeting situations when evaluating whether the project's future cash flows outweigh the cost of the funds to support those cash flows. The embedded cost of capital is *the cost of funds already raised-that is, what it costs the firm for the funds already supplied*. Since many firms more than one source of funds, their cost of capital should be weighted. However, there are some obstacles in estimating cost of capital for the firms. In case of calculating cost of debt (e.g.), *the yield on convertible debt, debt with variable interest rates that contain rate caps and floors, the yield on debt denominated in a foreign currency, leases for which no current yield is defined and debt that is not rated* create problems in estimation (Peterson and Peterson, 1996: 49).

Table 49: Estimations of Cost of Capital

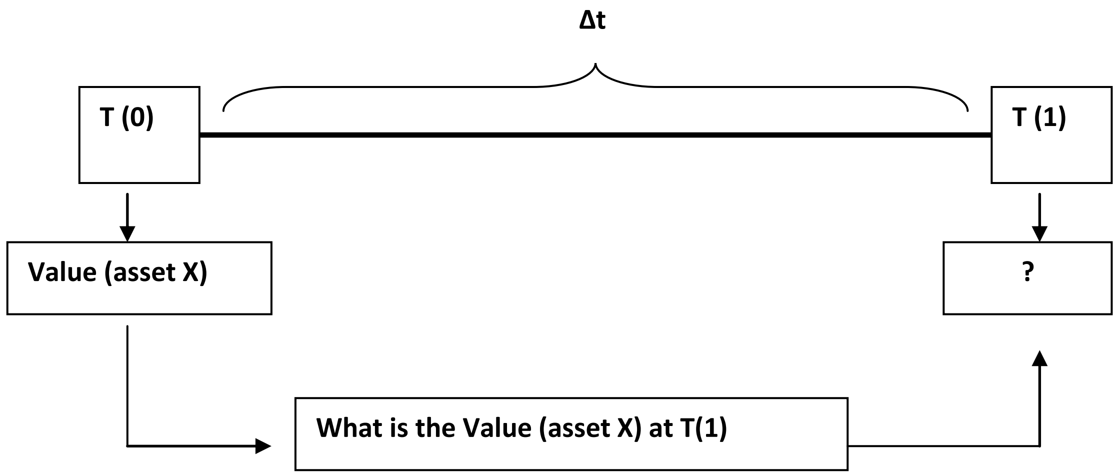
Source of Funds	Formula	Notations
Debt	$r_D = R_D(1-T)$	r_D :cost of debt after-tax R_D :cost of debt before-tax T: Tax rate
Preferred Stock	$r_{PS} = \frac{D_{PS}}{P_{PS}}$	P_{PS} :current value of preferred stock; D_{PS} : dividends paid over preferred stock r_{PS} : cost of preferred stock
Equity	$P = \frac{D}{(1+r_e)^1} + \frac{D}{(1+r_e)^2} + \ldots + \frac{D}{(1+r_e)^n}$ $r_E = \frac{D}{P}$	Using Gordon model with fixed dividend stream: P: stock price D: dividend r_E :cost of equity
	$P = \frac{D_0(1+g)^1}{(1+r_E)^1} + \frac{D_0(1+g)^2}{(1+r_E)^2} + \ldots + \frac{D_0(1+g)^n}{(1+r_E)^n}$ $r_E = \frac{D_1}{P} + g$	Using Gordon growth model: P: stock price D: dividend at time 0 g : dividend growth rate r_E : cost of equity
	Cost of Equity = Time Value of Money + Cost of Risk $r_E = r_F + \beta_A(R_M - r_F)$	Using CAPM: r_E : cost of equity r_F : risk free rate β_A : beta of stock A R_M : return of market portfolio

Table 49 demonstrates commonly used calculations in estimating costs of different sources of funds. In case of cost of debt, consideration of the tax deductibility of interest is taken into account. In case of cost of preferred stock, the cost is based on the valuation of perpetuity. In case of cost of equity, there are two alternatives offered: Gordon models and CAPM. Assuming that firm pays a fixed amount of dividend forever, the result is the same as the one in preferred stock whereas assuming that firm pays irregular dividend with a constant growth rate, then the result is sum of dividend yield and growth rate of dividend. There are other forms of Gordon models such as two stage growth model which is skipped here. The second alternative is the one that is using CAPM to calculated cost of equity which is relying on the time value of money and cost of risk. This is where it can be shown clearly how risk increases cost of equity. Despite the fact that if cost of risk increases, then simply cost of equity will increase. However, the following simple justification of Çelik (2009: 7) gives slightly more accurate picture in explaining this claim.

Economists usually make specified assumptions to clarify the situation in which their predictions will be held. Starting with a general case to emphasize how a value of asset can be determined in one period model.

Assumption 1: There is only one period but two dates where transaction takes place.
Assumption 2: There is zero interest rate.
Assumption 3: There is zero inflation.
Assumption 4: There is zero risk.
Assumption 5: For rest of the factors that may affect the transaction is constant at two dates (ceteris paribus).

Figure 20: Valuation of an Asset



$$Value(asset\ X)_{T_0} = Value(asset\ X)_{T_1} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (37)$$

Under the assumptions 1 to 5, it is clear that it is about certainly dealing with a sure value due to the fact that we fixed every factor that may affect the value of an asset in one way or another in next period. This is the starting point to illustrate from certain value to uncertain.

Relaxing assumption 2: There is a constant interest rate that can be earned in the market (later we will define this rate as risk free).

$$Value(asset\ A)_{T_0} = Value(asset\ A)_{T_1} \div (1 + r_c)^{\Delta t} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (38)$$

Introducing a constant interest rate lead us to discount the next period value to the present, as it is well documented in financial text books as present value calculation usually used to evaluate the required rate of project.

Relaxing assumption 2 and 3: There is a constant interest rate denoted as r_c that can be earned in the market and an inflation rate, denoted as i (inflation is usually assumed that it is adjusted in risk free rate or in risk premium whereas it is necessary to demonstrate how it takes place in valuation).

$$Value(asset\ X)_{T_0} = Value(asset\ X)_{T_1} \div (1 + r_c + i)^{\Delta t} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (39)$$

The value of a Turkish Lira today is not equal to the value of a Turkish Lira tomorrow if there is an inflation and equivalently opportunity cost. The impact of inflation results on nominal returns and we usually deduct the impact and gain the real return. Therefore, the inflation rate may be added to constant rate to discount the next period value to the present.

Relaxing assumption 2, 3, and 4: There is a constant interest rate denoted as r_c that can be earned in the market, an inflation rate, denoted as i and the risk that gives a premium denoted as r_p (risk premium is a rate that is required for investors to take the risk. Otherwise, why investors invest if there is a certain rate that can be earned without taking any risk). Since there is an uncertainty, we will expect what will be the value of asset X at time T(1).

The fundamental relation between risk and return is assumed to be linear at least at theoretical point of view. In addition, it is also assumed that investors should be compensated for bearing the risk. This is called premium for bearing the risk. The way we assumed that the rate for bearing risk is a certain rate on the contrary to adjusting it for investors' behaviors or market structure. This is overly simplified the problem whereas it is useful to demonstrate it and compare the result with what Capital Asset Pricing Model (CAPM) suggests.

$$Value(asset\ X)_{T_0} = E(Value(asset\ X))_{T_1} \div (1 + r_c + i + r_p)^{\Delta t} \qquad (40)$$

If we rearrange the expression (40) as $V(asset\ X)_{T_0} = \frac{E(V(asset\ X))_{T_1}}{(1 + r_c + i + r_p)^{\Delta t}}$ and since this is one period model, Δt is set to 1 and we assume that inflation is inherit in risk premium or in constant interest rate in addition to defining constant interest rate as risk free and risk premium as $\beta \times excess\ market return$ it would have been a celebrated model of asset pricing that is Sharpe-Lintner Capital Asset Pricing Model. CAPM states that expected return (μ_X) of an asset is equal to risk free rate (r_f) plus asset's risk premium ($\beta_X(\mu_m - r_f)$). (μ_m is denoted hypothetical market portfolio return which consists of all assets).

$$\mu_X = r_f + \beta_X(\mu_m - r_f) \qquad (41)$$

Rearranging the CAPM in terms of returns:

$$\mu_X = r_f + \beta_X\left(\mu_m - r_f\right) \longrightarrow \mu_X = \frac{E(P_{X1}) - P_{X0}}{P_{X0}} \quad \text{and } \lambda = \mu_m - r_f$$

Then after the relevant adjustment we will have the following equation:

$$P_{X0} = \frac{E(P_{X1})}{\lambda\beta_X + r_f + 1} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(42)$$

As it is depicted, expressions (40) and (42) are quite similar even though their theoretical backgrounds are not identical. The difference in both equations is what constitutes denominator in discount factor. Equation (42) also shows that denominator is discount rate of expected value and/or any future cash inflows. Therefore, if denominators which are partly composed of systematic risk rises, the discount rate will increase as well.

Despite the fact that there is a clear tradeoff between cost of capital and risk, there is no single article that used cost of capital as a variable in predicting bankruptcy in the extensive literature reviewed in chapter one. There is another interesting component of cost of capital in relation to rating that corporate rating determines the level of cost of capital for the corporations. These both theoretical and empirical signs perhaps were not enough to make cost of capital being used as a variable in prediction. However, the other side of story might be about having difficulties in estimating cost of capitals for the firms. In any case, proposed model gives a clear understanding among risk, cost of capital and bankruptcy process so that the linkages can be reformulated in future empirical researches.

2.2.5. Bankruptcy Process Construct

The proposed model assumes that bankruptcy process contains both a process in which financial distress takes place and a process in which bankruptcy formation comes into existence in the form of liquidation and restructuring (or reorganization). This does not necessarily mean that every financial distress is resulted in liquidation or restructuring. The reasons behind this argument are that financial distress and bankruptcy formation are not mutual exclusive process – one triggers another and the probability of default is getting higher for firms in financial distress than those of financially sound firms. Therefore, process of financial distress and bankruptcy formation constitute bankruptcy process together.

The proposed model shed a light on how firms' dynamics are related to bankruptcy process within the structure of value added and value dilution. Ratner, et al., (2009: 3) gives rather more operational reasons behind financial distress and called them operational distress including *competition from other companies, competition from replacement products and services, the departure of key employees or management, rapid changes in raw material quality or availability, changes in cost structure that cannot be passed on to consumers, or a change in the demand for the company's products or services.* The number of such reasons can be extended whereas the proposed model shows a map to follow in approaching whole story of bankruptcy process by taking firms' dynamics into account. That is why Ratner, et al., (2009: 3) pointed out that no matter what reasons behind operational stress, *declining revenues or market share, increasing operating expenses, decreasing operating margins, and liquidity constraints* can be financial outcome.

Despite the fact that there are three stages defined within the proposed model as an option / a situation in bankruptcy process, financial distress – liquidation – restructuring, there are different forms of restructuring such as prepackaged bankruptcy or negotiation of debt composition depending upon firms characteristics either in the court or out of the court.

2.2.5.1. Financial Distress

Financial distress is sub-process of bankruptcy defined as *difficulty in paying debts or buying needed assets* (Ross, et al., 2004: 27). The proposed model shows that the pre-stage of bankruptcy formation is the process in which firms have difficulties in meeting the needs of funds' providers. Therefore, it *is likely to occur when the company's existing leverage is excessive, and the company finds it hard or impossible to make scheduled debt or principal payments* (Ratner, et al., 2009: 3). One argument given as an example of such situation is that when the firms have financed long-term assets through short-term financing. This creates a problem of reducing working capital.

Determining characteristics of firms in financial distress are not straightforward. The majority of existed literature skips to clarify what characterizes financial distress and try to focus on the variables that differentiate firms into bankrupt and non-bankrupt. However, financial distress cost becomes a key attribute to pay attention when the firm is defined as financially distress. Ratner, et al., (2009) pointed out two alternatives for the firms when they are not able to get rid off financial distress: (i) surrender its assets to its secured creditors (or be subject to foreclosure by the secured creditors) and/or (ii) cease operations, liquidate its remaining assets, and satisfy its debts to the extent possible.

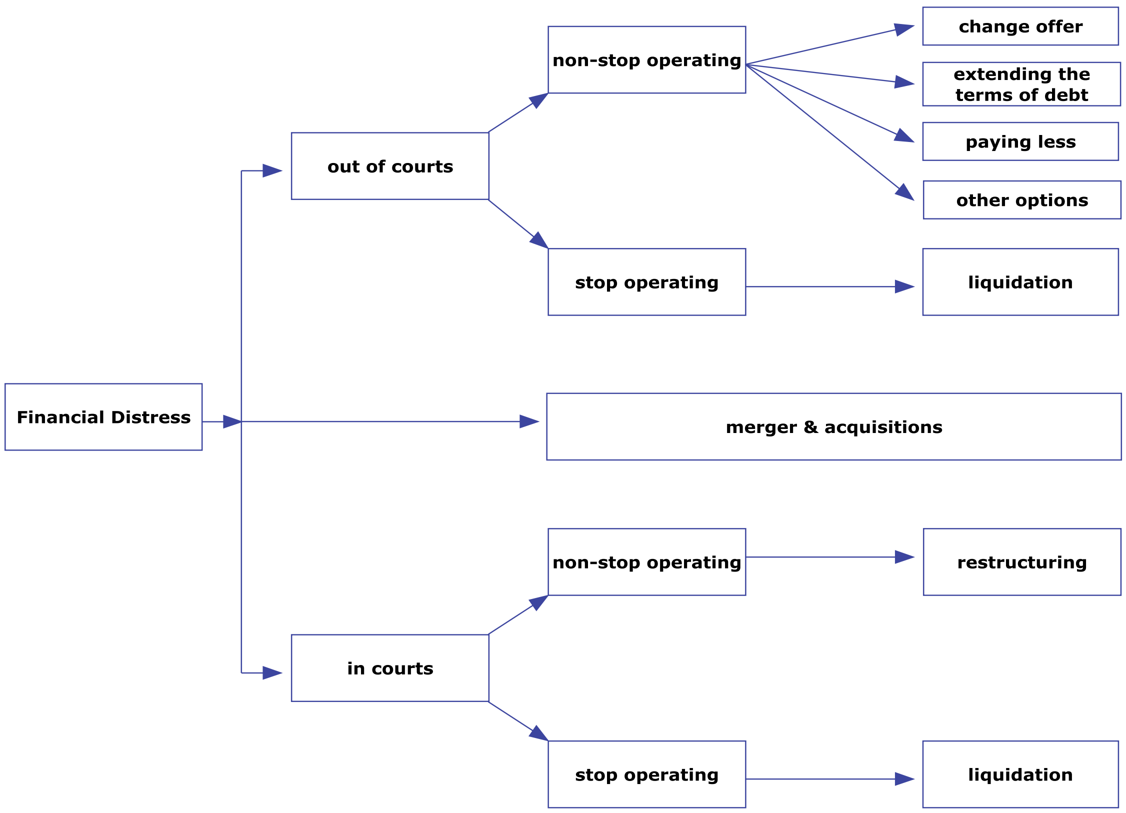
Legislative procedures of bankruptcy process can be quite complex in all over the World. There are two commonly cited Codes of Bankruptcy in USA[20]: Chapters 7 which *allows the liquidation to be handled by a court-appointed trustee pursuant to the applicable provisions of the Bankruptcy Code* and Chapter 11 which leads the *confirmation of a plan of reorganization* (Ratner, et al., 2009: 5).

Figure 21 demonstrates the alternatives that may simplify the possibly outcomes from financial distress. There are three alternatives proposed as a possible outcome from financial distress whereas it should be underline the fact that there is a forth possibility that the firm may overcome its financial distress and maintain its operations without having a different ownership structure. The first alternative is the one takes place within the legislative structure. In this way, firm may be liquidated or restructured. In the second alternative, firm starts to negotiate its liabilities with funds'

[20] There are more than these two codes whereas the legislative structure of bankruptcy is out of scope of the thesis.

providers in order to redesign its debt. If a solution exists, it will continue its operations. If not, liquidation in court becomes the only alternative. The third one is less known than the other two due to its formation. In this way, firm is getting involved in merger and acquisition.

Figure 21: Possible Post-Stages of Financial Distress



Source: adopted from Weston, Mitchell and Mulherim (2003: 340).

2.2.5.2. Liquidation

Liquidation is the most dramatic outcome of bankruptcy. Chapter 7 of the Federal Bankruptcy Reform Act of 1978 in USA deals with "straight" liquidation. The following sequence of events is typical (Ross, 2004: 595):

1. A petition is filed in a federal court. Corporations may file a voluntary petition, or involuntary petitions may be filed against the corporation by several of its creditors.

2. A trustee-in-bankruptcy is elected by the creditors to take over the assets of the debtor corporation. The trustee will attempt to liquidate the assets.

3. When the assets are liquidated, after payment of the bankruptcy administration costs, the proceeds are distributed among the creditors.

4. If any proceeds remain, after expenses and payments to creditors, they are distributed to the shareholders.

The distribution of the proceeds of the liquidation occurs according to the following priority list (Ross, 2004: 595):

1. Administrative expenses associated with the bankruptcy

2. Other expenses arising after the filing of an involuntary bankruptcy petition but before the appointment of a trustee

3. Wages, salaries, and commissions

4. Contributions to employee benefit plans

5. Consumer claims

6. Government tax claims

7. Payment to unsecured creditors

8. Payment to preferred stockholders

9. Payment to common stockholders

2.2.5.3. Restructuring

Bankruptcy Reorganization Corporate reorganization takes place under Chapter 11 of the Federal Bankruptcy Reform Act of 1978. The general objective of a proceeding under Chapter 11 is to plan to restructure the corporation with some provision for repayment of creditors. A typical sequence of events follows (Ross, 2004: 595):

1. A voluntary petition can be filed by the corporation, or an involuntary petition can be filed by creditors.

2. A federal judge either approves or denies the petition. If the petition is approved, a time for filing proofs of claims is set.

3. In most cases, the corporation (the "debtor in possession") continues to run the business.

4. The corporation (and, in certain cases, the creditors) submits a reorganization plan.

5. Creditors and shareholders are divided into classes. A class of creditors accepts the plan if a majority of the class agrees to the plan.

6. After its acceptance by creditors, the plan is confirmed by the court.

7. Payments in cash, property, and securities are made to creditors and shareholders. The plan may provide for the issuance of new securities.

8. For some fixed length of time, the firm operates according to the provisions of the reorganization plan.

Legislative structure of bankruptcy in Turkey is carried out within bankruptcy and restructuring codes ('İcra ve İflas Kanunu', '5092 Sayılı Sermaye Şirketleri ve Kooperatiflerin Uzlaşma Yoluyla Yeniden Yapılandırılması Hakkındaki Kanun' and '4743 Sayılı Mali Sektöre olan Borçların Yeniden Yapılandırılması Hakkındaki Kanun' (Sayılgan and Coşkun, 2009; Coşkun and Sayılgan, 2008)). Restructuring through negotiation is usually taken place within so called İstanbul Approach in Turkey.

CHAPTER THREE

ESTIMATION OF THE PROPOSED MODEL

3.1. INTRODUCTION

The purpose of this chapter is to estimate the proposed model developed in chapter two. In the context of present study, the main testable proposition is about how to differentiate distress and non-distress firms within the scope of the model. In order to perform the required tests, univariate and multivariate statistical analysis are conducted. In the context of univariate analysis, parametric and non-parametric independent sample tests are applied depending upon the normality test of the variables. In the context of multivariate analysis, multivariate logistic regressions are conducted for the purpose of determining the variable that affect the probability of belonging the specified sample.

The analysis is conducted on manufacturing firms listed in Istanbul Stock Exchange (ISE) for the period from 2007 to 2011. The analyses are carried out within the structure of cross-sectional framework. The data including financial statements and their footnotes, stock prices, special reports, annual reports, etc. are derived mainly from the websites of ISE, Public Disclosure Platform (PDP), Capital Markets Board of Turkey and the firms.

Evaluation processes of estimated models are carried out at four stages. The first stage gives an examination of overall accuracy of classification, Type I and Type II Error rates. The second stage examines significance of coefficients of the estimated models. The third stage evaluates signs of coefficients of the estimated model with respect to the proposed model. Finally at the last stage, the overall model fit is analyzed. Empirical results of proposed model indicate that the estimated models give promising results in case of one and two years before the final condition of the firms. Estimated models perform over 90% correct classifications for 2010 and 2011.

This chapter is structured as follows: (i) development of the model construct measures will be introduced; (ii) the variable set and their descriptive statistic will be given in order to examine the structure and distribution of variables; (iii) univariate analysis will be conducted for each model construct through parametric and non-parametric independent sample tests; (iv) multivariate analysis will be carried out via multivariate logistic regressions; (v) research constraints, future implications and concluding remarks take place at final stage.

3.2. DEVELOPMENT OF CONSTRUCTS MEASURES

Estimating the proposed model depicted in Figure 8 requires the determination of the best measures for each construct. The development of the measures for each construct measures plays a crucial role to confirm the propositions of our model. In the context of present study, the main testable proposition is how to differentiate distress and non-distress firms within the scope of the model. This testable hypothesis is commonly followed in related literature given in chapter one.

Figure 8: Proposed Model

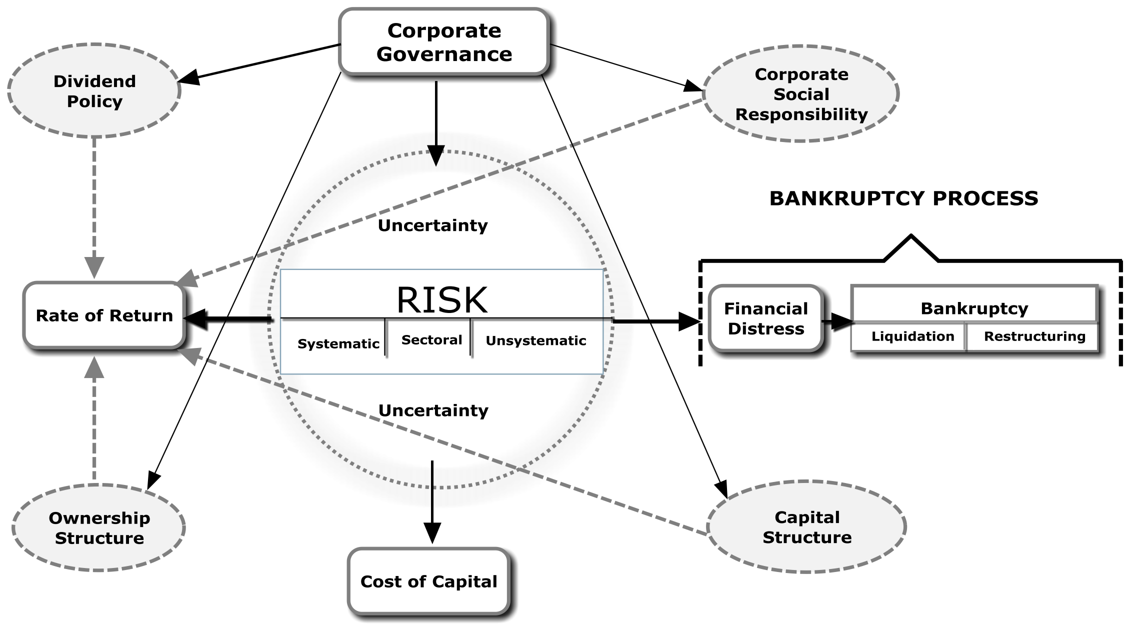


Table 50 shows the relevancy of each construct and sub-construct for the empirical study of this thesis. The constructs those are measured and used in the analyses are considered as relevant or partially relevant. On the other hand some of those cannot be measured and used are considered as irrelevant.

Corporate governance construct consists of five sub-constructs: corporate governance, dividend policy, capital structure, ownership structure and corporate social responsibility. Relevancy and partially relevancy imply that a construct is measured and used in empirical analysis. A construct that is not relevant for the study is denoted as not relevance. The "rate of return" construct can be measured by the accounting and economic rate of return in addition to the market rate of return. In our analysis since the former two measures have some disadvantages relative to the latter, they were not considered within the analyses. In addition, three variables which are mentioned in the following section, are used to measure the market rate of return as the only measure of the rate of return construct.

The "cost of capital" construct consists of cost of debt, cost of equity and weighted average cost of capital components. The calculation of the "cost of capital" directly by implying the methods given in chapter two is not possible for the firms included in the analysis (on average 150 firms for five year) because of the missing and non-disclosure data on this issue. Therefore, the cost of debt is considered alone as a dummy variable for this construct. It takes value of one if the firm is rated by a rating agency and zero otherwise.

The "bankruptcy process" consists of three sub-constructs namely financial distress, liquidation and restructuring. Firms those are liquidated and restructured are not taken into account in our analysis due to lack of their indicators required to estimate the model properly. Therefore, our sample consists of the firms that are financially distress. It does not include bankrupt firms.

The "risk" construct of our model consists of systematic, unsystematic and sectoral risk. Since the sectoral and sub-sectoral betas are highly correlated with the market beta denoting the systematic risk, these two variables were not considered within the analyses.

The detailed information on these measures is given in the following sections. It need to be underlined the fact that some measures are in the form of dichotomous variable taking the value of one and zero; and some are in the form of continuous variable. Therefore, each is calculated and used in the most appropriate way depending on their availability. For instance, corporate governance measure is structured as a dummy variable due to unavailability of corporate governance rate for all firms in our analysis. Firms that are included in the ISE Corporate Governance Index are denoted as one and zero otherwise. However, considering a variable in the form of a dummy variable still give us an opportunity to conduct statistical analysis.

Table 50: Constructs Measures

Construct		Code of Sub-construct	Sub-construct	Relevance for the Study
CORPORATE GOVERNANCE		CG	Corporate Governance	Partially relevance
		DP	Dividend Policy	Relevance
		CS	Capital Structure	Relevance
		OS	Ownership Structure	Relevance
		CSR	Corporate Social Responsibility	Relevance
RISK	UNS.	CFR	Cash Flow Risk	Relevance
		SSR	Short-Term Solvency Risk	Relevance
		LSR	Long-Term Solvency Risk	Relevance
		PRR	Profitability Risk	Relevance
		AUR	Asset Utilization Risk	Relevance
	SEC.	Beta (SS)	Sub-Sector Beta	Relevance
		Beta (S)	Sector Beta	Relevance
	SYS.	Beta (M)	Market Beta	Relevance
RATE OF RETURN		ARR	Accounting Rate of Return	Not Relevance
		ERR	Economic Rate of Return	Not Relevance
		MRR	Market Rate of Return	Relevance
COST OF CAPITAL		COD	Cost of Debt	Partially relevance
		COE	Cost of Equity	Not Relevance
		WACC	Weighted Cost of Capital	Not Relevance
BANKRUPTCY PROCESS		FD	Financial Distress	Relevance
		LQ	Liquidation	Not Relevance
		RO	Reorganization	Not Relevance

Notes: UNS: Unsystematic Risk; SEC: Sectoral Risk; SYS: Systematic Risk

3.2.1. Corporate Governance Measures

Corporate governance measures are structured according to their availability and suitability to the aim of the study. Firms that are actively traded in ISE[21] are graded by independent corporate governance rating firms licensed by Turkish Capital Market Board. These rating are considered by ISE to determine Corporate Governance Index (XKURY) which has developed since 2007 for the purpose of measuring the price and return performance of companies with a corporate governance rating of minimum 7 to 10. There are four dimensions of corporate governance principles including shareholders (25%), public disclosure (35%), stakeholders (15%) and board of directors and executives (25%). Each of these dimensions has several other sub-elements. However, as depicted, these four main dimensions have different weights in calculating the rate. Since there are only a few manufacturing firms in the Corporate Governance Index, corporate governance indicator was considered as a dummy variable. It takes one if the firm is included in the index and zero otherwise.

Similarly the dividend policy is also denoted as dichotomous variable as a result of the fact that considerable numbers of firms do not distribute dividends. Although the dividend yields were calculated for the firms that pay dividends, considering this variable in a dummy structure form might be more appropriate for the analysis.

The capital structure variable was used both in categorical and continuous forms. As a continuous variable, the total debt/total asset ratio was used; as categorical variable, this ratio was categorized into three segments such as equity intensive form in which the ratio takes a value higher than 66.6% of equity in the capital structure; debt intensive form in which the ratio takes a value higher than 66.6% of debt in the capital structure and weighted form in which the ratio takes a value between 33.3% and 66.6% in the capital structure.

Ownership structure is represented by three continuous variables such as the share of the first largest shareholder, the total shares of the first three largest shareholders and the shares that are publicly held. It is more appropriate to measure the

[21] For companies included in ISE Corporate Governance Index, the annual listing/registration fee is applied as 50% of the tariff for the first two years; 75% of the tariff for the following two years and then continue as 90% of the tariff (www.ise.gov.tr).

ownership structure by using the pre-mentioned continuous variables rather than categorical variables since the latter may not provide a meaningful information whether the firm is centralized or decentralized.

The last construct related to the corporate governance is the corporate social responsibility. There are no indicators that can be used to measure the corporate social responsibility of the firms in Turkey. However, Corporate Social Responsibility Association of Turkey is developing a scale for rating the firms. This initiation has not been activated and widespread in Turkey. That is why there is no available data for the firms analyzed in the study. In order to eliminate this problem, the mentioned scale is conducted through a sort of content analysis. The scale consists of five constructs including Corporate Strategy, Management and Processes (10%), Economic (30%), Social (30%), Environmental (25%) and Corporate Social Responsibility Report (5%). The content analysis is conducted based on the scale and the availability of information about the firms. all information were collected by searching the annual reports and web sites of the firms and then decide whether a firm has a project within the scope of corporate social responsibility or not. The rate is calculated based on the scale weights. If the firm has a project, it takes the value of one and zero otherwise. Then after, sum-product of each construct constituted the final rate. As a result, a continuous variable was obtained. In addition we structure a categorical variable based on this rate such as very intensive (a rate higher than 66.6%), moderate (a rate between 33.3% and 66.6%) and low intensive (a rate lower than 33.3%).

Table 51: Corporate Governance Constructs Measures

Code	Construct	Variable Description			
CG	Corporate Governance	Dummy	1: Rated	0: Non-Rated	
		Rate	Present	Not present	
DP	Dividend Policy	Dummy	1: Payer	0: Non-Payer	
		Dividend Yield	Present	Not present	
CS	Capital Structure	Dummy	1: equity intensive (equity≥66.6%)	2: debt intensive (debt≥66.6%)	3: weighted (33.3<CS<66.6)
		Rate (Total Debt/Total Asset)	Present	Present	Present
OS	Ownership Structure	First Owner	Share	Present	
		First Three Owner	Share	Present	
		Open Public	Share	Present	
CSR	Corporate Social Responsibility	Dummy	1:very intensive (Index Value ≥66.6%)	2: moderate (33.3< Index Value <66.6)	3:non intensive (Index Value ≤33.3%)
		Index (calculated for the study)	Present	Present	Present

3.2.2. Risk Measures

The risk construct contains three sub-constructs: systematic risk, sectoral risk and unsystematic risk. Systematic and sectoral risks are calculated as beta coefficient of the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965). In case of calculating market beta, ISE100 Index is used as a proxy for market portfolio. On the other hand, sectoral indices are used as a proxy for calculating sectoral beta's. Calculating beta coefficient is carried out within data window of five consecutive years based on monthly adjusted returns. For instance, beta for 2011 is obtained from data within the period of 2007-2011; beta for 2010 is obtained within the period of 2006-2010, and so on. Estimating systematic and sectoral risks within data window of five years is assumed to be better approximation relative to shorter or longer periods for Turkish capital market. Unsystematic risks are calculated based on five sub-constructs: cash flow risk, short-term solvency risk, long-term solvency risk, profitability risk and asset utilization risk. Each of these sub-constructs is determined mainly for the type of industry namely the manufacturing industry that is considered in the analyses.

The determination of the best proxy for the risk is open to debate. In this case, two types of procedures can be introduced such as *input risk measures* and *output risk measures.* Input risk measures indicate the risks that play a role in the process. In most cases, systematic risk is not clearly defined. Instead, it is assumed that beta coefficient can be a good approximation for measuring systematic risk. Therefore, the procedure of measuring output risks is done through some already existed numbers, (or output). It is not exactly defining what constitutes this proxy properly which means that the factors that affect output risks are not elaborated. That is why; this procedure can be better defined as output risk proxies. On the other hand, input risk measures can be obtained in conducting primary data research through which perceived risks factors are derived from practitioners via scale based questionnaires. Kumpasoğlu and Çelik (2012) conducted such type of investigation in determining systematic, sectoral and unsystematic risk constructs for pharmaceutical industry in Turkey. They surprisingly reported that there might be more than one systematic risk if the input risk measures are obtained through primary data research. However, manufacturing industry in Turkey contains on average more than 150 firms in which seven sub-sectors are defined. Therefore, conducting scale based questionnaires for each sub-sector for estimating input risks of such sample increases cost of research for the analysis.

The number and type of unsystematic risks are specifically designed for the structure of manufacturing industry. The proposed model does not state what constitutes for systematic, sectoral or unsystematic risks that can be used in estimation. All the variables regarding to the model constructs are open to debate whereas the main linkages between risk and other constructs are clear to test it. Especially unsystematic risk variables are determined based on the most widely used proxy in literature given in chapter one. Scholars have had different arguments for using these variables whereas there is a role of each variable in this research that gives some signal about firms' unsystematic characteristics such as cash flow, solvency, profitability etc. In addition, some of unsystematic variables which are derived from literature cannot be calculated due to inappropriate characteristics of firms' financial statements. For this reason, some variables are omitted.

Table 52 demonstrates the set of variables calculated for systematic, sectoral and unsystematic risks. Unsystematic variables are listed based on their usage in literature. For example, CFR1 is the most used variable under the construct of cash flow. Another important aspect of these variables is that some of them are not used in multivariate analysis due to their high correlation, insignificance of coefficient and/or negligible marginal benefit for the model.

Table 52: Risk Constructs Measures

Code	Construct	Variable Code	Variable Description
SYS.	Market Beta	Beta (M)	COV (Market Return; Firm X Return)/VAR (Market Return)
SEC.	Sector Beta	Beta (S)	COV (Sector Return; Firm X Return)/VAR (Sector Return)
	Sub-Sector Beta	Beta (SS)	COV (Sub-Sector Return; Firm X Return)/VAR (Sub-Sector Return)
CFR	Cash Flow Risk	CFR1	Cash Flow from Operations / Total Liabilities
		CFR2	Cash Flow from Operations / Total Assets
		CFR3	Cash Flow from Operations / Current Liabilities
		CFR5	Cash Flow from Operations / Sales
SSR	Short-Term Solvency Risk	SSR1	Current Assets / Current Liabilities
		SSR2	Net Working Capital / Total Assets
		SSR3	Quick Assets / Current Liabilities
		SSR4	Current Assets / Total Assets
		SSR5	Cash / Current Liabilities
		SSR6	Cash / Total Assets
		SSR7	Quick Assets / Total Assets
		SSR8	Current Liabilities / Total Assets
		SSR9	Net Working Capital / Sales
		SSR10	Net Working Capital / Total Equity
		SSR11	Current Liabilities / Total Equity
		SSR12	Current Liabilities / Total Liabilities
LSR	Long-Term Solvency Risk	LSR1	Total Liabilities / Total Assets
		LSR3	Total Equity / Total Asset
		LSR4	Total Liabilities / Total Equity
		LSR6	Total Equity / Fixed Assets
		LSR7	Fixed assets / Total Assets
PRR	Profitability Risk	PRR1	Net Income / Total Assets
		PRR2	Earnings Before Interest & Taxes / Total Assets
		PRR4	Net income / Total Equity
		PRR5	Net Income / Sales
		PRR6	Earnings Before Interest & Taxes / Sales
AUR	Asset Utilization Risk	AUR1	Sales / Total Assets
		AUR2	Inventory / Sales
		AUR3	Sales / Total Equity
		AUR4	Sales / Receivables
		AUR5	Sales / Net Working Capital
		AUR6	Cost of Goods Sold / Inventory
		AUR8	Sales / Inventory
		AUR9	Accounts Receivable / Current Assets
		AUR12	Sales / Cash
		AUR13	Sales / Quick Assets
		AUR14	Sales / Fixed Assets

Notes: UNS: Unsystematic Risk; SEC: Sectoral Risk; SYS: Systematic Risk; COV: Covariance; VAR: Variance

3.2.3. Rate of Return Measures

The model proposes three alternatives to measure value addition for the firms such as accounting, economic and market rate of return. Market rate of return is chosen for the present study due to disadvantages of accounting and economic rate of return. While the accounting rate of return does not contain risks and expectations, economic rate of return does not contain expectations. On the other hand, market (based) rate of return is assumed to be better approximation that incorporates risks and expectations for the firms.

In calculating market rate of return, three variables are determined for each year. The first one is the average adjusted (stock splits and dividend) monthly rate of return of the common stocks of the firms for one-year. This variable shows twelve-month average rate of return. The second variable is the average adjusted monthly return for five-year period. The third variable is that annual change in market value for the firms. Table 53 gives the details about these variables.

Since the main proposition of the model is to show how one can differentiate distressed and non-distressed firms, the other possible propositions related with the rate of return are out of scope of the thesis. However, one of the future research implications can be centered on determination of rate of return.

Table 53: Rate of Return Constructs Measures

Code	Construct	Variable Code	Variable Description
ARR	Accounting Rate of Return		Not Included into Analysis
ERR	Economic Rate of Return		Not Included into Analysis
MRR	Market Rate of Return	R2011 R2010 R2009 R2008 R2007	Average monthly return (annually); Stock Split and Dividend Adjusted
		R0711 R0610 R0509 R0408 R0307	Average monthly return (5-year period); Stock Split and Dividend Adjusted
		XRMV2011 XRMV2010 XRMV2009 XRMV2008 XRMV2007	Market value change (annually); End of year price used; [Market Value (T_1)-Market Value (T_0)]/ Market Value (T_0)

3.2.4. Cost of Capital Measures

In this study the cost of capital as a variable was not used for the analysis properly. The model assumes that risk affect the level of cost of capital. The calculation of the “cost of capital” directly by implying the methods given in chapter two is not possible for the firms included in the analysis (on average 150 firms for five year) because of the missing and non-disclosure data on this issue. Therefore, the cost of debt was considered alone as a dummy variable. It takes value of one if the firm is rated by a rating agency and zero otherwise.

Therefore, an indirect approach is followed. Some firms are rated by credit rating companies such as S&P, Fitch, Moody’s and etc. These ratings show a proxy for firms’ cost of debt. After examining the rating conditions of the firms, a dummy variable is structured as the value of one if a firm is rated and zero otherwise.

Cost of capital has a limited role in the analyses conducted in the scope of the study. Here, the effect of credit ratings on cost of debt was only considered for 2011 whereas the rating figures were not available for the rest of the analysis period.

Table 54: Rate of Return Constructs Measures

Code	Construct	Variable Code	Variable Description	
COD	Cost of Debt	Dummy	1: Rated by Credit Rating Firms	1: Not Rated by Credit Rating Firms
		Rate	Present	Not Present
COE	Cost of Equity		Not Included into Analysis	
WACC	Weighted Cost of Capital		Not Included into Analysis	

3.2.5. Bankruptcy Process Measures

The model assumes that there are two sub-processes of bankruptcy process namely financial distress and bankruptcy. In this process, bankruptcy takes at least two forms such as liquidation and restructuring. In the context of present study, bankrupted firms were not included into distressed sample due to unavailability of some variables such as corporate social responsibility, corporate governance rating etc.

The most important part of research design is the determination of distressed and non-distressed firms' samples for the fact that discriminating variables are dependent on these sample characteristics. Table 55 gives the detailed descriptions of these criteria, On the side of determining distressed firms, five criteria were chosen. From Table 55, Criteria of (ii), (iv) and (v) were used previously in literature (Aktaş, et.al, 2003; Vuran, 2009). The other two criteria of (i) and (iii) were determined for their applicability in the analyses. On the side of determining non-distressed firms, the procedures were designed from the model constructs such as corporate governance rating, corporate social responsibility index, dividend policy etc. However, there is an obligatory criterion for a non-distressed firm that a firm should be included into the same sub-sector as counterpart of distressed firm. For instance, if there are three distressed firms in food industry, there must be three non-distressed firms in non-distressed sample. Then after, the procedure is designed for direction of the model constructs that are the part of corporate governance related to risk levels indirectly.

Table 55: Bankruptcy Process Constructs Measures

Code	Construct	Variable Code	Variable Description	
FD	Financial Distress	Dummy	1: Distressed (distressed firm sample)	2: Non-Distressed (Non-Distressed firm sample)
		Criteria	(i) Included into Watchlist Companies Market; (ii) Had Total Debt greater than Total Asset; (iii) Prepared Financial Statement based on Turkish Bankruptcy Code of 324; (iv)Announced Loss for Three consecutive year; (v) Had execution for debt.	(i) Included into sub-sector distressed firms chosen (obligatory criteria); (ii) Had corporate governance rate; (iii) Had (relatively) high corporate social responsibility rate; (iv) Had dividend payment
LQ	Liquidation		Not Included into Analysis	
RO	Reorganization		Not Included into Analysis	

3.3. DESCRIPTIVE STATISTICS

This section gives descriptive statistics for selected variables. These statistics were demonstrated for the purpose of depicting general structure of variables from Table 56 to Table 60. These statistics are reported based on dichotomous and categorical variables of corporate governance, dividend policy, cost of debt, corporate social responsibility and financial distress for the analysis period from 2007 to 2011. Number of observations and mean values are reported for summary statistics whereas univariate and multivariate analyses will be mentioned in forthcoming sections.

On the side of selected variables of Market Beta, CFR1, SSR1, LSR1, PRR1, AUR1, Average monthly return (annually), Average monthly return (5-year period) and Market value change (annually), the criteria are set based on the role of these variables in univariate and multivariate analyses. In case of choosing Market Beta, CFR1, SSR1, LSR1, PRR1, AUR1 as risk variables, several methodological rules were applied. These rules are (i) significance of their coefficient, (ii) correlations with others; (iii) marginal contribution to the empirical model. In case of choosing Average monthly return (annually), Average monthly return (5-year period) and Market value change (annually) as rate of return variables, their informative characteristics became important whereas they were not further examined in univariate and multivariate analyses due to the scope of the thesis.

These descriptive statistics do not contain any statistical examination. However, general distribution and structure of a variable can be reviewed. Corporate governance as a dichotomous variable shows that there are four (4) firms rated in 2007; eight (8) in 2008; eleven (11) in 2009; fifteen (15) in 2010 and seventeen (17) in 2011 implying that there is an increasing tendency for the firms to be rated. Dividend policy, as payers and non-payers, shows that there is no high deviation among the number of firms that distributed dividends through the analysis period. Cost of debt as a sub-construct of cost of capital gives an unsatisfactory composition for the firms. The data are just available for 2011 in which nine (9) firms were rated by credit rating firms. Corporate social responsibility (CSR) index was calculated for each firm within the analysis period as a continuous variable. This variable restructured into categorical variable as very intensive, moderate and non-intensive (firm in CSR). There is a very important finding obtained that an increasing trend in the number of firms that want to be intensive and a decreasing trend in the number of non-intensive firms in CSR. The last variable is the type of samples analyses conducted on which are distressed, non-distressed and other firms. The numbers of distressed firms are twenty (20) in 2007; twenty-three (23) in 2008; twenty-six (26) in 2009; thirty-one (31) in 2010 and twenty-four (24) in 2011.

Table 56: Descriptive Statistics of Corporate Governance

		2011		2010		2009		2008		2007	
Selected Variable	CG	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
Market Beta	RATED	17	,99294	15	,9160	11	,9138	8	,8050	4	,9725
	NONRATED	139	,83201	136	,7904	134	,8067	135	,7925	137	,7761
CFR1	RATED	17	,0335	15	,1933	11	,1436	8	,0175	4	,0350
	NONRATED	134	,2731	135	,1403	133	,3458	135	,2964	137	,3550
SSR1	RATED	17	2,1094	15	1,9302	11	1,3482	8	1,3150	4	1,5675
	NONRATED	139	2,2818	136	2,1570	134	2,3537	135	2,2870	137	2,3653
LSR1	RATED	17	,5259	15	,4934	11	,5764	8	,6575	4	,6000
	NONRATED	139	,6321	136	,5395	134	,5110	135	,5390	137	,4820
PRR1	RATED	17	,0559	15	,0590	11	,0473	8	,0125	4	,0625
	NONRATED	139	,0038	136	,0210	134	,0295	135	-,0021	137	,0450
AUR1	RATED	17	1,1365	15	1,0023	11	1,0891	8	1,1688	4	1,3075
	NONRATED	139	,9448	136	,9134	134	,8430	135	1,0092	137	1,0758
Average monthly return (annually)	RATED	17	-,1818	15	3,5853	11	8,2173	8	-6,0213	4	1,1500
	NONRATED	139	,8768	136	4,3537	134	7,5616	135	-4,6510	137	2,9290
Average monthly return (5-year period)	RATED	17	2,2465	15	2,0347	11	1,7618	8	,5850	4	2,5425
	NONRATED	139	2,2817	136	2,0620	134	2,1704	135	1,3344	137	3,1141
Market value change (annually)	RATED	17	-9,9841	15	57,2513	11	1,5218	8	-63,4712	4	10,9050
	NONRATED	138	15,5684	134	65,8081	134	1,0219	135	-47,8007	137	35,3542

Notes: CG: Corporate Governance; N: Number of Firms; Market Beta: COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

Table 57: Descriptive Statistics of Dividend Policy

		2011		2010		2009		2008		2007	
Selected Variable	DP	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
Market Beta	PAYER	58	,77483	50	,7728	45	,7409	57	,7463	59	,7900
	NONPAYER	98	,89378	101	,8177	100	,8481	86	,8243	82	,7756
CFR1	PAYER	58	,5303	49	,1802	45	,6789	57	,4630	59	,6749
	NONPAYER	93	,0689	101	,1288	99	,1719	86	,1601	82	,1093
SSR1	PAYER	58	2,7491	50	2,7556	45	3,3642	57	3,2209	59	2,8576
	NONPAYER	98	1,9753	101	1,8270	100	1,7883	86	1,5776	82	1,9721
LSR1	PAYER	58	,4047	50	,3629	45	,3300	57	,3786	59	,3432
	NONPAYER	98	,7483	101	,6200	100	,5996	86	,6564	82	,5876
PRR1	PAYER	58	,0853	50	,0714	45	,0589	57	,0891	59	,1136
	NONPAYER	98	-,0354	101	,0016	100	,0182	86	-,0613	82	-,0034
AUR1	PAYER	58	1,0248	50	,9980	45	,9784	57	1,1316	59	1,1742
	NONPAYER	98	,9307	101	,8848	100	,8091	86	,9429	82	1,0163
Average monthly return (annually)	PAYER	58	,8367	50	5,3800	45	6,6471	57	-3,5370	59	2,1907
	NONPAYER	98	,7168	101	3,7315	100	8,0453	86	-5,5169	82	3,3734
Average monthly return (5-year period)	PAYER	58	2,2619	50	2,3460	45	2,3471	57	1,8744	59	3,3764
	NONPAYER	98	2,2873	101	1,9173	100	2,0460	86	,9069	82	2,8974
Market value change (annually)	PAYER	58	15,8176	50	58,1424	45	77,8116	57	-44,9374	59	22,3820
	NONPAYER	97	10,9411	99	68,3832	100	1,1865	86	-51,1562	82	43,4951

Notes: DP: Dividend Policy; N: Number of Firms; Market Beta: COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

Table 58: Descriptive Statistics of Cost of Debt

		2011		2010		2009		2008		2007	
Selected Variable	COD	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
Market Beta	RATED	9	,91111	NA	NA	NA	NA	NA	NA	NA	NA
	NONRATED	147	,84578	NA	NA	NA	NA	NA	NA	NA	NA
CFR1	RATED	9	-,0800	NA	NA	NA	NA	NA	NA	NA	NA
	NONRATED	142	,2668	NA	NA	NA	NA	NA	NA	NA	NA
SSR1	RATED	9	2,7522	NA	NA	NA	NA	NA	NA	NA	NA
	NONRATED	147	2,2331	NA	NA	NA	NA	NA	NA	NA	NA
LSR1	RATED	9	,5022	NA	NA	NA	NA	NA	NA	NA	NA
	NONRATED	147	,6278	NA	NA	NA	NA	NA	NA	NA	NA
PRR1	RATED	9	,0522	NA	NA	NA	NA	NA	NA	NA	NA
	NONRATED	147	,0069	NA	NA	NA	NA	NA	NA	NA	NA
AUR1	RATED	9	1,0378	NA	NA	NA	NA	NA	NA	NA	NA
	NONRATED	147	,9613	NA	NA	NA	NA	NA	NA	NA	NA
Average monthly return (annually)	RATED	9	-,3578	NA	NA	NA	NA	NA	NA	NA	NA
	NONRATED	147	,8299	NA	NA	NA	NA	NA	NA	NA	NA
Average monthly return (5-year period)	RATED	9	1,8511	NA	NA	NA	NA	NA	NA	NA	NA
	NONRATED	147	2,3040	NA	NA	NA	NA	NA	NA	NA	NA
Market value change (annually)	RATED	9	-12,9000	NA	NA	NA	NA	NA	NA	NA	NA
	NONRATED	146	14,3480	NA	NA	NA	NA	NA	NA	NA	NA

Notes: COD: Cost of Debt; N: Number of Firms; Market Beta: COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

Table 59: Descriptive Statistics of Corporate Social Responsibility

		2011		2010		2009		2008		2007	
Selected Variable	CSR	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
Market Beta	very intensive	56	,84661	45	,8280	47	,8731	41	,8305	38	,7826
	moderate	28	,76679	32	,6469	26	,6771	27	,7122	24	,8150
	non intensive	72	,88403	74	,8550	72	,8265	75	,8020	79	,7710
CFR1	very intensive	55	,5707	45	,2387	47	,4211	41	,7051	38	,7818
	moderate	27	,1696	32	,2006	25	,3096	27	,2963	24	,2571
	non intensive	69	,0174	73	,0641	72	,2783	75	,0433	79	,1633
SSR1	very intensive	56	2,3143	45	2,1370	47	2,5923	41	2,5602	38	3,1532
	moderate	28	1,8361	32	2,4500	26	2,4588	27	2,6770	24	2,2262
	non intensive	72	2,3892	74	1,9965	72	2,0063	75	1,8935	79	1,9881
LSR1	very intensive	56	,4279	45	,4002	47	,4043	41	,4237	38	,3350
	moderate	28	,9732	32	,4155	26	,4277	27	,3570	24	,4258
	non intensive	72	,6332	74	,6685	72	,6207	75	,6803	79	,5757
PRR1	very intensive	56	,0718	45	,0579	47	,0617	41	,0351	38	,1318
	moderate	28	-,1329	32	,0238	26	,0035	27	,0507	24	,0554
	non intensive	72	,0164	74	,0050	72	,0206	75	-,0400	79	,0010
AUR1	very intensive	56	1,1425	45	,9999	47	1,0394	41	1,1495	38	1,0568
	moderate	28	,8950	32	,9846	26	,6742	27	,9426	24	1,0592
	non intensive	72	,8557	74	,8481	72	,8133	75	,9735	79	1,1018
Average monthly return (annually)	very intensive	56	,4505	45	4,3291	47	8,2409	41	-5,1237	38	2,4626
	moderate	28	,4279	32	6,8081	26	6,4323	27	-2,6715	24	1,3817
	non intensive	72	1,1329	74	3,1515	72	7,6262	75	-5,2515	79	3,5333
Average monthly return (5-year period)	very intensive	56	2,1089	45	2,2247	47	2,2785	41	1,3344	38	3,4005
	moderate	28	2,9029	32	2,7247	26	2,1935	27	1,8093	24	2,6992
	non intensive	72	2,1662	74	1,6709	72	2,0292	75	1,0836	79	3,0734
Market value change (annually)	very intensive	56	1,8798	45	77,2516	47	1,1738	41	-56,3407	38	31,0397
	moderate	28	26,0750	32	88,4641	26	69,1977	27	-32,3607	24	16,3929
	non intensive	71	16,1034	72	46,8040	72	1,1182	75	-50,3620	79	41,9519

Notes: CSR: Corporate Social Responsibility; N: Number of Firms; Market Beta: COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

Table 60: Descriptive Statistics of Financial Distress

		2011		2010		2009		2008		2007	
Selected Variable	FD	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
Market Beta	Other	108	.88556	89	.8580	93	.8350	97	.8275	101	.8036
	Distress	24	.87042	31	.6358	26	.7321	23	.6704	20	.6365
	Non-Distress	24	.66667	31	.8116	26	.8252	23	.7713	20	.8160
CFR1	Other	103	.1843	88	.2119	92	.4379	97	.3376	101	.4423
	Distress	24	-.0700	31	.1610	26	.2431	23	.4291	20	.2285
	Non-Distress	24	.8279	31	-.0581	26	.0369	23	-.1070	20	-.0230
SSR1	Other	108	2.3056	89	2.4343	93	2.6332	97	2.6362	101	2.6793
	Distress	24	2.1825	31	2.2067	26	2.1415	23	1.7983	20	1.8660
	Non-Distress	24	2.1517	31	1.2015	26	1.1404	23	.9648	20	1.1190
LSR1	Other	108	.4603	89	.4254	93	.3961	97	.4516	101	.3979
	Distress	24	1.5112	31	.4128	26	.4588	23	.4761	20	.4225
	Non-Distress	24	.4508	31	.9715	26	1.0015	23	1.0117	20	.9895
PRR1	Other	108	.0496	89	.0412	93	.0401	97	.0325	101	.0806
	Distress	24	-.2479	31	.0722	26	.0465	23	.0143	20	.0880
	Non-Distress	24	.0862	31	-.0701	26	-.0181	23	-.1596	20	-.1740
AUR1	Other	108	.9877	89	.8953	93	.8370	97	.9888	101	1.0985
	Distress	24	.6525	31	1.0889	26	1.0192	23	1.1778	20	1.1890
	Non-Distress	24	1.1800	31	.8331	26	.7923	23	.9822	20	.8945
Average monthly return (annually)	Other	108	.7433	89	4.6651	93	7.4211	97	-4.9339	101	2.5906
	Distress	24	.8942	31	4.4832	26	7.1608	23	-4.0791	20	3.1150
	Non-Distress	24	.7100	31	2.9584	26	8.7427	23	-4.5065	20	4.0960
Average monthly return (5-year period)	Other	108	2.4402	89	2.1551	93	2.2384	97	1.4743	101	3.3724
	Distress	24	1.7562	31	2.2032	26	2.1773	23	1.2913	20	2.8945
	Non-Distress	24	2.0692	31	1.6403	26	1.7477	23	.5270	20	1.9150
Market value change (annually)	Other	107	13.9189	87	73.4071	93	1.0381	97	-50.8432	101	32.8260
	Distress	24	8.9658	31	66.1006	26	94.3473	23	-47.0817	20	43.0160
	Non-Distress	24	11.4254	31	40.0490	26	1.2538	23	-41.1387	20	35.5695

Notes: FD: Financial Distress; N: Number of Firms; Market Beta: COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

3.4. UNIVARIATE ANALYSIS OF PROPOSED MODEL CONSTRUCTS

This section gives the results of univariate analysis. Univariate analysis is applied based on one variable. This analysis is centered on three different samples' characteristics. These samples are distressed firms, non-distressed firms and other firms. These findings were presented based on two comparisons: distressed firms to non-distressed firms and distressed firms to other firms from Table 61 through 65. Variables that are subjected to univariate analysis are the same as those of multivariate analysis. In other words, univariate analysis is limited to those of multivariate analysis despite the fact that univariate analysis that conducted on each variable defined in this study is not reported for space limitation and purpose of comparison with multivariate analysis. Since it is assumed that distressed and non-distressed firms constituted different characteristics, independent sample tests are applied. In this case, there are two methods used in evaluating mean differences among these samples. These methods are depending upon distribution of subjected variables. If variables are normally distributed, then one of the parametric tests, independent sample t-test, is applied. If variables are not normally distributed, then one of the non-parametric tests, Mann-Whitney U-test, is applied. Examining distribution of variables via normality tests show that the results are mixed as denoted in from Table 61 to 65. Therefore, results of both tests should be interpreted under the assumption of normality of variables. In addition, reported significance levels are controlled for variance inequality and given for 2-tailed.

The variables are all continuous and representing risk constructs in order to test differentiation of samples' characteristics. These variables are Market Beta, CFR1, SSR1, LSR1, PRR1, and AUR1. As stated previously, these variables are determined by several methodological rules in sense that there is no any other better combination available among other variables calculated. That is why; this section gives the results of these variables. Reported results are given within the analysis period for each year separately.

Table 61 demonstrates the results of independent sample test for two comparisons of 2011. The first comparison is about mean differentials of distressed and non-distressed firms. The second one is about mean differentials of distressed and other firms. The present empirical study does want to test the mean difference hypotheses for the first comparison. In a formal statement, it is going be tested that there is no mean difference between the samples. Therefore, it is expected to reject this hypothesis for each variable. Results indicating that these hypotheses are rejected for Market Beta, CFR1, SSR1, LSR1, PRR1, and AUR1 at 10% significance level through t-test and Mann-Whitney U-test. For example, mean difference is not rejected for SSR1 if parametric test is applied whereas it is rejected when non-parametric test of Mann-Whitney U is applied due to its non-normality distribution. The results should be interpreted under the normality assumption of the variables. The results for second comparison show differently that it is not possible to reject the mean difference for Market Beta.

Table 61: Independent Sample Test Results for 2011

		N	Mean	Std. Deviation	t (Sig. (2-tailed))	Mann-Whitney U ((Sig. (2-tailed))		N	Mean	Std. Deviation	t Sig. (2-tailed)	Mann-Whitney U ((Sig. (2-tailed))
Market Beta	Distress*	24	,87042	,274820	**2,939**	157,00	Distress*	24	,87042	,274820	**-,226**	1276,5
	Non-Distress*	24	,66667	,199601	**(,005)**	(,007)	Other*	108	,88556	,301483	**(,822)**	(,908)
CFR1	Distress**	24	-,0700	,26408	-1,638	**94,00**	Distress**	24	-,0700	,26408	-3,497	**786,50**
	Non-Distress**	24	,8279	2,67209	(,108)	**(,000)**	Other**	103	,1843	,49534	(,001)	**(,005)**
SSR1	Distress**	24	2,1825	4,23404	,034	**135,00**	Distress**	24	2,1825	4,23404	-,138	**676,00**
	Non-Distress**	24	2,1517	1,45591	(,973)	**(,002)**	Other**	108	2,3056	2,24643	(,891)	**(,000)**
LSR1	Distress**	24	1,5112	2,69598	**1,921**	**174,00**	Distress**	24	1,5112	2,69598	**1,908**	**795,00**
	Non-Distress*	24	,4508	,21528	**(,067)**	**(,019)**	Other*	108	,4603	,22842	**(,069)**	**(,003)**
PRR1	Distress**	24	-,2479	,93875	**-1,736**	**67,00**	Distress**	24	-,2479	,93875	**-1,551**	**446,50**
	Non-Distress*	24	,0862	,08972	**(,096)**	**(,000)**	Other*	108	,0496	,08072	**(,134)**	**(,000)**
AUR1	Distress*	24	,6525	,50581	**-2,973**	158,00	Distress*	24	,6525	,50581	**-2,899**	838,50
	Non-Distress*	24	1,1800	,70700	**(,005)**	(0,007)	Other*	108	,9877	,54120	**(,006)**	(,006)

Notes: *Normally Distributed; **Not Normally Distributed; N: Number of Firms; Market Beta: COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

Table 62 demonstrates the results of independent sample test for two comparisons of 2010. The results are indicating that these hypotheses are rejected for Market Beta, CFR1, SSR1, LSR1, PRR1, and AUR1 at 10% significance level through t-test and Mann-Whitney U-test. The results for second comparison show differently that it is not possible to reject the mean difference for Market Beta, CFR1, SSR1, LSR1, and AUR1.

Table 62: Independent Sample Test Results for 2010

		N	Mean	Std. Deviation	t (Sig. (2-tailed))	Mann-Whitney U ((Sig. (2-tailed))		N	Mean	Std. Deviation	t (Sig. (2-tailed))	Mann-Whitney U ((Sig. (2-tailed))
Market Beta	Non-distress*	31	,6358	,24390	**-2,457**	305,50	Distress*	31	,8116	,31508	**-,756**	810,50
	Distress*	31	,8116	,31508	**(,017)**	(,013)	Other*	89	,8580	,28631	**(,451)**	(,001)
CFR1	Non-distress**	31	,1610	,45374	2,095	**287,50**	Distress**	31	-,0581	,36484	-2,857	**1292,00**
	Distress**	31	-,0581	,36484	(,040)	**(,006)**	Other**	88	,2119	,63865	(,028)	**(,667)**
SSR1	Non-distress**	31	2,2067	1,39161	2,678	**146,00**	Distress**	31	1,2015	1,55974	-3,392	**1353,00**
	Distress**	31	1,2015	1,55974	(,010)	**(,000)**	Other**	89	2,4343	2,18431	(,001)	**(,877)**
LSR1	Non-distress*	31	,4128	,19496	**-2,705**	**241,00**	Distress**	31	,9715	1,13339	**2,665**	**1350,00**
	Distress**	31	,9715	1,13339	**(,009)**	**(,001)**	Other*	89	,4254	,22031	**(,012)**	**(,863)**
PRR1	Non-distress*	31	,0722	,07587	**5,829**	**58,00**	Distress**	31	-,0701	,11280	-5,200	**1066,00**
	Distress**	31	-,0701	,11280	**(,000)**	**(,000)**	Other**	89	,0412	,06526	(,000)	**(,060)**
AUR1	Non-distress*	31	1,0889	,58338	**1,682**	386,00	Distress*	31	,8331	,61394	**-,531**	1135,00
	Distress*	31	,8331	,61394	**(,098)**	(,187)	Other*	89	,8953	,54357	**(,597)**	(,144)

Notes: *Normally Distributed; **Not Normally Distributed; N: Number of Firms; Market Beta: COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

Table 63 shows the results of independent sample test for two comparisons of 2009. The results are indicating that these hypotheses are rejected for CFR1, SSR1, LSR1, and PRR1 at 10% significance level through t-test and Mann-Whitney U-test whereas it is not possibly to reject the hypotheses for Market Beta and AUR1. The results for second comparison show that it is not possible to reject the mean difference for Market Beta and AUR1.

Table 63: Independent Sample Test Results for 2009

		N	Mean	Std. Deviation	t (Sig. (2-tailed))	Mann-Whitney U ((Sig. (2-tailed))		N	Mean	Std. Deviation	t (Sig. (2-tailed))	Mann-Whitney U ((Sig. (2-tailed))
Market Beta	Non-Distress*	26	,7321	,20754	**-1,397**	281,50	Distress*	26	,8252	,26928	**-,153**	1169,00
	Distress*	26	,8252	,26928	**(,169)**	(,306)	Other*	93	,8350	,29416	**(,878)**	(,799)
CFR1	Non-Distress**	26	,2431	,69596	1,441	**241,50**	Distress**	26	,0369	,21810	-3,260	**751,00**
	Distress**	26	,0369	,21810	(,156)	**(,078)**	Other**	92	,4379	1,10642	(,001)	**(,003)**
SSR1	Non-Distress**	26	2,1415	1,50909	**3,035**	**177,50**	Distress*	26	1,1404	,74308	**-4,917**	**625,50**
	Distress*	26	1,1404	,74308	**(,004)**	**(,003)**	Other**	93	2,6332	2,56842	**(,000)**	**(,000)**
LSR1	Non-Distress*	26	,4588	,25602	**-2,832**	**172,00**	Distress**	26	1,0015	,94285	**3,252**	**461,50**
	Distress**	26	1,0015	,94285	**(,007)**	**(,002)**	Other*	93	,3961	,20780	**(,003)**	**(,000)**
PRR1	Non-Distress**	26	,0465	,11916	1,220	**139,00**	Distress**	26	-,0181	,24227	**-1,215**	**560,50**
	Distress**	26	-,0181	,24227	(,228)	**(,000)**	Other*	93	,0401	,05798	**(,235)**	**(,000)**
AUR1	Non-Distress*	26	1,0192	,48970	**1,609**	261,00	Distress*	26	,7923	,52644	**-,386**	1160,00
	Distress*	26	,7923	,52644	**(,114)**	(,161)	Other*	93	,8370	,52051	**(,700)**	(,753)

Notes: *Normally Distributed; **Not Normally Distributed; N: Number of Firms; Market Beta: COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

Table 64 demonstrates the results of independent sample test for two comparisons of 2008. Our results are indicating that these hypotheses are rejected for CFR1, SSR1, LSR1, and PRR1 at 10% significance level through t-test and Mann-Whitney U-test whereas it is not possible to reject the hypotheses for Market Beta and AUR1. The results for second comparison show that it is not possible to reject the mean difference for Market Beta and AUR1.

Table 64: Independent Sample Test Results for 2008

		N	Mean	Std. Deviation	t (Sig. (2-tailed))	Mann-Whitney U ((Sig. (2-tailed))		N	Mean	Std. Deviation	t (Sig. (2-tailed))	Mann-Whitney U ((Sig. (2-tailed))
Market Beta	Non-Distress*	23	,6704	,21955	**-1,254**	224,00	Distress*	23	,7713	,31737	**-,904**	898,00
	Distress*	23	,7713	,31737	**(,217)**	(,380)	Other*	97	,8275	,25552	**(368)**	(,148)
CFR1	Non-Distress**	23	,4291	1,60021	1,575	**161,00**	Distress**	23	-,1070	,32406	-,989	**640,00**
	Distress**	23	-,1070	,32406	(,122)	**(,021)**	Other**	97	,3376	2,14237	(,324)	**(,001)**
SSR1	Non-Distress**	23	1,7983	1,18572	**2,821**	**103,50**	Distress*	23	,9648	,77602	**-4,616**	**412,00**
	Distress*	23	,9648	,77602	**(,007)**	**(,000)**	Other**	97	2,6362	3,18991	**(,000)**	**(,000)**
LSR1	Non-Distress*	23	,4761	,22585	**-2,723**	**131,50**	Distress**	23	1,0117	,91582	**2,909**	**511,50**
	Distress**	23	1,0117	,91582	**(,009)**	**(,003)**	Other*	97	,4516	,23958	**(,008)**	**(,000)**
PRR1	Non-Distress*	23	,0143	,08805	**3,548**	**78,00**	Distress**	23	-,1596	,21798	**-4,082**	**342,00**
	Distress**	23	-,1596	,21798	**(,001)**	**(,000)**	Other*	97	,0325	,11972	**(,000)**	**(,000)**
AUR1	Non-Distress**	23	1,1778	,81531	**,942**	**243,00**	Distress*	23	,9822	,57187	**,052**	1113,00
	Distress*	23	,9822	,57187	**(,351)**	**(,644)**	Other*	97	,9888	,54208	**(,959)**	(,988)

Notes: *Normally Distributed; **Not Normally Distributed; N: Number of Firms; Market Beta: COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

Table 65 presents the results of independent sample test for two comparisons of 2007. The results are indicating that these hypotheses are rejected for Market Beta, CFR1, SSR1, LSR1, and PRR1 at 10% significance level through t-test and Mann-Whitney U-test whereas it is not possible to reject the hypotheses for AUR1. The results for second comparison show that it is not possible to reject the mean difference for Market Beta and AUR1.

Table 65: Independent Sample t-test Results for 2007

		N	Mean	Std. Deviation	t (Sig. (2-tailed))	Mann-Whitney U ((Sig. (2-tailed))		N	Mean	Std. Deviation	t (Sig. (2-tailed))	Mann-Whitney U ((Sig. (2-tailed))
Market Beta	Non-Distress*	20	,6365	,19427	**-2,087**	126,50	Distress*	20	,8160	,33194	**,169**	954,00
	Distress*	20	,8160	,33194	**(,044)**	(,047)	Other*	101	,8036	,29410	**(,866)**	(,699)
CFR1	Non-Distress*	20	,2285	,30474	**2,047**	**128,00**	Distress**	20	-,0230	,45709	-1,450	**694,50**
	Distress**	20	-,0230	,45709	**(,048)**	**(,051)**	Other**	101	,4423	1,41628	(,150)	**(,027)**
SSR1	Non-Distress**	20	1,8660	,72738	2,096	**72,00**	Distress**	20	1,1190	1,41810	-2,793	**327,50**
	Distress**	20	1,1190	1,41810	(,043)	**(,000)**	Other**	101	2,6793	2,41179	(,006)	**(,000)**
LSR1	Non-Distress*	20	,4225	,16322	**-3,065**	91,00	Distress*	20	,9895	,81101	**3,242**	427,50
	Distress*	20	,9895	,81101	**(,004)**	(,003)	Other*	101	,3979	,20276	**(,004)**	(,000)
PRR1	Non-Distress*	20	,0880	,06795	1,613	**44,50**	Distress**	20	-,1740	,72339	-1,571	**305,00**
	Distress**	20	-,1740	,72339	(,115)	**(,000)**	Other**	101	,0806	,09219	(,132)	**(,000)**
AUR1	Non-Distress*	20	1,1890	,65246	**1,543**	160,00	Distress*	20	,8945	,55061	**-1,426**	857,00
	Distress*	20	,8945	,55061	**(,131)**	(,286)	Other*	101	1,0985	,59073	**(,156)**	(,289)

Notes: *Normally Distributed; **Not Normally Distributed; N: Number of Firms; Market Beta: COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

3.5. MULTIVARIATE ANALYSIS OF PROPOSED MODEL

This section gives the results of multivariate analysis in which multiple logistic regression is used. The primary reason of conducting logistic regression is its flexibility in terms of assumptions imposed over other multivariate techniques such as discriminant analysis. Since methodological details of logistic regression and the purpose of usage in literature are discussed in chapter one, it is skipped to give these details in this section.

The preliminary analysis before conducting logistic regression is looking for highly correlated independent variables. Table 67 depicts (Pearson) correlation coefficient of independent variables for the analysis period. As depicted, high correlations (over 70%) were observed between PRR1 and LSR1 in 2011 and 2008. This problem appears clearer due their insignificant coefficients and negligible marginal contributions to the estimated models. Therefore, one of these highly correlated variables is excluded within nested models. In addition to the investigation of highly correlated variables among selected variables, there is a considerable amount of searching procedures applied among all the variables calculated. As a research constraint (choice), one variable per unsystematic construct is decided to use within the estimated model. The elimination criteria as mentioned before are meanly about their high correlation among variables within and out of constructs, significance of their coefficients and their marginal contribution to the estimated models. As a result, one variable representing systematic risk and five variables representing unsystematic risks were chosen. Sectoral risk is omitted from the estimated logistic models due to their high correlation with systematic risk.

Cross-sectional analysis is conducted for each year. Table 68 documents the findings of logistic regressions. There are two models estimated for each year. The first model namely default model is the one in which all variables are entered into the estimated models. The second one is the nested model in which only significant variables are entered into the estimated models.

Evaluation of the estimated model can be judged by four stages. At the first stage, overall accuracy of classification, Type I and Type II Error rates are evaluated. At the second stage, significance of coefficients is examined. At the third stage, signs of coefficients are evaluated with respect to the proposed model. Finally at the last stage, the overall model fit is evaluated.

Estimated models for 2010 and 2011 are performing quite impressive in terms of overall accuracy of classification, Type I and Type II Error rates. Overall classification of the default models for 2011 and 2010 are 95,8% and 96,8% respectively. Type I Errors of default models for 2011 and 2010, classifying distressed firm as non-distressed, are 4,2% and 6,5% respectively. Type II Errors of default models for 2011 and 2010, classifying non-distressed firm as distressed, are 4,2% and 0% respectively. On the other hand, Nested models produce very close rates as depicted in Table 68. Estimated models for other years, 2009, 2008 and 2007 show poor performance as it is a general consequence observed in literature. The main reason behind this deterioration is about distance to default or length of distress. Specifically, there are ten distressed firms taken place in all distressed sample within the analysis period which leads to an increase in this deterioration (Table 66). The reported accuracy rates for three and more years before default were commonly reported low in literature.

Table 66: Number of Common Distressed Firms

	2011	2010	2009	2008	2007
Distress firms	24	31	26	23	20
Common distress firms	10	10	10	10	10
Ratio	41,6%	32,2%	38,5%	43,4%	50%

Significance of coefficients is distributed differently among default and nested models due to structure of samples. SSR1 and PRR1 in default model of 2011 are insignificant whereas BETAm (market risk) is the only variable which is not significant at 10% level in 2010. However, significance level of this variable is quite close to 10% significance level (12%). Among estimated models, models of 2011 and 2010 contain more statistically significance variables than those of other years. One of the characteristics of distressed samples that may affect significance level of coefficients is the number of distressed firms which are changing within the analysis period.

Signs of the coefficients are parallel to their expectations. Market risk, CFR1, SSR1, LSR1, PRR1 and AUR1 have signs of positive, negative, negative, positive, negative and negative respectively. In more formal statement, market risk has positive effect on the probability of distress which means that improvement in the market risk position of a firm other things being equal, will have a positive effect on the probability of failure; CFR1 (cash flow) has negative effect on the probability of distress which means that improvement in the cash flow position of a firm other things being equal, will have a negative effect on the probability of failure; SSR1 (short-term solvency) has negative effect on the probability of distress which means that improvement in the liquidity position of a firm other things being equal, will have a negative effect on the probability of failure; LSR1 (long-term solvency) has negative effect on the probability of distress which means that improvement in the long-term debt position of a firm other things being equal, will have a positive effect on the probability of failure; PRR1 (profitability) has negative effect on the probability of distress which means that improvement in the profitability position of a firm other things being equal, will have a negative effect on the probability of failure; and AUR1 (asset utilization) has negative effect on the probability of distress which means that improvement in the asset utilization position of a firm other things being equal, will have a negative effect on the probability of failure.

The last evaluation stage is about how the estimated models fit the data. This evaluation is carried out by giving some model fit statistics such as -2 Log Likelihood statistics and Hosmer and Lemeshow Test p values in the line with pseudo R^2 of Cox & Snell and Nagelkerke R Square. However, it should be noted that and Hosmer and Lemeshow Test p values are more reliable when sample sizes are larger. Therefore, this statistic should be interpreted carefully. Except Hosmer and Lemeshow for the model estimated in 2011, all of these statistics are reported at significant levels.

Table 67: Pearson Correlation Coefficients for Selected Variables

	BETAm					CFR1					SSR1					LSR1					PRR1				
	2011	2010	2009	2008	2007	2011	2010	2009	2008	2007	2011	2010	2009	2008	2007	2011	2010	2009	2008	2007	2011	2010	2009	2008	2007
N	48	62	52	46	40	48	62	52	46	40	48	62	52	46	40	48	62	52	46	40	48	62	52	46	40
CFR1	-,076	-,027	-,064	-,031	-,246																				
SSR1	-,284	-,131	,034	-,118	,007	,000	-,118	,197	-,029	-,474**															
LSR1	,019	,176	-,026	,156	,044	-,085	-,007	-,066	-,043	,009	-,229	-,386**	-,481**	-,457**	-,489**										
PRR1	-,040	-,173	,086	-,199	-,052	,091	,149	,198	,150	,090	,285*	,279*	,273	,443**	,204	-,954**	-,620**	,091	-,806**	-,515**					
AUR1	,148	,148	,072	-,098	-,204	,011	,242	,071	-,051	,190	-,161	-,144	,007	-,131	-,106	-,187	-,049	-,035	,144	-,063	,216	,176	,388**	-,075	,318*

Notes: *. Correlation is significant at the 0.05 level (2-tailed).**. Correlation is significant at the 0.01 level (2-tailed). N: Number of Firms; BETAm (Market Beta): COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets.

Table 68: Logistic Regression Results

Year	Model(s)	Variables in the Equation								Percentage Correct			FD Firms / Total Sample	-2 Log Likelihood	Cox & Snell R Square	Nagelkerke R Square	Hosmer and Lemeshow Test p values
										Type I Error	Type II Error	Overall Accuracy					
2011	All Variables (Default Model) a,b		constant	BETAm	CFR1	SSR1	LSR1	PRR1	AUR1				50%				
		Coef.	-5,10	5,53	-8,73	,366	4,93	-2,69	-2,67	4,2 (1/24)	4,2 (1/24)	95,8 (2/48)		23,779	,590	,786	,013
		Sig.	,053	,027	,039	,258	,025	,687	,029								
	Statistically Significant Variables in default Model a,b		constant	BETAm	CFR1	SSR1	LSR1	PRR1	AUR1								
		Coef.	-2,34	4,70	-9,54		3,56		-3,23	12,5 (3/24)	4,2 (1/24)	91,7 (4/48)		26,442	,566	,755	,002
		Sig.	,165	,034	,023		,046		,013								
2010	All Variables (Default Model) a,b		constant	BETAm	CFR1	SSR1	LSR1	PRR1	AUR1				50%				
		Coef.	,640	5,18	-14,09	-3,51	11,88	-68,88	-4,74	6,5 (2/31)	0 (0/31)	96,8 (2/62)		18,266	,664	,886	,904
		Sig.	,855	,12	,018	,036	,019	,008	,038								
	Statistically Significant Variables in default Model a,b		constant	BETAm	CFR1	SSR1	LSR1	PRR1	AUR1								
		Coef.	2,05		-10,77	-2,49	10,39	-58,29	-3,44	9,7 (3/31)	6,5 (2/31)	91,9 (5/62)		21,244	,647	,862	,738
		Sig.	,543		,021	,048	,034	,003	,036								
2009	All Variables (Default Model) a,b		constant	BETAm	CFR1	SSR1	LSR1	PRR1	AUR1				50%				
		Coef.	-1,10	2,60	-1,42	-,683	2,14	-,706	-1,11	34,6 (9/26)	26,9 (7/26)	69,2 (16/52)		50,098	,345	,460	,411
		Sig.	,603	,153	,211	,251	,187	,899	,186								
	Statistically Significant Variables in default Model a,b		constant	BETAm	CFR1	SSR1	LSR1	PRR1	AUR1								
		Coef.	1,88		-2,00	-1,13				26,9 (7/26)	46,2 (12/26)	63,5 (19/52)		58,584	,229	,305	,292
		Sig.	,007		,072	,005											
2008	All Variables (Default Model) a,b		constant	BETAm	CFR1	SSR1	LSR1	PRR1	AUR1				50%				
		Coef.	-1,23	,778	-2,93	-,531	2,24	-7,14	-,355	21,7 (5/23)	21,7 (5/23)	78,3 (10/46)		38,155	,427	,569	,476
		Sig.	,560	,677	,170	,418	,145	,183	,594								
	Statistically Significant Variables in default Model a,b		constant	BETAm	CFR1	SSR1	LSR1	PRR1	AUR1								
		Coef.	-2,18		-2,82		2,82	-9,38		26,1 (6/23)	17,4 (4/23)	78,3 (10/46)		39,486	,410	,547	,455
		Sig.	,026		,094		,057	,064									
2007	All Variables (Default Model) a,b		constant	BETAm	CFR1	SSR1	LSR1	PRR1	AUR1				50%				
		Coef.	-8,20	5,53	,217	,553	8,84	-31,09	-,845	15 (3/20)	10 (2/20)	87,5 (5/40)		19,321	,595	,793	,982
		Sig.	,185	,257	,948	,635	,060	,113	,509								
	Statistically Significant Variables in default Model a,b		constant	BETAm	CFR1	SSR1	LSR1	PRR1	AUR1								
		Coef.	-1,76	3,16	-3,98					25 (5/20)	25 (5/20)	75 (10/40)		45,438	,221	,295	,108
		Sig.	,201	,099	,060												

Notes: a. Constant is included in the model. b. The cut value is ,500; N: Number of Firms; BETAm (Market Beta): COV (Market Return; Firm X Return)/VAR (Market Return); CFR1: Cash Flow from Operations / Total Liabilities; SSR1: Current Assets / Current Liabilities; LSR1: Total Liabilities / Total Assets; PRR1: Net Income / Total Assets; AUR1: Sales / Total Assets; FD: Financial Distress.

3.6. RESEARCH CONSTRAINTS

The empirical investigation conducted to test the proposed model has some constraints. It should be noted that this is the first attempt to test the proposed model. Therefore, choices of research tools, data, analysis period, variables that best represent each of model constructs etc. can be varied among researchers. In the context of present research, the structure of several variables affected their role in statistical examinations such as corporate governance index and cost of capital. The most important constraints, however, is that discriminative power of risks on the state of being distressed is tested. There is no any statistical investigation about discriminative power of risks on rate of return. Another important research constraint is that default firms are not included within the sample of distressed firms due to unavailability of some variables for default firms. One common procedure followed in estimating bankruptcy prediction models is to divide samples into testing and estimation structure. Dividing samples into such framework is useful when there is no theoretical model that can help to show the direction about variable set. In the context of empirical investigation, there is no need to construct testing sample and estimation sample due to proposed model proposition. Since comparisons of previously developed models are not the main purpose, there is no comparison of the proposed models with previously developed models about bankruptcy process.

3.7. FUTURE IMPLICATIONS

The proposed model was tested in manufacturing industry of listed firms in Turkey whereas there is no constraint of conducting it in any other industry. However, it should be noted that the variables that best represent model constructs should be specific to each industry or sector. Modification on selecting variables for each construct can be developed in further studies. One may use much better approximation for systematic risk or another construct. In addition, if distressed samples contain bankrupt firms, the results of the empirical model can be more apparent. The proposed model can be used by all stakeholders as a general road map that shows firms dynamics in related to value addition and dilution processes.

CONCLUDING REMARKS

The main purpose of the thesis is to propose a theoretical model that incorporates the dynamics of the firms with bankruptcy process. There are three chapters in which the thesis is structured. The first chapter gives an extensive literature review written on bankruptcy process and its related fields. The second chapter introduces the proposed model for bankruptcy developed in the context of the thesis. The third chapter documents the results of empirical investigation of the proposed model.

Framework of micro credit risk metrics is structured into three categories. The first category includes Theory based Models. These models are developed and/or proposed as a conceptual framework in predicting defaults. In this case, conceptual framework determines which constructs (factors) and/or variables are appropriate in predicting bankruptcy. The second category contains Statistical based Models. These models are developed as a result of statistical examination of firms' data. The main argument proposed here is that the best available discriminating or classifying variables are assumed to be the predictors of defaults without relying on theoretical justification. Third category involves Artificially Intelligent Models. These models are resemble to Statistical based Models in the sense that they do not relying on a theoretical foundations. In a dissimilar way, these types of models apply different sets of algorithms (neural networks, decision tress etc.) to classify or differentiate the bankrupt and non-bankrupt firms.

In the first chapter as stated an extensive literature review is given on the related literature. In this literature, the proposed model can be seen as competing one with those of Theory based Models due to lack of any theoretical (conceptual) framework behind Non-Theory based Models. However, it is claimed that the proposed model overcome the pitfalls of existed Theory based Models and can be a *'new'* road map for all Non-Theory based Models to be replicated. In related literature, researchers have analyzed a set of variables that best discriminate bankrupt/non-bankrupt and/or default/non-default firms. The structure of the proposed model gives an opportunity to researchers to comprehend the main dynamics of the firms in related to value generation process. The proposed model shows a direction of selecting the variables and possible explanation behind. For example, in the context of the proposed model, the risk indicators are the first time introduced for bankruptcy processes.

The estimated models were evaluated by four stages. At the first stage, overall accuracy of classification, Type I and Type II Error rates are examined. At the second stage, significance of coefficients is elaborated. At the third stage, signs of coefficients are evaluated with respect to the proposed model. Finally at the last stage, the overall model fit is analyzed. Empirical results of proposed model indicate that the estimated models give promising results in case of one and two years before the final condition of the firms. Estimated models perform over 90% correct classifications for the last two years. In terms of overall accuracy, Type I and Type II Error, performance of proposed model outperformed the entire theoretical based models depicted from Table 31 to Table 36. Despite the fact that it is not logical to compare the performance of proposed model with statistical and AIES models due to differences in estimation procedure, there is still comparative advantage of the proposed model over statistical and AIES models. The difference in estimation procedure is about deriving the variables among testing sample (initial sample) and then estimating these selected variables in estimation sample. This procedure is crucial for the fact that there is no theoretical model behind statistical and AIES models that show the relevant constructs and/or variables. As a result, the performance of the estimated model of statistical and AIES is much higher in testing sample then that of estimation sample. If the performance of the proposed model is compared with those of statistical and AIES models which are coming from estimation sample, then it is safe to state that the proposed model outperformed most of the implications.

The main contribution of the thesis is to introduce a conceptual model that incorporates the firm dynamics with value addition and dilution process of the firms. Therefore, the proposed model can be estimated with different methodologies and data in all over the World. In term of practical implication, it assumed that the proposed model will be benefited by all stakeholders including executives, investors, creditors, auditors and all other market participants as a general road map in financial World.

Executives can benefit from the model in a way to construct a well-functioning corporate governance mechanism for their firms. Initial condition for having such mechanism requires understanding the linkages among corporate governance, risk, cost of capital and value generation process. The proposed model shows a clear picture of these linkages. Investors can benefit from the model for evaluating their investments in a sense that how much required return they can expect. If the firms (their investments) are run in a risky environment, then the proposed model gives a road map for evaluating the mechanism (return performance). Essentially, investors may understand the linkages among the risk and their investments. Creditors can benefit from the model by evaluating the methodology that they use in rating the firms. The proposed model is a new challenge for creditors to re-think how to rate the firms. Auditors and all other market participants can have an opportunity to benchmark their existed methods with the propositions of the model for their operations. For example, if a firm is audited in such a way that the auditing report does not show the realm for the firm, then market participant may suspect by consulting the structure of the model. In addition it helps the academicians to consider many factors of distress or bankruptcy rather than only the financial indicators in their further studies.

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