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Comparative predictability of failure of financial institutions using multiple models

Abstract

The impact of failure of financial institutions is beyond just the failure of a public corporation. The failure of financial institutions in the USA, is a clear evidence that the greater macro impact is beyond just the failure of few financial institutions. It can bring down the entire economy and can have global devastating impact. By realizing the grave systemic risk of the failure, US government is forced to intervene and bail out many institutions for greater macroeconomic reasons. It raises the view that perhaps the current regulating policies and methods are lacking efficiency in predicting the possibility of failure beforehand and hence are not effective in preventing that to happen. This research applies several existing methods of institutional failure and test the signaling ability of each method in predicting the bankruptcy beforehand. The authors apply Moody's financial ratios, Standard and Poor's financial ratio, Vaziri's financial ratio, Altman's Z score and then applying logit model and discriminant analysis, the authors test each of these model's predictive ability for future use. The paper analyzes the reasons like changes in market, policy, economy, and political influence which have led to bankruptcy. Banks or financial institutions from Europe, the United States and Asia are considered as samples. Samples are taken from the same period to analyze the effect of different methods. The results from this analysis should help us find the most significant method that could be used to identify the risk, so that necessary action could be taken to prevent the effect or reject the project which could lead to bankruptcy in the future. This research would also offer policy recommendations for regulating agencies as to which factors should be analyzed deeply and how to implement a preventive measure ahead of any potential problems.

Keywords: bank failure, prediction, logit, Z score.
JEL Classification: G17, G21, F37.

Introduction

Banks and financial institutions are the backbone of a country. When banks go bankrupt it affects the economy of the country and risk of recession to the country and to integrated global economy. Asset markets would experience high level of volatility through huge movements in the exchange rates, interest rates and commodity prices. Banks and financial institutions must add risk management to their investments decisions, as the level of risk is unpredictable. Financial risk cannot be forecasted as it does not rise by a single factor; it is a result of multiple exposures. If risk management system is implemented in the right way, it would help nullify systematic and market risks. However, if the bank does not follow zero tolerance for irresponsible speculation, the effect of risk management system would be nullified. Strategies for risk management should be revised with changes in market and requirements.

Many banks and financial institutions were affected in late 2000s due to Global Financial Crisis. Affected banks and financial institutions are merged, taken over by other banks or financial institutions, partly nationalized by the government, or liquidated. Some of the reasons behind this crisis include: subprime mortgages, collateralized debt obligations, frozen credit markets, and credit default swaps.

The purpose of this study is to determine the causes for financial distress which lead to bankruptcy of financial institutions and banks in the USA, Asia and Europe in late 2008. Understanding the causes would help the banks from taking projects that could lead to bankruptcy and increase capital for times of distress. Several models exist in the literature. We apply and compare the forecasting ability of each of those models. These models are: Moody's, Standards & Poor's, Z-score model, and Vaziri's system. Using these models, we attempt to identify major signals and to find out if there is significance between their mean and deviations. The major signals include: excessive loan/asset growth, excessive lending concentrations, deteriorating financial ratios, tracking loan recoveries to gross loan charge-offs, deposit rates higher than market rates, off-balance sheet liabilities, delayed financials, change in auditors, change in management, use of political influence, rumors in the money market, share price volatility, and deteriorating economy.

1. Literature review

Various studies attempt to analyze the reason behind the financial crisis and determine the type of risk management that banks can adopt to prevent heavy losses in the future. Various risk models like GARCH, GJR and EGARCH are used to measure Value-at-Risk to determine the requirement of capital (Michael McAleer, Juan-Angel Jimenez-Martin,

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and Teodosio Perez-Amaral, 2009). Bank-level governance, country-level governance, country-level regulation, and bank balance sheet and profitability which could have also affected the performance of banks before late 2008 crisis (Andrea Beltratti and Rene M. Stulz, 2009). Banks who took high risk were not well capitalized (Simon Kwan and Robert A. Eisenbeis, 1995) as they did not absorb any risk (George S. Oldfield and Anthony M. Santomero, 1997). Also method like EWMA (Riskmetric, 1996; Zumbauch, 2007) is used in a unified framework and notation. This research finds that results from these models to reduce Daily Capital Charges (DCC) show that GARCH is the best for the period of January 3, 2008 to June 6, 2008. Andrea Beltratti and Stulz discuss the reasons behind the poor performance of banks during the financial crisis. The authors analyze different reasons including ineffective regulations, difference in regulation of financial institution, governance of banks, difference in balance sheets and profitability to be one of the reason behind this crisis. Governance is taken as one of the factor in analyzing the performance because it plays an important role in the performance of a bank (Kirkpatrick, 2008; Peong Kwee Kim, Devinanga Rasiah, 2010). Anti-Director index was used to measure share holders role in pushing the banks to take more risk (La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1998). The allocation of capital based on the risk is affected by exogenous and endogenous factor (Shrieves and Dahl, 1992; and Jacques and Nigro, 1995). Capital is increased based on the increase in risk due to regulatory pressure. In this paper, Bank Risk, Capitalization and Inefficiency by Simon Kwan and Robert A. Eisenbeis, the authors discusses about the agency theory and models like bank leverage, risk taking and inefficiencies.

Managers when acting as agents to stockholders do not give proper information and take big risk by investing in inefficient project (Jensen, 1986). When the cash flow is high it could lead stockholders to inefficient investment as when there is low cash flow and absence of NPV for the investment project could led to efficient investment (Stultz, 1990). Choice of leverage could solve half of this problem (Jensen, 1986). When the company is in debt, the manager will work efficiently and the debt will reduce the free cash flow that was associated with agency cost. The purpose of this model was to show that inefficiency is associated with firm asset risk, growth of the firm and leverage, like the companies investing in negative net present value projects and banks investing in poor quality loans. This debt would push the managers to help grow the firm in size and try to make it an efficient firm.

If the wealth of the firm is related with the firm's performance then the managers will be more risk averse (Huges, Lang, Mester and Moon, 1994). As a result the managers will not take risk and they invest in less risky project. The loan taken to invest in these risk-less projects would be seen as inefficiency. Leverage decision for the bank depends on deposit insurance and regulation. If the deposit insurance is wrongly priced it will misguide in taking heavy risk. This model was not considered due to bankruptcy cost which would decrease the value of the firm (Kwan, 1990; and Keeley, 1988). The theory also suggests that the firm would take more risk to counterbalance the capital required instead of pushing the growth of the firm. Taking more risk would affect the safeness of the bank (Koehn and Santomero, 1980; and Kim and Santomero, 1988). Increasing the capital will help the debt holders from being exposed to high risk (Furlong and Keeley, 1990). We sobserved that the firms whose growth is rapid tries to take more risk and tradeoff with loss of charter value and human capital. In Model Choice and Value-at-Risk Performance by Cris Brooks and Gita Persand, the authors feel that internal risk management models help to reduce the risk by calculating the capital requirement. In this paper the authors discuss the agreement between the investment banking and regulatory communities. The authors use different methodologies to find the problem that exist in statistical modeling that are used to find market-based capital risk requirements. They find some drawbacks in all methods and conclude that the simpler is the method the more accurate is the results. High-profile derivatives disaster suggests that there is a requirement for good risk management system (Jorion, 1995). The authors compare the model suggested by Basle Committee with other methods to measure risk.

Companies that practices risk management are more tolerant to volatility than companies that do not have risk management. Risk management allows the companies to take big risk (Stulz, 1996). Considering the theoretical studies done by Smith and Stulz they find that companies with large equity stake are more risk averse.

Filling a bankruptcy will cost 3% to 25% of their total market capitalization (Gilson, 1990). Second, a financially distressed company can use U.S. Bankruptcy code which states that the companies can reorganize itself by filling bankruptcy protection instead of filling bankruptcy. As this code buys some more time for the companies to get relief from the financial pressure. The firm get a duration of two years under bankruptcy protection (Eberhart, Altman and Aggarwal, 1999).

Companies that are in the financial distress can file for Chapter 7 or Chapter 11 which are for reorganization. Most of the companies choose Chapter 11 over Chapter 7. Entering Chapter 11 has some benefits such as avoiding pre-filing of certain transfers, and negotiations with creditors with single plan. The investor do a prepackage bankruptcy which allows the company to talk with creditors before filing for Chapter 11 so that they can continue with normal operation (Jorion, 1997). Most corporations have hedging and insurance to reduce their risk, but hedging only diversifies the risk. As these risks are transferred into another form of risk like, market risk transferred to credit risk (Kimball, 2000). Nearly 40% of the firms that were used as sample in 1979-1988 were not able to get back (Hotchkiss, 1995). This risk management tool was prefected by the top management even though it might be dropped during reorganization (Smith Jr., and Stulz, 1985). When a management acts as an agent it results in a conflict of interest and try to find benefit from filing Chapter 11 (Stulz, 1996). Stockholders lose a lot from their prepayment investments as the firm pays a small percentage in order to speed up the bankruptcy process (Trottman, 2003). Bankruptcy not only affects the stockholders but also the creditors and employees.

2. Data and methodology

The financial institutions selected for this study are from the USA, Asia and Europe. 100 banks are selected as samples of which 3 are acquired banks, 17 are helped by the government after the crisis, 20 banks have claimed bankruptcy and 60 of them are active banks. The banks are studied for 10 years (2001 to 2010). The reason for choosing this period was that most banks went bankrupt at this time. There was less information about bankrupt banks as they were not acquired or merged.

We choose 5 methodologies to investigate financial distress and bankruptcy which are Moody's, Standard and Poor's, Vaziri's, Z-score model, and Logit model. Different financial ratios required for the models were calculated and analyzed. To find if there were any risk management system at place the policies and procedures for lending were studied and the bank's liquidity was identified using risk management models. To find if there were any government regulations that influenced the failure of banks, secondary data was collected and studied.

2.1. Moody's financial ratios. Moody's system helps a bank to find out the probability of default and if default occurs how much will be the loss. Moody's model helps to identify if a bank is efficient to pay off its debt. It also helps investors to find if the bank is capable of asset and shareholders' equity into profit. It helps to identify if the banks are liquid enough to pay off their short-term debt. Ratios used in this paper to analyze it is as follows: Interest Coverage Ratio (EBIT/Interest Expense, EBITDA/Interest Expense) and Asset Coverage Ratio could be used to find if the financial institution are capable of paying their leverage. The excess cash available for interest payment shows that there is less risk involved. Leverage ratios (Total Liability/Total Asset, Equity/Total Liability, Short-Term Debt/Equity Book Value) is used to determine the debt of financial institution. The higher the ratio, the higher is it's debt and the more risky it is. Liquidity Ratios (Current Asset/Current Liability, Intangible Asset/Total Asset, Cash/Net Sale, Working Capital/Total Asset, Cash/Total Asset) can be used to determine if banks have enough liquid assets to meet their short-term debt obligation. Ratios must be higher to reduce the risk. Profitability ratio (ROA) determines if banks have some earnings after their expence to estimate how profitable the institution is. High percentages are indicators that the bank is doing well.

2.2. Standards & Poor's financial ratios. S&P's system can be used to determine the probability of bank's default. It helps to find, how much the banks are in debt and to find if they can pay off their debt. This method shows if the banks have made profit with the money they borrowed. It includes ratios like Coverage ratios (EBIT/ Interest Expense, EBITDA/ Interest Expense, Net Operating Income/Total Debt) which could be used to find if the financial institution are capable of paying their leverage. The excess cash available for interest payment shows that there is less risk involved. Leverage Ratio (Total Debt/EBIT, Total Debt/EBITDA, Total Debt/Capitalization) is used to determine how much the financial institution is in debt. The higher the ratio, the higher is it's debt and more risky it is; and Profitability ratios (ROE, Net Operating Income/Sale) which help to determine if the bank is doing an idle investment with the shareholders' investment by generating profit.

2.3. Vaziri's model. Vaziri's system includes most of the ratios in Moody's and S&P's system and other financial ratios like efficiency ratio which could be used to determine if the bank is stable or at high risk. Vaziri's model identifies how heavily the banks are leveraged and if they can pay off their debt. It also helps to identify if the banks are efficient and if they are able to make profit with the money they borrowed. Vaziri's model helps to identify the reason for the bankruptcy of banks in long run. Ratios for this method includes: Coverage ratios (Current Ratio, Quick Ratio, Cash Velocity, Time Interest

Earn), Leverage ratios (Total Liability/Total Asset, Short Term Debt/Equity Book Value, Equity/Total Liability), Profitability ratios (ROE, Net Income/Sale, Retained Earnings/ Total Asset, EBIT/Total Asset, Net Income/Total Asset), and Efficiency ratios (Asset Turnover, Fixed Asset Turnover, Inventory Turnover, Inventory to Net Working Capital).

2.4. Z-score model. For Z-score, we developed the model which is established by Edward I. Altman. Altman applied the statistical method of discriminant analysis to a dataset of publicly held manufactures. The estimation was originally based on data from publicly held manufacturers, but was re-estimated based on other databases for private manufacturing, non-manufacturing and service companies. In this paper, we use Z-score models for predicting bankruptcy which was developed by Altman (1968, 1983, 1993) for non-manufacturing industries.

Z-model: $Z = 6.56X_1 + 3.26X_2 +$

$+ 6.72X_3 + 1.05X_{4*},$

where X_1 is the Working Capital/Total Assets, X_2 is the Retained Earnings/Total Assets, X_3 is the Earnings before Interest and Taxes/Total Assets, X_4 is the Book Value Equity/Book Value of Total Liabilities.

X_1: Working Capital/Total Assets (WC/TA). This ratio measures the net working capital relative to the size of the assets used in the business. It is used as a measure if liquidity standardized by the size of the firm.

X_2: Retained Earnings/Total Assets (RE/TA). This variable relates the total retained earnings of the firm to the total assets employed. It is able to capture the cumulative profitability of the firm since inception. Also, since young firms tend to have low RE/TA ratios, this variable may capture the age of the firm as well.

X_3: Earnings before Interest and Taxes/Total Assets (EBIT/TA). The operating profitability in relation to total assets measures the productivity of the assets or the earning power.

X_4: Book Value Equity/ Book Value of Total Liabilities (BE/TL). This differs from X_4 in that it uses the book value rather than the market value of equity. This ratio is appropriate for a firm that is not publicly traded, and hence the Z-model with this variable definition is called the Z'-model or the private firm model. Bank was considered bankrupt if value is less than 1.1. Zone of ignorance is defined if values fall between 1.1-2.6, and if values are greater than 2.6, it is considered non-bankrupt.

2.5. Logit ananlysis. Logit analysis was developed and established by James Ohlson which used discriminant analysis to identify bankruptcy. This model predicts the probability of occurrence of an event. The model used for this analysis is: $y = -1.32 -$ $- 0.407$(Size) + 6.03(Total Liabilities/Total Assets) − − 1.43(Working Capital/Total Assets) + 0.0757 (Current Liabilities/Current Assets) − 2.37(Net Income/ Total Assets) − 1.83(Working Capital flow from Operations/Total Liabilities) + 0.285(1 if net income was negative for the last two years; 0 if net income was not negative for the last two years) − 1.72(1 if Total Liability exceed Total Assets; 0 if Total Liability do not exceed Total Assets) − 0.521(Change in Net Income/Sum of Absolute Values of Current and Prior Years' Net Incomes). Size is the natural logarithm of (Total Assets/GNP Implicit Price Deflator) with a base of 100. *Y* value which is calculated from this equation is then transformed into a probability, which is the calculated as:

Probability of bankruptcy = $1 / (1 + \hat{e} - y)$,

$e = 2.718282$.

3. Findings and results

Subprime mortgage loan was the main reason for the bankruptcy of all banks and financial institutions. Nearly 80% of the mortgages that were given out were adjustable-rate mortgages. The price of housing went up in mid-2006 and fell after that which made it impossible to refinance. Securities that used subprime mortgages lost their values and led to failing economy. This entire problem began when US government was giving only 1% interest for Treasury bond and lending money. Banks started borrowing more money, and they had limited rules regarding lending money to people. They started taking more risk by financing to everyone, even people with damaged credit history. This type of loan rose from $100 billion in 1999 to $625 billion by 2005 (Bloomberg, 2011). Government wanted more home owners and they were more interested in revising more regulations than implementing them, such as Basel II (Michael McAleer, Juan-Angel Jimenez-Martin, and Teodosio Perez-Amaral, 2009). Feds oversight was also one of the reason behind bankruptcy of so many banks (Bloomberg, 2011). Other than government regulations that led to bankruptcy, some banks also had internal problems. American International Group, Inc. (AIG) had change it's management in 2005 when Greenberg was replaced by Martin J. Sullivan. AIG's credit rating had reduced a lot leading to liquidity crisis in September 16, 2008. Sumitomo Trust & Banking Co. Ltd., was affected by the changes that occurred in Japanese banking financial structure. Abbey National bank gave out many mortgage loans in 1980's for 15 years. With the fluctuation in interest rates the bank extended

loan payments which led to the downfall with the subprime mortgage crisis. Northern Rock was greatly affected by the U.S. subprime mortgage crisis. To liquidate the assets and to pay back their loans Amcore Financial Inc. filed bankrupt. The results of each models are shown in the following tables.

Table 1. Moody's model

Moody's model	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
Failed banks correctly predicted	8	11	10	14	12	10	10	7	9	11
Non-failed banks correctly predicted	68	61	59	54	57	60	57	57	47	47
Type I error	12	9	10	6	8	10	10	13	11	9
Type II error	12	19	21	26	23	20	23	23	33	33
Incorrectly predicted in total	24	28	31	32	31	30	33	36	44	42
Correctly predicted in total	76	72	69	68	69	70	67	64	56	58
% of failed banks correctly predicted	40.00%	55.00%	50.00%	70.00%	60.00%	50.00%	50.00%	35.00%	45.00%	55.00%
% of non-failed banks correctly predicted	85.00%	76.25%	73.75%	67.50%	71.25%	75.00%	71.25%	71.25%	58.75%	58.75%
% of total incorrectly predicted	24.00%	28.00%	31.00%	32.00%	31.00%	30.00%	33.00%	36.00%	44.00%	42.00%
% of total correctly predicted	76.00%	72.00%	69.00%	68.00%	69.00%	70.00%	67.00%	64.00%	56.00%	58.00%

Moody's model predicted that 11 banks would be bankrupt a year before the bank filed for bankruptcy and 10 banks before two years of bankruptcy. Of 20 banks that filed for bankruptcy 18 of them filed in 2010 and 2 of them in 2011. Studies suggest that models can predict perfect bankruptcy two years before the file for it. The percentage of correct prediction ranges from 69% to 76%. This shows that this model is 72.5% reliable on average. This model also shows that most of the banks had high leverage and has less liquidity.

Table 2. S&P's model

S&P's model	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
Failed banks correctly predicted	1	1	7	7	5	5	6	2	4	16
Non-failed banks correctly predicted	79	78	62	76	76	77	76	64	79	47
Type I error	19	19	13	13	15	15	14	18	16	4
Type II error	1	2	18	4	4	3	4	16	1	33
Incorrectly predicted in total	20	21	31	17	19	18	18	34	17	37
Correctly predicted in total	80	79	69	83	81	82	82	66	83	63
% of failed banks correctly predicted	5.00%	5.00%	35.00%	35.00%	25.00%	25.00%	30.00%	10.00%	20.00%	80.00%
% of non-failed banks correctly predicted	98.75%	97.50%	77.50%	95.00%	95.00%	96.25%	95.00%	80.00%	98.75%	58.75%
% of total incorrectly predicted	20.00%	21.00%	31.00%	17.00%	19.00%	18.00%	18.00%	34.00%	17.00%	37.00%
% of total correctly predicted	80.00%	79.00%	69.00%	83.00%	81.00%	82.00%	82.00%	66.00%	83.00%	63.00%

S&P's model, though shows that percentage of correct prediction is 80%, lacks to predicts the failure of banks in advance. The correct prediction of failed banks is only 5% in 2010 and 2009 and only 35% in 2008 and 2007, which shows that it is not reliable in predicting bankruptcy.

Table 3. Vaziri's model

Vaziri's model	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
Failed banks correctly predicted	10	8	9	13	6	9	9	5	10	3
Non-failed banks correctly predicted	72	74	75	71	76	71	70	75	73	77
Type I error	10	12	11	7	14	11	11	15	10	17
Type II error	8	6	5	9	4	9	10	5	7	3
Incorrectly predicted in total	18	18	16	16	18	20	21	20	17	20
Correctly predicted in total	82	82	84	84	82	80	79	80	83	80
% of failed banks correctly predicted	50.00%	40.00%	45.00%	65.00%	30.00%	45.00%	45.00%	25.00%	50.00%	15.00%
% of non-failed banks correctly predicted	90.00%	92.50%	93.75%	88.75%	95.00%	88.75%	87.50%	93.75%	91.25%	96.25%
% of total incorrectly predicted	18.00%	18.00%	16.00%	16.00%	18.00%	20.00%	21.00%	20.00%	17.00%	20.00%
% of total correctly predicted	82.00%	82.00%	84.00%	84.00%	82.00%	80.00%	79.00%	80.00%	83.00%	80.00%

Vaziri's model predicts much better than Moody's and S&P's model. Percentage of correct prediction is almost 80% for all years and percentage of correctly predicted failed banks is 45% before two years of actual failure.

Table 4. Logit model

Logit model	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
Failed banks correctly predicted	10	8	9	5	3	6	4	3	2	6
Non-failed banks correctly predicted	78	79	78	78	79	78	79	79	79	80
Type I error	10	12	11	15	17	14	16	17	18	14
Type II error	2	1	2	2	1	2	1	1	1	0
Incorrectly predicted in total	12	13	13	17	18	16	17	18	19	14
Correctly predicted in total	88	87	87	83	82	84	83	82	81	86
% of failed banks correctly predicted	50.00%	40.00%	45.00%	25.00%	15.00%	30.00%	20.00%	15.00%	10.00%	30.00%
% of non-failed banks correctly predicted	97.50%	98.75%	97.50%	97.50%	98.75%	97.50%	98.75%	98.75%	98.75%	100.00%
% of total incorrectly predicted	12.00%	13.00%	13.00%	17.00%	18.00%	16.00%	17.00%	18.00%	19.00%	14.00%
% of total correctly predicted	88.00%	87.00%	87.00%	83.00%	82.00%	84.00%	83.00%	82.00%	81.00%	86.00%

Percentage of correct prediction of logit model is almost the same as of Vaziri's model. Both models show that they are 50% reliable.

Table 5. Z-score model

Z-score model	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
Failed banks correctly predicted	16	16	15	15	14	15	12	14	13	13
Non-failed banks correctly predicted	79	68	56	54	50	52	51	49	45	46
Type I error	4	3	7	7	8	5	8	6	7	7
Type II error	1	14	24	26	30	28	29	31	35	34
Incorrectly predicted in total	5	17	31	33	38	33	37	37	42	41
Correctly predicted in total	95	84	71	69	64	67	63	63	58	59
% of failed banks correctly predicted	80.00%	80.00%	75.00%	75.00%	70.00%	75.00%	60.00%	70.00%	65.00%	65.00%
% of non-failed banks correctly predicted	98.75%	85.00%	70.00%	67.50%	62.50%	65.00%	63.75%	61.25%	56.25%	57.50%
% of total incorrectly predicted	5.00%	17.00%	31.00%	33.00%	38.00%	33.00%	37.00%	37.00%	42.00%	41.00%
% of total correctly predicted	95.00%	84.00%	71.00%	69.00%	64.00%	67.00%	63.00%	63.00%	58.00%	59.00%

Of all the models Z-score gives the best prediction. It's prediction percentage of failed banks is 80% and shows 75% correct prediction before two years. Shareholders can relay more on this model.

Conclusion

In this research we apply several existing methods of institutional failure and test the signaling ability of each method in predicting the bankruptcy beforehand. The financial institutions selected for this study are from the USA, Asia and Europe. 100 banks are selected as a sample of which 3 of them are acquired banks, 17 of them are helped by the government after the crisis, 20 banks have claimed bankruptcy and 60 of them are active banks. The banks are studied for 10 years (2001 to 2010). We apply Moody's financial ratios, Standard and Poor's financial ratio, Vaziri's financial ratio, Altman's Z-score and then applying logit model and discriminant analysis. We test each of these model's predictive ability for future use. Moody's model predicted that 11 banks would be bankrupt a year before the bank filed for bankruptcy and 10 banks before two years of bankruptcy. Of 20 banks that filed for bankruptcy 18 of them filed in 2010 and 2 of them in 2011. Studies suggest that models can predict perfect bankruptcy two years before they file for it. The percentage of correct prediction ranges from 69% to 76%. This shows that this model is 72.5% reliable on average. This model also shows that most of the banks have high leverage and less liquidity. S&P's model, though shows that percentage of correct prediction is 80%, lacks to predicts the failure of banks in advance. The correct prediction of failed banks is only 5% in 2010 and 2009 and only 35% in 2008 and 2007, which shows that it is not reliable in predicting bankruptcy. Vaziri's model predicts much better than Moody's and S&P's model. Percentage of correct prediction is almost 80% for all years and percentage of correctly predicted failed banks is 45% before two years of actual failure. Percentage of correct prediction of logit model is almost the same as of Vaziri's model. Both the models show that they are 50% reliable. Of all the models Z-score model gives the best prediction. It's prediction percentage of failed banks is 80% and shows 75% correct prediction before two years. Shareholders can relay more on this model. We analyze the reasons like changes in market, policy, economy, and political influence which have led to bankruptcy. Banks or financial institutions from Europe, the United States and Asia are considered as a sample. Sample is taken from the same period to

analyze the effect of different methods. The results from this analysis should help us find the most significant method that could be used to identify the risk, so that necessary action could be taken to prevent the effect or reject the project which could lead to bankruptcy in the future.

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