AN EVALUATION OF BUSINESS FAILURE PREDICTION METHODS: LITERATURE SURVEY   "

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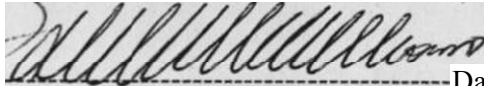
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DECLARATION

This work has been compiled from the referenced sources and submitted for examination by my personal self and to that do I attest by signing as under

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ABSTRACT

Since the fall of Babel [the largest enterprise in the history of mankind], human corporations are always faced with the risk of failure. Just like human beings survive on sufficiency of human blood, so do businesses survive on the sufficient flow of corporate blood (funds or finances). Consequently, business failure (bankruptcy) is a concern of accounting and finance which are micro-economic tentacles of the theory of finance as applied to corporations. Both areas have grown up till they are currently pursued both professional and academic areas of specialization. Unlike accounting where the conceptual framework of has been configured, the theoretical framework of finance has not been configured despite its enormous body of known theories. This is a major contribution of this paper in its effort to locate concerns of business failure.

Beaver (1966/7) provided the earliest documented business bankruptcy prediction model. Altman (1968) perfected on the art and developed a Multiple Discriminant Analysis (MDA) model (dominantly called Z-Score Model) which dominated business failure prediction worldovertill late 1980. Due to technological advancement and continued increased business failures especially in the 1970's and 1980's, all over the world, alternative failure prediction models started emerging in the late 1980's and especially in the decade of 1990-1999. These non-classical models lent themselves to use large data of varying nature deviating from the classical statistical (quantitative) based models. Incidentally effectiveness of classical statistical models and non-classical models have been found more or less the same except for the timing of when the signal is emitted.

Because of timing of signals, environmental differences, industry uniqueness, diversity of information containing variables and other regional specific factors, business failure prediction practice is currently shifting from MDA models to alternative non-classical methods especially Logit Analysis Model, Multidimensional Framework Analysis, Artificial Neural Networks among others. Despite all this effort, business continue to fail; hence the question, why do businesses continue to fail? Which of these many models are relevant to East African firms? Is the usage of the models proper?

LIST OF ACRONYMS

CBK   Central Bank of Kenya

CUSUM   Cumulative Sum (Theodosius, 1993)

DEHA   Dynamic Event History Analysis (Hill et al., 1996)

DMP   Dynamic Multi-dimensional Performance (Maltz et al., 2003)

DT   Machine Learning Decision Tree (Back at el., 1997; Joos et al., 1998)

LGP   Linear Goal Programming (Gupta et al., 1990)

LGR   Linera Gamblers Ruin (Wilcox, 1973, 1976)

LA   Logit Analysis (Ohlson, 1980)

LPM   Linear Probability Model (Gupta et al., 1990)

MDS   Multi-Dimensional Scaling (Mar-Molinero and Ezzamel, 1991)

MDA   Multi-Discriminant Analysis (Altman, 1968)

MGHDIS   Multi-Group Hierarchical Discrimination (Zopoudinis, 1987)

NN   Artificial Neural Network (Odom and Sharda, 1990)

PA   Probit Analysis (Zmijewiski, (1984)

SA   Survival Analysis (Lane et al., 1986)

SOM   Self Organizing Maps (Martin-del-Brio and Serrano-Cinca, 1993)

RPA   Recursive Partitioning Analysis (Frydman et al. 1985)

FR   Fussy Rule Based Classification (Spanos, 1999)

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CHAPTER I

1.0   BUSINESS BANKRUPTCY PROBLEM

1.1   **Introduction: Do Businesses Fail?**

"One of the most significant threats for many businesses today, despite their size and the nature of their operation, is insolvency,"[1]. History has shown that in the years 1980 and 1990 more business failed than at any other time since 1930s world over. Rees (1995) observed that 50% of businesses in United Kingdom (UK) failed within five years of their inception in the two decades.

Business failure is not discriminative of the size of business or the location of [whether it is in developed or developing country]. Holland (1998) carried a study in U.S.A. on small business failure and observed that on average 90% of small businesses failed in the years 1996 and 1997. A similar research was carried out in Uganda which established an 89% business failure rate in the year 2005 (Tushabomwe-Kazooba, 2006). Courses of small business failure both in USA and Uganda were similar with identical recommended solutions. The famous cases of Enron Pic, WorldCom Pic eliminate any reason to exempt multinational corporations from the risk of bankruptcy. Firm's industry as well does not matter. Firms in the manufacturing sector, merchandising entities, service organizations, financial based etc fail just as much alike as in any other business sector (Leblanc and Gillies, 2003).

1.2   Business Failure Defined

Business [corporate] failure generally means the inability of a business entity or corporation to achieve its intended objectives. According to Agarwal and Taffler, (2005); a firm demonstrates features of ailments if: one; it is put under statutory administration; or secondly; when it is undertaking capital reconstruction, or thirdly; when it is receiving government support or/and guarantees. Or fourthly, when it has been put under intensive care monitoring slot by banks regulatory and monitoring unit (case of financial institutions). Or fifthly, when a firm has been subjected to loan covenants negotiations for lenders to hedge against insolvency risks. Or sixthly, is when a firm has been put under

statutory receivership or seventhly, when a firm has been caused to undergo creditors' voluntary liquidation. Any firm which would depict any of the above features would be deemed to be experiencing business failure or financial distress symptoms.

> According to U.K. insolvency Act of 1986,
> "a company is said to be insolvent if it either does not have enough assets to cover its debts [i.e. the value of assets is less than the amount of liabilities], or it is unable to pay its debts as they fall due."[2]

Upon becoming insolvent, the Act provides for five options: a firm may be put under i) statutory administration, ii) undergo voluntary company arrangement, iii) be put under receivership, or iv) be liquidated and v) dissolution.

1.3 Business Failure: Cited Facts

Collapse of businesses has an economic value tag attached to it. Evidence has shown that the market value of distressed firms decline substantially prior to the firm's eventual failure (Warner, 1977; Charalambous et al., 2000). Consequently the suppliers of capital, investors and creditors risk loosing enormous wealth. The management and the employees too loose the basis of their livelihood in the event of failure of an enterprise. In measurable terms, small business failure in USA in the year 1996 amounted to US$ 29 billion (Ksh 1,943 billion) as compared to 1997's US$40 billion (Ksh 2,680 billion Kenya shillings) dollars in loss arising from 76,000 for 1996 and 86,000 for 1997 small businesses which failed (Holland, 1998).

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> "in the past two decades (1980's and 1990's) at a higher rate than at any time since 1930s. . . . .with certain sectors of the U.K economy such as small industrial businesses ....experiencing failure rates as high as 50% over a five year period."[3]

The economic cost of business failure evidently depicts declining market value of depressed firms prior to failure, this results in the loss of value to shareholders (Warner, 1977; Charalambous, 2000). Others affected include creditors, prospective investors, as well as management and employees who are severely affected. Auditors too may be prosecuted for failing to provide an early warning in the process of executing their

services. A good example is the case of Anderson and Young firm of auditors over the case of Enron, a case in hand (Zavgren, 1983; Laitinen and Kankaanpaa, 1999).

In USA, banks failed at a rate of "seven (7) per year from 1950 to 1980, but has since escalated to an average of 175 per year from 1986 through 1991."[4] scholars have further noted that

> "U.S. commercial banking industry experienced problems of bank failures in the late 1980 and early 1990, problems of magnitude not seen since the Great Depression. Almost 1,500 banks covered by the Federal Deposit Insurance Corporation (FDIC) Bank Fund failed in the years 1980 to 1993, including a three digit failures between 1985 and 1992 that picked at 206 in 1989."[5]

Conversely, the 206 failed banks in 1989 held a total of US$29, 000,000,000 ($29 billion US dollars) in assets; while 124 banks failed in the year 1991 which held a total of US$ 63, 000,000,000 ($63 billion US dollars) FDIC (1991, 1992). This is enormous loss of investors' resources that is washed down the drain.

Kenyan [an East African country] history of bank failures is evidence that this is not a foreign problem, but a problem similarly experienced in and within its surrounding. The scenario depicts an equally depressing trend in 1980s' and 1990s'. Kenya as an illustration of countries in the Eastern Africa recorded seventeen (17) bank failures since December 1984 up to September 2007 along with twenty four (24) financial institutions within that same period (CBK, Inspectorate Report, 2007). This is a total of forty-one (41) collapsed financial institutions in a period ranging from 1983 to 2007 (24years). Eleven (11) of the institutions failed in 1980's, twenty six (26) in the years 1990s and the remaining three (3) in the years 2000's about twenty four years period. The total value of resources (capital) that sunk with these enterprises amounted to Ksh 61.312, billion which constituted 30.77% of the financial sector capital invest in the same period of time (CBK, Inspectorate Report, 2007). Although this is hardly one billion US dollar (US $ 0.915 billion), yet given the size of the Kenyan economy, this is a devastating loose to the entire economy. This obviously raises concern as to the relevance and effectiveness of the regulatory agencies in this country and subsequently this underscores the necessity of an early warning system for financial institutions as well as business sectors within the East African Region.

1.4   Handling Business Failure: Whose concern?

Businesses subsist on financial resources. This is an area of study that deals with the management of the blood stream (funds/finances) of organizations. It is within this area that business failure should be addressed. It is imperative then that a historical preview of finance is explored. This will link up with the threat that has befallen the very baby which finance attempts to nurture and cause to survive, thereby asserting the futility of the existence of finance.

1.4.1   Overview of the Modern Theory of Finance

Finance is an independent area of study [for professionals and academicians] with clearly defined scope, purpose and boundaries rooted in the entire theory of economics.

> "Over *the* years a branch of applied microeconomics has developed into what is currently known as Modern Finance Theory". *Accordingly there are* "six seminal and internally consistent theories upon which modern finance is founded are: i)Utility Theory; ii) State Preference theory iii) Mean-Variance Theory iv) Arbitrage Pricing Theory v) Option Pricing Theory and vi) The Modigliani and Miller Theorems"[6] [italics provided].

The diagram (Fig.l) below attempts to depict the theoretical framework of finance as an area of study. The elements which constitute finance theory are financial market, theory of choice, objects of choice, seminal finance theories, efficient market hypothesis and then the application areas. Each is briefly highlighted below.

1.4.1.1 Financial Market Place

The existence of Capital Market place is a necessity if the economy has to allocate its resources optimally amongst players in a finance economy. This is essential to economic development in monetary terms (Fisher 1930).   Financial market is a fundamental pillar in the theory finance. As a consequence, finance theory assumes various states of market ranging from perfectly competitive market to absolutely imperfect (monopolistic) market situation when analyzing a theory situation (Miller and Modigliani, 1961 and Modigliani and Miller, 1958, 1963).

Fig 1: THEORETICAL FRAMEWORK OF MODERN FINANCE

SPECIFIC APPLICATION
AREAS OF FINANCE

EFFICIENT CAPITAL MARKET
HYPOTHESIS

SEMINAL THEORIES OF FINANCE

OBJECTS OF CHOICE

THEORY OF CHOICE

MARKET ENVIRONMENT
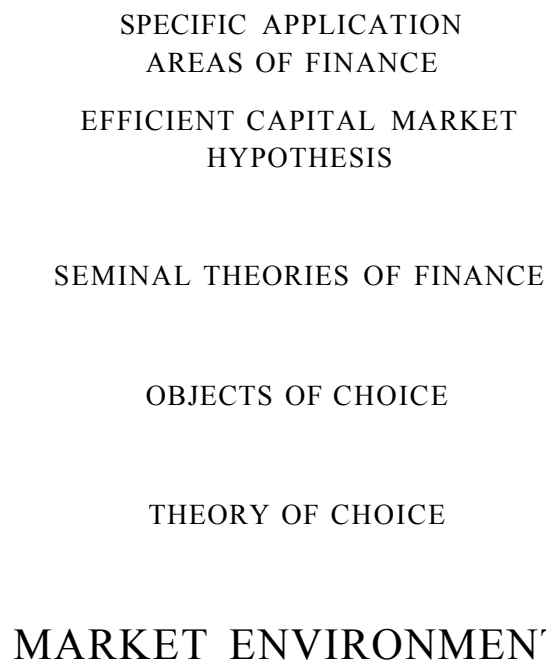
SOURCE: Promulgated by Author from Finance Literature [2007]

1.4.1.2 The Theory of Choice (Utility Theory)

This theory has two dimensions; one is theory of investor choice between different bundles of commodities or alternative timeless risky alternatives. This is popularly known as Theory of Utility. Secondly is the Utility Theory of choices over time. These establish the basis of rational decision-making in the face of risky alternatives (Markowitz, 1958). The main question is: "How do people make choices?" This theory has five fundamental axioms of choice in financial economics (often termed Axioms of Cardinal Utility) as was conceptualized by Fama and Miller (1972). These axioms are basic assumptions about an individual person's behavior which provide the minimum set conditions for consistent and rational behavior. This is not disregarding other theories of human behavior inbuilt in other "social sciences such as anthropology, psychology, political science, sociology which provide great insight into the theory of choice."[8] The Five axioms are: i) Comparability/completeness, b) transitivity/Consistency, c) strong independence, d) measurability and e) ranking Fama

and Miller (1972). The theory also encompasses utility functions for risk averse, neutral which defines three states of human response when faced with risky situation and the use of mean and variance as choice criterion (Tobin 1958).

1.4.1.3 Objects of Choice:

Objects of choice refer to phenomenon upon which choice decisions have to be made. These are the objects, issues, cardinal principles bases, purposes upon which finance decisions are made. Essentially these are the principles pillars upon which financial economics revolve. They are referred to as seminal theories of finance in the figure 1. above which include i) The State Preference Theory, ii) Mean-variance Theory (valuation models), iii) Option Pricing Theory, iv) Theory of Mergers and Reconstruction, iv) Corporate Governance Theory describe this phenomenon. They constitute targets for which choices can be made.

a) State-Preference Theory

This is a theory which enables both firms and individuals to make optimal choices in their investments. Accordingly state-preference theory "analyzes how optimal individual investment decisions and optimal firm investment decisions are determined under conditions of uncertainty."[9] In determining the future values of securities, the famous Arrow-Debreu State-Preference framework is represented by a set of possible state-contingent pay-offs (Arrow, 1964; and Debreu, 1959). This framework helps project future values of securities.

Hirshleifer (1964) pioneered in demonstrating the use of state-preference theory in allocating capital in an uncertain world. In his second seminal paper of 1965, Hirshleifer advanced a theoretical approach in investment decisions under uncertain market situation. The application of the State-Preference theory in investment decisions under uncertainty was demonstrated in his third paper of 1966. A similar work was done by Myers (1968) where a demonstration of a Time-State Preference model was applied in the valuation of corporate securities. These four scholars mentioned above pioneered the generation and application of State-Preference theory to corporate finance. Payoffs offered to different states of nature constitute the fundamental objects of choice. Ideally

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this guides the decision process of investors. Individuals as well as institutional investors will always invest where their investment promises the highest pay-offs which incidentally matches the lowest investment cost as well.

b) Mean-Variance Portfolio Theory

This theory provides a framework for measuring objects of choice. Indifference curves are used to depict the measures. Indifference curves of the individual choices are defined in terms of means (averages) and variances of the assets rates of return. Variance "is defined as the expectation of the squared difference from the mean (average) or the square of standard deviations"[10]. This is termed the "most important developments in *finance* in the last few decades, *which* is the ability to talk about risk in a quantifiable manner,"[11] [Italics provided]. Quantification of risk has provided the means and ability to measure the price of risk correctly accurately and precisely thus enabling valuation of assets fairly accurately (Cramer, 1961).

c) Valuation Models

Two valuation models have since been developed to value the marketable securities. These are first; Capital Asset Pricing Model (CAPM). This model was developed almost concurrently by Treynor (1961) and Sharpe (1963, 1964). A typical CAPM model was $£(/?,)= R, +[E(R_m)\sim R_f]/J_t$ where $£(/?,)$ = Expected rate of return on asset i, R_t = Risk-free rate of return, $E(R_m)$ = Expected market rate of return, $/?,$ = Variance of risky asset i (a measure if risk on asset i). This constituted the initial CAPM which when plotted graphically yields Security Market Line. CAPM was based on several assumptions whose relaxation has continuously varied the model slightly. Lintner's (1965) variation and refinement later in 1969 concluded that the existence of heterogeneous expectations (which indicates that the market portfolio is not necessarily efficient) makes the model non-testable empirically.

Brennan (1970) examined the model in the event of differential tax rates on capital gains and dividends. He concluded that was beta still an appropriate measure of

risk. He however included an extra term in the model which captures the expected returns dependence on dividend.

Mayers (1972) examined CAPM in the existence of Nonmarketable Assets. He assumed a case where the cost of transacting in an asset is infinite or assumed that the asset was not marketable. He took an example of human capital which cannot be sold in form of a human being. Black (1972) explained the paradox on how the model would change when investors cannot borrow or lend at risk-free rate. He established that **CAPM** does not require the existence of a risk-free asset except that the expected rate of return on the zero beta portfolios replaces the rate of return on the risk-free asset. This model constituted an after-tax CAPM which is popularly called two-factor model.

Merton (1973) developed a newer version of CAPM which assumed inter alia that i) trading takes place continuously over time and ii) that the returns on the assets are distributed log-normally. This model provides that the equilibrium rates of return on all risky assets are a function of the covariance of each asset with the market portfolio. Merton advanced a three-fund separation model where the third fund was necessary for hedging against unforeseen changes in the future risk-free rate. This model assumed a multi-period scenario yielding an inter-temporal CAPM.

Second model is the Arbitrage Pricing Theory (APT) model which was formulated by Ross (1976). This model attempted to a large extends to resolve CAPM's shortcomings. The model offers a testable method to measure the value of assets. It is however a general model in application since it assumes that the rate of return on any marketable asset is linear. Hence Ross assumed a competitive market environment with several assets influencing the price of each other in a multi-period framework.

d) Option Pricing Theory

Trading in options started in the USA. In 1973 the Chicago Board of Option Exchange (CBOE) was the first organized board that traded in standardized options contracts. By the end of 1974 the volume of business in option was larger than that of New York Stock Exchange. So what then is an option? This is a contract allowing a person to buy (Call Option) or sell (Put Option an underlying security within a stipulated time while benefit lasts (Copeland and Weston, 1988).

e) Modigliani and Miller Theorems

Miller and Modigliani initiated discussion on two different fronts that have been adopted both as thematic components in finance theory and in corporate finance theory. First is The role of capital structure (corporate financing) and dividend policy on the value of the firm. In their paper titled, "The Cost of Capital, Corporation Finance, and The Theory of Investment," of 1958 which was followed by their 1963 seminal paper titled, "Corporation Income Taxes and the Cost of Capital," they raised a concern regarding the role of capital financing mix. Their initial argument is that the value of a levered firm and the value of un-Ievered firm is the same except for the gain that will arise from the tax shield related to the deductible interest on the leverage. The second front is how the value of a firm is affected by dividend policy. This was initiated in their seminal paper of 1961 titled, "Dividend Policy, Growth and the Valuation of Share," the initial position is that dividend policy does not affect the current value of a firm. The prominence of the two lines of argument have not only found place in corporate finance, but as land mark features of theory financial economics. Hence the term, their culmination into the "Miller and Modigliani Theorems" as cited in this paper.

1.4.1.4 Efficient Capital Market Hypothesis

The earliest work on the Efficient Market Theory was by Bachelier (1900) in which he characterized pricing in security market as efficient (Meggison, 1996). He developed models describing the pricing of options and demonstrated efficient distribution of price changes. This work was however unnoticed for over fifty (50) years. The next job was done by Cowles (1933) where he documented the inability of forty-five professional agencies to forecast stock price changes. He argued that when a market is efficient, it is not possible to make economic profits by trading on the available information. The concept of share prices depicting a random walk, which means that the current price is independent of the previous price levels. This observation was advanced by statisticians across several years which included Working (1934), Kendall (1953), and Orsborne (1962).

This concept was confirmed by Samuelson (1965) and Mandelbrot (1966) within the finance theory. They however argued that the randomness of prices is caused by changes in the new information on the market which is reflected in the changed share price. As a consequence, unexpected security price changes must be independent through time if expected economic profits are to be zero. This culminated into the Rational Expectation Hypothesis as promulgated in Economics theory.

Efficient Market Hypothesis [EMH] assumes a perfect frictionless capital and money market (Fama, 1970). The ability with which information is in-calculated in the share prices or exchange rates of foreign currency in any given market determines the level of efficiency in that market. Fama (1970) advanced three levels of efficiency on that basis. First is the weak form of efficiency where the market includes all information contained in the past price movements into the current prices of financial instruments traded on the capital market. The second form is the semi-strong form where information about past and current events and occurrences are captured by the market. Thirdly, concerns the strong form where the market receives past, present and information on planned events and includes all this in the prices of instruments being traded on the financial markets.

1.5   Specific Applications of Theory of Finance

A combination of Objects of Choice and the Theory of Choice yields a study of predictability of possible combinations of monetary assets that would earn the most benefit possible in an uncertain market equilibrium framework. Under this the concept of risk and its pricing is included in the decision model. Other theories that are re-examined in an equilibrium market framework are: Capital Asset Pricing Model, Arbitrage Pricing Theory. Pricing of contingent claim Future Contract and Option Pricing are included within the market equilibrium framework.

It is vital to emphasis that finance as a discipline of financial decision-making attempts to explain how individuals and their agents make choices among alternatives that have uncertain payoffs over time. The decision process is applicable in various areas of human life including in international finance, Financial Accounting, Public finance, banking, corporate finance, security analysis, insurance, capital/ financial market finance,

corporate reorganization, corporate governance (Copeland and Weston, 1988). The above areas or segments of the application of finance appear in the conceptual diagram as application areas in a box.

Corporate finance is an application area of the theory of financial economics. Jensen and Smith (1984) outline the following as fundamental building blocks of Modern Corporate Finance: i) Efficient Market Theory, ii) Portfolio Theory, iii) Capital Asset Pricing Theory (Treynor, 1961; Sharpe, 1964; Lintner, 1965), iv) Option Pricing Theory (Black and Scholes (1973) and v) Agency Theory (Zeckhauser, 1971; Ross, 1973 Jensen & Meckling, 1976). They further classified the following areas as Critical *Financial* Policy issues for Corporations: i) Capital Budgeting Decisions, ii) Capital Structure Policy (Modigliani and Miller, 1958 and 1963), iii) Dividend Policy (Miller and Modigliani, 1961).

1.6   Developments in Finance 1995-2007

The years 1980's and 1990s have seen more business failure than ever before in the world history. The collapse of businesses has an economic value tag attached to it. Evidence has shown that the market value of distressed firms declines substantially prior to the firm's eventual failure (Warner, 1977; Charalambous et al., 2000). Consequently the suppliers of capital, investors, creditors risk loosing enormous wealth. The management and the employees too loose the source of their livelihood in the event of failure of an enterprise. In measurable terms, small business failure in USA in the year 1996 amounted to US$ 29 billion (Ksh 1,943 billion) as compared to 1997's US$40 billion (Ksh 2,680 billion Kenya shillings) dollars in lose arising from 76,000 for 1996 and 86,000 for 1997 small businesses which failed (Holland, 1998).

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"in the past two decades (1980's and 1990's) at a higher rate than at any time since 1930s. . . . .with certain sectors of the U.K economy such as small industrial businesses . . ..experiencing failure rates as high as 50% over a five year period."[12]

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In USA, banks failed at a rate of "seven (7) banks per year from 1950 to 1980, but has since escalated to an average of 175 per year from 1986 through 1991."[13] It was noted further by other scholars who documented that

> "U.S. commercial banking industry experienced problems of bank failures in the late 1980 and early 1990, reached . . . *a* magnitude *that has* not *been* seen since the Great Depression. Almost 1,500 banks covered by the Federal Deposit Insurance Corporation (FDIC) Bank Fund failed in the years from 1980 to 1993, including a three digit failures between 1985 and 1992 that picked at 206 in 1989" [italics provided], [1]

Conversely, 206 banks failed in USA in the year . 1989 which held a total of US$29, 000,000,000 ($29 billion US dollars) in assets while 124 banks failed in 1991 which held a total of US$ 63, 000,000,000 ($63 billion US dollars) FDIC (1991, 1992). This is indeed enormous loss of investors' resources earned painfully but simply washed down the drain.

The Kenyan case provides evidences that this is not a foreign problem, but a problem within our own court yard. The scenario has depicted a repetitive behavior since 1960's when this country attained independence. Kenya as an illustration has recorded seventeen (17) bank failures since December 1984 up to September 2007 along with twenty four (24) Financial institutions within that same period (APPENDIX IX). This is a total of forty-one (41) collapse of financial institutions in a period ranging from 1983 to 2007. Eleven (11) of the institutions failed in 1980's, twenty six (26) in the years 1990s and the remaining three (3) in the years 2000's.about twenty years period. The total value of resources (capital) that sunk with these enterprises amounted to Ksh 61.312, billion Kenyan money which constituted 30.77% of the financial sector's total capital investment in assets in the same period of time. Although this is hardly one billion US dollar (US $ 0.915 billion), yet given the size of the Kenyan economy, this is a devastating lose to the economy.

The injury caused by business failure is well summarized in the following

"which rocked the capital markets, led to loss of fortunes by the rich and bankrupted the poor, destroyed the confidence and faith of investors of institutions that are fundamental to making capital market systems."[15]

This obviously raises sufficient concern as to i) the relevance and effectiveness of the regulatory agencies where this is relevant especially in the banking and non-banking financial institutions, ii) The relevance and effectiveness of the board of governors. This is raising an issue against corporate governance of the firms, iii) There rises a necessity to have in-place an efficient and effective timely business diagnostic system and procedures (often called business failure prediction system). This should be able to detect an impending financial distress and to transmit an early warning to the relevant authorities for remedial measures. This paper now continues to examine business diagnostic methods and procedures, often called business failure prediction methods; their effectiveness and relevancy.

REFFERENCE

1.   Charitou et al. 2004, pp. 465.
2.   ibid, 465
3.   Ibid, 465.
4.   Barr and Siems, 1996, p. 1.
5.   Miller and Noulas 1998, p. 1
6.   Copeland and Weston, 1988, pp iii
7.   Ibid, 1988 p, 1
8.   Ibid, 1988 p, 77
9.   Ibid, 1988, p, 109
10.   Ibid, 1988, p 150
11.   Ibid, 1988, p. 145
12.   Charitou et al. 2004, pp. 465
13.   Barr and Siems, 1996, p. 1
14.   Miller and Noulas 1998, p. 1
15.   Leblanc and Gillies 2003, p.2

CHAPTER II

2.0   CURRENT LITERATURE IN BUSINESS FAILURE

2.1   Introduction

Since late 1960,s serious investigation into possibility of developing suitable business failure prediction models to help avert enormous loss resulting from business bankruptcy commenced (Altman, 1984; Dimitras, et al 1996, Altman & Narayanan 1997). Consequently, many types of models and methods of predicting business failure have been developed with varying assumptions and computational complexities. The classical cross-sectional methods have proved to be the most popular business-failure prediction methods (Zavgren, 1983; and Atiya, 2001).

2.2   Classical and Statistical Failure Prediction Methods

These are in four categories i) Univariate Analysis by Beaver (1967) who developed a Univariate Discriminant Analysis Method, ii) Risk Index Models by Tamari (1966) then improved on by Moses and Liao (1987). iii) Multivariate Discriminant Analysis (MDA) by Altman (1968). iv) Conditional Probability Models which has three categories i.e. Ohlson's (1980) Logit Analysis [Logistic Regression Analysis]; Zmijewski's (1984) Probit Analysis and Linear Probability Analysis. Up to the end of 1980s, MDA ruled the prediction processes. Conditional Probability Models namely are a result of overwhelming continued business failures in the 1980 and 1990s coupled with technological advancement. They are more sophisticated methods are robust since they are not constrained by statistical assumption of MDA. Below is a brief preview of these methods which have proved most popular in business failure prediction process.

2.2.1   Univariate Models

The earliest documented business failure prediction model was done by Beaver (1966) following increased business failure in USA. Beaver's (1967) was a Univariate model which was developed on the basis of non-failing and failing firms' financial ratios. In his 1967 research, he applied a dichotomous classification test in attempt to identify

ratios that would best classify the failing and non-failing firms. Beaver (1967)'s work was disadvantaged by four critical shortcomings. First, the model was based on a stringent assumption that the form of the relationship which existed between a measure (i.e. a ratio) and the failure status was linear. This linearity assumption does not hold in practice since many ratios display a non-linear relationship with the failure status (Keasey and Watson, 1991).

Secondly, since only one ratio can be used each one time an assessment is being done, the use of several ratios yield conflicting classification of the same firm (Altman, 1968; Zavgren, 1983). The third misshape is that the use of financial ratios in a Univariate model conceals the importance of any one variable in the model. This is a result of variables being highly correlated (Cybisnski, 1998), besides the model does not provide variable weighting. The fourth disadvantage is actually the very models own advantage i.e. its simplicity to use. The simplicity in the model presupposes a firm's financial status as represented by the entire financial statements can simply be represented by a single ratio. This is contrary to current sophisticated, multidimensional financial statements of corporations. Finally, Beaver's model uses cut-off points which are chosen by trial and error using ex post data. This implies that the actual status of the companies in the sample is known. Hence cut off points are sample specific and this may misclassify other units outside the sample (Bilderbeek, 1973).

2.2.2   Risk Index Models

Tamari (1966) developed a model which generated a "risk index" as a pointer to the state of the firm. The model was a simple "point system" but superior to Beaver (1967)'s because one, it utilized different ratios which were considered as good measures of financial health of a firm. Secondly, the model assigned more weights to more important ratios. Moses and Liao (1987) improved on tamari's model by advancing another 'risk index' model which could be arrived at by i) using a Univariate analysis to determine an optimal cut off point to each financial ratio, ii) For each ratio, dichotomous variable is created to which a score of one(l) or zero(O) is assigned if the firms variable exceeds the optimal cut off point or does not exceed the optimal cut off point respectively. A major draw back on the model has been its subjective weighting of ratios.

2.2.3 Multiple Discriminant Analysis

In 1968, Altman (1968) in his thesis titled, 'Financial Ratios, Discriminant Analysis and the prediction of corporate Bankruptcy,' which was published in The Journal of Finance advanced a Z-Score Multiple Discriminant Analysis (MDA) model. In 1977 Altman et al (1977) improved on the model to take account of changes in the accounting standards. The resultant seven factor model was refereed to as ZETA Model. This model has dominated the usage of business failure prediction market world over singularly till after 1980s when other models started to emerge (Dimitriras et al., 1996). Despite the emergence of newer models, Altman's Z-score model has remained a base line model upon which other models results are benchmarked (Altman and Narayanan, 1997), there by rendering it the most standard model world over.

Discriminant analysis fails on the assumption of normality of input variables. It also assumes linearity of behavior of variables and that the variables of the two categories would behave differently. The other limitation is that the model utilizes statistical data only. Consequently, qualitative information-rich data is not capable of being captured in this analysis.

2.2.4 Conditional Probability Models

Three models are under this category. They include Logit Analysis propounded by Martin (1977) and perfected by Ohlson (1980), Probit Analysis advanced by Zmijewski (1984) and Linear Probability Models. Of the three, Logit Analysis is the most applied in business failure prediction. It assumes a logistic distribution (Maddala, 1977; Hosmer and Lemeshow, 1989) unlike Probit Model which assumes a cumulative normal distribution (Theil, 1971).

Logit Analysis model is a non-linear likelihood estimation procedure which combines several attributes into a multivariate probability score for each firm. The score will indicate whether the firm is within a "Failure Probability Category" or "Vulnerability of Failure Category" on a one (1) to zero (0) continuous line scale where the fail status is coded zero (0) and health status is coded one (1).

Logit Analysis (LA) has several advantages which make it more favorable. First, unlike MDA, LA has no restrictive assumption on the distribution of independent

variables. Consequently it does not require multivariate normally distributed interdependent variables (otherwise expressed, independent variables equal dispersion matrices) Ohlson, 1980; Zavgren, 1983; Joos et al., 1998). That is why it is considered less demanding since it operates with disproportional samples. Secondly, the output of LA process is a score between 1 (one) and 0(zero). This in itself indicates the failure probability of the company (Ooghe, 1993). Thirdly, each coefficient in the model is a measure of the significance of its independent variable in predicting the failure or non-failure state of the firm (Zavgren, 1985). This however is conditional on the fact that multi-nonlinearity shall be non-existence in amongst the variables. The Fourth advantage is inbuilt in the nonlinear function of the Logit model. The shape of the function provides a cushion such that compared with a firm of average health, an extremely unhealthy firm must experience a proportionately larger amelioration (deterioration) in order to adversely affect its financial health score on a Logit Analysis (LA) score (Laitinen and Kankaanpaa, 1999). Finally, Logit Analysis accommodates the use of dummy variables since it allows the inclusion of qualitative variables with non-continuous data (Keasey and Watson, 1987; Joos et al., 1998).

Despite the benefits, LA model requires that one; the dependent variables are dichotomous, with the groups being discrete, non-overlapping and identifiable. Two, the model is extremely sensitive to Multi-collinearity which demands total exclusion of highly correlated variables (Ooghe et al. 1993; Ooghe et al. 1994; Joos et al., 1998). Three, LA model is sensitive to any extreme outlying variable (extreme non-normality). This must be eliminated before the process is undertaken (McLeay and Omar, 2000).

2.2   Non-Classical Failure Prediction Methods

Despite the prominence classical methods have enjoyed, academic researches are inventing alternative failure prediction methods taking advantage of progress in information technology, enhanced computational skills and artificial intelligence. The most popular of these methods are Survival Analysis (Lena et al., 1986), Machine Learning Decision Trees (Quilan, 1986; Joos et al., 1988) and Artificial Neural Networks (Odom and Sharda, 1990).

2.3.1   Survival Analysis (Lena et al, 1986)

Also called Hazard Model, this statistical technique was drawn from "Survival Analysis" hence its name. The analysis yields "a hazard model" which utilizes the coefficients of the independent variable to predict the probability of occurrence of dichotomous dependant variable (Deliman, 1996). In business-failure prediction process, the technique weighs financial ratios and creates a score for each company in order to be classified as failed or health firm. The technique has the following assumptions; first, the failing and the non-failing firms belong to the same group of non-failing firms as long as survival lasts. Secondly, non-failing firms are firms which have been right censored (i.e. firms which are not under observation) status (Lane et al., 1986). Thirdly, the dependant variable is the "survival time" which is at the minimum as long as the total time from the start of research period to the end of period lasts (Shumway, 1999).

Some of the critical advantages of survival models over classical models are (Luoma and Laitinen, 1991; Shumway, 1999) include first, the models allows the use of more data than and a large number of variables than statistical methods. Secondly, the interpretation of results of hazard models is easy. In each case, a positive coefficient means that an increase in the corresponding indicator leads to a decrease in survival probability, which implies an increase in failure probability risk. Thirdly, the model allows inclusion of a wider variety of variables in the analysis, thus becoming more comprehensive. Fourthly, the analysis does not assume that failure is a steady state. Hence, it resolves the problems of static models by clearly accounting for the time dimension of the firm.

Survival Analysis has a number of disadvantages. The first is that the model is suitable for prediction within a period of 12 months only. It is a short-term failure prediction model which cannot span beyond one year period. Secondly, with specific respect to Cox Model, the model is adversely affected by multi-collinearity problem. Consequently, strong correlation between the independent variables must be eliminated before the model is applied (Lane et al, 1986). Thirdly, the model assumes survival calculation times arbitrarily. This is caused by the fact that the closing date of an annual accounting period is considered the natural stating point of the failure process (Luoma and Laitnen, 1991).   Fourthly, the results of survival analysis prohibit statistical

inference, which is the purpose of statistical analysis. This may occur when the number of failing and non-failing firms in the estimation sample happens to affect the hazard rates. Consequently, survival analysis results are ample and specific results of the survival analysis of the relevant firm being modeled (Luoma and Laitnen, 1991). Finally, the Survival Efficiency analysis in failure prediction is greatly determined by the diversity of the failure process found in the estimation sample.

2.3.2   Machine Learning Decision Trees (Quilan, 1986; Joos et al., 1988)

Machine Learning technique is a non-parametric business-failure prediction method. It involves pattern recognition of phenomenon being studied. The model is based on "learning processes" derived from asset of rules (Quilan, 1986). Other similar learning approaches include the Covering Approach and the Genetic Algorithms Approach (Back et al., 1997). Decision Trees are results of processes of supervised learning. This is a discretization of continuous-value variables, which is done according to discretization algorithm concept which concept guides the process of learning. Branching is caused by decision rules that guide the splitting (Quilan, 1986 and Joos et all., 1988).

Decision Trees model has a number of advantages over the classical models, i) Since machine learning is a non - parametric method, there are no strong statistical demands on statistical assumptions concerning data in the training sample. This makes its application straight forward, ii) Decision Trees Model is robust since it handles wide variety of data including quantitative data, qualitative data and incomplete data (Joos et al, 1998). The model is not affected by extreme outlier variables, iii) The method is simplistic and therefore appealing to users. According to Joos, et al., (1998) decision trees are user friendly; it does not require complicated expertise to be able to apply the model. Results are also easy to understand,   iv) The graphical presentation format of decision trees is easy to read and it allows an identification of the most significant attribute and the least significant feature (Daubie et al. 2002). v) Decision tree method can deal with noise or non-systematic enors in the values of attributes or class information.

Drawbacks to this model include one; decision trees require specification of prior probabilities and misclassification costs. Both factors need to be incorporated in the

learning process to which factors, decision trees are most sensitive than in the case of MDA models. Secondly; the assumption that the failing and non-failing firms are discrete, non-overlapping, and identifiable sometimes does not hold. Three, the model does not provide interpretation of the relative importance of predictor variables or attributes. Consequently, the model does not pride guidance on the weighting of significant variables in the model. Four, decision trees cannot be used to classify firms in the same risk category since the model is a discrete scoring system that classifies forms into risk categories. Finally, the model cannot be applied to new cases so as to asses their failure risk states of other firms other than for the one the training and modeling is done.

2.3.3   Artificial Neural Networks |ANN](Odom and Sharda, 1990)

This method was drawn from biological science. Atiya (2001) termed it Multiplier Network. Odom and Sharda (1990) did the first works of ANN in business prediction of bankruptcy. This was followed by numerous studies making the model dominate the literature on business failure prediction in the 1990s (Cadden, 1991, Coats and Fant, 1993; Fletcher and Goss, 1993, Altman et al. 1994; Daubie and Meskens, 2002 etc.). ANN is computer-based analyses that consist of interconnected artificial neurons. The model consists of a set of input nodes that constitute the input layer followed by one or more neuron layers hidden behind the input layer of neurons (Tam and Kiang, 1992; Boritz et al, 2000). Data is input into the model there by facilitating a training process which is based on 'supervised learning'. Once trained, the model is able to predict and distinguish between healthy firms and failing firms.

Merits of ANN include; first; ANN is robust and capable of analyzing complicated and enormous patterns of data with micro-accuracy at a super speed (Shachmurove, 2002). Secondly, the method is able to learn from examples without any programmed knowledge (Back et al 1996). Thirdly, the method is not subject to restrictive statistical conditions including linearity condition., normality of sample, multi-collinearity etc, on the contrary the relationship between failure risk on financial ratios shows saturation effects while the effects of financial ratios on non-failure risk are multiplicative thus rendering the effect of non-linearity advantageous. Fourthly, as a consequence of (iii) above, non-numeric data can easily be included in the ANN since it

would not contravene linearity condition, which condition does not exist. (Coats and Fant, 1993). Next advantage is according to Hawley et al., 1990; Turker, 1996); Shachmurove, (2002). They observed that ANN model is suitable for pattern recognition and classification in unstructured environments with noisy data which is characterized by incompleteness and inconsistent.

Demerits limit the predictive power of the ANN include i) the fact that what goes on in the ANN computer is indiscernible by a user this is the "black box Problem". ANN does not provide room for one to understand what happens within its program, ii) ANN is very sensitive to "garbage-in-garbage-out" problem. This necessitates the selection of quality variables form extensive variables available. The exercise is translated into a time-consuming exercise, iii) Since ANN uses trained data, it runs the risk of over-parameterization (over-fitting). The most possible result is a sample specific model with a low ability to inferential statistics and generalization to other firms. Every time the model has to be done, it must be retrained, iv) The. researcher usually designs physical architecture of ANN through trial and error method. A network with multiple layers requires a number of layers and a number of nodes which are decided upon arbitrarily. The higher the number of layers, the more complex neural network is which results in higher internal validity. This compounds the problem of higher degree of over-fitting and hence a lower external validity, v) ANN requires a large training sample of input -output values in order to sufficiently train the network.

2.3.4   CUSUM Model (Theodossiou, 1993)

CUSUM stand for Cumulative Sum. This implies cumulating of financial information. This methodology was applied to business failure prediction for the first time by Theodossiou (1993) in his study titled, 'Predicting Shifts in the Mean of Multi-variety Time Series Process: An Application in Predicting Business Failure." This was followed by Kahya & Theodossiou (1996) in a study titled, "Predicting Corporate Financial Distress: A Time Series CUSUM Methodology" In both studies, 'CUSUM model' was used to predict business failure and corporate financial distress on the basis of financial accounting information as input variables.

The CUSUM model is a dynamic extension of MDA which analyses time series behavior of financial accounting variable vectors. CUSUM has the ability to distinguish between transitory changes in financial variables that result from a serial correlation which is a situation in which positive deviations from the mean structure of the variables follow positive deviations in subsequent periods while negative deviations follow negative deviations. Alternatively non-transitory changes that result from permanent shifts in the mean structure due to financial variables shift from "good performance" joint distribution to a "bad performance" joint distribution. A shift in the joint distribution of a firm's financial variables is considered as a signal that the firm tends towards failure. In this way, the CUSUM models predict a firm's tendency towards failure. The sequential procedure is based on the sequential probability ratio test and the theory of "optimal stopping rules" (Kahya & Theodssiou, 1996). The model involves solving an optimization problem concerning the CUSUM parameters, which determine the "sensitivity" of the model to distributional changes (i.e. the time between the occurrence of change and its detection in the distribution of a firm's financial variables). In the optimization problem, the expected error costs of Type I and II errors are minimized (Theodossiou, 1993).

All the merits and demerits of MDA are equally the merits and demerits of CUSUM Model. The unique advantages are, i) the method analyses a firm's financial health, based on financial accounting information and capital market variables about the present and the past performances of a firm under investigation, ii) The method also has a very short memory with respect to a firm's good performances over the years, while it has a very long memory regarding bad performances.

2.3.5 The Fuzzy Rules-based Classification Model (Spanos et al. 1999)

The model is based on "Fuzzy Knowledge Based Decision Aiding Method". This method was first used by Spanos et al. (1999) in business failure prediction. This method starts from a number of if-then rules, which are based on already existing, qualitative knowledge on corporate failure and are determined by the decision maker. These if-then rules make a link between a number of conditions concerning predefined variables and the failure status. Next the relevance of each if-then rule is tested on an estimation data

set. Each rule is attributed to a rating index, between zero and one, which denotes the probability of correctness of a rule. Finally, according to the decision maker's preferences, a certain set of fuzzy rules- the 'fuzzy rules set'- is exported to a "Fuzzy Rules-Based Classification Model" and, according to this model firms are classified as failing or non-failing.

An important advantage of the fuzzy rule model is its intuitive basis. The modeler has a leeway to use intuition in deciding what element to include. A negative feature of the fuzzy rule model is that it strongly depends on the arbitrarily determined if-then rules, based on the knowledge of the decision maker.

2.3.6   Dynamic Event History Analysis [DEHA] (Hill et al., 1996)

Hill et al., (1996), applied DEHA method for the first time in business failure prediction. They showed the difference between financially distressed firms which eventually survive and those that did not survive (eventually) did wind up. DEHA considers business failure as a process and not an instant occurrence. To transform a firm from a healthy and vibrant condition to unstable and financially distressed condition; and eventually to bankrupt position was analyzed using longitudinal data of the firm under investigation. This method used a computerized package which has classification processes using data drawn from different periods of the same firm under investigation.

The model has one major advantage over the rest since it moves away from the snapshot focus of the classical statistical models. It recognizes that corporate failure is a dynamic process that starts with some initial conditions and involves changes in these conditions over time. These changes do provide signals on financial state of a firm. The secondly; the model allows for time-varying independent variables [which may vary over the observation period] and for censored cases. Thirdly, the 'conditional probability' feature of the DEHA method is very appealing, because it closely corresponds to reality. It is a reality that the failure probability of a firm in the future strongly depends upon the current financial status of the firm. This feature is well captured by DEHA.

2.2.7   Catastrophe Theory or Chaos Theory (Scapens et aL, 1981)

Scapens et al. (1981) were the first scholars who considered company failure as a catastrophic event and who used 'Catastrophe Theory' to explain corporate failure. Similarly, Lindsay & Campbell (1996) used 'Chaos Theory' in order to develop a corporate failure prediction model. A chaos theory model regards companies as chaotic systems which depict unstable and unpredictably volatile [i.e. chaotic] behavior in their returns to investment when they are the system [firm] is well and financially sound and stable. This behavior changes to fairly stable form [less volatile, fairly predictable] when the system [firm] attains a state of financial distress. Chaos theory has two key assumptions namely first, that firms are deterministic and predictable entities in behavior, but over short periods of time only, due to extreme sensitivity to the initial prevailing conditions.

Secondly, the theory assumes that healthy or non-failing firms depict more chaos in their share prices than unhealthy firms. This assumption stems from the application of the chaos theory statement i.e. "healthy systems exhibit more chaos than unhealthy systems." Ordinarily, the returns of a firm approaching failure are assumed to be less chaotic than the returns of the same firm in an earlier time period. Chaos theory model requires a suitable measure of chaos. Lindsay & Campbell (1996) measured the amount of chaos of a firm by means of the "Lyapunov Exponent": the larger this exponent is in the model, the sooner the company becomes unpredictable.

A merit of the chaos theory method is i) first; it involves a dynamic analysis of a firm's financial health, ii) It considers the amount of chaos in different time periods. However, a demerit of the chaos theory [catastrophe theory] model is that its validity depends on a strong assumption which may be easily violated. Once the assumption is violated, chaos model would be misapplied and so render its results invalid.

2.3.8   Multi-dimensional Scaling [MDS] (Mar-Molinero and Ezzamel ,1991)

Mar-Molinero & Ezzanel (1991) introduced the technique of 'Multidimensional Scaling' (MDS) into the domain of corporate failure. They explored the relationship between samples of financial ratios that can be used to describe the financial health of a firm. Neophytou & Mar-Molinero (2001) applied MDS to the prediction of corporate

failure and the examination of which attributes explain failure. MDS starts from a dataset of companies and attributes of companies (e.g. financial ratios). The MDS treats companies as variables and the attributes as cases. Based on a table of distances (the 'distance matrix' also called the 'Dissimilarity Matrix') it produces a graphical representation of the structure of the dataset in the form of a map (Mar-Molinero & Serrano-Cinca, 2001; Neophytou & Mar-Molinero 2001).

First, each company is represented as a point in an X-dimensional space, of which the position is determined by a set of coordinates. The number of dimensions (X) in which the map is drawn, is decided by the researcher. Next, MDS determines which dimensions provide an adequate representation of the most important features in the data. In view of determining these dimensions (Y), one may conduct a Logit Analysis using the firm's coordinates in the X-dimensional space as explanatory variables and a dichotomous dependent variable expressing the failure status. The result is an MDS map with Y dimensions in which each failing or non-failing company is represented as a point. This matrix is a square matrix that contains information about the proximity or similarity between firms. The number of rows and columns in this matrix is equal to the number of companies in the sample.

This is an important decision, as the number of dimensions influences the quality of the map, its interpretability, its ease of use and its stability. Finally, the data are interpreted by means of a 'profit analyses'. This is a regression-based method that attempts to explain how each of the particular attributes (e.g. Financial ratios) is associated with the position of a firm in the Y- dimensional space. It consists of a set of regressions- one regression for each of the attributes in which the value of the attribute is used as the dependent variable and the firm's coordinated in Y-dimensional space as the independent variables. If the R2 of a regression falls below a certain cut-off value, the corresponding attribute is considered to be not relevant to the failure classification problem. The presentation of the result of the profit analysis in the Y-dimensional map clearly indicates how the various attributes relate to the different dimensions (Mar-Molinero & Serrano-Cinca, 2001; Neophytaou & Mar-Molinero 2001). The only requirements for MDS are (1) that there is 'a message' in the data and (2) that the ratios are standardized, when they are initially measured in different units.

Merits of MDS include first; the end result of MDS is a statistical map, which has a very intuitive interpretation. In contrast with many other statistical methods, the results can be interpreted without a deep understanding of the underlying statistical principles of the method. Consequently, MDS is a flexible, powerful tool and yet an easy approach to apply. Secondly, MDS has the robustness in the presence of outliers (discordant observations) and the ability to cope with highly correlated data. Thirdly, MDS does not make any assumptions about the distribution of the data. Fourthly, MDS can cope with redundant information; there is therefore no need to conduct an initial analysis of data involving editing and reductions. All possible variables or firm attributes can be included into the analysis. Fifthly, an interesting feature of MDS is that it is able to explain the possible 'causes' of failure nevertheless.

Some drawbacks of MDS are i), if based on annual account information, such as financial ratios, it is limited to their use of only one annual account which is the recent most financial statements. Several problems and criticism arise when company failure is predicted on the basis of only one single annual account, ii), MDS is not explicitly meant to be used in a predictive context for failure prediction of new cases. Specific procedures need to be applied to such new cases (Mar-Molinero & Serrano-Cinca, 2001; Neophytaou and Mar-Molinero, 2001).

2.3.9   Multi-Logit Model (Peel and Peel, 1988)

The Multi-Logit Model was introduced to business failure prediction by Peel & Peel (1988). The model allows the use of data simultaneously from several years (unlike the classical which considers data from only one year each time) before failure. It also simultaneously discriminates between failing and non-failing firms for several reporting periods prior to failure. The model is based on the stringent assumption of 'signal consistency', which implies that for each firm, data for consecutive years prior to failure can consistently provide useful signal about the a firm's state of healthy, i.e. whether it is at risk of financial stress or not.

The advantage this model is it predicts corporate failure using information from several consecutive years. This is contrary to classical statistical failure prediction models. Along with it is a drawback; the model entirely depends on the assumption of

'Signal Consistency'. Unfortunately this assumption is very easy to be violated when undertaking a study practically. The researcher should be careful not to violet the assumption otherwise the result may be rendered valueless.

2.3.10 Linear Goal Programming [LGP] (Gupta ct al., 1990)

This is a method derived from mathematical programming. It was applied to business failure prediction by Gupta et al (1990) in classification of bankrupt and non-bankrupt firms. The technique calculates inter-group scores between the failing and non-failing companies. Individual firm's score is computed which enables the technique to provide a boundary for group discrimination. The results are translated in to a Hyper Plane, which is used to distinguish between the failing and the non-failing firms.

The merits of this method include i) the technique is not bound by usual statistical restrictions for it to operate as is the case with MDA methods, ii) The method is user friendly, easy to apply and understand, iii) The interpretation of results is clear and straightforward. Consequently, no special skills are required to understand the results.

2.3.11 Multi-Criteria Decision Aid Approach [MCDA] (Zopoudinis, 1987)

MCDA method was first used by Zopudinis (1987) in his work titled, "A Multi-Criteria Decision-making Methodology for the Evaluation of Risk and Application." The method allows assessment of the firms risk using qualitative and quantitative data (financial ratios). The method assumes that the decisions makers' preference concerning categorization of firms is monotonic function of attributes, which can generate utility functions.

Two levels of classification are applied to arrive at the results. First procedure classifies a firm as a failing organization if the utility of the firm corresponding with the utility function for the failing firm is higher than the utility corresponding with the non-failing function. The second procedure involves determining optimal classification rule. Optimal classification is a cut off value that distinguishes between the utility corresponding to non-failing firms' utility function and the failing firms' utility functions. A firm is classified as failing if its utility difference is below the optimal cut-off value and as a success firm if it's utility is above the optimal cut-off value.

The 'Multi-Group Hierarchical Discrimination' (MGHD1S) (Doumpos and Zopoudinis, 1999) method of business failure prediction is an extension of this technique better results. This model includes a derivation of two additive utility functions. One utility function representing failing firms while another function represent non-failing firms. This is quite similar to the main MCDA upon which, MGHDIS is its extension .

There are several advantages attached to this model. First, the model uses both statistical quantitative variables as well as non-quantitative (qualitative) data. This makes the model both parametric and non-parametric in nature. Secondly, the model's results are   easy to interpret since the cut off point (optimal point) is very clearly defined. Finally, the model is not bedeviled by statistical assumptions of normality of the sample, multi-colinearity.

2.3.12 Rough Set Analysis (Slowinski and Zopudinis, 1995)

Slowinski and Zopoudinis (1995) pioneered in the application of this method in evaluating business failure. In their work titled "Application of the Rough Set Approach to Valuation of Bankruptcy Risk," they considered evaluation of failure risk as a multi-attribute sorting process (Pawlack, 1982). The process classifies sets of firms according to sets of identical multi-valued attributes. The attributes included financial ratios as well as other non- quantitative attributes of firms.

A training sample is used to develop decision rules which are referred to as deterministic and non-deterministic sorting rules. These rules take the form "if-not rules." The training data constitutes a set of firms identified by a set of firm attributes.   The process takes three stages namely: i) creation of minimal subsets compared with core attributes, ii) A decision table is created on which basis redundant data attributes are eliminated, iii) Then the decision table is used to sort out and classify failing and non-failing firms.

Advantages include one; the model uses qualitative data as well as quantitative data. Two, the model therefore is not constrained by restrictive statistical assumptions that are necessary requirements when dealing with quantitative statistical models. Three, the model accommodates all variables, outliers, erroneous etc. The key drawback of the model is that it requires the conversion of quantitative data into qualitative measures.

2.3.13 Expert System (Messier and Hansen, 1988)

This is a computerized learning algorithms based system which utilizes artificial intelligence. Ordinarily an expert knowledge base is Concorde using simulation and other intelligence configuration of 'if....then' training tools. Messier and Hansen (1988) initiated the application of this methodology in business failure and later Hawley et al., (1990). Basic merits of this approach include first; flexibility. The computer Expert Model is flexible enough to accommodate any kind of variable (quantitative or otherwise) and unlimited volume of data. Secondly, the model has no specific demands on fundamental statistical assumptions. Three, since the system used utilizes "if-then rules" It can easily be applied to different practical new cases. Consequently it is a user friendly modeling approach and flexible as well.

A few drawbacks include the fact that the model is not easy to apply intuition to the "knowledge base". Secondly, the process of converting knowledge into "if- then rules" is tedious and time consuming. This is the programming process which then establishes the expert system. Thirdly, expert systems are considered inflexible since they are not able to use intuitive learning to adapt to the "if-then rules" to changing situations. Finally, the expert system cannot accommodate incomplete data, noisy data, erroneous input variables and outliers. Consequently, it requires thoroughly defined and refined input data.

2.3.14 Self Organizing Maps [SOM] (Martin-del-Bro and Serrano-Cinca, 1993)

Martin-Brio-and Serrano-Cinca applied this method for the first time in 1993 as recorded in the works of Daubie and Meckens (2002) titled, "Business Failure Prediction: A Review and Analysis of the Literature." The method uses quantitative financial data and it is similar to ANN except that the training process of SOM is not supervised like ANN. This method has all the advantages of ANN and its demerits. Other merits include one; the method is useful in detecting regions of increased failure risk in organizations. Two, the method is good at monitoring/viewing the evolution of conditions of company risk over time. And three, the technique offers some possibilities to explore typical failure paths. One drawback is worth mentioning; the model involves arbitrary decisions of the user in selecting a set of independent input variables (Kaviluto and Bergius, 1998).

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CHAPTER III

3.0 CLASSICAL VS NON-CLASSICAL PREDICTION MODELS

Table 2.1 below provides an analysis of the summery of some prediction models developed in 1990 viz a vi the traditional MDA, Logit Analysis and Probit Analysis and Non-classical models. It is evident from Table 2.1 above that the most dominantly used model was MDA which had twenty eight [25] comparative empirical studies followed by seventeen [17] studies which applied Logit Analysis. The most next dominantly applied model is the Artificial Neural Networks (ANN) which registered twenty one [21] studies.

3.1 Performance is Similar for both Classical and Non-classical Models

A general observation of the studies analyzed confirm that the performances of the compared models were based on one specific data set, yet an accurate comparison of performance results may still be impossible, because the models used different variables. However, comparison of the models was on the basis of their ability to predict correctly and no t the utilization of the same variables to yield comparable results. Some studies concluded that the newly modeling techniques lead to similar results as the classical models. Laitinen & Kankaanpaa (1999) conduct a very comprehensive comparative study, involving MDA, Logit Analysis, RPA, Survival Analysis and ANNs and conclude that, generally, there is no superior method of classification. Depending on whether the ex post classification results or the ex ante prediction results are used, the ranking of the methods differs, fhe only difference in predictive performances which was found to be significant is the difference between the LA model and SA, one year prior to failure. Here, the LA performed better than the SA model. Similarly, Neophytou et al. (2001) compared the performances of ANNs and LA models and found that ANNS and LA models are both reliable alternatives for company failure prediction.

3.2   **Non-classical Models Outperform the Classical Models**

Doumpos & Zopoudinis (1999) conducted a comparative study on the techniques of linear MDA, logit analysis and multi-group hierarchical discrimination (MGHDIS), using the same variables for the three methods (i.e. an equal comparative basis). They found (1) an inferior performance of the Logit Model over the MGHDIS model. Theodossiou (1993) provided evidence for the CUSUM model being clearly superior in performance, when compared to an MDA model. Shumway (1991) compared two pairs of models,

Table 2.1: Overview of the Conclusions of Comparative Studies on Modeling Methods

Author	Year	MDA	LA	PA	LPM	MGH	CUSUM	DT	SA	RPA	FR	NN	
Frydaman et al	1985	X								X			2
Cadden	1991	X										X	2
Odom & Sharda	1990	X										X	2
Coats & Fant	1991	X										X	2
Luoma & Laitinen	1991	X	X						X				3
Theodossiou	1993	X					X						3
Coats & Fant	1993	X										X	2
Fletcher & Goss	1993	X										X	2
Udo	1993	X										X	2
Chung & Tarn	1993	X										X	2
Weymaere/&Martens	1993	X	X									X	3
Zain	1994		X									X	2
Wilson & Sharda	1994	X										X	2
Altman et al.	1994	X										X	2
Boritz et al.	1995	X	X	X								X	4
Triqueiros/Taffler	1996	X										X	1
Back et al	1996	X	X									X	3
Back et all	1997	X	X									X	3
Bardos & Zhu	1997	X	X									X	3
Hekanaho	1998		X							X		X	3
Joos et al.	1998b		X					X					2
Laitnen/Kankaanpaa	1999	X	X						X	X		X	5
Doumpos//Zopoudinis	1999	X	X		X								3
Shumway	1999	X	X						X				3
Yang et al	1999		X									X	2
Doumpos /Zopoudinis	1999	X	X		X								3
Spanos	1999	X	X	X						X			4
Pompe/Bilderbeck	2000	X										X	2
Neophytou et al	2001	X										X	2
TOTAL	29	25	15	2	0	2	1	1	3	3	1	21	70

Source: Generated from form Surveyed Studies, 2007

MDA and Logit Analysis and Survival Analysis. He found that Survival Analysis was superior to both MDA and Logit Analysis.

First, the MDA model of Altman (1968) was compared with a hazard model containing the same variables and, secondly, the logit model of Zmijwski (1984) was compared with a similarly constructed hazard model. The survival analysis technique reported equal or better out-of sample predictions performance than MDA. Luoma & Laitinen (1991), on the contrary, found that MDA and Logit Analysis models outperformed Survival Analysis model. Frydman et al. (1985) compared the technique of RPA [this is a survival analysis model] to MDA and conclude that, dependent on the choice of misclassification costs, the RPA model would not always outperform the MDA model. Spanos (1999) compares the accuracy of a fuzzy rule-based classification model with the accuracy of MDA, Logit Analysis and Probit Analysis and concluded that the Fuzzy Rule-Based Classification model on overall provided the best results.

Studies comparing the ANN method to the classical statistical techniques and other methods are widely divergent in conclusions. In most studies, the ANN's have proved superior in performance than MDA, Logit. Analysis, and Probit Analysis. Odom & Sharda (1990), Coats & Fant (1992) and Coats & Fant (1993) concur and so assert that the ANN technique is clearly superior to the MDA method. Wilson & Sharda (1994) also compared MDA with ANN and confirmed the superiority of ANN method. They used the back-propagation algorithm approach of ANN, in predicting failure one year prior to failure. The same position was determined by Fletcher & Goss (1993) and Udo (1993) who; in separate studies compared ANN and Logit Analysis. They observed that ANN was better in performance than Logit models in extracting information from attributes for forecasting bankruptcy. Chung & Tarn (1993) performed a comparative analysis of a back-propagation ANN and two types of decision tree algorithms. They concluded that ANN method is superior both in one year prediction and two (2) years prediction prior to the firms' failure. Weymaere & Martens (1993) carried out a study whose results added weight to the superiority of ANN models over MDA and Logit Analysis, especially for the medium term (3 years) analysis. Only for short term failure prediction, did the logistic regression model seem to perform as equally well as ANN.

In addition, when the data are first subjected to a principal component analysis, the NN technique significantly outperforms the traditional models. Bardos & Zhu (1997) compare both logit analysis and ANNs with the linear MDA method and conclude that

the logit model does not perform better than the MDA model, while a simple ANN with eight input variables performs slightly better than MDA, especially for the non-failing firms. Zain (1994) compares a ANN with a logit model and finds that, 3 years prior to failure, the ANN has the best classification results, while one year prior to failure, and the Logit model performs best. When comparing the stability of the models, the NN technique appears to be the best method. Further still, in a study by Black et al, (1996) in which a genetic algorithm-based ANN was compared with the techniques of MDA and Logit analysis. One and three years prior to failure, MDA showed the best results.

3.3   **Classical Models Outperform Non-classical Models**

In contradiction to the above mentioned studies which attributed superior qualities to the ANN technique, some scholars have found identical or inferior performance of ANN over classical statistical models. Some of these studies are first, Trigueiros and Taffler (1996) who pointed out that there is little evidence that the artificial intelligence ANN approach dominates the conventional multivariate models, particularly in the case of out-of-sample prediction. They argue that the relative performance of ANNs as compared to traditional statistical models depends on the sample size used. ANN models have increased prediction accuracy when small samples are used. In the case of a small sample, the ANNs are likely to show a very high number of fitted coefficients, in some cases even higher than the number of cases in the model fitting, and hence this over-fitting may result in an overstated accuracy for the ANN in comparison to the other techniques.

Secondly, it is within this context that Altman et al (1994), using a large sample, carried a study in which they established little or no significant differences in classification performance between Artificial Neural Networks (ANN) and conventional multivariate statistical techniques. Thirdly, in a similar study, Pompe & Bilderbeek (2000), did demonstrate that in the case of large samples, ANN models and linear MDA models performed equally, while in the case of small estimation and training samples, ANN models deliver better results than linear MDA.

Fourthly, when comparing different modeling techniques on a large sample of 570 companies, "Hekanaho (1998) also did find that the differences between the various

induction methods [Recursive Partitioning Analysis, and Genetic Algorithms] especially between rule-based learning and ANN's are quite small and inconsistent when the sample size is large. Then ANN models and rule-based learning models may perform better than Logit Analysis. On the contrary, Back et al. (1997) did demonstrate that ANN models (and machine learning models) perform better than MDA and logit models when the sample size is large (400 cases), while there is no best performing method when the sample size is smaller (i.e. 200 or 100).

Fifthly, some studies indicate that ANN models have poorer performances than other methods. Boritz et al. (1995) too did find that ANN models have no superior classification abilities as compared to MDA, Logit and Probit Analysis. Only for particular combinations of proportions of failing and non-failing firms in the training and validation samples and for particular misclassification costs for type I and Type II errors, the ANN shows superior results. Furthermore, the results of a comparative study of Yang et al. (1999) indicated that Logit models perform better than models based on ANNs. In the sixth case, though Weymaere & Martens (1993) confirmed the superiority of ANN over MDA and Logit Analysis over three years' period, in the short term (1 year and 2 years prior to failure) failure prediction, the Logistic Regression Model (Logit Analysis) performed better than ANN and MDA model similarly.

The above analysis provides comparative view performance of different predictive methods against ANNs. The analysis indicates that, although the alternative methods are computationally more complex and sophisticated than the classical cross sectional statistical methods, it is not clear whether they produce better performing corporate failure prediction models. Therefore, scholars, analysts and monitoring agencies as well as credit rating bodies should apply preferably a number of models at any one time in predictive process. Whatever other models that may be applied; most recommended methods that should not be omitted from the analysis are MDA, LA, ANN.

4.0 THE FUTURE OF BUSINESS FAILURE STUDIES

4.1 Prediction Techniques for Current Decade 2000-2009

Table 4.1 below is an attempt to assemble latest studies undertaken in this decade of 2000-2009. Evidently up to the first half of the decade, more studies are going on. The survey whose results are captured in table 4.1 indicated that captured a total of 25 studies of which only four utilized MDA while 11 applied Logit Analysis and 7 applied an integrated approach MDS which utilizes a diversity of variables. Four (4) of the studies applied ANN technique. The trend is moving away from known MDA to integrated

Table 4.1: Business Failure Studies 2000-2007

Author	Year	MDA	LA	PA	LPM	MGH	CSM	DT	SA	RP	FR	NN	MA
		BUSINESS FAILURE STUDIES IN FROM 2000 TO PRESENT											
Pompe & Bilderbeck	2000	X										X	
Maimbo	2000	Camel											
McLeay/d Omar,	2000		X										
Atiya,	2001											X	
Charituoet al	2001		X	X									
Neophytou et al	2001	X										X	
Neophytou and Mar-Moiinoro	2001	MDS											
Mar-Molincro & Serrano-Cinca	2001	MDS											
Kauflman/**Wang**	2001								X				
Barniv *el al.* *	2002												
Ooghe/Balcaen •	2002	X	X	X	X								
Bhattachaijee**	2002	MDS											
Daubie et **al**	2002							X					
Lizal	2002		X										
Charituo & TrigtoRis	2002		X										
Heyden**	2003	MDS											
Thomhill /Amit	2003		X						X		X		
Becchetti / Sierra	2003		X										
Ooghe et al	2003	OJDV											
Chariou et al	2004		X									X	
Oshinsky & Olin (UN)	2004		X										
Argawal&Taffler	2005	X											
Ooghe, etal	2005	X	X		X								
Curry et al *	2005	SMA											
Hailing & Heyeden	2006		X						X				
TOTAL	25	4	11	2	2	0	0	1	3	0	1	4	

Source: Generated from Studies Surveyed

KEY

**Bhattacharjee et at. (2002)- applied Multidimensional Framework (MDS)
**Curry et al. (2005)- Applied Security Market Analysis
**Deakins (1972) - used Univariate analysis and MDA concurrently.
**Edmister (1972) - applied Zero-One Regression method.
**Heyden (2003)- applied Multidimensional Framework (MDS)
***Wilcox's (1973, 1976) - Method applied was Linear Gamblers Ruin method.
**Johnson and Melicher (1994) -Applied Multinomial and Logit analysis methods.
**Barniv *et al. (2002)*- Applied Ordered Logit Analysis.
**Moses and Liao (1967) - Risk Index
**Maltz et al. (2003)- DMP (Dynamic Multidimensional Performance framework model)
**Ooghe and Balcaen (2002)-MDA, LDA, LR, CP a comparative study
**Ooghe, et al. (2005)-LDA, CP, SIM, LA
**Neophytou and Mar-Molinero 2001-Multidimensional Scaling-MDS

multidimensional models which can utilize a diversity of variables. Most of the models are listed in the Key to Table 4.1 above. This is also a decade when the collapse is for giants. With the likes of WorldCom and Enron's failure, more caution should be raised on the practice of and the usage of failure prediction methods, models and techniques. Who fails when business fails? Is it the management, or the shareholders or the governors? It is worth noting that MDA is still being used along with other methods especially Logit analysis.

Table 4.2 below provides a summery of the studies captured in this survey and the techniques used. It is evident that business failure innovation was highest in the decade of 1990-1999 decade. A total of 174 studies were captured in the survey of which [MDA (66), Logit (44), Probit (4) Risk Index (1), Univariate (2) and Multilogit (2)] 120 are classical statistical methods while the rest are from the alternative method of 1990 with Artificial Neural Network leads with 19 studies alone.

This implies that classical statistical methods were still reliable in 1990-1999 decade despite their shortcomings. This is an indication of the validity of the classical methods, their uses other methods to support or confirm their reliability for East African countries. It should however be observed that the trend of study is now changing from intensive MDA models to MDS Models which are capable of handling a number of diverse input variables with lesser restrictive assumptions. It remains to be discovered whether it is the techniques which are faulty or some other unknown phenomenon since even with all this, business still collapse. A study should be advanced to apply MDA, LA,

PA, MDS, ANN, and SA which are popular. It will however venture into trying to determine the purported usage of failure prediction methods.

Table 2.3: Summery of studies and Methods Applied

	1960-69	1970-79	1980-89	1990-99	2000-07	Total
Cumulative Sum				1		**1**
DEA				1		**1**
Decision Tree				1		**1**
DMP					1	**1**
Fussy Rule				1	1	**2**
Logit Regre'n		**1**	2			3
i Linear DA					2	**2**
Logit Analysis			7	26	11	**44**
MDA	1	15	15	31	**4**	**66**
MDS				1	7	**8**
MGHDIS				1		**1**
Multi-Logit Ans			1	1		**2**
1 Neural Network				18	**4**	**22**
Probit Analysis			2		2	**4**
Risk Index	1					**1**
Survival Analysis			2	**4**	3	**9**
Simple IM					**1**	**1**
Regre'n Probit Analysis				1		**1**
1 Univariate	3					3
Zero-One Regression		1				**1**
TOTAL	**5**	**17**	**29**	**87**	**36**	**174**

Source: Generated from Studies Surveyed, 2007

4.2   The Way Forward in Failure Prediction Practice

Following the literature surveyed above for the 2000-20007, it is evident that many businesses are collapsing allover the world, businesses of all types and all sizes. In Charan and Useem's words

> "each month seems to bring the sound of another giant crashing to earth, Enron, WorldCom, Global Crossing, K-mart, Polaroid, Arthur Anderson, Xerox, Qwest, they fall singly, they fall in groups, they fall with a heavy thud of employees laid off, families hurt, shareholders furious . . . . and not just any companies, but big, important, FORTUNE 500 companies that are not supposed to collapse."[1]

Business bankruptcy is with us.

The numerous studies proof how all possible effort is being put in place to try resolve the problem. Predictive techniques, methods, systems have been advanced. Different types of predictor variables have been utilized, financial statement ratios, Capital Market ratios, Cash flow related variables, environmental inputs, quantitative and qualitative, intuitive inputs as well, historical and imaginative, and all have been tried on. And with them, great predictive results; they have achieved, yet businesses continue to collapse.

Then some insight is required, first, every region, country and state should model their own predictive models which are suitable to their environmental circumstances. Have we done that for our country? Should not some one check this out? This is the purpose of this study. Secondly, the very purpose for which predictor models, techniques and methods are meant seems to be missed out. Both management, regulatory agencies, shareholders and financial consultants as well as the auditors seem to believe that the predictor serve the purpose of fixing destiny of their businesses instead of serving as monitoring and detective tools. Surely they should only serve as what prenatal clinics serve to expectant mothers. Is this how they are received and used? What is the attitude of our managers regarding these predictors? How do they use them? Do they have diagnostic monitoring systems in their organizations? This is what a study should be designed to check out.

Thirdly, the industry ordinarily teams up with universities to search for diagnostic or predictive systems which then are applied in the industry to evade business failure. A case in hand is Hall and Hayden (2006) where the department of Finance, Vienna University teamed up with the Banking Analysis and Inspection Division of the Austrian National Bank developed a customer styled bank monitoring system which the Austrian National Bank uses to monitor its financial institutions. Austria is one country that has never experienced bank failure. Sorry, the "Logit model used in Hall and Hayden is used by Austrian National Bank ....therefore we cannot describe this model in full," what model is Central Bank of Kenya, Uganda and Tanzania using for their monitoring function,? Are they imported or customer designed? How often are these models revised to capture changes in the environment? How efficient and ineffective is it given the

continuing bank failure in Kenya? This study is determined to investigate into this matter and provides a way forward not for banks only but for all businesses.

Finally, since each country comes up with its own designed models, a study should be designed provide a system of diagnosis that will be relevant to East African countries.

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