# Do Fire Sales Really Exist? An Empirical Study on Distressed Targets' Premiums

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# ABSTRACT

Firms can be de-listed from public market due to different reasons. They could go bankrupt which would be a negative outcome for their shareholders, they could merge with or acquired by other firms, or they could go private, outcomes that are usually pleasant for their stakeholders. What if a firm becomes an acquisition target in the period right before going bankrupt? Is it still a positive event for shareholders or because of the firms distressed situation there will be no positive return for them? We estimate the likelihood of firm failure and examine the premium offered for distressed public firms in both contractions and normal economic periods. We use Survival Analysis and Artificial Neural Networks, both using multi-period inputs, to categorize firms into distressed and not-distressed groups. These models claim to be more successful compared to the single-period static models widely used in the extant literature. Results of analyzing 1378 targets in different market conditions shows that acquirers tend to overpay for distressed targets and even more in contraction periods. on the other hand, we observe a huge discount when we calculate the mean target premium in reference to targets' highest price in the 52-week period before the announcement . It seems that acquirers bid reference is not the current market valuation, but the targets best position in the one year prior to announcement.

## DEDICATION

To my wife, for her endless love, support and encouragement

## ACKNOWLEDGEMENTS

I would like to thank my supervisor, Dr. Sandra Betton, for her support and guidance throughout the research.

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# CHAPTER 1
# Introduction

## 1.1 Introduction

Firms can be de-listed from public market due to different reasons.They could go bankrupt, which would be a negative outcome for their shareholders; they could merge with or get acquired by other firms, or they could go private, outcomes that are usually positive for stakeholders. But what if a firm becomes an acquisition target in the period right before it would otherwise go bankrupt? Is it still a positive event for shareholders or because of the firms distressed situation, there will be little positive gain for them? In this research, we analyze how being distressed, or more specifically being close to filing for bankruptcy, affects targets' gain from M&A activity. We compare distressed and normal (not distressed) targets' premiums. In order to accomplish this, we first estimate a failure prediction model to categorize targets into distressed and non-distressed groups. Having these two target categories will are able to analyze the difference between the two groups in terms of the premiums they receive at acquisition. The study consists of two main parts; failure prediction which helps us in categorizing targets, and an event study looking at the two categories in order to compare their characteristics in terms of their gains at deal announcement. What happens to near-to-failure targets' when acquired is not extensively studied in the mergers and acquisitions literature. Very few empirical studies have been done on the amount of target premium and what drives it. To the best of our knowledge, Ang and Mauck (2011) is the nearest study to this subject. They study distressed firms, not exactly those near to filing for bankruptcy but those experiencing financial difficulties, asserting that "Fire Sales", a situation where firms have to sell their assets at deep discounts, do not really exist when targets' premium reference is its price right before the announcement. Some other studies, although not directly looking at the same question, seem to contradict the Ang and Mauck conclusion. Studies by Koutsomanoli-Filippaki and Mamatzakis (2009), Shleifer and Vishny (1992) and Wang et al. (2009), show that firms with less liquidity and profits suffer more in stock market crashes and cause lower premiums for the target shareholders, are some examples of these researches.

Even though the Ang and Mauck (2011) paper analyzes financially distressed targets' premiums deeply, in both recessionary and normal economic periods, we believe that their criteria for defining distressed firms can be improved by using more well-studied models, which are supported by bankruptcy prediction studies. We may deviate from their definition of "distressed firms" by choosing more strict criteria to isolate near-to-failure firms. More precisely, Ang & Mauck used (1) two [consecutive] years of negative net income, (2) negative equity, (3) the Altman Z-score (Altman, 1968), and (4) the Ohlson O-score (Ohlson, 1980), and categorized more than 34% of their sample as distressed. Using more sophisticated newer models, we introduce another definition of distressed firm; we investigate M&A activity gains to targets that are close to bankruptcy filing.

We are specifically interested in the distressed firms' premium when they are targeted by acquirers and if these premiums are different in size with those of non-distressed firms. We compare these premium differences in both contractionary and normal economic periods.

To have a more reliable sample categorization, we use Survival Analysis and Artificial Neural Networks, both using multi-period variables as their inputs, along with a logit regression model (commonly used in the current literature) to categorize firms as distressed or not-distressed. There are various studies claiming that multi-period- input models are more powerful compared to single-period-input static models.

A brief literature review follows the introduction section. This section covers two strands of related literature; bankruptcy prediction and distressed target abnormal returns around M&A activity announcements. Section 2 discusses both data and methodology. Data description, manipulation and cleaning as well as a comprehensive presentation of different methodologies used in the study are covered in this section. Results are presented in section 3, and section 4 concludes the study.

### 1.2 Literature Review

The main focus of the study is the difference between premiums paid to distressed vs. non-distressed targets. This can be related to two different branches of the finance literature; mergers and acquisitions of distressed firms, and bankruptcy prediction. This is because a very important and sophisticated part of the study would be isolating distressed targets. For this reason, alongside the M&A activity related literature, the bankruptcy prediction models' literature review is also included. As very few studies directly address fire sales of distressed targets, the corresponding part in the literature review is shorter than the bankruptcy prediction discussion.

### 1.2.1 Distressed Targets' Mergers and Acquisitions

Targets, experiencing financial difficulties and/or operating at the time of financial crisis, face liquidity and solvency problems. These problems may reduce their negotiating power in acquisition talks, which may end up in a reduction of shareholders' take out from the acquisition event. If these conditions exist, chances are that targets get paid the "Fire sale" price, a very deep discount to the firms' true value had they not been in their current difficult situation.

There are very few studies directly addressing the acquisition of distressed firms. To the best of our knowledge, Ang and Mauck (2011), is the closest and most comprehensive one. Ang and Mauck (2011) report a higher premium for distressed firms compared to non-distressed ones, and even higher premiums during a financial crisis period, concluding that "fire sale" discounts are not present for distressed firms. They assert that their results are based on using the targets' recent stock price as the reference point as these prices are the true value of firms that are being transferred to the acquirer. Ang and Mauck (2011) report contrary results using the 52-week highest prices as the reference point. Their sample from SDC M&A data set contains

5794 acquisitions from 1977 to 2010. They use four different methods to identify distressed targets: (1) two years of negative net income, (2) negative equity, (3) the Altman Z-score (Altman, 1968), and (4) the Ohlson (Ohlson, 1980) O-score, and categorize 34.72% of targets as distressed firms.

Another research, Khatami, Marchica, and Mura (2013), studies a large sample of firms engaging in M&A events and finds that "financial constraints of target companies significantly increase acquisition premiums and abnormal returns for both parties". They use three of the five criteria namely dividend payout ratio, size, interest coverage ratio and KZ index (Kaplan-Zingales index, an index to measure the extent of reliance on external financing) to rank firms and then used different quintiles of firms for their study. This approach sounds to be more complete than the one used in Ang and Mauk (2011). The result associated with the bidder performance is not in line with previous study as Khatami et al. (2013) reports higher acquisition premiums for the bidders probably because they would eventually be able to turn the target around using less costly external financing available to them, while Ang and Mauk (2011) reports a lower premium at announcement and a lower long-term performance for bidders buying distressed firms compared to others.

Other studies are related to the topic in a non-direct way; studies looking at distressed firms and how distress affects their efficiency, performance, and stock prices together with those looking at partial asset fire sales are among them. Research by Koutsomanoli-Filippaki and Mamatzakis (2009), Shleifer and Vishny (1992), and Wang et al. (2009) show that less liquid firms and those with poorer performance indicators experience higher price falls in market contractions, are among the most relevant studies.

### 1.2.2 Forecasting Bankruptcy

A general definition of business failure is the firm's inability to pay its debt holders, preferred stockholders, or its suppliers. Firms may officially file for bankruptcy or try to restructure their capital at the time that they are close to failure. Firm failure is important to all its stakeholders including lenders, employees, clients, suppliers, community, and of course its shareholders and management team. For this reason it is very helpful to be able to predict a possible future failure in order to make use of the situation. This can be the gain to the near-failure firm itself from implementing corrective actions in order to lessen the distress costs, or possible profit the potential acquirers can make by paying less for the currently-distressed target. All these reasons suggest the importance and use of failure prediction models.

The literature on bankruptcy prediction models is very rich and researchers properly paid a tremendous amount of energy in researching all kinds of prediction models. From multiple discriminant analyses (MDA) with many restrictive statistical assumptions to less limited logistic regression (logit) models to "recursive partitioning algorithms" like survival analyses and iterative learning models like neural networks, many theoretical and empirical contributions can be found in the existing finance and accounting literature.

One way to categorize the models is their input structure. Most of the primary bankruptcy prediction models like logistic regression or MDA use single-period data as their input. These static models are prone to criticisms suggesting that their outputs are biased and inconsistent because they fail to take into account the nature of the bankruptcy data; the fact that failure is happening during a longer than one year period of time. On the other hand, there exist other models like survival analyses and artificial neural networks that use multi-period variables as their inputs. There are many studies that compare the two types of model and suggest that the latter are more powerful than the former. Another way to categorize prediction models is their restrictive assumptions about independent variables and their distributions. Static prediction models, such as MDA, logit, and probit, all have different types of degrees of restrictive statistical assumptions. On the contrary, iterative learning models, trying to develop prediction algorithms using previous data on the subject, usually do not have the same assumptions about the distribution characteristics of the inputs. Neural networks and inductive learning systems are two examples of such methods.

Beaver (1966) is the pioneer study in using accounting ratios to predict firms' failure. He uses ratio analysis to predict firm failures. With a sample of 79 large failed firms from Moody's Industrial Manual, and their control pairs from the same industry and asset size, he analyses the financial reports by firms one year prior to their de-listing. Using 30 ratios and ex-post cut-off points he categorizes firms into two groups and concludes that financial ratios are useful for predicting firm failure status compared to random prediction. He introduces "working capital to debt" and "net income to total assets" ratios as the best discriminant factors. He continues his studies on the subject in Beaver (1968a) where he uses the same data as Beaver (1966) but this time paying attention to the differences in the predicting ability of ratios and researching the causes of these differences. His second paper in 1968, still using the same body of data from Moody's, looks at market prices of firms as well as financial ratios and "the degree of association" between them in predicting failure. Ratios measuring liquidity, profitability, and solvency are the most useful ones based on these studies although the order of their importance is not clear as it changes from study to study.

Altman's study, Altman (1968), is the first to use a multivariate statistical model in order to predict firm failure and the Altman Z-Score credit risk model, introduced in this paper, is still one of the common models highly used by practitioners. Altman criticizes the use of ratio analysis in predicting failure and instead uses a multiple discriminant model. He argues that as these types of models incorporate several variables at the same time, they would lead us to more accurate failure predictions compared to ratio analyses models. His sample consists of 66 corporations, all manufacturers and mostly large ones, 33 of them bankrupt. As his biggest criticism of the previous studies is focused on analyzing only one variable at a time he decides to select important ratios, to assign weights to each of them and to estimate with an index (z-score, he calls it) which contains all the important variables for predicting failure, instead of looking at one variable at a time. Altman uses multiple discriminant analysis (MDA), which has been used in biological and behavioural sciences before his study. After all, Altman's Z-score failed to predict bankruptcy when using data other than one year prior to the event. Beaver (1966) on the other hand, while using one variable at a time, could predict failure up to 5 years before the actual failure event.

Another study, Deakin (1972), adds Beaver's best ratios to Altman's model. The new model worked better in sample but it was not acceptable because of its poor out of sample results. In another attempt, Diamond, in his PhD thesis in 1976 tried to improve the Deakin/Altman model using more sophisticated models such as stepwise discriminant analysis, principal component analysis, and optimal discriminant plane techniques with no apparent success. In 1977, Altman, Haldeman and Narayanan updated the sample originally used in Altman (1968) and added some refinements to the existing model in order to improve the model's classification accuracy. Altman, Haldeman and Narayanan (1977) introduced an enhanced model, called ZETA, the second generation of Z-score in which they "incorporated refinements in the utilization of discriminant statistical techniques".(Altman 1977, P.1)

Studies by White and Turnbull (1975a,b) and Santomero and Vinso (1977) were the first to introduce the probability of failure. Ohlson (1980) is another related study using conditional logit model and incorporates Maximum Likelihood Estimation to avoid problems associated with MDA models used by Altman among others. Ohlson's sample consists of 105 bankrupt and 2058 non-bankrupt firms. Ohlson reports four significant variables to predict firm failure one year ahead with *size* as the most important one. Ohlson is the first researcher to use an unbiased sample in his studies. His results are important and suggest that all previous studies may have overstated their prediction powers by using samples with half the firms being bankrupt (Morris 1997).

All mentioned studies use accounting data, which some researchers criticize as not being the most helpful data because of the existence of different accounting standards and the problems associated with the time gap between the availability of data and actual event time.

Queen and Roll (1987) try to predict firm mortality using size, price, return, volatility, and beta. They focus on market information, mainly to avoid the problems mentioned above about accounting variables. Theodossiou (1993) uses multivariate cumulative sum (CUSUM), a sequential dynamic model, to predict financially distressed firms by trying to identify the time when a firm goes from healthy to troubled position. Other studies like Healy (1988) and Shumway (1988) also used such models to predict failure.

Other authors, such as Pagano, Panetta, and Zingales (1998) and Denis, Denis, and Sarin (1997), estimate multiple-period logit models that can be interpreted as hazard models.

Schumway (2001) uses hazard models arguing that these models are "more appropriate than single period models for forecasting bankruptcy"(Schumway 2001, P.1). He claims that static models look basically at a single point in time and miss the information about firms as they change period by period and therefore the models' results are biased and inconsistent. To overcome these problems he proposes a multi-period hazard model, which is "simple, consistent, and accurate"(Schumway 2001, P.1). The reasoning here is that changes are happening in multiple periods and looking at a series of data points instead of just a single one helps to model the bankruptcy prediction easier and more reliable. Schumway's model outperformed static models in his out-of-sample forecasts.

Another class of models that is being used more frequently in the recent years is artificial intelligence algorithms or Neural Networks. These models were first used in bankruptcy prediction papers in 1990 with a work by Odom and Sharda (1990). They used Altman's factors as their neural network model's input and reported more accurate results compared to the ones from the MDA model that Altman estimated on a data set consisting of 128 firms. Altman, in Alyman (1994) uses Neural Networks on Italian data and cautiously reports a "balanced degree of accuracy" between linear discriminant models and Neural Networks. Both models were successful in predicting 90% of cases in the studied database. A number of other studies compared the NN with MDA, most of them concluding the better performance of NN (Coats and Fant (1993) , Kerling and Poddig (1994), Boritz and Kennedy (1995), Leshno and Spector (1996) among many others). Empirical studies such as Odom and Sharda (1990), Tam and Kiang (1992), and Messier and Hansen (1988) provide results showing the out-performance of such models comparing to statistical ones. Zhang, Hu, Patuwo, and Indro (1999), also compared Artificial Neural Networks with logistic regression and reported a "significantly better estimate of the classification rate for the unknown population as well as for the unseen part of the population" of neural networks. Lee and Choi (2013), compared neural networks with MDA model and asserted that "neural network model better capture the nonlinear pattern between independent variables and bankruptcy than MDA."

# CHAPTER 2
# Data and Methods

## 2.1 Data

We aim to conduct a comparison between distressed and non-distressed targets' average gain in the process of being merged with or acquired by another firm. The study needs two different event data sets, a data set containing bankrupt firms with their filing dates and a data set covering merger and acquisition events. We also need firm specific and market information for the period we are looking at, namely 1980 to 2013. Each of these data sets and their manipulating and cleaning processes are presented in this section.

### 2.1.1 Bankruptcy Data

A sample of bankrupt firms and their corresponding data such as bankruptcy filing date, performance, annual reports, and market information is needed to estimate failure prediction models. We tried to gather as many failed firms as possible in order to increase the prediction power of our categorization models. Our sample of failed firms consists of all the reported bankruptcies with the information we needed from SDC bankruptcy data set, the CRSP (The Centre for Research in Security Prices) monthly database, and UCLA-LoPucki Bankruptcy Research Database.

After removing firms with no usable identifier or filing date and deleting duplicate observations, the final sample of failed firms consists of 1384 bankruptcies filed during 1980 and 2013. Firm specific fundamental data is from Standard & Poor's COMPUSTAT yearly database and market information are from the CRSP daily monthly database as well as National Bureau of Economic research. After removing firms with no usable data in any of these data sources the final sample came to 813 failed firms with a complete set of data needed to run analyses. The logic behind the choice of inputs will be presented in upcoming sections. Figure 2–1 shows number of bankruptcies in each of these databases as well as number of covered firms in the CRSP data set in each year. Table 2–1 follows with the same information and extra statistics. The main restriction was the lack of an adequate number of data points for each firm prior to their bankruptcy filing. For example, for Survival Analysis and Artificial Neural Network models, the need for at least of 3 years of data for each firm reduced the sample size substantially.

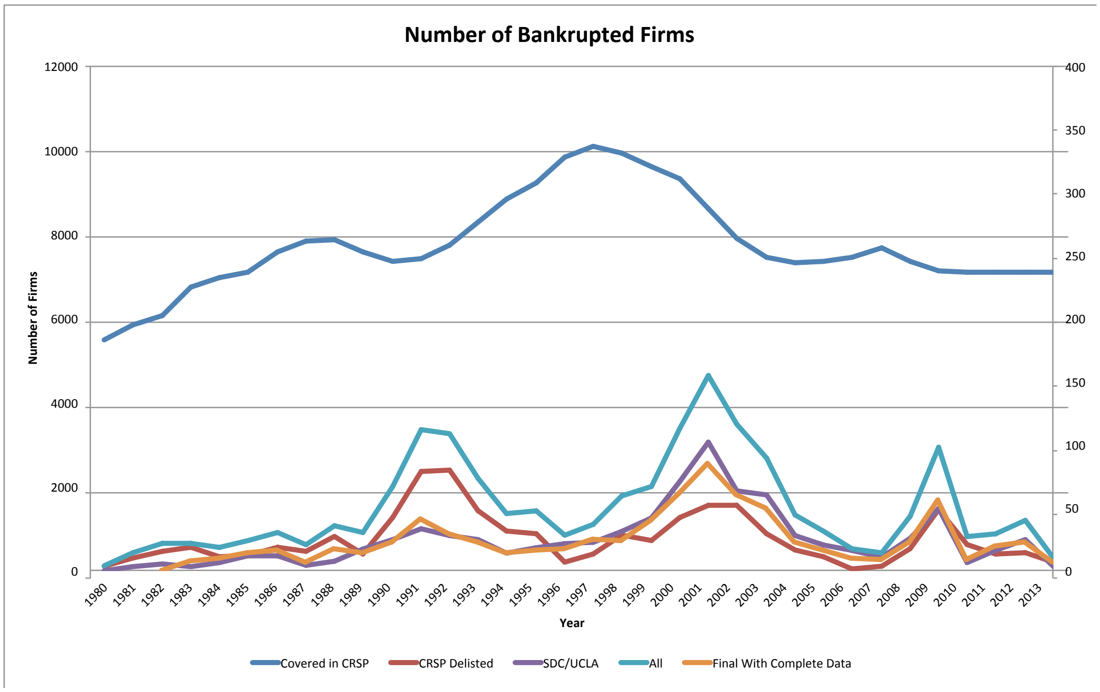


Figure 2–1: Number Of Bankruptcies;

The graph shows the Number of Bankruptcies reported in each of the data sets used, namely UCLA and SDC combined, and CRSP. Number of firms covered by CRSP data set is also included in order to facilitate the comparison.

To estimate the prediction models, we need a match for each failed firm. The matching process is based on firms' industry, size in terms of total assets, age, and data year. To find matching firms, bankrupt firms were removed from the COMPUSTAT and the CRSP databases and matched firms were selected from remaining firms that had the minimum number of data points needed for analyses. As for industry, the 3-digit Standard Industrial Classification (SIC) code is used to find peer firms, in the case of not having a suitable match based on other criteria, the 2-digit SIC code is used. In terms of data year, if more than one match is found for a bankrupt firm, the one with available data closer to the failed firm bankruptcy filing date is selected. After removing financial and utility firms, and firms with no match at all (this happened for 5 firms), the final complete sample consists of 1626 firms, 813 of them having filed for bankruptcy, and each having at least 3 years of yearly data points.

Table 2–1: Number Of Bankruptcies;

This table illustrates the number of failed firms, those filed for bankruptcy, in the period between 1980 to 2013 in United States of America. Failed firms from both the CRSP and the SDC/UCLA data sets are presented. Number of covered firms by the CRSP in any year, and percentage of failed firms in the CRSP covered firms are presented, too. Column "All" reports the final count of failed firms from all data sets after removing duplicates. The last column shows the count of the final sample with all the firms having all the variables needed to estimate the models.

| Year | No.of Firms Covered (CRSP) | CRSP Delisted | % Of Bankruptcy (CRSP) | SDC/UCLA | All | Final With All Data |
|---|---|---|---|---|---|---|
| 1980 | 5549 | 5 | 0.09% | 1 | 6 | |
| 1981 | 5895 | 11 | 0.19% | 5 | 16 | |
| 1982 | 6119 | 16 | 0.26% | 7 | 23 | 1 |
| 1983 | 6782 | 19 | 0.28% | 4 | 23 | 9 |
| 1984 | 7012 | 12 | 0.17% | 8 | 20 | 11 |
| 1985 | 7144 | 13 | 0.18% | 13 | 26 | 15 |
| 1986 | 7617 | 19 | 0.25% | 13 | 32 | 17 |
| 1987 | 7881 | 16 | 0.20% | 6 | 22 | 8 |
| 1988 | 7898 | 28 | 0.35% | 9 | 37 | 18 |
| 1989 | 7608 | 14 | 0.18% | 18 | 32 | 15 |
| 1990 | 7406 | 42 | 0.57% | 26 | 68 | 24 |
| 1991 | 7466 | 78 | 1.04% | 34 | 112 | 41 |
| 1992 | 7766 | 80 | 1.03% | 29 | 109 | 30 |
| 1993 | 8325 | 48 | 0.58% | 26 | 74 | 24 |
| 1994 | 8852 | 32 | 0.36% | 15 | 47 | 15 |
| 1995 | 9243 | 30 | 0.32% | 19 | 49 | 17 |
| 1996 | 9832 | 8 | 0.08% | 22 | 30 | 18 |
| 1997 | 10073 | 14 | 0.14% | 24 | 38 | 26 |
| 1998 | 9920 | 29 | 0.29% | 32 | 61 | 25 |
| 1999 | 9611 | 25 | 0.26% | 43 | 68 | 40 |
| 2000 | 9314 | 42 | 0.45% | 71 | 113 | 62 |
| 2001 | 8622 | 52 | 0.60% | 102 | 154 | 85 |
| 2002 | 7942 | 52 | 0.65% | 64 | 116 | 61 |
| 2003 | 7500 | 30 | 0.40% | 60 | 90 | 50 |
| 2004 | 7364 | 17 | 0.23% | 29 | 46 | 23 |
| 2005 | 7382 | 12 | 0.16% | 21 | 33 | 17 |
| 2006 | 7473 | 2 | 0.03% | 17 | 19 | 11 |
| 2007 | 7705 | 4 | 0.05% | 12 | 16 | 10 |
| 2008 | 7407 | 18 | 0.24% | 27 | 45 | 23 |
| 2009 | 7175 | 49 | 0.68% | 50 | 99 | 56 |
| 2010 | 7126 | 21 | 0.29% | 8 | 29 | 10 |
| 2011 | 7143 | 14 | 0.20% | 17 | 31 | 20 |
| 2012 | 7136 | 15 | 0.21% | 26 | 41 | 23 |
| 2013 | 7142 | 8 | 0.11% | 4 | 12 | 8 |
| **Total** | | **875** | | **862** | **1626** | **813** |

### 2.1.2 Mergers and Acquisitions Data

The M&A sample is from SDC U.S. Mergers and Acquisitions database. SDC is by far one of the most widely used M&A database. The same limitations as those found in creating the bankruptcy data set are present for the M&A data set. Firms should have at least 3 years of data for all of the independent variables used in the prediction models as well as all control variables we need to analyze the target abnormal return around the event announcement. Of the primary SDC M&A dataset, after merging with COMPUSTAT and CRSP data sets and removing firms with insufficient data points, a sample of 1378 firms is finalized to be used in analyses.

## 2.2 Variable Selection

Independent variables, which one and how many to use, can be selected based on different criteria. In terms of number of observations for each firm-variable, many -mostly older- studies used one single data point, mostly one year prior to the event, while others use several data points for each firms-variable, having in mind that the failure is a result of a process happening in the firm from years prior to the actual event. The degree of prediction model power associated with these two different choices is a controversial question we examine in the first part of this study.

As for which explanatory variables to use in the first place, the main criterion for selecting them is their popularity, which is the frequent appearance in the related literature. The idea is that these frequently used variables are proved to be effective in the prediction process. As a large number of variables, both from firms' fundamentals to market and economy data, were introduced in related literature, a systematic and intuitive way would be to try to cover all aspects of firms' characteristics in selecting variables.

Courtis (1978) categorizes 79 financial ratios in three main groups: (a) profitability ratios; (b) managerial performance ratios and (c) solvency ratios. Market, industry and macroeconomic variables are added in years to come by other researchers. For example Foster (1986) and Rose et al. (1982) use macroeconomic variables in their prediction models. This study uses variables, mostly ratios, to capture profitability, performance, and solvency as well as market condition and firm specific risk. Table 2–2 presents the final explanatory variables as inputs for failure prediction models and these variables' sources. The following Table, 2–3 summarizes the simple statistics calculated for each independent variable.

Table 2–2: Independent variables, Their Descriptions and Sources;
Table summarizes Independent variables used to model bankruptcy prediction, their description and their corresponding dataset.

| | Description | Source |
|---|---|---|
| Size | Log of Firm's Market Value | COMPUSTAT |
| QATL | Quick Assets Divided by Total Liabilities | COMPUSTAT |
| STA | Sales Divided by Total Assets | COMP \CRSP |
| TDTA | Total Debt Divided by Total Assets | COMPUSTAT |
| NISHE | Net Income Divided by Shareholders Equity | COMPUSTAT |
| Contraction | Dummy variable equal 1 if date is reported as Contraction | NBER |
| R2 | The R-Squared from the regression (firm return over Market's) | CRSP |
| Age | Number of Years Appearing In COMPUSTAT database | COMPUSTAT |

Table 2–3 is divided into three sections, summarizing all, bankrupt, and non-bankrupt firms in order to make it easier to compare values between the two main categories.

Table 2–3: Statistics

Table summarizes independent variables by illustrating their Mean, Standard Deviation, Minimum, and Maximum. These statistics are reported for both all firm-year data in the database and last-year data. This is because logit models uses just one year of observations for each firm while other models use multiple-year observations. Table also compares statistics for All, Failed and Not-Failed groups. The number of observations are: All: 6683, Bankrupt:3527, non-bankrupt:3126 for all-years and 1626, 826, 806 respectively for last-year columns.

| | | All | | | | Last Year | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Variable | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max |
| All | size | 4.17 | 1.90 | -4.45 | 12.15 | 3.78 | 2.03 | -4.45 | 11.58 |
| | QATL | 0.80 | 2.45 | 0.00 | 130.68 | 0.62 | 1.40 | 0.00 | 30.74 |
| | STA | 1.27 | 0.98 | 0.00 | 17.40 | 1.33 | 1.07 | 0.00 | 9.46 |
| | TDTA | 0.35 | 0.35 | 0.00 | 7.49 | 0.43 | 0.50 | 0.00 | 7.49 |
| | NISHE | -0.13 | 18.85 | -699.39 | 944.37 | -0.48 | 9.90 | -211.54 | 73.96 |
| | Contraction | 0.11 | 0.32 | 0.00 | 1.00 | 0.11 | 0.31 | 0.00 | 1.00 |
| | R2 | 0.06 | 0.10 | 0.00 | 0.93 | 0.06 | 0.11 | 0.00 | 0.75 |
| | Age | 13.33 | 6.49 | 3.00 | 34.00 | | | | |
| Bankrupt | size | 4.07 | 1.72 | -4.45 | 10.43 | 3.51 | 1.76 | -4.45 | 9.72 |
| | QATL | 0.65 | 2.92 | 0.00 | 130.68 | 0.38 | 0.90 | 0.00 | 18.32 |
| | STA | 1.26 | 1.04 | 0.00 | 17.40 | 1.34 | 1.13 | 0.00 | 9.46 |
| | TDTA | 0.42 | 0.37 | 0.00 | 7.49 | 0.53 | 0.56 | 0.00 | 7.49 |
| | NISHE | -0.26 | 25.84 | -699.39 | 944.37 | -0.88 | 13.47 | -211.54 | 73.96 |
| | Contraction | 0.11 | 0.32 | 0.00 | 1.00 | 0.14 | 0.35 | 0.00 | 1.00 |
| | R2 | 0.05 | 0.08 | 0.00 | 0.61 | 0.04 | 0.07 | 0.00 | 0.58 |
| | Age | 13.44 | 6.81 | 3.00 | 34.00 | | | | |
| Not-Bankrupt | size | 4.26 | 2.06 | -4.38 | 12.15 | 4.04 | 2.23 | -4.33 | 11.58 |
| | QATL | 0.96 | 1.85 | 0.00 | 59.55 | 0.87 | 1.73 | 0.00 | 30.74 |
| | STA | 1.28 | 0.91 | 0.00 | 8.18 | 1.33 | 1.02 | 0.00 | 8.18 |
| | TDTA | 0.27 | 0.30 | 0.00 | 4.23 | 0.33 | 0.42 | 0.00 | 4.23 |
| | NISHE | 0.01 | 6.57 | -134.47 | 225.22 | -0.07 | 3.77 | -44.69 | 50.09 |
| | Contraction | 0.11 | 0.32 | 0.00 | 1.00 | 0.07 | 0.26 | 0.00 | 1.00 |
| | R2 | 0.07 | 0.12 | 0.00 | 0.93 | 0.08 | 0.14 | 0.00 | 0.75 |
| | Age | 13.21 | 6.15 | 5 | 34 | | | | |

### 2.3 Methodology

We use survival analysis, logit regression, and Artificial Neural Networks to predict bankruptcy in order to categorize the M&A activity targets into distressed versus non-distressed firms. The ultimate idea is to compare the target shareholder premiums for these two groups. The premium is calculated in terms of target stock price jump around the event announcement. A more comprehensive discussion on premium calculations is presented in the following sections. Methodologies used to construct a failure prediction model, are presented here in more detail.

#### 2.3.1 Survival Analysis

Survival Analysis is a data analytic approach, which addresses problems that either "time until an event" or "hazard rate at each point in time" is output variable of interest. The approach has been existed for a long time and was used in warfare reliability estimation in the onset of the World War II. In the post-war period, the model found its way to private industry clients like financial and health care enterprises. The original "event" to study was death and hence the name "survival analysis". The analysis has many applications now such as predicting time to death, stock market crash, bankruptcy, or machinery failure among others.

In survival analysis jargon, *time* refers to survival time because it is the duration that the subject of the study has survived before the event happened. In bankruptcy prediction literature, *time* represents the period that firm has survived until the bankruptcy event happened. What is very important to note is that survival analysis must consider the ”not happening” of the event, too. This is called “censoring” and it refers to a situation that “survival time” is not known exactly because subject either does not experience the event, or exits the sample because of a reason other than the event itself. Firms that do not file for bankruptcy in the sample period or those which are dropped from the sample because of other reasons such as mergers are among censored data points in the sample. Taking censored observations into account and incorporating their information into the analyses is one of the advantages of survival analyses over ordinary regression models. Thanks to having a two-part dependent variable compared to a normal one-part variable that is used in regression analyses, the survival model has the ability to include censored observations in the analysis. The dependent variable contains information about both the event status, which means if it has happened or not, and the time to the happened event. Having this kind of dependent variable, one can then estimate two functions that are dependent on time, namely the survival and hazard functions. The survival and hazard functions are key concepts in survival analysis for describing the distribution of event times. The survival function gives, for every given time, the probability of surviving (or not experiencing the event) up to that time. The hazard function gives the potential that the event will occur, per time unit, given that the study subject, firms in our case, has survived up to the specified time.

Figure 2–2 shows the survival analysis input structure. The first firm, Firm ID = 1, has filed for bankruptcy in year 4, this event is shown as Failed = 1 in the last column. This firm has 4 years of data corresponding to 4 years before its filing. As no bankruptcies were filed during the first 3 years, the Failed  Censored variable equals "0" for these years, and as firm has survived during all these years the survival time goes from 1 to 4 which shows the period that firm has survived until the bankruptcy occurred. The third firm, Firm ID = 3, has 4 years of data, too. As opposed to the first firm, this firm has never filed for bankruptcy. We show this not-presence of the event by putting zeros for all firm-year observations. This firm is an example of a censored firm. This firm has never experienced the event we are studying (bankruptcy) in our sample.

| Firm ID | Survival Time | Indep 1 | Indep 2 | ... | Indep N | Failed(1)/ Censored(0) |
|---|---|---|---|---|---|---|
| 1 | 1 | | | | | 0 |
| 1 | 2 | | | | | 0 |
| 1 | 3 | | | | | 0 |
| 1 | 4 | | | | | 1 |
| 2 | 1 | | | | | 0 |
| 2 | 2 | | | | | 0 |
| 2 | 3 | | | | | 1 |
| 3 | 1 | | | | | 0 |
| 3 | 2 | | | | | 0 |
| 3 | 3 | | | | | 0 |
| 3 | 4 | | | | | 0 |

Figure 2–2: Survival Data Sample

Our goal from using survival analysis is to estimate and interpret the hazard function from our data, compare hazard probabilities and assess the relationship between independent explanatory variables and survival times. To accomplish these, we need the mathematical model of survival analyses. The model we use here is one of the most popular ones, the Cox proportional hazard (PH) model.

### 2.3.2 Survival Analysis - The Model

Survival analysis model relates the time before an event occurs to one or more independent variables that the researcher believes may be associated with that quantity of time. In a proportional hazards model, the unique effect of a unit increase in an independent variable is multiplicative with respect to the hazard rate.

Before calculating hazard rate we need to introduce some basic survival model background; Assume a random variable, 'time', records our study survival time. The probability density function PDF, or $f(t)$, describes the likelihood of observing our random variable at time $t$ among all other survival times. The probability of observing a survival time comes from incorporating this density function over a range of survival times.

The cumulative distribution function (cdf), or $F(t)$, is the probability of observing the random variable 'time' less than or equal to some time $t$. We can show this probability mathematically as $P(Timet)$ and calculate it by adding up all probabilities up to time $t$:

$$F(t) = \int_0^t f(u)du \tag{2.1}$$

What is interesting to us is to have a simple transformation of this function, which we calculate Survival Function. It describes surviving not before but after our time, $t$. Mathematically it is calculated by subtracting our $F(t)$ function from one:

$$S(t) = 1 - F(t) \tag{2.2}$$

Coming back to hazard rate, which basically calculates the relative probability of the event occurring at time $t$, conditional on the study subject's survival up to that time. Hazard rate is calculated from following equation.

$$h(t) = \frac{f(t)}{S(t)} \tag{2.3}$$

In this way, the hazard rate basically expresses the instantaneous rate of failure at any specific time $t$ and ignores the accumulation of hazard up to that time. The cumulative hazard function, sums hazards over the period of time. The formula to calculate it is shown below:

$$H(t) = \int_0^t h(u)du \tag{2.4}$$

The Cox proportional hazard (PH) model, is the most popular hazard model. Its advantage is that the baseline hazard, $h_0(t)$, is an unspecified function. This is why the model is a semi-parametric and is the best choice when no known parametric model is proved to be useful for the study. The positive point of this Cox PH model is that it is a robust model, so that the results from using the Cox model will closely approximate the results for the correct parametric model.

The model has two forms, one, which incorporates just time-independent variables, and the extended one, which allows the use of time-dependent variables. We use the extended Cox PH model as our data nature consists of time-dependent explanatory variables. The general model of the extended Cox PH model is presented here:

$$h(t, X(t)) = h_0(t) exp[\sum_{i=1}^{p1} \beta_i X_i + \sum_{i=1}^{p2} \sigma_j X_j(t)] \tag{2.5}$$

$$X(t) = \{(\underbrace{X_1, X_2, ..., X_{p_1}}_{\text{Time-Independent}}, \underbrace{X_1(t), X_2(t), ..., X_{p_2}(t)}_{\text{Time-Dependent}})\} \tag{2.6}$$

The model shows the hazard rate at time, t, for a firm with specification represented by time-dependent variables denoted by X. In this way, independent explanatory variables in X are being modeled to predict firm's hazard rate at each point in time. The extended Cox PH models consists of two parts, baseline hazard function $h_0(t)$ and an exponential function which contains both time-independent, $X_i$ and time-dependent variables, $X_j(t)$.

The regression coefficients in the extended Cox PH model are estimated using Maximum Likelihood procedure. The regressions were run in STATA survival analysis package.

The hazard ratio for extended Cox PH model is calculated from following formula:

$$\frac{\hat{h}(t, X^*(t))}{\hat{h}(t, X(t))} = exp[\sum_{i=1}^{p1} \hat{\beta}_i [X_i^* - X_i] + \sum_{j=1}^{p2} \hat{\delta}_j [X_j^*(t) - X_j(t)]] \tag{2.7}$$

The formula shows the ratio of hazards at a particular time, $t$. Two different variables denoted by $X^*(t)$ and $X_i$ are time-dependent and time-independent explanatory variables, respectively. It is evident here that the hazard ratio is not constant and it is a function of time, and particularly it is positively related to time if $\delta_j$ is positive.

### 2.3.3 Neural Networks

Dr. Robert Hecht-Nielsen, the inventor of one of the first neuro-computers, defines an Artificial Neural Network as: "...a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs." ("Neural Network Primer: Part I" by Maureen Caudill, AI Expert, Feb. 1989)

ANNs have many applications in business. They can be used for approximation, optimization, prediction, and classification. Some tangible neural network applications are analyzing signals to detect explosives, mostly in airline security systems, helping to recognize the shape and evolution of interest rate curves in order to improve asset allocation process, and predicting stock price index. (li, 1994)

ANNs are algorithms trying to model the human cerebral cortex on a much smaller scale. They comprise of several layers, each containing a number of interconnected nodes (artificial neurons) with an activation function. Nodes are inspired from natural human neurons, which receive signals through their synapses located on the dendrites. If the received signal is strong enough to surpass the neuron's threshold, the neuron is activated, and sends a signal through its axon. The natural neuron scheme is shown in 2–3.

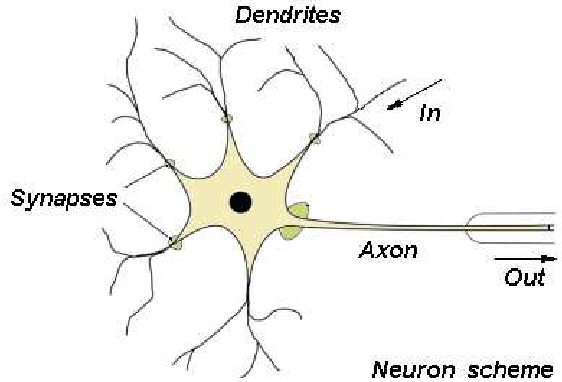


Figure 2–3: Natural Neuron Scheme

Source: Introduction to Neural Network AGH University of Science and Technology, http://home.agh.edu.pl/ vlsi/AI/intro/

In ANNs, an *input layer* transfers the input data multiplied by *weights* to one or several *hidden layers* in which a mathematical function decides the activation of each node. The output, which is computed by nodes function and is based on the inputs and their corresponding weights, then appears in the *output layer*. In this way, by adjusting the input weights we can get the output we want for the specific inputs that we feed to the network. The process of adjusting weights for all the nodes in each model (this could be hundreds of thousands of nodes) to get the desirable result, is called *training* process. A schematic of the introduced structure is graphed in 2–5.

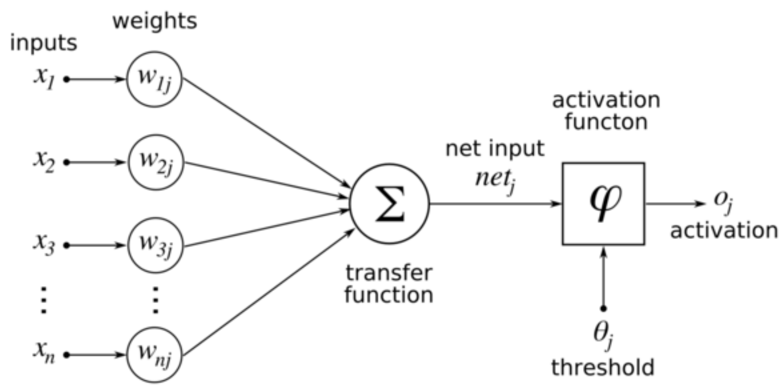


Figure 2–4: Artificial NeuronSource:Diagram of an artificial neuron, Wikipedia.org

We use a ANN simulator to model our bankruptcy prediction tool. The Neural Network simulator first divides the input data into three categories: *Training*, *Validation*, and *Test* subsets. The first step is calculating the gradient, changes that need to be done to nodes' weights and biases using training subset. Next in the training process, the error on the validation set is observed. *Training* and *validation* sets errors usually decrease during the initial phase of the training. The only time when *validation*set error rises is the time that model starts to over-fit the data. The network weights and biases are saved at the minimum of the *validation* set error. The *test* is only used to compare different artificial neural network models but is not used in the modelling process, itself.

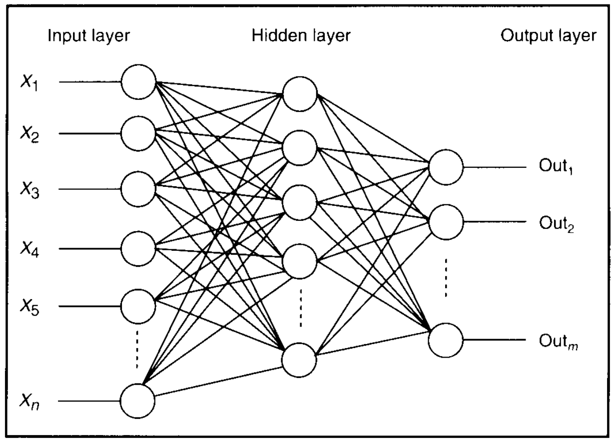


Figure 2–5: Neural Network Scheme

Source:Neural Networks in Trading, MechanicalForex.com

### 2.3.4 Event Study

Event study is a method to evaluate the effects of a specific event such as merger and acquisition, dividend change, and proxy contest on the value of the firm as well as being a test for market efficiency. Because of this two-sided issue, it is usually said that an event study is always a joint test. Basically by doing event study, one can study the market reaction to a specific event. Two types of event studies are usually done in finance: short-horizon and long-horizon studies, which refer to study window the researcher choose to analyze. There is no fixed window definition for short and long-run studies, for example Kothari and Warner (2006) defined the windows of less than a year as a short-run while others like Mackinlay (1997) suggested a very smaller periods such as 20-day period for their short-run studies.

The following assumptions have to be made in order to use the event study methodology: that financial markets are at least semi-strong efficient, that there is an available asset pricing model to measure the returns adjusted for everything but the event itself, that the stock returns are normally distributed, that in the period of study no other information other than event exist, and that there is no risk shift as a result of the event.

**Short-Run Event Study**

In the short run event study the idea is basically to calculate the predicted return predicted by an asset pricing model and comparing it with the actual return at the time of the event. The abnormal return calculated from subtracting these two returns would be the effect of the event on the firm value. In this sense, it is obvious that the event study test is a joint test meaning that it assumes that the asset pricing model is appropriate for estimating the returns and as no one can be confident of the measurement model, the study is always testing both asset pricing model and market efficiency together. There are two different methods for conducting an event study: Classic Two-Stage and Dummy variable methods. The general procedure of a two-stage event study is used in this study.

The pre-study step would be selecting the event and finding appropriate dates corresponding to the selected event. For this study, the event is acquisition of other firms and the announcement date is used to study the event. The next step is defining the event window. After defining the inputs and windows, the first step of the event study is to estimate the normal return using a simple market model.

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it} \tag{2.8}$$

The abnormal returns are then can be calculated by comparing the estimated normal firm return using $\alpha_i$ and $\beta_i$ with the actual observed returns.

$$CAR = \Sigma(Actual(r_{it}) - E(r_{it})) \tag{2.9}$$

We use 250 days ending at 45 days prior to the event as estimating windows. *Eventus* package is used to run all the event studies.

# CHAPTER 3
## Results

In order to analyze the differences between announcement gains of distressed and non-distressed targets, we need a model to categorize targets into these two groups. We compare three different bankruptcy prediction models and use the most reliable one to categorize targets. These models are Survival Analyses, Logit, and Artificial Neural Networks.

It is well documented in the literature that Survival Analysis, as it takes the year-by-year changes in different variables into account, can predict bankruptcy better than other models (Shumway, 2001). More recent studies assert that Neural Networks are highly powerful, too. As, to the best of our knowledge, there was no comparison of ANN and Survival Analysis models in the literature, we decided to compare their prediction power by using same set of data as their input. Logitistic regression model is also included in the comparison, because it is one of the easiest, most straightforward, and powerful methods of categorization, which is used by many researchers in the related papers. Using the biggest sample possible covering bankruptcies reported in SDC database as well as CRSP from 1980 to 2013, we run all three models, namely survival analysis, logistic regression analysis, and artificial neural networks to predict bankruptcy as a final consequence of firm being distressed for a long time.

This study is different from that of Ang and Mauck (2011) in a particular way. We look at nearly bankrupt firms as opposed to distressed firms, which are proxied by having reported two years of consecutive negative net income.

In the following sections we investigate the in-sample power of each model and we use the most powerful one to categorize our M&A targets during the period between 1980 and 2013. A sample of 1626 firms with all needed data available is used in this step. Following the categorization, a thorough study on both target and bidders' stock market reaction to announcement as well as target's premium is presented.

### 3.1 Survival Analysis

A survival analysis was conducted in order to predict hazard rates in the upcoming year for each target. The analysis is done using 1626 firms and 6683 firm-year observations. Half of the analyzed firms have filed for bankruptcy during the time period between 1980 and 2013, and the rest are their matches based on industry, age, size measured by the log of total assets, and data year. The entire analyzed firms in the sample have all the independent variables reported in the corresponding years.

We used eight explanatory variables to create the hazard model. Most of these variables are selected from previous studies showing their significant effect on distress prediction; others were included as possible effective not-previously-used variables.

Independent variables, their descriptions, and their calculation formula and source is presented in Table 2–2.

Table 3–1: Independent variables, Description, Source

| | Description | Source |
|---|---|---|
| Size | Log of Firm's Market Value | COMPUSTAT |
| QATL | Quick Assets Divided by Total Liabilities | COMPUSTAT |
| STA | Sales Divided by Total Assets | COMPUSTAT \CRSP |
| TDTA | Total Debt Divided by Total Assets | COMPUSTAT |
| NISHE | Net Income Divided by Shareholders Equity | COMPUSTAT |
| Contraction | Dummy variable equal 1 if date is reported as Contraction in NBER | NBER |
| R2 | The R-Squared from the regression (firm return over Market's) | CRSP |
| Age | Number of Years Appearing In COMPUSTAT database | COMPUSTAT |

The correlation matrix of the independent variables is shown in Figure 3–2. The highest correlation factor is 0.55 between $R2$ and Size. Overall, the correlations are in the acceptable range and they seem not to impose a significant co-linearity problem according to Farrar and Glauber (1967).

Table 3–2: Independent variables' Correlation Matrix;
Table shows the correlation coefficient among independent variables, high correlation may cause problems in regression estimates.

| | Size | QATL | STA | TDTA | NISHE | Contraction | R2 | Age |
|---|---|---|---|---|---|---|---|---|
| Size | 1 | | | | | | | |
| QATL | -0.0186 | 1 | | | | | | |
| STA | -0.2079 | -0.0905 | 1 | | | | | |
| TDTA | -0.0913 | -0.2056 | -0.0559 | 1 | | | | |
| NISHE | 0.016 | -0.0013 | -0.0228 | 0.0259 | 1 | | | |
| Contraction | 0.0401 | 0.0039 | -0.02 | 0.0421 | 0.0276 | 1 | | |
| R2 | 0.5528 | -0.0135 | -0.1315 | -0.0707 | 0.0058 | 0.1603 | 1 | |
| Age | 0.1779 | -0.0475 | 0.0597 | -0.0234 | -0.0051 | 0.0795 | 0.2385 | 1 |

The survival analysis results are reported in Table 3–3. Two different models were run; one with exact explanatory variables' values and one incorporating their winzorised values at 0.5 percent level. The first column represents the regression results using the exact values while the results using winzorised values are reported in the second column.

Size coefficient is not statistically significant but the sign is in line with previous studies showing that smaller firms tend to be more prone to bankruptcy. Quick assets to total liability, the second independent variable, is negative and statistically significant in one percent level. Firms with less liquidity and at the hand assets, as a ratio to total liability, are closer to experience a failure in the times of hardship as their safety cushion to cover their short-term liabilities is smaller. A similar relation is observable for the Sales to Total Assets variable. Higher Total Debt to Total Assets is positively related to bankruptcy probability in the following year, and is significant at the 5 percent level. The more debt the firm uses in its capital structure the higher the bankruptcy risk. This theory is covered in corporate finance literature as the "bankruptcy cost of debt", the main reason that firms have a limit to use debt financing although the method has significant advantages. Net income to Shareholder's equity coefficient is positive and significant in the first column but negative and insignificant in winsorized analysis. The negative result is more inclined to previous studies as, intuitively, firms with the ability to generate higher net incomes tend to be more able to prevent distress. Contraction has a significant positive relation with bankruptcy and firm's risk measure, defined by the r-squared from regressing firm's daily return over market return in the previous year, and age are negatively related to the probability of default in the coming year. The r-squared shows the degree to which market return can describe firm's return so the higher r-squared means less firm specific risk. A negative coefficient suggests that less risky firms have lower probability of failure.

We used STATA statistical package to perform the survival analysis on bankruptcy data. Helpful graphs from the software are presented here in order to better summarize the results as well as to help recognize the power of the prediction. Figure 3–1 shows the hazard function and the hazard change as time passes. As it can be observed from the graph, hazard rate increases as the time of bankruptcy, here year 5, approaches.

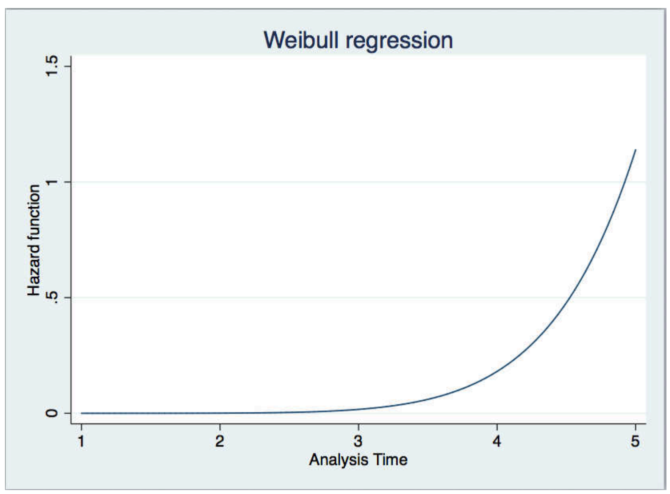


Figure 3–1: Hazard Rate Change As time Passes

Figure 3–2 illustrates the mean hazard rate in different years for both bankrupt and not-bankrupt firms, the hazard rate for bankrupt firms increases more in the years previous to bankruptcy filing.

Table 3–3: Survival Analysis Regression Results;

Table reports the Survival Analysis output. Size is the log of total assets, QATL is the quick assets to total liability ratio, STA is calculated by dividing sales by total assets, TDTA is total debt to total assets ratio, NISHE is net income to shareholder's equity ratio, Contraction is the dummy variable which is equal 1 if in economic contraction and zero otherwise, R2 is the r-squre of the regression of firm's return on market's return, and Age is the number of years in Compustat. Multiple-year observations for all the mentioned independent variables were used to run the Cox proportionate hazard model in order to assess the relationship between firm failure and its hypothesized drivers. Two columns of coefficients are presented; Column 1 reports the coefficients from the analysis using actual independent variables values while Column 2 reports the output of the model using winsorised values in order to remove outliers.

| | (1) | (2) |
|---|---|---|
| VARIABLES | Coeff. | Coeff. Win. |
| Size | -0.0370 | -0.0364 |
| | (0.0235) | (0.0247) |
| QATL | -0.398*** | -0.463*** |
| | (0.0826) | (0.0917) |
| STA | -0.0767** | -0.0839** |
| | (0.0374) | (0.0398) |
| TDTA | 0.139** | 0.272*** |
| | (0.0685) | (0.0979) |
| NISHE | 0.000624*** | -0.0106 |
| | (0.000136) | (0.0118) |
| Contraction | 0.370*** | 0.368*** |
| | (0.109) | (0.109) |
| R2 | -2.488*** | -2.498*** |
| | (0.581) | (0.605) |
| Age | -0.0340*** | -0.0338*** |
| | (0.00684) | (0.00682) |
| Constant | -14.22*** | -14.15*** |
| | (0.511) | (0.511) |
| Observations | 6,683 | 6,683 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

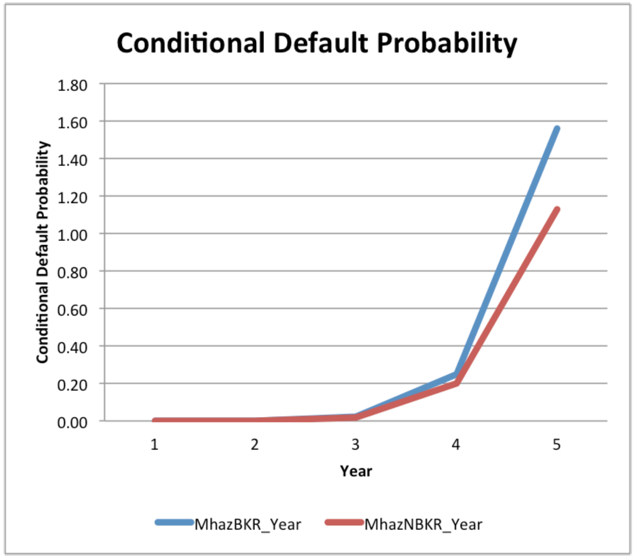


Figure 3–2: Conditional Default Probability;

BKR is associated to bankrupt firms and NBKR to not-bankrupt ones. The hazard rate for each year is reported.

The following graphs present the histograms of hazard rates for the two categories, namely bankrupt and not-bankrupt firms. The histogram is skewed to left toward lower hazard rates for the non-bankrupt firms and more inclined to right and higher rates for distressed firms. Although the difference is observable between the two groups, it seems that the distinction is not very clear, and the model may not have the acceptable power to predict bankruptcy accurately.

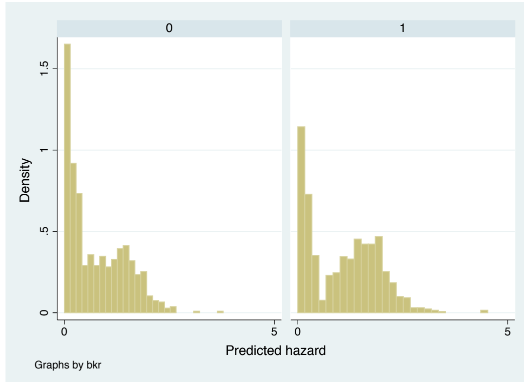


Figure 3–3: Probability Distribution of bankruptcy; Two-sided Histogram; Zero (0) corresponds to non-bankrupt firms while One (1) represents bankrupt ones.

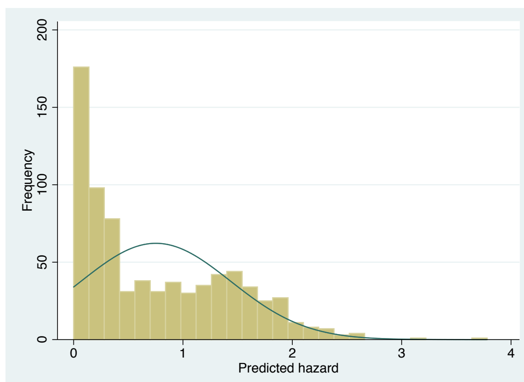


Figure 3–4: Probability Distribution of bankruptcy for Non-bankrupt firms

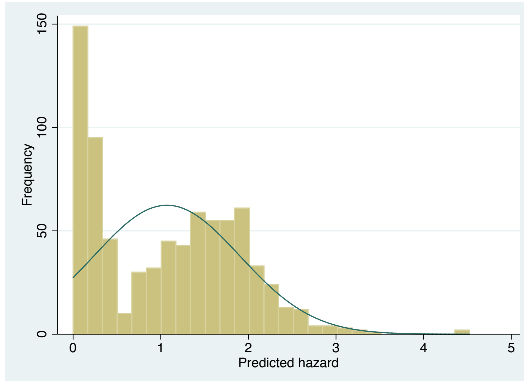


Figure 3–5: Probability Distribution of bankruptcy for bankrupt firms

The prediction power of the model can be evaluated more precisely by constructing a Confusion Matrix using predicted values for firms in the sample. This matrix shows the percentage of correct and incorrect predictions of the model in different categories, more specifically it calculates the types I and II errors of the prediction model. The in-sample confusion matrix for survival prediction model is presented in Figure 3–6.

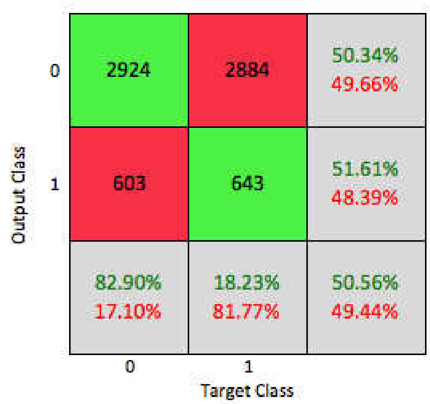


Figure 3–6: Survival Confusion Matrix

From the confusion matrix, the model predicts 50.56 percent of the bankruptcies correctly, which is very poor and not really different from pure chance. The model tends to over-predict the non-bankrupt firms and categorize them in the distressed group. In other words the model's type I error is high but it does a fairly acceptable job in categorizing healthy firms into the correct group. Overall, it seems that the survival model does not have the needed prediction power to be used for further analyses. This contradicts the studies reporting results in favour of the model. This may be because of the nature of the data set used here and its differences with previously used samples. Existing studies tend to use a few years of data and a limited number of firms, while we use the biggest sample for which we could get the needed variables. The independent variables used were also different from those in previous studies.

## 3.2 Logit Model

The second model, one of the most popular ones in the failure prediction literature, is a simple straightforward logistic regression model. The dependent variable is *1* when firm is bankrupt and *0* otherwise. We use the same explanatory variables as those used in modelling survival analysis. The main difference here is that the logit model uses only one year of data, contradicting survival analysis, which uses 5 years of data, to predict. Each firm's last year of observation is used, which corresponds to firm's situation right before the official bankruptcy filing. The regression output is presented in Table 3–4.

Table 3–4: Logit Analysis Regression Results;

Table reports the Logit Regression output. Size is the log of total assets, QATL is the quick assets to total liability ratio, STA is calculated by dividing sales by total assets, TDTA is total debt to total assets ratio, NISHE is net income to shareholder's equity ratio, Contraction is the dummy variable which is equal 1 if in economic contraction and zero otherwise, R2 is the r-squre of the regression of firm's return on market's return, and Age is the number of years in Compustat. Single-year observations for all the mentioned independent variables were used to run the logit model in order to assess the relationship between firm failure and its hypothesized drivers. Two columns of coefficients are presented; Column 1 reports the coefficients from the analysis using actual independent variables values while Column 2 reports the output of the model using winsorised values in order to mitigate the effects of outliers.

| EQUATION | VARIABLES | (1) | (2) |
|---|---|---|---|
| bkr | Size | -0.0296 | -0.0316 |
| | | (0.0327) | (0.0349) |
| | QATL | -0.580*** | -0.702*** |
| | | (0.104) | (0.114) |
| | STA | -0.0779 | -0.0962* |
| | | (0.0512) | (0.0561) |
| | TDTA | 0.615*** | 0.799*** |
| | | (0.156) | (0.176) |
| | NISHE | 0.000424 | -0.0307 |
| | | (0.000629) | (0.0197) |
| | Contraction | 0.885*** | 0.910*** |
| | | (0.189) | (0.191) |
| | R2 | -4.007*** | -4.181*** |
| | | (0.710) | (0.756) |
| | Constant | 0.0843 | 0.0971 |
| | | (0.211) | (0.226) |
| | Observations | 1,626 | 1,626 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The general regression results, in terms of signs and significance levels of coefficients, for logistic and survival analysis models are closely related. The first difference is Sales to Total Assets ratio, which is significant in survival analysis, but not in the non-winzorised-data logistic regression, coefficients' signs are negative in all cases and they are significant in winzorised-data regression, too. A similar result is observable for Net Income to Shareholder Equity ratio. Fewer data points seem to be the reason for observed differences.

The prediction power of logit model is higher than survival model. As Figure 3–7, the logistic model confusion matrix, points out, the model correctly predicts 65.40 percent of times. Judging by comparing model accuracy calculated from both the confusion matrices, the logit model is significantly more accurate than the survival model. This shows that although we are using less data in this model than we do in survival analysis, we are able to predict failure more accurately.

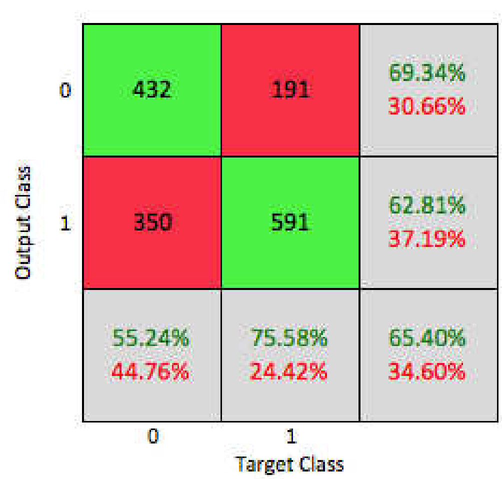


Figure 3–7: Logit Model Confusion Matrix

### 3.3 Neural Network

Artificial Neural Networks, containing highly interconnected processing elements, are algorithms that try to imitate human cerebral cortex in a much smaller scale. These models had been used in predicting bankruptcies from early 1990s and several studies reported better performance compared to logit and multiple discriminant analyses (MDA) models. We use *Matlab's Neural Network Toolbox* to train and simulate the appropriate Neural Network Model to predict bankruptcy. The same data that were used in survival analysis and logistic regression model are used here. Data set consists of five years of observations for our eight explanatory variables for 813 bankrupt as well as 813 matched firms from non-bankrupt group. The network has three layers, input, hidden, and output; there are 10 cells in the hidden layer of the network and output layer produces a number between zero and one, zero means not distressed and one corresponds to distressed firms. A schematic of the Artificial Neural Network used is shown in figure 3–8.

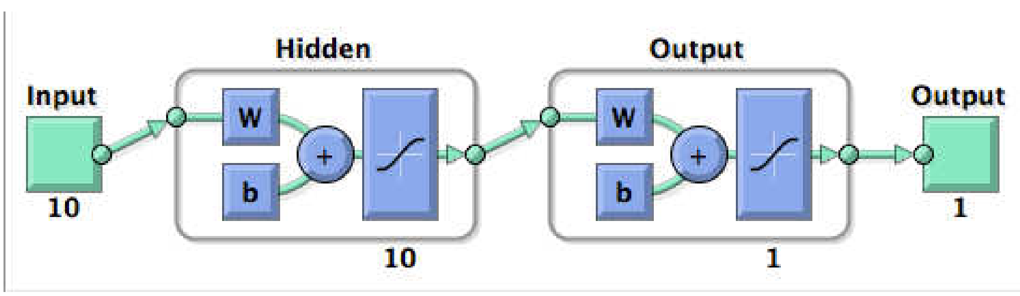


Figure 3–8: Artificial Neural Network Schematic, Source: Matlab Software Output

Matlab NN toolbox produces many helpful graphs to report the neural network training and simulation outputs. The training output is presented in Figure 3–9. The training process reaches its minimum error criteria after 40 iterations. The graph shows that the neural network has achieved the acceptable low error using training and validation subsets. The training report shows the prediction ability of the network.

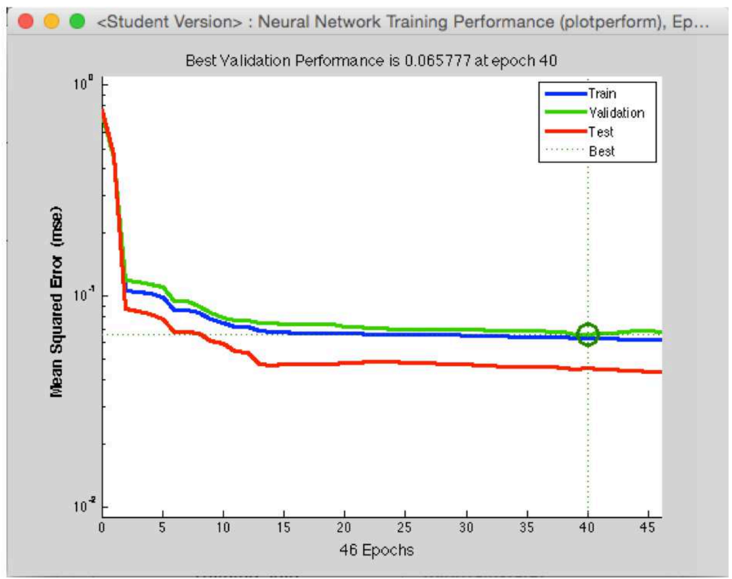


Figure 3–9: NeuralNetwork Training Process output

A more intuitive graph is presented in Figure 3–10. The Receiver Operating Characteristic (ROC) curve is a plot of the true positive rate (sensitivity, which measures the proportion of actual positives which are correctly identified as such) versus the false positive rate (1 - specificity (measures the proportion of negatives which are correctly identified as such)) as the threshold is varied. A perfect test would show points in the upper-left corner, with 100% sensitivity and 100% specificity. The diagonal line in the graph shows a 50-50 chance line. The plot for our model is closer to the corner than to the centre line, which means a high power of the model compared to pure chance.

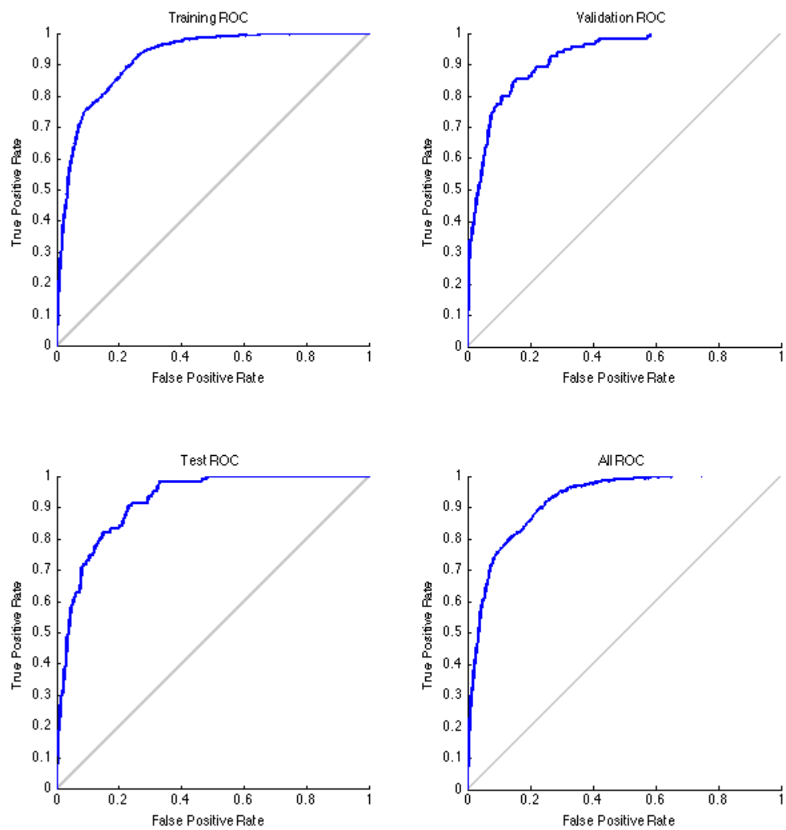


Figure 3–10: Neural Network OPC Chart

Like previous models, we present the Neural Network Confusion Matrix in order to show the prediction power of the trained network. The overall accuracy of the model is 91.4%, a higher accuracy than previous two models. The Confusion Matrix of the Neural Network Model is shown in 3–11.

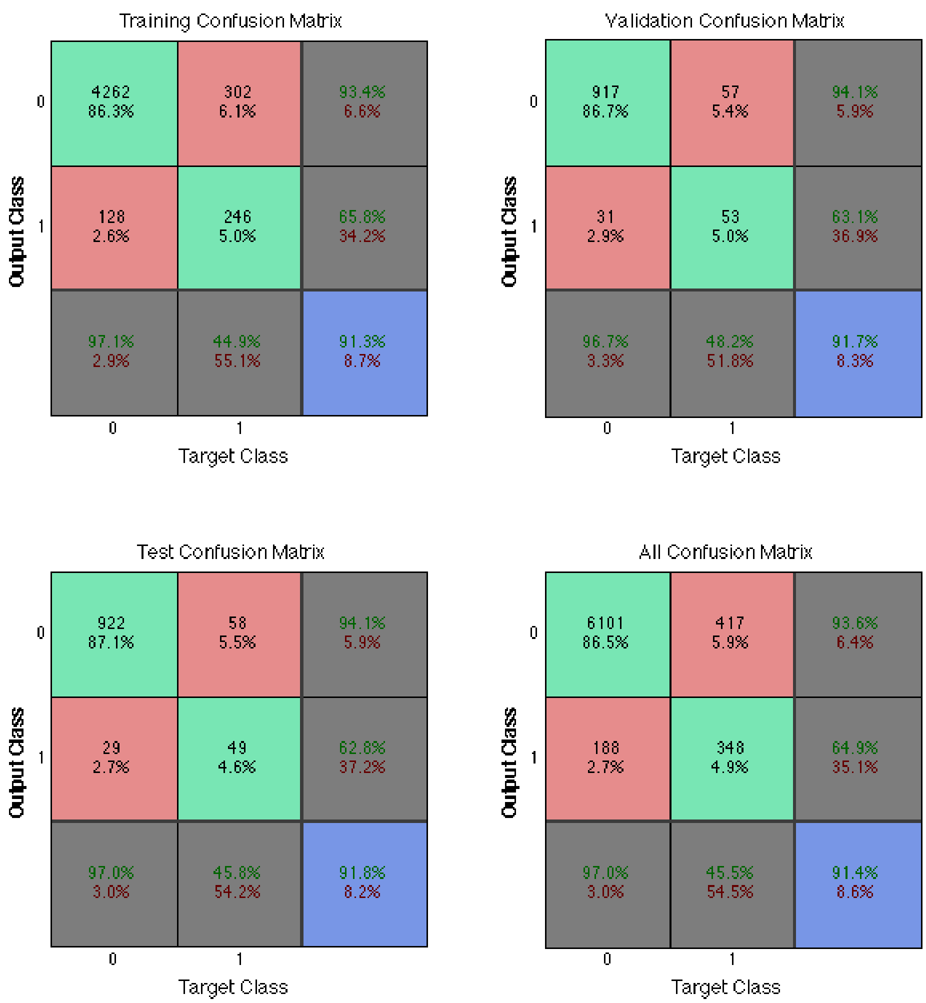


Figure 3–11: Neural Network Confusion Matrix

Comparing the prediction powers of the three models, all using the same sample as their input, it is evident that Artificial Neural Network is more powerful in terms of bankruptcy prediction ability. We used this trained model to categorize our M&A data set targets into two categories; distressed vs. normal. The next step is comparing the announcement return associated to these two target groups.

## 3.4 Targets' Premium Analysis

Regarding the bankruptcy prediction models comparisons, The Artificial Neural Network model was selected to categorize each M&A target in SDC database into two categories, distressed and not-distressed.

Based on the categorization using the trained Neural Network, we conduct an event study on both groups around the merger's announcement date. The idea here is that the market reacts differently to a merger announcement in which the target is in distress and to the one that is not. The event study is done on both targets and bidders and the categorization is dependent on the target status, distressed or not.

The targets' event study result is presented in Figure 3.4. The difference in the mean cumulative abnormal return is identifiable in the graph. The average CAR touches 48% for near-failure firm at announcement while the percentage for normal firms is just 28%. The difference is significant at five percent level for the period of 61 days covering 30 days before M&A activity announcement to 30 days after the announcement.

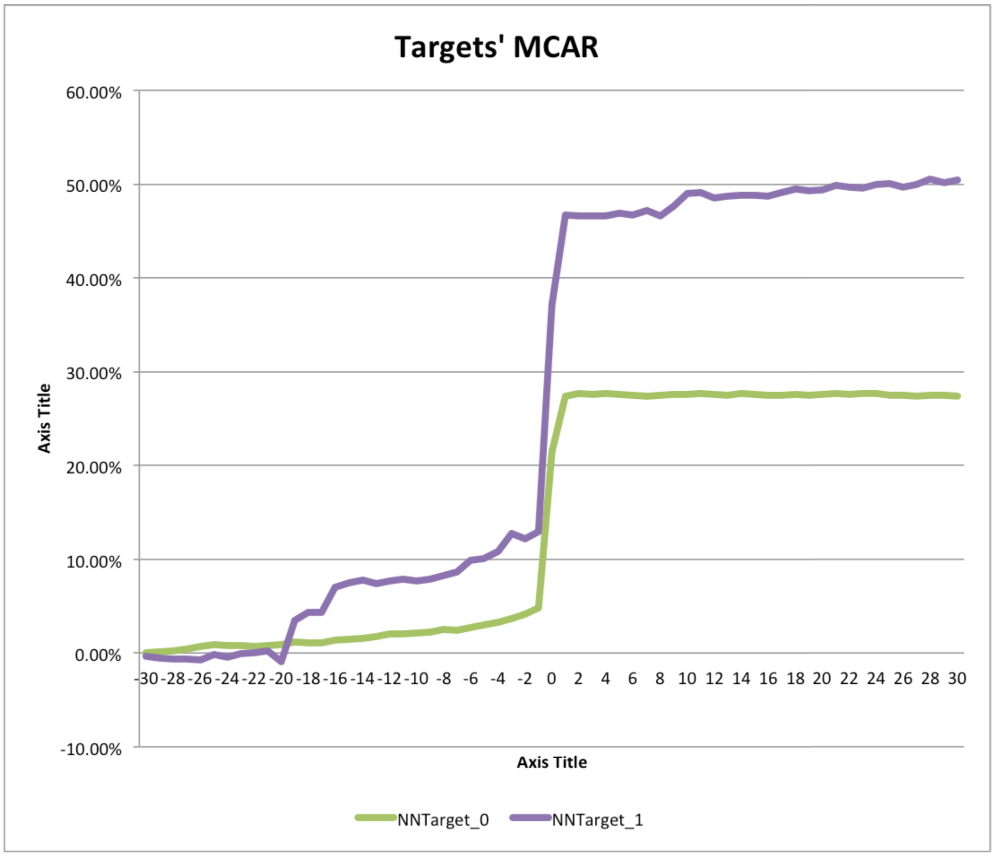


Figure 3–12: Mean Cumulative Abnormal Returns, Targets;
NNTarget_0 corresponds to non-bankrupt targets, NNTarget_1 to bankrupt targets

The higher abnormal return associated with the announcement of the acquisition of a distressed firm can be resulted from the acquirers optimistic bid based on her view on the existing disqualified management team and unfavorable financial situation - cost of equity and debt to name some - and her ability to make better use of target assets in place after changing the management team and optimizing the financial situation. It appears that target shareholders are definitely winners of the acquisition as they are paid a big premium, but a total return analysis is needed to see if the event makes dollar value. Target stakeholders are being paid way more than their current stake in the firm and this pushes the target price up in reaction to the news. This result is in line with Ang and Mauck (2011) as they also report higher premiums for their distressed targets, too. The issue here is that their distressed sample consists of many firms with mild difficulties that reported two years of negative net income. Chances are that bidders' view on these targets is correct and by executing some actions, they may be able to turn the targets around. But our firms are close-to bankruptcy, which means that a great potential of coming back on feet is gone already. The higher premiums that we observe for distressed group compared to normal group can be related to mentioned non-positive mergers activity like management personal goals; it is often asserted in researches that many M&A activities have reasons other than efficiency and synergy like hubris and the management inspiration of empire building. We estimate an event study on bidders around the announcement of the event to see the market's reaction to the announcement in terms of bidders' average price change. The results show a value destruction and negative reaction to the news. Figure 3.4 shows bidders' abnormal return around the announcement. Both groups experience a decrease in their stock price around the merger announcement, which is well documented and reasoned in the M&A literature, but those who bid to acquire distressed targets face a bigger loss.

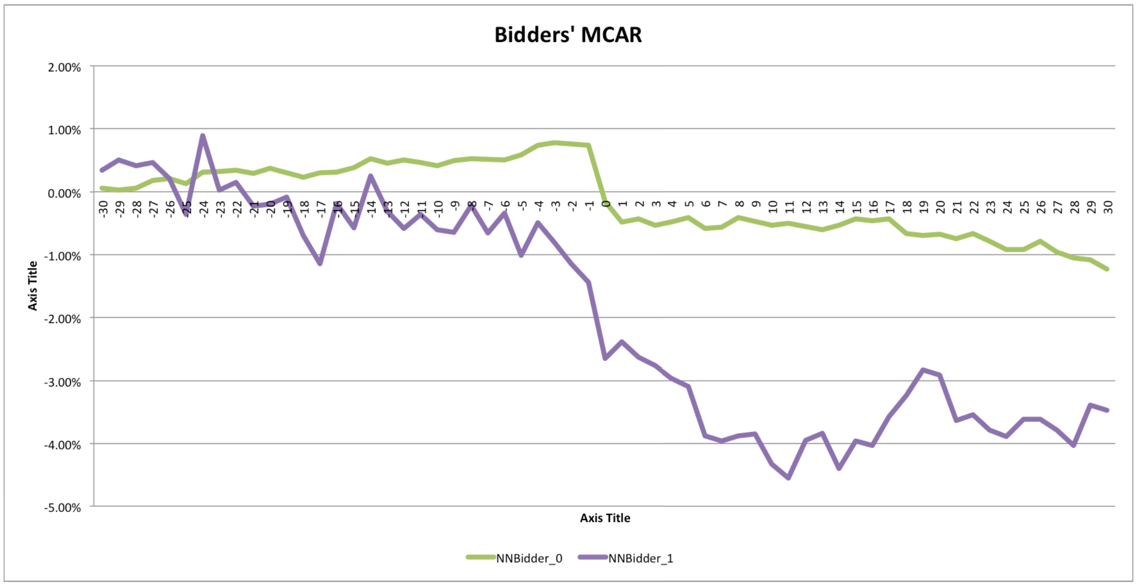


Figure 3–13: Mean Cumulative Abnormal Returns,idders;

NNTarget_0 corresponds to non-bankrupt targets, NNTarget_1 to bankrupt targets; NNTarget_0 corresponds to non-bankrupt targets, NNTarget_1 to bankrupt targets

The higher negative effect of the bid on bidders targeting distressed firms can be associated to the market not being as optimistic as bidders themselves about their ability to turn around targets as much as they are ready to pay in the form of premium to distressed firms' shareholders. In other words, market asserts that bidders are overpaying for the targets. Figure 3.4 shows the total average size-weighted abnormal return for both bidders and targets around the announcement date. As we observed a negative return for the bidders and a positive one for the targets in the previous analyses, from this graph we conclude that target's abnormal return is so high that it compensates for the negative return associated with bidders.

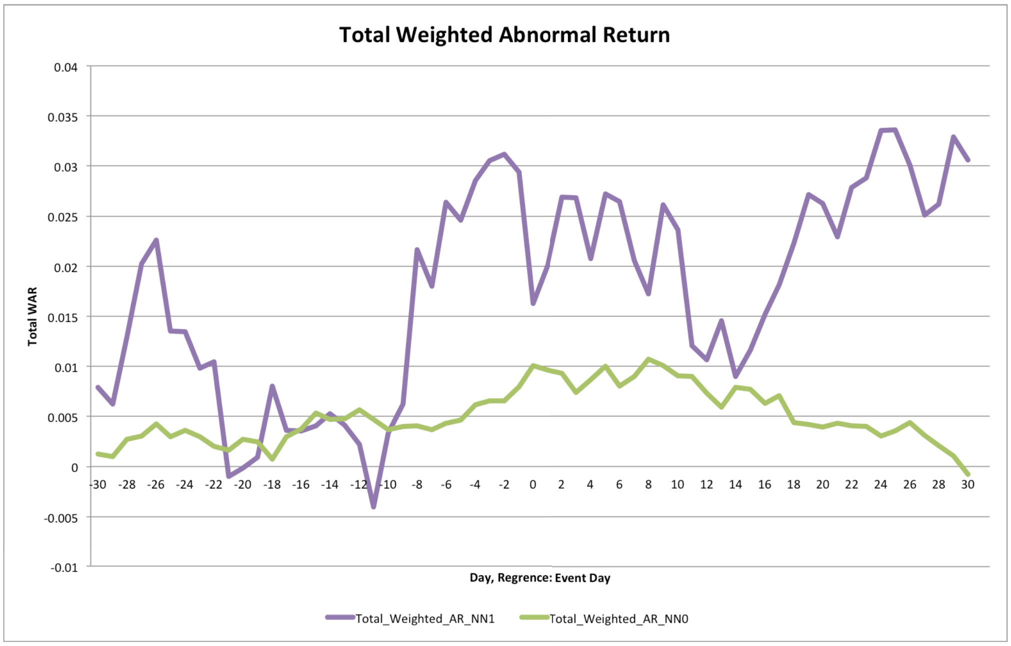


Figure 3–14: Mean Weighted Cumulative Abnormal Returns, Bidder and Target Combined

We use a regression analysis to investigate the relationship between target premium and the category of target, our neural network model output, in more depth. We control for known premium drivers namely, tender offer dummy, market to book ratio, size, horizontal versus vertical acquisition, unsolicited deals, method of payment, and the bid price to 52 week high ratio. Table 3–5 presents the basic statistics of merger and acquisition sample used in the study. The table has two section; distressed and non-distressed firms characteristics are reported in sections one and two respectively.

Correlations between all the used variables were calculated to check for possible col-linearity issue. The biggest correlation is 25% between Horizontal and Consideration offered variables. All others are less than 15%, and no correlation problem exists. Table 3–6 is the regression analysis output. Variables were added to control for the most known drivers of premium differences. The type of payment (ConsiderationOffered variable takes the value of *1* if target is paid by cash and *0* otherwise), market to book ratio, tender offer, horizontal vs. vertical acquisition, and contraction dummy are among control variables. The result shows that the category dummy variable (NN_Out which is 1 if the firm is categorized as bankrupt and 0 otherwise) is positive and statistically significant at one percent level. This is in line with our observation from mean cumulative abnormal return graph. The cumulative abnormal return during the period beginning one day prior to the announcement to one day after it is higher if firm is predicted to be bankrupt in near future.

Table 3–6: Abnormal Return Regression;

Table reports the regression of $(-1, 1)$ window abnormal return associated to targets on Categorization Dummy Variable as well as control variables to isolate the effect of being distressed in captured target stock price appreciation around the announcement. NN_Out is the dummy variable which equals 1 if firm is predicted to be bankrupt and zero therwise, ConsiderationOffered is 1 if method of payment is *Cash*, MB is market to book ratio, TenderOffer dummy is 1 if the acquisition method is tender offer and 0 otherwise, Unsolicited is 1 if the acquisition is unsolicited and zero otherwise, Horizontal dummy variable if both target and bidder are from same industry and 0 otherwise, OfferTo52High is the ratio of the offer price to 52-weeks high price, contraction is a dummy variable equal 1 if the economy is in a contraction period based on NBER and zero otherwise.

| VARIABLES | (-1,1) AR |
|---|---|
| NN_Out | 0.108*** |
| | (0.0373) |
| ConsiderationOffered | 0.0863*** |
| | (0.0186) |
| MB | 0.00124 |
| | (0.00374) |
| TenderOffer_Dummy | 0.0958*** |
| | (0.0296) |
| Unsolicited_Dummy | -0.0714** |
| | (0.0282) |
| Horizontal | 0.0327* |
| | (0.0181) |
| OfferTo52High | 0.0156* |
| | (0.00833) |
| contraction | 0.0657*** |
| | (0.0238) |
| Constant | 0.161*** |
| | (0.0201) |
| Observations | 1,378 |
| R-squared | 0.053 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3–7 presents the average dollar gain associated to both bidders and targets in 5 different time periods around the announcement. The dollar gains are calculated using the median market values of bidders and targets and the different abnormal returns observed for different groups and time periods. The results are in accordance with returns reported earlier. Although the size of targets are much smaller than those of bidders (median bidder market value is $33,279,820 while median target has a value of $1,996,020) the dollar gain to targets are so high which is a big success for target managers as they could create a huge gain for their shareholders in expense of the bidders. All the differences between pairs of dollar gains reported in the Table 3–7 are statistically significant at one and five percent levels. Bidders lose much more money around announcement if they bid for a distressed target. In a regression, not reported here, we added the interaction term, $NN_Out * MB$ to investigate the interaction effect. The term was not significantly different from zero suggesting no interaction effect.

Table 3–7: Dollar Gain;

Table presents the dollar gain associated to both bidders and targets in 5 different time periods around the announcement. All the gains are in million dollars.

| | Bidder(Not Dist.) | Bidder(Dist.) | Target(Not Dist.) | Target(Dist.) |
|---|---|---|---|---|
| (-30,-10) | 136,447.26 | 13,311.93 | 45,509.26 | 154,292.35 |
| (-9,-3) | 123,135.33 | -46,591.75 | 32,934.33 | 99,801.00 |
| (-2,2) | -402,685.82 | -532,477.12 | 479,244.40 | 676,850.38 |
| (3,10) | -33,279.82 | -539,133.08 | -1,397.21 | 47,904.48 |

To further analyze the target gain, and the possibility of the fire sale acquisition, the average target's cumulative abnormal return during the time frame covering one day before to one day after the announcement, and two different premiums calculated using targets' market price one week before the announcement and 52-week high share price as reference were compared for both distressed and non-distressed firms for both contraction and normal economic periods. Table 3–8 shows the comparison. A two-sample *t-test* was done on all the compared pairs. All of the differences are statistically significant in one percent level.

Table 3–8: Average Premiums;

table illustrates average target's cumulative abnormal return during the time frame covering one day before to one day after the announcement, and two different premiums using target's current market price and 52-week high share price as reference compression netween distressed and non-distressed firms and both contradiction and normal economic periods

| | Contraction | | Normal | |
|---|---|---|---|---|
| | Bankruptcy Prediction | | Bankruptcy Prediction | |
| | 1 | 0 | 1 | 0 |
| (-1,1) | 0.3779 | 0.2838 | 0.3014 | 0.2181 |
| Premium 1 | 0.5792 | 0.4363 | 0.5783 | 0.3705 |
| Premium 2 | -0.2616 | -0.1847 | -0.1492 | -0.005 |

Targets tend to receive a huge gain with reference to their current market valuation (Premium 1), but to be sold for a fire sale price with reference to their 52-week high share price. Targets' value have decreased due to their bankruptcy risk acceleration, but bidders seem to make their acquisition decisions based on the targets' previous high values, observed way before the market incorporated the risk to the price, instead of current real ones. This may be the result of the hope that they have of the tools and the ability needed to extract more gains from the targets. The market on the other hand penalizes bidders more in distress target bids insisting on its current target valuation.

Table 3–5: M&A Statistics;
Table presents basic statistics, Mean, Standard Deviation, Minimum, and Maximum, for the control variables used in the analyses. Data are from SDC Mergers and Acquisition database as well as CRSP and NBER. TenderOffer is 1 if the bid is tender offer, MB is the Market-To-Book Ratio, Contraction equals 1 if announcement is made in contraction periods, Size is log of Total Assets, Horizontal is 1 if bidder and acquirer are in the same industry, Unsolicited is 1 is the bid is unsolicited, Cash deal is one is consideration offered is cash, (-1,1) CAR is target's announcement cumulative abnormal return, and OfferTo52High is the ratio of Offer Price to target's 52-week highest price.

| | **Variable** | **Obs** | **Mean** | **Std. Dev.** | **Min** | **Max** |
|---|---|---|---|---|---|---|
| Distressed(NN) | TenderOffer | 90 | 0.13 | 0.34 | 0 | 1 |
| | MB | 90 | 2.52 | 4.35 | 0.01 | 27.83 |
| | Contraction | 90 | 0.68 | 0.47 | 0 | 1 |
| | Size | 90 | 4.36 | 1.41 | 1.29 | 7.48 |
| | Horizontal | 90 | 0.43 | 0.50 | 0 | 1 |
| | Unsolicited | 90 | 0.08 | 0.27 | 0 | 1 |
| | Cash Deal | 90 | 0.54 | 0.50 | 0 | 1 |
| | Target (-1,1) CAR | 90 | 0.34 | 0.47 | -0.92 | 2.06 |
| | OfferTo52High | 78 | 1.34 | 3.13 | 0.09 | 24.25 |
| Non-Distressed(NN) | TenderOffer | 1288 | 0.09 | 0.28 | 0 | 1 |
| | MB | 1288 | 5.74 | 13.71 | 0.01 | 368.22 |
| | Contraction | 1288 | 0.19 | 0.39 | 0 | 1 |
| | Size | 1288 | 5.70 | 1.80 | 0.66 | 12.39 |
| | Horizontal | 1288 | 0.45 | 0.50 | 0 | 1 |
| | Unsolicite | 1288 | 0.10 | 0.30 | 0 | 1 |
| | Cash Deal | 1288 | 0.51 | 0.50 | 0 | 1 |
| | Target (-1,1) CAR | 1286 | 0.23 | 0.30 | -0.75 | 4.18 |
| | OfferTo52High | 1109 | 1.04 | 0.74 | 0.06 | 15.50 |

# CHAPTER 4
# Conclusion

Acquisition of a distressed firm is with no doubt the best for the target shareholders, but may not be as helpful as it seems to bidders. Results of analyzing 1378 targets in different market conditions shows that acquirers tend to overpay for targets in distress all the time and even more in contraction periods. Calculating target premiums base on 52-week highest share price, a fire sale discount will be apparent. It seems that acquirers' bid reference point is not the current market valuation, but the target's best position in one year prior to announcement. This may be because bidder thinks it can extract value way more than current management team. Market looks at this kind of transactions even more unfavorable than regular acquisitions. The results are in line with Ang and Mauck (2011) paper. In order to categorize targets we compare three different categorization tools, namely Survival Analysis, Logistic regression, and Artificial Neural Network. We then choose the best model to predict target's distress level. Artificial Neural Network model, among compared models, is the most powerful and hence the used model.

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