*World Journal of Social Sciences*
*Vol. 2. No. 3. May 2012. Pp. 41 - 47*

# Financial Distress Signaling & Corporate Social Responsibility

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*IN the wake if the most recent global financial crisis, a large number of companies in United States, Europe and Japan have gone bankrupt, whereas many others have resorted to bankruptcy protection measures. Many of these companies were never thought to be vulnerable to bankruptcies or forced liquidations. In this context, it is becoming more and more pertinent and significant to study the early signs of financial distress and looming bankruptcy. Financial distress and consequent business failure is no more a phenomenon peculiar to small and medium enterprises; rather companies of all sizes are failing causing enormous economic and social problems to the society. Neither investors nor the business managers can afford to ignore any possibility of unexpected business failure; hence they are always looking for a reliable indicator of the financial health or otherwise of the business. This situation brings into focus a rather important issue i.e. handling of corporate social responsibility (CSR) by businesses and the industries, especially the financial industry. Inability of businesses, industries and regulatory institutions to safeguard the interests of stakeholders by not informing and warning them of the crisis in the making is evident beyond any doubt. In this paper we bring into focus the clear nexus that exists between early warning systems (EWSs) and CSR. We shall attempt to point out that EWSs are not only a mere financial indicator for interested investors, rather they, if properly developed and relayed, have an important bearing upon how effectively CSR is disposed off.*

**JEL Classification:** G17, G24, G33, M14

## 1. Introduction

Period before and around recent global financial crisis is characterized by a general lack of financial control & regulation. Resultantly we have seen that a large number of companies and funds in United States, Europe and in Japan have gone bankrupt or have resorted to bankruptcy protection measures. Financial icons like Lehman Brothers, Morgan Stanley, Merrill Lynch and Bear Sterns etc. resorted to extreme measures to deal with impending financial failure. It is beyond doubt that all these companies as well as other analysts from the industry were unable to forewarn the stakeholders and communities in general about the looming financial catastrophe. The obvious casualty during all this time on the corporate and academic level was the ability to dispense with Corporate Social Responsibility (CSR) related to financial industry's performance.

CSR is of paramount importance for businesses in every industry; however, financial industry has a greater role in this context. Financial sector serves as backbone of any economy; because on its proper functioning depends success or failure of many other businesses. The paper aims to understand the nature of the issue and details out

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This research and paper was financed by a grant by Young Scientist Research Program 2010-2012 (*Kakenhi-WakateKenkyu* B) of the Japan Society for Promotion of Sciences (JSPS), Japan

enormous potential value in securing the financial future of our globally integrated societies by examining the role of EWSs in the context of CSR. The paper spells out the relevance or otherwise of conventional prognostics models for predicting bankruptcy of individual financial institutions and the industry in general.

## 2. Conventional EWSs

Over last many decades, a number of financial distress prognostics or models have been developed and applied to gauge or predict the potential of business failure. Some of these models were based upon financial ratio analysis, whereas others attempted to predict business failure from cash flow patterns or from the stock returns.

To begin with, in general, profitability, liquidity, and solvency ratios were used as the most significant bankruptcy indicators. Many studies cited a particular financial ratio as being the most effectual indication of looming problems than another being used by a different model. However, other than establishing few generalizations about the financial distress signaling, these approaches offered little in particular or with clarity. The methodologies applied were basically *univariate*, where individual signals of looming business failure were given undue importance. Such methodologies are prone to flawed analysis and may result in confusion; e.g. a poor profitability/insolvency record may signal impending financial distress, however an above average liquidity may be indicating otherwise.

Conventional EWS models, likes of Altman (1968), Springate (1978) and Fulmer (1984), were developed for predicting bankruptcy in a time and space that were entirely different in which today's businesses and financial institutions operate. Recent global financial crisis is certainly an eye opener in this context; where most of these models proved to be of no help at all in prediction of the looming financial catastrophe. Off-balance sheeting, conduits, special purpose vehicles (SPVs), Special Investment Vehicles (SIVs) are just a few examples out of a host of innovative financial practices that have very smartly outclassed conventional approaches of bankruptcy prediction. It seems appropriate, however, that we first give background of various financial distress prognostics developed and used over time. Later on we shall attempt to understand their relevance and efficacy through an objective discussion combining with other relevant factors and the concept of corporate social responsibility attached to these warning systems.

### *Univariate Prognostics*

The earliest attempts at predicting financial distress were mostly *univariate* prognostics. Beaver (1966) attempted to predict financial distress using accounting and financial variables. He presented the theoretical framework that can be described as 'the cash flow or liquid asset-flow model'. Deakin (1972) employed 14 identical variables that Beaver analyzed, applying them within a series of multivariate discriminant models.

Edimister (1972) attempted to forecast failure by using financial ratios to predict small business failures. Blum (1974) developed the 'failing company model' for use by antitrust division of the US Justice Department. Libby (1975) investigated whether accounting ratios could be used to forecast business failure, finding that the loan officers' predictive accuracy was superior to random assignment and concluded that the ratios could help in predicting business failure. Wilcox (1971) investigated into the applications of the 'gambler's ruin model' to business risk focusing on the net liquidation value and factors that cause it to fluctuate. Martin (1977) made use of logit analysis. Similarly, Ohlson (1980) and Fulmar (1984), tried to find a way to quantify the probability of bankruptcy using *probit* analysis. Although these models and studies did establish certain significant simplification vis-à-vis the performance and trends of particular measurements, the adaptation of these results for assessing bankruptcy likely-hood of firms is still far from satisfactory. The potential ambiguity inherent in these approaches, as to the relative performance of a firm, is obvious as would be the case with any *univariate* analysis; hence, we needed multiple discriminant prognostics (MDP).

***Multiple Discriminant Prognostics***

MDP analysis is a statistical approach to categorize an observation into one of several *a priori* groupings. An important milestone in MDP was Z-Score. Altman (1968) built a comprehensive, statistical model using MDP analysis; many practitioners due to its easy application used the model. The measure has been found an accurate financial distress prognostic for less than 2 years prior to bankruptcy, but the accuracy ebbs away as the lead time increases. The model can however falter due to certain types of accounting irregularities, remember Enron's case. A later improvement to the Altman's Z-score was made by Altman et al (1977) i.e. the Zeta score. The Zeta model signals falteringly for a period of little over 2 years prior with a success classification of over 90% for one year and 70% accuracy beyond. But recent global financial crisis has made it clear it beyond any doubt that all these so called advancement were not able to predict the onset of the problems. Also, lacking in these prognostics is the ability to predict the systematic financial bankruptcy. Even Fulmer (1984) serves partially; hence there is a need of a comprehensive EWS.

According to Altman et al. (1981), 'multiple discriminant analysis are used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, for example, male or female, bankrupt or non-bankrupt'. In conducting a multiple discriminant analysis, therefore, first we need to establish precise group classifications. The number of original groups can be more than one. However, many researchers regard the analysis as "multivariate discriminant analysis" only when the number of groups exceeds two, while it refers to the multivariate nature of the analysis. After identifying the groups, we collect the data for the objects in the groups. In its simple form, the multivariate discriminant analysis attempts to derive a linear combination of these characteristics which "best" discriminates between the groups. For example, if a firm has financial ratios that can be expressed in quantifiable terms for all of the companies in the analysis, the analysis determines a set of discriminant coefficients. Finally, if these coefficients are applied to the actual financial ratios, we should find a basis for classification into one of the mutually exclusive groupings in order to develop financial distress prognostics.

Discriminant function, used in discriminant analysis, is a latent variable that is fashioned as a linear arrangement of discriminating (independent) variables. Such a discriminant function, of the form transforms the individual variable values to a single discriminant score, or Z value, which is then used to classify the object.

$$Z^i = V_1X_1 + V_2X_2 + \ldots + V_nX_n$$

## 3. The Z –Score

An important milestone in bankruptcy prognostics was the development of Z-Score by Edward Altman (1968) who abandoned the search for a single ratio and built a comprehensive, statistical model using multiple discriminant analysis. Edward I. Altman (1968) developed a model using financial statement ratios and multiple discriminated analyses to predict bankruptcy for publicly traded manufacturing firms. Altman tried to extend the above-referred studies by building upon their findings, thereby combining numerous measures into an important predictive model. While doing so, Altman emphasized the ratio analysis as an analytical technique rather than relegating its use in the business of financial distress prediction He, however, maintained that to use financial ratios, it is important to identify, first, which ratios are most important in detecting bankruptcy potential; second, what weights should be attached to those selected ratios, and lastly how should the weights be objectively established.

Altman (1993) took an initial sample of 66 firms, divided them into two groups of 33 failed firms and 33 non-failed firms. The failed group was composed of manufacturing firms that filed a bankruptcy petition under chapter X of the national bankruptcy act of the U.S. from 1946 through 1965. The aim was to examine a list of ratios in period t in order to make predictions about other firms in the following period (t + 1). However it was constrained by data limitations. Altman took a carefully selected sample of non-bankrupt firm, keeping in mind the industry and size differences. The group consisted of a paired sample of manufacturing firms chosen on a stratified random basis; which were stratified by industry and size, the mean asset size of the firms in Group 2 was slightly greater than that of Group 1, but matching exact asset size of the two groups was considered unnecessary.

Furthermore, the financial data were collected for the firms selected. Altman compiled a list of 22 financial ratios and classified each into one of five categories liquidity, profitability, leverage, solvency, and activity. The ratios were not selected on a theoretical basis, but rather, on the basis of their popularity in the literature. Altman (1993) stated that the five variables were selected from the original list of 22 variables, which were doing the best overall job together in the prediction of corporate bankruptcy.

Altman constructed his discriminant function as follows:

$$Z^{ii} = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$$

The measure has been found an accurate financial distress prognostic for up to two years prior to bankruptcy, but the accuracy ebbs away as the lead-time increases. The probability of failure is measured by the yearly change in the ratio values. The model holds true despite certain types of accounting irregularities.

A later improvement to the Altman's original Z-score developed by Altman, Haldeman, and Narayanan in 1977 was the Zeta score. The Zeta model was accurate up to five years prior with a success classification of over 90% for one year and 70% accuracy up to five years.

## 4. Bankruptcy & Credit Rating

Many rating agencies like S&P, Moody and Fitch rely on early warning systems in predicting the impending insolvency or otherwise of the institutions under study. They broadly use above-mentioned bankruptcy measuring indicators and they give ratings to businesses and to the financial products issued by them. This can be a reliable system to some extent, but not always and not entirely. There are two problems here, *one*, they rely on warning prognostics that warn most of the time on the nick of the time i.e. when the crisis is already brewing for sometime. *Second*, the management of rating agencies in itself casts a shadow on the way ratings are calculated and issued. In run up-to the global financial crisis of 2007, we saw many of these credit rating agencies hand in glove with the agents of the crisis. We found that rating business was shadowed by conflict of interest situations where rating agencies were consulting the very institutions they were issuing ratings on. This shady way of conducting the rating business led them to issuing faulty and misleading rating to the financial products held by a large number of public. AAA ratings were issued to inferior financial products. Financial innovation can also be blamed to some extent for misleading the rating agencies reliant on conventional methods to assess financial health or sickness of the institutions and products being rated. SIVs, SPVs and conduits are a few examples of innovative financial products that needed deeper understanding and clearer conscience by the rating agencies. Slackness and inadequacy of the regulatory mechanisms added fuel to fire, and we found ourselves engulfed in an all-encompassing fire that was already too late to be brought under control. As a result, we saw a large number of stakeholders across the globe suffering in unprecedented ways casting irreparable damage to the trust of financial industry and its attitude towards corporate social responsibility.

## 5. Corporate Social Responsibility & EWSs

EWSs have a greater connection to CSR, as they allow businesses to be better understood by the societies; as we can estimate the financial health of a business on time and remedial measures can be taken on time if a business is in financial trouble. Also, stakeholders in particular and societies as a whole will be better informed of the success or likely failure of a particular business on time. Failure of EWSs does not necessarily affect immediate stakeholders of a business only, rather they affect societies at large and have a greater relevance to the way corporate social responsibility is addressed by the businesses and the industries involved. The problem is not only with the technical measures available; rather the malaise goes further beyond. We see that credit rating business, the financial innovation, the regulatory mechanisms and the warning systems all need to work in sync in order to ensure that CSR is handled in a manner that will ensure our societies' financial and moral fabric.

We as researchers and analysts have a responsibility to ensure that societies get the information and analysis needed to protect them financially. The inadequacy of the existing early warning systems is obvious from the discussion in the earlier sections of this paper. The development of more reliable early warning systems will forewarn in case a financial crisis is in the making and businesses will also be able to attend to their CSR in a meaning full way. The 2007 global financial crisis and more recent crises in other parts of the world like in Greece and associated global pain has necessitated a comprehensive and urgent look into the causes, issues and remedies of the current malaise in most practical and useful manner so that financial future of our communities around the globe could be safeguarded against similar financial tsunamis in the future. This will have to work on two scales i.e. (1) by establishment of a stable and reliable financial architecture of high quality and an oversight mechanism that ensures the system does not get train wrecked, (2) and by ensuring that we have a reliable EWS that allows ample time for fire fighting measures needed to prevent a total collapse of the system, in case a disaster is in the making.

## 6. Conclusion

The paper raised very important research questions regarding the adequacy and effectiveness of conventional financial distress prognostics in predicting and forewarning financial bankruptcy of the businesses and industries. We attempted to discuss the makeup and relevance of such prognostics in a world where it is very important to have timely and adequate warning of a financial crisis in the making before it starts affecting large number of people and communities. We established that EWSs have a very important connection with ensuring financial security of our communities. However, these warning systems in conjunction with flawed regulatory mechanisms, compliant rating agencies and conflict of interests have misled us in a fatal way. The corporate social responsibility concept embedded in the forewarning systems has been grossly ignored and hence these warning systems have failed the purpose of their existence in a big way. Whether the models are still useful for predicting bankruptcy; as they were developed for predicting bankruptcy in a time and space that were entirely different from the financial and business world in which we live today. The globalization and interconnections amongst various peoples, communities and countries means that a failure in part of the world will most likely affect people living in far off places too. This has resulted in loss of trust and dependability on not only the warning systems rather on the entire financial system as whole. There appears to be a greater need for developing and testing the efficacy of models other than the Z-score or Zeta-Score in signaling the financial distress. Inadequacy of existing models in predicting financial distress in technology companies calls for development of new models and newer coefficients for the existing models. Development of additional models based upon new and cutting edge approaches like artificial neural networks sounds an exciting idea. Also, we shall need greater transparency in areas of financial regulation, credit rating business and handling of corporate social responsibility attached with that in general.

## Endnotes

[i] $V_1$, $V_2$ . . . $V_n$ are discriminant coefficients, and $X_1$, $X_2$ . . . $X_n$ are independent variables. The Multivariate Discriminant Analysis computes the discriminant coefficient; $V_i$ while independent variables $X_i$ are actual values.
[ii] Z = overall index, X1 = working capital/total assets, X2 = retained earnings/total assets, X3 = earnings before interest and taxes/total assets, X4 = market value equity/book value of total liabilities, X5 = sales/total assets, and X1, working capital/Total Assets

## References

Altman, EI 1968, 'Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy', *The Journal of Finance*, 3(4): 589-609.
Altman, EI 1984, 'A Further Empirical Investigation of the Bankruptcy Cost Question', *Journal of Finance*, 39(4): 1067-1089.
Barnes, P 1987, 'The Analysis and Use of Financial Ratios: A Review Article', *Journal of Business Finance & Accounting*, 14(4), 449-461.

Beaver, W 1966, 'Financial Ratios as Predictors of Failure: Empirical Research in Accounting', Selected Studies supplement to the *Journal of Accounting Research,* 4(1): 71-127.
Blum, MP 1974,'Failing Company Discriminant Analysis', *Journal of Accounting Research*, 12(1): 1 -25.
Deakin, EB 1972, 'A Discriminant Analysis of Predictors of Business Failure', *Journal of Accounting Research*, 10(1): 167-179.
Dichev, ID 1998, 'Is the Risk of Bankruptcy a Systematic Risk?' *The Journal of Finance* 53, 1131-1147.
Edmister, RO 1972, 'An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction', *Journal of Finance and Quantitative Analysis*, 7(2): 1477-1493.
Falkensten E, Boral, A & Carty, L 2000, 'Risk Calc™ Private Model: Moody's Default Model for Private Firms', *Global Credit Research*.
Fulmer, JG, Moon, JE, Gavin, TA & Erwin, MJ 1984,'A Bankruptcy Classification Model For Small Firms', *Journal of Commercial Bank Lending* pp. 25-37.
Hair, J 1992, *Multivariate Data Analysis (2nd Ed.),* New York, USA: Macmillan Publishing Company.
Libby, R 1975, 'Accounting ratios and the prediction of failure: some behavioral evidence"', *Journal of Accounting Research*, 13, pp. 150-161.
Lindhe, L 2000,'Macroeconomic Indicators of Credit Risk in Business Lending', *Economic Review 1*, Sveriges Riks bank, 68-82.
Luther, RK 1998, 'An Artificial Neural Network Approach to Predicting the Outcome of Chapter 11 Bankruptcy', *Journal of Business & Economics Studies*, 1998: 57-73.
Martin, D 1977, 'Earliy Warning of Bank Failure: A Logit Regression Approach' *Journal of Banking and Finance* 1: 249-276.
Ohlson, JA 1980,'Financial Ratios and Probabilistic Prediction of Bankruptcy', *Journal of Accountancy Research*, Vol. 18, 109-131
Vassalou, M & Yuhang, X 2004, 'Default Risk in Equity Returns', *Journal of Finance* 59, 831-868.
Whitaker, R 1999, 'The Early Stages of Financial Distress', *Journal of Economics and Finance*, 23(2), 123-133.
Wilcox, JW 1971, 'A Simple Theory of Financial Ratios as Predictors of Failures', *Journal of Accounting Research*, 9(2), 389-395.
Zhang, G, Hu, MY, Patuwo, BE & Indro, DC1999,'Artificial Neural Networks in Bankruptcy Prediction: General Framework and Cross-Validation Analysis', *European Journal of Operational Research*, 116(1): 16- 32.