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Financial Distress Prediction of Indian Companies: Future Perspectives

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Abstract: The worldwide financial crises highlighted the serious deficiencies in risk models used for credit risk management. Previous studies show a trend of changes in the choices of variables in the default prediction models. Initially researchers have used only accounting variables while framing various models but now several other factors within and outside organizational variables such as market and macroeconomic variables also being taken into consideration for designing various models. Much of the previous work in financial distress prediction focuses on static predictions and uses static variables in estimating the predictive model. Therefore, there is a need of the models which can make dynamic predictions with the use of dynamic variables. This advance warning will help management to take appropriate steps and decisions to avoid financial distress which will help to mitigate the cost associated with financial distress and resulting business failure.

Keywords: Financial distress, Market variables, Macroeconomic variables

INTRODUCTION

Timely prediction of failure of a business firm is an important issue in the present economic system, considering the effect of global financial crisis to the world economy in the past decade Donato and Nieddu (2016).The worldwide financial meltdown highlighted the weaknesses in risk models used in credit risk management Jorion (2009). The financial crisis resulted into many companies facing risk of failure around the world. The financial crisis highlighted that even the healthy global firms must frequently observe their financial position and of the firms with which they deal with Korol (2013).

Recently the International Monetary Fund (IMF) report prepared by Jung and Lindner (2014), highlighted the financial weakness in the Indian corporate sector. The results of stress tests on corporate balance sheets in India, has found that with decreasing profitability and high level of leverage, Indian firms are facing severe problems in repayment of loans taken in the past. This is ultimately posing risk for the quality of loan portfolio of commercial banks in India. According to the IMF, corporate debt at risk increasing significantly and under the severe unfavourable conditions it can increase further. Failure of a firm has lot of cost associated for its various stakeholders like employees in terms of job losses, loss of capital for creditors.

In the recent years, many researchers have tried to predict business failures. Different researchers have used different ways to define financial distress of a firm. There is a lack of an exact definition of financial distress. A business is in mild financial distress when it face difficulty paying its debts on time. A business is in serious distress when it has filed a petition for relief from its creditors under some legal channel, or when it has consented to a filing by its creditors. The filing shows either the firm failure to pay the debts on time or its inability to pay them within the near future. Mild financial distress may just be a cash flow problem on temporary basis while serious financial distress results into insolvency or business failure. A company is in default when it violates the terms and conditions of loan or bond in-denture. It is necessary to differentiate between technical defaults and payment defaults. A technical default happens when the debtor violates a loan agreement. Technical defaults not often lead to serious distress among companies. They are generally solved by negotiating with creditors.

Different countries have different ways to deal with the companies suffering from financial distress. In the US, financially distressed businesses commonly filed under chapter 11 of the bankruptcy code Bernardo and Welch (2015) ,but in the UK, as there is no specific law related to this, it is usually liquidation, administration or receivership that is often used when predicting business failure. Different studies have taken different ways for defining financial distress depending upon the purpose of the study been conducted Pompe and Bilderbeek (2005). Like Beaver (1966) used bankruptcy, bond defaults, overdrawn bank accounts and non-payments as events of financial distress. But such an occurrence does not necessarily imply the end of a business: only in a serious situation does credit default lead to the failure of a business. According to Karels and Prakash (1987), "there are many definitions of failure taken for prediction studies in the past. Some researchers define distress as when a firm actual filing for bankruptcy; others define it as suffering financial stress or an inability to pay financial obligations". Asquith et al (1994) defined it as negative EBITDA interest coverage and other Hofer (1990) as negative net income before special items. Campbell et al (2008) taken financial driven delisting and default credit rating as the cases of financially distressed. More specifically, Pindado et al (2008); Tinoco and Wilson (2013) discussed the finance-based definition of financial distress and argued that its definition should be consistent with an ex-ante prediction method, i.e. independent of its outcome."So they defined financial distress to be that EBITDA are lower than the financial expenses or a decline in its market value for two consecutive years."

Earlier there was no single comprehensive and integrated policy to deal with financial distressed firms in India. The rules related to financially distressed cases were covered in the Companies Act, 1956 and the Sick Industrial Companies Act, 1985 Bapat and Nagale (2014). "In India, an industrial company (being a company registered for not less than five years) which has at the end of any financial year accumulated losses equal to or exceeding its entire net worth would be referred to the Board for Industrial and Financial Reconstruction (BIFR) as a sick industrial company. But recently with the passage of insolvency and bankruptcy code bill, a single law to deal with distressed firms, promoters, employees, creditors and other stakeholders is applicable In India. This law will ensure a time bound process of winding up a distressed company" Roychoudhury (2016). Noticeably definitions of financial distress are more flexible due to their background of studies and availability of data. A broader definition of corporate default or financial distress makes modelling easier by increasing the sample size of the distress firms, but at the same time it brings difficulties in interpreting the results of different dependent variables. This study focuses on investigating an ex-ante model for predicting financial distress by using a financially-based definition of distress that is independent of its legal implications, as per the criteria suggested by Pindado et al (2008). According to this criteria, a firm is classified as financially distressed not only when it will be registered with BIFR but also "(i) whenever its earnings before interest and taxes depreciation and amortisation (EBITDA) are lower than its financial expenses for two consecutive years; and (ii) whenever market value of its share will fall for two consecutive years". This criteria estimates the capacity of a firm to service its financial obligations which will help in advance detection of distress state of a firm. This classification will be reliable with an ex-ante prediction method and will be independent of its legal outcome. Taking data of sick companies suffering from severe financial distress, along with the observations on the basis of finance based definition will also help in detecting early stages of distress among various companies.

Survey by World Bank (Doing business in 2005 -India Regional Profile) "has concluded that it took 10 years on an average to wind up / liquidate a company in India as compared to 1 to 6 years in other countries. Such lengthy time-frames are unfavourable to the interest of all stakeholders. The process should be time-bound, aimed at maximising the chances of preserving value for the stakeholders as well as the economy as a whole". No firm, even during a time of prosperity, can be convinced of its future prospects. Korol (2013). According to study by Jardi and Severin (2010) failure of a business is not an unexpected event rather it is the result of a failure path, which may consist of a number of phases, each characterized by specific signs of failure. As failure is not a sudden phenomenon and if the advance warning signals are detected, the more time managers will have for preparing and reacting in subsequent phases of the crisis. Therefore, forecasting default of companies is an area which has become quite significant in recent times. "Lenders in India are able to recover only 20% of their loans when businesses go bankrupt and average time of 4.3 years is taken for insolvency proceedings. This compares to 70% recovery rate in developed countries and about 1.7 years of average time taken for insolvency proceedings in developed economies. Currently, Indian economy is reeling under mounting bad loan pressure. By far bad loans have risen to around Rs. 4,43,691 crore" Jung and Lindner (2014). Thus lenders and investors along with various regulators require timely information on the default risk probability of the firm within lending and investment portfolios. Early warning of financial distress or business default has become an important research area for financial risk management. Any prediction technique should be able to provide warning with a adequate time lag to allow for remedial actions. If the time span is sufficient, then timely actions can be taken to correct the state of financial distress. Lenders like banks can restrict themselves from lending money to the firms that are bound to fail or are expected to face distress in the near future. The investors can prevent capital loss by not investing in the companies that are likely to face financial trouble. It will also help various firms willing to maintain long-term relationships with other companies and hence willing to deal with only those companies that will not witness any failure in future , hence increasing the prolonged existence of their trade contacts.

PREVIOUS STUDIES AND DISCUSSION

Variables used in previous studies

Reviewing the earlier studies shows a trend of changes in the choice of variables in the default prediction models. Initially researchers have used only accounting variables while framing various models but now several other factors within and outside organizational variables such as market and macroeconomic variables also being taken into consideration for testing various models. Using market and macroeconomic variables together with financial ratios will lead to the better accuracy of designed models Agarwal and Taffler (2008).

Financial variables in Financial Distress Prediction

Beaver (1966) model of predicting financial distress with financial ratios on a sample of 79 firms for the period from 1954 to 1964 using univariate analysis. The study found that cash flow to total debt as the best predictors of failure but the predictive power of liquid asset ratio was found weak. The result found better classification of non-failed firms as compared to failed firms by using financial ratios. Altman (1968) derived a prediction model with multiple discriminant analysis for publicly held manufacturing corporations. The model used five different financial ratios (Working capital/Total assets, Retained earnings/Total assets, Earnings before interest and taxes/Total assets, Market value of equity/Book value of total debt and Sales/Total assets from a initial set of twenty two ratios. These financial ratios were taken on the basis of their recognition in the prior studies and their significance. Ohlson (1980) applied different ratios like current ratio, working capital to total assets ratio, total liabilities to total assets, net income to total assets ratio, funds applied from operations to total liabilities for classification between distress and non distress firms. Altman (2000) developed ZETA model for estimating a firm's financial problems. This model resulted in significant advancements by achieving 90% accuracy in predicting a company's bankruptcy for a year ahead, and 70% accuracy for five years in advance. Tian (2015) investigated the importance of financial ratios in prediction of future default risk of firms and found these ratios to be useful predictors of financial distress among companies.

Market variables in Financial Distress Prediction

Apart from financial variables, other variables also been considered to improve predictive accuracy of default prediction models or to explain the causes of business stress. Those efforts include incorporation of macroeconomic factors Duffie et al (2007). According to Tinoco and Wilson (2013), "market prices will act as a complement to the financial ratios and macroeconomic variables by enhancing the predictive power of the general model, and not as competing or mutually exclusive alternatives that should be used in isolation." The reason is that market prices will discount financial statement data as well as other information which is not reflected in financial data of the company, potentially making markets a more efficient processor of all available public information than accounting data alone and therefore increasing the overall accuracy of financial distress prediction model. Shumway (2001) used market capitalization and volatility of stock return in his study. Market capitalization was taken to reflect the fact that when a firm approaches default, it is usually discounted by the market. Volatility of stock return was considered due to fact that higher volatility of stock is caused by higher volatility of cash-flows, which in turn puts a firm at higher risk of not being able to meet its interest payments. Moreover, Beaver et al (2005) supported this view by indicating that adding market based variables into the hazard model enhanced the predictive power relative to the model with accounting ratios only. Chava and Jarrow (2004) demonstrated that market variables reflect all publicly available information regarding firm distress. It was showed that predictive power of the market based model will significantly outperformed an accounting based model as stock prices discount future financial position of the company. Campbell et al (2008) further propose the use of the logarithm of market capitalization to that of S&P 500 index.

Macroeconomic variables in Financial Distress Prediction

From the last few years, there has been increasing focus to examine how business failures are impacted by macroeconomic changes. Macroeconomic variables are added to the model to correct the variable of mismatch in timing. Time varying macroeconomic covariates help to observe macroeconomic changes through time.Agrawal and Maheshwari (2014) identified and examined the effect of the macroeconomic situation in forecasting the financial distress. This study examined the interrelation of the rate of decline of businesses with different macroeconomic variables like credit availability, economic cycles and investor confidence. It was found that one of the most vital reasons of failure is credit squeeze, particularly in the period of restrictive monetary and debt policy. Tirapat and Nittayagasetwat (1999) examined various macroeconomic variables like monthly changes in production manufacturing index, consumer price index, interest rate and money supply for assessing effect on financial distress in case of firms in Thailand. Liu (2009) examined the corporate failures in U.K. with respect to various macroeconomic factors. The study found that failures can be impacted by the various macroeconomic conditions like credit policy, profits and inflation. Liu (2004) studied the robustness of prediction model by including macroeconomic factors like fluctuations of foreign exchange and interest rates as a proxy with respect to various macroeconomic changes. The result showed accuracy of financial distress prediction increases by incorporating macroeconomic variables in the model. Rosch and Scheule (2005) developed a multifactor model for estimating default rates. It was found that default rates fluctuate cyclically and systematic risk factors has some degree of influence on it. The result suggested that by identifying these risk factors and incorporating them into the main model improves model performance and reduces the possibility of model misspecification. Bonfim (2009) examined the linkage between credit risk and macroeconomic developments like CPI, inflation, bank interest rates, bond yields and GDP. It was found that by taking macroeconomic variables the accuracy level of estimating potential default increased significantly. Mare (2015) analyzed the impact of economic conditions on the small bank failure in Italy by taking variables like interbank deposit rate, region unemployment. The result found increase in failure risk of banks with deteriorating economic conditions. Macroeconomic variables are not taken as predictors but they should be taken as control variables. The purpose is to include controls for the state of the economy as the sample observations arranged in an event time. However, unlike firm-specific covariates, macroeconomic factors vary over time but not by case. So for all companies existing in a period, macroeconomic conditions will have the same impact on each Agarwal and Taffler (2008).

MODELING TECHNIQUES USED

Different researchers have used different techniques to estimate the financial distress prediction depending upon the nature of sample taken in different countries across the world. In the previous studies, techniques like multiple discriminant analysis, logit model etc were frequently used Altman and Narayanan (1997). Earlier univariate modelling methods were quite popular for modelling financial distress prediction and non distress firms. Beaver (1966) used this method for classification between distress and sound firms. The significance of each financial ratio was determined individually as per its ability to correctly discriminate between the two groups of firms. Hence, if a firm value is higher than a particular cut-off point then it would signify sound financial position otherwise weak. But this technique neglect multidimensional nature of failure Keasey and Watson (1991). As there multiple factors determine the financial position of a company, so a single ratio cannot explain the phenomena accurately. Altman (1968) had developed a model using multivariate discriminant analysis where a z-score was estimated to observe the distress among firms. The main focus of multivariate analysis is to incorporate the values of different ratios into a single weighted index rather taking one ratio at a time, as in case of univariate analysis. This technique has been used by other researchers like Blum (1974); Karels and Prakash (1987). Further Ohlson (1980); Westgaard and Van der Wijst (2001); Shumway (2001); Nam et al (2008); Altman et al (2010) used logit model in prediction of distress among companies. It is based on cumulated logistic probability function and this model will give probability whether a particular company is in financially distress or non distress state. Apart from the traditional statistical techniques, few other alternative non parametric techniques were also used by various researchers. Altman et al (1994); Tsai et al (2009); Iturriaga and Sanz (2015) done default prediction using neural network modelling techniques. "A neural network technique is a multilayer preceptron for financial distress prediction. In this method, the hidden layer determines the mapping relationships between input and output layers and the relationships between neurons are stored as weights of the connecting links. Neural network technique has some advantages over the traditional statistical methods due to its strong mapping ability based on the network structure" Jo and Lee (1997). Also, in this method, the statistical relationships among the various factors are not necessarily to be taken into consideration Wilson and Sharda (1994). But due to its complex nature, researchers generally found it difficult to apply. Another artificial intelligence technique, support vector machines was applied by Min and Lee (2005); Yang et al (2011). "It is based on the structural risk minimization principle rather than the empirical risk minimization principle. A support vector machine is a commanding and promising data classification and function estimation tool." Shin et al (2005). But after comparing the accuracy of support vector machines with neural network, Bose and Pal (2006) found this technique less effective as compare to later one.

IGNORANCE OF TIME DIMENSION FOR FORECASTING FAILURE

One of the main weaknesses in the earlier financial distress modelling techniques is ignorance of time dimension. Most researchers have used single-period classification models Altman (1968); Ohlson (1980); Bandyopadhyay (2006) for default prediction which are known as static models by taking multiple-period data. The main focus area was to make a dichotomous decision at a particular point in time that whether a firm will fail or not Shumway (2001). Single period static methods may not have much accuracy level when they are applied to financial conditions other than those under which they were originally developed Grice and Dugan (2001). As firms financial health changes with passage of time, the results given by static models are biased and inconsistent. Test results that are based on static models may be incorrect Shumway (2001). It was suggested that a dynamic hazard model is better to a traditional static forecast model in that it incorporates the time-varying explanatory variables and treats a firm's health as a function of its most recent financial state Campbell et al (2008). Generally failure is the outcome of a series of cascading events rather than a sudden, unexpected event. In the majority of the instances, firms go through different stages before witnessing ultimate failure Karas and Reznakova (2015). Financial distress is not a unexpected event; impossible to forecast. So if prior warning signals are detected, there will be more time available for managers to prepare and act to avoid possible future crisis. Therefore it will be important to frame techniques that can reasonably forecast the performance of a firm over a period of time and which can further help management of these companies to take possible remedial actions to avoid any kind of major financial distress. Forecasting the occurrence of an event then becomes less vital than anticipating the dynamics of a behaviour that could lead to failure. Jardin and Severin (2010). Past studies in financial distress prediction focuses on static predictions and uses static variables in developing the predictive model. In this study the main emphasis is to test dynamic predictions and to use dynamic variables in estimating the model. With dynamic variables the model estimation allows for changes in the financial characteristics of a company over time. Karas and Režòáková (2015).

CONCLUSION

Considering the fact that, in India number of companies experiencing financial distress has increased in recent times. There is a rising trend of default in the times of global slowdown. The existing methods to assess the sign of distress among companies have shortcomings which need further improvement. Previous studies have not considered combine effect of financial ratios, market and macroeconomic variables for prediction of financial distress in Indian context in a comprehensive manner. Therefore future studies should help in identifying companies that are at risk of facing potential financial distress in future. This advance warning will help management to take appropriate steps and decisions to avoid financial distress which will help to mitigate the cost associated with financial distress and resulting business failure. Lenders like banks could better control their risk exposure and potential future bad debts. It will also help banks to track of borrower's financial profile and identifying sickness at the initial stages, when a unit will actually start becoming weak. Portfolio managers and investors could better assess the risk profile of their investments and diversify by avoiding investing in future potential failures. Stakeholders such as suppliers and customers would have better information about the company's financial soundness which will help in their long-term exclusive engagements with those entities. There is a need to explore those issues in order to frame effective rules & policies dealing with these cases and overall betterment of the financial system.

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