When Companies Fail: Predicting Bankruptcy and the Return on investments to Shareholders after Chapter 11

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Abstract

After the failure of many high profile firms, bankruptcy prediction and bankruptcy recovery prediction has become a topic of high interest. In the wake of WorldCom ($103 billion, in total assets prior to bankruptcy), Enron ($63 billion), Conseco ($61 billion), and Kmart ($14 billion) [1], many people have been left wondering if there had been telltale signs for each, so that they might have been able to sell stocks, recall loans, or even fix the problems.

Economic changes such as exchange rates [2], fraud, torts filed against a company, or problems with specific issues like; asbestos (Eagle-Picher Industries Inc, Federal-Mogul Corporation, and Kaiser Aluminum Corp.), environmental (Gulf USA Corp. and The Jesup Group Inc.), patents (Paragon Trade Brands, Inc. and Smith International Inc.), or pension funds (CF & I Steel Corp., Geneva Steel Holdings Corp., and Kaiser Steel Corp)[3], can all be major factors in a company's bankruptcy. Fraud may cause a company to go into bankruptcy or be used by a company to hide that it is going into bankruptcy.

This study focuses on the return of investment in companies filling for Chapter 11 bankruptcy in the USA. The models created provided insight into the prediction of return to using only the information at the time of Chapter 11 bankruptcy filing. The first section is a literature review and discusses: background information on bankruptcy that is important, a history of bankruptcy prediction and models used, and a discussion of software packages available. The second section details the models created: with a discussion of aims, methods, data used, and presents findings and analysis. Models created include statistical and soft computing methods using the following software packages: PolyAnalyst, See5, Cubist, CTree, MDA, Neuralyst, and hybrids of them as well. The Third section discusses the implementation of software, which incorporates all of the models presented in the second section with discussions on: methodology, user interface, requirements, and future directions. The final section is a discussion of the future directions for research, which are exciting and promising.

1 Chapter 1: Literature Review

1.1 Why predict bankruptcy?

"[Bankruptcy would be] like stepping into a tepid bath and slashing your wrists: You might not feel yourself dying, but that's what would happen [4]."

In the wake of Enron ($63 billion, in total assets prior to bankruptcy), WorldCom ($103 billion), Kmart ($14 billion), and Conseco ($61 billion)[1], many people have been left wondering if there had been telltale signs for each, so that they might have been able to sell stocks, recall loans, or even fix the problems. Bankruptcy prediction is important for various reasons. Banks that are making loans would like to be able to tell if a company would go into bankruptcy and when. Collectors would like to know in advance of other collectors so that they may put leans on other assets (secure the loans) or call loans in before other competing creditors. Currently the volume of outstanding debt to corporations in the US is very high. By lowering this debt, it would be possible for banks to offer reduced (more fair) loan interest rates. Accounting firms would also like to be able to detect the 'warning signals' for fraudulent entities and entities heading towards bankruptcy in order to save money on costly lawsuits resulting from reviews which did not detect the problem. Companies themselves would like to be able to identify that they had a problem, determine causes and fix possible problems, allowing it's own safety, and providing a competitive edge. Stock investors would also benefit by knowing when a company would go bankrupt and ultimately if they would recover from bankruptcy, in order to protect their investments and tap into potential new investments.

Not only would bankruptcy prediction software help investors, banks, companies, and rival companies, it would also allow the general pubic to feel more at ease with companies and the economy as a whole. Or would it? There are many legal, political, and social concerns with bankruptcy prediction software as well; such as if a company is wrongly predicted to go bankrupt whom do they sue? Do they sue the designers for creating a bad model, the company who created the program for false prediction, the entity using the software for relying on that information, the government for allowing the software on the market, etc? Bad classifications may be more costly than bankruptcy classification if the lawsuits out weigh the benefits or company relations were too badly hurt. While these are not the focus of this paper, they do present issues that need to be mentioned and reviewed, because all current models for bankruptcy prediction can not give a 100% guarantee in their predictions. Environmental factors such as exchange rates, unemployment rates, company location, new laws, public opinion, etc cannot all be incorporated accurately into the model. However, even if they could be incorporated, the hypothesis would have the same problems that the stock market hypothesis, called the Efficient Market Hypothesis (EMH), has. As applied to stock markets, this hypothesis says that because all information relevant to the market, is already known and acted rationally on by all participants, a trader can not hope to make money over time because it assumes the market is random after all the known data is removed (based on the random walk theory) [5, 6]. Weaknesses of this hypothesis are that it would be mathematically impossible to prove, because randomness cannot be proved (trying to prove randomness is the basis of chaos theory) and with EMH, the assumption that all investors will react the same way to the information is not valid (such as the example of fraud used in/with bankruptcy). Also there are clear signs that this is not true in stock markets because there are trends and the markets can be manipulated [7].

Economic changes such as exchange rates [2], fraud, torts filed against a company, or problems with specific issues like; asbestos (Eagle-Picher Industries Inc, Federal-Mogul Corporation, and Kaiser Aluminum Corp.), environmental (Gulf USA Corp. and The Jesup Group Inc.), patents (Paragon Trade Brands, Inc. and Smith International Inc.), or pension (CF & I Steel Corp., Geneva Steel Holdings Corp., and Kaiser Steel Corp)[3], can all be major factors in a company's bankruptcy.

Fraud may cause a company to go into bankruptcy or be used by a company to hide that it is going into bankruptcy. Detecting fraud can be done with methods such as; cash flow analysis [8], chaos theory [5, 9], using Benford's Law [10], Artificial Neural Networks [11], Rule-based systems [12], just to mention a few.

1.2 Bankruptcy Background Information

1.2.1 History of bankruptcy prediction

"Being in the microcomputer business is like going 55 miles an hour 3 feet from a cliff [13] [on his company's bankruptcy]."

Beaver [14] is often referred to as one of the founders of bankruptcy research for his univariate bankruptcy model, created in 1966 using financial data. Later in 1968, Altman [15] extended Beaver's model with the use of multi-discriminant analysis (MDA) to create a model that was meant to determine if a company was a 'survivor' or in 'financial distress'. Models using MDA picked up in popularity and were done by various researchers partially because of their ease of implementation and accuracy; Altman, Haldeman, and Narayanan [16] created a model for USA companies. The majority of distress prediction models have been done on US firms due to the availability of data; however in 1994 there were at least three-dozen studies devoted to other countries [17]. MDA analysis continues to be one of the benchmark methods despite heavy criticism [18-21]. Most of the arguments against discriminant analysis were based on the requirements imposed by the statistical method such as; a multivariate normal distribution (often violated by using dummy variables for example), only providing an ordinal ranking, and the difficulty in determining the significance level of variables in the overall score. In 1980, Ohlson [22] made critical contributions to bankruptcy prediction by pointing out how previous researchers like Altman had overstated predictive ability because their test samples included far more distressed companies than would be normal (In Altman's study about 50% of the companies were distressed, when in reality less than 5% would go bankrupt in a year normally) [23]. Because of MDA criticism, logit was used by Ohlson [22] and Peel, Peel, Pope [24]. Multinomial logit was used by Lau [25] and probit by Pacy and Pham [26]. Also during this time recursive partitioning was used [27, 28]. In 1980, companies failed every forty-five minutes explaining the higher rate of bankruptcy research and variety at that time [29].

Bankruptcy and distress prediction are considered classification problems or cross-sectional since the goal is to place companies into classes of being in distress or not. Some of the general classification problems using soft computing included; survival analysis [30], goal programming [31], multicriteria decision/support methods [32], rough sets methods [31], expert systems [33, 34], neural networks [35], Cox's Proportional Hazards Model [36], and self-organizing maps [37]. In the area of distress prediction for financial institutions, credit union failure prediction models for Australian companies were created [21, 38-40] as well as ones for US banks entering failure [30]. For a more in-depth look, see appendix VI.

Soft computing methods specifically applied to bankruptcy prediction include probabilistic neural networks [41] and back propagation neural networks [31, 41]. These soft computing models were specifically important because they offer qualitative methods that traditional quantitative tools in statistics and economics cannot quantify because of the complexity in translating the systems into precise functions [42].

Various methods used in prediction have been studied as well as the use of different ratios and factors incorporated into models for predicting distress; environmental factors, interest rates, employment rates, and factors that point to competition in the industry. Rose et al. [43] used macroeconomic factors, as did Platt and Platt [44] who also incorporated business running costs, such as how much it would cost for a new business to form. Receiver operating characteristics curves used for bankruptcy return prediction by [45] used firm specific and economy wide data, it was determined that there was little difference, whether overall economic data was used in the model or not.

In Patti Cybinski's paper [46], it is noted that, especially in the past, the focus of research has been more concerned with performing bankruptcy prediction rather than explaining why it occurred or was even approached from a scientific manner. This is of particular interest here because some of the more complex and more promising methods are actually moving farther away from truly being able to explain how they are working and what their results stem from or mean. For example, neural networks now offer qualitative methods that traditional quantitative tools in statistics and economics cannot quantify because of the complexity in translating the systems into precise functions [42].

1.2.2 Bankruptcy in the USA

"Capitalism without bankruptcy is like
Christianity without hell [47]."

Bankruptcy may be inevitable and even beneficial as a driving force. In the USA there are many types of bankruptcy, some personal, some commercial, and some are both. In 1898, bankruptcy law was first created in the USA and has been amended various times since; in 1938 with the Chandler Act and in 1978 with the Bankruptcy Reform Act [48]. The definition of bankruptcy given in the dictionary is; "A debtor that, upon voluntary petition or one invoked by the debtor's creditors, is judged legally insolvent. The debtor's remaining property is then administered for the creditors or is distributed among them [49]." In the USA, legal bankruptcy proceedings may be voluntary or involuntary (initiated by the debtor or by the creditors). With bankruptcy, preferred creditors (such as unpaid employees and the federal government) are paid first in full and the remainder of the proceeds from assets are shared among the remaining creditors [48].

The majority of distress prediction models have been done on US firms due to the availability of data, however, in 1994 there were at least three-dozen studies devoted to other countries [17]. This is interesting since bankruptcy laws differ greatly worldwide and therefore results would most likely vary significantly. For example, in many countries, such as Germany, bankruptcy laws are so costly to execute and are such a hassle that many companies will try to avoid them and settle privately, outside of the courts [50], which would make it even harder to correctly identify companies in distress in these countries. Because of the different laws and lack of data, it is arguable that many of the current empirical research studies may not really be applicable to other countries. This would be an interesting idea to research further.

One of the key differences in the US bankruptcy laws from other countries is the existence of the form of bankruptcy termed Chapter 11 (discussed more in the following section), which is ideally designed to promote business initiative by removing criminal and civil threats from unintentional failure. Chapter 11 even allows a company the option to reorganize rather then simply requiring all assets to be liquidated. Corporate management even has more control of the company now than in the past as is provided for in the 1978 revision of the code. These more lenient provisions from 1978 have led to an increase in filings in the 1980s and 1990s and congress is still debating changes to law to reverse this.

One prime example of Chapter 11 debates in action is the case of Polaroid which has been hailed as what would appear to be, *"...a textbook case of how bankruptcy proceedings can help a failing company emerge with a promising future [51]."* However in the same breath Frieswick states that it seemed to be taking advantage of the system and that *"...the Polaroid case as a demonstration of what's wrong with corporate-bankruptcy reorganization [51]."* He claims that because the system focuses so much on debtors that it makes the system less fair for creditors and stakeholders. Frieswick [51] also cites that the financial and operational steps taken prior to bankruptcy is not scrutinized enough. While Polaroid's bankruptcy in 2001 was a slow process it had been falling since 1984, when their earnings had dropped dramatically. By 1998 their losses were in the tune of $51 million and were at their lowest in almost a decade. At this time Polaroid began changing their whole strategy in attempts to recapture lost markets [52]. Things were looking up in 1999 with record sales of 9.7 million in instant cameras and as the number-one digital camera seller in the US mass-merchandising channel [52], although only fleeting. Some of the most cited reasons for Polaroid's bankruptcy have been their slowness to take up digital photography [53] [51, 54], poor management [51], one hour photos [53], high debt from fending off a hostile takeover by Shamrock Holdings in 1989 [53], and a slow down in travel after September 11th leading to few camera and film sales [54]. But the real crook of the matter is that according to some the company that bought Polaroid paid too little and quickly dropped it's debts. Polaroid owns more than 1,000 patents and $1.5 billion or more in worldwide asset value, yet cost less than $80 million to buy. Was this a fair price? Even Polaroid's initial petition on 1 July 2001 listed worldwide assets of $1.8 billion and liabilities of only $948.4 million (although due to declines in revenue they claim to not have the ability to pay loans and bonds).

1.2.2.1 Chapter 11 Bankruptcy

Chapter 11 is a form of bankruptcy in the USA. Chapter 11 was created in order to let companies have more time to either attempt to recover from bankruptcy or allow companies to attempt to reduce losses through planned methods such as; giving managers a break from collectors for a time, loan renegotiation, allow time for liquidation (in order to get better value from sales), or allow companies to reorganize the company structure. For a company to file for chapter 11 they must submit a plan of how and what they are aiming for and how they expect to get there. In the filing process, courts first must approve the plan submitted and then the company is released from Chapter 11. An in-depth diagram which details this process from LoPucki's website is shown in Appendix I. When a company is released from bankruptcy, shareholders either lose all value or have some worth.

Another form of bankruptcy is Chapter 7. Chapter 7 is chosen less often since creditors usually get back less than they do under chapter 11. However, chapter 11 allows companies to get themselves into worse debt and allows new loans to take higher precedent over previous loans. Various research projects have been devoted to determining which type of bankruptcy creditors should push for in order to get the most value for their specific situation. When a loan is re-negotiated under chapter 11 to a lower amount, even if the company is able to pay the creditor back later the full amount (after reorganizing) it is not required to. Due to the risks associated with bankruptcy, many times crediting companies will close the company down sooner than it should have (getting less of their debt repaid than what might have been possible with more time), this leads to races among the collectors, since whoever is the collector to collect first gets the most, while the others may get nothing. In many situations, if all creditors had waited, there may have been better and fairer payments possible for all [50]. Because of this, not only would it be beneficial to know if a company is going into bankruptcy before other companies know, it would also be beneficial to judge if the company would be able to recover or provide shareholders with any return on their investment [50].