

Can Post Bankruptcy Performance be Predicted?

by

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Abstract

While there have been several studies on factors that predict the default probability of companies going into bankruptcy, it is also important to explore if there are any indicators of post-emergence success for companies that emerge from the bankruptcy process. Being able to predict a company's performance once it emerges from the Chapter 11 process would result in several benefits. The bankruptcy procedure in courts would get expedited, thereby reducing the sometimes exorbitant fee paid by companies for this process. Some guidance would be provided to stakeholders receiving new equity or debt in the emerging company, and to those receiving equity rights in the plan. Furthermore, the providers of exit financing would also benefit. This paper searches for indicators of the difference between successful and unsuccessful emergences from bankruptcies. The main variables examined are the Altman Z-score, Altman Z" score, size of board, percentage of insiders on the board, access to debtor-in-possession financing, presence of a pre-packaged plan, and stock prices prior to filing for bankruptcy as predictors. Success in this study is defined using stock performance of companies once they emerge from bankruptcy. Companies that have zero or positive excess returns versus the S&P 500 index are classified as successful, while companies with significant negative excess returns are classified as unsuccessful. The results show that it is difficult to predict post-emergence success using pre-bankruptcy data. However, when used in certain multivariate regression models, presence of a pre-packaged plan, Altman Z" scores, and percentage of insiders on the board can be significant indicators of post-emergence success.

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Table of Contents

I.	Introduction.....	5
	i Bankruptcy Reorganization.....	6
	ii Measuring Post-Emergence Success.....	7
II.	Literature Review.....	7
	i Z-Score.....	8
	ii Z” Score.....	9
	iii Determinants of Post-Emergence Performance.....	11
III.	Hypothesis.....	12
IV.	Data and Methodology.....	14
	i Data Collection and Characteristics.....	14
	ii Equity Performance Post-Emergence: Dependent Variable.....	15
	iii Potential Indicators of Post-Emergence Success: Independent Variables....	17
	iv Methodology.....	18
V.	Results.....	19
	i Z and Z” Scores from Quarter before Bankruptcy.....	19
	ii Z and Z” Scores from One Year before Bankruptcy.....	22
	iii Size of Board and Percentage of Insiders on the Board.....	26
	iv Access to DIP Financing and Pre-Packaged Plan.....	28
	v Stock Prices Prior to Filing.....	29
	vi Multiple Regression Analysis using all Indicators.....	31
	vii Stepwise Regression Analysis (Forward Selection) using all Indicators.....	32
VI.	Conclusion.....	34
VII.	Appendix.....	37
VIII.	References.....	50

I. Introduction

Corporate bankruptcies often have devastating effects on a country's economy and overall productivity. They affect the various stakeholders involved in them, such as the shareholders and creditors of the company, employees, management, etc. Furthermore, they also have large direct and indirect costs. Companies such as Enron and Lehman Brothers have paid over \$1 billion and \$2 billion respectively in just advisory fees. Given the vast implications of bankruptcies, there has been a lot of academic research around the factors that predict the risk of bankruptcy in the first place. Academics have attempted to make many bankruptcy prediction models, of which the Altman Z Score model is the most well-known. However, it is also important to explore the possibility of there being factors that can predict the post-emergence success or failure of a firm once it emerges from a bankruptcy. Being able to predict this could expedite the bankruptcy process in courts, thus reducing the sometimes exorbitant advisory fees paid by the companies for this process. It could also serve as a guide to prospective providers of exit financing, as well as help determine whether the new securities received in the reorganization should be held or sold upon emergence.

This paper aims to examine several factors of companies before they go bankrupt, and search for a relationship between these factors and the post-emergence success of companies. Using the Altman Z-score, Altman Z' score, size of board, percentage of insiders on board, ability to secure debtor-in-possession financing, presence of a pre-packaged plan, and stock prices prior to filing as predictors, the study searches for indicators of the difference between successful and unsuccessful emergences from bankruptcies. Theoretically, companies that perform better post-emergence should have higher Z and Z' scores than the companies that

didn't perform as well. This hypothesis is tested using Z and Z' scores from one quarter and one year prior to the bankruptcy filing. Additionally, a smaller board with fewer insiders, ability to secure debtor-in-possession financing, presence of a pre-packaged plan, and relatively high stock prices prior to filing might also indicate positive post-emergence performance for a company. If significant, the results from this paper could help make the decision of liquidation versus reorganization clearer for distressed firms going into the bankruptcy process.

i. Bankruptcy Reorganization

As previously mentioned, the costs of bankruptcies can be extremely high for society. Due to this, there are several laws and procedures in place to protect the interests of the various claimholders of bankrupt companies. Once a company is in a position where it is unable to repay its debts to its creditors, both liquidation and reorganization are available courses of action for it. A bankruptcy judge should allow the company to reorganize under Chapter 11 if its intrinsic or economic value exceeds its current liquidation value. However, if the company's current liquidation value exceeds its intrinsic or economic value, it should file for Chapter 7 and liquidate instead.

Though this method of classifying a Chapter 11 versus a Chapter 7 candidate seems simple theoretically, it can often become complex when applied practically. There are several different ways of measuring the intrinsic value of a company, and doing so involves many inherent assumptions. Thus, when making this judgment, people can often ascribe inappropriate valuations to companies and incorrectly classify them as reorganization candidates when they should've been liquidated, or vice versa. This is evident when data is examined to uncover the large number of Chapter 22 filings, i.e. companies that filed for bankruptcy again after going through the Chapter 11 process once already. To reduce these erroneous classifications and

subsequently have quicker bankruptcy procedures in courts, it would be helpful to have concrete, objective indicators of potential success for companies after they reorganize.

ii. Measuring Post-Emergence Success

To find indicators of post-emergence success, it is essential to first define what this success means. One way to measure success is to classify companies that emerged from the Chapter 11 process as successful, and to classify those that didn't emerge as unsuccessful. To be even more specific, the post-emergence operating or stock performance of the emerged companies could be used as a measure of success as well. This paper aims to use the post-emergence stock performance of companies that emerged from Chapter 11 bankruptcies as a measure of success. Specifically, success would be measured based on the company's excess stock returns, i.e. stock performance of the company after it emerges from the bankruptcy, relative to the overall market equity index performance in the same period. If the company performed at least in line with the market, and had no or positive excess returns, it would be classified as a success emergence. However, if it had negative excess returns, it would be classified as an unsuccessful emergence.

II. Literature Review

In 1966, William H. Beaver attempted to predict the probability that a firm will fail. In his study on "Financial Ratios as Predictors of Failure", he calculated thirty different financial ratios for his sample of failed firms versus non-failed firms. He then conducted t-tests and compared the mean values, to show that there was a significant difference in the means of the ratios of firms for at least five years before failure, and this difference increased as failure

approached. Using univariate analysis, Beaver finally concluded that cash flow to total debt was the best ratio to predict the distress and potential failure of a company.

i. Z-Score

Following this, in 1968, Edward Altman published his research on predicting distress and quantifying default probability using a Multiple Discriminant Analysis (MDA) which could take into account multiple variables. He ultimately selected 5 variables that together could accurately classify 95% of the sample of manufacturing firms correctly, one year prior to bankruptcy. The credit result that his model computed was called the Z-score. Later, using bond rating equivalents, his paper on the mortality rate approach (1989) predicted the probability whether a firm will go into bankruptcy within two years. The Z-score could be calculated as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

where:

X_1 = working capital / total assets

X_2 = retained earnings / total assets

X_3 = earnings before interest and taxes / total assets

X_4 = market value of equity / total liabilities

X_5 = sales / total assets

To assess default likelihood, the Z-score model classified all the companies into three distinct zones of discrimination as follows:

$Z > 2.99$ – “Safe” Zone

$1.81 < Z < 2.99$ – “Gray” Zone

$Z < 1.81$ – “Distress” Zone

On the basis of the Z-score, equivalent U.S. bond ratings can be assigned to companies using bond rating equivalents from Altman's (1989) mortality rate approach. This is shown in Table 1. Altman later (1995) modified the Z-score model to make some adjustments, and came up with a Z'' score for manufacturing and non-manufacturing companies/emerging markets.

ii. Z'' Score

Since the original sample of firms used by Altman in his study only included manufacturing firms, he modified (1995) the Z-score model to create a new Z'' score for both manufacturing and non-manufacturing firms and firms in emerging markets. In this model, the author excluded X_5 , i.e. sales/total assets. He did this because he wanted to minimize the potential industry effect that could take place when an industry-sensitive variable such as total asset turnover was included. A constant of +3.25 was also added to the model so that scores with a score of zero could be standardized and equated to a D (default) rated bond. The Z'' score could be calculated as follows:

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

On the basis of this Z'' score, an equivalent U.S. bond rating can be given to companies. This is shown in Table 2 on the following page. Furthermore, default probabilities can also be assigned according to these equivalent U.S. bond ratings derived from the Z and Z'' scores. This is shown in Table 3 on the following page.

Table 1: Median Z-Score by S&P Bond Rating for U.S. Manufacturing Firms: 1992-2017

Rating	2017 (No.)	2013 (No.)	2004-2010	1996-2001	1992-1995
AAA/AA	4.20 (14)	4.13 (15)	4.18	6.20*	4.80*
A	3.85 (55)	4.00 (64)	3.71	4.22	3.87
BBB	3.10 (137)	3.01 (131)	3.26	3.74	2.75
BB	2.45 (173)	2.69 (119)	2.48	2.81	2.25
B	1.65 (94)	1.66 (80)	1.74	1.8	1.87
CCC/CC	0.73 (4)	0.23 (3)	0.46	0.33	0.40
D	-0.10 (6) ¹	0.01 (33) ²	-0.04	-0.20	0.05

*AAA Only

¹From 1/2014 – 11/2017, ²From 1/2011 – 12/2013

Source: Compustat Database, mainly S&P 500 firms, compilation by NYU Salomon Center, Stern School of Business.

Table 2: Bond Rating Equivalents based on Average Z" Scores

U.S. Equivalent Rating	Average Z" Score
AAA	8.15
AA+	7.60
AA	7.30
AA-	7.00
A+	6.85
A	6.65
A-	6.40
BBB+	6.25
BBB	5.85
BBB-	5.65
BB+	5.25
BB	4.95
BB-	4.75
B+	4.50
B	4.15
B-	3.75
CCC+	3.20
CCC	2.50
CCC-	1.75
D	0.00

Source: Altman and Hartzell (1995).

Table 3: Mortality Rates by Original Corporate Bond Rating (1971 – 2017)

U.S. Bond Rating		Years after Issuance									
		1	2	3	4	5	6	7	8	9	10
AAA	Marginal	0.00%	0.00%	0.00%	0.00%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%
	Cumulative	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.03	0.03	0.03
AA	Marginal	0.00	0.00	0.02	0.02	0.01	0.01	0.00	0.01	0.01	0.01
	Cumulative	0.00	0.00	0.02	0.04	0.05	0.06	0.06	0.07	0.08	0.09
A	Marginal	0.00	0.01	0.04	0.04	0.05	0.04	0.02	0.01	0.05	0.02
	Cumulative	0.00	0.01	0.05	0.09	0.14	0.18	0.20	0.21	0.26	0.28
BBB	Marginal	0.22	1.51	0.70	0.57	0.25	0.15	0.09	0.08	0.09	0.17
	Cumulative	0.22	1.73	2.41	2.97	3.21	3.36	3.45	3.52	3.61	3.77
BB	Marginal	0.54	1.16	2.28	1.10	1.37	0.74	0.77	0.47	0.72	1.07
	Cumulative	0.54	1.69	3.94	4.99	6.29	6.99	7.70	8.14	8.80	9.77
B	Marginal	1.90	5.36	5.30	5.19	3.77	2.43	2.33	1.11	0.90	0.52
	Cumulative	1.90	7.16	12.08	16.64	19.78	21.73	23.56	24.41	25.09	25.48
CCC	Marginal	5.35	8.67	12.48	11.43	3.40	8.60	2.30	3.32	0.38	2.69
	Cumulative	5.35	13.56	24.34	32.99	35.27	40.84	42.20	44.12	44.33	45.83

Source: Updated from Altman (1989).

iii. Determinants of Post-Emergence Performance

There has been some research specifically on determinants of emerging from a bankruptcy. Edith Hotchkiss' study in 1993 argued that the most important determinant for post emergent success was the firm's size (measured by assets at the time of bankruptcy petition). She defined success in her study as successfully reorganizing rather than liquidating after the Chapter 11 bankruptcy process. Since many firms downsize while they are in the process of emerging from a bankruptcy, the ability to divest their assets and use that money to fund operations was a significant indicator of their emergence according to Hotchkiss' study.

More recently, another study conducted by Dahiya in 2003 showed that the most important determinant is the ability of the firm to secure debtor-in-possession financing. Debtor-in-possession financing is a unique kind of secured financing that is available to firms filing for Chapter 11 bankruptcy. Dahiya also defined success as reorganization versus liquidation after the Chapter 11 process. Using a large sample of firms that filed for Chapter 11, his study concluded

that DIP financing is not only associated with a higher probability of emergence, but also a shorter time spent in bankruptcy. Furthermore, the study also examined whether the identity of the DIP financier, i.e. whether it was a prior lender or a new lender influenced the outcome. It found that prior lenders were significantly associated with a reduced time in bankruptcy, since the firm is strengthened by the prior relationship the DIP financier has with it.

Apart from this, several studies have assessed post-bankruptcy performance based on firms' profitability and cash flows in relation to comparable firms in similar industries. According to Hotchkiss (1995), two thirds of firms that emerged from a bankruptcy underperformed industry peers for up to five years following the bankruptcy. Her study also showed that as much as up to 40 percent of firms continued to experience operating losses in the three years after emergence, and that 30 percent of firms reenter bankruptcy or privately restructure their debt. Hotchkiss attributed this poor post-bankruptcy performance to the continued involvement of prebankruptcy management in the restructuring process.

However, another study by Eberhart, Aggarwal, and Altman (1999) provided a contrast to Hotchkiss' results. This study showed significant excess stock market returns in the 200 days following emergence for firms that emerged between 1980 and 1993 with publicly listed equity. It also examined the reaction of the sample firms' equity returns to their earnings announcements after emergence, and found positive reactions. This suggested that the excess stock market returns could have been driven by the market's expectational errors about how companies would perform at the time of emergence from Chapter 11.

Another interesting study on post-bankruptcy performance was also conducted by Hotchkiss and Mooradian (1997). This study found that firms that distressed debt investors (or "vultures") had a role in improving the performance of companies after Chapter 11. The study's

sample had 288 companies, of which 172 had a “vulture” investor involved in the restructuring and the remaining 116 had no significant ownership by “vultures”. 32 percent of the 116 companies without “vultures” experienced negative pre-interest operating performance in the year after emergence. However, only 12% of the 172 companies with “vultures” had negative operating results.

III. Hypothesis

The primary research hypothesis for this study is that high Z and Z' scores before a bankruptcy are indicative of a high stock performance post-emergence from the bankruptcy. Since these measures are the most well-known predictors of corporate distress and the probability that a firm will go bankrupt, this study aims to examine if they can also indicate how well a firm will perform once it comes out of a bankruptcy. As previously mentioned, the main difference between the two scores is that the Z score is more appropriate for manufacturing firms, while the Z' score is better for non-manufacturing firms.

The next two potential predictors, i.e. size of board and percentage of insiders on the board are both corporate governance factors. In general, since companies that have good corporate governance perform better than those who don't, the hypothesis for these factors is that companies that have an optimal board size (defined for the purposes of this study as less than eight board members) and those which have fewer insiders on the board (less than 17% of the total board) are more likely to perform better after emerging from the bankruptcy process.

Ability to secure debtor-in-possession financing is a factor added by the author based on the previous study conducted by Dahiya in 2003. According to that study, the most important determinant for post-emergence success for any firm was its ability to secure debtor-in-

possession financing. However, since this study was conducted more than 10 years ago, the author wanted to check if this relationship continues to exist. The hypothesis for this factor is that a firm's ability to secure debtor-in-possession financing would be a positive indicator for its performance after it emerges from the bankruptcy process. This hypothesis is based on the results from Dahiya's study.

For presence of a pre-packaged plan, the hypothesis is that if there was a pre-packaged or negotiated plan, then the company performs better post-emergence. This is because the duration of the bankruptcy is shorter in the presence of such a plan. A pre-packaged bankruptcy is one in which the reorganization plan has already been accepted by the creditors before the company declared insolvency. Thus, it makes the bankruptcy process simpler and faster to get out of.

Finally, the last factor in this study is stock prices prior to filing. The hypothesis for this is that if the stock price one week prior, one month prior, or six months prior to filing were relatively high (higher than the median stock price for the sample sets), this could mean that the market is positive about the restructuring potential of the firm. Thus, higher stock prices prior to filing would indicate better performance post-emergence.

IV. Data and Methodology

i. Data Collection and Characteristics

Using a sample period of 15 years from 2002-2016, a list of 650 companies that successfully emerged from bankruptcies in this timeframe was compiled. This was done using an existing database (Altman-Kuehne/NYU Salomon Center Chapter 11 Emergences) that consisted of companies with high yield debt. Due to the limited data available on private companies, and the author's definition of post-emergence success to be excess stock returns of the company

versus the returns on the overall market equity index, this research is limited to companies that emerged out of bankruptcies as public companies listed on a stock exchange. Thus, all companies that emerged as private entities, were acquired by another larger company, merged with another company, or liquidated, were removed from the sample. This led to the elimination of 550 companies, leaving 100 companies in the sample set.

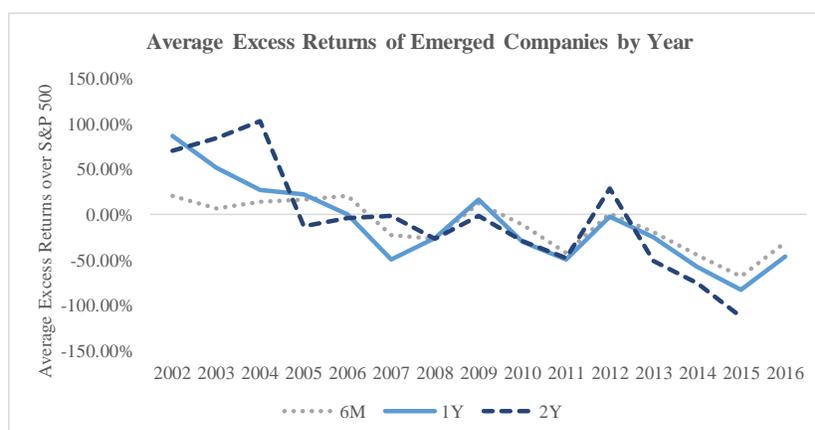
Next, the author collected Chapter 11 emergences from the Bankruptcy Almanac (New Generation Research) for public companies without high yield debt, which added another 130 companies to the sample set. However, despite increasing to 230 companies, the sample set ultimately had 89 companies because 141 companies had to be eliminated due to inadequate data availability. These 141 companies emerged from bankruptcies in this time period as public companies, but since they were traded over-the-counter, information about their stock returns was not available. A list of the final 89 companies used in this study can be found in the appendix (Exhibit A), along with their effective dates of emergence from the Chapter 11 bankruptcy process.

ii. Equity Performance Post-Emergence: Dependent Variable

Using this remaining list of 89 successful emergences, equity performance of each of the companies on the list was measured. Specifically, 6-month, 1-year, and 2-year stock returns for these companies were computed. This was done using daily stock return data for each of the companies from the CRSP database on WRDS (Wharton Research Data Services). The same database was also used to compute the returns on the S&P 500 Index for the time periods corresponding to the emergence dates for each company. Finally, the return from the S&P 500 Index was subtracted from each company's stock return in the corresponding period, to get each company's excess 6-month, 1-year, and 2-year stock returns. The average excess returns of the

emerged companies over the S&P 500 Index for each year between 2002 and 2016 can be seen in Graph 1 on the next page. The exact numbers and information used to make this graph can be found in a table in the appendix (Exhibit B). It is evident from the graph that there has largely been a downward trend in the excess returns over the S&P 500 Index returns of emerged companies for the past 15 years. A possible reason for the largely decreasing excess returns could be the increasingly better performance of the S&P 500 Index over the years from 2000-2008 and then from 2010-2016. There is an upward spike in the excess returns graph in 2009, which could be attributed to the financial crisis when the S&P 500 Index fell a lot.

Graph 1: Average Excess Returns of Emerged Companies over S&P 500 Index by Year



As previously mentioned, the companies that had excess returns of zero percent and above were categorized as successful emergences for the purposes of this study, whereas companies with negative excess returns were categorized as unsuccessful. This led to the creation of six sample sets of data. Overall, 46% of all companies were successful in the 6-month period, 36% were successful in the 1-year period, and 49% were successful in the 2-year period. Table 4a summarizing this data can be found below, and the lists of companies that fell into each of these categories can be found in the appendix (Exhibit C) along with their excess returns.

Table 4a: Successful versus Unsuccessful Emergences in the 6-Month, 1-Year, & 2-Year Periods

	6M	1Y	2Y
Successful			
<i>Number</i>	41	31	36
<i>Percentage</i>	46%	36%	49%
Unsuccessful			
<i>Number</i>	48	54	37
<i>Percentage</i>	54%	64%	51%
Total	89	85	73

Though for the purposes of this study the author defines zero or positive excess returns over the S&P 500 as successful emergences, it is also helpful to look at the data obtained about the absolute returns of post-emergent companies. Excess returns are useful for creditors of the company who are only invested in the stock market, to compare the performance of these companies versus the rest of the market. However, absolute return data can be useful for creditors whose portfolio may include investments in bonds, and not just equities. When this data was examined, the results were similar to that of the data of excess returns. Overall, 51% of the companies were successful and had zero or positive excess returns in the 6-month period, 46% in the 1-year period, and 55% in the 2-year period. These numbers are slightly higher than the numbers for the excess returns, and this is a better benchmark for creditors with diversified investments to use. Table 4b summarizing this data can be found below.

Table 4b: Successful versus Unsuccessful Emergences in the 6-Month, 1-Year, & 2-Year Periods

	6M	1Y	2Y
Successful			
<i>Number</i>	45	39	40
<i>Percentage</i>	51%	46%	55%
Unsuccessful			
<i>Number</i>	44	46	33
<i>Percentage</i>	49%	54%	45%
Total	89	85	73

iii. Potential Indicators of Post-Emergence Success: Independent Variables

For the first two factors that could be indicators of post-emergence success, i.e. the Altman Z-Score and Altman Z' Score, financial data about the companies was compiled using the Capital IQ database. This data was then used to calculate Z and Z' scores at two time observations – one year before the company filed for bankruptcy (T_1), and the quarter before the company filed for bankruptcy (T_2).

For the corporate governance factors, i.e. size of board and percentage of insiders on board, data was obtained using the DEF 14A SEC filings for each company in the quarter before the company filed for bankruptcy. Specifically, the percentage of insiders were obtained by checking how many board members were reported to be “independent” in each of these filings. Independent board members are those who do not have material or pecuniary relationships with the company or related persons, except sitting fees. Of the 89 companies in the sample set, data for the size of the board of directors was found for all 89 companies, however data about the independence of the board was found for 63 companies because it wasn't clearly stated in the filings for the other 26 companies.

Data for ability to secure debtor-in-possession financing and presence of a pre-packaged or negotiated plan was obtained using the Bankruptcy Almanac. Of the 89 companies in the sample set, 50 companies got access to debtor-in possession financing during their Chapter 11 bankruptcy process. 25 companies had a pre-packaged or negotiated plan before they entered into the Chapter 11 process.

Finally, the data for the stock prices prior to filing was obtained using the Capital IQ database. Specifically, for each company, the stock price one week prior, one month prior, and six months prior to the day it filed for bankruptcy was obtained.

iv. Methodology

Using the data collected above, the author calculated the means, medians, and standard deviations of the Z and Z'' scores for the six sample sets of successful and unsuccessful emergencies, over the three different time periods used in the study (6-month, 1-year, and 2-year). According to the means of the different sample sets, bond rating equivalents were also assigned to each of the sample sets using Tables 1 and 2. Next, to determine if there was a statistically significant difference between the means obtained for the successful versus unsuccessful groups for each period, the author employed 2-sample t-tests, assuming unequal variances. Thus, three different t-tests were conducted for each of the three periods.

The author then conducted a linear regression using the sample set of the Z scores in the quarter before bankruptcy, Z'' scores in the quarter before bankruptcy, Z -scores one year prior to bankruptcy, and Z'' scores one year prior to bankruptcy each as the independent variables, and the 6-month, 1-year, and 2-year excess returns each as the dependent variables. A multiple regression analysis was also conducted using different combinations of the sets of Z and Z'' scores as independent variables and regressing them against the 6-month, 1-year, and 2-year excess returns.

Similarly, for the other indicators used in this study (size of board, percentage of insiders on board, access to DIP financing, pre-packaged bankruptcy, and stock prices prior to filing) linear regressions were conducted using these as independent variables and the excess returns as

dependent variables. Furthermore, these variables were also coded as categorical independent variables (either 1 or 0) and regression analysis was conducted using those as well.

Finally, all the indicators used in the study was taken together to conduct a multiple regression and then a stepwise regression analysis, specifically forward selection, to check which model would optimize the r-square (predictive power) and most accurately predict the post-emergence success of companies emerging out of Chapter 11.

V. Results

i. Z and Z'' Scores from Quarter before Bankruptcy

Summary Statistics

For the three time periods, the summary statistical data for the Z-scores the quarter before the bankruptcy for successful and unsuccessful emergences was as follows in Tables 5 to 7:

Table 5: Summary Statistics of Z and Z'' Scores from the Quarter before Bankruptcy (6-months)

<i>For 6-Month Period</i>	Successful Emergences Z-Score (41 companies)	Unsuccessful Emergences Z-Score (48 companies)	Successful Emergences Z''-Score (41 companies)	Unsuccessful Emergences Z''-Score (48 companies)
Mean	-0.29	-5.11	-2.55	-13.92
Median	-0.39	0.12	-1.43	-0.90
Standard Deviation	1.83	28.18	4.86	64.69
Bond Rating Equivalent	D	D	D	D
No. of Companies with a Positive Z/Z'' Score	18	23	15	15

Table 6: Summary Statistics of Z and Z'' Scores from the Quarter before Bankruptcy (1-year)

<i>For 1-Year Period</i>	Successful Emergences Z-Score (31 companies)	Unsuccessful Emergences Z-Score (54 companies)	Successful Emergences Z''-Score (31 companies)	Unsuccessful Emergences Z''-Score (54 companies)
Mean	-0.12	-4.10	-2.31	-11.37
Median	-0.39	0.12	-1.22	-0.88
Standard Deviation	1.71	26.44	4.57	60.67
Bond Rating Equivalent	CCC	D	D	D
No. of Companies with a Positive Z/Z'' Score	15	24	13	15

Table 7: Summary Statistics of Z and Z'' Scores from the Quarter before Bankruptcy (2-years)

<i>For 2-Year Period</i>	Successful Emergences Z-Score (36 companies)	Unsuccessful Emergences Z-Score (37 companies)	Successful Emergences Z''-Score (36 companies)	Unsuccessful Emergences Z''-Score (37 companies)
Mean	-0.47	-5.20	-3.07	-13.77
Median	-0.28	0.14	-1.33	-0.88
Standard Deviation	2.98	31.88	7.03	73.15
Bond Rating Equivalent	D	D	D	D
No. of Companies with a Positive Z/Z'' Score	17	20	13	15

As is evident from the tables above, the averages of the Z and Z'' scores from one year before the bankruptcy were negative for both successful and unsuccessful emergences. Thus, the equivalent bond ratings for the successful and unsuccessful sample sets in all time periods were D, except for the set of successful emergences in the one-year period, which had a bond rating of CCC based on the average Z-Score. Furthermore, for all the sample sets, the unsuccessful emergences had a greater or equal number of positive Z and Z'' scores versus the successful emergences. This result illustrates that Z and Z'' scores may not be good indicators of post-emergence success.

Though all the average scores were negative, indicating that the firms were in distress, the sample sets of the successful emergences had lower negative average Z and Z'' scores versus those of the sample sets of unsuccessful emergences. However, at the same time, the standard deviations of the sample sets of unsuccessful emergences were high, indicating that the differences in the means of the unsuccessful and successful emergences could be insignificant. To test this hypothesis, the author employed the use of a 2-sample t-test assuming unequal variances. As expected, this test yielded no statistically significant difference between the means of the successful emergences and the unsuccessful emergences in any of the three time periods. The results from these t-tests are in the appendix under Exhibit D.

Linear Regressions

The author conducted linear regressions using Z-Scores and Z'' Scores from the quarter before bankruptcy as independent variables, and 6-month, 1-year, and 2-year excess returns as dependent variables. The results of the regressions yielded the following p values and r-squares:

<i>p value, r-square</i>	Z-Scores from Quarter before Bankruptcy	Z'' Scores from Quarter before Bankruptcy
6M Excess Returns	0.128, 2.64%	0.125, 2.68%
1Y Excess Returns	0.211, 1.87%	0.209, 1.89%
2Y Excess Returns	0.238, 1.96%	0.243, 1.91%

As is evident from the table above, none of the p-values were significant (<0.05), and the r-squares of the regressions were also very low ($<3\%$ for all the regressions). Furthermore, the t-statistics from the regressions were not greater than 2 or less than -2, indicating that these coefficients in the regressions were not significant. Thus, none of the linear regression models using Z or Z'' scores from the quarter before bankruptcy have any predictive power in indicating post-emergence success using excess returns.

ii. Z and Z'' Scores One Year before the Bankruptcy

Summary Statistics

For the three time periods, the summary statistical data for the Z-scores one year before the bankruptcy for successful and unsuccessful emergences was as follows in Tables 8 to 10:

Table 8: Summary Statistics of Z and Z' Scores from One Year before Bankruptcy (6-months)

For 6-Month Period	Successful Emergences Z-Score (41 companies)	Unsuccessful Emergences Z-Score (48 companies)	Successful Emergences Z''-Score (41 companies)	Unsuccessful Emergences Z''-Score (48 companies)
Mean	0.38	-0.25	-0.73	-2.05
Median	0.39	0.42	-0.11	-0.19
Standard Deviation	1.34	3.89	3.07	8.61
Bond Rating Equivalent	B	D	D	D
No. of Companies with a Positive Z/Z'' Score	24	29	19	21

Table 9: Summary Statistics of Z and Z' Scores from One Year before Bankruptcy (1-year)

For 1-Year Period	Successful Emergences Z-Score (31 companies)	Unsuccessful Emergences Z-Score (54 companies)	Successful Emergences Z''-Score (31 companies)	Unsuccessful Emergences Z''-Score (54 companies)
Mean	0.42	-0.15	-0.83	-1.78
Median	0.10	0.47	-0.66	-0.07
Standard Deviation	1.39	3.68	2.94	8.23
Bond Rating Equivalent	B	D	D	D
No. of Companies with a Positive Z/Z'' Score	17	30	13	22

Table 10: Summary Statistics of Z and Z' Scores from One Year before Bankruptcy (2-years)

For 2-Year Period	Successful Emergences Z-Score (36 companies)	Unsuccessful Emergences Z-Score (37 companies)	Successful Emergences Z''-Score (36 companies)	Unsuccessful Emergences Z''-Score (37 companies)
Mean	0.05	0.07	-1.52	-1.62
Median	0.24	0.57	-0.11	-0.02
Standard Deviation	2.33	4.01	5.01	9.03
Bond Rating Equivalent	D	D	D	D
No. of Companies with a Positive Z/Z'' Score	20	26	17	18

The averages of most of the Z and Z' scores one year before bankruptcy were also mostly negative or very close to zero, with a few exceptions. Once again, the unsuccessful emergences had a greater number of positive Z and Z' scores versus the successful emergences. However, the equivalent bond ratings from the averages were D for the unsuccessful and successful sample sets in most periods, except for the sets of Z-scores of successful emergences in the 6-month and 1-year periods, which had a bond rating of B. This result indicates that Z-scores one year before bankruptcy may be a good indicator of post-emergence success. To test this hypothesis, the

author once again employed the use of a 2-sample t-test assuming unequal variances. However, this test yielded no statistically significant difference between the means of the successful emergences and the unsuccessful emergences in any of the three time periods. The results from these t-tests are in the appendix under Exhibit E.

Linear Regressions

The author conducted linear regressions using Z-Scores and Z' Scores from one year before the bankruptcy as independent variables, and 6-month, 1-year, and 2-year excess returns as dependent variables. The results of the regressions yielded the following p values and r-squares:

<i>p value, r-square</i>	Z-Scores from One Year before Bankruptcy	Z' Scores from One Year before Bankruptcy
6M Excess Returns	0.150, 2.73%	0.285, 1.31%
1Y Excess Returns	0.285, 1.38%	0.387, 0.90%
2Y Excess Returns	0.812, 0.08%	0.866, 0.04%

Similar to the regressions with Z and Z' scores from the quarter before bankruptcy, in these linear regressions also none of the p values were significant (<0.05), and the r-squares of the regressions were also very low ($<3\%$ for all the regressions). Once again, the t-statistics from these regressions were also not greater than 2 or less than -2, indicating that these coefficients in the regressions were not significant. Thus, linear regression models using Z or Z' scores from one year before bankruptcy do not have any predictive power in indicating post-emergence success using excess returns. Specifically for the 2-year excess returns, p values were very high and r-squares extremely low, indicating that Z and Z' scores from one year before bankruptcy are especially not good indicators of long-term post-emergence success.

Multiple Regressions

In addition to the linear regressions conducted above, the author also conducted several combinations of multiple regressions to check if the predictive power and statistical significance of the model improved with multiple variables used together. Of the different combinations used, two models yielded variables with some statistical significance.

The first model was one where Z-scores from the quarter before bankruptcy, Z'' scores from the quarter before bankruptcy, Z-scores from one year before bankruptcy, and Z'' scores one year before bankruptcy were used as independent variables. The dependent variable was the 6-month excess returns. The r-square yielded by this model was 7.24%, and the p values and t-statistics were as follows:

<i>p value, t-statistic</i>	<i>Z-Scores from Quarter before Bankruptcy</i>	<i>Z'' Scores from Quarter before Bankruptcy</i>	<i>Z-Scores from One Year before Bankruptcy</i>	<i>Z'' Scores from One Year before Bankruptcy</i>
6M Excess Returns	0.269, -1.11	0.233, 1.20	0.054, 1.95	0.049, -1.99

As can be seen above, the p value for Z'' scores from one year before bankruptcy was significant, and the p values for Z scores from one year before bankruptcy was also very close to being statistically significant at 0.05. Furthermore, the predictive power of this model was also higher than that of the models using linear regressions. Thus in a model where all these indicators are regressed together against 6-month excess returns, the Z and Z'' scores from one year before bankruptcy can be good indicators of post-emergence success. However, contrary to the hypothesis of the study, the Z'' scores from one year before bankruptcy have a negative coefficient in the regression, which implies that lower Z'' scores one year before the bankruptcy result in higher post-emergence 6-month excess returns. For Z-Scores, the coefficient was positive, so in line with the hypothesis, higher Z-Scores before bankruptcy lead to higher returns.

The second model that yielded a statistically significant p value was one where the Z'' scores from the quarter before bankruptcy and Z'' scores from one year before bankruptcy were used as independent variables. The dependent variable was the 2-year excess returns. The r-square yielded by this model was 6.06%, and the p values and t-statistics were as follows:

<i>p value, t-statistic</i>	Z'' Scores from Quarter before Bankruptcy	Z'' Scores from One Year before Bankruptcy
2Y Excess Returns	0.038, 2.12	0.083, -1.76

The table above shows that the p value for Z'' scores from the quarter before bankruptcy was significant, and the p value of Z'' scores from one year before the bankruptcy was also significantly lower than that yielded by the linear regression model of Z'' scores one year before versus 2-year excess returns. Though not high in itself, the predictive power of this model was also higher than that of the models using linear regressions. Thus in a model using Z'' scores from the quarter before and one year before a bankruptcy, the Z'' score from the quarter before a bankruptcy can be a significant indicator of post-emergence success using 2-year excess returns. Specifically, as predicted in the hypothesis, since the Z'' score has a positive coefficient, a higher Z'' score from the quarter before bankruptcy results in higher excess returns. The full results of the regressions of the both the models described above can be found in the appendix under Exhibits F and G.

iii. Size of Board and Percentage of Insiders on the Board

Summary Statistics

To check if the size of board and percentage of insiders can be indicators of post-emergence success, the author used these two indicators as independent variables in linear regressions, where the dependent variable was the excess returns of the companies in the sample

set. Insiders are defined as those who have material or pecuniary relationships with the company or related persons. The summary statistics of the size of board and percentage of insiders for the sample set were as follows:

	Size of Board	% of Insiders on Board
Mean	8.7	20%
Median	8.0	17%
Standard Deviation	2.1	11%

Regressions

Based on these statistics, the author first decided to use the medians of both these variables to convert the samples to categorical variables. All companies that had a board size of 8 or under were coded as 1 and companies with over 8 board members were coded as 0. Similarly, for percentage of insiders, all companies with less than 17% insiders were coded as 1 and those with more than 17% were coded as 0. Based on this, the regression analysis was conducted. The results of the regressions yielded the following p values and r-squares:

<i>p value, r-square</i>	Size of Board	% of Insiders on Board
6M Excess Returns	0.032, 5.15%	0.036, 7.04%
1Y Excess Returns	0.170, 2.25%	0.004, 13.82%
2Y Excess Returns	0.512, 0.61%	0.022, 10.52%

For size of board, the p value was only significant when the size of the board was regressed against the 6-month returns. However, since the r-square was only 5.15%, this shows that the model didn't have much predictive power. For percentage of insiders, the p values were significant for all three periods (6-month, 1-year, and 2-year). Of the three periods, the r-square was the highest for the 1-year excess returns, i.e. that model had the highest predictive power. Thus it can be concluded that size of board can possibly be an indicator of post-emergence

success using 6-month returns, and percentage of insiders can be an even better predictor using returns from all three periods. To further investigate this, the author decided to run linear regressions using the data of these variables as continuous variables. These regressions yielded the following p values and r-squares:

<i>p value, r-square</i>	Size of Board	% of Insiders on Board
6M Excess Returns	0.060, 4.01%	0.109, 4.17%
1Y Excess Returns	0.569, 0.39%	0.026, 8.41%
2Y Excess Returns	0.865, 0.04%	0.111, 3.22%

The p values for size of board were all insignificant, however when regressed against 6-month returns the p value was 0.06, which is very close to the statistically significant level of 0.05. The coefficient in this regression was positive, implying that a larger board would lead to higher 6-month excess returns. However, as with the regression using categorical variables, the r-squares for all the models using size of board were very low, indicating low predictive power.

For percentage of insiders, the p value was significant at 0.026 when regressed against the 1-year excess returns. The r-square for this model was also the highest of all the other models, at 8.41%. Thus, based on these results, the percentage of insiders on a board can be a significant indicators of post-emergence success using 1-year excess returns. However, contrary to the hypothesis in this paper, since the coefficient yielded from this regression was positive, this implies that a higher percentage of insiders on the board would lead to higher one-year excess returns for companies post-emergence. The result for this regression model can be found in the appendix under Exhibit H.

iv. Access to DIP Financing and Pre-Packaged Plan

Summary Statistics

Of the 25 companies in the sample set that had a pre-packaged plan and 50 companies that had access to debtor-in-possession financing, there were 13 companies that had both. When the excess returns of these 13 companies were examined, 5 had positive excess returns in the 6-month period, while 8 had negative excess returns. In the one-year period, 4 had positive excess returns, 8 had negative excess returns, and data was unavailable for 1 company. Finally, in the 2-year period, 5 had positive excess returns, 4 had negative excess returns, and data was unavailable for 4 companies. Thus having both of these factors was not very common. However, the companies that had both factors also had a similar split between successful (positive excess returns) and unsuccessful (negative excess returns) emergences when compared to the larger sample set of 89 companies. Thus, their performance was not significantly better than others.

Regressions

To check if access to DIP financing and a pre-packaged plan can be indicators of post-emergence success, the author used these two variables as categorical variables in linear regressions, where the dependent variable was the excess returns of the companies in the sample set. If a company had access to DIP financing it was coded as 1, otherwise it was coded as 0. Similarly, if a company had a pre-packaged plan it was coded as 1, otherwise it was coded as 0. The results of these regressions yielded the following p values and r-squares:

<i>p value, r-square</i>	Access to DIP Financing	Pre-Packaged Plan
6M Excess Returns	0.432, 0.71%	0.150, 2.37%
1Y Excess Returns	0.903, 0.02%	0.200, 1.97%
2Y Excess Returns	0.299, 1.52%	0.951, 0.01%

As is evident from the results above, neither access to DIP financing nor a pre-packaged plan yielded any significant p values. Thus, it can be concluded that none of these variables are significant indicators of post-emergence success after a bankruptcy, defined by excess returns.

v. Stock Prices Prior to Filing

Summary Statistics

To check if a significantly high stock price prior to filing for bankruptcy can be an indicator of post-emergence success, the author used this indicator as an independent variable in a linear regression, where the dependent variable was the excess returns of the companies in the sample set. The author decided to use the stock price one week, one month, and six months prior to filing for bankruptcy for this purpose. The summary statistics of these stock prices for the sample set were as follows:

	Stock Price One Week Prior to Filing	Stock Price One Month Prior to Filing	Stock Price Six Months Prior to Filing
Mean	\$33.02	\$39.01	\$90.53
Median	\$1.71	\$1.65	\$3.68
Standard Deviation	\$136.91	\$167.89	\$419.01

Regressions

Based on these statistics, the author decided to use the median of this variable to convert the sample set to a categorical variable, since the standard deviations were too high to use the mean. Thus all companies that had a stock price higher than \$1.71 one week prior to filing for bankruptcy were coded as 1, and all companies that had a stock price lower than \$1.71 were coded as 0. Similarly for one month and six months prior, companies with stock prices above \$1.65 and \$3.68 respectively were coded as 1, and ones with stock prices below these values were coded as 0. The results of the regressions yielded the following p values and r-squares:

<i>p value, r-square</i>	Stock Price One Week Prior to Filing	Stock Price One Month Prior to Filing	Stock Price Six Months Prior to Filing
6M Excess Returns	0.849, 0.08%	0.656, 0.46%	0.319, 2.07%
1Y Excess Returns	0.707, 0.32%	0.683, 0.42%	0.522, 0.94%
2Y Excess Returns	0.894, 0.05%	0.655, 0.59%	0.928, 0.02%

As can be seen from the data above, the p values for stock prices one week, one month, and six months prior to filing were extremely high, and all the r-squares extremely low. This indicates that stock prices prior to filing aren't good indicators of post-emergence success using excess returns, and these models have no predictive power. However, one reason that these models didn't work could be because using stock prices as categorical variables yield very simplistic models. Furthermore, the cutoff chosen to code the variables could be imprecise, thus compromising the power of the model. To overcome these limitations, the author decided to use the actual stock prices from one week, one month, and six months prior to filing as continuous variables in linear regressions to see if the same results were reached. The p values and r-squares of these regressions were as follows:

<i>p value, r-square</i>	Stock Price One Week Prior to Filing	Stock Price One Month Prior to Filing	Stock Price Six Months Prior to Filing
6M Excess Returns	0.188, 3.74%	0.212, 3.60%	0.227, 3.02%
1Y Excess Returns	0.327, 2.19%	0.340, 2.28%	0.397, 1.64%
2Y Excess Returns	0.217, 4.20%	0.221, 4.38%	0.193, 4.53%

Similar to the previous results, these models also yielded no statistically significant p values and low r-squares, indicating little predictive power. However, compared to the previous results, the p values in these models were generally lower and r-squares were higher. Thus, while using stock prices as continuous instead of categorical variables increased the predictive power and statistical significance of the models, these were still not high enough to show that stock prices prior to filing can be significant indicators of post-emergence success using excess returns.

vi. Multiple Regression Analysis using all Indicators

After conducting regressions using all the indicators in this study separately, the author conducted a multiple regression analysis using all the indicators together. Three different multiple regressions were conducted. They used 6-month returns, 1-year returns, and 2-year returns respectively as the dependent variables, and all the indicators put together as the independent variables. Though these models had higher r-squares than the models using indicators separately, none of the variables in the models had statistically significant p values. The r-squares were 22.1%, 19.81%, and 40.6% respectively for the 6-month, 1-year, and 2-year excess return models. For the 6-month model the variable with the lowest p value was pre-packaged plan with a p value of 0.115, for 1-year it was percentage of insiders with a p value of 0.456, and for 2-year it was stock price six months prior to bankruptcy with a p value of 0.118. Thus while the models explained a lot of the variation in the data, they were not significant, indicating that these variables taken together are not good indicators of post-emergence success. To check if any of the variables could be significant by pairing them with only some of the other indicators in a regression using a pre-determined alpha level, the author decided to also conduct a stepwise regression analysis.

vii. Stepwise Regression Analysis (Forward Selection) using all Indicators

Stepwise regression is a statistical method to fit regression models in which predictive variables are chosen using an automatic stepwise procedure. At each step of the regression, a variable is either added or subtracted from the total set of variables, to ultimately come up with a model where having more or less variables would decrease the r-square. This study specifically uses the forward selection method. This method involves having no variables in the beginning, and then adding the variable (if any) at each step, whose inclusion would have a statistically

significant improvement of the fit of the model and increase the r-square. Variables are added at every step, until there are no more statistically significant variables to add to the model.

6-Month Returns

Using 6-month excess returns as the dependent variable, a forward selection stepwise regression analysis was conducted using all the indicators studied in this paper. The alpha level set for a variable to enter the model was chosen to be 0.15. The result of this regression yielded the following steps:

	-----Step 1-----		-----Step 2-----	
	Coef	P	Coef	P
Constant	-0.1288		-0.1113	
Pre-Packaged	-0.197	0.066	-0.208	0.050
Z" Score One Year Before			0.00829	0.150
S		0.30059		0.29537
R-sq		9.86%		15.60%
R-sq(adj)		7.13%		10.33%
R-sq(pred)		0.00%		4.15%
Mallows' Cp		-4.39		-4.08

As per this analysis, the best predictors of 6-month excess returns post emergence are a pre-packaged plan and the Z" score one year before bankruptcy, which together yield an r-square of 15.60%. The p value for pre-packaged plan is statistically significant in the second step, when paired with the Z" score one year before bankruptcy. The coefficient for the pre-packaged plan however is negative, indicating that the presence of a pre-packaged plan corresponds to a decrease in the 6-month excess returns post-emergence for the companies. This is contrary to the hypothesis in this paper that the presence of a pre-packaged plan would increase post-emergence success.

1-Year Returns

Using 1-year excess returns as the dependent variable, a forward selection stepwise regression analysis was conducted using all the indicators studied in this paper. The alpha level set for a variable to enter the model was chosen to be 0.15. The result of this regression yielded the following steps:

-----Step 1-----		
	Coef	P
Constant	-0.2878	
Z-Score One Year Before	0.0338	0.066
S		0.41279
R-sq		10.47%
R-sq(adj)		7.58%
R-sq(pred)		0.00%
Mallows' Cp		-5.55

As per this analysis, the best predictor of 1-year excess returns post emergence is the Z-score one year before bankruptcy, which yields an r-square of 10.47%. The p value for this indicator is not statistically significant at 0.066, but is very close to the 0.05 statistically significant level. Since the coefficient for this is positive, it indicates that in line with the hypothesis for this study, a higher Z-Score one year before bankruptcy would yield higher one-year excess returns post-emergence for the companies.

2-Year Returns

Using 2-year excess returns as the dependent variable, a forward selection stepwise regression analysis was conducted using all the indicators studied in this paper. The alpha level set for a variable to enter the model was chosen to be 0.15. The result of this regression yielded the following steps:

-----Step 1-----		
	Coef	P
Constant	-1.149	
Size of Board	0.1085	0.057
S		0.62611
R-sq		12.74%
R-sq(adj)		9.51%
R-sq(pred)		0.00%
Mallows' Cp		-0.03

As per this analysis, the best predictor of 2-year excess returns post emergence is the size of the board, which yields an r-square of 12.74%. The p value for this indicator is not statistically significant at 0.057, but is very close to the 0.05 statistically significant level. Since the coefficient for this is positive, this indicates that a larger board would lead to higher 2-year excess returns post-emergence for the companies.

VI. Conclusion

The evidence from this research confirms that it is difficult to predict post-emergence success of companies after they emerge from the Chapter 11 process, using indicators from before the bankruptcy. It can be logically assumed that it is hard to do so because when a company emerges from the Chapter 11 process, it is both operationally and financially very different from how it was structured when it was going into bankruptcy.

Size of board was not a significant factor in this study, possibly because boards usually change their size post-emergence from bankruptcy. Access to debtor-in-possession financing has been shown to be an indicator of post-emergence success in previous studies, but was not a significant indicator from the results of this paper. This discrepancy may have arisen due to the different definition of “success” used by the author of this paper. Finally, stock price prior to

filing was not a good indicator as well, possibly because market sentiment about the companies that were going bankrupt was wrong.

Though the stepwise regressions yielded the best predictors for each of the three sets of excess returns used in this study, most of the values weren't statistically significant. Similarly, from the various multiple and linear regressions conducted earlier in the study, very few yielded statistically significant values. A summary of the indicators that were significant is as follows:

Indicator	Model where it was Significant	p value	r-square	Sign of Coefficient
Pre-packaged plan	Stepwise Regression for 6-month excess returns	0.050	15.60%	Negative
Z" scores from quarter of bankruptcy	Multiple Regression for 2-year excess returns	0.038	6.06%	Positive
Z" scores from one year before bankruptcy	Multiple Regression for 6-month excess returns	0.049	7.24%	Negative
Percentage of Insiders on Board	Linear Regression for 1-year excess returns	0.026	8.41%	Positive

This table shows that while financial indicators like Z and Z" scores are best used for their original purpose, i.e. to predict the risk of bankruptcy in the first place, they could also be used to predict post-emergence success in certain models. This could be because if a company's financial health was better before the bankruptcy, it is more likely that it would perform well after emerging from the bankruptcy. Similarly, access to pre-packaged plans was a significant indicator in the stepwise regression model. But contrary to the hypothesis, the results showed that not having this plan was better for post-emergence success. A possible reason for this could be that if creditors already know a bankruptcy is imminent due to a pre-packaged plan, they may be more aggressive in collecting from the company. This would put additional financial stress on the company, affecting its post-emergence performance too. Finally, a higher percentage of insiders on the board could be an indicator of better post-emergence performance. This could be the case because insiders are involved in the day-to-day operations of a company and thus may be able to take better decisions about the company versus independent directors.

Though it is evident that the indicators described above were significant in certain regression models, the predictive power of these models was not very high. However, based on these results, more work can be done using these indicators to determine if they can predict post-emergence success. One possible study can be to further explore these indicators using a more flexible definition of success, for e.g. whether the companies emerge from the Chapter 11 process or not. A limitation of this study could've been the stricter definition of success to be positive excess returns post-emergence, compared to the definitions of success used in other similar studies. Additionally, another limitation of this study could've been the size of the sample set, since only 89 companies were used. Using a larger sample set from a wider time period could yield different results.

Appendix

A. List of 89 companies in sample set

Name of Company	Effective Data of Emergence
Arch Coal, Inc.	10/05/2016
Basic Energy Services, Inc.	12/23/2016
C&J Energy Services Ltd.	01/06/2017
Goodrich Petroleum Corporation	10/12/2016
Halcon Resources Corporation	09/09/2016
Key Energy Services, Inc.	12/15/2016
Midstates Petroleum Company	10/21/2016
Penn Virginia Corporation	09/12/2016
SandRidge Energy, Inc.	10/04/2016
Swift Energy Company	04/22/2016
Verso Corporation	07/15/2016
NII Holdings, Inc.	06/26/2015
Eagle Bulk Shipping Inc.	10/15/2014
Genco Shipping & Trading Limited	07/09/2014
Overseas Shipholding Group, Inc.	08/05/2014
USEC Inc.	09/30/2014
W.R.Grace and Co.	02/03/2014
Ambac Financial Group, Inc.	04/29/2013
Anchor BanCorp Wisconsin Inc.	09/27/2013
Dex One Corporation	04/30/2013
Eastman Kodak Company	09/03/2013
Otelco Inc.	05/24/2013
Delta Petroleum Corporation	08/31/2012
Dynegy Holdings, LLC	10/01/2012
Filene's Basement, LLC (Syms)	09/17/2012
Lee Enterprises, Incorporated	01/30/2012
FairPoint Communications, Inc.	01/24/2011
General Motors Corporation	03/31/2011
Tronox Incorporated	02/14/2011
AbitibiBowater Inc.	12/09/2010
Chemtura Corporation	11/09/2010
Cooper-Standard Holdings, Inc.	05/27/2010
General Growth Properties, Inc.	11/09/2010
GSI Group Inc.	07/23/2010
Luna Innovations Incorporated	01/12/2010
R.H.Donnely Corporation	01/29/2010
Six Flags, Inc.	05/03/2010
Smurfit-Stone Container Corp.	06/30/2010
Spansion Inc.	05/10/2010
U.S.Concrete, Inc.	08/31/2010
Vermillion, Inc.	01/22/2010
Visteon Corporation	10/01/2010

Name of Company	Effective Data of Emergence
Xerium Technologies	05/25/2010
Apex Silver Mines Limited	03/24/2009
Charter Communications, Inc.	12/01/2009
CIT Group Inc.	12/10/2009
Energy Partners, Ltd.	09/21/2009
Idearc Inc.	12/31/2009
Lear Corporation	11/09/2009
Pilgrim's Pride Corporation	12/28/2009
Spectrum Brands, Inc.	08/28/2009
Calpine Corporation	01/31/2008
Dana Corporation	02/01/2008
Delta Air Lines, Inc.	04/30/2007
Global Power Equipment Group Inc.	01/22/2008
SeraCare Life Sciences, Inc.	05/17/2007
Armstrong World Industries, Inc.	10/04/2006
Integrated Electrical Services, Inc.	05/15/2006
Kaiser Aluminum Corporation	07/06/2006
Owens Corning	10/31/2006
Silicon Graphics, Inc.	10/17/2006
USG Corporation	06/20/2006
Winn Dixie Stores, Inc.	11/21/2006
Hawaiin Airlines, Inc.	06/02/2005
Loral Space and Communications Ltd.	11/22/2005
Mirant Corporation	01/03/2006
Trico Marine Services	03/15/2005
US Airways Group, Inc.	09/27/2005
Amerco	03/15/2004
Northwestern Corporation	11/02/2004
Pacific Gas and Electric	04/12/2004
Chart Industries	09/15/2003
Conseco, Inc.	09/10/2003
GenTek, Inc.	11/10/2003
Hayes Lemmerz International	06/03/2003
Kmart Corp	05/05/2003
Leap Wireless International	08/16/2004
Magellan Health Services, Inc.	01/05/2004
NRG Energy	12/05/2003
Redback Networks, Inc.	01/02/2004
SpectraSite Holdings, Inc.	02/10/2003
Warnaco Group, Inc.	02/04/2003
Wheeling-Pittsburgh Steel Corp.	08/01/2003
Dade Behring Holdings, Inc.	10/03/2002
Teligent, Inc.	09/12/2002
Komag, Inc.	06/30/2002
NTL Inc	01/13/2003
Zilog, Inc.	05/13/2002
Mpower Holding Corporation	07/31/2002

B. Average Excess Returns of Emerged Companies over S&P 500 Index by Year

Year	#	6M	1Y	2Y
2002	5	20.04%	86.79%	70.10%
2003	10	6.29%	51.43%	83.75%
2004	6	13.69%	26.76%	103.21%
2005	4	16.26%	22.23%	-12.78%
2006	8	20.45%	-0.02%	-3.88%
2007	2	-22.96%	-49.55%	-1.51%
2008	3	-26.92%	-26.50%	-27.19%
2009	8	12.55%	16.27%	-1.84%
2010	14	-11.21%	-29.95%	-29.43%
2011	3	-42.79%	-49.91%	-48.29%
2012	4	0.74%	-2.52%	28.99%
2013	5	-19.48%	-24.98%	-51.64%
2014	5	-44.84%	-57.88%	-76.23%
2015	1	-68.29%	-83.41%	-113.11%
2016	11	-31.21%	-46.59%	N/A
All Years	89	-5.65%	-2.43%	4.88%

C. Successful versus Unsuccessful Emergences in 6-Month, 1-Year, and 2-Year Periods

List of Successful Emergences in 6-Month Period

Name of Company	Excess Returns
Arch Coal, Inc.	12.72%
Anchor BanCorp Wisconsin Inc.	0.02%
Eastman Kodak Company	4.62%
Dynegy Holdings, LLC	19.98%
Filene's Basement, LLC (Syms)	14.22%
Chemtura Corporation	11.34%
Cooper-Standard Holdings, Inc.	18.95%
General Growth Properties, Inc.	7.58%
Six Flags, Inc.	41.63%
Smurfit-Stone Container Corp.	2.14%
Apex Silver Mines Limited	73.84%
Charter Communications, Inc.	17.14%
CIT Group Inc.	29.58%
Energy Partners, Ltd.	29.01%
Lear Corporation	7.06%
Spectrum Brands, Inc.	4.47%
Calpine Corporation	0.25%
Global Power Equipment Group Inc.	31.10%
Armstrong World Industries, Inc.	21.14%
Kaiser Aluminum Corporation	21.04%

List of Successful Emergences in 6-Month Period

Name of Company	Excess Returns
Owens Corning	13.04%
Silicon Graphics, Inc.	41.50%
Winn Dixie Stores, Inc.	109.31%
Mirant Corporation	12.16%
Trico Marine Services	31.99%
US Airways Group, Inc.	76.99%
Amerco	45.23%
Northwestern Corporation	12.27%
Pacific Gas and Electric	7.27%
Conseco, Inc.	3.24%
Kmart Corp	23.51%
Leap Wireless International	31.72%
Magellan Health Services, Inc.	18.16%
NRG Energy	21.42%
SpectraSite Holdings, Inc.	6.74%
Warnaco Group, Inc.	12.95%
Dade Behring Holdings, Inc.	28.93%
Teligent, Inc.	2.23%
Komag, Inc.	88.22%
NTL Inc	67.16%
Mpower Holding Corporation	21.58%

List of Unsuccessful Emergences in 6-Month Period

Name of Company	Excess Returns
Basic Energy Services, Inc.	-41.80%
C&J Energy Services Ltd.	-35.71%
Goodrich Petroleum Corporation	-45.80%
Halcon Resources Corporation	-41.21%
Key Energy Services, Inc.	-54.34%
Midstates Petroleum Company	-18.53%
Penn Virginia Corporation	-29.71%
SandRidge Energy, Inc.	-22.83%
Swift Energy Company	-20.79%
Verso Corporation	-45.29%
NII Holdings, Inc.	-68.29%
Eagle Bulk Shipping Inc.	-44.50%
Genco Shipping & Trading Limited	-72.10%
Overseas Shipholding Group, Inc.	-45.48%
USEC Inc.	-54.06%
W.R.Grace and Co.	-8.03%
Ambac Financial Group, Inc.	-7.30%
Dex One Corporation	-49.57%
Otelco Inc.	-45.20%
Delta Petroleum Corporation	-13.76%
Lee Enterprises, Incorporated	-17.48%
FairPoint Communications, Inc.	-70.12%
General Motors Corporation	-20.30%
Tronox Incorporated	-37.96%

List of Unsuccessful Emergences in 6-Month Period

Name of Company	Excess Returns
AbitibiBowater Inc.	-10.82%
GSI Group Inc.	-12.17%
Luna Innovations Incorporated	-46.64%
R.H.Donnely Corporation	-49.78%
Spanion Inc.	-0.84%
U.S.Concrete, Inc.	-4.68%
Vermillion, Inc.	-54.55%
Visteon Corporation	-14.17%
Xerium Technologies	-44.93%
Idearc Inc.	-42.91%
Pilgrim's Pride Corporation	-17.77%
Dana Corporation	-47.24%
Delta Air Lines, Inc.	-6.78%
SeraCare Life Sciences, Inc.	-39.15%
Integrated Electrical Services, Inc.	-44.82%
USG Corporation	-9.76%
Hawaiin Airlines, Inc.	-38.38%
Loral Space and Communications Ltd.	-5.55%
Chart Industries	-7.93%
GenTek, Inc.	-26.74%
Hayes Lemmerz International	-32.37%
Redback Networks, Inc.	-32.51%
Wheeling-Pittsburgh Steel Corp.	-5.11%
Zilog, Inc.	-40.74%

List of Successful Emergences in 1-Year Period

Name of Company	Excess Returns
Ambac Financial Group, Inc.	30.52%
Anchor BanCorp Wisconsin Inc.	0.96%
Filene's Basement, LLC (Syms)	47.28%
General Growth Properties, Inc.	5.55%
Six Flags, Inc.	90.61%
Apex Silver Mines Limited	123.83%
Charter Communications, Inc.	34.78%
CIT Group Inc.	33.81%
Energy Partners, Ltd.	25.11%
Lear Corporation	30.77%
Global Power Equipment Group Inc.	54.17%
Kaiser Aluminum Corporation	54.18%
Winn Dixie Stores, Inc.	20.77%
Mirant Corporation	22.60%
Trico Marine Services	25.74%

List of Successful Emergences in 1-Year Period

Name of Company	Excess Returns
US Airways Group, Inc.	105.51%
Amerco	90.01%
Northwestern Corporation	12.95%
Pacific Gas and Electric	17.48%
Chart Industries	56.73%
Kmart Corp	224.54%
Leap Wireless International	64.37%
Magellan Health Services, Inc.	20.05%
NRG Energy	56.08%
SpectraSite Holdings, Inc.	37.45%
Warnaco Group, Inc.	16.29%
Dade Behring Holdings, Inc.	82.84%
Teligent, Inc.	169.02%
Komag, Inc.	226.22%
NTL Inc	285.01%
Mpower Holding Corporation	19.71%

List of Unsuccessful Emergences in 1-Year Period

Name of Company	Excess Returns
Arch Coal, Inc.	-0.86%
Basic Energy Services, Inc.	-52.07%
Halcon Resources Corporation	-58.18%
Key Energy Services, Inc.	-82.90%
Midstates Petroleum Company	-47.46%
Penn Virginia Corporation	-37.89%
SandRidge Energy, Inc.	-22.81%
Verso Corporation	-70.52%
NII Holdings, Inc.	-83.41%
Eagle Bulk Shipping Inc.	-59.45%
Genco Shipping & Trading Limited	-92.79%
Overseas Shipholding Group, Inc.	-50.19%
USEC Inc.	-67.48%
W.R.Grace and Co.	-19.51%
Dex One Corporation	-48.37%
Eastman Kodak Company	-36.23%
Otelco Inc.	-71.76%
Delta Petroleum Corporation	-16.04%
Dynegy Holdings, LLC	-14.95%
Lee Enterprises, Incorporated	-26.36%
FairPoint Communications, Inc.	-84.55%
General Motors Corporation	-23.57%
Tronox Incorporated	-41.62%
AbitibiBowater Inc.	-39.05%
Chemtura Corporation	-26.12%
Cooper-Standard Holdings, Inc.	-5.93%
GSI Group Inc.	-13.85%

List of Unsuccessful Emergences in 1-Year Period

Name of Company	Excess Returns
Luna Innovations Incorporated	-73.22%
R.H.Donnely Corporation	-101.80%
Spancion Inc.	-17.01%
U.S.Concrete, Inc.	-52.94%
Vermillion, Inc.	-93.17%
Visteon Corporation	-35.55%
Xerium Technologies	-26.85%
Idearc Inc.	-79.67%
Pilgrim's Pride Corporation	-32.55%
Spectrum Brands, Inc.	-5.92%
Calpine Corporation	-15.46%
Dana Corporation	-54.23%
Delta Air Lines, Inc.	-54.83%
SeraCare Life Sciences, Inc.	-44.26%
Armstrong World Industries, Inc.	-8.39%
Integrated Electrical Services, Inc.	-19.47%
Owens Corning	-24.74%
Silicon Graphics, Inc.	-17.23%
USG Corporation	-27.86%
Hawaiin Airlines, Inc.	-41.52%
Loral Space and Communications Ltd.	-0.82%
Conseco, Inc.	-22.32%
GenTek, Inc.	-1.59%
Hayes Lemmerz International	-67.82%
Redback Networks, Inc.	-44.28%
Wheeling-Pittsburgh Steel Corp.	-70.05%
Zilog, Inc.	-63.85%

List of Successful Emergences in 2-Year Period

Name of Company	Excess Returns
Anchor BanCorp Wisconsin Inc.	18.25%
Dynegy Holdings, LLC	27.95%
Lee Enterprises, Incorporated	140.82%
Chemtura Corporation	4.39%
Cooper-Standard Holdings, Inc.	3.53%
General Growth Properties, Inc.	35.22%
Six Flags, Inc.	169.21%
U.S.Concrete, Inc.	17.78%
Charter Communications, Inc.	107.24%
CIT Group Inc.	1.91%
Energy Partners, Ltd.	28.14%
Lear Corporation	20.99%
Spectrum Brands, Inc.	2.03%
Dana Corporation	1.99%
SeraCare Life Sciences, Inc.	23.78%
Kaiser Aluminum Corporation	13.22%
Winn Dixie Stores, Inc.	45.23%
Loral Space and Communications Ltd.	1.94%

List of Successful Emergences in 2-Year Period

Name of Company	Excess Returns
Mirant Corporation	39.24%
Trico Marine Services	4.76%
US Airways Group, Inc.	2.59%
Amerco	312.90%
Northwestern Corporation	32.50%
Pacific Gas and Electric	26.07%
Chart Industries	216.64%
GenTek, Inc.	90.67%
Leap Wireless International	178.32%
Magellan Health Services, Inc.	4.95%
NRG Energy	94.59%
Redback Networks, Inc.	64.52%
Warnaco Group, Inc.	49.87%
Dade Behring Holdings, Inc.	193.16%
Teligent, Inc.	56.29%
Komag, Inc.	175.51%
NTL Inc	253.60%
Mpower Holding Corporation	25.36%

List of Unsuccessful Emergences in 2-Year Period

Name of Company	Excess Returns
NII Holdings, Inc.	-113.11%
Eagle Bulk Shipping Inc.	-112.60%
Genco Shipping & Trading Limited	-103.02%
USEC Inc.	-70.96%
W.R.Grace and Co.	-18.35%
Ambac Financial Group, Inc.	-17.71%
Dex One Corporation	-106.72%
Eastman Kodak Company	-67.61%
Otelco Inc.	-84.42%
Delta Petroleum Corporation	-35.06%
Filene's Basement, LLC (Syms)	-17.77%
FairPoint Communications, Inc.	-76.16%
General Motors Corporation	-28.23%
Tronox Incorporated	-40.47%
AbitibiBowater Inc.	-57.02%
GSI Group Inc.	-43.64%
Luna Innovations Incorporated	-81.96%
R.H.Donnely Corporation	-115.14%

List of Unsuccessful Emergences in 2-Year Period

Name of Company	Excess Returns
Spanion Inc.	-57.38%
Vermillion, Inc.	-109.93%
Visteon Corporation	-43.52%
Xerium Technologies	-104.15%
Apex Silver Mines Limited	-24.53%
Idearc Inc.	-103.52%
Pilgrim's Pride Corporation	-47.00%
Calpine Corporation	-12.83%
Delta Air Lines, Inc.	-26.80%
Global Power Equipment Group Inc.	-1.24%
Armstrong World Industries, Inc.	-7.67%
Integrated Electrical Services, Inc.	-42.23%
Owens Corning	-9.87%
Silicon Graphics, Inc.	-25.19%
USG Corporation	-43.76%
Hawaiin Airlines, Inc.	-60.38%
Conseco, Inc.	-17.11%
Hayes Lemmerz International	-102.03%
Zilog, Inc.	-99.81%

D. Two-Sample T-Tests for Z and Z' Scores from Quarter prior to Bankruptcy**Two-Sample T-Test and CI: Successful Z 6M, Unsuccessful Z 6M**

Method					
μ_1 : mean of Successful Z 6M					
μ_2 : mean of Unsuccessful Z 6M					
Difference: $\mu_1 - \mu_2$					
Equal variances are not assumed for this analysis.					
Descriptive Statistics					
Sample	N	Mean	StDev	SE Mean	
Successful Z 6M	41	-0.29	1.83	0.29	
Unsuccessful Z 6M	48	-5.1	28.2	4.1	
Estimation for Difference					
Difference	95% CI for	Difference			
4.83	(-3.38, 13.03)				
Test					
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$				
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$				
T-Value	DF	P-Value			
1.18	47	0.243			

Two-Sample T-Test and CI: Successful Z 1Y, Unsuccessful Z 1Y

Method					
μ_1 : mean of Successful Z 1Y					
μ_2 : mean of Unsuccessful Z 1Y					
Difference: $\mu_1 - \mu_2$					
Equal variances are not assumed for this analysis.					
Descriptive Statistics					
Sample	N	Mean	StDev	SE Mean	
Successful Z 1Y	31	-0.12	1.71	0.31	
Unsuccessful Z 1Y	54	-4.1	26.4	3.6	
Estimation for Difference					
Difference	95% CI for Difference				
3.97	(-3.27, 11.22)				
Test					
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$				
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$				
T-Value	DF	P-Value			
1.1	53	0.276			

Two-Sample T-Test and CI: Successful Z 2Y, Unsuccessful Z 2Y

Method					
μ_1 : mean of Successful Z 2Y					
μ_2 : mean of Unsuccessful Z 2Y					
Difference: $\mu_1 - \mu_2$					
Equal variances are not assumed for this analysis.					
Descriptive Statistics					
Sample	N	Mean	StDev	SE Mean	
Successful Z 2Y	36	-0.47	2.98	0.5	
Unsuccessful Z 2Y	37	-5.2	31.9	5.2	
Estimation for Difference					
Difference	95% CI for Difference				
4.73	(-5.94, 15.41)				
Test					
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$				
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$				
T-Value	DF	P-Value			
0.9	36	0.375			

Two-Sample T-Test and CI: Successful Z" 6M, Unsuccessful Z" 6M

Method					
μ_1 : mean of Successful Z" 6M					
μ_2 : mean of Unsuccessful Z" 6M					
Difference: $\mu_1 - \mu_2$					
Equal variances are not assumed for this analysis.					
Descriptive Statistics					
Sample	N	Mean	StDev	SE Mean	
Successful Z" 6M	41	-2.55	4.86	0.76	
Unsuccessful Z" 6M	48	-13.9	64.7	9.3	
Estimation for Difference					
Difference	95% CI for Difference				
11.37	(-7.48, 30.21)				
Test					
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$				
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$				
T-Value	DF	P-Value			
1.21	47	0.231			

Two-Sample T-Test and CI: Successful Z" 1Y, Unsuccessful Z" 1Y

Method					
μ_1 : mean of Successful Z" 1Y					
μ_2 : mean of Unsuccessful Z" 1Y					
Difference: $\mu_1 - \mu_2$					
Equal variances are not assumed for this analysis.					
Descriptive Statistics					
Sample	N	Mean	StDev	SE Mean	
Successful Z" 1Y	31	-2.31	4.57	0.82	
Unsuccessful Z" 1Y	54	-11.4	60.7	8.3	
Estimation for Difference					
Difference	95% CI for Difference				
9.07	(-7.57, 25.70)				
Test					
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$				
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$				
T-Value	DF	P-Value			
1.09	54	0.279			

Two-Sample T-Test and CI: Successful Z" 2Y, Unsuccessful Z" 2Y

Method				
μ_1 : mean of Successful Z" 2Y				
μ_2 : mean of Unsuccessful Z" 2Y				
Difference: $\mu_1 - \mu_2$				
Equal variances are not assumed for this analysis.				
Descriptive Statistics				
Sample	N	Mean	StDev	SE Mean
Successful Z" 2Y	36	-3.07	7.03	1.2
Unsuccessful Z" 2Y	37	-13.8	73.1	12
Estimation for Difference				
Difference	95% CI for Difference			
10.7	(-13.8, 35.2)			
Test				
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$			
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$			
T-Value	DF	P-Value		
0.89	36	0.382		

E. Two-Sample T-Tests for Z and Z" Scores from One Year before Bankruptcy**Two-Sample T-Test and CI: Successful Z 6M, Unsuccessful Z 6M**

Method				
μ_1 : mean of Successful Z 6M				
μ_2 : mean of Unsuccessful Z 6M				
Difference: $\mu_1 - \mu_2$				
Equal variances are not assumed for this analysis.				
Descriptive Statistics				
Sample	N	Mean	StDev	SE Mean
Successful Z 6M	41	0.38	1.34	0.21
Unsuccessful Z 6M	48	-0.25	3.89	0.56
Estimation for Difference				
Difference	95% CI for Difference			
0.632	(-0.566, 1.830)			
Test				
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$			
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$			
T-Value	DF	P-Value		
1.06	59	0.296		

Two-Sample T-Test and CI: Successful Z 1Y, Unsuccessful Z 1Y

Method					
μ_1 : mean of Successful Z 1Y					
μ_2 : mean of Unsuccessful Z 1Y					
Difference: $\mu_1 - \mu_2$					
Equal variances are not assumed for this analysis.					
Descriptive Statistics					
Sample	N	Mean	StDev	SE Mean	
Successful Z 1Y	31	0.42	1.39	0.25	
Unsuccessful Z 1Y	54	-0.15	3.68	0.5	
Estimation for Difference					
Difference	95% CI for Difference				
0.576	(-0.540, 1.692)				
Test					
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$				
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$				
T-Value	DF	P-Value			
1.03	74	0.307			

Two-Sample T-Test and CI: Successful Z 2Y, Unsuccessful Z 2Y

Method					
μ_1 : mean of Successful Z 2Y					
μ_2 : mean of Unsuccessful Z 2Y					
Difference: $\mu_1 - \mu_2$					
Equal variances are not assumed for this analysis.					
Descriptive Statistics					
Sample	N	Mean	StDev	SE Mean	
Successful Z 2Y	36	0.05	2.33	0.39	
Unsuccessful Z 2Y	37	0.07	4.01	0.66	
Estimation for Difference					
Difference	95% CI for Difference				
-0.025	(-1.555, 1.506)				
Test					
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$				
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$				
T-Value	DF	P-Value			
-0.03	58	0.975			

Two-Sample T-Test and CI: Successful Z" 6M, Unsuccessful Z" 6M

Method				
μ_1 : mean of Successful Z" 6M				
μ_2 : mean of Unsuccessful Z" 6M				
Difference: $\mu_1 - \mu_2$				
Equal variances are not assumed for this analysis.				
Descriptive Statistics				
Sample	N	Mean	StDev	SE Mean
Successful Z" 6M	41	-0.73	3.07	0.48
Unsuccessful Z" 6M	48	-2.05	8.61	1.2
Estimation for Difference				
Difference	95% CI for Difference			
1.32	(-1.35, 3.98)			
Test				
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$			
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$			
T-Value	DF	P-Value		
0.99	60	0.326		

Two-Sample T-Test and CI: Successful Z" 1Y, Unsuccessful Z" 1Y

Method				
μ_1 : mean of Successful Z" 1Y				
μ_2 : mean of Unsuccessful Z" 1Y				
Difference: $\mu_1 - \mu_2$				
Equal variances are not assumed for this analysis.				
Descriptive Statistics				
Sample	N	Mean	StDev	SE Mean
Successful Z" 1Y	31	-0.83	2.94	0.53
Unsuccessful Z" 1Y	54	-1.78	8.23	1.1
Estimation for Difference				
Difference	95% CI for Difference			
0.95	(-1.52, 3.42)			
Test				
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$			
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$			
T-Value	DF	P-Value		
0.77	72	0.446		

Two-Sample T-Test and CI: Successful Z" 2Y, Unsuccessful Z" 2Y

Method					
μ_1 : mean of Successful Z" 2Y					
μ_2 : mean of Unsuccessful Z" 2Y					
Difference: $\mu_1 - \mu_2$					
Equal variances are not assumed for this analysis.					
Descriptive Statistics					
Sample	N	Mean	StDev	SE Mean	
Successful Z" 2Y	36	-1.52	5.01	0.84	
Unsuccessful Z" 2Y	37	-1.62	9.03	1.5	
Estimation for Difference					
Difference	95% CI for Difference				
0.1	(-3.31, 3.51)				
Test					
Null hypothesis	$H_0: \mu_1 - \mu_2 = 0$				
Alternative hypothesis	$H_1: \mu_1 - \mu_2 \neq 0$				
T-Value	DF	P-Value			
0.06	56	0.954			

F. Multiple Regression using Z and Z" Scores from Quarter and One Year before Bankruptcy, regressed on 6-month Excess Returns

Analysis of Variance					
Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	0.8399	0.21	1.64	0.172
Z-Scores from Quarter	1	0.1585	0.1585	1.24	0.269
Z" Scores from Quarter	1	0.1845	0.1845	1.44	0.233
Z-Scores from One Year before	1	0.4883	0.4883	3.81	0.054
Z" scores from One Year before	1	0.5092	0.5092	3.98	0.049
Error	84	10.7572	0.1281		
Total	88	11.5972			
Model Summary					
S	R-sq	R-sq(adj)	R-sq(pred)		
0.357858	7.24%	2.83%	0.00%		
Coefficients					
Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-0.0823	0.0566	-1.45	0.149	
Z-Scores from Quarter	-0.0504	0.0453	-1.11	0.269	608.07
Z" Scores from Quarter	0.0236	0.0197	1.2	0.233	605.47
Z-Scores from One Year before	0.1185	0.0607	1.95	0.054	22.74
Z" scores from One Year before	-0.0561	0.0281	-1.99	0.049	24.1
Regression Equation					
6M Excess Returns	=	-0.0823 - 0.0504 Z-Scores from Quarter + 0.0236 Z" Scores from Quarter+ 0.1185 Z-Scores from One Year before - 0.0561 Z" scores from One Year before			

G. Multiple Regression using Z" scores from Quarter and One Year before Bankruptcy, regressed on 2-year excess returns

Analysis of Variance						
Source	DF	Adj SS	Adj MS	F-Value	P-Value	
Regression		2	3.493	1.7467	2.26	0.112
Z" Scores from Quarter		1	3.47	3.4701	4.49	0.038
Z" scores from One Year before		1	2.392	2.3918	3.09	0.083
Error	70	54.115	0.7731			
Total	72	57.608				
Model Summary						
S	R-sq	R-sq(adj)	R-sq(pred)			
0.879241	6.06%	3.38%	0.00%			
Coefficients						
Term	Coef	SE Coef	T-Value	P-Value	VIF	
Constant	0.041	0.105	0.39	0.696		
Z" Scores from Quarter	0.00854	0.00403	2.12	0.038	4.13	
Z" scores from One Year before	-0.0509	0.0289	-1.76	0.083	4.13	
Regression Equation						
2Y Excess Returns	=	0.041 + 0.00854 Z" Scores from Quarter - 0.0509 Z" scores from One Year before				

H. Linear Regression using Percentage of Insiders on Board, regressed on 1-year excess returns

Analysis of Variance						
Source	DF	Adj SS	Adj MS	F-Value	P-Value	
Regression		1	1.183	1.1832	5.23	0.026
% of Insiders on Board		1	1.183	1.1832	5.23	0.026
Error	57	12.885	0.2261			
Lack-of-Fit	17	3.297	0.1939	0.81	0.674	
Pure Error	40	9.588	0.2397			
Total	58	14.068				
Model Summary						
S	R-sq	R-sq(adj)	R-sq(pred)			
0.475454	8.41%	6.80%	1.95%			
Coefficients						
Term	Coef	SE Coef	T-Value	P-Value	VIF	
Constant	-0.476	0.134	-3.57	0.001		
% of Insiders on Board	1.327	0.58	2.29	0.026	1	
Regression Equation						
1Y Excess Returns	=	-0.476 + 1.327 % of Insiders on Board				

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