LUND UNIVERSITY
School of Economics and Management

Master Thesis
Spring 2011

TURNAROUNDS

-MODELING THE PROBABILITY OF A TURNAROUND-

Supervisor:
Göran Andersson

Authors:
Eduard Ciorogariu
Andreas Goumas

ABSTRACT

The objective of this paper is to examine the possibility of predicting the recovery of a distressed firm into a turnaround based on its current financial situation and a set of variables that are considered of having a significant impact on the turnaround probability. To assess this problem 150 firms are used that were distressed at some point during the period 1991 to 2001. These firms were all listed in one of the major US stock exchanges and were all randomly chosen, with 86 failing to recover from distress and 64 making a successful turnaround. In order to establish a forecast model, two different quantitative econometrical methods are applied; Linear Discriminant Analysis and Logistic Regression. The model predicting the outcome of the 150 distressed firms with the highest accuracy is tested for its prediction power on a holdout sample that consisted of 3140 distressed firms. These 3140 firms were all listed at one of the major US stock exchanges and are distressed at some point during the period 2002 to 2008. The prediction accuracy of the best model amounted to 92.7 % in the in-sample and 89% in the holdout sample. The decisive variables that were selected by this model are firm size, severity of distress and total debt to total assets.

Finally, we compare the returns yielded by a portfolio consisting of the turnarounds that were predicted by the model out of the holdout sample to the returns generated by the S&P 500. The annual returns for the seven years back-testing period, 2004-2010, for our portfolio amounted to 18%, while the annual return for the S&P 500 was 4%.

Keywords: Financial distress, Turnaround, Turnaround prediction, Altman Z-score, Discriminant Analysis, Logistic model.

Table of Contents

Chapter 1

Introduction

1.1 Background

When plotting the movement of the S&P 500 over the last thirteen years, the index depicts four extreme turning points. Driven by the elation of the emergence of a New Economy, the S&P 500 surged at the end of the century and started to decline with the burst of the dot.com bubble at the beginning of 2001, hitting rock bottom two years later. In 2003, the index headed off to regain strength, reaching a new peak four years later. The outbreak of the financial crisis triggered a new downswing of the index at the end of 2007. After a year, the S&P 500 had to register an annual return of -38.5%[1], its lowest result in sixty years of history. During the first quarter of 2009 the index bounced back again and approaches its all-time high of 1565.15[2]. The share index seems to display a reverting pattern, enabling market participants to realise high capital gains, by selling when markets are at peak and buying when they bottom out.

While the strategy "Buy low – Sell high" adds up for indices, it might fail for a single share, because the risk of lasting underperformance or at worst bankruptcy cannot be diversified away. However, to generate high returns investors don't have to look out for the next global crisis that will cause indices to plummet before they rally again. There are plenty of company-specific financial crises occurring every year out of which a high-yield portfolio can be constructed. Recalling that the share price reflects the investors' expectations about the company's future performance, the stock of a firm sliding into financial distress is likely to slump, regardless of whether the distressed state is expected to be temporary or long lasting. A possible explanation for this behaviour is the market's inability to capture the economic fundamentals of distressed shares. Compliant with behavioural finance theory the convergence between irrationality and barriers to arbitrage impede a separation between transient and ongoing distressed stocks.[3] Moreover, since the variables of distressed companies outweigh the variables of non-distressed companies in number, complexity and

[1] http://www.forecast-chart.com/historical-sp-500.html
[2] Twin A. (2009-03-09), "For Dow another 12-year low", *CNN Money*, http://money.cnn.com/2009/03/09/markets/markets_newyork/index.htm
[3] Koller, Tim; Goedhart, Marc and Wessels, David, (2010)*Valuation: Measuring and managing the value of companies,* John Wiley & Sons, pp. 388

degree of uncertainty, deriving the intrinsic value of a distressed firm is a delicate endeavour, enticing many intrinsic investors to refrain from their initial intention to invest.[4] Hence, intrinsic investors fail to engage in a price correction and the stocks continue to fall. This implies an undervaluation of some of the firms that are in financial distress, allowing market participants to buy stocks with ample upside potential at marked-down prices. In fact, the degree of upside potential can be expressed as a function of markdown. To be a value-creating investment the share price needs to stop its downfall and start increasing again. It is expected that the downward trend of a financial distressed company is reversed by the implementation of a successful turnaround. Despite succeeded turnaround, market participants will place low expectations in the future performance of recent distressed companies, facilitating the management's task to exceed shareholder expectations, which winds up in an increase of the share price.[5]

There exist plenty of studies, intending to identify the decisive factors in the turnaround process. Some studies centre on quantitative variables, while other studies involve a combination of quantitative and qualitative variables, taking into account that management expertise and stakeholder support are crucial for conducting a successful turnaround. Researchers distinguish between an efficiency-oriented and an entrepreneurial-oriented strategy, firms can embark on during the turnaround process.[6] While several researchers like Zeni et. al (2010)[7] develop turnaround prediction models, only few of them test their model with respect to the stock returns yielded by the predicted turnarounds.

While investing in distressed companies is a popular research area, the bulk of research focuses on investing in defaulted debt securities. Edward Altman, the inventor of the Z-score that is widely used for determining distressed firms, has undertaken extensive research in this field. He concentrates on the "risk and return performance of defaulted debt".[8] In 2003 Altman and Pompeii laid out an analysis of the historical performance of investments in defaulted

---

[4] Klarman, Seth. A.,(1991),*Margin of safety: Risk-averse value investing strategies for the thoughtful investor*, Harper Business, pp. 189.

[5] Koller, Tim; Goedhart, Marc and Wessels, David, (2010)*Valuation: Measuring and managing the value of companies,* John Wiley & Sons, pp. 46.

[66] Smith, Malcom and Graves, Christopher, (2005), Corporate turnaround and financial distress, *Managerial Auditing Journal*, Vol. 20, Iss. 3, pp. 304-320.

[7] Zeni, Syahida Binti and Ameer, Rashid, (2010), Turnaround prediction of distressed companies: evidence from Malaysia, *Journal of Financial Reporting and Accounting*, Vol. 8, Issue 2, pp 143-159.

[8] Altman, Edward I., (1998). Market Dynamics and Investment Performance of Distressed and Defaulted Debt Securities, *New York University, Center for Law and Business*, Working Paper No. 98-022, pp. 2.

bonds and bank loans, covering the time period 1987 - 2001.[9] Practitioners like fund manager Joel Greenblatt, recommend against investing in distressed stocks, because in case of bankruptcy shareholder interests are the last to serve and equity holders might come away empty-handed. Thus, his focus lies also on investing in distressed bonds, bank loans and trade claims. However, this area is dominated by vulture investors, who can cope with the complexity of such investments, which results from the legal and financial issues brought about by different classes of creditors with different priorities and claims.[10]

Nevertheless, researchers and practitioners see a potential benefit from investing in companies that emerged from financial distress. Greenblatt states that recently emerged shares are available at substantial discount, partially because they suffer from low analyst coverage and partially because market participants still attach a high risk profile to the stock.[11] Another reason is that a big stake of creditors' bankruptcy claims rather tends to be converted into equity claims than paid out in cash. Former debt holders such as banks, bondholders and trade creditors have no incentive to engage in a long-term commitment in the emerged company and aim at cashing out by selling the new share (we assume that the participation of former shareholders was either bought up for a liquidating dividend or cancelled).[12] This creates a negotiating range, which permits interested investors to purchase the share at a discount. Altman et. al (1998)[13] investigated the stock performance of firms emerging from Chapter 11. The authors observed significant positive excess returns over the long-term (200 trading days from emergence date from Chapter 11) and ascribed it to the market's inefficiency, which causes a paucity of information that in turn leads to a stock's mispricing. Besides, the study points towards the existence of a positive relationship between the nature of securities accepted by creditors and the appearance of excess stock returns. According to this, stocks of emerged firms for which debt holders approved a complete equity-for-debt exchange demonstrate strong positive long-term abnormal returns.[14] The identified linkage between the type of arrangement the emerged firm and its debt holders agreed upon and its stock returns let us infer that the creditors dispose of information, which is not captured by the market, allowing them to compute the firm's intrinsic value. The conclusion is reasonable, as creditors

---

[9] Altman, Edward I. and Jha, Shubin, (2003), "Market size and investment performance of defaulted bonds and bank loans: 1987-2001", *Economic Notes,* Vol. 32, Iss. 2, pp. 147-176.
[10] Greenblatt, Joel, (1999), *You can be a stock market genius*, Fireside, pp. 166 – 168.
[11] Ibid, pp. 175.
[12] Ibid, pp. 169 – 170.
[13] Eberhart, Allan C., Altman, Edward I. and Aggarwal, Reena, (1998), The Equity Performance of Firms Emerging from Bankruptcy, *Journal of Finance,* Vol. 54, Iss. 5, pp. 1855-1868.
[14] Ibid, pp. 1865-1867.

like banks and other financial institutions e.g. life insurance, pension funds etc. are classified as informed investors and do not confront information asymmetry issues.[15] However, according to Kahl (2002)[16] debt holders cannot eliminate the degree of uncertainty in respect of the viability of distressed firms completely, which drives them to engender a decision model comprising three options: recovery, controlled liquidation and immediate liquidation. Consequent, if creditors agree to swap their entire debt position for equity, they have strong beliefs in the recovery potential and growth opportunities of the firm and choose the first option.

1.2 Discussion of the problem

Altman et. al (1998)[17] attested that stocks of financially distressed firms, which were likely to succeed in the turnaround process, yielded abnormal returns over a time frame of 200 trading days, outstripping market indices by roughly 20%. Indro et. al (1999)[18] established a model consisting of five variables, which can be applied to distinguish between successful and failed restructurings. They demonstrated that for a portfolio comprising distressed stocks and having an accumulated turnaround probability of more than 50%, excess compounded returns amount to 42% over a one-year period.

While most studies focus on firms that have submitted an official bankruptcy petition, such as e.g. filing under Chapter 11, our empirical research is not restricted to this formal procedure. We refrained from constraining our study on the stock performance of firms emerging from Chapter 11. In this manner, we took into consideration the findings of Hotchkiss (1995)[19], who challenges the accuracy of the Chapter 11 process in separating economically inefficient from economically efficient companies.

Instead, we consider the Altman Z-score to be more precise in distinguishing potential turnarounds from non-turnarounds, because it encompasses company-specific financial data,

---

[15] Ogden, Joseph P., Jen, Frank C. and O'Connor, Philip F.,(2003), *Advanced Corporate Finance. Policies and Strategies*, Prentice Hall.
[16] Kahl, Matthias, (2002), Economic Distress, Financial Distress and Dynamic Liquidation, *The Journal of Finance,* Vol. 57, pp. 135-168.
[17] Eberhart, Allan C., Altman, Edward I. and Aggarwal, Reena, (1998), The Equity Performance of Firms Emerging from Bankruptcy, *Journal of Finance,* Vol. 54, Iss. 5, pp. 1855-1868.
[18] Indro, D. C., Leach, R.T. and Lee, W. Y., (1999), Sources of gains to shareholders from bankruptcy resolution, *Journal of Banking & Finance*, Vol. 23, Issue 1, pp. 21-47.
[19] Hotchkiss, Edith S., (1995), Postbankruptcy Performance and Management Turnover, *Journal of Finance,* Vol. 50, Issue 1, pp. 3-21.

which makes it possible to pinpoint operational performance changes over time. Additionally, we investigate the impact of other quantitative variables on the likelihood of turnaround, aiming at determining the drivers that lie behind a successful restructuring.

1.3 Purpose

The underlying thesis follows the purpose of deriving the decisive variables that allow for distinguishing financially distressed firms with turnaround potential from those without. Based on a sample of 150 companies, it intends to conceive the main drivers in the turnaround process and their relation to the turnaround potential of a firm. Further, the identified drivers are used to establish a prediction model, which can be adopted for classifying financially distressed companies into turnarounds and non-turnarounds. To some extent, the thesis aims at analyzing whether recovery is achieved by focusing on efficiency-oriented or on entrepreneurial-oriented strategies. In addition, the thesis touches upon the opportunity that arises from investing in financially distressed firms with high turnaround potential, by exhibiting generated returns of the turnarounds detected in the holdout sample. In this manner, the thesis tends to pave the way for future, profound research in distress investing.

1.4 Limitations

The states Distress and Recovery are defined by a company's Z-score falling short of a given threshold and subsequently exceeding this threshold and are not dependent on an official filing for bankruptcy proceeding and a pursuant announcement of recovery. Hence, the sample might consist of some firms that did not file under the US Bankruptcy Code and might omit some firms that did so.

The sample employed to determine the decisive factors in the turnaround process contains companies listed at one of the three major US stock exchanges, New York Stock Exchange (NYSE), American Stock Exchange (NYSE Amex) and NASDAQ Exchange and embraces the time period 1991 to 2003. The main reason for deciding to collect data from the specified exchanges and over the specified period is to ensure the availability of a representative sample in terms of size and industry coverage. On top of that, the sample comprises only non-financial companies. The exclusion of financial firms from the study group is motivated by the belief that inclusion would lead to biased results. This expectation can be motivated by two points. Firstly, financial companies are characterized by an extremely high leverage ratio, so that their involvement would most likely distort the impact of debt on the turnaround process. Secondly, due to their importance for the overall economic stability of a country the probability of governmental interventions in case of distress is much higher than for non-financial companies. However, this study does not make a point of developing a way to identify companies, which will be bailed out with the utmost probability in the event of distress. Neither does it advise market participants to invest in such companies. The variables analysed by the study are of quantitative nature, as collecting reliable and satisfying qualitative data would require access to resources that were not approachable for us and would go beyond the time period scheduled for this work.

The data employed for back-testing the prediction power of the established model is also raised from the three major US stock exchanges.

1.5 Outline of the thesis

Chapter 1 – Introduction

The first chapter explains why we became interested in examining the drivers behind a successful turnaround. It states the opportunities arising for investors to make money by investing in financially distressed firms with a high turnaround potential. Studies of other researchers are named and the main conclusions are summarised. Some of the difficulties a financially distressed firm has to deal with in the process of restructuring are mentioned, providing an idea about the variables that play a decisive role in the turnaround process. The chapter ends with a listing of the study's limitations.

Chapter 2 – Theoretical foundation

The second chapter delves into the subject of identifying the determinants of a successful turnaround, so as to be able to distinguish firms with turnaround potential from firms that are likely to remain in distress, denoted as non-turnarounds. Prior research on turnarounds is covered and the key results of these studies are discussed.

The entire chapter provides the theoretical background on which the underlying thesis is based.

Chapter 3 – Data and Methodology

The third chapter gives a description of the process of data collection and brings in the variables that were considered in the empirical study. Hereby, it develops the hypotheses that are to be examined empirically. Last but not least, the two econometrical models that are applied to come up with the turnaround prediction model, Multiple Discriminant Analysis (MDA) and Logistic Regression (Logit Model), are introduced.

Chapter 4 – Empirical Results

The fourth chapter presents and further discusses the determinants that were found to be critical for a successful turnaround by each of the applied models. In this way, it comes up with four prediction models, which are assessed based on their in-sample accuracy. It also includes the back-testing of the two best prediction models. The excess returns of the holdout sample turnarounds, selected by the best prediction model, are computed. The input data of the final chosen model is subject to some statistical tests.

Chapter 5 – Conclusion

The fifth chapter aims at wrapping up the key findings of the implemented study. Besides, a recommendation about what issues future research in this area could cover is administered.

Chapter 2

Theoretical Framework

Plenty of research has been undertaken on turnarounds with the purpose of identifying the determinants of success. An overview of prior studies in this field is outlined in the appendix. While empirical studies use financial metrics and quantitative ratios to specify a successful turnaround, Balgobin et al. (2001)[20] provide a more qualitative definition:

"A corporate turnaround may be defined simply as a recovery of a firm's economic performance following an existence-threatening decline."

2.1 Prior research on turnarounds and its determinants

Empirical studies concentrate on the reasons that drive companies into such performance decline and the corresponding strategies the management team employs to reach rehabilitation. Schendel et al. (1976)[21] [22] and Hofer et al. (1978, 1980) [23] [24] attributed deteriorating firm performance to operational or strategic issues and emphasized the importance of correctly recognizing the source of decline, which enables the firm to adopt the adequate measures to reverse decreasing performance. They point out that failure to locate the catalyst of decline leads to the implementation of wrong measures and can hinder the firm to achieve a successful turnaround.

In the following sections several research studies on turnarounds are reviewed, outlining the causes of performance decline and the strategies and measures firms take to return to a stable state. This review provides the basis for the selection of the potential turnaround determinants analyzed in the underlying thesis.

[20] Balgobin, R. and Pandit, N., (2001), Stages in the Turnaround Process: The Case of IBM UK, *European Management Journal*, Vol. 19, Iss. 3, pp. 301-316.
[21] Schendel Dan E. and Patton, G.R., (1976), Corporate stagnation and turnaround, *Journal of Economics and Business,* Vol. 28, Iss. 3, pp. 236-242.
[22] Schendel, Dan, Patton, G.R. and Riggs, James, (1976), Corporate turnaround strategies: A study of profit decline and recovery, *Journal of General Management*, Vol. 3, Iss.. 3, pp. 3-12.
[23] Hofer, Charles W. and Schendel, Dan, (1978), *Strategy Formulation: Analytical Concepts*, West Publishing.
[24] Hofer, Charles W., (1980), Turnaround Strategies, *Journal of Business Strategy,* Vol. 1, Iss.1, pp. 19-31.

2.1.1 Causes of performance decline

Balgobin et al. (2001)[25] summarize the main performance decline triggers that were identified by six independent research studies. A separation is made between internal and external causes of performance decline, where internal causes refer to company-specific issues and external causes are affiliated to weak economic conditions or industry-specific issues.

External causes

External causes include downturn in demand, increase in competition and increase in input costs. The causes show a certain degree of interdependency, as fierce competition and increased input costs both are likely to affect demand negatively.

Fall in demand can be traced back to several other reasons, such as the contraction of the industry, an overall economic recession that weakens purchasing power or the failure of the company to meet customer expectations. While the first two affect all competitors within an industry, the last one applies to single companies. In regard of customer expectations, Lepak et al. (2007)[26] define the task of a firm in creating value for its customers. They call this the use value. In return, the customers are willing to provide the exchange value, which is measured in monetary units. If a company cannot constantly provide the value demanded by its customers at the expected conditions (e.g. quality, sales price), or if other companies have the resources to provide equal or higher value, or to provide the same value at improved conditions a firm-related cutback in demand should be expected.

The intensity of competition is determined by the characteristics of the industry. The concept of industrial organization competition summarized by Barney (1986)[27] considers the barriers established in an industry as one determinant of competitive pressure. These barriers involve barriers to entry, barriers to competition, barriers to imitation and barriers to exit.[28] Other decisive factors are the amount and size of rivals, the nature of products (customized vs. mass product) and the demand elasticity.[29] In addition, substitute products pose a threat, as firms might not recognize immediately to whom they lose market share, aggravating the necessity

[25] Balgobin, R. and Pandit, N., (2001), Stages in the Turnaround Process: The Case of IBM UK, *European Management Journal*, Vol. 19, Iss. 3, pp. 301-316.
[26] Lepak, David P., Smith, Ken G. and Taylor, M. Susan, (2007), Value Creation and Value Capture: A Multilevel Perspective, *Academy of Management Review,* Vol. 32, No. 1, pp. 180-194.
[27] Barney, Jay B., (1986), Types of competition and the theory of strategy: Toward an integrative framework, *Academy of Management*, Vol. 11, No. 4 , pp. 791-800.
[28] Ibid.
[29] Ibid.

to retaliate.[30] Lepak et. al (2007) mention the problem of value slippage[31], which leads to an erosion of the firm's competitive advantage and can be avoided by the establishment of isolating mechanisms[32] (e.g. patents, trademarks, special knowledge). Fierce competition will undermine the financial position of a company, as it has to engage in costly retaliation campaigns, such as price cuts or expensive marketing and promotion campaigns to guarantee competitiveness. Adopting the wrong retaliation tactics will lead to a further weakening of the firm's market position and absorption of financial means.

Price increases in input costs bring forth a rise in costs of goods sold, putting pressure on the gross profit margin. Given that companies are able to pass on the increase in costs fully to the customers, margins will not be suppressed. While this might be imaginable in a monopolistic market, it is unlikely to hold for a situation of perfect competition. Price pressure will originate from some companies that enjoy advantages on the input market e.g. strong bargaining power, bulk purchase etc. and squeeze margins of firms that do not dispose of these advantages by luring away customers.

Internal causes

Internal causes of performance decline involve poor management, inadequate financial control/policy and high cost structure. As for the external causes a kind of interdependency can be observed, as inadequate financial control/policy and high cost structure both can originate from poor management.

The management team needs to be endued with the capabilities to steer the company through times of prosperity and decline. There exists no commonly accepted definition of poor management performance, but some conclusions about its meaning can be drawn from the examined literature. According to Hedberg et al. (1976)[33] firm decline bears upon the omission of the management team to align the strategy of the company to its evolving environment. This problem tends to exacerbate for companies with a long track record, as the management team is prone to hubris and overconfidence and has strong beliefs in the

---

30 Koller et. al (2010), Valuation: Measuring and managing the value of companies, pp. 79-98

31 Lepak, David P., Smith, Ken G. and Taylor, M. Susan, (2007), Value Creation and Value Capture: A Multilevel Perspective, *Academy of Management Review,* Vol. 32, No. 1, pp. 180-194.

32 Ibid.

33 Hedberg, Bo L. T., Nystrom, Paul C. and Starbuck, William H., (1976), Camping on Seesaws: Prescriptions for a Self-Designing Organization, *Administrative Science Quarterly*, Vol. 21, No. 1, pp. 41-65.

underlying strategy, rendering it immune to necessary strategic change.[34] Harker (1996)[35] stresses the importance for a company to understand its industry, markets and customers, to know its position and future potential with respect to its industry and markets and to know its competitors and their position and future potential. Only if the management team is able to capture and process these variables, can it come up with an adequate strategy. Another important task of the management team is the delegation of responsibilities to lower hierarchical levels. Concentrating too much decision power at the top level can lead to inertia and delayed responsiveness to changes in customer preferences, as it was the case for IBM UK in the 90s.[36]

Regarding inadequate financial control/policy the focus lies on the firm's capital structure and the sources of financing.[37] Owing to the fact that interest expenses lower the taxable income and in this way increase the free cash flow to firm, the market value of the firm would be maximized by employing a gearing of 100%. However, with an increase in leverage the probability of future financial distress and the cost of financial distress also raise, which results in a depression of the firm's market value. This relationship is depicted by the following formula:

$$V_L = V_U * \tau_c * D - PV[E(CFFD)]$$

V_L = Market value of the levered firm

V_U = Market value of the unlevered firm

τ_c = Corporate tax rate

D = Face value of debt

PV[E(CFFD)] = Present value of expected cost of future financial distress

In addition, having an extremely high gearing might force a company to postpone or completely abandon some value creating investments, causing an underinvestment problem.

[34] Barker, Vincent L. and Barr, Pamela S., (2000), Linking top manager attributions to strategic reorientation in declining firms attempting turnarounds, *Journal of Business Research*, Vol. 55, Iss. 12, pp. 963-979.
[35] Harker, Michael, (1996), Managing company turnarounds: how to develop "destiny", *Marketing Intelligence & Plannings*, Vol. 14, Iss. 3 pp. 5-10.
[36] Balgobin, R. and Pandit, N., (2001), Stages in the Turnaround Process: The Case of IBM UK, *European Management Journal*, Vol. 19, Iss. 3, pp. 301-316.
[37] Ibid, pp. 303.

An example is provided to illustrate the underinvestment problem. Assumptions are based on Myers (1977)[38]:

It is assumed that the firm's assets in place V_A are equal to 0. The firm takes on risky debt P (P is defined as risky debt, as the firms has no assets in place and thus does not dispose of collaterals to secure the debt), which together with the contribution I (equity investments) of shareholders account for the required cash outlay to realize V_G, the real option. The debt is to be repaid after the expiration of the real option V_G and the owners know the value of the real option in the event of exertion, which is depicted V(s).

In such a case, shareholders will exercise the real option only on condition of:

$$V(s) > I + P$$

If the cash outlay (I + P) exceeds V(s), shareholders will refuse to exercise the real option, as their equity investment I will be higher than the market value of their shares.[39] Thus, even if the real option is value creating (V(s) > I), it won't be realized, because of the effect of the debt burden. This is also referred to as the debt overhang problem. Abandoning value creating projects can accelerate a firm's performance decline, as its competitive position might be undermined, triggering a decrease in operational performance. Generating fewer turnovers will raise the financial pressure, amplifying the debt overhang problem and prompting further sacrifice of value enhancing investments. However, the abandonment of promising projects must not always be the actuator of a drop in operational performance. Sales can also be depressed by the various external factors described in the previous section, like e.g. industry contraction. Although there exists no optimal debt-to-equity ratio, when deciding on leverage a firm should allow for a reasonable financial buffer to be able to absorb unexpected economic or industry-specific declines and leave the door open to undertake value enhancing investments when they appear.

With reference to the sources of financing, failure to abide by the maturity matching principle can bring a company into financial distress. In general, the maturity on an interest-bearing liability should coincide with the life expectancy of the asset or project, for which the credit is raised. Ignoring this guideline gives rise to either a refinancing risk or a debt overhang problem. In the case that the maturity of interest-bearing debt falls short of the life expectancy

---

[38] Myers, Stewart C., (1977), Determinants of Corporate Borrowing, *Journal of Financial Economics*, Vol. 5, No. 2, pp. 147-175.
[39] Ibid, pp. 153

of the asset/project, interest and principal payments might be due before the asset/project managed to generate any cash-flow. Hence, the company will try to roll over the outstanding debt. If the debt holder refuses refinancing, the firm will be forced to repay the credit immediately, although the asset/project missed to yield a return so far. This will lead to a financial bottleneck that can culminate in defaulting on debt. Alternatively, if the maturity of interest-bearing debt exceeds the life expectancy of the asset/project, the firm will have to bear an ongoing debt burden, which is related to an asset/project that does not generate cash-flows anymore. Thus, it would carry on the default risk and the outstanding debt would interfere with the realization of valuable real options (debt overhang problem).

Last but not least Balgobin et. al (2001) cite a high cost structure as a reason for performance decline. In case of IBM UK an overstated cost base was build up, because the top management expected revenues to grow at historical rates. When realized revenues did not comply with expected revenues, the company had to face a cost burden that outstripped the one of competitors significantly.[40] This example also elucidates the interdependency of performance decline causes, as the high cost base was a result of management's inability to correctly anticipate future market demand.

All in all, deteriorating performance can be traced back to several internal and external causes, which are closely intertwined and act jointly, making it impossible to relate performance decline to one single source. The table below provides an overview of the different research studies that focused on the same external and internal causes of decline.

Table 1: The Causes of Declining Performance

Researcher	Schendler et al. (1976)	Bibeault (1982)	Slatter (1984)	Thain et. al (1989)	Grinyer et. Al (1990)	Gopal (1991)
External causes						
Decrease in demand	x	x	x	x	x	x
Increase in competition	x	x	x	x	x	x
Increase in input costs	x	x	x	x	n.a.	x
Internal causes						
Poor management	x	x	x	x	x	x
Inadequate financial control/policy	n.a.	x	x	x	x	x
High cost structure	x	n.a.	x	x	x	n.a.

Source: Balgobin, R. and Pandit, N., (2001), Stages in the Turnaround Process: The Case of IBM UK, *European Management Journal*, Vol. 19, Iss. 3, pp. 301-316.

X = clearly referred to; n.a. = not referred to

[40] Balgobin, R. and Pandit, N., (2001), Stages in the Turnaround Process: The Case of IBM UK, *European Management Journal*, Vol. 19, Issue 3, pp. 308.

2.1.2 Strategies to reverse performance decline

This section outlines the various strategies that companies adopt, in order to cope with an existence-threatening decline and to achieve a successful turnaround.

According to Schendel et al. (1976)[41] a company can either apply an efficiency-oriented or an entrepreneurial-oriented strategy. Which strategy is chosen depends on the cause of the downturn. Efficiency-oriented restructurings imply the enforcement of retrenchment, which incorporates cost-cutting measures, downsizing and asset reduction, while entrepreneurial-oriented restructurings aim at aligning the underlying strategy to the prevalent market conditions.[42] The viewpoint of Schendel et. al (1976) is supported by Barker et. al (1997)[43], who distinguish between two sources of decline: industry-specific and firm-specific decline. Cameron et. al (1988)[44] explain firm-specific decline as the inability of a company to perform at eye level with its competitors, suffering from a competitive disadvantage. Thus, if a firm acts in a growing industry, but faces deteriorating performance, the adoption of an entrepreneurial-oriented strategy is compulsory. It can be concluded that companies, which suffer from performance decline due to a contraction of the industry, should put more weight on efficiency-oriented strategies.

As opposed to this, Robbins et. al (1992)[45] hold that independent of the cause of decline the implementation of efficiency-oriented strategies is crucial for succeeding with the turnaround.

Other researchers opt for separating the turnaround process into two subsequent stages: Stabilization and Recovery. The purpose of the first stage is to prevent a continuation in performance decline and to build the foundations for the implementation of recovery strategies. This process involves convincing stakeholders to support the turnaround intention, stop the financial drainage and ensure a constructive internal climate. In the second stage the recovery strategies are introduced, according to the trigger of decline. The necessity of

---

[41] Schendel, Dan, Patton, G.R. and Riggs, James, (1976), Corporate turnaround strategies: A study of profit decline and recovery, *Journal of General Management*, Vol. 3, Issue 3, pp. 3-12.

[42] Smith, Malcom and Graves, Christopher, (2005), Corporate turnaround and financial distress, *Managerial Auditing Journal*, Vol. 20, Issue 3, pp. 305.

[43] Barker, Vincent and Duhaime, Irene M., (1997), Strategic change in the turnaround process: Theory and empirical evidence, *Strategic Management Journal*, Vol. 18, Issue 1, pp. 13-38.

[44] Cameron, Kim S., Sutton, Robert I. and Whetten, David A., (1988), "*Readings in Organizational decline: Frameworks"*, Ballinger Publishing.

[45] Robbins, D. Keith, and Pearce, John A., (1992), "Turnaround: retrenchment and recovery", *Strategic Management Journal*, Vol. 13, Issue 4, pp. 287-309.

administering a two-stage approach is determined by the severity of distress, the firm size and the availability of free assets.[46]

Maintaining stakeholder promotion is critical for facilitating the continuation of the operational business. Companies that slide into financial distress are likely to experience a large number of resignations from key employees, resulting in a brain drain that aggravates the competitive situation. Suppliers and customers must be persuaded to uphold business relations with the firm and debt holders must be prepared to compromise on contractual terms.

In order to restore the stakeholders' trust in the firm's survival potential and accomplish its support, quick actions that yield immediate results are applied at the beginning of the turnaround process, aiming at improving efficiency.[47] These actions narrow down to cutbacks, which are concentrated on downsizing, reduction of inventory levels, cost of goods sold and selling, general and administrative expenses.[48] Cost cuttings and efficiency enhancements will free up resources that can be reallocated.[49] However, the assertion of cutbacks might backfire and even cause a further drop in firm efficiency. This can be expected when managers decide to cut costs on the wrong positions. For example, switching to cheaper suppliers might also have a degrading effect on product quality, causing more customers to discontinue business relations. Furthermore, the management's decision to lay off employees and undertake salary cuts and cancellations of one-time bonus payments can create a working climate that is characterized by insecurity about the workplace and frustration, releasing a loss of motivation and associated increase in absenteeism, more production of scrap, decreased product quality, extended processing time and delayed deliveries.[50] Arogyaswamy et. al (1997)[51] conclude that turnarounds and non-turnarounds have a strong tendency to engage in cutbacks. However, non-turnarounds apply this measure more excessively than turnarounds. Also, turnarounds are more successful in translating cutbacks to efficiency improvements than non-turnarounds. From this it can be concluded that managers of turnarounds pick the write spots for cost-

---

[46] Smith, Malcom and Graves, Christopher, (2005), Corporate turnaround and financial distress, *Managerial Auditing Journal*, Vol. 20, Issue 3, pp. 304-320, p. 305.
[47] Arogyaswamy, K. and Yasai-Ardekani, M., (1997), "Organizational Turnaround: Understanding the Role of Cutbacks, Efficiency Improvements, and Investment in Technology", *IEEE Transactions on Engineering Management*, Vol. 44, No. 1, pp. 3-11, p. 4.
[48] Ibid, p. 3.
[49] Smith, Malcom and Graves, Christopher, (2005), Corporate turnaround and financial distress, *Managerial Auditing Journal*, Vol. 20, Iss. 3, pp. 304-320, p. 306.
[50] Arogyaswamy, K. and Yasai-Ardekani, M., (1997), "Organizational Turnaround: Understanding the Role of Cutbacks, Efficiency Improvements, and Investment in Technology", *IEEE Transactions on Engineering Management*, Vol. 44, No. 1, pp. 3-11, p. 3.
[51] Ibid.

cutting and prove able to convince remaining employees from the necessity of the undertaken retrenchment measures. A more extensive form of cutbacks is operational asset reduction, which is carried out to lower the firm's capacity to the current production level. In so doing, manufacturing facilities are employed more efficiently and cash-inflows are generated[52] through the sales of assets, which can be used for lowering the debt burden or to make necessary capital expenditures, like maintenance investments in PP&E.

As has been represented at length, stopping performance decline presupposes the execution of retrenchment measures to improve efficiency. Hofer et al. (1980)[53] note that a financially distressed company will restructure its operations and thereby repel the threat of bankruptcy before it starts to analyze its strategic position in the market.

In the second stage, the distressed company will either continue to implement more profound, long-lasting operational changes or strive for a strategic reorientation, depending on the cause of decline. Yet, according to Grinyer et. al (1988)[54] a sustainable operational improvement is achieved, when turnarounds put emphasis on strategic reorientation, redefining their product and market portfolio. Strategic reorientation implies divesting in unrelated areas and investing in related areas, thereby strengthening the focus of the company on its core-capabilities. Basically, a company has to separate its products and markets following the criterion of value creation. Value-destroying business units are sold and value-destroying markets are abandoned. That way, the company obtains a cash-inflow in terms of the sales price and reduces cash-outflow, which was attributed to the maintenance of the sold business units and exited markets. The cash-inflow obtained from the divestments can be used partially to lower the debt burden and partially to invest into value-creating business units and markets. Nevertheless, depending on the severity of distress and the support from stakeholders, especially the willingness of debt holders to grant further moratorium or even provide additional financial funds, a company might be forced to sell off profitable business units to generate sufficient cash.[55] Schlingemann et. al (2002)[56] reinforce this assumption,

---

[52] Sudarsanam, Sudi and Lai, Jim (2001), "Corporate Financial Distress and Turnaround Strategies: An empirical analysis", *British Journal of Management*, Vol. 12, Issue 3, pp. 183-199, p. 185.
[53] Hofer, Charles W., (1980), Turnaround Strategies, *Journal of Business Strategy,* Vol. 1, Iss.1, pp. 19-31.
[54] Grinyer, Peter H., Mayes, David and McKiernan, Peter, (1988), *"Sharpbenders: The secrets of unleashing corporate potential"*, Blackwell Publishers, Oxford.
[55] Sudarsanam, Sudi and Lai, Jim (2001), "Corporate Financial Distress and Turnaround Strategies: An empirical analysis", *British Journal of Management*, Vol. 12, Issue 3, pp. 183-199, p. 186.
[56] Schlingemann, Frederik P., Stulz, René M. and Walkling, Ralph A. (2002), "Divestures and the Liquidity of the Market for Corporate Assets", *Journal of Financial Economics*, Vol. 64, Issue 1, pp. 117-144.

demonstrating that firms rather divest the most profitable segment over the least liquid segment and the most liquid segment over the least profitable segment.

In terms of asset investment, Hambrick et. al (1983)[57] argue that internal capital expenditures are geared towards obtaining efficiency improvements, by means of e.g. improved monitoring and steering of the process flow. Arogyaswamy et. al (1997)[58] demonstrate the importance of capital expenditure on PP&E in their study. However, they point out that the amount invested in PP&E is almost equal between turnarounds and non-turnarounds. Nevertheless, a significant difference exists regarding investments in R&D, which are clearly higher for turnarounds. They take the view that investing in new technology is vital for manufacturers to adapt to a changing environment[59] and meet market expectations. External investments in the sense of acquisitions can be conducted, as part of the strategic reorientation process to strengthen the product and market portfolio and accelerate revenue growth, given that the company disposes of sufficient financial slack.[60]

The table below summarizes the main measures implemented under the corresponding strategy.

Table 2: Turnaround strategies

Efficiency-oriented ***Retrenchment of the firm:***	**Entrepreneurial-oriented** ***Strategy alignment to changing environment through:***
reduction of operational cost	Investments in R&D
Downsizing	strategic asset divestment
Operational asset reduction	strategic asset investment
Internal capital expenditures	

57 Hambrick, Donald C. and Schecter, Steven M., (1983), “Turnaround Strategies for Mature Industrial-Product Business Units”, *Academy of Management Journal*, Vol. 26, No. 2, pp 231-248.
58 Arogyaswamy, K. and Yasai-Ardekani, M., (1997), “Organizational Turnaround: Understanding the Role of Cutbacks, Efficiency Improvements, and Investment in Technology”, *IEEE Transactions on Engineering Management*, Vol. 44, No. 1, pp. 3-11.
59 Ibid, p. 3.
60 Slatter, Stuart and Johnson, Gerry, (1984), “Corporate Recovery: Successful turnaround strategies and their implementation”, *Strategic Management Journal*, Vol. 7, Issue 1, pp. 99-100.

Chapter 3

Data and Methodology

This chapter describes the steps undertaken in our empirical research on determining the decisive factors for a successful turnaround. It provides information on applied sources, data collection and data processing and outlines the methodology employed to perform the research.

3.1 Sources of information

As our empirical research is to the greatest extent based on financial data, we perceived it as a vital prerequisite to obtain our input data from a single and reliable source. Taking into account that each database has established its own technique of providing financial information, such as balance sheet items, financial ratios, share prices etc., falling back on several databases could lead to distorted results and conclusions. Thus, all financial data used in our study is collected from the Standard & Poor's database.

In terms of literature employed for presenting the theoretical background of our study, we went back to course literature, course material and scientific articles, which were extracted from LibHub.

3.2 Criticism of sources

The financial data used in our empirical study was not generated at first hand, as we collected it from a database provider. It has to be taken into account that due to the extent of our sample and its encompassed time span, it would have been inefficient to extract the data separately from the balance sheet statements and the income statements of each company. In order to examine the reliability of the database, we randomly selected firms from our sample and cross-checked the provided data with the data reported in the respective SEC filings.

With respect to the literature applied for the theoretical background, we made reference to scientific articles published in distinct journals and to literature that covers the topic of restructuring financially distressed companies. With a view to critically scrutinize the readings, we abandoned demonstrating only the viewpoint and results of one researcher, but were constantly anxious to provide corroborating or confuting ideas of other research colleagues.

3.3 Definitions

Our sample consists of companies that are classified as either distressed firms or turnarounds. We applied the Altman Z-score to obtain a sample of distressed firms and to separate companies, which remained distressed from companies which achieved a turnaround.

Altman (1968)[61] introduced the Z-score as a measure of predicting the firm's probability of going bankrupt. It is defined as follows:

$$Z = 0.12X_1 + 0.14X_2 + 0.33X_3 + 0.006X_4 + 0.999X_5$$

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 equity/Book value of total liabilities
X_5: Sales/Total assets

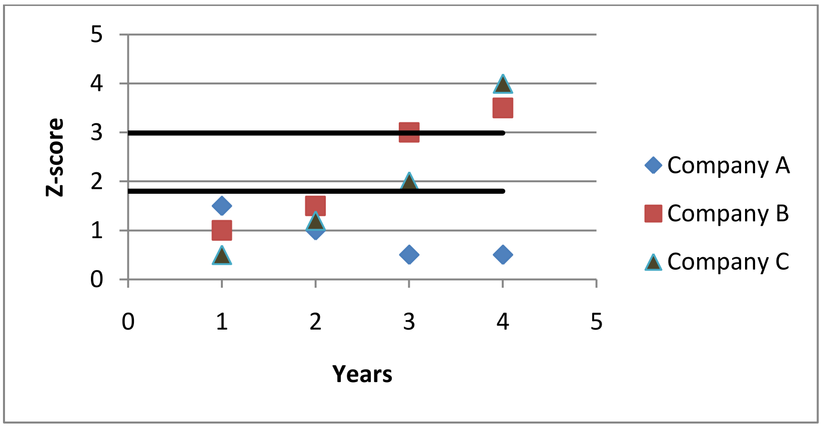
According to Altman, a Z-score of greater than 2.99 classifies the firm into the "non-bankrupt" zone. If the Z-score is below 1.8, the firm falls into the "bankrupt" zone and firms lying in-between 1.8 and 2.99 are assigned to the "zone of ignorance" or "grey area".[62]

We defined a firm as financially distressed, if it exhibited a Z-score below 1.8 for two consecutive years. In the event that the Z-score of the company increased above 1.8 in the third year and above 2.99 in the fourth year, or was above 2.99 for two successive years after being classified as financially distressed, it was perceived as a successful turnaround. Companies, whose Z-score remained below 1.8 for two further years were categorized as failed turnarounds.

---

61 Altman, Edward I., (2000). "Predicting Financial Distress of Companies: Revisiting the Z-score and Zeta Models", *New York University, Center for Law and Business*.

62 Ibid.



Graph 1: Illustration of z-score development for 2 companies

The above graph depicts three companies (A, B & C), which would have been eligible for our sample based on the development of their Z-scores over a total period of four years. All three firms had a Z-score below 1.8 for two consecutive years. However, in year 3 and 4 the Z-score of company B surpassed the critical threshold of 2.99, while the Z-score of company A stayed below the critical threshold of 1.8. The Z-score of company C went beyond the critical threshold of 1.8 in year 3 and exceeded the critical threshold of 2.99 in year 4. In this instance, we would have categorized firms B and C as successful turnarounds (1) and firm A as a failed turnaround (0). The two tables below summarize the main definitions, on which the entire study is based.

Table 3: Summary of definitions

Distressed firm:	two consecutive years of Z-score below 1.8
Successful turnaround:	two consecutive years of Z-score below 1.8 followed by ***either*** two consecutive years of Z-score above 2.99 ***or*** a Z-score above 1.8 in year 3 and a Z-score above 2.99 in year 4.
Failed turnaround:	two consecutive years of Z-score below 1.8 followed by two consecutive years of Z-score below 1.8

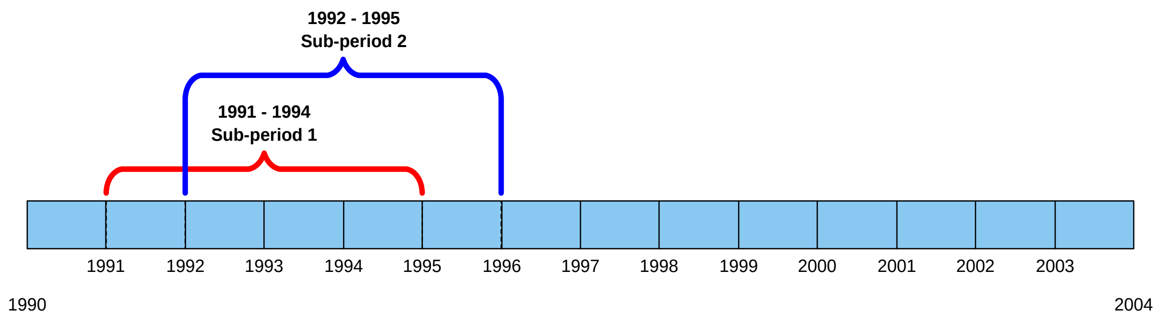
Table 4: Status based on Z-score

Status	**Year 1**	**Year 2**	**Year 3**	**Year 4**
0	< 1.8	< 1.8	< 1.8	< 1.8
1	< 1.8	< 1.8	> 1.8 >2.99	> 2.99

0 = failed turnaround 1 = successful turnaround

3.4 Data

The firms and the appertaining financial figures of our sample were gathered from the Standard and Poor's database. In order to obtain a reasonable sample size, we focused on a sample period ranging from 1991 to 2003, within which data was collected. This period was divided into ten sub-periods, with each sub-period covering four years.



Graph 2: Illustration of sample period and corresponding sub-periods

Graph 2 depicts the process of data collection over the sample period and emphasizes that data was gathered from each of the ten sub-periods.

Table 5: No. of firms per sub-period

Sub-period	Turnaround	Distress
1991-94	0	3
1992-95	1	1
1993-96	3	1
1994-97	6	5
1995-98	5	5
1996-99	2	6
1997-00	7	7
1998-01	11	16
1999-02	7	18
2000-03	22	24
Total	64	86

The precedent table displays the amount of firms collected from each sub-period, differentiating between turnarounds and distressed companies. The sample comprised a total of 150 companies, out of which 64 were classified as successful turnarounds and 86 were categorized as failed turnarounds.

Table 6 provides an overview of the industries that were covered by the data.

Table 6: No. of firms per covered industry

Industry	**Turnaround**	**Distress**
Automobiles & Components	0	2
Biotechnology	6	3
Capital Goods	8	9
Commercial & Professional Services	2	6
Consumer Services	1	8
Energy	5	12
Food, Beverage and Tobacco	3	2
Gold	5	0
Healthcare	9	7
Household & Personal Products	2	1
Materials	1	9
Media	0	8
Oil, Gas & Coal Exploration & Production	4	1
Retailing	1	3
Software and Services	2	3
Technology Hardware and Equipment	6	4
Transportation	0	8
Others	9	0
Total	64	86

Involving firms from different industries was important, because the study aims at deriving universal implications about decisive factors in the turnaround process and does not narrow down its research to a particular industry. Nevertheless, we excluded financial institutions from our sample, due to their highly levered capital structure and because some financial institutions enjoy governmental bankruptcy protection through bail-out guarantees.

All firms used in the study were publicly traded and listed at one of the following U.S. stock exchanges during the period 1991 to 2003:

i. (NYSE) − New York Stock Exchange
ii. (AMEX) − American Stock Exchange
iii. (NasdaqGM) − Nasdaq Global Market
iv. (NasdaqCM) − Nasdaq Capital Market
v. (NasdaqGS) − Nasdaq Global Select

We have chosen these exchanges, because when accumulated they rank first place in two categories over the whole length of our study period:

1. Amount of listed firms
2. Trading volume

A high amount of listed firms provides broad industry coverage, which is necessary concerning that we do not restrict our analysis to a specific industry.

The variable trading volume is a crucial determinant of stock returns. The Wall Street believes in a relationship between trading volume and stock returns, stating that "It takes volume to make the prices move"[63]. Ying (1966)[64] demonstrated that small trading volumes are related to negative returns (price fall) and large trading volumes are related to positive returns (price rise). Several other researchers substantiated a positive correlation between trading volume and stock returns. Below an excerpt of a list of studies on this issue is provided.

Table 7: Prior studies on correlation between returns and trading volume

Researcher	**Year**	**Sample Data**	**Sample Period**	**Interval**	**Positive Correlation found?**
Comiskey et. al	1984	211 common stocks	1976-79	yearly	Yes
Morgan	1976	44 common stocks	1926-68	monthly	Yes
Richardson et. al	1987	106 common stocks	1973-82	weekly	Yes
Jain et. al	1986	Stocks market aggregates	1979-83	hourly	Yes

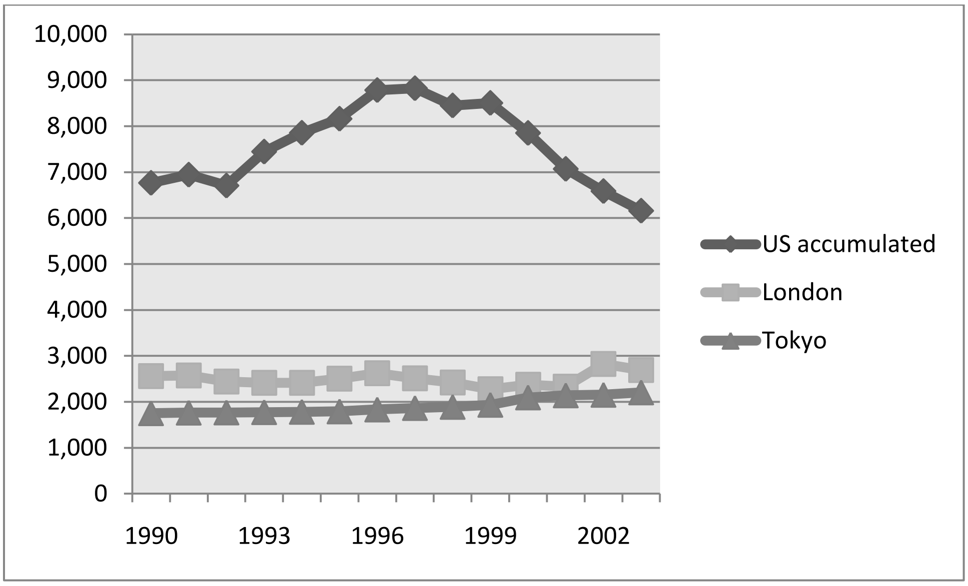
Source: Karpoff, Jonathan M., (1987), "The relation between price changes and trading volume: A survey", *The Journal of Financial and Quantitive Analysis,* Vol. 22, No. 1, pp. 109-126, p. 112.

A high trading volume is of interest for our study, since we also point to significant differences in stock returns of distressed firms and turnarounds.

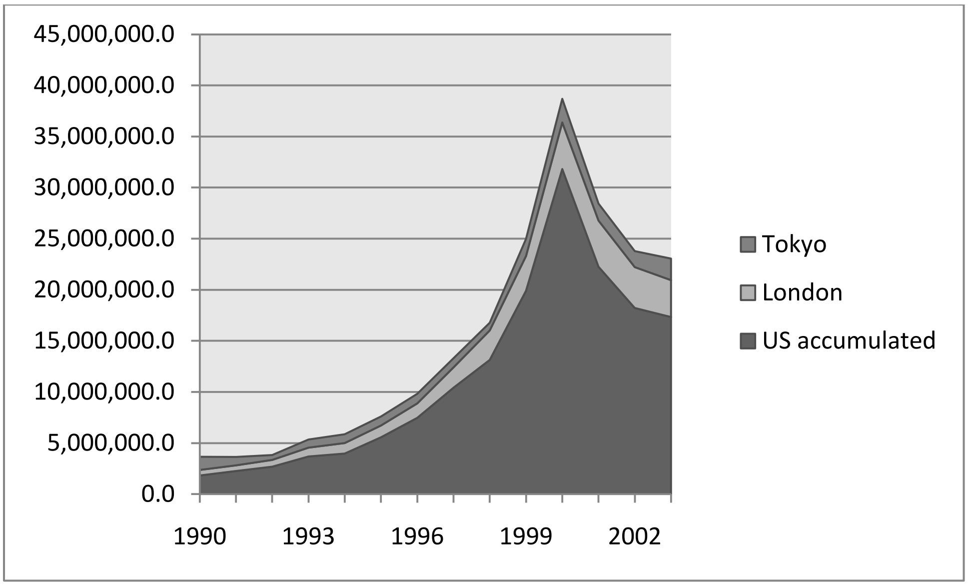
The amount of listed firms and trading volume was accumulated for the considered US stock exchanges and compared to the London SE and the Tokyo SE over the sample period. The

[63] Karpoff, Jonathan M., (1987), "The relation between price changes and trading volume: A survey", *The Journal of Financial and Quantitive Analysis,* Vol. 22, No. 1, pp. 109-126, p. 112.
[64] Ying, Charles C., (1966), "Stock Market Prices and Volumes of Sales", *Econometrica*, Vol. 34, No. 3, pp. 676-685, p. 676.

London SE and the Tokyo SE were chosen as benchmark stock exchanges, because they were ranked among the top five largest stock exchanges throughout the whole study period.[65]



Graph 3: Listed firms by stock exchange



Graph 4: Trading volume in USD millions by stock exchange

Graph 3 and 4 demonstrate that the involved US stock exchanges outperformed the London SE and the Tokyo SE in number of listed firms and trading volume throughout the whole sample period.

---

65 *World Federation of Exchanges*, http://www.world-exchanges.org/statistics/time-series/market-capitalization

3.5 Variables and hypothesis development

This section presents the variables we have taken into account in our empirical research. We assume that these variables have an impact on a company's probability to recover from financial distress. Therefore they act as discriminating predictors, enabling a separation of distressed companies into turnarounds and failed turnarounds (firms that remain in financial distress). A hypothesis was formulated for each variable.

3.5.1 Size (X1)

We measure size by means of total tangible assets. Some studies use total sales as an indicator of size. However, we follow Smith et. al (2005)[66], who relate the size of a company to its borrowing capacity. According to the Collateral Hypothesis, a firm's debt capacity is restricted to its collateralizable assets, which are represented by its total tangible assets. Thus, a firm with a higher debt capacity will have easier access to the credit market, to raise funds necessary for the restructuring. White (1989)[67] highlights the positive impact of the track record of large companies in raising external funds on their ability to obtain additional financial support. Besides, strong stakeholder support is expected for large firms, as their stakeholders have more to lose in the event of bankruptcy.[68] On top of this, large companies dispose of more assets that can be sold and more business units that can be divested, triggering a release of internally generated financial means, which contribute to the restructuring process by reducing the leverage or enabling the realization of value-creating investments. A contrary opinion is provided by Paint (1991)[69], who reveals a negative relationship between size and turnaround potential. According to him, smaller companies can adapt more readily to altering conditions of their environment.

Although small firms might be characterized by a flat hierarchy and exhibit few layers of management, allowing them to react fast to market changes, there access to external capital markets might be restricted, forcing them to resort to internal financial means. As we perceive

[66] Smith, Malcom and Graves, Christopher, (2005), Corporate turnaround and financial distress, *Managerial Auditing Journal*, Vol. 20, Iss. 3, pp. 304-320, p. 310.
[67] White, M. (1989), “Bankruptcy, liquidation and reorganization”, in: D.E. Logue (ed.), *Handbook of Modern Finance*, Warren, Gorham & Lamont, New York.
[68] Smith, Malcom and Graves, Christopher, (2005), Corporate turnaround and financial distress, *Managerial Auditing Journal*, Vol. 20, Iss. 3, pp. 304-320, p. 306.
[69] Paint, Laurie W., (1991), “An investigation of industry and firm structural characteristics in corporate turnarounds”, *Journal of Management Studies*, Vol. 28, Issue 6, pp. 623-643.

the availability of capital as a vital factor for a successful turnaround, we do not share Paint's viewpoint.

Hypothesis 1: Firm size and turnaround potential are positively correlated.

3.5.2 Severity of distress (X2)

Robbins et al. (1992)[70] investigate a positive relationship between the severity of distress and the degree of cutbacks and asset divestments. As stated by Slatter (1984)[71], the implementation of retrenchment measures might face organizational resistance, which results in a decrease of operational efficiency, thereby aggravating the distressed state. Sudarsanam et. al (2001)[72] indicate that the severity of distress negatively influences the required time for the restructuring and can inhibit the completion of certain restructuring measures. These measures primarily embrace actions aiming at reshaping the firm's strategy and call for capital expenditures. Debt holders might oppose the implementation of such actions, because they consume capital funds that can be used to settle part of their claims. The severity of distress is measured by the Z-score. Companies displaying a Z-score, which is below 1.8 or even negative, are considered to be severely distressed.

Hypothesis 2: Severity of distress and turnaround potential are negatively correlated.

3.5.3 Capital structure (X3, X4)

Klarman (1991)[73] points out that financial distress in the majority of cases can be traced back to excessive leverage. For a distressed firm reorganizing its capital structure and reducing the debt burden might be an essential step towards a successful turnaround. With respect to Gilson (1990)[74] an alleviation of the indebtedness can be reached by renegotiating existing debt contracts, in such a way that the creditor offers either a composition (reduction of interest or principal) or an extension or even an exchange of debt for equity or a combination of all

[70] Robbins, D. Keith, and Pearce, John A., (1992), "Turnaround: retrenchment and recovery", *Strategic Management Journal*, Vol. 13, Issue 4, pp. 287-309.
[71] Slatter, Stuart and Johnson, Gerry, (1984), "Corporate Recovery: Successful turnaround strategies and their implementation", *Strategic Management Journal*, Vol. 7, Issue 1, pp. 99-100.
[72] Sudarsanam, Sudi and Lai, Jim (2001), "Corporate Financial Distress and Turnaround Strategies: An empirical analysis", *British Journal of Management*, Vol. 12, Issue 3, pp. 183-199.
[73] Klarman, Seth. A.,(1991),*Margin of safety: Risk-averse value investing strategies for the thoughtful investor*, Harper Business.
[74] Gilson, Stuart C., (1990), "Bankruptcy, boards, banks and bondholders – Evidence on changes in corporate ownership and control when firms default", *Journal of Financial Economics*, Vol. 27, Issue 2, pp. 355-387.

three. Brown et. al (1993)[75] underscore the signaling effect of exchanges by stating that positive information is conveyed to the market, if a firm achieves an exchange with its banks. However, pushing through an exchange with bondholders transmits negative information, as contrasted with banks bondholders do not have the capabilities to assess a firm's recovery potential. In order to get a more precise picture of the indebtedness of a firm, we focused on the ratio total debt to total assets, which states how much of the total assets are externally financed. A decrease in the ratio can either stem from the implementation of debt reducing measures or from an internally financed increase of total assets. While it is obvious that deleveraging will promote recovery from financial distress, expanding the asset base will also foster the completion of a successful turnaround, given that the additional assets are value creating. Also, an increase in the equity position is expected to promote a successful turnaround, making it possible to interpret that existing shareholders believe in the turnaround potential of the firm.

Hypothesis 3: Change in total debt to total assets and turnaround potential are negatively correlated.

Hypothesis 4: Change in total equity and turnaround potential are positively correlated.

3.5.4 Long-term financial health (X5, X6)

Free cash-flow to total liabilities (X5)

Free cash-flow is the part of the cash-flow generated by a firm's operational business, which is left over after subtracting the capital expenditures that were reinvested back into the operations. It excludes the impact of financial and non-operating items and is available to debt holders and shareholders.[76] The ratio free cash-flow to total liabilities measures to what extent a firm is able to cover its liabilities by means of financial funds yielded from its operations. Sudarsanam et. al (2001)[77] employed PBITD (profit before interest taxes and depreciation) as a cash-flow proxy. We refrained from adopting the same cash-flow proxy and relied on free cash-flow. Unlike PBITD free cash-flow takes into consideration the cash-outflows resulting from tax payment and reinvestment in the operational business. Therefore, we contemplated

[75] Brown, David T., James, Christopher M. and Mooradian, Robert M., (1993), "The information content of distressed restructurings involving public and private debt claims", *Journal of Financial Economics*, Vol. 33, No. 1, pp. 93-118.
[76] Koller, Tim; Goedhart, Marc and Wessels, David, (2010)*Valuation: Measuring and managing the value of companies,* John Wiley & Sons, p. 135.
[77] Sudarsanam, Sudi and Lai, Jim (2001), "Corporate Financial Distress and Turnaround Strategies: An empirical analysis", *British Journal of Management*, Vol. 12, Issue 3, pp. 183-199.

that if a firm is in a distressed state and it strives for reorganization, expenses related to operations will still arise and give cause for reinvestments. We measure the change of the ratio free cash-flow over total liabilities. An increase of the ratio can either be affiliated to a reduction of total liabilities or to an increase of free cash-flow.

Hypothesis 5: Change of free cash-flow over total liabilities and turnaround potential are positively correlated.

Solvency ratio (X6)

We included the solvency ratio, which is defined as follows:

$$Solvency\ ratio = \frac{Net\ income + depreciation\ and\ amortization}{Total\ liabilities}$$

Non-cash expenses were added back to net income, to reflect the entire funds available for the redemption of a firm's liabilities. In contrast to times interest earned, the solvency ratio incorporates also cash that stems from non-operational actions, such as asset sales. As the occurrence of bankruptcy is often contingent on a firm's insolvency, we perceive an increase of the solvency ratio as a sign of financial recovery.

Hypothesis 6: Change of solvency ratio and turnaround potential are positively correlated.

3.5.5 Short-term financial health / Liquidity (X7, X8, X9)

Times interest earned (X7)

In accordance with Zeni et. al (2010)[78] we include the interest coverage ratio in our analysis. It measures if the financial funds generated by a firm's operations (EBIT) are sufficient to comply with its interest charges. An increase in the ratio can originate either from a rise in EBIT or from a decrease in interest charges. The latter can be motivated by a reduction of the debt burden through a composition, an exchange or a debt retirement.

$$Times\ interest\ earned = \frac{EBIT}{Interest\ expenses}$$

Hypothesis 7: Change of times interest earned and turnaround potential are positively correlated.

[78] Zeni, Syahida Binti and Ameer, Rashid, (2010), Turnaround prediction of distressed companies: evidence from Malaysia, *Journal of Financial Reporting and Accounting*, Vol. 8, Issue 2, pp 143-159.

Quick ratio (X8, X9)

By including the quick ratio in our analysis, we bear in mind the importance of financial liquidity for a company. The quick ratio is computed thusly:

$$Quick\ ratio = \frac{Current\ assets - inventories}{Current\ liabilities}$$

Remaining liquid is a prerequisite for being able to continue operations, since an illiquid firm might be confronted with the termination of its business relations with suppliers, as it cannot make timely payments. We examine the relation between liquidity, change in liquidity and turnaround potential. We included also change in liquidity by arguing that an increase of liquidity will invigorate stakeholder support, as suppliers can feel more certain about the firm meeting their financial obligations. Loyal suppliers might cause customers losing their fear regarding the firm's ability to carry out orders, making them to refrain from switching to competitors.

Hypothesis 8: Quick ratio and turnaround potential are positively correlated.

Hypothesis 9: Change of quick ratio and turnaround potential are positively correlated.

3.5.6 Profitability / Efficiency (X10, X11)

Free cash-flow to sales (X10)

We apply this ratio as a profitability measure, instead of using the profit margin. In comparison to earnings, free cash-flow provides a more undistorted measure of a company's profit creation, as it is not subject to estimation and judgment of the top management team. Earnings can be forged by earnings management and accrual manipulation, with the objective of artificially improving the firm's profit creation.[79]

Free cash-flow to sales states the amount of cash generated by a firm's revenues after subtracting capital expenditures. It gives an indication of a company's proficiency to control its cost structure. However, a low ratio cannot always be attributed to a high cost structure, but might result from undertaken investments in e.g. new technology, which would suppress free-cash flow downward. If the investments are value creating, cash-flows will be generated and the ratio will be revised upwards next year, under the assumption that new investments

[79] Dechow, Patricia M. and Schrand, Catherine M., (2004), "*Earnings Quality*", The Research Foundation of CFA Institute.

will start generating cash-flows one year after their implementation. We measure the change in free-cash flow to sales, as we believe that an increase of the ratio can be effectuated either by an improvement of the cost structure or by a cash-flow rise due to implemented value creating investments. An increase in profitability will promote the turnaround process, as the firm will be able to use free cash-flow for alleviating the indebtedness or for pursuing further value creating investments.

Hypothesis 10: Change of free cash-flow over sales and turnaround potential are positively correlated.

Operating profit margin (X11)

Hambrick et. al (1983)[80] and Robbins et. al (1992)[81] are in agreement about the necessity of enforcing retrenchment actions to pave the way for a turnaround. We adopt operating profit margin as a ratio of efficiency improvement through the consummation of cost-cutting measures. It is computed as follows:

$$Operating\ Profit\ Margin = \frac{EBIT}{SALES}$$

An increase in operating profit margin does most likely stem from a decrease in variable costs, like wages and raw material prices etc. Another possible source would be an acquisition, which would cause sales to rise at a faster pace than variable costs, due to the realization of synergies.

Hypothesis 11: Change of operating profit margin and turnaround potential are positively correlated.

3.5.7 Investments / Divestments (X12, X13, X14, X15)

Free assets (X12)

This variable is directly related to a firm's debt capacity. Smith et. al (2005)[82] define it as follows:

---

[80] Hambrick, Donald C. and Schecter, Steven M., (1983), "Turnaround Strategies for Mature Industrial-Product Business Units", *Academy of Management Journal*, Vol. 26, No. 2, pp 231-248.

[81] Robbins, D. Keith, and Pearce, John A., (1992), "Turnaround: retrenchment and recovery", *Strategic Management Journal*, Vol. 13, Issue 4, pp. 287-309.

[82] Smith, Malcom and Graves, Christopher, (2005), Corporate turnaround and financial distress, *Managerial Auditing Journal*, Vol. 20, Iss. 3, pp. 304-320.

$$Free\ assets = \frac{Total\ tangible\ assets - Secured\ loans}{Total\ tangible\ assets}$$

The ratio indicates a firm's amount of unutilized collateralizable assets. Thus, the higher the ratio the more leeway the firm enjoys in taking on additional debt, as new loans could be endowed with collaterals, permitting the creditors to seize ownership of the assets in the event of default. This facilitates the access to external capital for the distressed firm. Moreover, while covenants in the debt contract inhibit the sale of assets pledged as collateral, free assets can be sold, therefore representing a possible source of cash-inflow.

Hypothesis 12: Free assets and turnaround potential are positively correlated.

Degree of Downsizing (X13)

Robbins et. al (1992)[83] perceive the enforcement of retrenchment measures as the first step of a successful turnaround. Such measures are not constraint to headcount reduction, but involve cost-cutting efforts and asset divestments with a view to improving efficiency and generating cash flows. Based on Smith et. al (2005)[84] we define downsizing in the following way:

$$Degree\ of\ Downsizing = \frac{Tangible\ assets\ (t) - Tangible\ assets\ (t-1)}{Tangible\ assets\ (t-1)}$$

Hypothesis 13: Degree of downsizing and turnaround potential are positively correlated.

Goodwill (X14)

The position goodwill in the balance sheet statement contains the premiums paid for the acquisitions a company has undertaken.[85] We refer to change in goodwill as a measure of strategic asset investment/divestment. Goodwill impairments and amortizations were added back to avoid making wrong inferences about asset divestments that did not occur. Thus, changes in the goodwill position reflect acquisitions and divestments, respectively. Since several researchers suggest that a firm should consider strategic asset investments in the

[83] Robbins, D. Keith, and Pearce, John A., (1992), "Turnaround: retrenchment and recovery", *Strategic Management Journal*, Vol. 13, Issue 4, pp. 287-309.
[84] Smith, Malcom and Graves, Christopher, (2005), Corporate turnaround and financial distress, *Managerial Auditing Journal*, Vol. 20, Iss. 3, pp. 304-320.
[85] Koller, Tim; Goedhart, Marc and Wessels, David, (2010)*Valuation: Measuring and managing the value of companies,* John Wiley & Sons, p. 141.

turnaround process, in order to adjust its asset portfolio to the evolving environment[86], we investigate the relationship between goodwill increases and turnaround potential.

Hypothesis 14: Change in goodwill and turnaround potential are positively correlated.

R&D expenses (X15)

In regard to Hambrick et. al (1983)[87], we include R&D expenses as a measure of a firm's concentration on the development of new products, which shall promote the company in the process of strategic reorientation. However, we argue that constantly interpreting investments in R&D as a strategic measure would be wrong. A firm might expend R&D effort in developing new technologies or in designing innovative ways to organize and manage the process cycles, both of which would rather be related to an efficiency improvement than to a strategic reorientation. In addition, we decided not to focus on the ratio of R&D to sales, as has been done by Hambrick et. al (1983). Instead, we measure the change in R&D expenses over a one-year period. That way, we prevent the emergence of wrong conclusions about a firm's R&D policy, as a decline in the ratio could be explained by a cutback in R&D expenses or by an increase in sales, or by both.

Hypothesis 15: Change in R&D and turnaround potential are positively correlated.

3.5.8 Management Expertise (X16)

ROE (X16)

For a successful turnaround it is crucial that stakeholders and shareholders believe in the incumbent management team's ability to steer the company out of distress. Otherwise, they will refrain from promoting the turnaround attempt, putting at risk the firm's recovery.

Zeni et. al (2010)[88] included ROE (Return on equity) as a measure of top management expertise in their Z-score, which they developed for the Malaysian market.

We apply ROE as an indicator of the top management team's capability to initiate a process of recovery from distress and thereby ensure stakeholder and shareholder support.

---

[86] Sudarsanam, Sudi and Lai, Jim (2001), "Corporate Financial Distress and Turnaround Strategies: An empirical analysis", *British Journal of Management*, Vol. 12, Issue 3, pp. 183-199, p. 186.
[87] Hambrick, Donald C. and Schecter, Steven M., (1983), "Turnaround Strategies for Mature Industrial-Product Business Units", *Academy of Management Journal*, Vol. 26, No. 2, pp 231-248.
[88] Zeni, Syahida Binti and Ameer, Rashid, (2010), Turnaround prediction of distressed companies: evidence from Malaysia, *Journal of Financial Reporting and Accounting*, Vol. 8, Issue 2, pp 143-159.

Hypothesis 16: ROE and turnaround potential are positively correlated.

3.5.9 Overview of examined variables

The table below provides an overview of the variables taken into account in our empirical study. It also shows the encoding used in the statistical programs SAS and SPSS for each predictor. Besides, it states the scale unit employed to each variable and points out which empirical research motivated the inclusion of the variable.

Table 8: Overview of examined variabels

I. Size	**Encoding**	**Empirical support**
		White (1989)
		Smith et. al (2005)
Total tangible assets	X1	
II. Severity of distress		
Z-score	X2	Sudarsanam et. al (2001)
III. Capital structure		
		Gilson (1990)
∆ total debt/total assets	X3	Klarman (1991)
∆ total equity	X4	Klarman (1991)
IV. Long-term financial health		
		Sudarsanam et. al (2001)
∆ FCF/total liabilities	X5	Own intuition
∆ Solvency ratio	X6	Own intuition
V. Financial health/ Liquidity		
∆ Times interest earned	X7	Zeni et. al (2010)
Quick ratio	X8	Own intuition
∆ Quick ratio	X9	Own intuition
VI. Profitability/Efficiency		
∆ FCF/Sales	X10	Goumas et. al (2011)
		Hambrick et. al (1983)
		Robbins et. al (1992)
∆ EBIT/Sales	X11	Chowdhury et. al (1996)
VII. Investments/Divestments		
Free assets	X12	Smith et. al (2005)
		Robbins et.al (1992)
Degree of downsizing	X13	Smith et. al (2005)
		Hofer (1980)
		Grinyer et. al (1988)
∆ Goodwill	X14	Sudarsanam et. al (2001)
		Hambrick et. al (1983)
∆ R&D expenses	X15	Goumas et. al (2011)
VIII. Management Expertise		
		Abdullah et. al (2008)
ROE	X16	Zeni et. al (2010)

∆ = change no ∆ = no change (the variable was taken into account, instead of the change in the variable) yoy = year on year

Table 9 summarizes the examined hypotheses with respect to each variable.

Table 9: Summary of hypothesis formulation

I. Size	**Encoding**	**Correlation with turnaround potential**
Total tangible assets	X1	+
II. Severity of distress		
Z-score	X2	-
III. Capital structure		
Δ total debt/total assets	X3	-
Δ total equity	X4	+
IV. Long-term financial health		
Δ FCF/total liabilities	X5	+
Δ Solvency ratio	X6	+
V. Financial health/ Liquidity		
Δ Times interest earned	X7	+
Quick ratio	X8	+
Δ Quick ratio	X9	+
VI. Profitability/Efficiency		
Δ FCF/Sales	X10	+
Δ EBIT/Sales	X11	+
VII. Investments/Divestments		
Free assets	X12	+
Degree of downsizing	X13	+
Δ Goodwill	X14	+
Δ R&D expenses	X15	+
VIII. Management performance		
ROE	X16	+

3.6 Methodology

In order to investigate which of the outlined independent variables are most qualified to separate our sample into turnarounds and non-turnarounds, we run a linear discriminant analysis (LDA) and a logistic regression (LOGIT) on our sample data. Both methods will enable us to test the developed hypotheses and create a discriminant function (DF) and logistic function. They act as a prediction model, facilitating the categorization of financially distressed firms into turnarounds and non-turnarounds, based on a cut-off point. The DF obtained from the LDA and the logistic function given by LOGIT will be applied to a holdout sample for reasons of back-testing their prediction accuracy.

The statistical programs employed on the sample data were SAS (with respect to LDA) and SPSS (with respect to LOGIT).

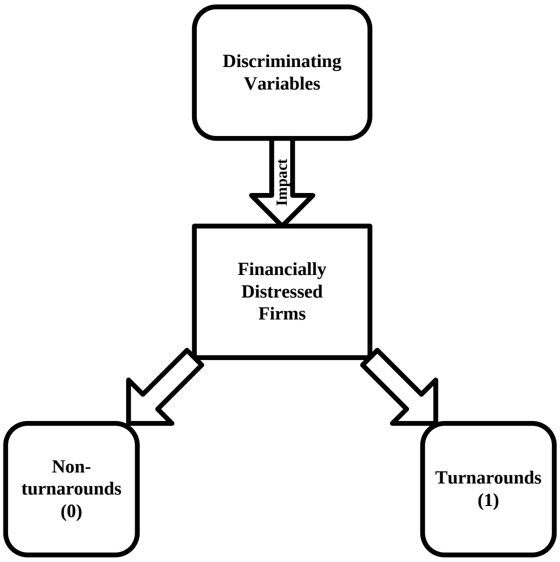
3.6.1 Linear Discriminant analysis (LDA)

LDA aims at ascribing an unknown subject (e.g. financially distressed firm) to one of two groups (e.g. turnarounds; non-turnarounds)[89], with the aid of discriminating variables (explanatory variables).

The DF is expressed by the following equation:

$$Z = \alpha + \beta_1 X_1 + \ldots + \beta_n X_n$$

Where,
Z = discriminant score
α = constant term
β = discriminant coefficients
X = discriminating variables

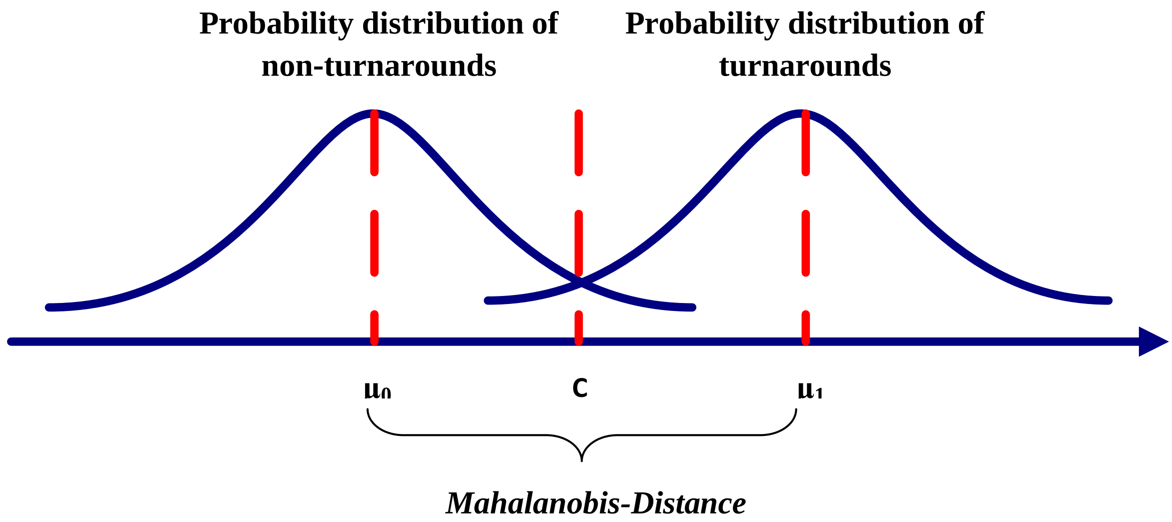


Graph 5: The discriminating process in the linear discriminant analysis

The discriminating process is described in the graph above. The dependent variable (e.g. turnaround outcome of financially distressed firms) is categorical and the two groups must be definite distinguishable from each other i.e. they need to be mutually exclusive.

[89] Lachenbruch, P. A. and Goldstein, M., (1979), "Discriminant Analysis", *Biometrics*, Vol. 35, No. 1, pp. 69-85.

The discriminating variables, which are considered to be suitable for differentiating the two groups from each other, are chosen according to their ability to maximize the distance between the means of the probability distributions of the two groups and included in the DF.[90]



Graph 6: Probability distributions of turnarounds and non-turnarounds and Mahalanobis-Distance

μ_0 = Mean of non-turnaround distribution based on DF μ_1 = Mean of turnaround distribution based on DF

C = Cut-off point

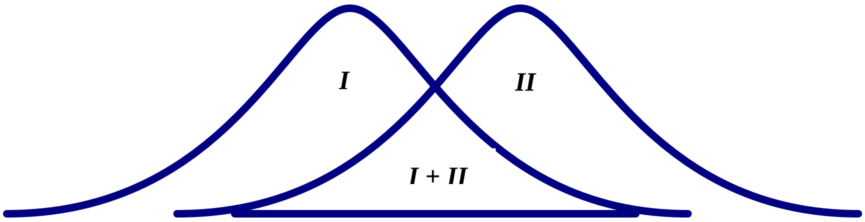
The probability distributions of the two groups are depicted in graph 6. LDA assumes that the explanatory variables follow a normal distribution, having equal variances and covariances.[91] The distance between the means of the two groups is called Mahalanobis-Distance and calculated thusly:

$$D^2 = \frac{(\mu_0 - \mu_1)^2}{S^2}$$

S^2 = pooled sample variance

With an increasing D^2 the overlapping area of the normal distributions becomes smaller, enabling an almost unambiguous differentiation between the two groups.

[90] Lachenbruch, P. A. and Goldstein, M., (1979), "Discriminant Analysis", *Biometrics*, Vol. 35, No. 1, pp. 69-85.
[91] Cox, D. R. and Snell, E.J., (1989), *"The analysis of binary data"*, 2nd Edition, Chapman and Hall.



Graph 7: Overlapping of the probability distributions of two populations I and II

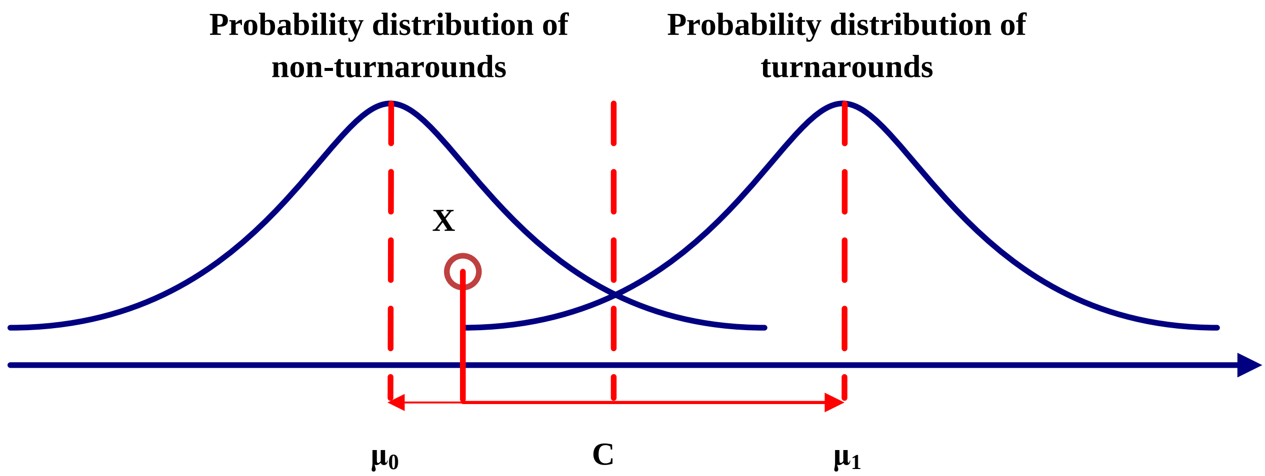
Graph 7 depicts an example of a small Mahalanobis-Distance between two population means, giving rise to a large overlapping area and increasing the probability of misclassification. In most cases, a perfect seperation of two populations cannot be achieved, so that the tails of the distributions will cross, leading to the emergence of type I and type II errors (misclassification errors).[92] In our particular study, a type I error corresponds to the classification of a non-turnaround as a turnaround and a type II error is equivalent to the classification of a turnaround as a non-turnaround.

So as to be able to categorize an observation in one of the two groups, a cut-off point needs to be determined. Graph 6 shows that the seperation line is located where the tails of the two groups' probability distributions cross. Thus, assuming a normal distribution, the cut-off point is given by the formula:

$$C = \frac{\mu_0 + \mu_1}{2}$$

For a new observation X the discriminant score must be calculated on the basis of the DF. If the discriminant score lies below the cut-off point, the observation is classified into group I and vice versa.

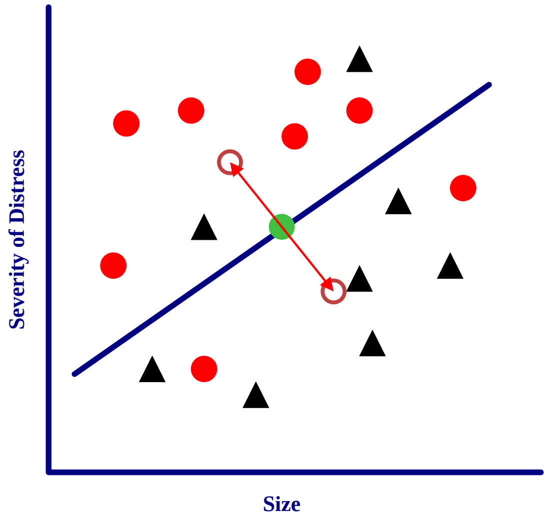
[92] Lachenbruch, P. A., (1968), "On expected probabilities of misclassification in discriminant analysis, necessary sample size, and a relation with the multiple correlation coefficient", *Biometrics*, Vol. 24, No. 4.



Graph 8: Classification of a new observation X

Graph 8 visualizes the classification of a new observation X in one of the two groups. The red circle depicts the discriminant score of the observation X. As the score is smaller than the cut-off point C, the observation is categorized into the group of non-turnarounds. Another approach is to argue that the discriminant score of X is closer to the mean of the probability distribution of non-turnarounds than to the mean of the probability distribution of turnarounds, leading to a classification into the first group.

As already stated, the independent variables involved in the DF are the most qualified for discriminating the two groups from each other. The graph below shows an example for two independent variables, applied to classify financially distressed firms into turnarounds and non-turnarounds.



Graph 9: Classification of financially distressed firms into turnarounds and non-turnarounds based on size and severity of distress

For this example the turnarounds are depicted by the black triangles and the non-turnarounds correspond to the red circles. It is apparent that the non-turnarounds are located in the northwestern part of the scatterplot, while the turnarounds lie southeasterly. The blue line, seperating the observations of the two groups, is called the linear discriminant boundary and is described by the following formula:

$$\beta_1 Size - \beta_2 Severity\ of\ distress - \alpha = 0$$ [93]

This formula complies with the DF formula. An observation that is situated on the discriminant boundary has a discriminant score equal to zero. As a consequence, observations located on one side of the boundary will be distinguished from observations located on the other side by having an opposite sign in the discriminant score. This is ensured by including the constant term α in the formula. The value of the discriminant score indicates the distance of the observation from the discriminant boundary.[94]

We used SAS to conduct the LDA. The program offers different approaches to create a subset of explanatory variables (predictors) out of an initial set of variables. The most important approaches are described briefly.

Means and correlation procedure:

SAS provides an overview of the means and the standard deviations for each variable that is entailed in both groups (0, 1). Taking e.g. the variable *Size*, the mean $\mu(Size_0)$ and the standard deviation $\delta(Size_0)$ are compared with the mean $\mu(Size_1)$ and the standard deviation $\delta(Size_1)$. The higher the difference in the two means and the lower the intra-group standard deviation, the better the variable *Size* discriminates between the two groups. Given close to each other located means and high intra-group standard deviation, increases the chance of overlapping probability distributions, producing large misclassification errors.

Stepdisc Forward Variables Selection

At the beginning, no variable is included in the model. Then, the variable exhibiting the highest discriminatory power is selected. In the following steps, the variables that paired with the initial variable lead to the highest increase of the model's discriminatory power are

[93] Cooper, Ron A. and Weekes, Tony J., (1983), "*Data, Models and statistical analysis*", Philip Allan Publishers Limited, New Jersey, USA, p. 280-285.
[94] Ibid.

included. The selection process stops as soon as no further significant increase in the model's discriminatory power is achieved.[95]

Stepdisc Backward Variables Selection

This selection procedure is equal to an elimination process. Initially, all variables are included in the model. Then, the variables having the smallest impact on the model's discriminatory power are excluded. In this manner, the process ensures that only the best predictors are kept in the DF.[96]

3.6.2 Binary Logistic regression model (Binary LOGIT)

Binary LOGIT is an alternative to LDA when the dependent variable is dichotomous. In contrast to LDA it does not require the explanatory variables to be normally distributed and have equal variance and covariance, making it a more flexible and robust model.[97] As financial data does not follow a normal but rather a leptokurtic distribution, binary LOGIT appears to be more appropriate for the underlying study.[98]

In practice, binary LOGIT is applied in many different fields, to determine the explanatory variables that cause a separation of two groups from each other. One example is the application of binary LOGIT in medical science to determine the factors for predicting the emergence of heart diseases. The dependent variable is binary and comprises the two outcomes *i. heart disease and ii. no heart disease*, which are equivalent to the two groups. The explanatory variables (predictors) that allow for a classification of a patient in one of the two groups would be e.g. age, weight, blood pressure, smoking habits etc.[99]

The explanatory variables can be of quantitative or binary character, or a mixture of both. The binary variable, whether dependent or explanatory, is encoded by the use of 0 and 1, where 0 denotes the absence of a situation and 1 denotes the presence of a situation respectively.

Thus, the binary logistic regression aims at explaining differences between two groups on the basis of a common set of variables. It identifies the explanatory variables, which are most

[95] SAS Institute Inc. 2010. *SAS/STAT® 9.22 User's Guide.* Cary, NC: SAS Institute Inc.
[96] Ibid.
[97] Hosmer, David W. and Lemeshow, Stanley, (2000), *"Applied Logistic Regression"*, 2nd Edition, John Wiley & Sons, Inc.
[98] Brooks, Chris, (2002), "*Introductory Econometrics for Finance*", 1st Edition, Cambridge University Press.
[99] Afifi, Abdelmonem and Clark, Virginia A., (1996), "*Computer-aided multivariate analysis*", 3rd edition, Chapman and Hall.

qualified to discriminate between two groups, as well as their direction and intensity of impact on the respective group.[100]

To give an example, based on our study the binary logistic regression extracts the relevant variables out of a set of fifteen variables, which best separate our sample into turnarounds and non-turnarounds. This allows us to make inferences about the decisive drivers in the turnaround process.

The logistic function is given by:

$$Logit(Y) = \ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + u^{101}$$

Where, Y = dependent binary variable
π = Probability of the outcome of category I e.g. turnaround
1-π = Probability of the outcome of category II e.g. non-turnaround
X = explanatory variable
α = intercept
β = regression coefficient
u = random disturbance term

The above equation shows that binary LOGIT predicts "the probability that a case will be classified into one as opposed to the other of the two categories of the dependent variable".[102] This is known as the odds ratio, which can be expressed as follows:

$$\frac{P\ (Y = 1)}{1 - P\ (Y = 1)} = \frac{\pi}{1 - \pi}$$

Where, P (Y = 1) = Probability of Y = 1
1 – P (Y = 1) = Probability of Y ≠ 1

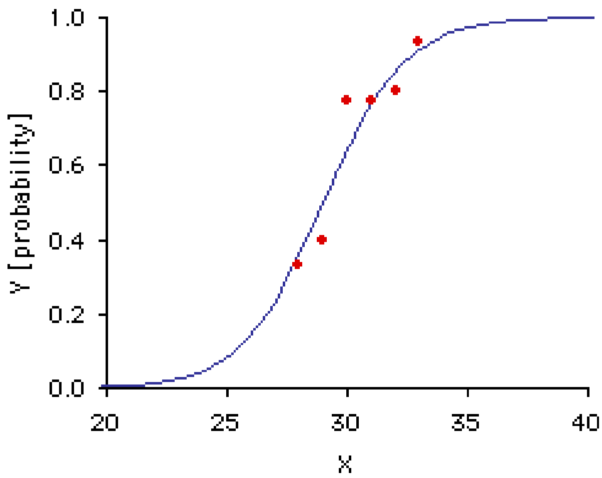
The probability of turnaround is defined by:

$$P_i = E(Y = 1|X_i) = \frac{1}{1 + e^{-(a + b_1 X_1 + b_2 X_2 + \cdots + b_i X_i)}}$$

This equation is known as the logistic regression equation.[103]

[100] Fromm, Sabine, (2005), "Binäre logistische Regressionsanalyse", *Universität Bamberg*.
[101] Peng, Chao-Ying J., Lee, Kuk L. and Ingersoll, Gary M., (2002), "An Introduction to Logistic Regression Analysis and Reporting", *The Journal of Educational Research,* Vol. 96, No. 1, pp. 3-14.
[102] Menard, Scott (1995), *"Applied Logistic Regression Analysis"*, 2nd Edition, Sage Publications, Inc.

Taking the natural logarithm of the odds ratio answers the purpose of constraining the estimated probability within the boundaries of 0 and 1.[104] In this way, values for the dependent variable will lie between 0 and 1, as shown in the graph below.



Graph 10: Logistic curve model for a dichotomous dependent variable[105]

For the logistic regression, SPSS sets the cut-off point automatically at 0.5. With respect to our study, we encoded turnarounds as ones and non-turnarounds as zeros. Thus, turnarounds should yield a score above 0.5 and non-turnarounds below 0.5 respectively, on condition that they are correctly classified. If graph 10 was the classification result of the binary LOGIT of financially distressed firms based on an explanatory variable e.g. size, according to the beforehand mentioned encoding, the four dots above 0.5 would match firms classified as turnarounds and the three dots below 0.5 would correspond to firms classified as non-turnarounds.

There exist two stepwise procedures to extract the most qualified predictors for discriminating between the two categories, out of a set of explanatory variables.

Forward Conditional Logistic Regression:

In the beginning block (step 0) no explanatory variable is included in the model, but only the intercept. Then, explanatory variables are entered in a stepwise procedure. First, the explanatory variable with the highest discriminatory power is included into the model, which

---

[103] Afifi, Abdelmonem and Clark, Virginia A., (1996), "*Computer-aided multivariate analysis*", 3rd edition, Chapman and Hall.
[104] Menard, Scott (1995), *"Applied Logistic Regression Analysis"*, 2nd Edition, Sage Publications, Inc.
[105] http://faculty.vassar.edu/lowry/lr1.gif

is consistent with the variable that has the highest statistically significant chi-square.[106] This variable causes "the greatest change in the log-likelihood relative to a model not containing the variable"[107]. The quality of fit of the model is indicated by the deviance (-2 Log likelihood). A decreasing deviance indicates that the model fits the data well.[108] This process is repeated until no further improvement in the model can be obtained, as no more statistically significant chi-squares are computed.[109] As including additional predictors to the model causes an upward bias of the goodness of fit measure, the model is penalized by an increase in degrees of freedom.[110]

Backward Conditional Logistic Regression:

The backward conditional logistic regression includes all of the variables in the beginning block (step 0) and stepwise removes variables, which are estimated as statistically insignificant. These are the explanatory variables, which demonstrate the largest p-value in terms of the likelihood ratio chi-square test.[111] It stops removing variables when all of the remaining predictors show a statistically significant contribution to the model.[112]

---

[106] Fromm, Sabine, (2005), "Binäre logistische Regressionsanalyse", *Universität Bamberg*.
[107] Hosmer, David W. and Lemeshow, Stanley, (2000), *"Applied Logistic Regression"*, 2nd Edition, John Wiley & Sons, Inc.
[108] Ibid.
[109] Fromm, Sabine, (2005), "Binäre logistische Regressionsanalyse", *Universität Bamberg*.
[110] Brooks, Chris, (2002), "*Introductory Econometrics for Finance"*, 1st Edition, Cambridge University Press.
[111] Afifi, Abdelmonem and Clark, Virginia A., (1996), "*Computer-aided multivariate analysis*", 3rd edition, Chapman and Hall.
[112] SPSS Regression 17.0

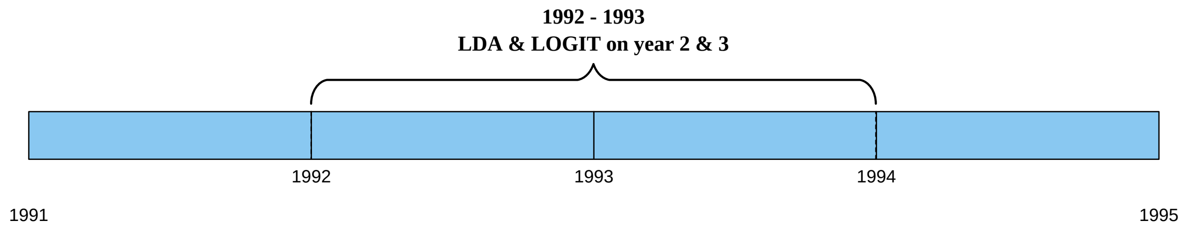
Chapter 4

Empirical Findings

In this chapter the empirical findings of our study are presented and discussed. The results obtained by the two approaches, LDA and LOGIT, are summarized and inferences about the factors playing a decisive role in the turnaround process are made. In addition, the findings provide answers regarding the rejection or non-rejection of the hypotheses developed in the previous chapter. The performance of the models is assessed based on their forecasting accuracy with respect to the in-sample data. The two models showing the highest in-sample prediction accuracy are evaluated based on their prediction performance on a holdout sample. Furthermore, the predictors proposed by the model presenting the best forecasting accuracy are tested for normality and heteroskedasticity, thereby making allowances for possible violations of the assumptions underlying LDA and LOGIT.

4.1 Initial situation

The time frame for investigating the impact of the explanatory variables on the turnaround outcome embraced year two and three of the four year window, which was exhibited in graph 2. We also took into account the period spanning year one and two, the two years for which all of the companies in our sample displayed a Z-score below 1.8. However, for this time period the degree of discrimination between the two groups was very low, leading to large misclassification errors. Below the time period of analysis is depicted graphically.



Graph 11: Time period of analysis regarding the impact of the explanatory variables on the turnaround outcome

4.2 Results of LDA

The LDA was performed by application of the statistical program SAS. The first step consisted of extracting the most qualified predictors out of our set of explanatory variables, followed by the derivation of the DF and computation of the cut-off point. SAS offers four approaches for determining the variables that discriminate best between two groups:

i. Means and correlation procedure
ii. Stepdisc Forward Variables Selection
iii. Stepdisc Backward Variables Selection
iv. Stepdisc Stepwise Variables Selection

All four procedures were taken into account. The results provided by each procedure are presented hereafter.

4.2.1 Means and correlation procedure (Model I)

The table below was generated by SAS and includes means and standard deviations for both groups and for each variable taken into consideration in our study.

Table 10: Means procedure

	Status 0		Status 1	
Variable	**Mean**	**Stand. Dev.**	**Mean**	**Stand. Dev.**
X1	7.647,47000	24.791,22000	479,80522	1.100,58000
X2	0,07189	2,24010	4,00548	2,80354
X3	0,00905	0,10599	-0,09743	0,16494
X4	0,02040	0,49043	0,67246	1,08285
X5	-0,00299	0,16569	0,02719	0,27306
X6	-0,00204	0,44957	0,28519	0,63444
X7	-0,08362	1,00394	0,07012	1,14753
X8	1,00256	1,08011	1,53116	1,19166
X9	-0,04107	0,32322	0,11107	0,39723
X10	-0,04533	0,22052	0,01140	0,24605
X11	0,05215	0,28629	0,05551	0,43024
X12	-0,03622	0,14050	-0,00097	0,10077
X13	0,03945	0,26643	0,15411	0,45012
X14	122,95094	573,49013	28,72262	175,23403
X15	-0,24562	18,23560	-0,99882	9,24052
X16	-0,05992	0,41028	0,02149	0,56350

Based on this table and on intuition a mean procedure prediction model was established. The variable X2 in table 10, equivalent to the Z-score, has a large difference in the means between the two groups. The intra-group standard deviation is almost equal for both categories. Thus, we included X2 as a predictor that allows for discrimination between the two groups. However, also X1 was included in our mean procedure prediction model, although the variable shows an extremely high intra-group standard deviation for both groups. Nevertheless, based on our intuition and the theoretical foundation presented in chapter 2, we believe that it is a decisive factor in the turnaround process, enabling a separation between turnarounds and non-turnarounds. We also examined the correlation matrix generated by SAS without finding significant correlations among the included variables. Several mean procedure prediction models were tested, covering various combinations of the explanatory variables. In the following, the mean procedure prediction model that revealed the highest in-sample forecasting accuracy is demonstrated. The DF of this model is given by:

$$Z_{CEGA} = -1{,}38222 - 0{,}0000265985 \times X_1 + 0{,}6268751 \times X_2 - 4{,}80063 \times X_3$$

X_1 = total tangible assets
X_2 = Z-score
X_3 = change in total debt/total assets

The relationship between the predictors suggested by the means and correlation procedure and the categories turnarounds and non-turnarounds is displayed in table 11.

Table 11: Relation between predictors and categories for X1 X2 X3

Variable	Coefficients (0)	Impact direction	Coefficients (1)	Impact direction
X1	0,0000216	+	-5,00E-06	-
X2	-0,0006751	-	0,6262	+
X3	0,41596	+	-4,38467	-

The table corroborates the discriminating power of the selected predictors, as their attached coefficients have an opposite sign for each of the two categories. According to the model, there exists a positive relation between size and non-turnarounds, while size and turnarounds are negatively related. Thus, the model suggests that smaller firms have a higher probability to be successful in the turnaround process. Even though the coefficient size is close to zero, it has a significant impact on the Z_{CEGA}, considering that the variable size includes large numerical values (firm's total assets). Moreover, firms for which the state of distress is less severe, as measured by the Altman Z-score (X2), are more likely to achieve a turnaround. The last variable considered to be decisive in the turnaround process is the change in the ratio total debt to total assets (X3). According to the model, a decrease in the ratio is associated with a successful recovery from financial distress. This empirical result was expected intuitively, as financial distress is traced back to excessive leverage, in most of the cases. The magnitude of the coefficient underpins the importance of the variable in the turnaround process, stating that a reduction of X3 will trigger a substantial increase in the discriminant score Z_{CEGA}.

We computed Z_{CEGA} scores for the firms in our in-sample and calculated the cut-off point, which accounted for – 0.00016632. The prediction accuracy of the model was estimated based on our in-sample, which involved 150 firms. The classification matrix is provided below.

Table 12: Classification Matrix in-sample X1 X2 X3

Status	0	1	Total
	83	3	86
0	96,51%	3,49%	100%
	8	56	64
1	12,50%	87,50%	100%
Total	91	59	150

The blue shaded areas in the classification matrix display the correctly categorized firms per outcome. The prediction accuracy on the in-sample amounted to 92.7%, which is computed by taking the sum of the correctly classified firms divided through the total number of firms. Misclassifications were restricted to 3 type I errors and 8 type II errors.

4.2.2 Stepdisc procedures (Model 2)

All of the three stepdisc procedures selected the same variables for inclusion in the final DF. Thus, the DF on the basis of the stepdisc procedures is given by:

$$Z_{CEGA} = -1{,}4729 - 0{,}00002637 \times X_1 + 0{,}6232226 \times X_2 - 4{,}4798 \times X_3 + \ 0{,}78661 \times X_6$$

X_1 = total tangible assets
X_2 = Z-score
X_3 = change in total debt/total assets
X_6 = change in solvency ratio

Table 13 provides an overview of the coefficients belonging to the probability distributions of turnarounds and non-turnarounds. They indicate direction and size of the impact of the respective explanatory variables on the turnaround process.

Table 13: Relation between predictors and categories for X1 X2 X3 X6

Variable	Coefficients (0)	Impact direction	Coefficients (1)	Impact direction
X1	0,0000216	+	-4,77E-06	-
X2	-0,0007326	-	0,62249	+
X3	0,42103	+	-4,05877	-
X6	0,01242	+	0,79903	+

The first three variables are equivalent to the variables chosen by the means and correlation procedure and their attached coefficients coincide in sign and are of similar magnitude. However, the stepdisc procedures selected X6 as an additional variable, which corresponds to the change in the solvency ratio. Although the coefficients of the predictor X6 are positive for both groups, the coefficient belonging to turnarounds is of larger numerical value, leading to the conclusion that companies with an increase in the solvency ratio are more likely to belong to the group of turnarounds.

The cut-off point for the DF of the second model was computed based on the Z_{CEGA} discriminant scores of the in-sample firms and amounted to -0.000165657. Below, the classification matrix for in-sample data is displayed.

Table 14: Classification Matrix in-sample X1 X2 X3 X6

Status	0	1	Total
	83	3	86
0	96,51%	3,49%	100%
	10	54	64
1	15,63%	84,37%	100%
Total	93	57	150

The in-sample forecasting accuracy of model 2 adds up to 91.33%, falling short of the prediction performance of model 1 by only 1.37%.

4.3 Results of LOGIT

The LOGIT was conducted by use of SPSS 17.0. Two procedures were applied to obtain the independent variables acting as predictors, so that two LOGIT functions were computed. The models were assessed regarding to their forecasting accuracy relative to the in-sample data. The procedures were performed at different confidence intervals, which varied from 95% to 85%, taking into account that additional variables might be viewed as significant for differentiating into the two groups, given lower confidence intervals. However, no additional variables were included in the LOGIT function at lower confidence intervals. Hence, the presented results were obtained at a confidence interval of 95%.

We excluded the variable severity of distress (X_2) from the set of potential discriminating variables. The LOGIT is based on a different algorithm than the LDA. It computes the probabilities of a company, being classified in one of two groups. As our definition of a turnaround was connected to a firm's Z-score, inserting the variable severity of distress (measured by Z-score) as a potential discriminator between turnarounds and non-turnarounds into the logistic algorithm of SPSS, yielded a logistic function consisting solely of the Z-score and displaying a prediction accuracy of 100%. Since this result is flawed, because of conformity between the defining variable and a potentially predictive variable, we conducted the LOGIT without inclusion of the Z-score.

4.3.1 Forward Conditional Logistic Regression (Model 3)

This procedure created a subset of three variables, which it regarded as eligible for categorizing financially distressed firms into turnarounds and non-turnarounds.

The LOGIT function is given by:

$$\mathrm{Y}_{\mathrm{CEGA}} = \ln\left(\frac{\pi}{1-\pi}\right) = -0{,}820 - 0{,}055 \times X_3 + 0{,}008 \times X_4 + 0{,}008 \times X_6$$

X_3 = change in total debt/total assets
X_4 = change in total equity
X_6 = change in solvency ratio

When interpreting the regression coefficients, it is important to bear in mind that the above LOGIT function complies with the log-odds of turnarounds.

Referring to the ratio total debt to total assets (X_3), LOGIT estimates a negative correlation between the predictor and the outcome turnaround. Hence, an increase in the ratio will lower the chances for turnaround, while a decrease will promote recovery from financial distress. As opposed to this, the model suggests that change in solvency ratio (X_6) is positively related with the probability of turnaround. The predictors X_3 and X_6 are represented in at least one of the two LDA-based models. Change in total equity (X_4), not taken into account by LDA, is expected to be positively connected with turnaround. Raising new equity will trigger an increase of the turnaround likelihood, as it reshapes the capital structure and allocates financial funds, which are disposable for deleveraging or investments in value-creating projects.

The cut-off point for the LOGIT was set automatically by SPSS at 0.5. For each firm the probability of turnaround is computed by means of the values of the predictors. A company is classified as a turnaround, if the computed probability exceeds 0.5. The in-sample classification matrix is provided below.

Table 15:Classification Matrix in-sample X3 X4 X6

Status	0	1	Total
	77	9	86
0	89.5%	10.5%	100%
	26	38	64
1	40.6%	59.4%	100%
Total	103	47	150

The in-sample forecasting accuracy of the model suggested by LOGIT forward amounts to 76.67%, being around 16% lower than the prediction accuracy given by LDA-model 1.

4.3.2 Backward Conditional Logistic Regression (Model 4)

The backward procedure included four variables in the LOGIT function. In addition to the three variables considered by the forward procedure, it also took into account total tangible assets (X_1).

$$Y_{CEGA} = \ln\left(\frac{\pi}{1-\pi}\right) = -0{,}221 - 0{,}00035 \times X_1 - 0{,}041 \times X_3 + 0{,}009 \times X_4 + 0{,}007 \times X_6$$

X_1 = total tangible assets
X_3 = change in total debt/total assets
X_4 = change in total equity
X_6 = change in solvency ratio

According to the model, total tangible assets negatively influence the turnaround likelihood, allowing us to infer that larger firms are less likely to recover from financial distress than smaller firms. The same conclusion was drawn from the LDA models. In respect of the other three variables, the relationship assumed by model 4 coincides with the relationship that model 3 predicted. To grasp the prediction accuracy of model 4, an in-sample classification matrix was generated.

Table 16:Classification Matrix in-sample X1 X3 X4 X6

Status	0	1	Total
	72	14	86
0	84%	16%	100%
	20	44	64
1	31%	69%	100%
Total	92	58	150

The model's forecasting accuracy accounts for 77.33%. Thus, the inclusion of total tangible assets as an additional predictor led to a marginal improvement of the prediction power by 66 basis points. However, also the second LOGIT model performs significantly poorer than the LDA models in categorizing financially distressed companies into turnarounds and non-turnarounds.

4.3.3 Model comparison, selection and interpretation of results

The table below provides an overview of the in-sample prediction accuracy and the number of misclassifications of all four models.

Table 17:Comparison of in-sample forecasting accuracy among models

	LDA		*LOGIT*	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Forecasting accuracy	92,70%	91,33%	76,67%	77,33%
Type I errors	3	3	9	14
Type II errors	8	10	26	20

The first LDA model shows the highest forecasting accuracy and makes the fewest misclassification errors, followed by the second LDA model. The LOGIT models are inferior to the LDA models, making three to five times more type I errors and two to three times more type 2 errors, which leads to a much lower forecasting accuracy.

As the performance of the two LDA models is almost equally good, we examine their ability to make correct forecasts by means of a holdout sample, which comprises 3140 companies. The classification matrices for both LDA models are displayed below.

Table 18: Classification Matrix Holdout Sample X1 X2 X3

Status	**0**	**1**	**Total**
	2606	327	2933
0	88,85%	11,15%	100%
	17	190	207
1	8,21%	91,79%	100%
Total	2623	517	3140

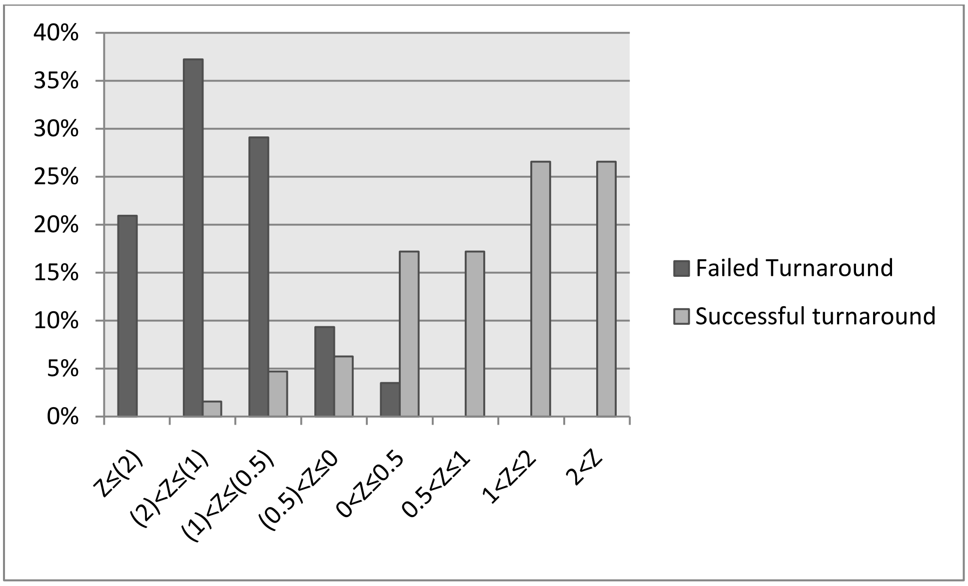
Table 19: Classification Matrix holdout sample X1 X2 X3 X6

Status	**0**	**1**	**Total**
	2481	452	2933
0	84,59%	15,41%	100%
	49	158	207
1	23,67%	76,33%	100%
Total	2530	610	3140

LDA model 1 has a prediction accuracy of 89% in the holdout sample. Type I and type II errors increased, as did the sample size. The considerable rise in type I errors is explained by the boost of non-turnarounds from 86 in the in-sample to 2933 in the holdout sample.

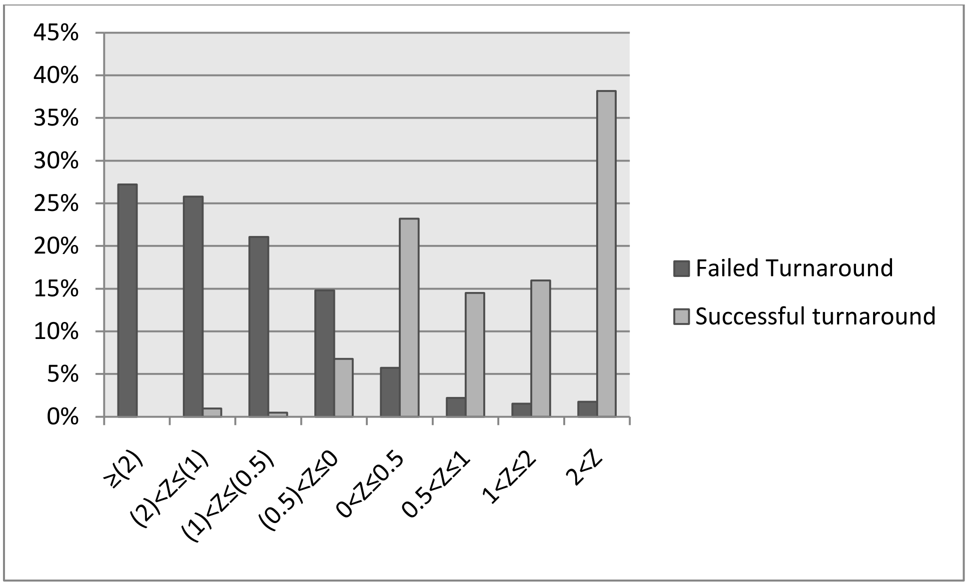
The second LDA model classifies only 84% of the cases correctly. Hence, model 2 misclassifies significantly more firms than model 1, especially in terms of type II errors, which occur almost three times as often as in the first model. On these grounds, LDA model 1 was chosen as the best model for discriminating between turnarounds and non-turnarounds.

The two graphs below visualize the model's forecasting accuracy for the in-sample and the holdout sample. Considering that the cut-off point of the LDA-model 1 was close to zero, the two graphs display very well the amount of committed type 1 and type 2 errors.



Graph 12: Z_{CEGA} scores for turnarounds and non-turnarounds

For the in-sample, all Z_{CEGA} scores of the type 1 errors were below 0.5, not so far away from the cut-off point. The most external type 2 errors were lying between -2 and -1. Allowing for a margin of safety, firms displaying Z_{CEGA} scores larger than 1, can be perceived as real turnaround candidates, with respect to the in-sample.



Graph 13: Z_{CEGA} scores for turnarounds and non-turnarounds

For the holdout sample the most external type 2 errors were again laying between -2 and -1. However, the type 1 errors were more dispersed with some exhibiting a Z_{CEGA} score larger than 2. Thus, although the probability of selecting a non-turnaround decreases with an increasing Z_{CEGA} score, the risk cannot be ruled out completely.

4.4 Model interpretation

Since this model contained only the three variables total tangible assets (X_1), the Z-score as a measure of distress severity (X_2) and the ratio total debt to total assets (X_3), no direct relationship could be identified between the dependent variable and the remaining thirteen explanatory variables outlined in table 8. Hence, the model assumes that they are statistically insignificant in determining the turnaround potential of a financially distressed company, leading to a rejection of the developed hypotheses for these particular variables. Table 20 displays the proposed impact of the three explanatory variables, which entered the final DF of model 1 and compares it to the impact revealed by the model.

Table 20: Comparison of expected and revealed impact of predictors

Variable	Expected impact	Revealed impact	Developed hypothesis
X1	+	-	rejected
X2	-	-	not rejected
X3	-	-	not rejected

4.4.1 Size (X_1)

With respect to firm size, measured by total tangible assets, we developed the hypothesis that the larger the firms the higher their turnaround potential. We motivated our hypothesis by stating that larger firms can easier access capital markets to raise external funds. Moreover they dispose of the possibility to sell assets, such as e.g. unrelated business units, to generate internal funds. However, our hypothesis was rejected, as the model reveals that smaller companies are more likely to succeed in the turnaround process. A reason for that can be their swiftness in implementing strategic changes, as was argued by Paint (1991)[113]. Another possible argument would be that small companies are accustomed to share a closer relationship with its stakeholders, because there are less hierarchical levels, which obstruct the flow of communication and information. As a consequence, it might be easier for smaller firms to assure stakeholder support compared to larger firms.

4.4.2 Severity of distress (X_2)

Measuring the severity of distress by the Z-score is reasonable, as it indicates the firm's probability of experiencing bankruptcy. Less severe distressed firms face fewer hurdles when

[113] Paint, Laurie W., (1991), "An investigation of industry and firm structural characteristics in corporate turnarounds", *Journal of Management Studies*, Vol. 28, Issue 6, pp. 623-643.

approaching capital markets and can easier convince stakeholders to support them in the restructuring process as firms in a more severe state of distress. The model did not reject our developed hypothesis, so that severity of distress is negatively related with turnaround potential.

In order to understand the concept of severity of distress, one has to keep in mind that it is measured by the Altman Z-score. For a company displaying a high Z-score, the state of distress is less severe than for a company with a low Z-score. This implies a negative correlation between Z-score and severity of distress. The coefficients in table 11 for X_2 refer to the Z-score. According to them, turnarounds (1) and Z-score are positively correlated, while non-turnarounds (0) and Z-score are negatively correlated, leading to a negative relationship between turnaround potential and severity of distress. The model suggests:

i. The higher the Z-score is, the more likely the turnaround outcome. As a high Z-score implies low severity of distress, the model suggests a negative relation between turnaround potential and severity of distress.
ii. The lower a firm's Z-score is, the more likely the non-turnaround outcome. As a low Z-score implies high severity of distress, the model suggests a negative relation between turnaround potential and severity of distress.

4.4.3 Total debt to total assets (X_3)

The model estimated a negative relation between change in the ratio total debt to total assets and turnaround potential, corroborating our hypothesis. Both, deleveraging and expansion of the asset base are assumed to support a firm in the process of recovery. Debt reduction will send out a positive signal, strengthening stakeholder support. Expanding the asset base by undertaking value-creating investments is an important step in the restructuring process of a firm striving for strategic reorientation and will generate future cash-flows, available for further investments or deleveraging.

Hence, we believe that changes in this ratio can reveal the implementation of efficiency-oriented or entrepreneurial-oriented strategies, or a combination of both. Therefore we scrutinized the in-sample firms to gauge what drives changes in total debt to total assets.

Table 21: Δ Total assets Δ Total debt Δ total sales

Variable	Turnarounds	Non-turnarounds	Total
+Δtotal assets	42	48	90
-Δtotal assets	22	38	60
Total	64	86	**150**
+Δtotal debt	17	43	60
-Δtotal debt	47	43	90
Total	64	86	**150**
+Δsales	50	54	104
-Δsales	14	32	46
Total	64	86	**150**

The above table depicts the changes in total assets, total debt and total sales for all firms in the in-sample, separated by turnarounds and non-turnarounds. We also focus on change in total sales, because we suppose that an increase in the asset base will trigger a rise in total revenues, given that value-creating investments have been undertaken. The rows highlighted in red depict significant differences between turnarounds and non-turnarounds. Considering that the in-sample consists of 43% turnarounds and 57% non-turnarounds, a difference of a factor larger than 1.5 between the two groups with respect to a variable was regarded as significant. It appears that non-turnarounds are more prone to reducing the asset base than turnarounds. Regarding total debt, turnarounds rather refrain from approaching external financer and centre on deleveraging. For non-turnarounds the situation is different, with half of them increasing the debt level and the other half decreasing it.

Aiming at obtaining a more concrete picture about the strategies employed by the firms in our sample, we examined the direction of change in the three variables stated in table 21 for each single company and formulated eight strategies, which were rated as efficiency-oriented, entrepreneurial-oriented or a combination of both and are displayed in graph 14. However, none of the strategies could be identified as being only efficiency-oriented.

Graph 14: Overview of developed strategies

Table 22 presents a summary of the classification of each in-sample company to a strategy group.

Table 22: Employed strategies by financially distressed firms

Strategies	Turnaround	Non-turnaround	Total
1	5	12	17
2	2	5	7
3	2	5	7
4	10	23	33
5	25	10	35
6	3	10	13
7	4	5	9
8	13	16	29
Total	64	86	150

Four of the eight strategies were highlighted due to their frequency in appearance among both groups and the fact that they were applied more often by one group than the other, rendering possible to make conclusions about differences in the strategies pursued by turnarounds and non-turnarounds.

Strategy 1:

Compliant with our sample this strategy was implemented by 12 non-turnarounds and 5 turnarounds. It is a combination between efficiency-oriented and entrepreneurial-oriented strategies, as asset divestments can be operational or strategic or both. Hence, turnarounds and non-turnarounds engaged in operational and/or strategic asset divestments, freeing up financial funds that can be used for deleveraging. Simultaneously, divestments led to reductions in turnover, due to decrease of capacitance and/or exit of business segments.

For non-turnarounds following this strategy, recovery might fail because the distress state is too severe, so that they are forced to sell the most profitable segment, as was proposed by Schlingemann et. al (2002)[114]. Even though this will cause a unique cash-inflow, the sale of the most profitable segment will deteriorate the firm's ability to generate turnover in the future.

Firms succeeding with this strategy, rather clean up their portfolio by divesting unrelated businesses and focusing on core capabilities.

Strategy 4:

This strategy was adopted twice as often by non-turnarounds than by turnarounds with respect to our sample. It is denoted as an entrepreneurial-strategy, where strategic asset investments are undertaken to re-orientate in the market. The strategic reorientation is financed with outside capital and leads to sales increases, as value-creating investments are assumed to be realized.

As contrasted with turnarounds, non-turnarounds sticking to this strategy might fail in the event that the rise in sales provided by new investments cannot absorb the aggravated gearing, resulting in an exacerbation of the distress state.

[114] Schlingemann, Frederik P., Stulz, René M. and Walkling, Ralph A. (2002), "Divestures and the Liquidity of the Market for Corporate Assets", *Journal of Financial Economics*, Vol. 64, Issue 1, pp. 117-144.

Strategy 5: More than twice as many turnarounds followed this strategy, compared to non-turnarounds. It is termed to be an entrepreneurial-oriented strategy, where firms undertake strategic investments through use of internal funds, which are obtained for example by raising new equity. The additionally generated sales increase the cash-flows, which in return are employed to pay down debt. Non-turnarounds might come unstuck with this strategy, if the undertaken investments do not generate sufficient cash-flows to reach a relief of the oppressive debt burden.

Strategy 6: This variable combination is predominant in the sub-sample of non-turnarounds. It is thought as an entrepreneurial-oriented strategy, which misses the point. An increase in total assets, whether it is related to capacity expansion or business diversification, should aim at triggering a rise in total sales, as exemplified by strategy 4. The appearance of the opposite can be motivated through value-destroying investments, for which costs exceed generated cash-flows. Such a situation paired with rising debt levels will worsen the severity of distress. For the three turnarounds displaying this variable combination, the change was marginal and might be induced by temporary demand fluctuations distorting forecasted capital budgeting. An example would be a company overestimating demand, leading to temporary inflated inventory levels.

Although, there seems to be a difference in strategies applied by turnarounds and non-turnarounds in the restructuring process, no specific strategy could be identified by our sample that was solely implemented by one of the two groups. Ultimately, all above outlined strategies, with exception of the flawed strategy 6, can result in a successful turnaround when implemented correctly. To choose the adequate strategy is task of the management team. For example, adopting an entrepreneurial-oriented strategy can bring about financial recovery, if the cause of distress lies in a misfit between strategy of the company and operating markets. Nevertheless, given that disadvantages in efficiency provoke financial distress, a strategic reorientation is unlikely to bring the company back on track. An important finding of this detailed analysis about what lies behind the changes in the ratio total debt to total assets is that there exists evidence of turnarounds making use of efficiency-oriented and entrepreneurial-oriented strategies.

4.5 Stock returns of turnarounds from the holdout sample

We computed the excess returns of the holdout sample firms that were identified as turnarounds by the LDA-model 1. The S&P 500 was used as a benchmark index. The results are presented in table 23.

Table 23: Excess returns of identified holdout sample turnarounds 2004-2010

	Yearly			*Cumulative*	
	Our model	**S&P 500**	**Excess Return**	**Our model**	**S&P 500**
2004	30.9%	12.0%	***18.9%***	1.31	1.12
2005	38.3%	4.9%	***33.4%***	1.81	1.17
2006	28.8%	15.8%	***13.0%***	2.33	1.36
2007	-9.3%	5.6%	-14.9%	2.12	1.44
2008	-47.1%	-37.0%	-10.1%	1.12	0.91
2009	111.7%	26.5%	***85.2%***	2.37	1.15
2010	34.9%	15.1%	***19.8%***	3.20	1.32
			Total Return	220%	32%

The yearly returns of the identified turnarounds substantially exceeded the returns yielded by the S&P 500. Only for 2007 and 2008, the time of the manifestation of the financial crisis, the returns realized by our model fall short of the returns provided by the S&P 500. A possible reason for this is that in times of crisis investors may be overly pessimistic and put not much faith in the prospects of a recently financial distressed company. Nevertheless, an average annual excess return of 14% over the average annual return yielded by the S&P 500 is a good reason for considering investing in turnarounds identified by our model.

4.6 Variable testing

As the chosen model is generated by LDA, we test whether the residuals of the included variables violate the assumptions that are imposed by discriminant analysis. The tests are restricted to the in-sample data.

4.6.1 Normality test

The Bera-Jarque test is applied to examine whether the residuals of the included variables are normally distributed. A normal distribution is characterized by its bell-shaped, symmetric form, having a kurtosis of 3. The null-hypothesis of the test assumes normally distributed residuals.[115] Table 24 summarizes the results of the Bera-Jarque test conducted in EViews.

[115] Brooks, Chris, (2002), "*Introductory Econometrics for Finance*", 1st Edition, Cambridge University Press, p. 181-182.

Table 24: Results of Bera-Jarque test

Variable	Skewness	Kurtosis	p-Value
X1	9,79	109,38	0,00
X2	0,45	8,45	0,00
X3	-0,26	7,91	0,00

The distributions of the residuals of the predictors were skewed and had excess kurtosis. Besides, the null-hypothesis of the Bera-Jarque test was rejected for all three variables, concluding that they are not normally distributed. We did not expect something different, as financial data uses to display a leptokurtic distribution.[116]

4.6.2 Heteroskedasticity test

LDA assumes constant variance in the residual terms of the model, which is denoted as homoskedasticity. The opposite is known as heteroskedasticity and describes the situation where the residual terms do not display a constant variance.[117] We apply the Breusch-Pagan-Godfrey test, in order to investigate whether our established LDA model shows signs of heteroskedasticity. The null-hypothesis of the Breusch-Pagan-Godfrey test assumes homoskedasticity of the residual terms. The test is performed in EViews and the test statistic is presented below.

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.777394	Prob. F(3,146)	0.1541
Obs*R-squared	5.285244	Prob. Chi-Square(3)	0.1521
Scaled explained SS	1.543019	Prob. Chi-Square(3)	0.6724

Graph 15: Breusch-Pagan-Godfrey test statistic output for LDA-model 1

The results of the Breusch-Pagan-Godfrey test provide no indication for heteroskedasticity. All three versions of the test statistic have p-values exceeding the critical threshold of 0.05, concluding that the null-hypothesis of homoskedasticity cannot be rejected. Thus, the chosen LDA model did not violate the assumption of constant variance.

4.6.3 Multicollinearity test

Last but not least, we address the problem of multicollinearity, which occurs when the predictors are highly correlated with each other. We define high correlation by a correlation

[116] Brooks, Chris, (2002), "*Introductory Econometrics for Finance*", 1st Edition, Cambridge University Press, p. 179-180
[117] Ibid, p. 147

coefficient greater or equal to 0.7. The following correlation matrix was generated by SAS and belongs to the first LDA model, which showed the highest prediction accuracy.

Table 25: Correlation Matrix X1 X2 X3 LDA model 1

Variables	**X1**	**X2**	**X3**
X1	1,000	-0,04786	0,09415
X2	-0,04786	1,000	-0,28953
X3	0,09415	-0,28953	1,000

As can be seen, the correlation among the predictors was very low and no correlation came close to the critical value of 0.7. Accordingly, our model does not face a multicollinearity issue.

Chapter 5

Conclusion

The underlying thesis aimed at deriving the decisive factors in the turnaround process and establishing a prediction model, thereby making possible to discriminate between future turnarounds and non-turnarounds. The employed models were Linear Discriminant Analysis and Logistic Regression and the model with the highest prediction accuracy was derived by the LDA-approach and amounted to 92.7%. Taking into account that testing the model's prediction accuracy on the same sample, which was used to establish the model, will trigger an upward bias in the results, the model was further evaluated based on its forecasting ability on a holdout sample consisting of 3140 financially distressed firms. A marginal decrease in the forecasting accuracy to 89% was recorded.

The selected variables failed to discriminate between turnarounds and non-turnarounds for the first two years, where all companies in our sample displayed a Z-score below 1.8. A significant discrimination between the two groups was obtained when focusing on year 2 and 3, where some companies realized an alleviation of the severity of distress, while for other firms the distress state remained unchanged or even became worse.

With respect to the included predictors, the chosen model restricted itself to 3 explanatory variables, which were firm size, severity of distress and total debt to total assets. While the developed hypotheses for severity of distress and total debt to total assets were corroborated by the empirical results of the chosen LDA-model, the hypothesis that firm size and turnaround potential are positively related was rejected. Hence, for our sample smaller firms are more likely to succeed in the turnaround process than larger firms. A possible explanation is that smaller firms can implement entrepreneurial-oriented strategies faster and meet with less resistance from high-level, old-established managers, who might interpret strategic changes as a critique of their decision-making ability. Smaller firms tend to pursue a corporate policy that is less dominated by complex hierarchical structures, which impede quick decision-making. As severity of distress is measured by the Altman Z-score, this variable substantiates the importance of the implementation of efficiency-oriented strategies to improve financial performance, because the score is compounded of five variables that fall into the category of efficiency measures. Changes in the ratio total debt to total assets can be driven either by efficiency-oriented or by entrepreneurial-oriented strategies, or by a mix of both. Which strategy is adopted and to what extent is determined by the cause of distress.

Having at hand a turnaround prediction model with a high forecasting accuracy opens new possibilities in yielding excessive returns from investing in distressed companies that will transform to turnarounds. We briefly touched upon these opportunities by computing the excess returns of the holdout sample turnarounds over the S&P 500, which amounted to 14% on an annual basis.

Last but not least, we suggest that further research should aim at modeling the impact of qualitative variables on the turnaround potential, such as internal firm climate and CEO turnover. Moreover, other quantitative variables that are less firm-specific and more industry-specific should be considered, like e.g. the growth of the industry a company is classified to.

References

Published References

Afifi, Abdelmonem and Clark, Virginia A., (1996), "*Computer-aided multivariate analysis*", 3rd edition, Chapman and Hall.

Altman, Edward I., (1998). "Market Dynamics and Investment Performance of Distressed and Defaulted Debt Securities", *New York University, Center for Law and Business*, Working Paper No. 98-022.

Altman, Edward I., (2000). "Predicting Financial Distress of Companies: Revisiting the Z-score and Zeta Models", *New York University, Center for Law and Business.*

Altman, Edward I. and Jha, Shubin, (2003), "Market size and investment performance of defaulted bonds and bank loans: 1987-2001", *Economic Notes*, Vol. 32, Issue 2, pp. 147-176.

Arogyaswamy, K. and Yasai-Ardekani, M., (1997), "Organizational Turnaround: Understanding the Role of Cutbacks, Efficiency Improvements, and Investment in Technology", *IEEE Transactions on Engineering Management*, Vol. 44, No. 1, pp. 3-11.

Balgobin, R. and Pandit, N., (2001), "Stages in the Turnaround Process: The Case of IBM UK", *European Management Journal*, Vol. 19, Issue 3, pp. 301-316.

Barker, Vincent L. and Barr, Pamela S., (2000), "Linking top manager attributions to strategic reorientation in declining firms attempting turnarounds", *Journal of Business Research*, Vol. 55, Issue 12, pp. 963-979.

Barker, Vincent and Duhaime, Irene M., (1997), Strategic change in the turnaround process: Theory and empirical evidence, *Strategic Management Journal*, Vol. 18, Issue 1, pp. 13-38.

Barney, Jay B., (1986), "Types of competition and the theory of strategy: Toward an integrative framework", *Academy of Management*, Vol. 11, No. 4 , pp. 791-800.

Brooks, Chris, (2002), "*Introductory Econometrics for Finance"*, 1st Edition, Cambridge University Press.

Brown, David T., James, Christopher M. and Mooradian, Robert M., (1993), "The information content of distressed restructurings involving public and private debt claims", *Journal of Financial Economics*, Vol. 33, No. 1, pp. 93-118.

Cameron, Kim S., Sutton, Robert I. and Whetten, David A., (1988), "*Readings in Organizational decline: Frameworks"*, Ballinger Publishing.

Cooper, Ron A. and Weekes, Tony J., (1983), "*Data, Models and statistical analysis*", Philip Allan Publishers Limited, New Jersey, USA.

Cox, D. R. and Snell, E.J., (1989), *"The analysis of binary data"*, 2nd Edition, Chapman and Hall.

Dechow, Patricia M. and Schrand, Catherine M., (2004), “*Earnings Quality”*, The Research Foundation of CFA Institute.

Eberhart, Allan C., Altman, Edward I. and Aggarwal, Reena, (1998), The Equity Performance of Firms Emerging from Bankruptcy, *Journal of Finance,* Vol. 54, Issue 5, pp. 1855-1868.
Fromm, Sabine, (2005), “Binäre logistische Regressionsanalyse”, *Universität Bamberg*.

Gilson, Stuart C., (1990), “Bankruptcy, boards, banks and bondholders – Evidence on changes in corporate ownership and control when firms default”, *Journal of Financial Economics*, Vol. 27, Issue 2, pp. 355-387.

Greenblatt, Joel, (1999), *“You can be a stock market genius*”, Fireside.

Grinyer, Peter H., Mayes, David and McKiernan, Peter, (1988), *“Sharpbenders: The secrets of unleashing corporate potential”*, Blackwell Publishers, Oxford.

Hambrick, Donald C. and Schecter, Steven M., (1983), “Turnaround Strategies for Mature Industrial-Product Business Units”, *Academy of Management Journal*, Vol. 26, No. 2, pp 231-248.

Harker, Michael, (1996), Managing company turnarounds: how to develop “destiny”, *Marketing Intelligence & Plannings*, Vol. 14, Issue 3 pp. 5-10.

Hedberg, Bo L. T., Nystrom, Paul C. and Starbuck, William H., (1976), Camping on Seesaws: Prescriptions for a Self-Designing Organization, *Administrative Science Quarterly*, Vol. 21, No. 1, pp. 41-65.

Hofer, Charles W., (1980), Turnaround Strategies, *Journal of Business Strategy,* Vol. 1, Iss.1, pp. 19-31.

Hofer, Charles W. and Schendel, Dan, (1978), *Strategy Formulation: Analytical Concepts*, West Publishing.

Hosmer, David W. and Lemeshow, Stanley, (2000), *“Applied Logistic Regression”*, 2nd Edition, John Wiley & Sons, Inc.

Hotchkiss, Edith S., (1995), Postbankruptcy Performance and Management Turnover, *Journal of Finance*, Vol. 50, Iss. 1, pp. 3-21.

Indro, D. C., Leach, R.T. and Lee, W. Y., (1999), Sources of gains to shareholders from bankruptcy resolution, *Journal of Banking & Finance*, Vol. 23, Iss. 1, pp. 21-47.

Kahl, Matthias, (2002), Economic Distress, Financial Distress and Dynamic Liquidation, *The Journal of Finance*, Vol. 57, pp. 135-168.

Karpoff, Jonathan M., (1987), “The relation between price changes and trading volume: A survey”, *The Journal of Financial and Quantitive Analysis,* Vol. 22, No. 1, pp. 109-126.

Klarman, Seth. A.,(1991),*Margin of safety: Risk-averse value investing strategies for the thoughtful investor*, Harper Business.

Koller, Tim; Goedhart, Marc and Wessels, David, (2010)*Valuation: Measuring and managing the value of companies*, John Wiley & Sons.

Lachenbruch, P. A., (1968), "On expected probabilities of misclassification in discriminant analysis, necessary sample size, and a relation with the multiple correlation coefficient", *Biometrics*, Vol. 24, No. 4.
Lachenbruch, P. A. and Goldstein, M., (1979), "Discriminant Analysis", *Biometrics*, Vol. 35, No. 1, pp. 69-85.

Lepak, David P., Smith, Ken G. and Taylor, M. Susan, (2007), Value Creation and Value Capture: A Multilevel Perspective, *Academy of Management Review*, Vol. 32, No. 1, pp. 180-194.

Menard, Scott (1995), *"Applied Logistic Regression Analysis"*, 2nd Edition, Sage Publications, Inc.

Myers, Stewart C., (1977), Determinants of Corporate Borrowing, *Journal of Financial Economics*, Vol. 5, No. 2, pp. 147-175.

Ogden, Joseph P., Jen, Frank C. and O'Connor, Philip F.,(2003), *Advanced Corporate Finance. Policies and Strategies*, Prentice Hall.

Paint, Laurie W., (1991), "An investigation of industry and firm structural characteristics in corporate turnarounds", *Journal of Management Studies*, Vol. 28, Issue 6, pp. 623-643.

Peng, Chao-Ying J., Lee, Kuk L. and Ingersoll, Gary M., (2002), "An Introduction to Logistic Regression Analysis and Reporting", *The Journal of Educational Research*, Vol. 96, No. 1, pp. 3-14.

Robbins, D. Keith, and Pearce, John A., (1992), "Turnaround: retrenchment and recovery", *Strategic Management Journal*, Vol. 13, Issue 4, pp. 287-309.

Schendel Dan E. and Patton, G.R., (1976), "Corporate stagnation and turnaround", *Journal of Economics and Business*, Vol. 28, Iss. 3, pp. 236-242.

Schendel, Dan, Patton, G.R. and Riggs, James, (1976), "Corporate turnaround strategies: A study of profit decline and recovery", *Journal of General Management*, Vol. 3, Iss.. 3, pp. 3-12.

Schlingemann, Frederik P., Stulz, René M. and Walkling, Ralph A. (2002), "Divestures and the Liquidity of the Market for Corporate Assets", *Journal of Financial Economics*, Vol. 64, Issue 1, pp. 117-144.

Slatter, Stuart and Johnson, Gerry, (1984), "Corporate Recovery: Successful turnaround strategies and their implementation", *Strategic Management Journal*, Vol. 7, Issue 1, pp. 99-100.

Smith, Malcom and Graves, Christopher, (2005), Corporate turnaround and financial distress, *Managerial Auditing Journal*, Vol. 20, Iss. 3, pp. 304-320.

Sudarsanam, Sudi and Lai, Jim (2001), "Corporate Financial Distress and Turnaround Strategies: An empirical analysis", *British Journal of Management*, Vol. 12, Issue 3, pp. 183-199.

White, M. (1989), "Bankruptcy, liquidation and reorganization", in: D.E. Logue (ed.), *Handbook of Modern Finance*, Warren, Gorham & Lamont, New York

Ying, Charles C., (1966), "Stock Market Prices and Volumes of Sales", *Econometrica*, Vol. 34, No. 3, pp. 676-685.

Zeni, Syahida Binti and Ameer, Rashid, (2010), Turnaround prediction of distressed companies: evidence from Malaysia, *Journal of Financial Reporting and Accounting*, Vol. 8, Issue 2, pp 143-159.

Internet References

Buffet, Warren E., (2008), "Buy American, I Am", *The New York Times*, http://www.nytimes.com/2008/10/17/opinion/17buffett.html

Forbes (2010): http://www.forbes.com/lists/2010/10/billionaires-2010_Warren-Buffett_C0R3.html

Twin A. (2009-03-09), "For Dow another 12-year low", *CNN Money*, http://money.cnn.com/2009/03/09/markets/markets_newyork/index.htm

World Federation of Exchanges: http://www.world-exchanges.org/statistics/time-series/market-capitalization

Historical Chart of S&P 500: http://www.forecast-chart.com/historical-sp-500.html

VassarStats, Logistic: http://faculty.vassar.edu/lowry/lr1.gif

Manuals

SAS Institute Inc. 2010. *SAS/STAT® 9.22 User's Guide.* Cary, NC: SAS Institute Inc.

SPSS Regression 17.0

Database

Statndard and Poor's Database (http://www.standardandpoors.com)

Appendix

Appendix 1: Overview of prior studies on turnaround determinants

Researchers	**Types of turnaround and nonturnaround firms**	**Measures of management actions**	**Actions associated with turnaround or improved financial performance**
Schendel and Patton (1976)	Manufacturing firms matched by SIC code	Financial ratios	Decreased costs/sales Increased sales Increased investment
Hambrick and Schecter (1983)	Mature, industrial product SBUs	Financial ratios and some perceptual measures	Decreased R&D expenditures/sales Decreased marketing expenditures/sales Decreased receivables/sales Decreased inventory/sales Increased employee productivity Increased plant & equipment newness Increased market share
Ramanujam (1984)	Undiversified manufacturing firms	Financial ratios	Decreased cost of goods sold/sales Decreased inventory/sales Decreased receivables/sales Increased sales
Thietart (1988)	SBUs across varying industry environments	Financial ratios and some perceptual measures	Combination of actions that cut costs and increase productivity
Robbins and Pearce (1992)	Textile firms 1976 - 85	Financial statement changes, some perceptual measures	Asset reduction Cost reduction
Arogyaswamy (1992)	Manufacturing firms	Financial ratios, financial statement changes	Decreasing at least three of the following: Employees/Sales Receivables/Sales Inventory/Sales Cost of goods sold/sales SGA Expenses/sales Combining above efficiency posture with increased R&D or plant expenditures Increasing R&D expenditures Not decreasing at least three of the following: Employees Receivables Inventory Cost of goods sold SGA expenses

Appendix 2: Firms included in the in-sample

In-sample companies by turnaround outcome

Non-turnarounds	Turnarounds
AeroCentury Corp. (1998-99)	Abaxis Inc. (1997-98)
Air Methods Corp. (1996-97)	AmSurg Corp. (1998-99)
AK Steel Holding Corporation (1998-99)	Ariad Pharmaceuticals Inc. (1997-98)
Akamai Technologies Inc. (2000-01)	ASM International NV (1997-98)
AMR Corporation (1999-00)	Atwood Oceanics, Inc. (1993-94)
Apache Corp. (1995-96)	Aurizon Mines Ltd. (2000-01)
Appliance Recycling Centers of America Inc. (1996-97)	BioDelivery Sciences International Inc. (2000-01)
Arabian American Development Company (1999-00)	Biogen Idec Inc. (1993-94)
Avis Budget Group, Inc. (1999-00)	Biolase Technology, Inc. (2000-01)
Bally Technologies, Inc. (1996-97)	Bio-Reference Laboratories Inc. (1998-99)
Belo Corp. (1997-98)	Birner Dental Management Services Inc. (2000-01)
Belo Corp. (1998-99)	Blue Dolphin Energy Company (1994-95)
Boyd Gaming Corp. (1999-00)	China Yuchai International Limited (2000-01)
Breeze-Eastern Corporation (2000-01)	Comfort Systems USA Inc. (2000-01)
Cabot Oil & Gas Corporation (1994-95)	Concurrent Computer Corporation (1995-96)
Cabot Oil & Gas Corporation (1996-97)	CPI Aerostructures Inc. (2000-01)
Carriage Services Inc. (1999-00)	Cray Inc. (2000-01)
Chyron Corporation (2000-01)	Eldorado Gold Corp. (2000-01)
CNH Global NV (1998-99)	Energy Conversion Devices, Inc. (1998-99)
Comstock Resources Inc. (1998-99)	EOG Resources, Inc. (1998-99)
Corrections Corporation of America (1999-00)	Fieldpoint Petroleum Corp. (1996-97)
Craft Brewers Alliance, Inc. (2000-01)	FLIR Systems, Inc. (1999-00)
Crown Holdings Inc. (1998-99)	Food Technology Service Inc. (1995-96)
CSX Corp. (2000-01)	Fuel-Tech, Inc. (1999-00)
Earthstone Energy, Inc. (1998-99)	Gardner Denver Inc. (1995-96)
El Paso Corp. (2000-01)	Golden Star Resources, Ltd. (1998-99)
Female Health Co. (1997-98)	H&R Block, Inc. (1999-00)
Fonar Corp. (2000-01)	Hallador Energy Company (1996-97)
Ford Motor Co. (1992-93)	Headwaters Inc. (1998-99)
Forest Oil Corp. (1999-00)	Hollywood Media Corp. (1997-98)
Furmanite Corporation (1995-96)	Hurco Companies Inc. (1994-95)
GATX Corp. (1991-92)	ImmuCell Corp. (1994-95)
Good Times Restaurants Inc. (2000-01)	Imperial Sugar Co. (1999-00)
GP Strategies Corp. (2000-01)	Insignia Systems Inc. (1997-98)
Gray Television Inc. (2000-01)	InterDigital, Inc. (1992-93)

Non-turnarounds	Turnarounds
Hallador Energy Company (1998-99)	Inventure Foods, Inc. (1998-99)
HearUSA Inc. (2000-01)	Itron, Inc. (1999-00)
Hecla Mining Co. (1996-97)	Ivanhoe Mines Ltd. (2000-01)
Heska Corp. (2000-01)	Kinross Gold Corporation (2000-01)
Hexcel Corp. (2000-01)	Laboratory Corp. of America Holdings (1998-99)
Hill-Rom Holdings, Inc. (1999-00)	Magnetek Inc. (1998-99)
Hill-Rom Holdings, Inc. (2000-01)	Medifast Inc. (1999-00)
HKN, Inc. (1999-00)	Medifast Inc. (2000-01)
icad Inc. (1998-99)	MEMC Electronic Materials Inc. (2000-01)
InsWeb Corp. (2000-01)	New Dragon Asia Corp. (2000-01)
International Shipholding Corp. (1994-95)	NovaGold Resources Inc. (2000-01)
Isle of Capri Casinos Inc. (1998-99)	Onyx Pharmaceuticals, Inc. (1997-98)
Iteris, Inc. (2000-01)	Orbit International Corp. (1998-99)
Joe's Jeans Inc. (2000-01)	Palatin Technologies Inc. (1997-98)
LodgeNet Interactive Corporation (1997-98)	Quest Diagnostics Inc. (1998-99)
MEDTOX Scientific Inc. (1999-00)	Retractable Technologies Inc. (2000-01)
Mercer International Inc. (1999-00)	RTI International Metals, Inc. (1994-95)
Norfolk Southern Corp. (1997-98)	Schawk Inc. (1995-96)
Norfolk Southern Corp. (1999-00)	Simulations Plus Inc. (2000-01)
NTN Buzztime Inc. (1998-99)	Stericycle, Inc. (1994-95)
Occidental Petroleum Corporation (1998-99)	Stericycle, Inc. (1999-00)
Orbit International Corp. (2000-01)	Tri-Valley Corp. (1995-96)
Parker Drilling Co. (2000-01)	Tri-Valley Corp. (2000-01)
Perma-Fix Environmental Services Inc. (1994-95)	Unisys Corporation (1993-94)
Pride International Inc. (1997-98)	Unit Corp. (1993-94)
PRIMEDIA Inc. (1999-00)	Universal Security Instruments Inc. (2000-01)
Ramtron International Corp. (1998-99)	Valero Energy Corp. (1994-95)
Reynolds American Inc. (2000-01)	Verint Systems Inc. (2000-01)
Ryder System, Inc. (1994-95)	Western Digital Corp. (1998-99)
Service Corp. International (1994-95)	
Service Corp. International (1995-96)	
Sinclair Broadcast Group Inc. (1998-99)	
Six Flags Entertainment Corp. (2000-01)	
Southwall Technologies Inc. (1998-99)	
StemCells Inc. (1997-98)	
Streamline Health Solutions, Inc. (1999-00)	
Swift Energy Co. (1991-92)	

Non-turnarounds

Temple-Inland Inc. (1991-92)
Tenneco Inc. (1999-00)
The Hallwood Group Incorporated (1998-99)
The Interpublic Group of Companies, Inc. (2000-01)
Titan International Inc. (2000-01)
Titanium Metals Corporation (1999-00)
Union Pacific Corporation (1997-98)
Unisys Corporation (1996-97)
Valhi, Inc. (1995-96)
Viad Corp (1995-96)
Waste Connections Inc. (2000-01)
Waste Management, Inc. (1999-00)
Willis Lease Finance Corp. (2000-01)
Xerox Corp. (1999-00)

Appendix 3: Scores model 1-4, in-sample

Z(CEGA) scores and predicted probabilities, models 1-4, in-sample

LDA-models		LOGIT-models	
Model 1	**Model 2**	**Model 3**	**Model 4**
-1,41	-1,49	0,34	0,48
-1,06	-1,18	0,31	0,45
-0,72	-0,77	0,32	0,12
-3,18	-2,99	0,02	0,08
-2,27	-2,61	0,15	0,00
-0,54	-0,63	0,32	0,17
-3,42	-3,61	0,03	0,09
-1,55	-1,57	0,30	0,43
-2,27	-2,41	0,38	0,00
-2,53	-2,71	0,02	0,04
-0,79	-0,84	0,31	0,17
-0,64	-0,74	0,33	0,18
-0,68	-0,80	0,30	0,30
-1,46	-1,85	0,08	0,13
-1,54	-1,76	0,16	0,26
-0,66	-0,80	0,35	0,42
-1,07	-0,77	0,45	0,51
-3,43	-2,27	0,54	0,67
-1,52	-1,64	0,36	0,00
0,16	0,19	0,54	0,61
-1,33	-0,91	0,49	0,44
-0,73	-0,81	0,31	0,44
-1,20	-1,34	0,21	0,01
-1,25	-1,32	0,32	0,00
-5,25	-4,71	0,71	0,77
-2,61	-2,83	0,17	0,00
-8,76	-8,45	0,19	0,32
-0,79	-2,20	0,18	0,28
-6,66	-6,68	0,34	0,00
-0,34	-0,42	0,35	0,34
-0,61	-0,69	0,32	0,43
-0,72	-0,78	0,36	0,23
-0,46	-0,43	0,33	0,47
-0,58	-0,81	0,33	0,44
-0,08	-0,27	0,86	0,85
-1,46	-1,68	0,34	0,46
-1,72	-1,54	0,60	0,68
-1,65	-2,16	0,15	0,26

Model 1	Model 2	Model 3	Model 4
-5,61	-4,60	0,36	0,49
-1,50	-1,11	0,41	0,48
-0,37	-0,39	0,36	0,06
-0,52	-0,58	0,42	0,17
-5,32	-5,63	0,12	0,21
-3,43	-3,40	0,28	0,43
-4,79	-4,76	0,29	0,42
-0,74	-0,85	0,29	0,37
-0,46	-0,52	0,66	0,69
-1,97	-2,20	0,27	0,39
0,03	0,13	0,64	0,70
-1,28	-1,34	0,10	0,15
-1,01	-0,72	0,39	0,55
-0,66	-0,87	0,30	0,40
-1,30	-1,44	0,29	0,00
-1,15	-1,22	0,32	0,00
-3,81	-4,50	0,37	0,53
-0,75	-0,72	0,56	0,00
-0,71	-0,67	0,39	0,52
-1,36	-1,58	0,16	0,22
-0,58	0,18	0,72	0,79
-1,07	-1,23	0,27	0,24
-2,68	-2,96	0,10	0,08
-2,44	-3,83	0,32	0,46
-1,39	-1,85	0,16	0,00
-0,57	-0,70	0,30	0,09
-0,85	-0,93	0,33	0,04
-0,77	-0,85	0,36	0,02
-1,01	-1,13	0,31	0,19
-1,28	-1,41	0,28	0,14
-1,41	-1,58	0,24	0,36
-5,21	-5,16	0,15	0,25
-0,91	-0,99	0,39	0,52
-0,35	-0,42	0,43	0,54
-0,85	-0,95	0,31	0,01
-1,38	-1,51	0,16	0,12
0,01	-0,26	0,38	0,48
-1,00	-0,99	0,39	0,02
-0,71	-0,80	0,24	0,33
-0,34	-1,42	0,16	0,23
-1,50	-1,48	0,35	0,00

Model 1	Model 2	Model 3	Model 4
-1,15	-1,54	0,21	0,04
-0,46	-0,55	0,38	0,34
-0,57	-0,66	0,30	0,35
-0,72	-0,76	0,38	0,00
-1,02	-0,99	0,43	0,25
-1,18	-1,26	0,30	0,40
-1,38	-1,46	0,33	0,00
2,08	3,30	0,61	0,70
-0,76	-0,91	0,20	0,33
0,18	0,15	0,67	0,76
2,11	2,01	0,79	0,81
0,89	0,82	0,44	0,54
3,99	3,92	0,70	0,78
2,08	1,93	0,88	0,88
6,06	6,73	0,57	0,66
0,34	1,05	0,96	0,98
-0,21	-0,03	0,39	0,53
0,43	0,67	0,45	0,57
-0,22	-0,20	0,25	0,40
0,41	1,08	0,60	0,36
1,01	0,95	0,45	0,50
0,70	0,70	0,42	0,57
1,74	2,79	0,97	0,98
0,19	0,16	0,66	0,76
5,47	6,57	0,87	0,89
1,54	1,54	0,86	0,93
1,39	1,15	0,44	0,31
-1,08	-1,38	0,07	0,16
5,38	6,19	0,99	0,99
2,64	1,56	0,98	0,97
2,02	1,34	0,21	0,33
0,65	0,75	0,49	0,60
1,78	2,88	0,98	0,98
0,14	0,20	0,32	0,17
2,81	2,76	0,51	0,62
4,55	5,58	0,99	0,99
10,02	9,85	0,81	0,82
0,91	0,90	0,77	0,83
0,26	0,07	0,27	0,41
0,27	-0,82	0,08	0,13
2,04	2,07	0,14	0,27

Model 1	Model 2	Model 3	Model 4
0,54	0,74	0,57	0,61
-0,69	-1,45	0,14	0,32
1,51	1,65	0,72	0,78
-0,22	-0,21	0,28	0,38
0,53	0,71	0,46	0,59
7,57	7,50	0,89	0,94
1,41	1,40	0,24	0,34
0,37	1,20	0,60	0,69
-0,51	-0,43	0,05	0,11
0,41	0,39	0,45	0,33
1,57	0,35	0,60	0,66
4,55	4,41	0,98	0,98
1,35	1,64	0,60	0,67
4,74	4,68	0,76	0,85
0,72	0,59	0,54	0,64
0,83	1,06	0,87	0,90
0,15	0,15	0,26	0,39
1,31	1,30	0,79	0,89
0,59	1,12	0,64	0,26
-0,25	-0,34	0,32	0,45
1,48	2,40	0,85	0,86
1,03	1,02	0,57	0,48
1,01	1,12	0,62	0,69
1,14	1,04	0,60	0,64