Understand Corporate Rationales for Engaging in Reverse Stock Splits – A Data Mining Application

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Abstract

There has been much written on the individual topics of bankruptcy prediction, corporate performance, and reverse stock splits. However, there is little research into the relationship between reverse stock splits and corporate performance as well as bankruptcies. The purpose of this study is to provide and empirically support rationales for reverse splits by classifying reverse splitting firms into two groups, those declaring bankruptcy within 2 years and those remaining solvent. The apparent rationales for engaging in reverse splits differ between the two groups, i.e., weak firms attempting to increase their stock price while solid firms seeking to reposition their stock in the market. Two alternative approaches, Altman's Z-scores and artificial neural networks, are used for classifying reverse splitting firms into the two groups. A comparison is then made of the relative success of Z-scores and neural networks in the classification. This study should generate an understanding of corporate rationale for engaging in reverse splits and the relative success of Z-scores and artificial neural networks in forecasting the two groups.

Key words: Reverse Stock Splits, Bankruptcy, Artificial Neural Networks, Altman's Z-scores, Data Mining.

1. Introduction

Data mining is the process of automated discovery of interesting patterns, trends, and correlations hidden in a corporate database by sifting through large amount of data [11]. It provides a means for extracting new non-obvious information from the growing base of data warehouses to create competitive advantages for organizations.

Data mining tasks can be broadly categorized into four dimensions: classification, estimation, segmentation/clustering, and description/summarization [24]. Depending on the primary goal of the task, the outcome of data mining process can be predictive models or descriptive information. The predictive models produced by data mining process are good for classification or estimation tasks while the descriptive information is used for segmentation/clustering and summarization type of problems. Predictive data mining is a learning process that finds trends, patterns and subtle relationships in data that allow the prediction of future results. Descriptive data mining process focuses on exploring and visualizing the data to find interesting patterns or relationships [16]. Each data mining application has different goals and circumstances and hence, requires different sets of data mining techniques. The most widely used data mining techniques come from a variety of fields including: query tools; statistical methods such as regression, discriminant analysis, logistic models, multidimensional analysis, factor analysis, and data visualization; also machine learning techniques such as decision trees, expert systems, association rules, neural networks, fuzzy logic, and genetic algorithms. Each technique has advantages and disadvantages [8, 17, 21, 24, 26]. The most dominant data-mining tool/techniques at present is neural networks [5, 21]. The application of neural networks techniques to data mining has the advantage of freeing the process from pre-determined models and to detect nonlinear relationships automatically. In this study, we applied both traditional statistical and neural networks approaches to understand the rational for companies to conduct reverse stock splits.

Corporations use stock splits re-price their stock in the market. In a reverse split the number of shares decreases and the per share market price increases, while the opposite is truce for a forward (normal) split. Both forward and reverse splits are considered as non-economic events since the total market capitalization of the stock is essentially the same on a pre- and post- split basis. In this study, we focus on the underlying rationales for reverse splits.

In general, firms engaging in reverse splits are sending one of two possible messages to the investment and community [18, 23]. First, some view a reverse split as a desperation move by a sinking firm to increase its low-stock price to a more respectable trading range and, thereby, gain respect from the investment and lending communities. On the other hand, a firm with solid financial fundamentals may use a reverse split to reposition its low-priced stock to be more congruent with the shares of similar firms in the market.

This article presents the results of a two-part research effort. First, this study classifies reverse splitting firms into two groups, firms that declare bankruptcy within 2 years and firms that remain solvent. We assert that the apparent rationales for engaging in reverse splits differ between the two groups, i.e., weak firms attempt to increase their stock price while solid firms seek to reposition their stock in the market. Two alternative approaches are employed for classifying reverse splitting firms into the two groups, Altman's Z-scores and artificial neural networks. Both approaches are used to measure the likelihood of bankruptcy. We expect that weak firms will declare bankruptcy within two year while solid firms will remain solvent and performance well in the stock market. Second, a comparison is then made of the relative success of Z-scores and neural networks in forecasting bankruptcy and classifying the reverse splitting firms into two groups. The results of the study should generate an understanding of corporate rationale for engaging in reverse splits and the relative success of Z-scores and artificial neural networks in forecasting corporate bankruptcy and performance.

Section 2 briefly describes Altman's Z-scores and artificial neural networks approaches used in this study to classify reverse splitting firms into the two groups. Section 3 presents the experiment design and results of this study. Section 4 concludes the paper with our preliminary findings.

2. Evidence on Bankruptcies and Reverse Splits

Over the years, there has been much written on the individual topics of bankruptcy prediction [1, 2, 3, 4, 9] and reverse stock splits [2, 14, 15]. However, there is little research into the relationship between reverse stock splits and corporate bankruptcy as well as performance.

Early seminal studies concerning bankruptcy prediction were made by Altman [1] and Beaver [4]. Beaver evaluated more than thirty separate financial factors and determined that the ratio of cash flow/total debt had the strongest prognostic power. Altman used multivariate discriminant analysis to construct an algorithm using a combination of five prognostic financial ratios to calculate a compound prognostic factor Z-score. Later studies made further investigations of the prognostic power of financial ratios for predicting bankruptcy. Studies by Altman, Handleman, and Narayanan [2], Boritz [6], Collins [10] and Philosophov and Philosophov [19] investigated the prognostic power of financial ratios within the framework of discriminant analysis and linear regression models.

On the other hand, numerous studies of stock splits have dealt primarily with stock market reaction and possible impact on cash flows. In general, these studies indicate that stock splits do not directly affect the cash flow of the firms and positive market reactions associated with forward stock splits [7, 13]. Negative market reactions were noted for reverse splits [15, 25]. However, these studies were unable to definitely explain the negative abnormal returns associated with reverse splits

This article fills a gap in our knowledge of reverse stock splits and corporate bankruptcy as well performance. The purpose of this article is to generate an understanding of underlying motivations for engaging in reverse stock splits and whether artificial neural networks are a useful tool for forecasting bankruptcy of reverse splitting firms and the rational behind a reverse split.

3. Altman's Z-score model and the artificial neural networks.

3.1 Altman's Z-Score Model

Financial ratios have been widely used by financial institutions as well as academicians to measure the solvency of business firms [4]. Instead of using ratio analysis to assess the performance of business firms, Altman in his seminal paper entitled "Financial Ratios, Discriminant Analysis and the Prediction of Corporate

Bankruptcy" [1] used a multiple discriminant analysis to discriminate between bankrupt and non-bankrupt firms based on five financial ratios. A so-called Z-score is derived based these ratios. Altman defined the following predetermined cutoff ratios: $Z < 1.81$ for bankruptcy, $1.81 \leq Z \leq 2.99$ for zone of ignorance, and $Z > 2.99$ for non-bankrupt. A bankrupt firm is one that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act. Based on empirical results, Altman suggested that "the Z-score model is an accurate forecaster of failure up to two years prior to distress" [4].

3.2 Artificial Neural Networks

Artificial neural networks models are based on the neural structure of the brain. The brain learns from experience and so do artificial neural networks. Simply stated, a neural network consists of many simple highly interconnected processing units, the neural network equivalent of neurons, operating in parallel. Processing units are connected via a network of links carrying the output of one processing unit as input to another processing unit. There are weights associated with the links that represent the connection strengths between two processing units. The connection strengths determine the relationship between the input and the output of the network and thus, in a way, represent the knowledge stored in the network. Neural network acquire this knowledge through a process of training during which the connection strength between the nodes are modified. Once trained, the neural network retains this knowledge and it can be used for the particular task it was designed to do.

Previous research has shown that artificial neural networks are suitable for pattern recognition and pattern classification tasks due to their nonlinear nonparametric adaptive-learning properties. Artificial neural networks have been successfully applied to many financial problems including bankruptcy prediction. In most cases, artificial neural networks produce significantly better prediction accuracy than classical statistical techniques [22].

4. Experiment

The experiment was conducted in two stages. During the first stage, we determine the best network configuration by systematically trying out on different network architectures, input and output functions, and learning algorithms. After we have decided the best network architecture to use for our study, we run the same network architecture using the same set of training data 20 times, each time with different randomly generated initial weights to average the effect of different starting points on the results of the network.

Mergent's Dividend Record (http://www.mergent.com/publish/history.asp) was used to identify those firms that engaged in reverse splits in the period 1999-2000. Z-scores and the related financial ratios for each firm were collected from Compustat (http://www.compustat.com/www/db/na_descr.html). Finally, Bankruptcydata.com (http://www.bankruptcydata.com) was used to identify which of these firms filed for bankruptcy in the two years subsequent to the reverse split. A total of 59 companies executed reverse split in year 1999 and 46 in year 2000. Among the 59 companies in 1999, 10 of them filed bankruptcy in the subsequent two-year period. For the year 2000 data, 12 out of the 40 companies filed bankruptcy in the subsequent two-year period. In order to build the neural networks model, we need to separate the data into two sets, one set for training the neural networks and the other set for testing. We used the 1999 data as the basis for our training sample. All of the companies that failed in the two-year period subsequent to the reverse split were included in our training set. As a control measure, a failed company was matched with a non-failed company that has a Z-score greater than or equal to 3 for the year of the reverse split. According to Altman [3], a z-score of greater than or equal to 3 signifies that the company is financially in good health. There are only 9 companies that qualified for the training set. Therefore, there are a total of 19 companies in the training set, 10 failed and 9 non-failed. For the testing data, we included all companies performed reverse splits in year 2000.

The data sample consists of the same five financial ratios used in calculating Z-scores. They are Working Capital/Total Assets, Retained Earnings/Total Assets, EBIT/Total Assets, Market Value of Equity/BK of Debt, and Sales/Total Assets. In this research, a feed forward network with back propagation [20], the most widely used learning algorithm, is implemented. In classification problems, the most popular network architecture used is the multi-layer feed forward. In this research, a multi-layer feed forward network of three layers and five hidden nodes was implemented. An input preprocessor that normalizes the input values based on the mean standard deviation (Mean/SD) is applied, and a dot product function is used to aggregate input values. Learning rate is set fixed at 0.0005. A sigmoid function is used as the output function to normalize the output to a value between zero and one that can then be interpreted as the probability of a class outcome. The employment of a sigmoid function can also attenuate the effect of outliner values and improve the overall performance of the network. After some preliminary runs, the results show that the network usually converges between 5000 to 10000 epochs. Therefore, the network is set to run 10000 iterations for all experiments. The results are shown in Tables 1a and 1b.

Table 1a. Test data ordered by neural network results

NN Avg	Status	Predicted Outcome
0.033	**bankrupt**	Bankrupt
0.039	operating	
0.041	**bankrupt**	
0.053	**bankrupt**	
0.078	**bankrupt**	
0.081	**bankrupt**	
0.084	**bankrupt**	
0.097	operating	
0.110	operating	
0.138	**bankrupt**	
0.157	operating	
0.163	operating	
0.164	**bankrupt**	
0.173	operating	
0.195	operating	
0.197	operating	
0.238	operating	
0.239	operating	
0.257	**bankrupt**	
0.279	**bankrupt**	
0.299	operating	
0.365	operating	
0.366	operating	
0.388	operating	
0.406	operating	
0.462	**bankrupt**	
0.512	operating	
0.552	**bankrupt**	Area of Ignorance
0.661	operating	
0.694	operating	
0.734	operating	
0.820	operating	
0.874	operating	
0.880	operating	Non-bankrupt
0.893	operating	
0.899	operating	
0.907	operating	
0.909	operating	
0.948	operating	
0.948	operating	

Table 1b. Test data ordered by Z-scores

Z Score	Status	Predicted Outcome
-574.09	**bankrupt**	Bankrupt
-200.97	**bankrupt**	
-17.178	**bankrupt**	
-11.918	Operating	
-7.69	**bankrupt**	
-5.716	operating	
-4.36	**bankrupt**	
-4.137	operating	
-4.135	operating	
-3.196	operating	
-3.177	**bankrupt**	
-2.9	operating	
-2.365	operating	
-2.352	**bankrupt**	
-1.405	**bankrupt**	
-1.307	Operating	
-1.202	operating	
-0.927	operating	
-0.439	**bankrupt**	
0.301	**bankrupt**	
0.987	operating	
1.091	operating	
1.155	operating	
1.373	operating	
1.501	operating	
1.559	**bankrupt**	
1.789	operating	
2.087	operating	Area of Ignorance
2.5	operating	
2.764	operating	
2.774	operating	
2.842	operating	
2.901	operating	
4.201	**bankrupt**	Non-bankrupt
4.462	operating	
4.757	operating	
6.15	operating	
6.557	operating	
8.787	operating	
10.147	operating	

As suggested by Altman, the cut off ratios for Z-scores are: $Z < 1.81$ for bankruptcy, $1.81 \le Z \le 2.99$ for zone of ignorance, and $Z > 2.99$ for non-bankrupt.

The neural networks model we selected implemented a sigmoid function to normalize the output to a value between zero and one that can thus be interpreted as the probability of a class outcome. Usually a cut off value of

0.5 is used for dichotomous classification problem. In order to compare with the results of Z-scores, we need to divide the output of neural networks into three classes. Since the cutoff points for neural networks model are not known, we set the cutoff points for neural networks output to have the same number of companies in each class as Z-scores. Therefore, out of the total 40 companies, 27 companies were predicted as bankrupt, 6 in the area of ignorance, and 7 as non-bankrupt. Based on the above assumptions, we can compare the performance of the two methods by calculating their corresponding type I and type II errors. Table 2 shows the misclassification rate of both methods.

Table 2. Misclassification rate of neural networks and Z-scores

	Neural Networks	Z-scores
Type I	59.26%	56.26%
Type II	0	14.29%

Type I error is the ratio of non-bankrupt companies misclassified as bankrupt and type II error is the ratio of bankrupt companies misclassified as non-bankrupt. The impact of a type II is significantly more costly than a type I error for investors and lenders. The result shows that both methods have similar levels of type I errors but the neural networks model has no type II error while Z-scores has a type II error of 14.29%. As a consequence, the neural networks model outperformed Z-scores for this particular data set.

To understand the rationale behind a reverse split by a firm, total percent return data of the stock as well as that of the industry in 2003, two years from the splits, were obtained from morningstar.com (see Table 3). Note that data for some firms are not available. However, all firms with returns outperformed its industry for year 2003. The results suggest that companies remand solvent two year after its reverse stock split tend to outperform its peers. Therefore, the bankruptcy predication method can be used as a stock selection tool to separate the companies into two groups. If we use 0.5 as the cutoff for the two groups, there are eleven bankruptcy firms correctly classified as bankrupt while only one misclassified as non-bankrupt. Next, we compare the average stock return of the solvent firms versus their peers. We found that on average the non-bankrupt group outperformed their peers by 64.5% ((940.83-572)/572) while the bankrupt group outperformed their peers by 56.4% ((992.2-634.6)/634.6). The numbers have not yet included the negative returns of the twelve bankruptcy firms that shall substantially reduce the average stock return of the bankruptcy group.

5. Summary and Conclusions

There has been little research into the relationship between reverse stock splits and corporate bankruptcy as well as the rationale for a reverse split. This study classifies reverse splitting firms into two groups, those declaring bankruptcy within 2 years and those remaining solvency. The apparent rationales for engaging in reverse splits differ between the two groups, i.e., weak firms attempting to increase their stock price while solid firms seeking to reposition their stock in the market. Two alternative approaches, Altman's Z-scores and artificial neural networks, are used for classifying reverse splitting firms into the two groups. A comparison is made of the relative success of Z-scores and neural networks in the classification. The results indicate that neural networks approach outperforms Altman's Z-scores approach that is based on multiple discriminant analysis.

Neural networks are more costly than discriminant analysis since they are more computationally intensive than statistical methods and the selection procedures require a customized program. However, recent advances in technology have reduced the cost of computation and made neural networks an attractive alternative to statistical methods.

Regarding stock performance, our limited data indicate that all non-bankrupt firms with returns outperformed their peers for year 2003. The results from our preliminary study are encouraging. However, the number of reverse split firms during 1999-2000 is small. Therefore, more study is needed with a larger data set to validate our findings. Specifically, we will gather data on firms that engaged in reverse splits during a period of five years, 1997-2001. Another topic of interest is the immediate market reaction to reverse splits in terms of stock returns, This will be a replication of previous studies 14Han, Lamoutrux15] using an updated data set.

Table 3. Stock performance of the reverse split companies, ordered by neural networks output

Ticker	Record Date (split)	Z Score	NN Avg	Status	2003 % return	
					Stock	Industry
3SPWW	22-Nov-2000	-7.69	0.033	**bankrupt**		
HEC	8-Nov-2000	-5.716	0.039	operating	450	418
3VCLL	17-Apr-2000	-17.178	0.041	**bankrupt**		
3HCIS	20-Jan-2000	-3.177	0.053	**bankrupt**		
3OSRI	3-Mar-2000	-4.36	0.078	**bankrupt**		
CHOHQ	3-Apr-2000	-0.439	0.081	**bankrupt**		
3XDGI	24-Aug-2000	-574.092	0.084	**bankrupt**		
3WYOG	18-Feb-2000	-2.365	0.097	operating	na	
CAU	24-Mar-2000	-1.307	0.110	operating	239.4	192
3SHPH	1-Feb-2000	-200.965	0.138	**bankrupt**		
JUNI	13-Dec-2000	-4.137	0.157	operating	-80	-128.4
AGD	5-Dec-2000	0.987	0.163	operating	na	
3STTC	27-Nov-2000	1.559	0.164	**bankrupt**		
3URSI	5-May-2000	-2.9	0.173	operating	-20	-43.9
TTEN	18-Jan-2000	2.764	0.195	operating	na	
3PUBO	10-Nov-2000	2.087	0.197	operating	na	
3AIRP	4-Jan-2000	-11.918	0.238	operating	na	
KSU	12-Jul-2000	1.155	0.239	operating	19.3	-9.7
3NEGI	19-Oct-2000	-1.405	0.257	**bankrupt**		
3GSVE	14-Nov-2000	0.301	0.279	**bankrupt**		
IMNR	1-Feb-2000	-3.196	0.299	operating	55.5	-3.4
MATR	6-Dec-2000	1.091	0.365	operating	143	118
3TCHL	13-Dec-2000	2.901	0.366	operating	na	
3INRB	10-Oct-2000	1.501	0.388	operating	80	42
AVCS	1-Dec-2000	6.557	0.406	operating	105	50
3PMRT	30-Oct-2000	-2.352	0.462	**bankrupt**		
3MDTY	8-Dec-2000	1.373	0.512	operating	173	120.7
3NEXL	15-Jun-2000	4.201	0.552	**bankrupt**		
PTCH	27-Nov-2000	2.5	0.661	operating	private	
3DNKY	20-Apr-2000	1.789	0.694	operating	102.8302	-7.9
TPZ	22-Nov-2000	4.757	0.734	operating	na	
3JAYA	10-Jan-2000	-1.202	0.820	operating	na	
3HNNS	28-Sep-2000	6.15	0.874	operating	30	24.7
3SNKI	22-Dec-2000	2.774	0.880	operating	50	-14
3TNIS	25-May-2000	-4.135	0.893	operating	na	
SE	1-May-2000	2.842	0.899	operating	114	108.2
3AGIA	4-Feb-2000	4.462	0.907	operating	28	
TRCR	14-Jan-2000	-0.927	0.909	operating	460	417
TSTF	2-Jun-2000	10.147	0.948	operating	-17	-76.7
3HEAL	22-Dec-2000	8.787	0.948	operating	na	

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