CASH FLOW BASED BANKRUPTCY RISK AND STOCK RETURNS IN THE US COMPUTER AND ELECTRONICS INDUSTRY

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ABSTRACT

This thesis investigates the anomalous underperformance of distressed stocks in the US computer and electronics industry. It shows that such anomaly can be explained by a parallel analysis of risk based rational pricing and profitability (earnings) levels to returns relationship propositions. For the 1990 to 2006 period, distressed stocks have on average underperformed their non-distressed counterparts. However, once the conditional relationship with profitability is taken into account, the distress risk is rewarded by a continuous positive return hence priced appropriately.

In the computer and electronics industry growth stocks (low B/M) outperform on average value stocks (high B/M). The size factor has not been confirmed to be significant in explaining stock returns for this specific industry over the 1990 to 2006 period.

The study also reveals that B/M and size factors do not proxy for distress risk. The B/M factor follows an inverted u-shape along the distress risk deciles axis. As result, stocks in low and high distress portfolios share similarly low B/M values.

Cash flow based bankruptcy predictors estimated on a quarterly basis from a Cox proportional hazard model, that are used as proxy for a continuous distress risk factor in asset pricing tests, are able to predict bankruptcies at higher accuracy rates than the Z-Score as alternative measure.

DECLARATION

I declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Michael Kregar

COPYRIGHT STATEMENT

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This piece of work is dedicated to my wife Simone, my son Elliott and my daughter Goldie. God bless you.

CHAPTER 1: INTRODUCTION

The pricing of distress risk has become a frequently researched topic in recent years. Dichev (1998), Campbell, Hilscher and Szilagyi (2008), Agarwal and Taffler (2008) and others find contrary to the distress factor hypothesis (Fama and French, 1992, 1993; Chan and Chen, 1991) that high distress risk is not rewarded by higher but substantially lower than average stock returns. They conclude that it is very unlikely that a risk based rational pricing proposition could explain the anomalous underperformance of distressed stocks. Instead, they rather believe in a market underreaction hypothesis with respect to the pricing of distress risk and find potential answers in the field of behavioural finance.

In this study, I will be able to show that a parallel analysis of two propositions, the risk based rational pricing and the profitability/earnings levels to returns relationship can explain the average underperformance of such distressed stocks. When the conditional relationship with profitability is taken into account, the distress risk is rewarded by a continuous positive return and is found to be priced appropriately.

There is an extensive body of accounting literature that discusses the theory and empirical research on the relation between profitability reflected by earnings or cash flow information and stock returns (Ball and Brown, 1968; Easton and Zmijewski, 1988; Easton and Harris, 1991; Dechow, 1994, Beaver, 1998; and others). Several studies have documented that it is not only the changes in earnings but also the level of earnings that significantly and positively relate to stock prices (Easton and Harris, 1991; Penman, 1991, Ohlson and Shroff, 1992). Therefore, firms generating higher earnings or cash flow levels are also expected to earn higher average returns. In parallel, following a classical risk based rational pricing model like CAPM or its derivatives such as a Fama and French (1992) three-factor model, investors would expect a positive distress risk premium reward hence higher average stock returns for riskier investments.

Given the two propositions above, investors would expect higher average returns when investing in highly profitable but distressed stocks. However, for less profitable or even loss making companies that are highly distressed, the same investors may still expect to earn a distress risk premium but with a downward adjustment due to the lack of value prospects as proxied by low or negative earnings or operating cash flows. In other words, an investor or analyst may not only want to know the future payoff but also the risk as well as the conditionality between the two factors involved.

The approach of this study is twofold from a risk of failure and pricing point of view. The study focuses on and is limited to the industry “US Computer and Electronic Product Manufacturing”, which is one with the highest number of companies operating under permanent distress in the United States. In 2004, there were about 300 firms, which on average represent approximately 35% of this industry, operating under distress and facing a potential bankruptcy (PricewaterhouseCoopers, 2006). In 2005, there were 80 public companies filing Chapter 11, whereof 29 of these bankruptcies were related to the computer equipment and machinery manufacturing industry with assets at filing of $ 23.9b.

As shown in previous research (Campbell, Hilscher and Szilagyi, 2008; Agarwal and Taffler, 2008), distress risk values used in asset pricing tests are often proxied by bankruptcy risks obtained from a bankruptcy prediction model. Therefore, the first part of this study deals with the development of an industry specific cash flow based bankruptcy prediction model, which is able to classify and predict the event of bankruptcy at a relatively high level of accuracy. Most of the MDA or conditional probability models (Altman, 1968; Ohlson, 1980; Taffler, 1983, 1984; Zavgren, 1983; Aziz, Emanuel, Lawson, 1988; Shumway, 2001; Campbell, Hilscher, Szilagyi, 2008 and others) found in previous literature used publicly available financial statement and stock market data as well as other non-financial information to segregate into failure and non-failure firms. A variety of statistical methods and sets of accounting, market and non-accounting variables were tested. Bankruptcy prediction models are widely used in the banking sector as well as in other industries and provide some reasonable assessment on a firm’s risk of failure. A detailed literature review on bankruptcy prediction models is provided in section 2.1.

The second group of research, which is found to a lesser extent in literature has become an increasingly researched topic in recent years. It tests for the relationship between the bankruptcy models’ derived distress risk and related stock returns. The risk factor used in asset pricing tests is often proxied by the scores or probabilities derived from bankruptcy prediction models such as from Altman’s (1968) Z-score, Ohlson’s (1980) O-Score or more recently from a fitted probability model by Campbell, Hilscher and Szilagyi (2008).

The arguments for this relationship studies are that capital market agents in the aggregate would use multivariate information from financial statements and market data condensed in a bankruptcy prediction model and invest based on their given risk-return preferences. The studies found in the accounting and finance literature include the testing of the relationship between stock returns and bankruptcy risk, but also the market reaction from an information efficiency point of view and do range from short-term event to long-term association type of studies. Dichev (1998), Campbell, Hilscher and Szilagyi (2008), Agarwal and Taffler (2008) and others find contrary to the distress factor hypothesis of Fama and French (1992, 1993) or Chan and Chen (1991) that high bankruptcy risk is not rewarded by higher but substantially lower than average stock returns. They conclude that it is very unlikely that a risk based rational pricing proposition could explain the anomalous underperformance of distressed stocks. Instead, they rather believe in a market underreaction hypothesis with respect to the pricing of distress risk and find potential answers in the behavioural field of finance. A literature review on the pricing of distress risk is provided in section 2.2.

The study consists of two main parts. In the first part (Chapter 4), I have constructed a dynamic cash flow based bankruptcy prediction model in order to obtain probabilities of failure on a firm by firm basis. The predictors estimated on a quarterly basis using four-quarter accumulated financial statement data have the distinct advantage of pre-empting the information content provided by annual models. This industry specific model uses in contrast to many other studies non-arbitrarily selected cash flow variables that are calculated based on Lawson’s Cash Flow Identity (Lawson, 1971) using financial data from the statement of cash flows as required by the Statement of Financial Accounting Standards (SFAS) No. 95. The model therefore relies on publicly available financial statement data only and does not incorporate any equity market data as predictors in contrast to most of other models. This econometric model is constructed on the grounds of one of the more recent developments in this field by employing a hazard model (Shumway, 2001; Beaver, McNichols and Rhie, 2004; Campbell, Hilscher and Szilagyi, 2008). Since bankruptcy probabilities vary over time, a hazard model may produce more efficient and time-varying out-of-sample forecasts and as such may result in stronger association with stock returns (Shumway, 2001). Therefore, the cash flow predictors are estimated on a quarterly basis using the Cox proportional hazard model (Cox, 1972). The model’s prediction outcomes are validated by confirmative out-of-sample and favourable benchmark test results over Altman's Z-score using the receiver operating characteristic measure and can be considered to be robust. This Cox proportional hazard model not only predicts corporate failure, but also produces the probabilities of failure for each firm on quarterly basis which serve as a proxy for the continuous relative distress risk factor to be included in asset pricing tests.

The second part (Chapter 5) is dedicated to the pricing of the relative distress risk factor derived from the bankruptcy prediction model's probability of failure and the profitability levels proxied by an operating cash flow variable. The study has foreseen several tests to be conducted in order to accept or reject various hypotheses set in section 3.3, particularly related to the parallel analysis of the risk based rational pricing and the profitability/earnings levels to return relationship propositions.

The results of the hypotheses testing ought to provide answers with regards to the main research question if the anomalous market underperformance to distressed stock can be explained by the above mentioned parallel analysis and if a potential conditionality between the distress risk and profitability factors exists. The descriptive statistics show that on average, highly distressed stocks do underperform non-distressed firms. This finding is consistent with Dichev (1998), Campbell, Hilscher and Szilagyi (2008) and Agarwal and Taffler (2008). However, once the conditional relationship with profitability is taken into account, the distress risk is rewarded by a continuous positive return. Two-thirds of highly distressed companies in the computer and electronics industry have low or negative excess returns and low or negative profitability levels. The other third of distressed companies is profitable and earn superior returns compared to a) their non-distressed counterparts and b) to distressed but non-profitable companies. I also provide Fama-MacBeth (1973) t-statistics resulting from cross-sectional regressions run on several two-way and three-way intersecting and independently sorted portfolios. The t-statistics confirm in a joint setting the significance of the relative distress risk factor and current profitability levels, both derived from the cash flow based bankruptcy prediction model. In addition, I separately test for the potential conditionality of these two factors. Next, I conduct Pearson correlation tests and also run Fama-MacBeth (1973) cross-sectional regressions for both the distress risk and current profitability strength factors to see if they are independent from the Fama-French (1992) factors. The tests confirm that both new factors are independent from the Size and B/M factors. The descriptive statistics also reveal that the B/M factor follows an inverted u-shape along the distress deciles axis, which means that low and high distress risk deciles share similarly low B/M values. Furthermore, cross-sectional regression results confirm that adding both the distress risk and profitability strength factor improve the explanatory power over an initial Fama-French three-factor model and also that both factors are not subsumed by Size or B/M. Given the correlation, descriptive and inferential statistics' test results I can prove that the Fama-French (1992, 1993) distress factor proposition does not hold.

What is the main contribution of this study? Overall, I can show that the anomalous underperformance of distressed stocks in the US computer and electronics industry can be explained by the parallel analysis of two propositions; the risk based rational pricing and the positive relationship between profitability levels and stock returns. There is evidence that distressed stocks are rewarded with a positive continuous distress risk premium and appropriately priced once the conditionality with profitability is taken into account.

In addition, I present a dynamic cash flow based hazard model which predicts bankruptcies at higher accuracy rates than Altman's Z-score model as shown by a ROC model benchmark test. This model not only predicts corporate failure, but also produces probabilities of failure for each firm on quarterly basis which in turn serve as a proxy for the continuous relative distress risk factor to be included in asset pricing tests.

The study also shows that the distress factor hypothesis as proposed by Fama and French (1992) does not hold. Last but not least, growth stocks earn a higher premium than value stocks in the computer and electronics industry hence it reflects the opposite of what Fama and French (1992, 1993) have found for the market as a whole. This reversed effect of the B/M anomaly may be explained by the fact that the computer and electronics industry was growth oriented over this period of rapid technological advancement. Investors may have awarded high multiples relative to the book equity for these industry-specific companies by anticipating substantially higher future sales and earnings compared to the prevalent fundamentals given at the time of investment.

CHAPTER 2: LITERATURE REVIEW

2.1 Past Research on Bankruptcy Prediction Models

2.1.1 Introduction

The bankruptcy rates have risen remarkably in an environment of increased globalization and competition and as result causing very large direct (e.g. legal and accounting fees) and even much larger indirect costs to the economy as a whole. Therefore, it is not a surprise that the area of corporate failure prediction has become an important and popular area of research over the last four decades. Although, the majority of bankruptcy filings are made by private companies, most of the bankruptcy prediction studies predominantly focus on publicly traded companies for the simple reason of mandatory disclosure requirements of financial statement data (in the United States, 224,472 companies filed for Chapter 11 from 1980 to 1991 of which about 1200 public ones were involved (Altman, 1993). In the years from 1992 to 2005, another 1700 public firms have filed for Chapter 11, which is on average about 120 filings per year (PricewaterhouseCoopers, 2006). The PricewaterhouseCoopers' Phoenix Report from 2005/2006 also shows the materiality of bankruptcy with respect to total assets at the time of filing, which was $ 101.3 billion in 2005. The event or the risk of business failure may affect many parties (debtor, government, creditors, auditors, investors, turnaround specialists etc), either directly or indirectly.

Many researchers have constructed models with the aim to predict the failure or non-failure of distressed companies using all kind of variables such as financial ratios from financial statements, market-derived indicators, cash flow ratios, economic and industry specific indicators and many more in an endless number of combinations. One of the first bankruptcy prediction models, if not the first, was developed by Beaver (1966) which included a full set of financial ratios deriving from publicly available financial statements. Beaver (1968) used the univariate analysis (section 2.1.3.1), a single-period statistical method, which then was followed by some other multivariate models. The most popular statistical methods appear to be the cross-sectional ones such as the multivariate discriminant model (MDA). It was introduced by Altman (1968) and has been used for many years and in the 1980, it was followed by logit models (LA) (Ohlson, 1980). Another conditional probability model, the probit analysis (PA) has been introduced by Zmijewski (1984), but has not become as popular as the logit analysis in the application of bankruptcy prediction models (Balcaen and Ooghe, 2006). More recent, Shumway (2001) has introduced a simple hazard model which in contrast to static models mirrors the dynamic event of company failure much closer than any of the previous models.

Further below, I will first discuss some issues on failure and bankruptcy definitions, then describe some of the most popular statistical methods which were applied in past studies and I will also cover some methodological related issues or pitfalls.

2.1.2 Definition of "Firm's Bankruptcy or Failure"

The failure of firms can be understood in many different ways such as from an economical and legal or from a static and dynamic point of view. Expressions like failure, bankruptcy, corporate distress, insolvency, default and others are found in the literature and are very often used interchangeably in the same context without a clear distinction of meaning. Altman (1993), Balcaen and Ooghe (2006), Karels and Prakash (1987) and others provide some overview of corporate distress definitions. The first expression "economic failure" can be identified by net losses incurred or by lower average return on investments compared to alternative investments, which however do not ultimately lead to a discontinuation of a firm's operation (Laitinen, 1994). As such there is no single or specific event of failure from an economical point of view, but it is rather an occurrence over time. The second expression, an "insolvency issue" is found when a company cannot meet their financial obligations. However, insolvency also does not have to lead to a liquidation or discontinuation of a firm either and as such is also not considered to be a good indicator of distinction between failed or non-failed companies from a shareholders' total loss perspective. The next definition used, "defaults" as explained by Altman (1993), is also not a clear-cut event of bankruptcy and may not lead to a significant loss of shareholder's investment by liquidation. Defaults such as violation of covenants can be an indication of shortfall in cash generation and lack of liquidity, but are very often restructured with bank syndicates and therefore may continue their operations (Altman, 1993). Last but not least, the term bankruptcy, which is understood to be a legal act such as the filing under Chapter 11 in the United States is probably the best indicator of a company facing potential liquidation, but varies from country-to-country depending on their national bankruptcy codes. The bankruptcy term viewed as a legal act such as in the United States is the most often used criteria and common choice in the bankruptcy prediction literature. It is considered to be the "real" event when selecting bankrupt and non-bankrupt firms for modelling and testing purpose (Karels and Prakash, 1987).

This so-called "real" event has also some serious pitfalls to consider. One is that a chapter 11 filing may be done on a voluntary basis in order to prevent a firm's liquidation by a successful reorganization which in turn may not result in the discontinuation of a company at all. Therefore, it may not be classified as a genuine company failure in any model.

It is quite essential that the event of failure or bankruptcy is precisely defined and adequately incorporated in the design of a research project, which has not always been the case in past studies (Karels and Prakash, 1987). The omission of such a definition weakens the models' design and validation. Moreover, it may result in an arbitrary selection process of non-failure and failure companies (more about the arbitrary separation of populations; see dichotomous dependent variable section 2.1.4.4)

2.1.3 Statistical Methods Used in Bankruptcy Prediction Studies

2.1.3.1 Univariate Analysis

The univariate (discriminant) analysis has been used to create a bankruptcy prediction model based on financial ratios. It has been introduced in the 1960 by Beaver (1966, 1968), the pioneer in the studies of bankruptcy prediction models. He found that a number of ratios or indicators of a paired sample of failed and non-failed companies could predict company failure for a period of up to five years before such negative event actually occurs. Basically, he has been identifying the ratios by applying a dichotomous classification test and as result obtained the final set of six ratios of which of each had the best ability to predict the companies' failure. In his test, firms from a paired sample of 79 distressed and 79 non-distressed firms have been matched by asset size and industry (issues on sample selection, see section 2.1.4.3). Each ratio in the model was measured and analysed on a one-by-one basis against an "optimal cut-off point" – this is the value to be set in order to reach the lowest percentage of misclassifications. If a company's ratio value was below this so-called "cut-off point" it was considered to be a failing company, if its ratio value was found above the point, it was classified as non-failing. The model with its cut-off point has also been tested against a hold-out sample, a sample not been part of the model itself (validation; ex ante). The classification accuracy was measured by a total misclassification rate, which itself was split into type I and type II errors. Type I error was found when a company was classified as non-failed, but in reality failed and the type II error was found when a company was classified as failed, but did not fail.

Since the cost of type I and type II errors are not considered to be the same, the optimal cut-off point can be modified in order to achieve lowest error rates (Zavgren, 1983). In brief, the obvious advantage of Beaver's univariate analysis based model as concluded by a majority of researchers in this field is that it does not require any special statistical knowledge, but still provides a remarkably high predictive ability. It is a simple manual process of comparing ratio values with the cut-off point which in turn classifies firms into failed or non-failed.

However, the univariate analysis also has some serious constraints. The method works under the assumption of linear relationship between ratios and the outcome such as failure or non-failure. Studies have shown that most of the financial ratios relate in a non-linear manner. Second, the ratios are measured on a one-by-one basis (univariate) and may create some inconsistent result among the ratios. Third, most variables or ratios are highly correlated (Zavgren 1983) and therefore, it is also very difficult to assess the significance of ratios on an individual basis. Fourth, it is also quite obvious that a firm's financial condition is more likely to be assessed on the combination of multiple ratios rather than on a single ratio's outcome, which has led Altman (1968) to use the multiple discriminant analysis in order to overcome this deficiency (section 2.1.3.2). Last but not least, the optimal cut-off points for each variable are sample specific and trial-and-error based and as such may result in higher errors rates when conducting ex ante out-of-sample tests (Platt and Platt, 1990). Overall, the univariate analysis is no longer of relevance when considering the advantages of the models discussed in the next sections.

2.1.3.2 Multiple Discriminant Analysis (MDA)

Altman (1968) used the multiple discriminant analysis as statistical method, which allows classifying firms into two or more a priori groups such as failure or non-failure companies. His failure prediction model is called "Z-score model" and has been adjusted by the ZETA-analysis (Altman, Haldeman, Narayan 1977) in order to reflect the changes in accounting and reporting standards (ZETA-Model will not be discussed in further details). In contrast to the univariate analysis, it combines the ratios and “it attempts to derive a linear combination of these characteristics, which “best” discriminates between the groups” (Altman, 1968). In the 1970, it has been the most frequently applied method in the literature (Deakin, 1972; Edmister, 1972; Taffler and Tisshaw, 1977) and is still widely used and accepted.

The MDA is based on Lachenbach’s (1975) linear discriminant function:

$$\mathbf{D_i = D_0 + D_1X_{i1} + D_2X_{i2} + \;\ldots\; + D_nX_{in}}$$

with D_i = discriminant score for firm i

X_{ij} = value of the attribute X_j (with j = 1, , n) for firm i

D_j = linear discriminant coefficients with j = 0, 1, , n

The researcher’s inputs are variables or ratios which he believes will discriminate best between the two a priori groups, failure and non-failure. In contrast to the univariate analysis, variables may be included in a MDA model, which would not have been considered to be a best predictor when evaluating them individually for statistical significance. For this reason, Beaver’s (1966) set was not identical with Altman’s (1968) five variables. The MDA model brings the multi-dimensional input of selected ratios into a one-dimensional measure by forming a linear combination of the variables along some axis. The MDA determines the linear combination *n* attributes (financial ratios) with the widest separation of means and as such is providing the best discriminator between groups in the form of a score (D_i). I will not go into more details regarding the complex computations of an MDA model (further discussion see Zavgren (1984)).

As found when using the univariate analysis, Altman (1968) determined an optimal cut-off point or score in order to obtain the lowest error rates (type I and type II errors as discussed in the previous section). The Altman (1968) test included thirty-three manufacturers that filed bankruptcy and another equal number of non-bankrupt manufacturing firms, which were matched by asset size and industry for one year prior bankruptcy. The classification accuracy of the model has also been assessed on an overall as well as on a type I and type

II error basis. The result shows that Altman's (1968) model achieved a higher accuracy on year one prior bankruptcy (95%) than Beaver's (1966) univariate model. However, Beaver's model was more accurate in the years three to five prior bankruptcy. Nevertheless, the multivariate analysis is still intuitively more convincing than the univariate analysis. All researchers would most likely doubt that one single ratio was able to capture more complete information than a set of ratios reflected in a single Z-score (Zavgren, 1983). Altman's discriminant function was validated by using the same firms, but with ratios drawn from years two to five prior bankruptcy. Moreover, another sample with twenty-five distressed firms was tested based on the initially obtained coefficients in order to validate the predictive power of the model (ex ante). The test results of the out-of sample test showed some significant increase in type I error rate though.

Although, the multiple discriminant analysis has brought some improvements over the univariate analysis, there are quite some restrictions and issues to be considered when using the MDA as statistical method. The MDA requires that (Karels and Prakash, 1987):

a) the groups (dependent variables) are dichotomous (discussion see section 2.1.4.4)
b) the independent variables are multivariate normally distributed
c) variance-covariance matrices are equal across both groups of classification
d) the prior probability of failure and misclassification costs are specified

In practice, the requirements above are very often violated (Eisenbeis, 1977; Richardson and Davidson, 1984; Zavgren 1983). Almost none of the studies including the ones I have reviewed ever analyse whether or not they meet the above requirements (Balcaen and Ooghe, 2006). Therefore, the generalizations and conclusions in these studies may be somewhat questionable.

Financial ratios, also the ones used as independent variables in MDA models, are not normally distributed (Barnes, 1982) and therefore require some correction such as log transformation (Altman, Haldeman, Narayan 1977), quadratic transformation of variables (Joy and Tollefson, 1975) or other types of transformation. Some researchers may have chosen to eliminate outliers by deletion (Frecka and Hopwood, 1983) or windsorising as a widely used alternative. In general, I conclude that the multivariate normality assumption should be satisfied by one of the available remedies as suggested in the literature.

Another issue is the selection of an optimal cut-off score based on the assumption of minimized cost function. Type I and Type II errors are not equal from a cost point of view. From an investment banker's point of view, a type I error is significantly more costly than a type II error (loss of loans etc). However, from a mistakenly classified non-failed firm, the cost of type II error would be higher because of wrong signalling to creditors, customers, stockholders and other stakeholders (Zavgren, 1983). This can lead to significant opportunity costs, which however are almost immeasurable. For practical reasons, most, if not all, of the studies assume cost equality for both, type I and II error, with the result of an incorrect and biased setting of the "optimal" cut-off point. (Zavgren 1983). One solution is to specify lower and upper cut-off scores by achieving a zero per cent type I at the upper as well as a zero per cent type II error rate at the lower cut-off score point – the so-called "black-grey-white"-method (Edmister, 1972).

Another disadvantage is the fact that the MDA works on the assumption of linear relationship between the dependent dichotomous and the independent variables. Balcaen and Ooghe's (2006) point out that most of the variables such as financial ratios do not relate linearly to the financial condition of a company. The logit analysis, with a non-linear maximum likelihood estimator is a more appropriate method and can overcome this quite serious deficiency (see section 2.1.3.3).

Financial ratios among themselves are very often correlated by sharing the same denominator or nominator. Therefore, one would have to expect some issues regarding multicollinearity. However, Altman and Eisenbeis (1978) concluded that there is no such problem in the use of an MDA model, which definitely would pose an advantage over the logit analysis (see section 2.1.3.3.).

The introduction of the MDA model was an important milestone in the history of development of bankruptcy prediction models. Nevertheless, the disadvantages compared to the logit analysis and the following discussion will show why the MDA has frequently become a second choice of method in the literature.

2.1.3.3 Logit Analysis (LA)

In the 1980, the logit analysis (LA), a conditional probability model, which was introduced by Ohlson (1980), became one of the most popular statistical methods in the failure prediction literature. The LA is a non-linear maximum likelihood estimation procedure:

$$\mathbf{P_1(X_i) = 1 / [1 + exp –(B_0 + B_1X_{i1} + B_2X_{i2} + \ldots + B_nX_{in})] = 1 / [1 + exp –(D_1)]}$$

with $P_1(X_i)$ = probability of failure given the vector of attributes Xi

B_j = coefficient of attribute j with j = 1, , n and B_0 = intercept

X_{ij} = value of the attribute j (with j=1, ,n) for firm i

D_i = the “logit” for firm i

When a failed company is coded with 1 and the logit score results in a high P that means that there is a high probability of failure and vice versa. The logit analysis works based on “resemblance principle” as the MDA method does (Balcaen and Ooghe, 2006). The optimal cut-off point of the logit score (P_1X_i) has been assessed in Ohlson’s (1980) study based on the same assumption as in Altman’s (1968) study; to minimize the total cost of error assuming cost equality for type I and type II errors.

The result of Ohlson’s (1980) and also Zavgren’s (1982) studies did not show any improvement in the accuracy of classification compared to Altman’s (1968) and other authors’ MDA based models. However, there are still some distinct advantages over the MDA methods to be taken into account when selecting the appropriate statistical method. The logit analysis does not require normally distributed variables or equal dispersion matrices or prior probabilities of failure as MDA does (Ohlson, 1980; Zavgren, 1983). The logit analysis provides *direct* information on probabilities of failure as reflected by its logit score (P_1X_i), and as such is viewed as “the main contribution of this [LA] technique” (Zavgren, 1983). In addition, the estimated coefficients derived from a LA model can be evaluated for each independent variable separately regarding its statistical significance and its contribution to the model as a whole (Zavgren, 1983; Ohlson, 1980). This feature is not available with the MDA model (see section 2.1.3.2). Last but not least, the logit analysis works based on a non-linear maximum likelihood procedure, which overcomes the problem of non-linear relationship among variables as discussed with the MDA method (section 2.1.3.2).

Although, the LA model appears to be less restrictive and also less complicated than a MDA model, there are also some serious limitations discussed in the literature. One problem, which potentially could arise, is multicollinearity among independent variables since financial ratios have quite often the same numerator or denominator, a serious drawback of which the MDA is not subject to (section 2.1.3.2). Although, the LA model does not require normally distributed variables, it is still sensitive to extreme non-normality and to outliers as well as missing values (McLeay and Omar, 2000). Therefore, transformation including outlier deletion is recommended in order to obtain close to normality distribution (Balcaen and Ooghe, 2006) and may also be advisable when using the LA method (see discussion in section 2.1.3.2).

Overall, I conclude that for simple dichotomous classification into failing or non-failing group, the MDA model may still be the most appropriate method. The logit analysis has some clear advantage over the MDA model when it comes to the assessment of likelihood of failure (probabilities). In addition, the non-linear shape of LA method in contrast to MDA's linear functionality is quite appealing and avoids the transformation of variables (logs and quadratic terms).

2.1.3.4 Hazard Model – Cox Proportional Model

One of the more recent developments in this field is the application of a hazard model, which has been introduced by Shumway (2001) and which has been used by other researchers recently such as Beaver, McNichols and Rhie (2004) or Campbell, Hilscher and Szilagyi (2008). All previous models as discussed above are single-period or static models, which do not account for changes of a firm's characteristics over time. The static models typically are created by using financial data from one year prior to bankruptcy. In a second step, the researchers run their models for years two to five prior bankruptcy with coefficients obtained from year one and as result ignore any time varying characteristics of failing firms. In other studies, researchers create year specific models from t-1 to t-5 (multiperiod logit models) and use them as separate observations not linked to each other over time. Therefore, Shumway (2001) claims that all static models (MDA and LA) are inappropriate for forecasting bankruptcy. He suggests the use of a hazard model in connection with a logistic model, also known as survival or duration analysis, as the most adequate statistical method in this field. Although, Shumway (2001) has proven that logit and hazard models are closely related to each other, he provided some distinct advantages of a hazard model from an econometric point of view:

a) it accounts for time unlike static models as discussed earlier. The dependent variable in a hazard model is the time spent by a firm in a healthy group
b) bankruptcy probability varies over time. Circumstances may change that influence the probability of an individual firm facing bankruptcy. In effect, Kiefer (1988) says the conditional probability of exiting a state is not constant over time, a factor which by definition is not considered in a single-period model at all.
c) automatic adjustment for period at risk; some firms file bankruptcy while being at risk in the first year and others maybe after five or more years. Other companies may file bankruptcy without being at risk at all (voluntary filing)
d) it incorporates time-varying explanatory variables
e) it produces more efficient out-of-sample forecasts by utilizing more data than static ones.

Shumway (2001) also admits that hazard models are difficult to estimate due to their non-linear likelihood functions and time-varying covariates and basically refers to computer programs estimating hazard rates based on logistic estimation models. His work revealed that more than half of previously used accounting ratios were statistically not significant and as such he proposed a model that uses a very limited number of both accounting ratios and market-driven variables combined. The fact that a hazard model does account for time-series behaviour of variables is very much appealing since company failure may most likely occur over multiple periods and as such cannot be captured just by a snap-shot of a single annual financial statement. Nevertheless, hazard models are also sensitive to extreme outliers as well as missing values, an issue which can be solved as discussed under 2.1.3.3. The hazard model offers the probability of failure directly, which is not given by the MDA method (2.1.3.2) and also incorporates time-varying variables (aspect of panel data analysis), which is not given by the logit analysis (2.1.3.3). Therefore, I consider it as the most appropriate method to be used for developing the cash flow based bankruptcy prediction model as described in Chapter 4.

One of the most popular and widely-used hazard model is the Cox proportional hazards regression method (Cox 1972), a relative risk model. It is a semi-parametric model, which means that it does no more than analyzing the combined individual binary-outcome at each time of potential failure. The binary outcome in this study is either bankrupt = 1 or non-bankrupt = 0. The Cox proportional hazards regression model (Cox 1972) asserts that the hazard rate **h** at time **(t)** for the ***j*th** subject in the data **x** is

$$\mathbf{h(t|x_{\mathit{j}}) = h_0(t)\ exp(x_{\mathit{j}}\ \beta_{\mathit{x}})}$$

The $\mathbf{h_0(t)}$ is the baseline hazard, which has no parameterization and as such will not be estimated. Hence, this model does not make any assumption about the shape of the hazard over time and does not rely on distributional assumptions in contrast to other methods as discussed above (parametric part of the model). This is an important feature since the distribution cannot be specified. As result, the Cox model overcomes the violation of non-normality distribution and produces more efficient and robust results. The β_x regression coefficients are to be estimated from the data $\mathbf{x}_j$. The Cox model assumes a parametric form for the effect of the predictors on the hazard (non-parametric part of the model) and since this study is rather interested in the parameter estimates than the shape, the Cox model is considered to be the most appropriate choice of method. If the functional form of $\mathbf{h_0(t)}$ was known, parametric models such as Weibull or Exponential regression could have been chosen depending on the data's shape . Nevertheless, a wrong assumption about the distribution could then produce misleading results.

To obtain a bankruptcy prediction model by the application of the Cox proportional hazard model one needs to, besides structuring the data properly, consider the following:

a) The Cox model has no intercept since it is equal to the baseline $\mathbf{h_0(t)}$ and as discussed does not built on the distribution shape of the data used.

b) The interpretation of the hazard rate which results from the exponentiated individual coefficient is relatively easy. Nevertheless, a hazard rate is not a probability $\boldsymbol{p}$ and therefore, needs to be calculated as follows:

$$\boldsymbol{p} = \frac{\boldsymbol{h(t)}}{\boldsymbol{h(t)+1}}$$

Since, I would like to obtain the probability of failure for a single company with multiple covariates at a given quarter; I use the STATA "predict hr" function after running the Cox regression. This function will provide the overall hazard rate (hr) on an observation by observation basis within-sample, but also allows to be re-run out-of-sample for validation purpose. The probability of failure derived from a hazard model can be viewed as an equivalent to a discrete time multi-period logit model as shown by equation below:

$$\boldsymbol{P_{i,t}} = \frac{\boldsymbol{1}}{\boldsymbol{1+e^{-z}}}$$

where $\boldsymbol{p_{i,t}}$ stands for the probability that firm i will be bankrupt at time t , **e** for Euler's constant at 2.7183 and $^{-z}$ for $\beta_{1}x_{1} + \beta_{2}x_{2} + \ldots + \beta_{p}x_{p}$.

c) The Cox proportional hazard model is sensitive to the problem of multicollinearity. Therefore, the variables used for modelling will need to be evaluated by a correlation test. Strong correlations among independent variables should be avoided (Lane, Looney, Wansley 1986).

d) As with any other regression method, the Cox model's result needs to be checked for eventual misspecifications, outliers etc (Cleves, Gould, Gutierrez 2003).

2.1.4 Common Statistical and Methodological Issues

2.1.4.1 Selection of Independent Variables

No theoretical framework has been identified in existing bankruptcy literature, which could provide knowledge about the variables to be selected when building or testing a bankruptcy prediction model (Zavgren 1983). Therefore, many different set of variables can be found in the literature such as accounting, market-related or non-financial ratios based models in all kind of combinations. Most of the researchers in this area run empirical tests based on a number of different statistical methods and chose the variables of significance. Others take an existing model with a given set of variables obtained by previous research work and studies. In the past four decades, dozens of ratios have been tested and used in numerous bankruptcy prediction models without any underlying theory by some of the most prominent researchers in that field.

2.1.4.2 Lawson-Identity

Nevertheless, one study on bankruptcy prediction was conducted by using a framework for the selection of independent variables. Aziz, Emanuel and Lawson (1988) have obtained a set of cash flow related variables based on Lawson's cash flow identity (Lawson, 1971), which in sum can be described as follows:

Entity Cash Flows = Lender Cash Flows + Shareholder Cash Flows

The entity cash flow is the sum of the following:

Entity Cash Flows	**=**	**Operating Cash Flow**
	./.	**Net Investment in Fixed Assets**
	./.	**Liquidity Changes – Taxes paid**

Thus, the cash flow information derived from this identity includes operating cash flow, net capital investment, liquidity change, taxes paid on the left side and lender as well as shareholder cash flows on the right side of the equation as shown below (Aziz, Emanuel, Lawson 1988):

$$\mathbf{(k_j - h_j) \; - \; (A_j + R_j - Y_j) - H_j - t_j \;\; = \;\; (F_j - N_j - M_j) + (D_j - B_j)}$$

where,

$k_j - h_j$	is operating cash flow in year j (customer cash payments, k_j, less operating cash flow, h_j
$A_j + R_j - Y_j$	represents net capital investments as result of replacement investment, A_j, plus growth investment, R_j, less the proceeds from asset disposals, Y_j, in year j
H_j	reflects the change in liquidity in year j
T_j	for taxes assessed and paid in year j
F_j	represents interest payments in year j
N_j	is medium and/or long term debt raised or retired in year j
M_j	is short-term debt raised or repaid in year j
D_j	is dividends paid to shareholders in year j
B_j	represents equity capital raised or repaid in year j

Aziz, Emanuel and Lawson (1988) have tried to compare their cash flow based prediction model (CFB) with widely and most accepted models such as Altman's Z-Score and ZETA. The overall accuracy of the CFB model was in year one, three, four and five prior bankruptcy higher than the well known Z-Score, but lower in all years than the ZETA model. However, the CFB model had some better accuracy rates in identifying bankrupt firms than both ZETA and Z-Score in years three, four and five prior bankruptcy.

There are several pitfalls to consider when comparing different models as done by Aziz, Emanuel and Lawson (1988). First, it is unclear whether these accuracy differences relate to the selection of variables or the choice of statistical method. On one hand we have the Z-Score which stems from the multiple discriminant analysis method and on the other hand a cash flow based model using logit analysis. Second, the results from all these prediction models derive from different periods and samples and as such produce rather non-meaning comparisons. Third, Aziz', Emanuel's and Lawson's (1988) model consists of annual specific logit models, which means that for each year prior bankruptcy there is a specific model with variables having different coefficients. This CFB model cannot be used for hold-out sample tests since it is unclear which annual logit model's coefficient one would have to use. Last but not least, comparisons with other models can only hold if the same hold-out sample at the same period is run by each model's coefficients, which has not been done by this CFB study. Nevertheless, Aziz, Emanuel and Lawson (1988) rightly argue that corporate bankruptcy is closely related to a company's valuation and as such the Lawson's cash flow identity variables are expected to be stronger predictors. Others such as Ross, Westerfield and Jaffe (2002) also refer to flow-based insolvency, which occurs when a company's cash flow is insufficient to meet its financial obligation. Overall, it is intuitively appealing to estimate identity based cash flow failure predictors from a hazard proportional model using panel instead of cross-section data. That is the justification why I will apply Lawson's identity when developing a new bankruptcy prediction model. It is the only non-arbitrary type of selection of variables using an identity, which I have found so far in previous studies.

2.1.4.3 Sampling Method

In a perfect world, the sample drawn from a population should be representative for the population of all firms. However, most of bankruptcy prediction studies including the ones mentioned in this study are based on non-random sampling and therefore may be subject to biased parameter estimates and probabilities (Zmijewski, 1984). As result, most if not all, achieve remarkable results in within-sample classifications (ex post), but clearly fail when it comes to their predictive ability by validating the models with out-of-sample classification tests (ex ante). Platt and Platt (1990) analysed this issue and concluded that so-called well predicting models typically experienced a disappointing shortfall of ten or more percentage points from within-sample compared to out-of-sample classification test results. A few studies such as from Platt and Platt (1990), Platt and Platt (1991) and Pompe and Bilderbeek (2000) suggest the inclusion of industry-relative, size class specific or age specific variables in order to improve the predictive power of failure models.

Another issue to be considered when assessing the classification accuracy of tests is the "over-sampling" problem (Zmijewski, 1984). Bankrupt companies are selected based on their known status of failure and represent a much higher proportion of the population than in the real world, especially when using matched pairs of failing and non-failing companies (fifty per cent failed; fifty per cent non-failed matched by asset size and industry). This problem of choice-based sample bias (Zmijewski, 1984) leads to an overstatement of the ex-post accuracy of classification results and to misleading conclusions (Platt and Platt, 2002). In contrast, when failure companies are excluded from sampling due to their incomplete data, as it often occurs, an understatement of the classification accuracy may result (Zmijewski, 1984). Other reasons for classification misstatements are the violence of the stationarity assumption and data instability.

I conclude that a majority of bankruptcy prediction models are sample specific and choice-based (Zmijewski, 1984) and definitely have some weaknesses when it comes to the validation of their ex post results. Although, there are not that many remedies to overcome these deficiencies, the inclusion of industry-relative adjusted variables should definitely be considered.

Overall, some of the impressive classification results in past studies have to be critically appraised in respect to these methodological issues above. Furthermore, failure prediction models and their ex post results should always be validated by out-of-sample predictive tests (ex ante) in order to evaluate the model's robustness over time. As a result of the above, the sample in this study will be industry specific (section 4.4) and not use the matched pair method. In addition, out-of-sample tests will be run using a second sample from the same industry, but from a later period (see section 4.8.1).

2.1.4.4 Dichotomous/Discrete Dependent Variable

The multiple discriminant analysis, logit analysis as well as the hazard model require the dependent variable to be dichotomous. Therefore, the two populations of failing and non-failing firms need to be clearly identifiable and separable from each other. As previously discussed (definition of bankruptcy, section 2.1.2), the process of economic failure is not a dichotomous but rather a continuous process. Nevertheless, the legal bankruptcy is the most preferred type of event when it comes to the sample selection of failed companies. It provides a date of filing to the researcher, which she or he can consider to be objective and dichotomous. Since, I will work with dichotomous dependent variables (section 4.1) the appropriate method is either logit analysis, MDA or the hazard model but definitely not a least square regression analysis which is used for continuous dependent variables.

2.1.4.5 Non-Stationarity and Data Instability

The MDA and the logit model work under the assumption of stationarity (Mensah, 1984) and data stability over time (Zavgren, 1983). First, stationarity assumes that the relationship among dependent and independent are stable over time in order to achieve a strong forecasting power in ex ante tests. Second, data stability assumes that correlations among independent variables to be stable over time (Edmister, 1972).

Barnes (1987), Richardson and Davidson (1984), Mensah (1984) and others have shown in their studies that both assumptions were strongly violated in the studies of failure prediction literature. Both have shown evidence and concluded that financial ratios are unstable over time. As potential remedy, Balcaen and Ooghe (2006) suggest re-estimating the model's coefficient and optimal cut-off point where needed (basically applicable for aged models. Although, Begley, Ming and Watts (1996) find that re-estimating the coefficients does not improve a model's performance. Other researchers such as Platt and Platt (1990) found that industry-relative adjusted variables may help to overcome the instability over time problem.

Overall, there is not much offered in the literature to overcome these drawbacks connected with the use of financial ratios. However, a hazard model (section 2.1.3.4) may be more appropriate for the use of a multi-period bankruptcy prediction model and account for such instability patterns of ratios over time.

2.2 Past Research on the Pricing of Relative Distress Risk

The literature review on bankruptcy prediction models above has shown that financial ratios provide information with some predictive elements on the financial health of a firm. The pricing of such bankruptcy risk has become an increasingly researched topic in recent years.

First, the literature review on pricing of relative distress risk provides a brief overview of asset pricing models. There is no intention to present all of the manifold types of models and theories since it would not add any novelty and also not serve as linkage to the primary focus of my study. Hence, the outline comprises of and is limited to the capital-asset-pricing model (2.2.1) or CAPM (Sharpe, 1964; Lintner, 1965a, 1965b; Mossin, 1966), the Arbitrage Pricing Theory (2.2.2) or APT (Ross, 1976) and the three-factor model (Fama and French, 1992, 1993) which can be viewed to be both, an application of the APT or an extension of the CAPM.

Second, a review of past work on the pricing of relative distress risk is provided in section 2.2.4. This risk factor embedded in asset pricing tests is very often proxied by the scores or probabilities derived from bankruptcy prediction models such as from Altman's (1968) Z-score, Ohlson's (1980) O-Score or most recently from a fitted probability model by Campbell, Hilscher and Szilagyi (2008). The studies found in the accounting and finance literature include the testing of the relationship between stock returns and bankruptcy risk, but also the market reaction from an information efficiency point of view and do range from short-term event to long-term association type of studies.

2.2.1 Capital Asset Pricing Model (CAPM)

The capital-asset-pricing model or CAPM was originated by Sharpe (1964), Lintner (1965a, 1965b) and Mossin (1966) and is based on Markowitz's (1952) modern portfolio theory of mean-variance efficiency and optimal portfolio selection. The CAPM is probably the best known and still most widely used model in the world of finance. The CAPM seeks to explain linearly the relationship between risk and return in a rational equilibrium market by measuring the risk exposure in terms of the covariance between the return for an asset *i* and the returns of highly diversified market as a whole. This nondiversifiable or systematic risk factor is called beta β. It is the systematic risk only which is priced at equilibrium in the market. Assets which exhibit a large and positive beta measured by the covariance as mentioned above are considered to be more risky and hence demand a premium compared to low risk investments.

The CAPM assumes to arrive at equilibrium that

- there is a single identical period investment plan by all investors
- investors are without any restrictions able to lend and borrow at risk-free rate
- investors maximize the expected utility of terminal wealth
- there is a homogenous expectation by all investors
- Information is costless and available to all investors
- there are no transactions costs
- there are no taxes

The CAPM is reflected by the risk-reward equation (SML) as shown below:

$$\mathbf{E(R_i) = r_f + \beta_i (E(r_m) - r_f)}$$

Where: $E(R_i)$ denotes the expected return of $asset_i$

r_f is the return on the risk-free asset

r_m denotes the return on the market portfolio

β_i is the beta of $asset_i$

and β_i defined as follows:

$$\mathbf{\beta_i = (cov(r_i, r_m) / var(r_m)}$$

Where: $(cov(r_i, r_m)$ is the covariance for the $_ith$ asset with the market portfolio

$var(r_m)$ is the variance of the market portfolio

The Security Market Line (SML) equation above can be applied to any security, asset or portfolio. In a perfect CAPM world every asset lies on the SML. In the real world though, one can compare realized returns of an asset to expected returns based on CAPM. Obviously, there are differences categorized into underpriced assets (above SML) or overpriced assets (below SML) relative to the expected return of CAPM.

However, the CAPM is not free of criticism. Many empirical studies have shown that the CAPM model is poor in explaining and predicting stock returns. One problem often cited is that expectation is proxied by the use of historical return under the assumption that expected returns may be the same as realized returns hence following a historical pattern. Roll (1977) argued that the true market portfolio cannot get measured and thus it cannot be tested by the CAPM. The true market portfolio is unobservable as it would have to include all assets which comprises not only listed equity stock, but all other alternative asset classes one could think of. However, since CAPM tests do not use the market portfolio as described above, tests performed answer only if an index portfolio chosen was ex-post efficient or not. If an ex-post inefficient portfolio is chosen the CAPM may be wrongly rejected. If an ex-post efficient portfolio is chosen, one may wrongly accept the CAPM, even if the market portfolio was inefficient (Roll, 1977).

In addition, different beta estimation convention used lead to different outcome. All in all, these may be some of the reasons why the theoretical CAPM may not hold in practice.

The CAPM as a model has also experienced some extensions since the assumptions listed above are quite deviant from reality. Some of the most prominent and widely researched extensions are the zero-beta CAPM (Black, 1972), ICAPM (Merton, 1971, 1972, 1973) and CCAPM (Breeden, 1979). These models will not be discussed in further details as they are not of relevance for this study's research question.

2.2.2 Arbitrage Pricing Theory (APT)

An alternative view of asset pricing is provided by the Arbitrage Pricing Theory (APT). It has been developed by Ross (1976) and it distinguishes itself from the CAPM by its theoretical roots. The APT model follows the *law of one price* whereas the CAPM relies on *mean-variance efficiency* as mentioned under section 2.2.1. The *law of one price* implies that two identical assets sell for the same price. In particular, APT assumes a factor model of asset returns and is derived using portfolios, rather than individual securities. Common factors driving asset returns may include macroeconomic factors such as change in GDP, interest rates, inflation, oil prices etc., but also statistically explored factors of systematic risks. The absence of arbitrage over one-period portfolios of assets leads to a linear relation between the expected return and the covariance with the factors. Since the APT as theory does not specify the factors of systematic risks, one is left to find them themselves. This can be done by the use of macroeconomic variables as mentioned above or by exploring different portfolios for characteristics that can be used as factors such as the Fama and French (1992) three-factor model often considered to be an artifact of data mining (Black, 1993a, 1993b; MacKinlay, 1995). However, one of the main advantages of APT over CAPM is that it does not require an identification of the market portfolio and that APT can include multiple factors while CAPM relies on one factor, the beta, only. A multifactor model mirrors the reality probably better than CAPM does.

The APT equation below shows the linear relationship between the expected return on an $asset_i$ and the k-factor risks:

$$\mathbf{E(r_i) = r + \beta_{1,i}\lambda_1 + \beta_{2,i}\lambda_2 + \ldots + \beta_{k,i}\lambda_k}$$

Where: $E(r_i)$ denotes the expected return of $asset_i$

r is the risk-free rate

$\beta_{k,i}$ is the sensitivity of $asset_i$ to risk factor $_k$ (factor loading)

λ_k is the risk premium factor required by investors

The CAPM is not testable as result of the unobservability of the market portfolio. In contrast, the APT has been proposed as an empirically testable theory that applies to even subsets of assets contained in the market portfolio.

2.2.3 Fama and French Three-Factor Model (1992, 1993)

2.2.3.1 Fama-French Factor Model (1992)

Increasing empirical evidence (Ball, 1978; Basu, 1983; Stattman, 1980; Banz, 1981 and others) has shown that factors other than beta such as Earnings/Price (E/P), size or Book-to-Market (B/M) were stronger in explaining stock returns than the market model itself. Fama and French (1992) tested the univariate and multivariate roles of market beta, size, E/P, leverage and B/M ratios in the cross-section of average returns for NYSE, AMEX and NASDAQ non-financial stocks over the period 1963-1990. First, in their study they find that beta has almost no explanatory power, but that leverage, E/P, size and B/M are all significant in explaining cross-section average stock returns when measured on a univariate basis. Second, Fama and French (1992) also conclude that size and B/M are significant in explaining the returns and that both factors in a multivariate setup subsume the effects of leverage and E/P. The results of the multivariate tests show a negative relation between size and the average stock returns while the one between B/M and the returns is found to be positive. Overall, they argued that if securities are priced rationally, stocks' risks must be multidimensional.

2.2.3.2 Fama-MacBeth Methodology (1973)

The Fama and French (1992) coefficients were estimated using the Fama and MacBeth (1973) two-stage regression methodology also known as three-step approach. It is a landmark contribution towards the empirical testing of the CAPM and has become one of the widely used standard approaches in this field. The procedure was suggested to obtain standard errors that correct for cross-sectional correlation of the residuals.

First step is to estimate time-varying betas using a 5-year rolling window for *time-series regression* or alternatively applying the approach of full-sample betas (Cochrane, 2005) which assumes betas being constant. The literature review shows endless ways of calculating the "right" beta which deviate from the pre- and post-ranking method applied by Fama and MacBeth (1973). I will not cover the topic in further details but briefly describe the approach used in my study. In section 5.6, a time-varying beta is calculated using a rolling 24-month time-series regression (Agarwal and Taffler, 2008) prior the portfolio formation date on each portfolio against the monthly excess returns of the equal-weighted S&P 500 index. There is a trade off between the use of a longer versus a shorter window whereas using longer windows may result in more stable betas but become less time-varying and misestimated due the drift in beta over time. In addition, my study deals with the electronics and computer industry, a rather young industry with many distressed companies being listed less than five years. Given both, the nature of industry and the time-varying aspect of beta, I have found the Agarwal and Taffler's (2008) approach using a rolling 24-month window to be the most appropriate one for this study. The definition of beta is as follows:

$$\hat{\boldsymbol{\beta}}_i = \frac{\boldsymbol{Cov}\ (\boldsymbol{R}_i, \boldsymbol{R}_M)}{\boldsymbol{\sigma}^2(\boldsymbol{R}_M)}$$

Where:	$\hat{\beta}_i$	is the estimated beta; in my study as result of time-series regression over 24-month window prior portfolio formation date
	$Cov\ (R_i, R_M)$	is the covariance between the return on asset *i* and the return on the market portfolio *M*
	$\sigma^2(R_M)$	is the variance of the market *M*; S&P 500 index in this study

In a second step, OLS *cross-sectional regressions* are run at *each* time period instead of a single regression over the entire time span of the panel data.

$$\boldsymbol{R}_{it}^{e} = \boldsymbol{\lambda'}_t \hat{\boldsymbol{\beta}}_i + \boldsymbol{\varepsilon}_{it}$$

Where:	R_{it}^{e}	denotes the expected return of asset$_i$ at time $_t$
	$\lambda'_t \hat{\beta}_i$	is the estimate for period *t* where $\hat{\beta}_i$ is the regressor of asset *i*

This step which uses $\hat{\boldsymbol{\beta}}_i$ as regressor(s) results in a error-in-variables problem as betas are estimated and measured with an error. Fama and MacBeth (1973) offer one remedy to minimize this problem which is to let assets be portfolios consisting of such assets. The individual noise is expected to average out and thus to make the measurement error in beta smaller in the first-step regression. Hence, the above notation can be extended that there are *N* assets (i = 1 …..N) and *T* observed periods (t = 1…T), which results in running *T* regressions, each one consisting of *N* observations.

In a third step, the time-series averages of estimated coefficients allows to test whether the market beta and/or the additional size and B/M variables are significantly different from zero by the use of standard t-tests. In an excess return format, the resulting intercept (not noted in equation above) will basically undergo the same t-tests as the coefficient estimates. An efficient model would require its intercept to be economically and statistically indifferent from zero. To form the Fama and MacBeth (1973) t-statistics the following calculations need to be performed.

a) Time-series average of coefficient estimates

$$\bar{\lambda}_j = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_{j,t}$$

b) Standard error

$$\hat{\sigma}(\bar{\lambda}_j) = \sqrt{\frac{1}{T(T-1)}\sum_{t=1}^{T}(\hat{\lambda}_t - \bar{\lambda}_j)^2}$$

c) T-statistics

$$\hat{t}(\bar{\lambda}_j) = \frac{\bar{\lambda}_j}{\hat{\sigma}(\bar{\lambda}_j)}$$

The Fama and MacBeth (1973) methodology with a modified beta estimation approach as described above has been applied in my study as per section 5.6.

2.2.3.3 Fama-French Three-Factor Model (1993)

As an extension of the 1992 study, Fama and French (1993) study the size and B/M factors using a time-series regression approach of Black, Jensen and Scholes (1972). I will not describe this regression approach as it is not applied in my study. 25 intersecting size and B/M quintile portfolios are formed. Monthly excess returns of the portfolios are regressed on both stocks and bonds using five factors. The regressions on stocks reveal that the three factors market, size and Book-to-market are significant in explaining stock returns whereas the other two factors term to maturity and default risk are considered to be significant for bonds. As result, Fama and French (1993) constructed the following three-factor asset pricing model:

$$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + \varepsilon_i$$

Where: $\boldsymbol{R_i - R_f}$ is the monthly return of portfolio *i* less the risk free rate *f;* thus the monthly excess return

$\boldsymbol{R_M - R_f}$ is the risk premium on the market portfolio over the risk free rate

$\boldsymbol{SMB}$ is the return on a portfolio of small minus big stocks thus the mimicking portfolio for the size factor

$\boldsymbol{HML}$ is the return on a portfolio of high minus low B/M stocks thus the mimicking portfolio for the B/M factor

$\boldsymbol{\varepsilon_i}$ is a mean-zero stochastic error term

$\boldsymbol{\alpha_i}$ is the intercept alpha; expected to be indifferent from zero in this excess return form.

$\boldsymbol{b_i s_i h_i}$ are the sensitivities of the factors described above

In Fama and French's (1993) study, size and B/M factors are the only independent variables in the stock portfolio regressions that are significantly different from zero. Furthermore, in their three-factor setup the intercepts are, although not in all cases, close to zero and the beta is close to one. In addition, when portfolios are formed using other firm characteristics such as E/P, D/P and sales growth, the three-factor model is still able to explain the stock returns earned by such portfolios (Fama and French, 1995, 1996).

Overall, the three-factor model suggested by Fama and French (1993) provides an alternative to the CAPM for estimation of expected returns. In this model two factors are added to the market model; size and the book-to-market ratio as expressed in the study of 1992 or SML (Small minus Large) and HML (High minus Low) as finally constructed in Fama and French's 1993 three-factor model study. In short, they report a negative effect for size and a positive effect for B/M related to stock returns or in other words small firms earn on average higher stock returns than large companies and value stocks (high B/M) perform better than growth stocks (low B/M). However, there is also some contrary evidence that the size effect has become weak or even nonexistent starting in the 1980s (Dichev, 1998). Horowitz, Loughran and Savin (2000) find that the size effect was negative in the period 1982 – 1997, but on average insignificant for NYSE, AMEX and

NASDAQ stocks. The stability of the B/M premium over time has also been studied by Loughran (1997) who shows that the B/M factor was significantly positive over the 1974-1984 period, but turned to be negative thus growth stocks earning higher returns in the years from 1963 to 1973 as well as again from 1985 to 1995.

Fama and French (1992, 1993) developed a three-factor model attempting to overcome the weakness and inability of the CAPM to explain realized stock returns. The three-factor model has been often viewed as an extension of the CAPM 1-factor model such as the application of the APT or ICAPM model (Fama and French, 1996). Fama and French (1996) claim that many of the CAPM average-return anomalies are captured by their three-factor model. In this study, I will test the CAPM and the three-factor 1992 model also augmented by the relative distress and current profitability strength factors. I will run regressions using the Fama and MacBeth (1973) methodology only.

2.2.3.4 Criticism on Fama-French Three-Factor Model

The three-factor model has been questioned and challenged by several researchers even more as CAPM anomalies such as B/M and size emerged from empirical tests rather than groundbreaking theories. Some researchers claim that the CAPM holds and that the premium identified by Fama and French (1992, 1993) is the spurious result of the following three main accusations made:

1. Survivor Bias

Kothari, Shanken and Sloan (1995) argue that the Fama and French (1992) B/M anomaly story is subject to the survivorship bias. The survivorship bias has a tendency of failed companies being excluded from performance studies. As companies were added to the COMPUSTAT database retroactively with several years of historical data, distressed companies that failed may have never been entered the database while distressed companies that survived with high B/M may have been captured and therefore led to an overstatement of H. As result, Kothari, Shanken and Sloan (1995) claim that the B/M factor may be an artefact due to the survivor bias and if omitted failure companies were included the explanatory power and the anomaly of B/M possibly would have disappeared. However, subsequent studies have also shown that the survivorship bias has been minimal when testing value-weighted returns (Fama and French, 1996) and that this COMPUSTAT specific bias mainly affects pre-1977 observations (Chan, Jegadeesh and Lakonishok, 1995). Since I use COMPUSTAT data post-1977 the survivorship bias is not expected to be a major issue.

2. Data Mining

Lo and MacKinlay (1990), Black (1993) and MacKinlay (1995) argue that the CAPM anomalies could be the result of data dredging. The research on asset pricing anomalies has become very popular and many participants in this profession have dredged the same data again and again until they have or will have found anomalies such as B/M, size and other new factors. Obviously, models that are successful in explaining stock returns are targeted for publications whereas unsuccessful ones will disappear in the researchers' drawer or bin. In addition, researchers also argue that the three-factor model is sample specific and if it was tested out-of-sample thus in another period or in markets outside the US the anomalies would have disappeared and the three-factor model collapsed into the CAPM model. However, international studies which are considered to be out-of-sample tests have shown and confirmed the significance of previously identified CAPM anomalies in explaining stock returns (Chan, Hamao, and Lakonishok, 1991). In my study, the use of individual security non-portfolio regressions (Chan, Hamao, Lakonishok, 1991) is aimed to disprove the claim of the data snooping bias (sections 5.5.4 and 5.6.3). However, given the fact that I do not run out-of-sample regressions for validation purpose, the suspicion of a data snooping bias cannot be erased completely and remains a legitimate criticism.

3. Beta estimation

The third criticism is related to the estimation of the market beta. Kothari, Shanken and Sloan (1995) argue that the use of annual betas is more appropriate than monthly ones as the investment horizon of a typical investor is closer to one year than one month. Given the different approaches in beta estimation, I agree that results may vary from study to study depending on the beta estimation convention used and yes, if the true beta was found that the CAPM anomalies would eventually collapse. However, since the true market beta is unobservable and thus needs to be estimated, I can only share Fama and French's (1996) argument that multifactor models with *observable* variables may do a better job in estimating expected returns than an *unobservable* market beta does.

2.2.4 Bankruptcy Risk / Relative Distress Risk and Stock Returns

The studies found in the accounting and finance literature include the testing of the relationship between stock returns and bankruptcy risk, but also the market reaction from an information efficiency point of view and do range from short-term event to long-term association studies. In this entire document bankruptcy risk, failure risk or relative distress risk are used interchangeably.

As with bankruptcy prediction models, Beaver (1968) was also one of the first researchers, who tested the relationship between univariate bankruptcy predictors and stock returns. He concluded that the market already anticipated a firm's failure in advance and as such was superior to accounting information derived by a univariate bankruptcy prediction model (Beaver, 1966). However, this type of model cannot offer an appropriate answer to this specific question due to its limitations as discussed under 2.1.3.1.

Altman and Brenner (1981) tested the market responsiveness (timeliness) to information derived by a multivariate bankruptcy prediction model. The sample consisted of firms switching from a predicted non-failure to failure status signalled by Altman's Z-Score Model (1968). The study based on a CAPM 2-factor model revealed some negative abnormal returns for a period of up to twelve months after the release of financial statements. It indicated some market inefficiency especially related to distressed firms. Nevertheless, the bankruptcy prediction model's specifications have some limitations and therefore may result in some wrong classifications of failure and non-failure. The z-score model as applied in this study does not provide a probabilistic view of failure versus non-failure status, but only a dichotomous classification of either of these two states (section 2.1.3.2). A company which is considered to be a non-failure in one period and a failure in the subsequent period could be the result of a slight shift in Z-score crossing the cut-off point, which in turn is arbitrarily set by the researcher (discussion regarding cut-off point, see 2.1.3.2). First, the study did not include the magnitude of such classification shifts and second, the cut-off point arbitrarily set by the researcher could have been differently anticipated by the market. Therefore, it may not be a question of market inefficiency but rather of model misspecification or most likely of a combination of both.

Zavgren, Dugan and Reeve (1988) in contrast to Altman (1981) tested the relation between the probability of failure obtained by a logit model and the market reaction. The study mainly focused on unanticipated failures and non-failures, which basically limits the sample to type I and type II erroneous predictions produced by the logit model. Zavgren, Dugan and Reeve (1988) worked under the assumption that their bankruptcy prediction model's information content and predictive power was efficiently anticipated by the stock market regardless of type I or II errors. As a consequence, the study tested whether unexpected survivals or failures from a model perspective did result in significant abnormal returns once the misclassification became apparent to market participants. Assuming a semi-strong market efficiency and the predictive power as well as the validity of a bankruptcy model, investors could have expected abnormal positive returns for unexpected survival (firms initially predicted to fail – type II error) and the opposite outcome for unexpected failure (firms initially predicted to survive – type I error). However, the result revealed that firms surviving the subsequent twelve months after a one-year-ahead prediction of failure (type II error) experienced significant positive returns whereas firms failing with the twelve-month-period subsequent the prediction of survival showed no significant negative market reaction.

Fama and French (1992, 1993, 1995) conclude in their studies that both, size and level of book-to-market (B/M) ratio significantly explain stock returns on an aggregate level and that on average higher returns are earned by high B/M – small firms. They suggest that financial distress is proxied by the two variables above and consider such risk to be a systematic risk which cannot get diversified away. Their distress factor hypothesis incorporates the assertion that high returns for high B/M-small firms are the compensation for investors taking higher risk when investing in such distressed stocks. Thus, they argue that their three-factor model is consistent with rational pricing (section 2.2.3.1). Other studies use bankruptcy risk estimates from widely accepted bankruptcy prediction models as a proxy for a distress risk factor embedded in asset pricing tests. In contrast to Fama and French (1993, 1995, 1996) and Chan and Chen (1991), Dichev's (1998) test results demonstrates that bankruptcy risk is not rewarded by higher but substantially lower than average stock returns. He also finds that a distress risk factor derived from existing bankruptcy risk models' coefficient or probability of failure such as Z-score or O-score does not relate to size and/or B/M and argues that a risk-based explanation as provided by

Fama and French (1993) or Chan and Chen (1991) may not explain the anomalous underperformance of distressed stocks. In a very recent study, Campbell, Hilscher and Szilagyi (2008) have analyzed the distress risks and related average returns on portfolios sorted by fitted probabilities derived from their reduced-form econometric bankruptcy prediction model. Their study reveals that distressed firms have high market betas and high loadings on HML and SMB factors, but these firms do not earn a risk premium as proponents of a rational equilibrium explanation for distress risk would expect. The contrary has been found that distressed stocks earn lower average returns compared to those with a low distress risk profile - a finding that is consistent with Dichev (1998), Griffin and Lemmon (2002), Ferguson and Shockley (2003) as well as Agarwal and Taffler (2008). Campbell, Hilscher and Szilagyi (2008) consider and discuss three potential explanations for the anomalous low returns of distressed stocks as shown below.

The first explanation may be related to unexpected developments within their sample which may not replicate in future periods. A main impact has been identified by Kovtunenko and Sosner (2003) who find that institutions show strong preference for profitable over non-profitable stocks. In the 1980s and 1990s profitable stocks beat the market potentially triggered by institutional investors' increased demand for profitable stocks. Also, Cambpell, Hilscher and Szilagyi (2008) confirm that distressed stocks with low or declining ownership by institutional investors underperform significantly.

A second potential explanation that irrational or uninformed investors could have overpriced highly distressed stocks by not anticipating the low or negative future profitability prospects or by just being overly optimistic about future earnings has not been supported by the test results of Campbell, Hilscher and Szilagyi (2008). Downward adjustments in pricing of overvalued distressed stocks have not emerged when earnings announcements were made by such companies. Agarwal and Taffler (2008) tested whether momentum proxies for distress risk in the UK market. They argue that a low or negative risk premium would result from investors not reacting to the risk of failure which may result in distressed stocks not being adequately discounted and thus remain overpriced. Consequently, distressed companies are expected to earn low prior-year returns, a trend which may last to some time into the future. This again would produce a negative or low distress risk premium which is expected to be reflected by a momentum anomaly. It is consistent with Campbell, Hilscher and Szilagyi (2008) finding that prior-year returns are significant in predicting bankruptcy. Agarwal and Taffler (2008) though provide evidence that a negative distress risk premium appears to be present due to the market's underreaction and that the momentum effect is serving as a proxy for such distress risk. In addition, Agarwal and Taffler (2008) also find no evidential support of Fama and French's (1992, 1993) distress factor hypothesis where both size and B/M factors would proxy bankruptcy risk. This finding is consistent with Dichev (1998) and Campbell, Hilscher and Szilagyi (2008).

A third possible explanation that Campbell, Hilscher and Szilagyi (2008) have identified is that some of the distressed stocks may have attracted investors to eventually realize private benefits of control or positive skewness of returns (Barberis and Huang, 2007; Zhang, 2006). The first proposition could not get confirmed, but Campbell, Hilscher and Szilagyi (2008) show in their study that these stocks offered positively skewed returns.

The explanations for differentials in stock returns can be divided into two groups as summarized by Haugen and Baker (1996).

The first group (Fama and French, 1992, 1993, 1996; Ball, Kothari and Shanken, 1995; and others) considers the differentials in returns to be risk premiums, e.g. bankruptcy risk, which are expected and required by investors for bearing such risks when making investments. They basically support a risk adjusted rational pricing hypothesis.

The second group of researchers view these differentials in predicted returns as surprise to investors resulting from market over- and underreaction related factors (Chopra, Lakonishok and Ritter, 1992; Lakonishok, Shleifer, Vishny, 1994; Haugen, 1995; and others). Campbell, Hilscher and Szilgayi (2008) come to the conclusion that the distress anomaly influenced by behavioural factors such as low share price and low turnover, limited institutional ownership and analyst coverage make it too expensive to arbitrage. Agarwal and Taffler (2008) also provide evidence to support the market underreaction hypothesis related to pricing of distress risk which aims to explain the underperformance of distressed stocks. They find it rather difficult to link such underperformance to a rational asset pricing as distressed stocks show conflicting but expected characteristics of higher beta, higher B/M and smaller size as proposed by Fama and French (1992, 1993). This second group rather believes in a pricing bias hypothesis.

2.3 Profitability and Return Relationship

There is an extensive body of accounting literature that discusses the theory and empirical research on the relation between profitability reflected by earnings or cash flow information and stock returns. Ball and Brown (1968), the pioneers in the field of market-based accounting research, found that there is a significant relationship between the sign of unexpected earnings and the sign of related stock price changes. Further empirical research by Easton and Zmijewski (1988), Easton and Harris (1991) have confirmed that earnings are relevant for equity investors in their decision making process. Dechow (1994) and Charitou and Clubb (1999) also found evidence of value relevance in particular for earnings but also for cash flows over longer return intervals. Beaver (1998) provides a theoretical framework of three links between earnings and share prices as shown below:

1. The <u>current period earnings</u> provide information that predicts future period's earnings, which then
2. gives the base of information to form <u>expectations about dividends in future periods</u>, which then finally
3. has the information flow to <u>determine the share value</u>, or the present value of expected future dividends respectively.

In addition, several studies have also documented not only the relationship between *changes in earnings* but also the *level of earnings* and stock prices (Easton and Harris, 1991; Penman, 1991, Ohlson and Shroff, 1992). They concluded that both, changes and levels of earnings, are significantly related to stock returns and that the latter explains such returns no worse. Strong (1993) illustrates this by the following proposition:

<u>Returns and Earnings Changes</u>

The stock price is a multiple of earnings rather than the book value figure (Black, 1980).

$$\boldsymbol{V_{it}} = \emptyset_j \, \boldsymbol{E_{it}} \qquad (1)$$

where

V_{it} is the market value of company *j* at time *t*

$\emptyset_j$ is the p/e ratio or multiple for company *j*

E_{it} is the reported earnings of company *j* in period *t*

From equation (1) and by dividing by $\boldsymbol{V_{jt-1}}$, the equation for the relationship between earnings changes and stock returns can be derived as follows:

$$\boldsymbol{R_{jt}} \equiv \frac{\boldsymbol{V_{jt}- V_{jt-1}}}{\boldsymbol{V_{jt-1}}} = \emptyset_{\boldsymbol{j}} \frac{\boldsymbol{E_{jt}- E_{jt-1}}}{\boldsymbol{V_{jt-1}}} \qquad (2)$$

<u>Returns and Earnings Levels</u>

Strong (1992) also outlines the alternative approach of earnings levels being a measure of value under the assumption that shares of companies are traded at a given market-to-book-value ratio as follows:

$$\boldsymbol{V_{it}} = \boldsymbol{\varphi_j}\, \boldsymbol{B_{it}} \qquad (3)$$

where

$\boldsymbol{\varphi_j}$ is the ratio of a firm's *j's* market value to its book value of equity

$\boldsymbol{B_{it}}$ is the book value of equity of company *j* at time *t*

In a next step, the clean surplus condition in a simplified form, $B_{jt} - B_{jt-1} = E_{jt}$, is adopted to equation (3) which results in the following returns-earnings level equation:

$$\boldsymbol{R_{jt}} \equiv \frac{\boldsymbol{V_{jt}- V_{jt-1}}}{\boldsymbol{V_{jt-1}}} = \boldsymbol{\varphi_j} \frac{\boldsymbol{E_{jt}}}{\boldsymbol{V_{jt-1}}} \qquad (4)$$

As with Ohlson's theoretical framework, this clean surplus equation above assumes *risk neutral valuation* and the absence of arbitrage opportunities. In general, profitability is found to be positively related to higher stock returns not only by Fama and French (2006), but also by Haugen and Baker (1996) and Cohen, Gompers and Vuolteenaho (2002). In this study I will test for the earnings levels proxied by a scaled operating cash flow variable (OPCF).

CHAPTER 3: RESEARCH QUESTION AND HYPOTHESES

The research question below will be answered by testing the two sets of hypotheses as outlined in sections 3.2 and 3.3. All of them are shown in alternative form.

3.1 Research Question

Recent research (Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008; Agarwal and Taffler, 2008) have found that high bankruptcy risk is not rewarded by higher but significantly lower than average stock returns. Contrary to Fama and French's (1992, 1993) distress factor hypothesis following a risk based rational pricing proposition, they conclude that it is rather a market underreaction hypothesis with answers to be found in the field of behavioural finance.

In this study, I tackle the question of market underperformance of distressed stocks from a different angle. As discussed in section 2.3, profitability as reflected by earnings or cash flows is positively associated with stock returns which means that firms generating higher earnings or cash flows are also expected to earn higher average returns. In parallel, if we follow the classical risk based rational pricing model like CAPM or its derivatives as discussed in section 2.2.1, positive distress risk premium rewards hence higher average stock returns are expected for highly distressed stock, too.

Given the premium expectancy based on the distress risk factor hypothesis and the positive profitability/earnings levels to returns relationship proposition as discussed above, an investor would ask for higher average returns when investing in highly profitable but distressed stocks as result of both propositions. However, for less profitable or even loss making companies that are highly distressed, the same investor would still expect to earn a distress risk premium but with a downward adjustment due to the lack of value prospects as proxied by low or negative earnings or operating cash flows. In other words, the investor or analyst does not only want to know the future payoff but also the risk as well as the interaction between the two involved. Hence, it is also of interest to know if conditionality between the two factors profitability and distress risk exist.

The earnings levels - returns equation (4) in section 2.3 consists of a market-to-book variable (φ_j) and a scaled earnings (profitability) variable ($\frac{E_{jt}}{V_{jt-1}}$). As mentioned in section 2.3, the earnings levels –returns equation is risk neutral (Strong, 1992). Since the market-to-book variable from equation (4) is already part of the Fama-French 3-factor model, but in its inverse form as book-to-market variable, I will use this model and add a profitability level (OPCF) and a distress risk variable to test their explanatory power in explaining stock returns and the conditionality between the two factors. The distress risk factor derived from my cash flow based bankruptcy prediction model needs to be included, as B/M and Size may not relate to distress risk (Dichev, 1998). However, this assumption needs to be tested and confirmed, too (see hypotheses testing under 3.3).

Hence, testing the two propositions, the earnings levels to returns relationship and the distress risk factor hypothesis, combined in a modified Fama-French 3-factor model, I expect a theoretical model consisting of the following factors

book-to-market + profitability + distress risk

that would explain the underperformance anomaly of distressed stock. The variable size is expected to be insignificant as it does not play a role in any of these two propositions. Given beta's strong theoretical foundation, I will also include this factor when testing the models including the one above.

Overall, the main research question of this study is to find out if the anomalous market underperformance of distressed stock can be explained by a parallel analysis of risk based rational pricing and profitability/earnings levels to return propositions and if there is conditionality between distress risk and profitability levels. Also, I develop a cash flow based bankruptcy prediction model based on a theoretical framework (Lawson, 1971) that provides probabilities of bankruptcy risk serving as proxy for the pricing of relative distress risk. Therefore, the two sets of hypotheses below need to be tested.

3.2 Hypotheses Set 1 – Bankruptcy Prediction Model

The first set is subject to tests related to the validity and strength of predictive power of the cash flow based bankruptcy prediction model. If am not able to reject the hypothesis $H1_A$a) and $H1_A$b) (shown in alternative form), then I will have evidence that a dynamic cash flow based bankruptcy prediction model can predict the failure and non-failure of firms at low error rates and that the model is validated by out-of-sample and ROC benchmark tests. In addition, the asset pricing tests assume the incorporation of a continuous distress risk variable. This assumption needs to be tested by the third hypothesis within this first set. As result, the probabilities of bankruptcy risk then could serve as proxy for relative distress risk embedded in asset pricing tests.

$H1_A$a) A dynamic cash flow based bankruptcy prediction model can predict the failure or non-failure of firms at low type I and II error rates based on within-sample classification (section 4.9.4).

$H1_A$b) A dynamic cash flow based bankruptcy prediction model can predict the failure or non-failure of firms from out-of-sample tests (section 4.9.5) at the same or higher accuracy rate compared to the existing and widely accepted Z-Score Model (section 4.9.6) by using a ROC-model, and as such be used for further asset pricing tests (chapter 5).

$H1_A$c) A dynamic cash flow based bankruptcy prediction model produces continuous probabilities of default measure (sections 4.8.3 / 4.9.7).

3.3 Hypotheses Set 2 – Asset Pricing of Profitability and Relative Distress Risk

In order to test the hypotheses outlined below and to answer the research question as discussed in section 3.1, I will have to add two variables to the Fama-French (1992) 3-factor model.

First, earlier studies that have been testing the pricing of distress risk, often proxied such risk factor by the risk of failure derived from a bankruptcy prediction model (Campell, Hilscher and Szilagyi, 2008; Taffler and Agarwal, 2008 and others). The continuous distress risk variable used in this study will be taken from the cash flow based bankruptcy prediction model. Second, the variable OPCF is a scaled financial ratio which is made of a rolling four quarter accumulated operating cash flow before interest and taxes paid. Hence, it is understood to be used as proxy for profitability levels.

In order to test the final hypothesis, *$H2_A$c)*, and to answer the main research question whether the anomalous market underperformance of distressed stock can be explained by a parallel analysis based on risk based rational pricing and profitability/earnings levels to return relationship propositions and if there is a conditionality, two pre-conditions need to be fulfilled first.

The first hypothesis below, *$H2_A$a)*, should display the fact that there is a anomalous average underperformance of distressed stock as indicated by prior research (Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008; Agarwal and Taffler, 2008).

The second hypothesis, *$H2_A$b)*, should give certainty that Fama and French's distress factor hypothesis does not hold, hence that the distress risk factor derived from the cash flow based bankruptcy prediction model is not subsumed by Size or book-to-market factors and that it is of incremental independent explanatory power. Dichev (1998), Agarwal and Taffler (2008) and Campbell, Hilscher and Szilagyi (2008) find no evidential support of Fama and French's (1992, 1993) distress factor hypothesis where both size and B/M factors would proxy such distress risk.

The third hypothesis, *$H2_A$c)* , should be confirmed by descriptive and inferential statistics. The descriptive statistics should show that, on average, highly distressed stocks with positive or high profitability earn a premium while those with low or negative profitability produce a reduced or even negative stock return. The cross-sectional regressions' result of a modified Fama-French 3-factor model that includes beta, B/M, distress risk and profitability (as discussed under 3.1) is expected to confirm the descriptive statistics and to dominate the initial 3-factor model (Fama and French, 1992) in describing excess returns by a) an increase in explanatory power of the B/M factor evidenced by improved t-statistics, by b) distress risk and profitability (OPCF) showing both a significant positive premium following the two propositions of risk based rational pricing and positive earnings levels-return relationship and by c) a higher explanatory power of the model as a whole measured by adjusted R^2 while intercepts being indifferent from zero. In addition, a separate model consisting of the two variables profitability and distress risk *only* should confirm whether there is a conditionality between distress risk and profitability evidenced by their interaction term's significance level.

$H2_A$a) Distressed stocks underperform on average non-distressed stocks. *(descriptive statistics 5.6.1, Table 5.6.1.1 and 5.6.4)*

$H2_A$b): The Fama-French (1992, 1993) distress factor hypothesis where both size and B/M factors proxy distress risk does not hold. *(Descriptive Statistics 5.6.1, figure 5.6.1.4 / Pearson's rank correlation: test outline 5.5.3 and test results 5.6.2 / Cross-sectional regression: test outline 5.5.4 and test results 5.6.3)*

$H2_A$c): The anomalous market underperformance of distressed stock can be explained by a parallel analysis of risk based rational pricing and profitability/earnings levels to returns propositions. *(Descriptive statistics 5.6.1, Table 5.6.1.1,5.6.1.6, Figure 5.6.1.1, 5.6.1.6, 5.6.1.33) / Cross-sectional regression: test outline 5.5.4 and test results 5.6.3)*

CHAPTER 4: CASH FLOW BASED BANKRUPTCY PREDICION MODEL

The first phase of this research project is to construct a dynamic cash flow based bankruptcy prediction model. A highly predictive model with low type I and II error rates is obviously an important objective to be achieved in order to obtain valid empirical results. Therefore, I will first outline the details around the construction of the model as shown in this chapter. In a second phase (Chapter 5), I will run regression tests on various factor models which incorporate the relative distress risk and profitability strength factors derived from the cash flow based bankruptcy prediction model.

4.1 Choice of Dependent Variable

A precise definition of the dependent variable is crucial as discussed under 2.1.4.4. The majority of bankruptcy prediction models include companies filing Chapter 11. Beside those going into liquidation some either went through a successful reorganization or a merger & acquisition process. However, the companies of the latter group were not ceasing but continuing to exist from an operational point of view and eventually not experiencing a full loss from a creditor's perspective. Therefore, they will not be viewed as failure in this study. I suggest considering clear-cut failures such as liquidations emerging from Chapter 11 or 7 filings only. I will construct a model, which allows a radical division into healthy and unhealthy or rather dying firms (4.4).

4.2 Choice and Computation of Independent Variables

As discussed in section 2.1.4.1., the vast majority of bankruptcy prediction models use a set of independent variables based on previous studies and rather on a trial-and-error basis than theoretical framework. Therefore, I will apply an identity based cash flow model known as Lawson's Identity (section 2.1.4.2.) in developing and computing the independent variables.

The financial data to be used for the calculation of Lawson's Identity (Table 4.2.1) will be drawn from a statement of cash flows as required by Statement of Financial Accounting Standards (SFAS) No. 95 (Table 4.2.2). This Statement has been effective for firms reporting annual financial statements for fiscal years ending after July 15, 1988. The Financial Accounting Standards Board (FASB) has stated that SFAS No. 95 main purpose is to provide accurate information of a company's cash receipts and cash payment in addition to other accrual based accounting statements. This type of information also provides the information to financial analysts who in turn are able to evaluate a company's capability to generate future cash flows and the company's ability to meet its obligations such as paying interest on debts and servicing loans or to undertake investments and paying dividends. It basically provides all information needed to calculate the variables as defined by Lawson's Identity.

Lawson's Identity

$$(k_j - h_j) - (A_j + R_j - Y_j) - H_j - t_j = (F_j - N_j - M_j) + (D_j - B_j)$$

$k_j - h_j$	is operating cash flow in year j (customer cash payments, k_j, less operating cash flow, h_j
$A_j + R_j - Y_j$	represents net capital investments as result of replacement investment, A_j, plus growth investment, R_j, less the proceeds from asset disposals, Y_j, in year j
H_j	reflects the change in liquidity in year j
t_j	for taxes assessed and paid in year j
F_j	represents interest payments in year j
N_j	is medium and/or long term debt raised or retired in year j
M_j	is short-term debt raised or repaid in year j
D_j	is dividends paid to shareholders in year j
B_j	represents equity capital raised or repaid in year j

A positive $(k_j - h_j)$ reflects a cash inflow whereas positive values of all other variables above represent cash outflow and vice versa.

COMPUSTAT Computation of Lawson's Variables

The quarterly data obtained from COMPUSTAT is formed into six cash flow variables as described below. In a second step, each cash flow variable's current quarter and the three preceding ones are then summed up into a rolling full year in order to overcome the problem of seasonality effects and the issues related to accrual management (although not of significant relevance when using cash flow statement based data). This means that each observation will be made of a rolling four-quarter year, which always includes a fiscal year end close. In a third step, the rolling year cash flow variables are to be scaled to avoid the problem of heteroscedasticity. For feasibility reasons, as done in many other studies, the total asset value will be used as proxy. As result, the cash flow variables as shown will be created and used to develop a bankruptcy prediction model. The selections of independent variables follow a backward and forward inclusion and elimination process as done in many other empirical studies.

Lawson Variable		COMPUSTAT (Industrial Quarterly)
$A_j – R_j – Y_j$	=	DATA111
t_j	=	DATA116
H_j	=	DATA74
$D_j – B_j$	=	DATA89 – DATA84 – DATA93 – DATA114
$F_j – N_j - M_j$	=	DATA115 – DATA86 – DATA75 + DATA92 – DATA112
$k_j – h_j$	=	$(F_j – N_j – M_j) + (D_j – B_j) + (A_j + R_j – Y_j) + H_j + t_j$

Description COMPUSTAT DATA:

DATA115	Interest Paid - Net
DATA86	Long-Term-Debt Issuance
DATA75	Changes in Current Debt
DATA92	Long-Term-Debt Reduction
DATA112	Financing Activities – Other
DATA89	Cash Dividends
DATA84	Sale of Common and Preferred Stock

DATA93	Purchase of Common and Preferred Stock
DATA114	Exchange Rate Effect
DATA111	Investing Activities – Net Cash Flow
DATA74	Cash and Cash Equivalents – Increase/(Decrease)
DATA116	Income Taxes Paid

Table 4.2.1: Lawson-Identity: Overview Cash Flow Variables

STATA Variables	**COMPUSTAT Variables**	**Aziz/Lawson's Variables**
OPCF	**(F – N- M)** $\sum_{q-q\text{-}3}$ + **(D– B)** $\sum_{q-q\text{-}3}$ + **(A – R – Y)** $\sum_{q-q\text{-}3}$ + **H** $\sum_{q-q\text{-}3}$ + **t** $\sum_{q-q\text{-}3}$	**(k – h)** $\sum_{q-q\text{-}3}$
NCAPIN	DATA111	**(A – R – Y)** $\sum_{q-q\text{-}3}$
TAXP	DATA116	**t** $\sum_{q-q\text{-}3}$
CHLIQ	DATA74	**H** $\sum_{q-q\text{-}3}$
DIVEQ	DATA89-DATA84-DATA93- DATA114	**(D– B)** $\sum_{q-q\text{-}3}$
INTLIAB	DATA115-DATA86-DATA75 + DATA92 -DATA112	**(F – N- M)** $\sum_{q-q\text{-}3}$

Note:
$\sum_{q-q\text{-}3}$, stands for the current plus the three preceding quarter data, which adds to a rolling full year on a quarterly basis.

In addition, interaction variables are generated by the use of the above six variables:

STATA Interaction Variables		**Calculation**
OPCF_NCAPIN	=	OPCF * NCAPIN
OPCF_TAXP	=	OPCF * TAXP
OPCF_CHLIQ	=	OPCF * CHLIQ
OPCF_DIVEQ	=	OPCF * DIVEQ
OPCF_INTLIAB	=	OPCF * INTLIAB
NCAPIN_TAXP	=	NCAPIN * TAXP

NCAPIN_CHLIQ	=	NCAPIN * CHLIQ
NCAPIN_DIVEQ	=	NCAPIN * DIVEQ
NCAPIN_INTLIAB	=	NCAPIN * INTLIAB
TAXP_CHLIQ	=	TAXP * CHLIQ
TAXP_DIVEQ	=	TAXP * DIVEQ
TAXP_INTLIAB	=	TAXP * INTLIAB
CHLIQ_DIVEQ	=	CHLIQ * DIVEQ
CHLIQ_INTLIAB	=	CHLIQ * INTLIAB
DIVEQ_INTLIAB	=	DIVEQ * INTLIAB

Table 4.2.2: SFAS # 95: Statement of Cash Flows – Quarterly Format

	STATEMENT OF CASH FLOWS	COMPUSTAT
	Indirect Operating Activities	
+	Income Before Extraordinary Items	**DATA76**
+	Depreciation and Amortization	**DATA77**
+	Extraordinary items and Discontinued Operations	**DATA78**
+	Deferred Taxes	**DATA79**
+	Equity in Net Loss (Earnings)	**DATA80**
+	Sale of Property, Plant and Equipment and Sale of Investments – Loss / (Gain)	**DATA102**
+	Funds from Operations – Other	**DATA81**
+	Accounts Receivable – Decrease / (Increase)	**DATA103**
+	Inventory – Decrease / (Increase)	**DATA104**
+	Accounts Payable and Accrued Liabilities – Increase/ (Decrease)	**DATA105**
+	Income Taxes – Accrued – Increase / (Decrease)	**DATA106**
+	Assets and Liabilities – Other (Net Change)	**DATA107**
=	**Operating Activities – Net Cash Flow**	**DATA108**
	Investing Activities	
-	Increase in Investments	**DATA91**
+	Sale of Investments	**DATA85**
+	Short-Term Investments – Change	**DATA109**
-	Capital Expenditures	**DATA90**
+	Sale of Property, Plant and Equipment	**DATA83**
-	Acquisitions	**DATA94**
+	Investing Activities – Other	**DATA110**
=	**Investing Activities – Net Cash Flow**	**DATA111**
	Financing Activities	
+	Sale of Common and Preferred Stock	**DATA84**
-	Purchase of Common and Preferred Stock	**DATA93**
-	Cash Dividends	**DATA89**
+	Long-Term Debt – Issuance	**DATA86**
-	Long-Term Debt – Reduction	**DATA92**
+	Changes in Current Debt	**DATA75**
+	Financing Activities – Other	**DATA112**
=	**Financing Activities – Net Cash Flow**	**DATA113**
+	**Exchange Rate Effect**	**DATA114**
=	**Cash and Cash Equivalents – Increase / (Decrease)** (DATA108 + DATA111 + DATA113 + DATA114)	**DATA74**
Add'l Data	***Income Taxes Paid***	***DATA116***
	Interest Paid – Net	***DATA115***

4.3 Source of Data

Quarterly financial statement data is extracted from COMPUSTAT's Quarterly Industrial File via the Wharton Research Data Services (WRDS). Some of the information such as deletion code as well as deletion date is downloaded from COMPUSTAT Industrial Annual file. The data obtained from the quarterly and annual files are then merged into a combined new database. Although, COMPUSTAT does provide the reason for deletion such as chapter 11 or 7, the effective date of filing bankruptcy does not relate to such deletion date. Therefore, various sources were checked for bankruptcy filing dates for all bankrupt firms in question such as bankruptcyData.com, secinfo.com, findarticles.com, proquest.com, WSJ-Index and last but not least google.com.

4.4 Sample Selection - Bankrupt Companies

The industry "Computer and Electronic Product Manufacturing" – NAICS Code 334 is one with the highest number of companies operating under distress in the United States. According to the Phoenix Report 2005 – 2006 issued by PricewaterhouseCoopers (2006), the above industry had around 300 public firms in 2003 and 2004 operating under a permanent distress facing potentially bankruptcy, which reflects about 35% of all public firms within this industry in the US. PricewaterhouseCoopers (2006) used Standard & Poor's z-score model developed by Edward Altman and classified companies with z-scores below 1.81 as distressed. As per the definition of bankruptcy (4.1), bankrupt companies are selected meeting the following criteria:

a) NAICS Codes (North American Industry Classification System):

334	**Computer and Electronic Product Manufacturing**
3341	Computer and Peripheral Equipment Manufacturing
3342	Communications Equipment Manufacturing
3344	Semiconductor and Other Electronic Component Manufacturing
3345	Navigational, Measuring, Medical and Control Instruments Manufacturing

b) COMPUSTAT annual slot #35 explains the reason for deletion from the "Industrial Annual Research File" by the footnote codes below:

01	Acquisition or merger
02	Bankruptcy – Chapter 11
03	Liquidation – Chapter 7
09	Now a private company
10	Other

The quarterly data is taken from the COMPUSTAT Industrial File. The group of bankrupt companies consists of companies which went bankrupt under chapter 11 or chapter 7 and which were deleted from the "Industrial Annual Research File" by code 02 and 03. In addition, several companies reported under the code 10 were deleted not only because of voluntary delisting from stock exchange, but because of filing bankruptcy under chapter 11 or 7. Therefore, companies filing bankruptcy, but under footnote code 10 were also added to the group of bankrupt companies. Companies under code 01, 09 and even companies of active status (at discretion of respective stock exchange) may have filed for bankruptcy chapter 11, but are considered to be non-bankrupt in the sample for modelling purpose. The assignment of these companies to the non-bankrupt group goes under the assumption that filing for bankruptcy with subsequent successful restructuring by merger & acquisition, going private or remaining listed on the stock exchange does not constitute a bankruptcy resulting in full shareholder loss as defined under point 4.1..

c) For modelling purposes all companies listed on NYSE, NASDAQ, AMEX as well as OTCBB are included, provided that quarterly financial data has been reported as required by the SEC (US Securities and Exchange Commission). However, OTCBB companies will be dropped in chapter 5 where the pricing of bankruptcy risk is tested. This exclusion is due to the issue of thin trading. Nevertheless, these companies should not get missed for the modelling and for the purpose of validating this bankruptcy prediction model as long as SEC compliant data is available.

d) As previously mentioned, cash flow reporting under SFAS No. 95 (Table 4.2.2) became effective for firms reporting annual financial statements for fiscal years ending after July 15, 1988. Therefore, companies' quarterly data from the years 1988 to 2002 were included in the sample for modelling purpose.

e) The term of bankruptcy in this study follows the definition of legal act, which as discussed (2.1.2) is very much country specific. In order to obtain an acceptable dichotomous dependent variable, which follows the law of one national jurisdiction, companies listed in the United States but with headquarters abroad will be dropped from this sample (deletion of location code 99 in COMPUSTAT's Industrial File). Foreign (non-US) companies may have to comply with very different national laws and procedures and as such may distort the dichotomy of the dependent variable in question. Although, the timing difference between entering an acute state of failure and the act of filing bankruptcy may still vary from company to company within the United States, it is probably still the best indicator of companies facing potential liquidation and a full or near full shareholders' loss.

4.5 Sample Selection – Non-bankrupt Companies

The group of non-bankrupt firms is formed as follows:

a) Taken from same industries as bankrupt firms' definition under 4.4 a)

b) Companies which have not been deleted from the COMPUSTAT Industrial File in the years before 1988 until 2006, which also includes the 4-year-period after the 15 year window are considered to be non-bankrupt. This means that companies that may have filed for Chapter 11, but either

    i) remained listed at discretion of the board of stock exchange, which were not deleted on the COMPUSTAT Industrial File and finally survived as per end of 2006 or
    ii) "survived" as merger & acquisition candidate and finally have been deleted with code "01 Acquisition or merger" (COMPUSTAT annual slot #35) or
    iii) Went private under code "09 Now a private company" (COMPUSTAT annual slot #35)

are considered to be non-bankrupt companies. None of these companies' deletion on the COMPUSTAT Industrial File has been coded either "02 Bankruptcy – Chapter 11" or "03 Liquidation – Chapter 7", but with the codes as mentioned above. As per definition of bankruptcy and the related dichotomous variable, it is also justified to classify these companies as non-bankrupt since they survived in one way or the other until 2006 (after the sample period) and as such most likely have not resulted in a nearly full or full shareholders' loss. Also, the information for delisted companies other than bankruptcy are restricted and in most of the cases not accessible. Hence, any classification attempt for these companies may be subjective as the economic and legal outcome or development is unknown. As result, companies as described under ii) to iii) have been exiting the spell (code 0), but not as failure companies (code 1).

c) All other criteria for inclusion or exclusion of non-bankrupt companies are the same as described for the bankrupt ones above in section 4.4.

As per section 2.1.4.3, the sample should represent the population of all firms. Therefore, I will not use the quite often chosen method of matched pair (50 per cent of each group matched by asset size and industry etc). This would simply result in oversampling of bankrupt firms. Although, Aziz, Emanuel and Lawson (1988) state that an oversampling does benefit the overproportionally high cost of predicting a bankrupt firm. I argue that the cost of prediction is not of relevance for this study to be conducted, it is rather a question of feasibility. In addition, I also plan to measure the relationship between an industry specific portfolio's stock returns and the risk of failure proxied by this bankruptcy prediction model. Therefore, I will only choose one industry and construct a sample specific model in order to make this study feasible for the stated reasons below. All data, both accounting and market data will be drawn from and empirically tested for one specific industry only, but validated with out-of-sample tests (section 4.8) covering the period 2003 to 2006. For the within- and out-of-sample tests I will limit my work to the industry as defined in section 4.4 for the following reasons:

1. I do not expect to gain any additional knowledge by testing the market as a whole, which would be an enormous amount of data to be dealt with

2. Some studies found that bankruptcy predictors may vary from industry to industry. Therefore, I would have to include either additional dummies for specific industries when modelling or simply construct one industry specific model. The latter has been chosen for feasibility reasons and believing that a highly predictive model based on sufficient amount of data can be obtained and be used for relationship testing with equity returns.

4.6 Hazard Model – Cox Proportional Regression Modelling

The data set for bankrupt companies will include quarterly data which is formed into quarterly rolling years. This means that for each company's rolling quarter year there is one observation which includes the information such as ticker name, the cash flow variables as outlined under 4.2.1, the number of period of an observation (used as equivalent to trading age) as well as a binary variable indicating whether the firm has left the spell due to bankruptcy (Code = 1) or because of other reasons like merger & acquisition, delisting, going private or simply because the observations stopped with the 4th quarter in 2002. Unless it is the last observation prior filing bankruptcy, observations are coded with "0". For example, when a bankrupt company has reported 10 quarters of financial statement data prior bankruptcy filing, the 10th observation being the one prior bankruptcy is coded with "1" and all previous quarter observations are coded "0". For non-bankrupt companies all observations up to 60 quarter data (1988 to 2002) are coded "0" regardless when and why they have left the spell during the observation period. All values being lower than the 1st percentile or higher than the 99th percentile, will be replaced with the 1st or 99th percentile in order to remove outliers (section 2.1.3.4). Missing values (very few cases) are replaced by the prior quarter data. This is considered to be conservative since the model will have to deal with data which is more distant to the date of event.

A model with the highest predictive power will be obtained by the test of variables (section 4.2) using a Cox Proportional Hazard model. The stepwise approach is followed to select significant covariates and interactions, but also manually obtained combinations of covariates are examined. The variables selected are then tested for multicollinearity (section 4.7.2). The bankruptcy prediction model will be run for each bankrupt company and for each of the 12 quarters prior the unfortunate event in order to obtain an accuracy of classification matrix.

4.7 Robustness Checks

As with any other model such as ordinary least squares, there are also some checks to be done with the model obtained by the Cox regression. These checks include the testing of the proportional hazards assumption as suggested by Cleves, Gould and Gutierrez (2003) as well as some tests related to multicollinearity, a problem very often found in studies using accounting ratios.

4.7.1 Testing the Proportional Hazards Assumption

The tests based on re-estimation as well as based on Schoenfeld residuals are to be performed in order to obtain certainty that the model has been adequately parameterized and that a good specification for $\mathbf{x}\boldsymbol{\beta}_x$ has been selected.

The first test based on re-estimation is called a "linktest", which is a STATA function and translates into the following equation (Cleves, Gould and Gutierrez 2003):

$$\mathbf{LRH} = \boldsymbol{\beta}_1(\mathbf{x}\hat{\boldsymbol{\beta}}_\mathbf{x}) + \boldsymbol{\beta}_2(\mathbf{x}\hat{\boldsymbol{\beta}}_\mathbf{x})^{\mathbf{2}}$$

The linktest above provides the certainty that the coefficient on the squared linear predictor is significant and that if the hazard model is properly specified, one should not be able to find additional independent variables that are significant. First, β_x needs to be estimated from the standard Cox model and than β_1 and β_2 from a second round model. If we expect $x\beta_x$ to be the correct model specification, β_1 has to equal 1 and β_2 has to equal 0. In order to facilitate this above test, the linktest creates two new variables called **_hat** and **_hatsq**, which then gets refitted using these two variables as predictors. If the model is correctly specified one should expect variable **_hat** to be significant since it is the predicted value $\boldsymbol{\beta}_1(\mathbf{x}\hat{\boldsymbol{\beta}}_\mathbf{x})$. The second variable **_hatsq** $\boldsymbol{\beta}_2(\mathbf{x}\hat{\boldsymbol{\beta}}_\mathbf{x})^{\mathbf{2}}$ is expected to be insignificant because the squared predictions should not result in much explanatory power. Therefore, **_hat** should yield in a p-value lower or equal 0.05 and **_hatsq** should as result of insignificance have a p-value higher than 0.05. If the model detects the presence of omitted variables by **_hatsq** being significant, a partially new model needs to be reconfigured again. This test is performed under 4.9.3.1.

The second test of the proportional hazards assumption suggested by Cleves, Gould and Gutierrez (2003) is called the Schoenfeld residual test (1982).

$$r_s = c_i(x_{ik} - \hat{\bar{x}}_{w_i k})$$
$$where$$
$$\hat{\bar{x}}_{w_i k} = \frac{\sum x_{jk} e^{x_j'\hat{\beta}}}{\sum_{j \in R(ti)} e^{x_j'\hat{\beta}}}$$

The scaled Schoenfeld residuals $\mathbf{r_s}$ of time dependent covariates are used to be tested for a non-zero slope in a generalized linear regression. This can be performed by STATA's "stphtest" command (Grambesch and Therneau, 1994). It tests for each individual covariate as well as on global basis the null hypothesis of zero slopes. This happens by the regression of the residuals of each covariate over time. The expected value of the covariate at time *t* is a weighted average of the covariate, weighted by the likelihood of failure for each individual in the risk set at *t*. Since the Schoenfeld residuals are in principle independent from time, a non-zero slope or the rejection of the null hypothesis is an indication of violation of the proportional hazard assumption. Therefore, a level line close to zero has to result in order to hold the proportional hazard assumption. This test is performed in section 4.9.3.1.

4.7.2 Testing for Multicollinearity

Not having high multicollinearity is an assumption of Cox regression, as in other forms of regressions. One problem, which potentially could arise, is multicollinearity among independent variables since financial ratios have quite often the same numerator or denominator. In this study the common denominator is total assets, which has been used to scale the cash flow variables. If there were multiple highly correlated covariates, it is preferred to include only one variable from the set of correlated variables. Therefore, Spearman's rank correlation tests are conducted for each pair of variable. Spearman's test is an alternative to Pearson's correlation since it is more resistant to outliers and it is a non-parametric test which does not make any assumptions regarding frequency distribution of the variables. Since I use the semi-parametric Cox proportional model assuming a potential non-normality distribution, Spearman's test appears to be most appropriate for this purpose. In a perfect world, all independent variables would be completely independent and unrelated to each other, but reality shows though that virtually every multiple regression has some collinearity between the independent covariates. There are no clear-cut rules about the level of collinearity to be excluded from a model, but if it exceeds 0.75 it would probably make sense to drop one of the highly correlated variables and to rework the model specification again. This test is performed in section 4.9.3.2.

4.8 External Validation by Hold-Out Sample and Benchmark

In addition to the robustness checks as described in section 4.7, it is well documented that empirically derived bankruptcy models very often lose their predictive power or forecasting ability when applied ex ante (Grice and Ingram 2001; Begley, Ming and Watts 1996). One method for the model validation is the use of a hold-out sample. The idea is that the model obtained from the primary data set covering the years 1988 to 2002 will be run thru a new unrelated data set and tested for its accuracy rates of bankruptcy prediction classifications (section 4.8.1). In addition, the result of the hold-out sample will be benchmarked with Altman's Z-Score model by using a Receiver Operating Characteristics curve as discussed under section 4.8.2 below.

4.8.1 Hold-Out Sample

The selection of bankrupt and non-bankrupt companies follows the same procedures as described in sections 4.3 to 4.5. Also, the sample includes the companies from the same industries as outlined in section 4.4 and covers the period 2003 - 2006. The classification results are to be compared to the model sample (1988 to 2002) for both categories, the bankrupt and the non-bankrupt firms.

4.8.2 Receiver Operating Characteristic (ROC) Benchmark with Z-Score

The Receiver Operating Characteristics (ROC) curve, as discussed in all details by Sobehart et al. (2000), is a widely accepted method to measure the overall prediction accuracy across multiple models (Chava and Jarrow (2004); Agarwal and Taffler, 2008). The benchmark with Altman's Z-Score Model, as briefly discussed further below, is based on the application of the ROC model by using the hold-out sample for the years 2003 to 2006. This allows comparing both models with data not being used for modelling purposes. Following Agarwal and Taffler (2008), the areas under the curve are estimated by the use of the Wilcoxon statistic (Hanley and McNeil, 1982) and evaluated by the Hanley and

McNeil (1983) test statistics that adjust for the correlation resulting from the application of the two models on the same sample. The ROC curves are constructed by ranking a model's risk of failure from high to low and are linked with a firm's effective status of failure or non-failure for each quarter in the period from 2003 to 2006. The model measures to what extent firms failed are actually found within the first percentage of firms being predicted high risk failure candidates. This analysis (result see figure 4.9.4) will provide both the area under the curve (AUC) and, as a simple linear transformation (Engelmann et al., 2003; see below), the accuracy ratio (AR) for each of the models tested.

Accuracy Ratio = 2 * (area under ROC curve – 0.50)

An AUC value of 0.5 which is an AR of 0.00 is considered to be a random model which has no predictive ability. A perfect model would result in an AUC value of 1.0 corresponding to an AR of 1.00. The results of this benchmark are discussed under section 4.9.6 and depicted in figure 4.9.4.

The benchmark model as previously mentioned is the Z-Score model (Altman, 1968). This model derived from an MDA analysis as described in section 2.1.3.2 still enjoys popularity in the industry and is shown below:

$$\mathbf{Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5}$$

where:

X_1 = working capital/total assets

X_2 = retained earnings/total assets

X_3 = earnings before interest and taxes/total assets

X_4 = market value equity/book value of total liabilities

X_5 = sales/total assets

Z = overall index

The first difference between the cash flow based prediction model of this study and the Z-Score is obviously given by the fact the Altman's variables above are accrual based accounting ratios with the exception of market value equity. In this study cash flow based accounting variables are used only. The second difference is that the Z-Score model has not been developed using panel data company information, but it has been constructed using cross-section data only. Other differences of the Z-Score compared to the cash flow based prediction model is provided by the facts that a) it is a multiple non-industry specific model which primarily includes manufacturing firms, b) it has been based on a matched pair sample selection process of an initial 66 firms consisting of 33 healthy and 33 bankrupt firms only. As result, the Z-Score relies on much fewer observations than this study's cash flow derived model which is expected to be built on more than 1,000 firms consisting of almost 40,000 firm quarter observations. Although, it is not the ultimate goal to achieve better results by the use of this new cash flow based bankruptcy prediction model, it is of importance to obtain validation by the ROC benchmark and to provide probabilities of going bankrupt as well as cash flow coefficients for either type of companies. Overall, I expect to obtain a highly predictive model with an accuracy ratio of at least the same level as achieved by Altman's Z-Score, which can be used for the tests to be conducted as described in chapter 5. Both data sets, within- and out-of-sample are expected to provide the probabilities of failure as well as related cash flow coefficients which can be used for asset pricing and portfolio testing as outlined in section 5.1.

4.8.3 Distress Risk a Continuous Probability of Default Measure

As previously mentioned, the probabilities of bankruptcy risk derived from the cash flow based bankruptcy prediction model are used as a proxy for the asset pricing tests related to distress risk. Although, the predictive power of such model may be superior in an out-of-sample benchmark test, it still needs to be tested for its measure characteristic to see if it is a continuous or binary default risk measure. Depending on its outcome, the distress risk factor to be used for subsequent assets pricing tests would be either the probabilities of going bankrupt when continuous or simply binary with 0 or 1.

In section 4.9.7, the distress risk measure is tested by tabulating the probability of default deciles against the failure rates to evaluate first, if it is a continuous measure and second if there is an appropriate degree of association.

4.9 Results

4.9.1 Results on Selection and Data Obtained (Descriptive)

Following the selection process as outlined in sections 4.4 and 4.5, the summary statistics is reported as shown in Table 4.9.1.1. The statistics is limited to the four variables of the model obtained in section 4.9.2. The dataset consists of 39'164 quarterly calculated full years on quarterly rolling basis. This total number of observations stems from 1'183 firms. 2'309 observations are derived from 82 bankrupt firms as per Table 4.9.1.2 and another 36'855 observations from 1'101 non-bankrupt firms. The top 50 companies of the non-bankrupt firms are listed in Table 4.9.1.3 and the smallest 50 non-bankrupt ones are shown in Table 4.9.1.4. The summary statistics (table 4.9.1.1) reveals expected differences between the two groups. The overall operating cash flow variable (OPCF) which is scaled by total assets shows that the mean of *all* firm observations is negative 0.007. This means that this industry produces on average negative cash flows from operating activities. This is not surprising, since the PricewaterhouseCoopers study (2006) has indicated that more than 35% do operate in a near bankruptcy mode. I will not go into further discussion why under normal circumstances negative cash flows from operating activities may result in bankruptcy one day. Also, the scaled OPCF mean of -0.162 for the bankrupt group reflects higher cash drains compared to positive 0.003 for non-bankrupt companies, which supports the fact that positive cash flows from operating activities are vital. The next variable TAXP which reflects the cash flow component "tax paid" does also meet expectations, at least from an intuitive point of view. A negative TAXP in this study means that taxes were paid, which is normally the case when profits were produced as well as in most cases cash was generated and where potential losses from previous periods did not offset all taxes due from the current reporting period. Therefore, the mean of TAXP with -0.018 for the non-bankrupt group is more negative than the one for the bankrupt group. The third variable INTLIAB basically reflects the cash flow from debt financing activities including interest being paid. The mean of INTLIAB with -0.001 for non-bankrupt firms is less negative than the one for bankrupt firms with a mean of -0.017. The interpretation of negative mean for this variable is that there is a net cash outflow from long-term debt retirement over debt financing. Bankrupt companies may be forced to repay their debts at faster rate their non-bankrupt counterparts, which in turn may leverage their company given their healthy status even further. Debt financing may secure the company's financial position to a certain extent but it appears that it is more difficult to obtain for bankruptcy candidates, which in turn may lead to liquidity issues. Overall, the ability to repay debt and pay interests is considered to be obviously a stronger factor of survivability than increasing a company's debt position. The last interaction variable OPCF_TAXP is the product of OPCF and TAXP. The interaction term shows a conditionality between operating cash flow and taxes paid. This is obvious since a unit increase / (decrease) in operating cash flows (assuming the same impact on taxable profits) will increase / (decrease) the taxes to be paid accordingly.

Table 4.9.1.1 : Summary Statistics

Variable	Obs	Mean	Std. Dev.
OPCF	39'164	-0.007	0.632
INTLIAB	39'164	-0.002	0.159
TAXP	39'164	-0.017	0.028
OPCF_TAXP	39'164	-0.003	0.007

Bankrupt Firms

Variable	Obs	Mean	Std. Dev.
OPCF	2'309	-0.162	0.493
INTLIAB	2'309	-0.017	0.222
TAXP	2'309	-0.006	0.020
OPCF_TAXP	2'309	-0.001	0.005

Non-Bankrupt Firms

Variable	Obs	Mean	Std. Dev.
OPCF	36'855	0.003	0.638
INTLIAB	36'855	-0.001	0.154
TAXP	36'855	-0.018	0.028
OPCF_TAXP	36'855	-0.003	0.007

Table 4.9.1.2 shows the list of 82 bankrupt companies. It clearly demonstrates that companies of all kind of size measured by total assets prior bankruptcy have filed for bankruptcy and therefore are included in this sample. The largest three in the years 1988 to

2002 were Memorex Telex with assets exceeding $ 1bn, Commodore International with total assets of $ 266m or Everex Systems with $ 255m prior filing bankruptcy. Obviously the value of assets was significantly higher in the years prior failure. The smallest bankrupt firms measured by total assets prior bankruptcy filing were Solopoint with $ 212k, Zonic with $ 625k or Scientific Measurement System with $ 642k. The list also reveals that the majority of companies were delisted as result of filing bankruptcy under Chapter 11 and only a few went straight into liquidation thru Chapter 7.

For the non-bankrupt firms table 4.9.1.3 shows the largest 50 companies of this industry as per Q1 in 2000 consisting of reputable firms such as Intel Corp. with total assets of $ 48bn, Motorola Inc with $ 43bn, Hewlett Packard Corp with $ 34bn, Xerox Corp with $30bn or Compaq (before merger with HP) with $28bn to name a few. However, also in this group, small companies were included in the sample for modelling purpose. Table 4.9.1.4 shows the 50 smallest non-bankrupt firms of this industry as per Q1 in 2000 with total assets in the range of $ 1 to 4m only.

Table 4.9.1.2 : List of Bankrupt Companies – Original Sample (N=82)

Company Name	SMBL	Ttl Assets prior Filing in $'000	Filing Type	Filing Date
ACCENT COLOR SCIENCES INC	ACLR	2.441	CH 7	06/29/2001
ADAPTIVE BROADBAND CORP.	ADAPQ	130.879	CH 11	07/26/2001
ALLIANT COMPUTER SYSTEMS CP	3ALCS	40.739	CH 11	05/27/1992
ALLOY COMPUTER PRODUCTS INC	AYCP	3.596	CH 11	06/15/1992
ARIX CORP	8578B	9.488	CH 11	12/16/1991
ASD GROUP INC	ADGJ	6.279	CH 11	06/05/2001
ASTROSYSTEMS INC	3ASTZ	43.855	CH 7	11/02/1995
AT COMM CORP	3ATCME	2.600	CH 11	08/15/2001
AT&E CORP	7200B	10.085	CH 11	07/02/1991
AUREAL INC	AURLQ	18.199	CH 11	04/05/2000
AXIOHM TRANSACTION SOLUTIONS	AXHM10	153.657	CH 11	11/08/1999
CALCOMP TECHNOLOGY INC	3CLCP	183.067	CH 11	12/30/1998
CARVER CORP	CAVR	5.169	CH 11	01/31/1999
CEL COMMUNICATIONS	3CELCE	5.344	CH 11	08/22/1994
CELLEX BIOSCIENCES INC	3CLXX.	14.270	CH 11	10/06/1998
CHATCOM INC	CHAT	1.764	CH 11	09/08/1999
CINCINNATI MICROWAVE INC	CNMWQ	22.631	CH 11	02/14/1997
CIRCUIT SYSTEMS INC	CSYI	89.229	CH 11	09/05/2000
CODED COMMUNICATIONS CORP	CODDQ	1.926	CH 11	12/10/1998
COMMODORE INTL LTD	3CBUIF	265.800	CH 7	05/02/1994
COMPTRONIX CORP	3CPTX.	22.788	CH 11	08/12/1996
CRAY COMPUTER CORP	CRYYQ	26.166	CH 11	03/24/1995
DATA RACE INC	RACE	2.873	CH 7	06/28/2002
DIGITAL PRIVACY INC	3DGPVE	8.435	CH 11	09/01/1999

Cont. Table 4.9.1.2: List of Bankrupt Companies – Original Sample (N=82)

Company Name	SMBL	Ttl Assets prior Filing in $'000	Filing Type	Filing Date
DIGITAL TRANSMISSION SYSTEMS	DTSX	2.861	CH 11	06/03/2002
DYNATEC INTERNATIONAL INC	DYNX	4.982	CH 11	11/14/2001
EA INDUSTRIES INC	EAIN	43.072	CH 11	05/21/1999
EIP MICROWAVE INC	3EIPME	2.087	CH 11	05/11/1999
ELCOTEL INC	EWTLQ	56.800	CH 11	01/22/2001
EVEREX SYSTEMS INC	EVXS	254.818	CH 11	01/04/1993
FASTCOMM COMMUNICATIONS CORP	FSCXQ	3.048	CH 11	05/03/2002
FIBERCORP INTERNATIONAL INC	3FCIIE	3.771	CH 11	01/16/1996
FIFTH DIMENSION INC	3FIVDE	2.237	CH 11	01/06/1998
FINGERMATRIX INC	3FINX.	1.058	CH 11	09/22/1993
FIRST PACIFIC NETWORKS INC	FPNQ	11.502	CH 11	02/10/1997
GADZOOX NETWORKS INC	ZOOXQ	10.405	CH 11	08/22/2002
GENICOM CORP	GECMQ	191.482	CH 11	03/10/2000
GENISCO TECHNOLOGY	GESJ	4.215	CH 11	02/21/1995
GLOBAL TECHNOVATIONS INC	GTNOQ	59.291	CH 11	12/18/2001
HENLEY HEALTHCARE INC	HENL	0.075	CH 7	10/19/2001
HOME THEATER PRODS INTL INC	HTPI	34.206	CH 11	04/03/1996
INTEGRATED TELECOM EXPRESS INC	ITXI	28.035	CH11	10/08/2002
INTELLIGENT MED IMAGING INC	IMIIQ	3.514	CH 11	11/29/1999
IRT CORP	3IXTC	17.251	CH 11	07/27/1994
JETRONIC INDUSTRIES INC	JETN	14.990	CH 11	11/22/2000
MEDIA LOGIC INC	MDLG	5.641	CH 11	11/12/1998
MEMOREX TELEX	3MEMXY	1'041.538	CH 11	02/11/1994
MICRO SECURITY SYSTEMS INC	3MISYE	1.652	CH 11	07/21/1994
MICROENERGY INC	3MICRE	4.565	Liq.	08/27/1999
MONITERM CORP	MTRMQ	9.914	CH 11	11/11/1991

Cont. Table 4.9.1.2: List of Bankrupt Companies – Original Sample (N=82)

Company Name	SMBL	Ttl Assets prior Filing in $'000	Filing Type	Filing Date
MOSLER INC	4360B	196.053	CH 11	08/06/2001
NATIONAL MFG TECHNOLOGIES	NMFG	14.901	CH 11	11/14/2001
NEWSTAR MEDIA INC	NWST	21.233	CH 11	06/26/2000
NEXIQ TECHNOLOGIES INC	NEXQQ	12.645	CH 11	10/11/2002
NUMBER NINE VISUAL TECH CORP	IPMG	6.153	CH 11	12/20/1999
OMNI MULTIMEDIA GROUP INC	OMMG	25.396	CH 11	11/14/1997
PHOENIX LASER SYS INC	3PXSYE	9.636	Liq,	04/07/1994
PINNACLE MICRO INC	PNLEQ	4.275	CH 11	04/20/2000
PLATINUM ENTERTAINMENT INC	PTETQ	43.466	CH 11	07/26/2000
POWER DESIGNS INC	3POWDQ	1.945	CH 11	01/22/1998
PREMIER LASER SYS	PLSIQ	20.863	CH 11	03/10/2000
PRISM GROUP INC	3PRSME	7.132	CH 7	08/29/1996
REXON INC	REXQ	84.591	CH 11	09/13/1995
SABRATEK CORP	SBTKQ	151.878	CH 11	12/17/1999
SCIENTIFIC MEASUREMENT SYS	3SCMS	0.642	CH 7	12/13/2000
SHELDAHL INC	3SHELQ	56.936	CH 11	04/30/2002
SOLOPOINT INC	SLPT	0.212	Liq.	11/21/2000
SSE TELECOM INC	SSET	10.566	CH 11	05/17/2001
STORMEDIA INC	STMDQ	146.973	CH 11	10/11/1998
STREAMLOGIC CORP	3521B	49.789	CH 11	06/26/1997
SUNRISE TECHNOLOGY INTL INC	SNRS	18.863	CH 7	09/23/2002
SYMBOLICS INC	SMBXQ	11.311	CH 11	01/28/1993
SYQUEST TECHNOLOGY INC	SYQTQ	115.879	CH 11	11/17/1998
TEMPEST TECHNOLOGIES INC	3TEMK	4.344	liq.	04/15/1992
TSL HOLDINGS INC	TSLHQ	183.183	CH 11	03/05/1993
VIDIKRON TECHNOLOGIES GROUP	VIDI	11.480	CH 7	11/12/1999

Cont. Table 4.9.1.2: List of Bankrupt Companies – Original Sample (N=82)

Company Name	SMBL	Ttl Assets prior Filing in $'000	Filing Type	Filing Date
VOICE IT WORLDWIDE INC	3MEMO	4.356	CH 11	11/02/1998
VOXEL	VOXQ	2.468	CH 7	08/07/1998
WEITEK CORP	3WWTK	5.183	CH 11	12/11/1996
XETEL CORP	3XTELE	37.733	CH 11	10/21/2002
ZENITH ELECTRONICS CORP	ZE	317.500	CH 11	08/23/1999
ZONIC CORP	3ZNICE	0.625	CH 11	06/22/2001

Table 4.9.1.3: Top 50 Non-Bankrupt Companies – Original Sample

Ranked by Total Assets as of Q1/2000

No.	SMBL	Company Name	Ttl Assets $m
1	INTC	INTEL CORP	47'811
2	MOT	MOTOROLA INC	43'159
3	HPQ	HEWLETT-PACKARD CO	34'108
4	XRX	XEROX CORP	30'498
5	CPQ	COMPAQ COMPUTER CORP	28'001
6	RTN	RAYTHEON CO	27'002
7	CSCO	CISCO SYSTEMS INC	26'085
8	TXN	TEXAS INSTRUMENTS INC	17'500
9	SUNW	SUN MICROSYSTEMS INC	12'502
10	DELL	DELL INC	12'023
11	NOC	NORTHROP GRUMMAN CORP	9'389
12	GLW	CORNING INC	9'014
13	JDSU	JDS UNIPHASE CORP	7'944
14	EMC	EMC CORP	7'759
15	MU	MICRON TECHNOLOGY INC	7'735
16	SEG.	SEAGATE TECHNOLOGY	7'380
17	A	AGILENT TECHNOLOGIES INC	7'321
18	AAPL	APPLE COMPUTER INC	7'007
19	QCOM	QUALCOMM INC	6'144
20	SLR	SOLECTRON CORP	5'922
21	COMS	3COM CORP	5'813
22	MDT	MEDTRONIC INC	5'669
23	LORL	LORAL SPACE & COMMUNICATIONS	5'545
24	TMO	THERMO ELECTRON CORP	5'177
25	NCR	NCR CORP	4'794
26	AMD	ADVANCED MICRO DEVICES	4'638
27	GTW	GATEWAY INC	4'053
28	CNXT	CONEXANT SYSTEMS INC	3'844
29	LSI	LSI LOGIC CORP	3'514
30	SCI.1	SCI SYSTEMS INC	3'284
31	DHR	DANAHER CORP	3'206
32	ETS	ENTERASYS NETWORKS INC	3'167
33	ABI.CM	APPLERA CORP-CONSOLIDATED	2'754
34	ATML	ATMEL CORP	2'689
35	ADI	ANALOG DEVICES	2'669
36	SGID	SILICON GRAPHICS INC	2'516
37	TLAB	TELLABS INC	2'482
38	ADCT	ADC TELECOMMUNICATIONS INC	2'426
39	VSH	VISHAY INTERTECHNOLOGY INC	2'405
40	HRS	HARRIS CORP	2'383
41	XLNX	XILINX INC	2'349
42	MOLX	MOLEX INC	2'283
43	NSM	NATIONAL SEMICONDUCTOR CORP	2'273
44	AMKR	AMKOR TECHNOLOGY INC	2'066
45	BEC	BECKMAN COULTER INC	2'029
46	SANM	SANMINA-SCI CORP	1'934
47	LLL	L-3 COMMUNICATIONS HLDGS INC	1'912
48	IN	INTERMEC INC	1'813
49	VTSS	VITESSE SEMICONDUCTOR CORP	1'793
50	TER	TERADYNE INC	1'753

Table 4.9.1.4: Smallest 50 Non-Bankrupt Companies – Original Sample

Ranked by Total Assets as of Q1/2000

No.	SMBL	Company Name	Ttl Assets $m
1	3HSYN	HOMELAND SECURITY NETWRK INC	1
2	MGTC	MEGATECH CORP	1
3	CDOC	PANDA PROJECT INC	1
4	3DYTM	DYNATEM INC	1
5	NVEC	NVE CORP	1
6	3DIAC	DIAPULSE CORP OF AMERICA	1
7	3IAUS	INTL AUTOMATED SYSTEMS INC	1
8	3MMTC	MICRO IMAGING TECHNOLOGY INC	1
9	3ISEC	ISECURETRAC CORP	1
10	TTLO	TOROTEL INC	2
11	CLSI	CLANCY SYSTEMS INTL INC	2
12	DION	DIONICS INC	2
13	3CRLI	CIRCUIT RESEARCH LABS INC	2
14	SPHG	SP HOLDING CORP	2
15	3SPHG	SP HOLDING CORP	2
16	VRTC	VERITEC INC	2
17	3MDTA	MEGADATA CORP	2
18	3DLNKQ	DECISIONLINK INC	2
19	3CBEX	CAMBEX CORP	2
20	3VSNI	VISEON INC	2
21	3PKPT	PACKETPORT.COM INC	2
22	3BLFS	BIOLIFE SOLUTIONS INC	2
23	3DYXC	DIASYS CORP	2
24	3ADOT	ADVANCED OPTICS ELECTRONICS	2
25	3ELST	ELECTRONIC SYSTEM TECH INC	2
26	BSM	BSD MEDICAL CORP/DE	2
27	TLDT	TELIDENT INC	3
28	3CYBD	CYBER DIGITAL INC	3
29	PMDL	PACE MEDICAL INC	3
30	DLFG	DIGITAL LIFESTYLES GROUP INC	3
31	LGMTA	LOGIMETRICS INC	3
32	CRII	CELL ROBOTICS INTL INC	3
33	ISWI	INTERACTIVE SYSTEMS WORLDWDE	3
34	3IGTI	IMAGE GUIDED TECHNLGIES INC	3
35	3WTRO	WI-TRON INC	3
36	3IEHC	IEH CORP	3
37	3SNSGE	SENSE TECHNOLOGIES INC	3
38	CYDI	CYBRDI INC	3
39	DDVS	DISTINCTIVE DEVICES INC	3
40	3IDCP	NATIONAL DATACOMPUTER INC	3
41	SMTS	SOMANETICS CORP	3
42	ECI	ENCISION INC	3
43	3IZZI	INTEGRATED SECURITY SYS INC	3
44	USXX	US TECHNOLOGIES INC	4
45	TLTN	TELTONE CORP	4
46	3EDIG	E DIGITAL CORP	4
47	3SRMC	SIERRA MONITOR CORP	4
48	VLFG	VALLEY FORGE SCIENTIFIC CORP	4
49	3VYTC	VYTA CORP	4
50	3GVIS	GVI SECURITIES SOLUTIONS INC	4

4.9.2 Results on Hazard Model and Coefficients

Following the stepwise as well as a manual analysis procedure as mentioned in section 4.6, a hazard model has been derived from initially six cash flow and related interaction variables (see table 4.2.1). This model has been finally constructed not by the use of the backward and forward stepwise regression technique, but rather by manually compiling the covariates following the criteria of leverage (INTLIAB), operating cash flow (OPCF) and tax payments (TAXP). All three type of cash flow streams are thoroughly discussed and tested in previous studies and very often have found to be significantly related to bankruptcy risk:

Table 4.9.2.1: Cash Flow Bankruptcy Prediction Model: Coefficients & Hazard Rates

Variable	Coefficient	Hazard Ratio	P-Value
OPCF	-1.20624	0.2993203	0.0000
INTLIAB	1.07194	2.921037	0.0330
TAXP	28.64360	2.75E+12	0.0060
OPCF_TAXP	148.48430	3.06E+64	0.0350

As shown above, all four variables with p-values lower than 0.05 are significant. This suggests that these variables have statistically a significant impact on measuring the likelihood of transiting into bankruptcy. Additional robustness checks of the model are performed in section 4.9.3. The hazard ratios of the model clearly confirm the interpretation as given by the descriptive statistics (section 4.9.1). If a hazard ratio is less than one, it indicates a positive influence on the likelihood of observing a non-transition into bankruptcy and if a hazard ratio is more than 1 it obviously indicates the opposite, a positive relation to bankruptcy or an increased likelihood of failure. Now, following up the interpretation of each variable's mean value (section 4.9.1) the above model's impact on observations for each variable can be explained as follows:

OPCF which represents cash flows from operating activities is linked to a hazard ratio of 0.299. For each additional unit of positive cash flow, it is less likely to make the transition into bankruptcy, which makes perfectly sense also from a valuation point of view. TAXP is the cash flow component which indicates "Taxes paid". In this model, observations for taxes paid are negative numbers. Unless it is a matured start-up company with tax losses to be carry forward, profitable and cash generating companies pay taxes. This fact should by intuition result in a negative relation to bankruptcy and therefore in a lowered risk of going bankrupt. TAXP's hazard ratio is 2.75e+12 and above 1. The large coefficients on TAXP and OPCF_TAXP are the function of scale. Therefore, if a company pays high taxes it will produce a negative TAXP and as such reduce the likelihood of failure. In addition, TAXP has some incremental explanatory power to OPCF or vice versa. One could argue that TAXP and OPCF strongly correlate and as such lead to model misspecifications. However, TAXP gives also some information about a company's taxable income and related operating cash flows over time. Start-up companies with significant tax credits to be offset with future taxable income or restructured companies, which have incurred recurring hefty losses and negative cash flows followed by profitability are most likely at higher risk than stable long-lasting cash generating companies. The coefficient may provide this additional risk content and explanatory power to the model as a whole. Aziz, Emanuel and Lawson (1988) also found that TAXP was the most important contributor to the model followed by OPCF, but for all other four variables, ranks were considered to be unstable over time (Aziz, Emanuel, Lawson 1988). In this study however, another two variables were found to be significant over the entire time span. INTLIAB which basically reflects the lender's cash flow (short-term and long-term debt financing and repayment plus interest payments) also shows a hazard ratio of more than 1. The excess amount of repayments of debts over long-term and short-term debts raised is represented by a negative number, which means that if a company repays its loans on a net basis and if it pays its interest due there is an increased likelihood to survive. However, if a company raises additional debt, it may help to stabilize its financial condition on a short-term basis or finance future investments and anticipated dividend growth. Nevertheless, a company increasing its financial leverage reflected by a positive INTLIAB is more likely to transition into bankruptcy given the hazard ratio of 2.92 and its uncertainty of anticipated future dividend growth. It is a balancing act between leveraging a company and generating sufficient operating cash flows as reflected by the model's coefficients. These findings also confirm the results of previous studies (Zavgren, 1985 and Ohlson, 1980). The last variable OPCF_TAXP is an interaction variable of the first two mentioned above. Its hazard ratio lies in between the ones of OPCF and TAXP and as such has an interacting effect to the model as a whole. The remaining two variables NCAPIN (net capital investment) and DIVEQ (equity raised or repaid plus dividends paid) beside other interaction variables were not included first as result of insignificance with p-values higher than 0.05 and second to avoid statistical over-identification. Overall, it can be said that there is a clear divergence in the group means of variables as bankruptcy approaches (section 4.9.1). In addition, there is also empirical evidence given the model above that supports the use of cash flow variables based on Lawson's identity (section 4.2).

4.9.3 Results on Robustness Checks

As with any other model like those based on ordinary least squares, there are also some checks to be done with the Cox regression model. These checks include the testing of the proportional hazards assumption as suggested by Cleves, Gould, Gutierrez (2003) as well as some tests related to multicollinearity, a problem very often found in studies using accounting ratios. A brief overview related to these tests is provided in sections 4.7.1 and 4.7.2.

4.9.3.1 Test Results on Proportional Hazards Assumption

The first test on the proportional hazards assumption performed is the linktest. This test of the model specification as presented by Table 4.9.3.1 is done in accordance with section 4.7.1 to ensure that the model is correctly specified and no omitted variables are detected.

Table 4.9.3.1: Linktest

Linktest

_t	Coef.	Std. Err.	z	P>z	95% Conf. Interval	
_hat	1.157895	0.191320	6.05	0.00	0.78292	1.53288
_hatsq	-0.117174	0.098148	-1.19	0.23	-0.30954	0.07519

The variable _hat with its p-value 0.000 is significant, which is expected by the model. The second variable with a p-value of 0.23 is considered to be insignificant, which means that the model (Table 4.9.2.1) is specified correctly and that adding variables would not lead to an improvement of the model's explanatory power.

The second test on the proportional hazards assumption is one based on the analysis of Schoenfeld residuals as outlined in section 4.7.1. The test on each covariate as well as on the model as a whole (Grambesch and Therneau, 1994) revealed the following results as shown in Table 4.9.3.2:

Table 4.9.3.2: Schoenfeld Residuals Test

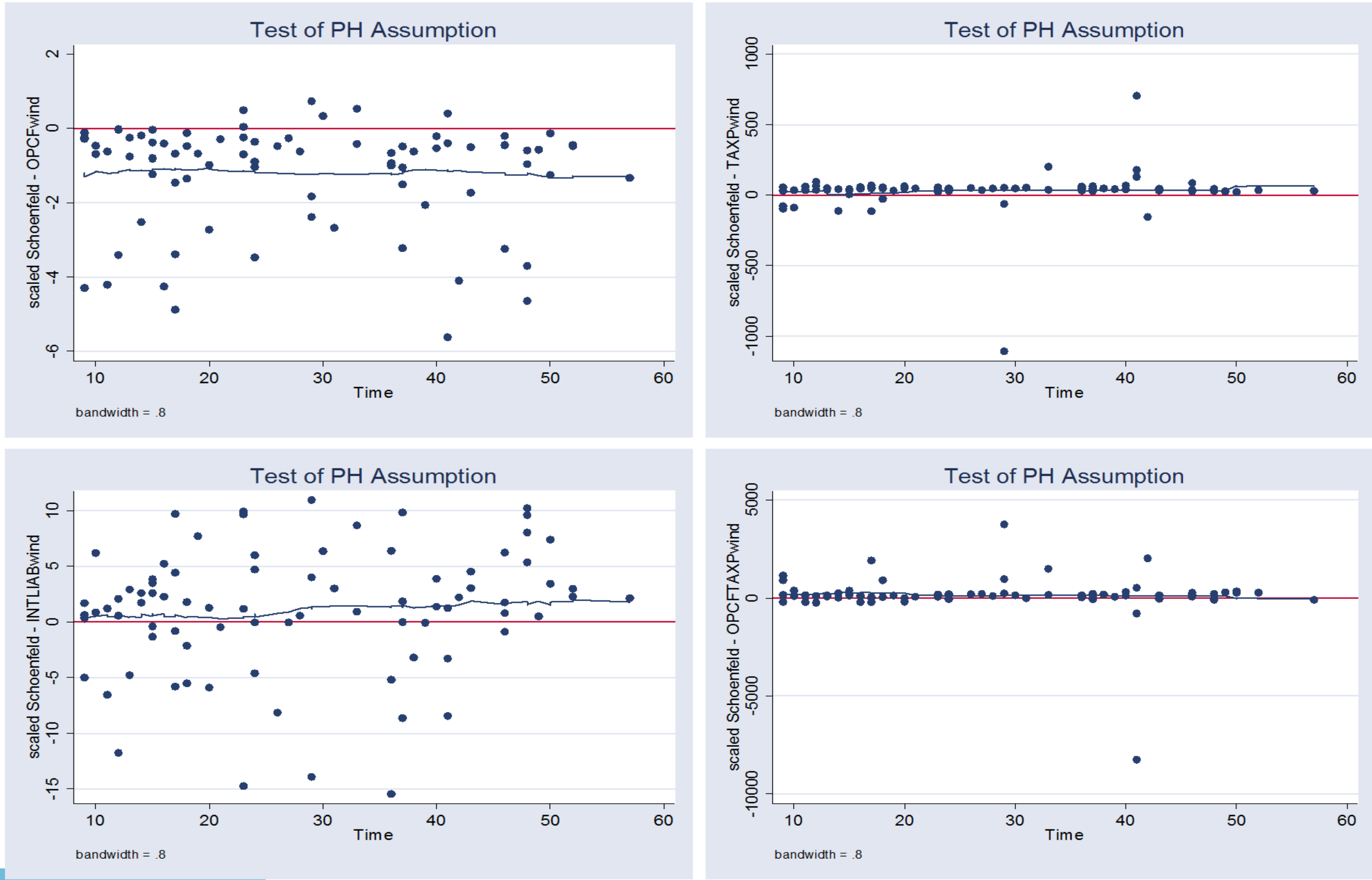
Test of proportional hazards assumption

Time: Time

	rho	chi2	df	Prob>chi2
OPCF	-0.03144	0.06	1	0.8097
TAXP	0.09852	2.15	1	0.1427
INTLIAB	0.17208	3.74	1	0.0531
OPCF_TAXP	-0.08614	1.77	1	0.184
global test		7.04	4	0.1339

The results for each covariate as well as for the global test show that the proportional hazards assumption holds. Since the Schoenfeld residuals are in principle independent from time, a non-zero slope or the rejection of the null hypothesis is an indication of violation of the proportional hazard assumption. Therefore, a level line close to zero has to result in order to hold the proportional hazard assumption. For that purpose, the plots, presented by Figure 4.9.1 were generated for each of the covariates to visually verify the zero slope assumption. The plots clearly show a line near zero and it also confirms that the Schoenfeld residuals of each covariate are time independent. The null hypothesis cannot be rejected and as such it can be concluded that model does hold the proportional hazard assumption.

Figure 4.9.1: Robustness Test: PH Assumption



4.9.3.2 Test Results on Multicollinearity

There is a necessity of avoiding strong correlations among independent variables as discussed in section 4.7.2. For this purpose, I have chosen Spearman's rank-based correlation to test for multicollinearity as often found with accounting ratio variables using either the same nominator or denominator. The results of these pairwise correlations performed are presented by Table 4.9.3.3.. The Spearman's rho shows some stronger correlation between the variables OPCF vs TAXP with -0.5480 and OPCF vs OPCF_TAXP with -0.6980 as well as TAXP vs OPCF_TAXP with 0.7141. This is an outcome which one would expect when testing for correlation between operating cash flow and taxes paid. A much lower level of association between independent variables is found among all other pairs tested. Overall, it can be said that the given the results, the model is properly specified and holds the proportional hazards assumption on an overall, but also on a covariate basis. A semi-strong correlation has been identified among operating cash flow and taxes paid variables, but the maximum association strength of approximately 0.70 is not expected to cause any serious issues related to multicollinearity. Therefore, no further adjustments to the model specifications are necessary as indicated by the model's underlying results.

Table 4.9.3.3: Spearman's Rank-Based Correlation Test

	OPCF	TAXP	INTLIAB	OPCF_TA
OPCF	1			
TAXP	-0.5480	1		
INTLIAB	0.2873	0.0105	1	
OPCF_TAXP	-0.6980	0.7141	-0.0880	1

4.9.4 Results on Within-Sample Classification

Probabilities for each quarter point of a company are calculated using the hazard model coefficients (section 4.9.2.1). The calculation of probabilities can be performed in STATA by the use of the "predict hr" function as discussed in section 2.1.3.4. The 12-quarter prior bankruptcy classification within-sample has revealed some deflating results in the first instance as presented in Table 4.9.5. At the cut-off point at probability 0.5, only 61% of bankrupt and 65% of non-bankrupt firms were correctly classified. This result needs to be put into perspective though since more than 35% of firms in the computer and electronics industry are operating under permanent financial distress as reported by

PricewaterhouseCoopers using Altman's S&P Z-Score model (PricewaterhouseCoopers LLP, 2006). Figure 4.9.2 presents the frequency distribution of probabilities for one, four, eight and twelve quarters prior bankruptcy all sub-divided into bankrupt and non-bankrupt firms. The graphs for non-bankrupt firms show expectedly a higher frequency at lower probability of failure levels but still has quite number of firms operating above 0.50 hence producing type II errors as discussed before. The graphs for bankrupt firms also depict clearly a higher frequency between 0.50 to 1.00. In order to ensure that the model does not flip flop around the cut-off of 0.50 producing type I and II errors, I have created another three classification matrices (Table 4.9.5) with different grey zones as suggested by previous studies. The first classification with a grey zone of a probability (p) between 0.495 and 0.505, which equals an error margin of +/- 0.5% consists of 4% of all observations. This means that any observation within the above range is excluded from the classification exercise. On average, the classification accuracy is found at 62% for bankrupt and 66% for non-bankrupt companies over a twelve- quarter period prior the event.

The second group with a grey zone of a p between 0.49 and 0.51 or an error margin of +/- 1.0% consists of 8% of all observations being excluded for classification. It yields in a twelve-quarter average accuracy rate of 63% and 66% for bankrupt and non-bankrupt companies.

The third group consisting of 11% of all observations being in the grey zone of p 0.485 and 0.515 or +/- 1.5% margin error has slightly higher accuracy rates of 65% or 66% over a twelve quarter period. Overall, the classification matrices show that this model predicts quite stable across different grey zones but at relatively low accuracy rates which confirms PricewaterhouseCoopers' 2006 study.

The model has also to be verified by a hold-out sample test (ex ante) and be benchmarked with the widely accepted Altman Z-Score model using the receiver operating characteristic measure for reasons mentioned under 4.8.

Table 4.9.5: Classification Accuracy: Original Sample

Within-Sample-Classification and Accuracy

Classification Accuracy without Grey Zone - 1183 Firm-Sample - cut of at p = 0.5

Quarters prior to Bankruptcy	bankrupt	non-bankrupt	Total	Type I error	Type II error
	correct prediction				
1	74%	61%	62%	26%	39%
2	67%	63%	63%	33%	37%
3	72%	62%	63%	28%	38%
4	70%	61%	62%	30%	39%
5	68%	63%	64%	32%	37%
6	65%	66%	66%	35%	34%
7	62%	67%	67%	38%	33%
8	57%	67%	67%	43%	33%
9	50%	67%	65%	50%	33%
10	46%	65%	64%	54%	35%
11	49%	69%	67%	51%	31%
12	51%	69%	68%	49%	31%
Avg 12 Quarters	**61%**	**65%**	**65%**	**39%**	**35%**

grey zone = 0%

Classification Accuracy with Grey Zone - 1183 Firm-Sample - excludes grey zone observations fm 0.495 - 0.505

Quarters prior to Bankruptcy	bankrupt	non-bankrupt	Total	Type I error	Type II error
	correct prediction				
1	74%	61%	62%	26%	39%
2	71%	63%	63%	29%	37%
3	73%	63%	63%	27%	37%
4	72%	62%	62%	28%	38%
5	68%	64%	64%	32%	36%
6	64%	67%	67%	36%	33%
7	63%	68%	67%	37%	32%
8	59%	68%	67%	41%	32%
9	51%	67%	66%	49%	33%
10	49%	66%	65%	51%	34%
11	51%	69%	67%	49%	31%
12	52%	70%	69%	48%	30%
Avg 12 Quarters	**62%**	**66%**	**65%**	**38%**	**34%**

grey zone = 4% of all observations in a +/- 0.5% Margin vs p 0.5

Classification Accuracy with Grey Zone - 1183 Firm-Sample - excludes grey zone observations fm 0.49 - 0.51

Quarters prior to Bankruptcy	bankrupt	non-bankrupt	Total	Type I error	Type II error
	correct prediction				
1	75%	62%	63%	25%	38%
2	74%	63%	64%	26%	37%
3	75%	62%	63%	25%	38%
4	74%	62%	63%	26%	38%
5	71%	64%	65%	29%	36%
6	65%	68%	68%	35%	32%
7	63%	68%	68%	38%	32%
8	60%	68%	68%	40%	32%
9	53%	68%	67%	47%	33%
10	48%	67%	65%	52%	33%
11	50%	69%	68%	50%	31%
12	53%	71%	70%	47%	29%
Avg 12 Quarters	**63%**	**66%**	**66%**	**37%**	**34%**

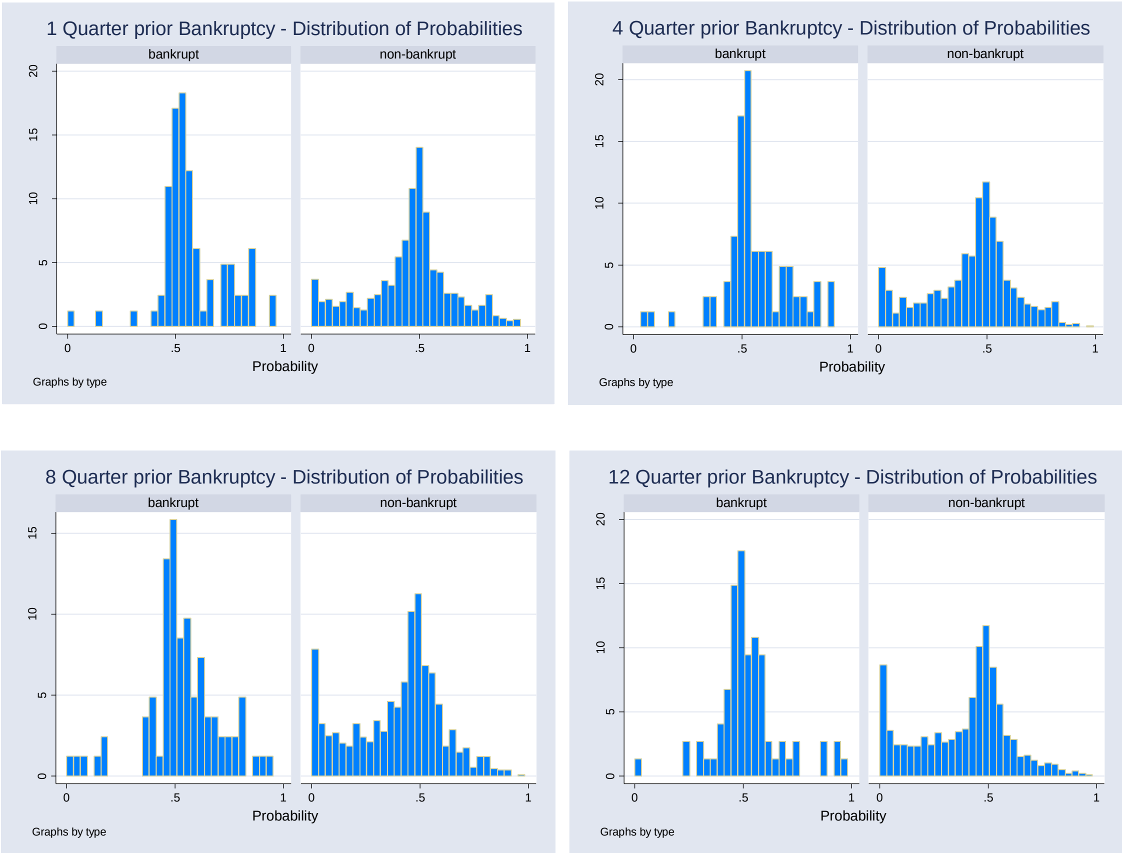
grey zone = 8% of all observations in a +/- 1% Margin vs p 0.5

Classification Accuracy with Grey Zone - 1183 Firm-Sample - excludes grey zone observations fm 0.485 - 0.515

Quarters prior to Bankruptcy	bankrupt	non-bankrupt	Total	Type I error	Type II error
	correct prediction				
1	78%	62%	63%	22%	38%
2	75%	63%	64%	25%	37%
3	77%	62%	63%	23%	38%
4	74%	63%	63%	26%	37%
5	72%	65%	65%	28%	35%
6	66%	68%	68%	34%	32%
7	63%	69%	68%	37%	31%
8	61%	69%	68%	39%	31%
9	54%	68%	67%	46%	32%
10	49%	67%	66%	51%	33%
11	53%	70%	68%	47%	30%
12	54%	71%	70%	46%	29%
Avg 12 Quarters	**65%**	**66%**	**66%**	**35%**	**34%**

grey zone = 11% of all observations in a +/- 1.5% Margin vs p 0.5

Figure 4.9.2: Frequency Distribution of Probabilities of Original Sample: 1, 4, 8 and 12 Quarters prior Bankruptcy



4.9.5 Results on Hold-Out Sample Classification

As mentioned in section 4.8, it is well documented that empirically derived bankruptcy models very often lose their predictive power or forecasting ability when applied ex ante (Grice and Ingram 2001; Begley, Ming and Watts 1996). Therefore, the model has to undergo a validation process where a hold-out sample is created and tested. The sample selected as described in section 4.8.1 consists of bankrupt and non-bankrupt firms from the same, the computer and electronics industry, but for the subsequent period 2003 - 2006. As result, I have obtained 984 firms consisting of 14 bankrupt (Table 4.9.6) and 970 non-bankrupt firms (part of Table 4.9.1.3 and 4.9.1.4). The list of bankrupt firms shows that companies of different size, measured by total assets prior filing, are included in the hold-out sample.

Table 4.9.6 List of Bankrupt Firms – Holdout Sample (N=14)

Company Name	SMBL	Ttl Assets prior Filing in $'000	Filing Type	Filing Date
AM COMMUNICATIONS INC	AMCM	33.302	CH 11	08/28/2003
ARIEL CORP	ADSPQ	4.103	CH 7	06/26/2003
ASTROCOM CORP	ATCCQ	0.573	CH 11	08/08/2003
ASTROPOWER INC	APWRQ	192.384	CH 11	02/01/2004
AUSPEX SYSTEMS INC	ASPXQ	26.087	CH 11	04/22/2003
DATAMETRICS CORP	3DMCP	4.127	CH 7	03/17/2003
EMCEE BROADCAST PRODUCTS INC	ECIN	5.093	CH 7	02/24/2003
IMAGE SYSTEMS CORP	IMSG	3.471	CH 7	02/25/2004
INTEGRATED TELECOM EXPRESS	3ITXIQ	110.774	CH 11	05/02/2003
METATEC INC	MTATQ	30.379	CH 11	10/17/2003
METAWAVE COMMUNICATIONS CP	MTWVQ	58.672	CH 11	01/31/2003
PHOTOELECTRON CORP	3PECN	4.458	CH 7	05/02/2003
PROXIM CORP	PROXQ	55.361	CH 11	06/11/2005
STRATESEC INC	SFTC	0.346	CH 11	04/28/2004

Again, four groups for the out-of-sample tests were created with identical grey zones as applied for the original sample classification. The results shown in table 4.9.7 reveal that the prediction accuracy of the hold-out sample is even higher for the group of bankrupt firms when comparing with the classification results of the original sample, but slightly lower for the non-bankrupt ones. The overall prediction rates of the group with a grey zone of p ranging from 0.495 to 0.505 are found at 79% and 63% and for the group with a grey zone of p ranging from 0.49 to 0.51 are at 78% and 64% . For the one with a p between 0.485 and 0.515 the accuracy rates are found at 83% and 64%. The total error rate of approximately 35% for all observations in the hold-out sample, particularly for non-bankrupt firms, reflects again about the number of companies operating under permanent financial distress as reported by the PwC study (PricewaterhouseCoopers LLP, 2006). PwC was using Altman's S&P's z-score model where firms with a score of lower than 1.81 were classified as distressed. In addition, a frequency distribution of probability graph for the hold-out sample as presented by Figure 4.9.3 follows the same pattern as depicted by Figure 4.9.2 where bankrupt firms move towards a probability of 1.0 when comparing twelve-quarter versus one-quarter prior bankruptcy. It can be said that the model can distinguish between the two groups of firms given the results of the distribution graphs and the hold-out sample prediction results. Also, the predictive power has been maintained based on the hold-out sample test results.

Table 4.9.7: Prediction Accuracy: Hold-Out Sample

Out-of-Sample-Classification and Accuracy

Out-of-sample Prediction without Grey Zone - 984 Firm-Sample - cut of at p = 0.5

Quarters prior to Bankruptcy	bankrupt	non-bankrupt	Total	Type I error	Type II error
	correct prediction				
1	80%	68%	68%	20%	32%
2	88%	67%	67%	13%	33%
3	70%	67%	67%	30%	33%
4	75%	68%	68%	25%	32%
5	77%	66%	66%	23%	34%
6	69%	65%	65%	31%	35%
7	69%	64%	64%	31%	36%
8	71%	65%	65%	29%	35%
9	57%	64%	64%	43%	36%
10	50%	64%	63%	50%	36%
11	46%	62%	62%	54%	38%
12	38%	62%	61%	62%	38%
Avg 12 Quarters	**66%**	**65%**	**65%**	**34%**	**35%**

grey zone = 0%

Out-of-sample Prediction with Grey Zone - 984 Firm-Sample - excludes grey zone observations fm 0.495 - 0.505

Quarters prior to Bankruptcy	bankrupt	non-bankrupt	Total	Type I error	Type II error
	correct prediction				
1	80%	65%	65%	20%	35%
2	88%	64%	64%	13%	36%
3	78%	64%	64%	22%	36%
4	82%	65%	65%	18%	35%
5	77%	63%	63%	23%	37%
6	82%	61%	62%	18%	39%
7	82%	61%	61%	18%	39%
8	91%	62%	63%	9%	38%
9	67%	61%	61%	33%	39%
10	70%	61%	61%	30%	39%
11	86%	62%	63%	14%	38%
12	67%	62%	62%	33%	38%
Avg 12 Quarters	**79%**	**63%**	**63%**	**21%**	**37%**

grey zone = 5% of all observations in a +/- 0.5% Margin vs p 0.5

Out-of-sample Prediction with Grey Zone - 984 Firm-Sample - excludes grey zone observations fm 0.49 - 0.51

Quarters prior to Bankruptcy	bankrupt	non-bankrupt	Total	Type I error	Type II error
	correct prediction				
1	80%	67%	67%	20%	33%
2	86%	65%	66%	14%	35%
3	75%	66%	66%	25%	34%
4	82%	67%	67%	18%	33%
5	75%	64%	64%	25%	36%
6	82%	64%	64%	18%	36%
7	80%	63%	63%	20%	37%
8	90%	63%	63%	10%	37%
9	64%	63%	63%	36%	37%
10	70%	62%	62%	30%	38%
11	86%	61%	61%	14%	39%
12	67%	60%	60%	33%	40%
Avg 12 Quarters	**78%**	**64%**	**64%**	**22%**	**36%**

grey zone = 10% of all observations in a +/- 1% Margin vs p 0.5

Out-of-sample Prediction with Grey Zone - 984 Firm-Sample - excludes grey zone observations fm 0.485 - 0.515

Quarters prior to Bankruptcy	bankrupt	non-bankrupt	Total	Type I error	Type II error
	correct prediction				
1	80%	67%	67%	20%	33%
2	86%	66%	66%	14%	34%
3	75%	67%	67%	25%	33%
4	78%	67%	67%	22%	33%
5	73%	65%	65%	27%	35%
6	80%	64%	64%	20%	36%
7	78%	63%	63%	22%	37%
8	89%	64%	64%	11%	36%
9	88%	64%	64%	13%	36%
10	86%	62%	63%	14%	38%
11	86%	61%	62%	14%	39%
12	100%	60%	61%	0%	40%
Avg 12 Quarters	**83%**	**64%**	**64%**	**17%**	**36%**

grey zone = 14% of all observations in a +/- 1.5% Margin vs p 0.5

Figure 4.9.3: Frequency Distribution of Probabilities of Hold-Out Sample: 1, 4, 8 and 12 Quarters prior Bankruptcy

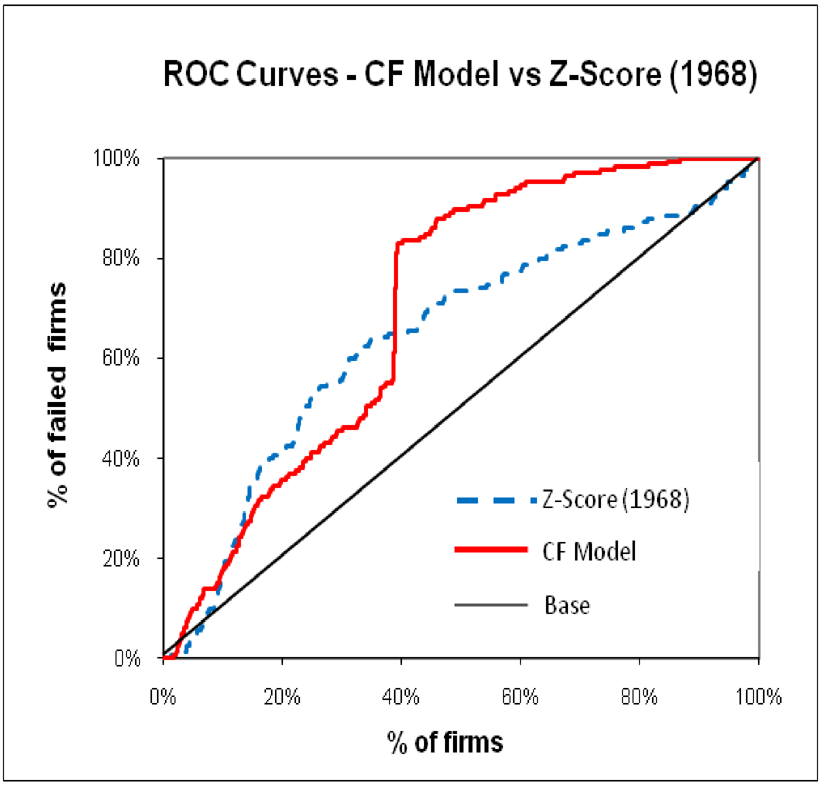
4.9.6 Results on ROC Analysis - Benchmark with Z-Score

The result of the hold-out sample (section 4.9.5) has to be benchmarked with Altman's Z-Score model by using the same companies over the same period of time (years 2003 to 2006) but with Altman's variables and his regression coefficients (4.8.2). For this purpose, an ROC curve analysis as described under section 4.8.2 has been performed.

Figure 4.9.4 presents the ROC curves for both, the Altman's Z-Score and the cash flow based model. The area under ROC curve for the cash flow based model with 0.70 is overall higher than the curve obtained for the Z-Score model with 0.64. It also shows that the cash flow model outperforms the Altman Z-Score significantly as indicated by the z value for statistical difference in performance of 2.36. Especially, the cash flow based model captures around the first 20% of failures with fewer firm observations compared to Z-Score. The Z-Score then does a better job in capturing the next 20 to 60% of failures. However, it then loses on predictive power for the remaining third of company failures occurred when comparing to the cash flow model.

The accuracy ratios of 0.40 for the cash flow based model and 0.29 for Altman's Z-Score model confirm that both models contain substantial information about future default when comparing with the base line and its accuracy ratio of 0.00.

Figure 4.9.4: ROC Accuracy Benchmark with Altman's Z-Score : Hold-Out Sample



Model	AUC	SE	AR
CF Model	0.70	0.0147	0.40
Z-Score	0.64	0.0228	0.29
Statistical difference in performance:			z = 2.36

The cash flow based prediction model demonstrates its validity by its results achieved when comparing to a widely accepted model such as Altman's Z-Score. These results can be explained by

a. different use of statistical method, e.g. hazard model versus Multiple Discriminant Analysis (panel versus cross-section data analysis)
b. the use of cash flow variables versus accrual based accounting data
c. the use of an industry specific model as provided by this study versus a multiple industry based model
d. the fact that Altman's Z-Score coefficients used for this benchmark were not re-estimated since 1968

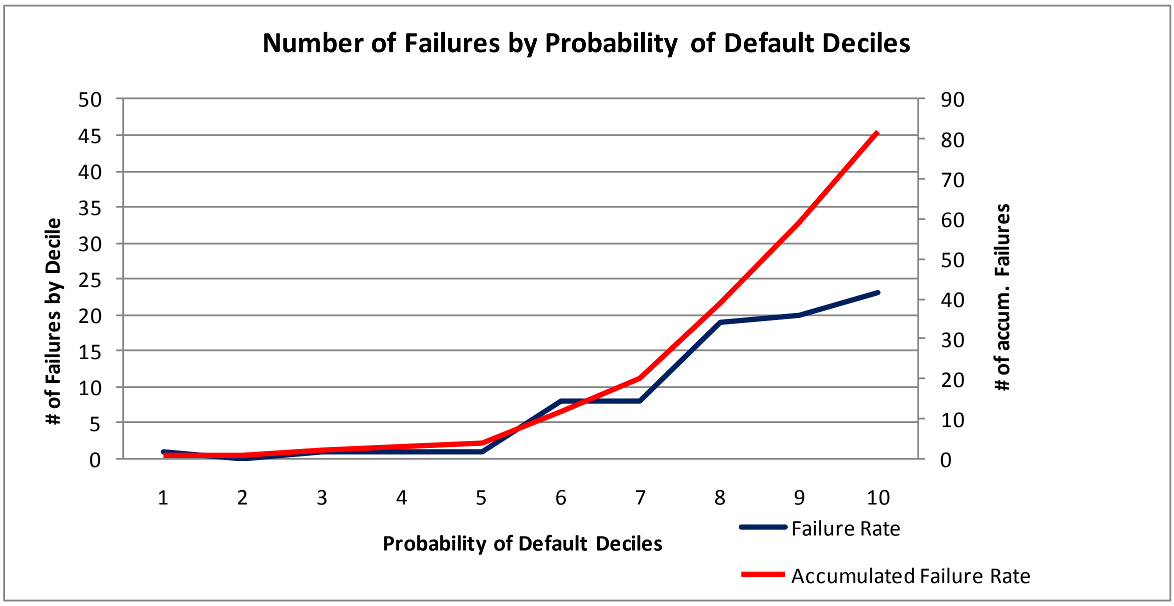
e. the fact that Altman's model was based on much fewer companies and related observations
f. the development of a quarterly moving average full year model in this study versus a year-end annual model as used by Altman and others
g. the fact that the dichotomy of bankrupt versus non-bankrupt may slightly differ between the two models, e.g. new bankruptcy code of 1978. Altman's model was created with data prior this new code in contrast to this study.

Since it is not the ultimate goal to find the most influential factor in improving accuracies of bankruptcy predictions, I will not analyze this subject any further. The use of a multi-period hazard model appears to be a more appropriate statistical method though than a single-period static MDA model as used by Altman.

4.9.7 Results on Continuous Distress Risk Tabulation

The characteristic of the distress risk measure has been evaluated by tabulating the probability of default deciles against the failure rates as described under 4.8.3. As per figure 4.9.5 and the strong correlation of 0.9168 between the probability of failure and the number of failures it is evident that the cash flow based bankruptcy prediction model produces a continuous distress factor. Therefore, the probabilities of failure obtained from the cash flow prediction model can be included as a continuous pricing factor into the asset pricing models as shown in chapter 5.

Figure 4.9.5: Probability of Default Deciles vs Failure Rates



Correlation Maxtrix:

	Probability	# of Failure
Probability	1.0000	
# of Failure	0.9168	1.0000

4.10 Bankruptcy Prediction Model: Summary Result and Conclusion

The bankruptcy prediction model using cash flow variables based on Lawson's Identity has brought up four variables of significance. Also, it is not of surprise that cash flows related to operating activities (OPCF), taxes (TAXP) as well as leverage and interest paid (INTLIAB) offer the most significant predictors from a bankruptcy risk point of view as these factors are very much related to a firm's valuation. The model has also shown that cash flows related to net capital investment (NCAPIN), the equity (DIVEQ) and change in liquidity (CHLIQ) do not contribute significantly to the model as a whole. The new cash flow based prediction model has been validated by robustness checks, hold-out sample tests and by a ROC benchmark with Altman's Z-Score model. The twelve-quarter average overall accuracy rates from within-sample classifications are in the range of 65% to 66% and confirm a) the stability of the model and b) the PricewaterhouseCoopers (2006) study. Figure 4.9.2 depicts the fact that the model is able to segregate between the groups of bankrupt and non-bankrupt firms. Although the test results are rather modest (section 4.9.4) it can be concluded that hypothesis $H1_A a)$ (see section 3.2 and paragraph below) shown in alternative form below cannot be rejected, which means that the model as stated under *$H1_A a)$* below can predict the failure or non-failure of firms at *relatively* low type I and II error rates. It has to be put in perspective with the situation of this specific industry as reported by PricewaterhouseCoopers (2006) where 35% of firms are found to be operating under permanent distress. The benchmark test with Altman's Z-score will reveal the model's underlying value.

> ***$H1_A a)$ A dynamic cash flow based bankruptcy prediction model can predict the failure or non-failure of firms at low type I and II error rates based on within-sample classification (section 4.9.4)***

The test results (section 4.9.3) from the model's robustness checks confirm that the model holds the proportional hazards assumption and also that it is not subject to the issue of multicollinearity. In addition, the out-of-sample tests as performed in section 4.9.5 show that the new cash flow based model is able to maintain its predictive power given its accuracy rates over the twelve-quarter period prior bankruptcy. The overall rate is found to be between 63% and 65% depending on the grey zone definition. Figure 4.9.3 again depicts the fact that the model can categorize into the two groups bankrupt and non-bankrupt. The ROC benchmark test results with Altman's Z-Score (section 4.9.6) also confirm the model's validity. The area under ROC curve for the cash flow based model is overall higher than the curve obtained for the Z-Score model. In addition, the cash flow model outperforms the Altman Z-Score significantly as indicated by the z value for statistical difference in performance. Given the fact that the cash flow based prediction model is robust and more accurate in comparison to Altman's Z-Score it can be concluded that hypothesis *$H1_A b)$* (see section 3.2 and paragraph below) cannot be rejected, which means that the model maintains its predictive power in hold-out sample tests and that it performs better than the Z-Score model, at least for bankruptcy predictions in the computer and electronics equipment industry. The probabilities obtained from this model can be used for further asset pricing tests (5.1).

> ***$H1_A b)$ A dynamic cash flow based bankruptcy prediction model can predict the failure or non-failure of firms from out-of-sample tests (section 4.9.5) at the same or higher accuracy rate compared to the existing and widely accepted Z-Score Model (section 4.9.6) by using a ROC-model, and as such be used for further asset pricing tests (chapter 5).***

The characteristic of the distress risk measure has been evaluated by tabulating the probability of default deciles against the failure rates. Figure 4.9.5 and the strong correlation of 0.9168 between the probability of failure and the number of failures show that it is evident that the cash flow based bankruptcy prediction model produces a continuous distress factor. Hence, *$H1_A c)$* cannot be rejected and the probabilities obtained from the bankruptcy prediction model can be used as continuous distress risk factor for further asset pricing tests (5.1).

$H1_A c)$ A dynamic cash flow based bankruptcy prediction model produces continuous probabilities of default measure (sections 4.8.3 / 4.9.7)

CHAPTER 5: ASSET PRICING OF PROFITABILITY AND RELATIVE DISTRESS RISK

5.1 Overview

In order to test for the hypotheses set in section 5.2 (or 3.3). several tasks will need to be performed. First, various portfolios as described in section 5.5.1 are formed and factors calculated on an equal-weighted basis. The portfolios are rebalanced on a quarterly basis using only publicly available data at the formation date. Therefore, a three-month reporting lag is assumed to avoid any look-ahead bias (Banz and Breen, 1996). The descriptive statistics emerged from the portfolio formation and factor calculations based on time-series averages over 204 months (1990 – 2006) and are provided for distress deciles sorted as well as for size-B/M-distress sorted portfolios in section 5.6.1 and for additional portfolio sorts in Appendix A. The descriptive statistics are reported in raw numbers (tables) and supplemented by graphs (figures) with corresponding comments and analyses. In section 5.6.2, Pearson correlation tests are conducted to check if all explaining variables are independent from each other and to obtain results in connection with the Fama-French (1992, 1993) distress factor hypothesis. Last but not least, Fama-MacBeth (1973) cross-sectional regressions are run on various sets of portfolios (section 5.6.3) to obtain t-statistics and adj. R^2 for different types of models such as CAPM, Fama-French (1992) three-factor model and augmentations of it including the relative distress risk and current profitability strength (OPCF) factors and related interaction term.

5.2 Hypotheses

The reasoning for the hypotheses below is provided in section 3.3.

$H2_A$a) Distressed stocks underperform on average non-distressed stocks. *(descriptive statistics 5.6.1, Table 5.6.1.1 and 5.6.4)*

$H2_A$b): The Fama-French (1992, 1993) distress factor hypothesis where both size and B/M factors proxy distress risk does not hold. *(Descriptive Statistics 5.6.1, figure 5.6.1.4 / Pearson's rank correlation: test outline 5.5.3 and test results 5.6.2 / Cross-sectional regression: test outline 5.5.4 and test results 5.6.3)*

$H2_A$c): The anomalous market underperformance of distressed stock can be explained by a parallel analysis of risk based rational pricing and profitability/earnings levels to returns propositions. *(Descriptive statistics 5.6.1, Table 5.6.1.1,5.6.1.6, Figure 5.6.1.1, 5.6.1.6, 5.6.1.33) / Cross-sectional regression: test outline 5.5.4 and test results 5.6.3)*

5.3 Data Source

Data for monthly stock returns are downloaded from the Wharton Research Data Service – Center for Research in Security Prices (CRSP) database. The monthly distress factors derived from the quarterly cash flow based bankruptcy prediction model are obtained from the calculations as described in chapter 4. The probabilities of bankruptcy are calculated on a quarterly basis. The same probability is assigned to each month within a quarter, e.g. January, February and March will have the same distress factor and will then be adjusted for the next three months and so forth.

5.4 Sample Selection

The sample will include all bankrupt and non-bankrupt companies as selected for the bankruptcy prediction model. Companies with the following NAICS Codes (North American Industry Classification System) are included:

334	**Computer and Electronic Product Manufacturing**
3341	Computer and Peripheral Equipment Manufacturing
3342	Communications Equipment Manufacturing
3344	Semiconductor and Other Electronic Component Manufacturing
3345	Navigational, Measuring, Medical and Control Instruments Manufacturing

The disclosure of Statement of Cash Flows was optional until SFAS No. 95 became a mandatory requirement in 1988. Therefore, the sample for the asset pricing tests will include monthly data for the period when distress factors became available, starting in year 1990 and ending in 2006. In addition, the sample size used to develop and test the bankruptcy prediction model is reduced by the fact that for asset pricing tests firms listed on the NYSE, AMEX and NASDAQ stock exchanges are included only. Although OTCBB stocks have to the meet the same SEC reporting standards and requirements they very often are the ones which were delisted from NYSE, AMEX or NASDAQ stock exchanges due to undercapitalization, small share price and other reasons. Subsequently, OTCBB stocks often file for bankruptcy Chapter 11 or 7 and as such have rightly been used for the development of the cash flow based bankruptcy prediction model in chapter 4. Nevertheless, OTCBB stocks are dropped due to unavailability of data (CRSP) and because of being subject to a potential thin trading problem.

The inclusion of stocks has to meet further criteria similar to the ones defined by Agarwal and Taffler (2008) and Campell, Hilscher and Szilagyi (2008). Stocks with a negative book-to-market ratio are excluded as its interpretation is rather difficult. The thin trading issue has been also considered for NYSE, AMEX and NASDAQ listed companies. In contrast to other studies (Agarwal and Taffler, 2008; Campbell, Hilscher, Szilagyi, 2008), portfolios are formed and rebalanced on a quarterly basis at the beginning of each quarter. Therefore, stocks which have not been traded in all three months of a quarter are excluded unless they were delisted before quarter end. However, almost no thin trading has been noted and thus it does not pose any serious problem for this study. As result, a total of 1'236 firms which corresponds to 112'631 firm months over the entire period or 520 firms on average per month are included in the sample to be tested.

Delisted returns provided by CRSP are used whenever available for companies being delisted. There are only a few instances where the latest available full month return is used instead.

5.5 Methodology, Design and Models

5.5.1 Portfolio Formation and Calculations

Different sets of portfolios are formed to test the hypotheses (section 5.2) and to validate the outcome. All characteristics used for portfolio formation as well as the calculations of returns and factors are equally weighted. The portfolios' characteristics are shown in form of descriptive statistics (section 5.5.2) and have to undergo correlations tests as shown in section 5.5.3. Cross-sectional regression tests (section 5.5.3) are run and t-statistics are provided by applying the Fama-MacBeth (1973) two-stage regression methodology. This study is limited to one industry and as consequence it deals with a fewer number of stocks compared to many other studies covering the market as a whole. Four- or three-way intersecting portfolios are preferred over two-way intersecting ones given the number of characteristics used in this study. However, the implementation of four-way intersecting portfolios is not feasible as it would drive down the number of stocks per portfolio too often below ten. Therefore, one set of three-way intersecting portfolios is formed to control for two characteristics at a given time. The characteristics used for these portfolios are distress risk, B/M and Size but not OPCF. As compromise, the OPCF characteristic is used in a two-way independent sort together with distress risk. Since I also test the Fama-French (1992) factors for their level of significance, I have also chosen to test two-way intersecting portfolios by the inclusion of a finer grid of B/M and size characteristics which are compromised when using three-way intersecting portfolios. I have chosen B/M and Size quartiles sorts for two-way intersecting portfolios and for both characteristics a breakpoint at the median for three-way intersecting portfolios. This allows maintaining a minimum number of stocks per portfolio and per period for the sets of portfolios to be formed. The independent sorting of stocks into distress risk deciles and quintiles instead of quartiles has some analytical reasons. From the 8^{th} to the 9^{th} decile or from the 4^{th} to the 5^{th} quintile the average probability of failure is switching from a lesser to a more likelihood of going bankrupt. This switching point would not have been visible with distress risk sorted by quartiles instead.

1. <u>Distress deciles sorted portfolio</u>

   The distress deciles sorted portfolios are calculated and rebalanced on a quarterly basis. This set of portfolios (Table 5.6.1.1) is formed for descriptive statistics purpose only. Most important, it provides the monthly excess returns across the distress risk levels on an equal-weighted basis. In addition, this one-way sort of relative distress risk provides a finer grid of this characteristic compared to all other portfolios formed in this study. This analysis also provides the average stock returns across distress deciles and the information needed in connection with hypothesis $H2_A a)$.

2. <u>Two-way intersecting portfolios (Appendix A)</u>

   Four sets of two-way intersecting portfolios are formed to control the distress factor by each of the other characteristics on an individual basis. Distress risk quintiles instead of deciles are used in order to ensure a minimum number of stocks per portfolio per period. The first set of 20 portfolios (Table 5.6.1.2, Appendix A) consists of Distress risk quintiles and OPCF quartiles constructed at their intersections (Distress (5) * OPCF (4)). This is the only portfolio formation that is not based on stock price transformation and the only set consisting of OPCF sorted portfolios. It reveals that distress risk controlled by profitability (OPCF) tends to be positive nearly linear in relation to monthly excess returns. The second set of 20 portfolios (Table 5.6.1.3, Appendix A) consists of Distress risk quintiles and Size quartiles (Distress (5) * Size (4)). The third set (Table 5.6.1.4, Appendix A) consists of Distress risk quintiles and B/M quartiles (Distress (5) * B/M (4)). The fourth set of 16 portfolios (Table 5.6.1.5, Appendix A) consists of Size and B/M quartiles (Size (4) * B/M (4)). All two-way intersecting portfolios are formed, calculated and rebalanced on a quarterly basis and equal-weighted.

3. <u>Three-way intersecting portfolios</u>

There is one set of three-way intersecting portfolios constructed (Table 5.6.1.6). Here, the distress portfolios are controlled by Size and B/M characteristics. In order to maintain a minimum number of stocks in each portfolio and period, I use Size and B/M halves with breakpoints at their median. This independent portfolio sorting and formation method results in 20 portfolios (Distress (5) * Size (2) * B/M (2)). The three-way intersecting portfolios are formed, calculated and rebalanced on a quarterly basis and equal-weighted.

4. <u>Distress Decile Portfolio by Positive / Negative OPCF</u>

OPCF reflects a company's scaled operating cash flow before interest and taxes paid. The Distress risk deciles will be segregated into positive and negative OPCF stocks (Figure 5.6.1.33), which reveals additional descriptive information on the interaction between Distress risk and OPCF as well as their relationship with returns, especially at highest distress risk levels.

5. <u>Calculation of Returns and Factors</u>

The stocks of the entire sample as defined and selected in section 5.4 will be grouped into various sets of portfolios of independent sorts (see 1. – 4. above). The descriptive statistics (section 5.5.2) and the cross-sectional regression analysis (section 5.5.3) are based on the Fama and MacBeth (1973) methodology. The calculation of factors and returns are the same for all portfolios and equally-weighted.

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}(distress_{it-1}) + \gamma_{5t}(OPCF_{it-1}) + \varepsilon_{it}$$

where:

R_{it}	is the equal-weighted return on portfolio *i* during month *t*
R_{Ft}	is the one month t-bill rate at the beginning of each month *t*
β_{it-1}	is the beta of portfolio *i* estimated at the portfolio formation date using a rolling 24-month window prior to formation date (further details see section 2.2.3.2)
$\ln(size_{it-1})$	is the natural logarithm of the average market capitalization of equity stocks in portfolio *i* at the portfolio formation date *t-1*
$\ln(B/M_{it-1})$	is the natural logarithm of the average B/M ratios of stocks in portfolio *i* at the portfolio formation date *t-1* [1]
$(distress_{it-1})$	is the distress risk factor proxied by the probability of bankruptcy risk (Chapter 4) of portfolio *i* at portfolio formation date [1]
$(OPCF_{it-1})$	is a scaled accumulated four-quarter profitability coefficient derived from the bankruptcy prediction model for portfolio *i* at the portfolio formation date [1]
ε_{it}	is a mean-zero stochastic error term

Book Equity (B/) is the book value of common stock plus balance-sheet deferred taxes. Values being lower than the 1st percentile and higher than the 99th percentile will be set to the values of 1st or 99th percentile of observations in order to eliminate extreme outliers. Rebalancing of portfolios occurs at the beginning of each quarter.

1 There is a 3-month reporting lag assumed to avoid any look-ahead bias (Banz and Breen, 1996). 92% of companies filed annual reports within 3 months (Penman, 1987) and 98% with 5 months (Alford, Jones, Zmijewski, 1994). Tests on 4- and 5-month lag models have shown a diminishing level of statistical significance. 6-month lag led to an overall insignificance of factors and models involved.

5.5.2 Descriptive Statistics

Descriptive statistics and related figures including comments are provided for all sets of portfolios (5.5.1) as listed below:

Portfolio Set	**Table**	**Figures**
Distress Risk Probability Decile Portfolios	5.6.1.1	5.6.1.1 to 5.6.1.6

Size Median * B/M Median * Distress Quintiles	5.6.1.6	5.6.1.29 to 5.6.1.32

<u>Portfolio Sets in APPENDIX A:</u>

OPCF Quartiles * Distress Quintiles	5.6.1.2	5.6.1.7 to 5.6.1.10
Size Quartiles * Distress Quintiles	5.6.1.3	5.6.1.11 to 5.6.1.16
B/M Quartiles * Distress Quintiles	5.6.1.4	5.6.1.17 to 5.6.1.22
Size Quartiles * B/M Quartiles	5.6.1.5	5.6.1.23 to 5.6.1.28

For each portfolio of the above sets of portfolios the following descriptive statistics are provided:

- Panel A.: Monthly Mean Excess Return
- Panel B: Mean Beta
- Panel C: Mean ln(Size)
- Panel D: Mean ln(B/M)
- Panel E: Mean Distress Probability
- Panel F: Mean OPCF
- Panel G: Average Size – Market Cap in $m
- Panel H: Average Number of Stocks (per month)

Besides providing a descriptive overview of the mean statistics for differently formed portfolios based on various characteristics, it also is used for testing the hypothesis *$H2_A a$)* as described in sections 3.3.

5.5.3 Multicollinearity Tests

One problem, which potentially could arise, is multicollinearity among independent variables since financial ratios have quite often the same numerator or denominator. If there were multiple highly correlated covariates, it is preferred to include only one variable from the set of correlated variables. Therefore, Pearson's rank correlation tests are conducted for each pair of variable. In a perfect world, all independent variables would be completely independent and unrelated to each other, but reality shows though that virtually every multiple regression has some collinearity between the independent covariates. There are no clear-cut rules about the level of collinearity to be excluded from a model, but if it exceeds 0.80 it would probably make sense to drop one of the highly correlated variables. In addition, these correlation tests are also used to evaluate the distress factor proposition made by Fama and French (1992) and Chan and Chen (1991). In their studies they argue that size and B/M factors in a multi-factor asset pricing framework proxy for bankruptcy risk (further details see 2.2.4). Assuming that the distress risk factor derived from the bankruptcy prediction model is valid and the Fama-French distress factor hypothesis is considered to be true, the correlation particularly between B/M and the distress risk factor is expected to be very strong. For this specific purpose (hypothesis $H2_A b)$, sections 3.3 or 5.2) the correlations among these variables for individual stocks (Table 5.6.2.1, Appendix B) but also for the following portfolios are tested:

Portfolio Set	**Table**
Size Median * B/M Median * Distress Quintiles	5.6.2.4

Portfolio Sets in APPENDIX B:

OPCF Quartiles * Distress Quintiles	5.6.2.2
Size Quartiles * Distress Quintiles	5.6.2.3
B/M Quartiles * Distress Quintiles	5.6.2.5

The tests are performed on a monthly basis. The correlation coefficients reported in the tables above are the time-series average of 204 months.

5.5.4 Cross-Sectional Regression Tests

The descriptive statistics provided in section 5.5.2 describes specifically the mean statistics of all characteristics involved in forming the various sets of portfolios and eventually explaining monthly average stock returns. Besides the first findings from the descriptive statistics I also test for the factors' and the models' significance levels in explaining the monthly excess stock returns related to hypotheses $H2_A a)$ and $H2_A c)$ (see details in sections 5.2 and/or 3.3). For that purpose I apply the Fama and MacBeth (1973) cross-sectional regression methodology which is discussed in more details in section 2.2.3.2. The following sets of portfolios' monthly excess stock returns will be tested:

Portfolio Set	Descriptive Table No.	Regression Table No.
Size Median * B/M Median * Distress Quintiles	5.6.1.6	5.6.3.4

Portfolio Sets in APPENDIX C:

OPCF Quartiles * Distress Quintiles	5.6.1.2	5.6.3.1
Size Quartiles * Distress Quintiles	5.6.1.3	5.6.3.2
B/M Quartiles * Distress Quintiles	5.6.1.4	5.6.3.3
Size Quartiles * B/M Quartiles	5.6.1.5	5.6.3.5

As a robustness check, all asset pricing tests are also conducted with individual securities' regressions. The use of individual securities (Chan, Hamao, Lakonishok, 1991) is aimed to disprove the claim of the data snooping bias (Lo and MacKinlay, 1990; Black, 1993, MacKinlay, 1995) (see section 2.2.3.4).

Portfolio Set – Robustness Checks	Regression Table No.
Individual Stock Regression	5.6.3.6

Most of the empirical validations of the CAPM are conducted based on studies related to Fama and French's (1992, 1993) three-factor model. Several modified versions of the three-factor model are tested on a univariate as well as multivariate basis. Beta, the market factor, remains a factor for all models to be included in this study because of its strong theoretical framework except for the testing of the interaction term (model 12).
The following models are tested:

CAPM

1. $R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \varepsilon_{it}$

Fama & French 3-Factor (1992)

2. $R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} \ln(size_{it-1}) + \gamma_{3t} \ln(B/M_{it-1}) + \varepsilon_{it}$

Multi-Factor

3. $R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} \ln(size_{it-1}) + \gamma_{3t} \ln(B/M_{it-1}) + \gamma_{4t} (distress_{it-1}) + \varepsilon_{it}$

4. $R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} \ln(size_{it-1}) + \gamma_{3t} \ln(B/M_{it-1}) + \gamma_{5t} (OPCF_{it-1}) + \varepsilon_{it}$

5. $R_{it} – R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} \ln(size_{it-1}) + \gamma_{3t} \ln(B/M_{it-1}) + \gamma_{4t} (distress_{it-1}) + \gamma_{5t} (OPCF_{it-1}) + \varepsilon_{it}$

6. $R_{it} – R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} \ln(size_{it-1}) + \gamma_{3t} \ln(B/M_{it-1}) + \gamma_{4t} (distress_{it-1}) + \gamma_{5t} (OPCF_{it-1}) + \gamma_{6t} (distress*OPCF_{it-1}) + \varepsilon_{it}$

7. $R_{it} – R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{4t} (distress_{it-1}) + \varepsilon_{it}$

8. $R_{it} – R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{5t} (OPCF_{it-1}) + \varepsilon_{it}$

9. $R_{it} – R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{4t} (distress_{it-1}) + \gamma_{5t} (OPCF_{it-1}) + \varepsilon_{it}$

10. $R_{it} – R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{3t} \ln(B/M_{it-1}) + \gamma_{4t} (distress_{it-1}) + \gamma_{5t} (OPCF_{it-1}) + \varepsilon_{it}$

11. $R_{it} – R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} \ln(size_{it-1}) + \gamma_{4t} (distress_{it-1}) + \gamma_{5t} (OPCF_{it-1}) + \varepsilon_{it}$

12. $R_{it} – R_{Ft} = \alpha_{it} + \gamma_{4t} (distress_{it-1}) + \gamma_{5t} (OPCF_{it-1}) + \gamma_{6t} (distress*OPCF_{it-1}) + \varepsilon_{it}$

where:

R_{it}	is the equal-weighted return on portfolio *i* during month *t*
R_{Ft}	is the one month t-bill rate at the beginning of each month *t*
β_{it-1}	is the beta of portfolio *i* estimated at the portfolio formation date using a rolling 24-month window prior to formation date (further details see section 2.2.3.2)
$\ln(size_{it-1})$	is the natural logarithm of the average market capitalization of equity stocks in portfolio *i* at the portfolio formation date *t-1*
$\ln(B/M_{it-1})$	is the natural logarithm of the average B/M ratios of stocks in portfolio *i* at the portfolio formation date *t-1* [1]
$(distress_{it-1})$	is the distress risk factor proxied by the probability of bankruptcy risk (Chapter 4) of portfolio *i* at portfolio formation date [1]
$(OPCF_{it-1})$	is a scaled accumulated four-quarter profitability coefficient derived from the bankruptcy prediction model for portfolio *i* at the portfolio formation date [1]
ε_{it}	is a mean-zero stochastic error term

Book Equity (B/) is the book value of common stock plus balance-sheet deferred taxes. Values being lower than the 1st percentile and higher than the 99th percentile will be set to the values of 1st or 99th percentile of observations in order to eliminate extreme outliers. Rebalancing of portfolios occurs at the beginning of each quarter.

1 There is a 3-month reporting lag assumed to avoid any look-ahead bias (Banz and Breen, 1996). 92% of companies filed annual reports within 3 months (Penman, 1987) and 98% with 5 months (Alford, Jones, Zmijewski, 1994). Tests on 4- and 5-month lag models have shown a diminishing level of statistical significance. 6-month lag led to an overall insignificance of factors and models involved.

5.6 Results: Empirical Analysis

5.6.1 Results Descriptive Statistics

The main objective of the descriptive statistics is to test the hypotheses in full and/or in part especially related to *$H2_A a$), $H2_A b$)* and *$H2_A c$)* as outlined in section 3.3. In addition, it describes the mean values of different characteristics related to stock returns by various portfolio sorts as outlined in section 5.5.2. The statistical significance of factors describing these returns is documented by the Fama and MacBeth (1973) t-statistics and is covered in sections 5.5.4 and 5.6.3.

A first overview is provided by a distress risk deciles sorted portfolio (Table 5.6.1.1 and Figures 5.6.1.1 to 5.6.1.6). The monthly average excess returns slightly decrease from 1.4% to 1.3% over the first five distress risk deciles but then increase up to 1.7% at 8^{th} decile. The 8^{th} distress decile has a mean distress risk probability *p* of 0.50 as shown in panel E. A bankrupt stock is by definition rather found with a probability of failure larger than *p* 0.50 hence at the 9^{th} and 10^{th} deciles. These two deciles show a strong shortfall in mean excess returns with 1.1% and 0.9% respectively when comparing to the group of non-bankrupt securities in the 8^{th} distress risk decile, but also when benchmarking with the lowest distress risk portfolios. The excess return analysis as illustrated by figure 5.6.1.1 indicates that distressed stocks underperform on average the non-distressed ones.

The apparent average underperformance of highly distressed stocks may eventually be described by other characteristics than by the distress risk factor itself. Figure 5.6.1.6 shows that on average, companies having a distress risk factor of equal or less *p* 0.50 (up to the 8^{th} decile) have a positive OPCF (scaled operating cash flow before interest and taxes paid) while distressed companies at the 9^{th} and 10^{th} deciles generate a negative OPCF. It appears that the current profitability strength measured by OPCF could be an important factor in describing stock returns not only for highly distressed, but stocks in general. In short, firms with a relative distress risk higher than *p* 0.50 generate on average negative operating cash flows. Figure 5.6.133 shows that stocks generating positive operating cash flows (OPCF) maintain a positive risk-return relationship also at highest distress level whereas the group of negative OPCF earn low average returns at comparable distress risk levels. This suggests that the underperformance of highly distressed stocks may be explained by the conditionality between the continuous distress risk and the current profitability strength factor proxied by OPCF.

In a two-way intersecting OPCF-Distress set of portfolios (Table 5.6.1.2, Figures 5.6.1.7 to 5.6.1.10 – all in Appendix A), the descriptive statistics indicate that distressed companies of the 5^{th} distress risk quintile earn lower returns than those in the 4^{th} quintile unless they are highly profitable as shown by Figure 5.6.1.7 (Appendix A). This is also confirmed when distress risk deciles sorted by positive and negative OPCF portfolios (Figure 5.6.1.33).

Figure 5.6.1.29 of three-way sorted Size - B/M - Distress portfolios reveal that only big companies with high B/M maintain the positive distress risk premium up to the 5^{th} quintile of distress risk as these companies generate on average still positive operating cash flows throughout all distress risk levels. (Table 5.6.1.6, Figure 5.6.1.32). Two-way sorted B/M - Distress risk portfolios (Table 5.6.1.4, Appendix A) confirm the above findings where distress risk is positively priced up to the 4^{th} distress risk quintile with an average p of 0.49, but it then diminishes once stocks are distressed and unprofitable. Figure 5.6.1.29 sums it up. Big Size – high B/M companies in the computer and electronics industry earn lower returns compared to other portfolios, but appear to maintain a positive continuous distress risk premium up to the highest distress risk quintile as result of still producing positive cash flows or current profitability strength.

So, if the financial distress factor hypothesis of Fama and French (1992) holds and my distress risk factor as used in this study is valid I then should expect to see the average B/M factor increasing and the average Size factor decreasing along the low to high distress risk quintiles or deciles axes. The distress deciles sorted portfolios, however, give a different picture. Table 5.6.1.1, Panel D, and Figure 5.6.1.4 show that low and high distressed stocks share a similar level of mean ln(B/M) values. The ln(B/M) values increase from the lowest to the 5^{th} distress decile but then drop again rather than analogously increase with distress risk levels. It depicts an inverted u-shape and confirms Dichev's (1998) finding. As a consequence, portfolios ranked by B/M quartiles would cause low and high distressed stocks to be combined in the first B/M quartile since they share similarly low ln(B/M) values. Dichev (1998) concludes that highly distressed stocks have a low rather than high

B/M and earn low returns which is consistent with my finding as reflected by Figures 5.6.1.1 and 5.6.1.4. Table 5.6.1.5 in Appendix A illustrates the descriptive statistics of 16 independently sorted Size - B/M portfolios and confirm Dichev's (1998) finding in so far that the distress risk probability for low B/M stocks is found at *p* 0.42, going down to *p* 0.34 and then upwards again to *p* 0.35 and *p* 0.39 for the high B/M portfolio. This u-shape of probability of failure risk distribution along the B/M quartiles axis (Figure 5.6.1.27, Appendix A) seems to confirm that both stocks with high and low distress risks are averaged in the low B/M portfolio. However, there is also a different result for the Size factor which does expectedly decrease along the axis of distress risk deciles (Figure 5.6.1.3) thus eventually mirrors distress risk. Further tests on these two factors will be conducted in sections 5.5.3 and 5.5.4.

<u>Other results</u>

Besides the results above, the descriptive statistics also provides monthly average excess return information on a portfolio by portfolio basis. The highest excess returns are achieved by a high OPCF – High Distress portfolio with a monthly average of 2.8% (Table 5.6.1.2, Appendix A). This is also in line with the above findings. The first is that firms with a higher profitability achieve higher returns while loss making companies which are proxied by negative operating cash flows before interest and taxes paid earn on average lower returns (earnings levels – returns relationship proposition, section 2.3). The second in parallel is that it appears that distress risk is positively priced thus highly distressed stocks earn a higher premium than non-distressed stocks following a risk based rational pricing proposition. As result, the cross-sectional regressions tests of these two factors may occur jointly given the potential conditionality between these two factors. Both factors, distress and OPCF are tested for statistical significance in a number of multivariate settings (section 5.6.3).

Figure 5.6.1.25 indicates that growth stocks may actually earn higher returns than value stocks which is specific to this industry and eventually to the period tested. On average, low B/M stock earned a monthly excess return of 2% whereas high B/M only 0.8% for the 1990 – 2006 period (see comments regarding periodically changing signs of B/M and size factors in section 2.2.3.3).

Another interesting finding is that the average beta is quite linearly increasing along the Distress risk deciles and quintiles axes (Figures 5.6.1.2 and other figures in Appendix A). This somewhat confirms that the distress risk probabilities derived from the bankruptcy prediction model appear to measure the underlying risk of failure with a right tendency. However both, the market factor and the distress risk factor as univariates may not be able to explain the distressed stocks' average underperformance in a linear fashion.

Given the results above it appears that $H2_A a)$ cannot be rejected. Additional cross-sectional regressions need to be performed to confirm the statistical significance of the above results (sections 5.5.4 and 5.6.3). The additional finding that the B/M factor is following an inverted u-shape along the low to high distress risk axis is in contrast with the distress factor proposition made by Fama and French (1992). It indicates that $H2_A b)$ cannot be rejected. However, the Size factor appears to mirror somewhat the distress risk factor, but it needs to be confirmed by correlation and cross-sectional regression tests. A final conclusion for this hypothesis related to the Fama-French distress factor proposition has to be made in connection with the test results in sections 5.6.2 and 5.6.3.

Table 5.6.1.1: Descriptive Statistics across Distress Deciles

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently ranked on Distress by probability of failure deciles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, ln(B/E) and ln(Size) are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. Distress risk and OPCF factor values are obtained from the bankruptcy prediction model. Monthly mean excess return is the time-series average of the difference between monthly stock returns and the one-month t-bill rate at the beginning of each month. Mean betas of portfolios are estimated at the portfolio formation date. For the final month of a firm's life, delisting returns provided by CRSP are included and if not available the last reported full-month return instead (very rare). Mean ln(Size), mean ln(B/M), mean Distress probability and mean OPCF are the time-series averages over a 204-month period of the respective factor's regression coefficients obtained on a monthly basis. On average, 520 NYSE, NASDAQ or AMEX listed companies from the computer and electronics industry are included on a monthly basis. Comments on the descriptive statistics below are provided in connection with figures 5.6.1.1 to 5.6.1.6.

A. Monthly Mean Excess Return

Distress Deciles	**Low**	2	3	4	5	6	7	8	9	**High**	**Avg**
Mean	0.014	0.014	0.013	0.013	0.013	0.016	0.018	0.017	0.011	0.009	0.014

B. Mean Beta

Distress Deciles	**Low**	2	3	4	5	6	7	8	9	**High**	**Avg**
Mean	1.44	1.44	1.45	1.47	1.60	1.68	1.70	1.62	1.77	1.67	1.58

C. Mean ln(Size)

Distress Deciles	**Low**	2	3	4	5	6	7	8	9	**High**	**Avg**
Mean	19.23	19.35	19.13	19.02	18.76	18.54	18.10	17.61	17.52	17.79	18.50

D. Mean ln(B/M)

Distress Deciles	**Low**	2	3	4	5	6	7	8	9	**High**	**Avg**
Mean	-1.11	-0.85	-0.69	-0.60	-0.59	-0.65	-0.70	-0.73	-0.93	-0.95	-0.78

E. Mean Distress Probability

Distress Deciles	**Low**	2	3	4	5	6	7	8	9	**High**	**Avg**
Mean	0.03	0.11	0.21	0.30	0.38	0.44	0.47	0.50	0.55	0.65	0.36

F. Mean OPCF

Distress Deciles	**Low**	2	3	4	5	6	7	8	9	**High**	**Avg**
Mean	0.287	0.192	0.150	0.119	0.096	0.074	0.047	-0.007	-0.158	-0.300	0.050

G. Average Size - Market Cap in $ m

Distress Deciles	**Low**	2	3	4	5	6	7	8	9	**High**	**Avg**
Mean	3'820	2'500	2'630	1'850	1'080	976	612	493	316	594	1'487

H. Average Number of Stocks (per month)

Distress Deciles	**Low**	2	3	4	5	6	7	8	9	**High**	**Avg**
Mean	52	52	52	52	52	52	52	52	52	52	52

Figures 5.6.1.1 to 5.6.1.6 derived from Table 5.6.1.1

The figures below depict the mean statistics

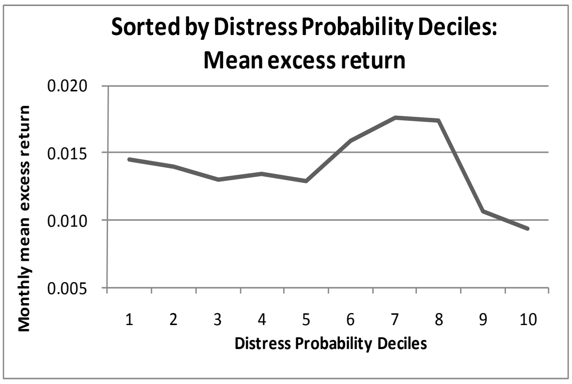


Figure 5.6.1.1. Monthly Excess Returns by Distress. The figure plots the monthly excess mean returns by distress sorted portfolios. Returns increase up to 8th decile and sharply fall at highest distress levels of probability of failure > 0.5.

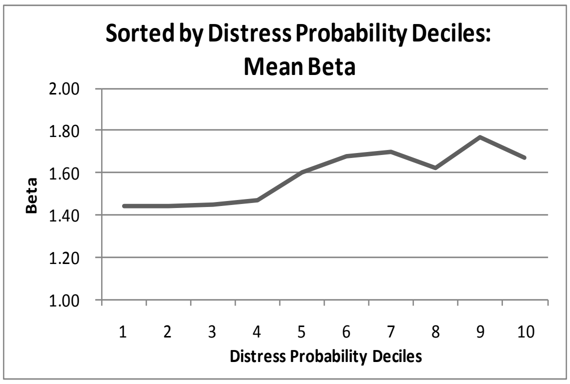


Figure 5.6.1.2. Mean Beta by Distress. The figure plots the mean betas by distress sorted portfolios. The mean betas increase in line with distress risk, but do not drop at 9th distress decile with probability of failure > 0.5. Hence beta and distress risk appear to mirror risk but both may not capture underperformance of highly distressed stocks on a univariate basis.

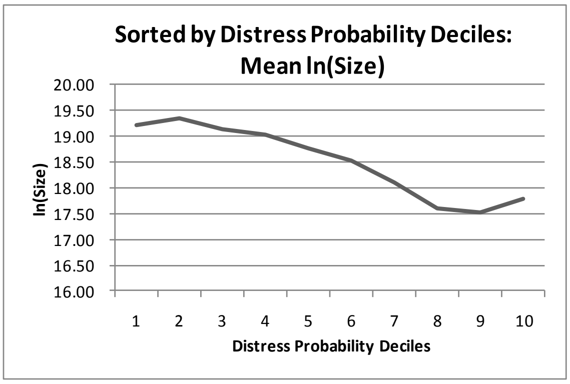


Figure 5.6.1.3. Mean ln(Size) by Distress. The figure plots the monthly mean ln(size) factor (Fama & French, 1992) by distress sorted portfolios. On average, smaller companies are at higher distress risk compared to large ones.

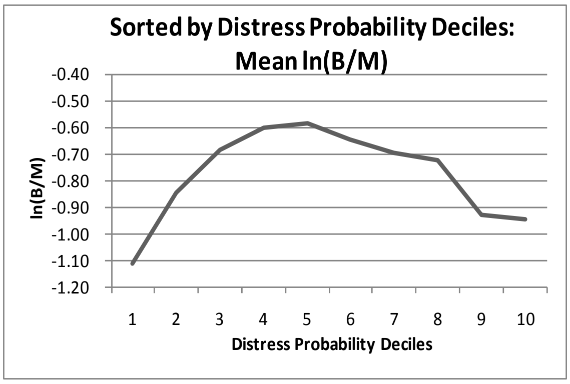


Figure 5.6.1.4. Mean ln(B/M) by Distress. The figure plots the mean ln(B/M) factor (Fama & French, 1992) by distress sorted portfolios. The mean B/M increases in line with distress risk and drops at 6th decile or a probability of failure > 0.44. It follows an inverted u-shape as described by Dichev (1998).

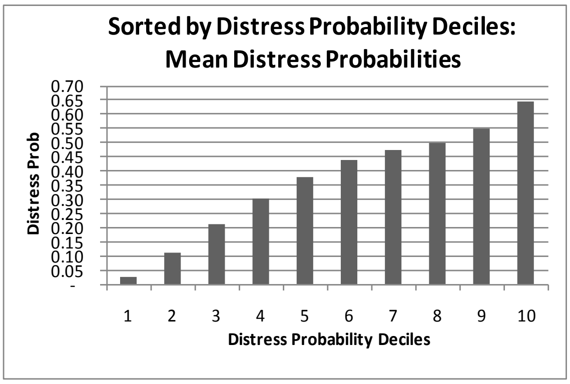


Figure 5.6.1.5. Mean Probability of Failure by Distress. The figure plots the monthly mean probability of failure by distress sorted portfolios. The 8th decile depicts a mean probability of failure 0.5 and the 9th 0.55.

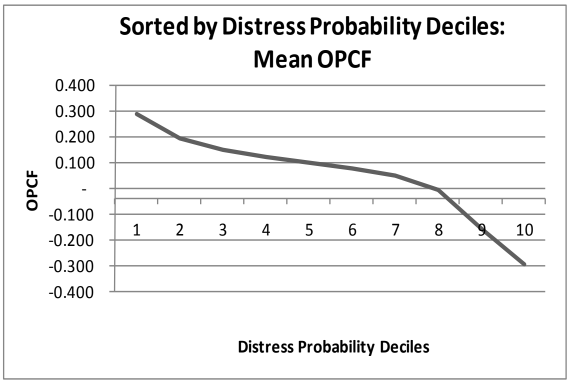


Figure 5.6.1.6. Mean OPCF by Distress. The figure plots the mean OPCF factor by distress sorted portfolios. The mean decreases in line with distress risk. A positive OPCF reflects a positive operating cash flow, which is found at lower distress. Cash burning companies are on average found at > 8th deciles.

Table 5.6.1.6: Descriptive Statistics across Size & B/M Halves and Distress Quintiles

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently ranked on Size and B/M halves at their median breakpoints and independently ranked on Distress by probability of failure quintiles. 20 portfolios are then formed at intersections of Size halves, B/M halves and Distress quintiles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, ln(B/E) and ln(Size) are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. Distress risk and OPCF factor values are obtained from the bankruptcy prediction model. Monthly mean excess return is the time-series average of the difference between monthly stock returns and the one-month t-bill rate at the beginning of each month. Mean betas of portfolios are estimated at the portfolio formation date. For the final month of a firm's life, delisting returns provided by CRSP are included and if not available the last reported full-month return instead (very rare). Mean ln(Size), mean ln(B/M), mean Distress probability and mean OPCF are the time-series averages over a 204-month period of the respective factor's regression coefficients obtained on a monthly basis. On average, 520 NYSE, NASDAQ or AMEX listed companies from the computer and electronics industry are included on a monthly basis. Comments on the descriptive statistics below are provided in connection with figures 5.6.1.29 to 5.6.1.32.

A. Monthly Mean Excess Return

Size/BM/Prob	Low	2	3	4	High	Avg
Big/High	0.005	0.007	0.007	0.009	0.013	0.008
Big/Low	0.018	0.019	0.020	0.022	0.015	0.019
Small/High	0.007	0.008	0.012	0.016	0.007	0.010
Small/Low	0.019	0.021	0.018	0.022	0.011	0.018
Avg	0.012	0.014	0.014	0.017	0.012	0.014

B. Mean Beta

Size/BM/Prob	Low	2	3	4	High	Avg
Big/High	1.55	1.61	1.87	2.08	2.04	1.83
Big/Low	1.56	1.65	1.91	2.09	2.02	1.85
Small/High	1.17	1.14	1.33	1.42	1.57	1.33
Small/Low	1.16	1.30	1.37	1.46	1.64	1.39
Avg	1.36	1.43	1.62	1.76	1.82	1.60

C. Mean ln(Size)

Size/BM/Prob	Low	2	3	4	High	Avg
Big/High	19.5	19.7	19.8	19.7	19.5	19.6
Big/Low	20.5	20.6	20.1	19.6	19.5	20.1
Small/High	17.1	17.1	16.9	16.7	16.6	16.9
Small/Low	17.5	17.6	17.3	17.1	17.2	17.3
Avg	18.7	18.7	18.6	18.3	18.2	18.5

D. Mean ln(B/M)

Size/BM/Prob	Low	2	3	4	High	Avg
Big/High	-0.40	-0.33	-0.27	-0.28	-0.29	-0.31
Big/Low	-1.43	-1.27	-1.33	-1.53	-1.76	-1.46
Small/High	-0.19	-0.04	-0.00	0.00	0.00	-0.04
Small/Low	-1.13	-1.12	-1.28	-1.42	-1.60	-1.31
Avg	-0.79	-0.69	-0.72	-0.81	-0.91	-0.78

E. Mean Distress Probability

Size/BM/Prob	Low	2	3	4	High	Avg
Big/High	0.09	0.26	0.40	0.48	0.57	0.36
Big/Low	0.06	0.24	0.40	0.48	0.59	0.35
Small/High	0.08	0.27	0.42	0.49	0.58	0.37
Small/Low	0.05	0.27	0.42	0.49	0.63	0.37
Avg	0.07	0.26	0.41	0.48	0.59	0.36

F. Mean OPCF

Size/BM/Prob	Low	2	3	4	High	Avg
Big/High	0.200	0.130	0.091	0.046	-0.001	0.093
Big/Low	0.263	0.164	0.110	0.035	-0.202	0.074
Small/High	0.198	0.109	0.068	0.019	-0.135	0.052
Small/Low	0.257	0.122	0.059	-0.009	-0.432	-0.001
Avg	0.230	0.131	0.082	0.023	-0.193	0.055

G. Average Size - Market Cap in $ m

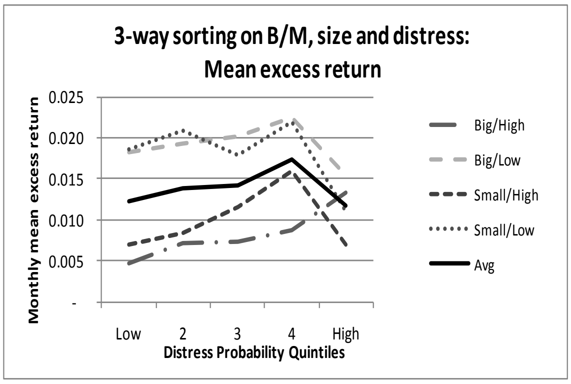
Size/BM/Prob	Low	2	3	4	High	Avg
Big/High	779	1'320	1'240	1'020	767	1'025
Big/Low	6'010	5'090	2'270	1'460	1'510	3'268
Small/High	43	45	39	35	31	39
Small/Low	61	64	54	48	46	55
Avg	1'723	1'630	901	641	588	1'097

H. Average Number of Stocks (per month)

Size/BM/Prob	Low	2	3	4	High	Avg
Big/High	16	28	27	14	10	19
Big/Low	55	37	30	24	21	33
Small/High	22	31	35	43	37	34
Small/Low	12	8	13	24	36	19
Avg	26	26	26	26	26	26

Figures 5.6.1.29 to 5.6.1.32 derived from Table 5.6.1.6

The figures below depict the mean statistics



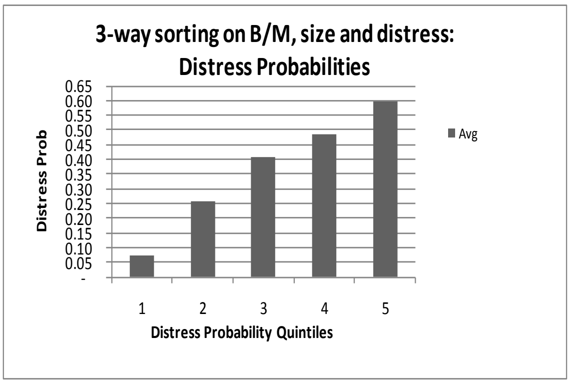
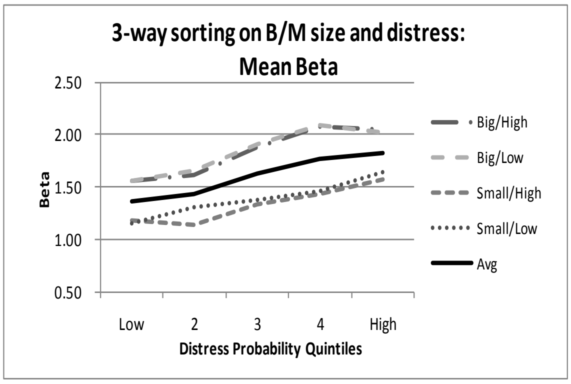


Figure 5.6.1.29. Monthly Excess Returns by Size, B/M and Distress. The figure plots the monthly excess mean returns by distress, B/M and Size sorted portfolios. Returns increase up to the 4th quintile. With exception of Big/High portfolio returns fall at highest distress levels of probability of failure > 0.5. Risk premium at highest distress level is maintained only by companies producing high operating cash flows. The Big/High portfolio shows a portfolio of companies generating positive operating cash flow as depicted in figure 5.6.1.32.

Figure 5.6.1.30. Mean Probability of Failure by Size, B/M and Distress. The figure plots the monthly mean probability of failure by B/M, size and distress sorted portfolios. The 4th quintile depicts a mean probability of failure 0.48 and the 5th 0.59.



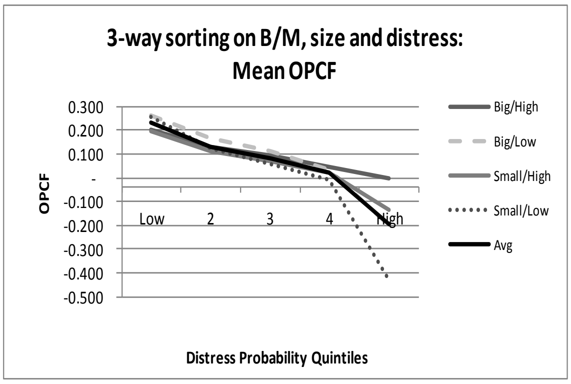


Figure 5.6.1.31. Mean Beta by Size, B/M and Distress. The figure plots the mean betas by distress, B/M and Size sorted portfolios. On average, betas increase linearly with distress risk. Big companies have higher betas, hence higher risk and not surprisingly earning higher returns as per figure 5.6.1.29. However, the betas of high versus low B/M are indifferent. If an increasing beta reflects an increasing risk then B/M cannot be considered to be a substitute of distress risk.

Figure 5.6.1.32. Mean OPCF by Size, B/M and Distress. The figure plots the monthly mean probability of failure by distress, B/M and Size sorted portfolios.. OPCF diminishes at increasing level of distress risk regardless of size or B/M. However, at the 5th quintile, the Big/High portfolio still generates positive operating cash flows whereas all other fall into a cash burning area as reflected by a negative OPCF. The Small/low portfolio shows the most negative operating cash flow. The risk-return relationship within the 5th quintile or mean probability > 0.48 can only be maintained by the Big/High portfolio (see figure 5.6.1.29). This suggests that highly distressed but profitable companies earn a distress risk premium.

Figures 5.6.1.33 The figures below depict the mean statistics

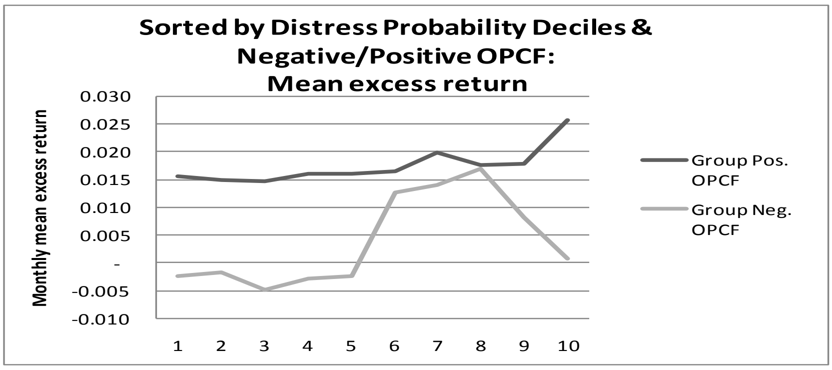


Figure 5.6.1.33. Monthly Excess Returns of Positive and Negative OPCF by Distress. The figure plots the monthly excess mean returns of positive and negative OPCF by distress sorted portfolios. On average, stocks generating a positive operating cash flow maintain the risk-return relationship across the distress deciles. Although, cash burning stocks earn increasing returns along the distress levels, the 9th and 10th deciles experience a deterioration of mean excess returns and mean OPCF. Note: the 1st five deciles of positive OPCF have a very limited number of observations and may be understated.

5.6.2 Results Multicollinearity Tests

The Pearson correlation tests as described in section 5.5.3 are performed on a portfolio by portfolio as well as on an individual stock basis. The 204 months' time-series average of correlation coefficients as shown by table 5.6.2.4 (and tables 5.6.2.1, 5.6.2.2, 5.6.2.3, 5.6.2.5 in Appendix B) clearly indicate that distress risk is independent from both the Size and B/M factors. On the 3-way sorted portfolio Size-B/M-Distress, the Size and Distress risk factor correlate with -0.1682. The B/M and Distress factors' correlation is -0.0622.

The coefficients for OPCF and distress are on average semi-strong (Table 5.6.2.4 / Tables in Appendix B, 5.6.2.1, 5.6.2.2, 5.6.2.3, 5.6.2.5) which does not require any further modifications of the factor model. Correlations among other variables are considered to be rather weak and therefore unproblematic except the one between the interaction variable Distress*OPCF and OPCF.

Therefore, no further change in model specification is needed. Overall, the results indicate that there is no issue of multicollinearity and that the Distress factor proxied by the cash flow based bankruptcy prediction model's probability of failure is independent of Size and B/M. In view of hypothesis $H2_A b)$, sections 3.3 and 5.2, it appears that B/M and Size capture something else than distress risk or at least not such risk only.

Table 5.6.2.4 Pearson correlations - Size, B/M and Distress sorted portfolios

The Pearson correlation tests are performed on a monthly basis. The correlation coefficients are the time-series average of 204 months. The table below shows weak correlations among independent variables. The only exceptions noted are the interaction variable Dis*OPCF showing some very strong correlation with OPCF and a strong correlation between OPCF and Distress.

	Beta	Size	B/M	Distress	OPCF	Dis*OPCF
Beta	1					
Size	0.4629	1				
B/M	-0.1571	-0.2719	1			
Distress	0.3537	-0.1682	-0.0622	1		
OPCF	-0.2136	0.2690	0.2120	-0.8047	1	
Dis*OPCF	-0.0758	0.2353	0.3394	-0.4432	0.8486	1

5.6.3 Results Cross-Sectional Regression Tests

The main objective of the cross-sectional regressions is to test for statistical significance of factors and models related to the hypotheses *$H2_A$a)* to *$H2_A$c)* which are formulated in sections 5.2 and/or 3.3. The statistical significance of factors explaining monthly excess average stock returns is provided by the Fama and MacBeth (1973) t-statistics. Further explanations to this approach are found in section 2.2.3.2.

All commentary on the cross-sectional regression results below correspond to following Tables 5.6.3.4 and 5.6.3.6 as well as those in Appendix C (Tables 5.6.3.1, 5.6.3.2, 5.6.3.3, 5.6.3.5) if not mentioned otherwise. However, as discussed in section 5.5.1, the involvement of all characteristics in forming portfolios is preferred hence a three-way independently sorted set of portfolios in this study is to be favoured over single or two-way sorts. Therefore, the main focus in analyzing the statistical significance of factors and models lies on the three-way intersecting Size-B/M-Distress portfolios (Table 5.6.3.4).

a) <u>CAPM</u>

A first regression test is made using the market factor only (Panel A). The regressions show an unsurprising result as documented by many other studies that the market β itself cannot describe monthly stock returns, also not within this industry specific study. The intercept α should be equal to zero if the CAPM or multi-factor model is well specified and expressed by an excess return format. The t-statistics for the βs range from 0.44 to 1.67 and thus they are not significantly different from zero. The αs, which are expected to be economically and statistically indifferent from zero, are higher than the βs and in most cases significantly different from zero with t-statistics found in the range of 1.14 to 2.39. Given the above result, it looks like β is dead or at least flat.

b) 3-Factor Fama-French (1992)

The second specification tested is the Fama and French (1992) model which includes factors for Size and B/M (Panel B). This model also provides the basis for measuring the incremental impact of added factors such as relative distress risk and current profitability strength (OPCF). The three-factor model regression reveals that B/M has some strong explanatory power in almost all sets of portfolios and models with the exception of portfolios sorted without the B/M characteristics (Table 5.6.3.1, 5.6.3.2 in Appendix C). However, the average slope of B/M is negative, a contrary outcome to other studies (see section 5.6.1), but consistent with the descriptive statistics' results reported by Figure 5.6.1.25 in Appendix A. In a set of three-way intersecting portfolios with Size (2), B/M (2) and Distress (5) characteristics (Table 5.6.3.4) the slope for B/M is -0.0065 with a highly significant t-statistics of -3.90. Similar values are found with other portfolio formations as long as the B/M characteristics sort is included. Hence, growth stocks earn a higher premium than value stocks in the US computer and electronics industry. Loughran (1997) shows in his study that the B/M factor had changing signs over several periods and that it was negative for the years 1985 to 1995. This anomaly could be explained by the fact that the computer and electronics industry was growth oriented over this period of rapid technological advancement. Investors may have awarded high multiples relative to the book equity for these industry-specific companies by anticipating substantially higher future sales and earnings compared to the prevalent fundamentals given at the time of investment.

The other two factors, Size and β are both insignificant in describing stock returns (see section 2.2.3.3). The βs show in some portfolios (Table 5.6.3.2, Appendix C) even a negative slope. This finding is consistent with Fama and French (1992), Lakonishok and Shapiro (1986) and others. The Size factor is insignificant in both univariate and multivariate regression tests. This finding is not of surprise as the size effect has been found to be weak or even nonexistent starting in the 1980s (Dichev, 1998).

The third group of specifications (Panel C) includes various multi-factor model combinations. The focus lies on the Distress risk and current profitability strength (OPCF) factors which are tested in different settings as discussed below.

c) Distress Risk Factor

Model 3) reflects the Fama and French (1992) three-factor model augmented by the Distress factor only. In all set of portfolios except Table 6.5.3.5 (Appendix C), the distress factor premium without the profitability factor cannot explain stock returns significantly. The same is true when the CAPM is extended by the distress factor as shown with model 7). The distress risk factor cannot grasp monthly excess stock returns linearly as concluded in section 5.6.1 (descriptive statistics) as it appears that non-distressed stocks are rewarded on average with a positive distress risk premium depending on profitability strength, but that distressed stocks as a separate group on average underperform. Nevertheless despite its insignificance as a univariate, the positive slope of distress can be interpreted to be a premium reward as expected by a risk based rational pricing proposition (section 3.1).

d) OPCF Factor as proxy for Profitability Levels

The current profitability strength factor which is proxied by the OPCF coefficient shows some stronger explanatory power when used as augmentation of the Fama-French three-factor model or the CAPM. Model 4) shows again the Fama and French (1992) specification augmented by the OPCF factor is significant at 0.10 level in a three-way-sorted portfolio (Table 5.6.3.4). In particular, this factor is highly significant in OPCF sorted portfolios (Table 5.6.3.1, Appendix C) with t-statistics of – 3.89. The positive slope of OPCF can be interpreted to be a premium reward as expected by the earnings levels to return relationship proposition (section 3.1). Model 8) is the market model extended by the OPCF factor only confirming the above results.

e) Distress and OPCF in a Joint Setting and Conditionality between the two Factors

As discussed under c) a stand-alone relative distress risk factor cannot describe stock returns which is also not a surprise when looking into the descriptive statistics (Figure 5.6.1.1, 5.6.1.29). However, the descriptive statistics (Figure 5.6.1.33) also reveal that the distress risk factor conditional on profitability (OPCF) may price a positive distress risk premium.

Based on the research question and the hypotheses set in section 3.3, various models that include distress risk and profitability (OPCF) factors are tested jointly in a multivariate setting. The focus lies on model 10) derived from two theoretical propositions discussed in section 3.1 as well as model 12) which should provide evidence of the conditionality between distress risk and profitability levels (OPCF).

Nevertheless, the first specification discussed is model 5) which is a five-factor model made of Fama-French's (1992) three-factor plus distress risk and profitability (OPCF). In all sets of portfolios the five-factor model has significantly improved the explanatory power (adj R^2) over the Fama-French's three-factor model. In addition, the Distress risk and OPCF factors are in most of the cases highly significant at 0.01 level and do help increasing the t-statistics of the B/M and Size factors too. An increased distress risk provides a positive distress risk premium on a continuous basis in a joint setting with profitability (OPCF) hence it follows a risk based rational pricing proposition as discussed in section 3.1. The profitability (OPCF) factor also shows a positive slope in a joint setting with distress risk and confirms the positive profitability (earnings) levels to return relationship also discussed in section 3.1. Comparing model 5) and 10) with model 2) also indicates that the inclusion of the distress risk and profitability (OPCF) factors improves the t-statistics of both the B/M and size factors. Hence, the Distress risk and OPCF factors are not subsumed by the size or B/M factors. The improvement of t-statistics of B/M and Size by adding the distress risk and OPCF factors confirm the findings of section 5.6.2 where B/M and Size is found to capture something other than distress risk. If such risk was proxied by B/M or Size, one should have expected that either of these variables to become less significant or even insignificant in explaining returns. This also confirms the findings as described in section 5.6.1 where B/M illustrates an inverted u-shape along the distress risk deciles axis.

Overall, the B/M factor is highly significant at 0.01 level in any of the model specifications tested whereas Size and β are insignificant with less than one standard error from zero. In the Fama-French (1992) three-factor model 3), the B/M factor shows a negative slope of -0.0065 with a t-statistics of -3.90 which means that growth stocks earned on average a premium over value stocks in the period from 1990 to 2006. The five-factor model 5) which adds the two factors Distress risk and OPCF on top of model 3) improves the t-statistics of B/M from -3.90 to -5.07. In addition, Distress risk with a positive slope of 0.0293 and a t-statistics of 3.68 and OPCF with a positive slope of 0.0437 and a t-statistics of 4.50 are both highly significant. The adjusted R^2 has improved from 0.20 for the three-factor to 0.29 for the five-factor model.

Model 10) is a four-factor model which serves as a proxy for the model specification based on the two theoretical propositions as discussed in section 3.1 and 3.3. which does not include factor Size. The results are quite similar to model 5) and the α with a positive 0.0012% and a t-statistics of 0.22 is indifferent from zero both economically and statistically. Besides beta, all three factors are highly significant where distress risk as well as profitability (OPCF) show a positive slope hence a premium as expected by both theoretical propositions discussed in section 3.1. The adjusted R^2 has only slightly improved from 0.20 for the three-factor to 0.21 for the four-factor model. Although not disclosed, the same model without beta has resulted in very similar results.

Model 12) tests the interaction term between distress risk factor and profitability (OPCF) to see if there is a conditionality. Although, the main effects lose statistically some meaning as expected, they still are significant at 0.05 level. The interaction term with a t-statistics of -2.22 is significant at 0.05 level for the three-way sorted portfolio (Size-B/M-Distress risk) as well as for all other non-size sorted portfolios at either 0.05 or 0.10 level (Table 5.6.3.1, 5.6.3.3, all in Appendix C). The robustness check (Table 5.6.3.6) also confirms the conditionality between the two factors with a high significance at 0.01 level.

Overall, model 5) produces the strongest model with the highest R^2 and highest t-statistics for B/M, distress risk and profitability (OPCF) factors. Although the size factor is insignificant, it still adds some explanatory power to the model as a whole when comparing to model 10).

f) Robustness Checks

Besides the empirical successes of Fama and French (1992, 1993) factor models, there has also been some legitimate criticism from notable researchers. Data snooping bias has been a particular concern (Lo and MacKinlay, 1990; Black, 1993; MacKinlay, 1995) and may never be eliminated completely. One remedy to disprove the claim of the data snooping bias is to run regressions on individual securities as discussed in section 2.2.3.4. The outcome of the individual stocks regressions (Table 5.6.3.6) confirms the results obtained from portfolio regressions as discussed under paragraph f) above. The three-factor model's B/M factor shows a negative slope of – 0.0069 and is highly significant with a t-statistics of – 4.62 . The five-factor model 5) which includes Distress risk and OPCF factors also improves the t-statistics of B/M from – 4.62 to – 5.86. The Distress risk factor with a positive slope of 0.0156 and a t-statistics of 2.76 and OPCF with a positive slope of 0.0303 and a t-statistics of 5.90 are both highly significant and show the same signs as those found in the portfolio regressions. The adjusted R^2 of the five-factor model 5) over the three-factor model 2) is slightly higher.

Model 10), the four-factor model which excludes factor Size has quite similar results to those of model 5) where α, the pricing error, is positive 0.0009% with a t-statistics of 0.18 thus both economically and statistically indifferent from zero. As with the three-way-sorted portfolio set, all factors except beta are highly significant at 0.01 level. The distress risk factor and OPCF, both, show a positive slope and confirm the portfolio testing and related theories.

Model 12) also confirms the existing conditionality between distress risk and profitability (OPCF) with all factors including the interaction term being highly significant.

The results, derived from the non-portfolio regressions, may counter at least in part the criticism of data snooping bias. There are no essential differences noted between the portfolios' and individual securities' regression test results. Nevertheless, this industry specific study which can be considered to be a sub-sample of previous market studies thus a remedy to overcome such bias has shown that growth Stock (low B/M) has earned a superior premium over value firms. Also, it is evidenced that the Size factor has no significance in explaining average monthly stock returns, but that distress risk and OPCF factors when measured jointly are highly significant in doing so and that in a separate setting both factors interact.

Table 5.6.3.4: Size (2) x B/M (2) x Distress (5) - 20-Portfolio Regression

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently grouped into high and low B/M as well as small and big Size halves and also independently ranked on Distress by probability of failure quintiles. B/M and Size halves are obtained by the median of observations. 20 portfolios are then formed at intersections of B/M and Distress halves as well as Distress quintiles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. β_{it-1} is the beta of portfolio *i* estimated at the portfolio formation date. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, $\ln(B/E)_{it-1}$ and $\ln(Size)_{it-1}$, are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. $Distress_{it-1}$ and $OPCF_{it-1}$ as well as the interaction variable $distress*OPCF_{it-1}$ are obtained from the bankruptcy prediction model. R_{it} is the equally weighted return on portfolio *i* during month *t*. R_{Ft} is the risk free rate proxied by the one-month t-bill rate at the beginning of each month *t*. Values being lower than the 1st or higher than the 99th percentile are set equal to next largest or smallest values of the ratios (0.01 and 0.99 fractiles) in order to eliminate the influence of extreme outliers. The Fama-MacBeth (1973) or FM cross-sectional regression estimates are obtained for the CAPM, the 3-Factor Fama & French (1992) and other multi-factor models related to distress and OPCF as shown below for each of the 204 months from January 1990 to December 2006. The average slopes are the time-series averages of the equal-weighted monthly regression estimates and figures shown in brackets are the respective FM t-statistics.

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}(distress_{it-1}) + \gamma_{5t}(OPCF_{it-1}) + \gamma_{6t}(distress*OPCF_{it-1})$$

	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	adj R^2
A. CAPM								
1)	0.0116 *	0.0012						0.06
	(2.39)	(0.44)						
B. FF - 3-Factor								
2)	0.0091	-0.0009	0.0000	-0.0065 ***				0.20
	(0.48)	(-0.32)	(0.05)	(-3.90)				
C. Multi-Factor								
3)	0.0094	-0.0011	0.0001	-0.0066 ***	0.0012			0.27
	(0.51)	(-0.47)	(0.06)	(-4.05)	(0.18)			
4)	0.0238	0.0013	-0.0010	-0.0076 ***		0.0134 *		0.27
	(1.33)	(0.54)	(-0.95)	(-4.55)		(1.71)		
5)	0.0098	-0.0010	-0.0007	-0.0090 ***	0.0293 ***	0.0437 ***		0.29
	(0.54)	(-0.40)	(-0.68)	(-5.07)	(3.68)	(4.50)		
6)	0.0031	-0.0015	-0.0006	-0.0091 ***	0.0319 **	0.0432	0.0031	0.30
	(0.08)	(-0.61)	(-0.54)	(-4.74)	(2.14)	(1.44)	(0.08)	
7)	0.0118 **	0.0007			0.0016			0.13
	(2.68)	(0.25)			(0.22)			
8)	0.0126 *	0.0008				0.0017		0.15
	(2.08)	(0.27)				(0.21)		
9)	0.0083	0.0004			0.0107	0.0137		0.15
	(1.42)	(0.15)			(1.48)	(1.53)		
10)	0.0012	-0.0022		-0.0078 ***	0.0229 ***	0.0318 ***		0.21
	(0.22)	(-0.81)		(-4.67)	(2.88)	(3.22)		
11)	-0.0070	-0.0013	0.0009		0.0161 **	0.0185 **		0.22
	(-0.41)	(-0.49)	(0.90)		(2.22)	(2.12)		
12)	-0.0030				0.0350 **	0.0638 **	-0.0787 **	0.10
	(-0.35)				(2.41)	(2.19)	(-2.22)	

*** Significant at 0.01 level
** Significant at 0.05 level
* Significant at 0.10 level

Table 5.6.3.6: Individual Stock Regression

As robustness check, the Fama-MacBeth (1973) regressions are conducted for each individual security, hence without portfolio formation. These tests on individual securities should preclude the criticism of data snooping bias (Lo & MacKinlay, 1990). A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. β_{it-1} is the beta of security *i* estimated for each month. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, $\ln(B/E)_{it-1}$ and $\ln(Size)_{it-1}$, are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks *i* for each of the 204 months. $Distress_{it-1}$ and $OPCF_{it-1}$ as well as the interaction variable $distress*OPCF_{it-1}$ are obtained from the bankruptcy prediction model. R_{it} is the equally weighted return on security *i* during month *t*. R_{Ft} is the risk free rate proxied by the one-month t-bill rate at the beginning of each month *t*. Values being lower than the 1st or higher than the 99th percentile are set equal to next largest or smallest values of the ratios (0.01 and 0.99 fractiles) in order to eliminate the influence of extreme outliers. The Fama-MacBeth (1973) or FM cross-sectional regression estimates are obtained for the CAPM, the 3-Factor Fama & French (1992) and other multi-factor models related to distress and OPCF as shown below for each of the 204 months from January 1990 to December 2006. The average slopes are the time-series averages of the equal-weighted monthly regression estimates and figures shown in brackets are the respective FM t-statistics.

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}(distress_{it-1}) + \gamma_{5t}(OPCF_{it-1}) + \gamma_{6t}(distress*OPCF_{it-1})$$

	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	adj R^2
A. CAPM								
1)	0.0137 **	0.0003						0.00
	(2.39)	(0.55)						
B. FF - 3-Factor								
2)	0.0165	0.0001	-0.0004	-0.0069 ***				0.02
	(0.94)	(0.15)	(-0.45)	(-4.62)				
C. Multi-Factor								
3)	0.0263 *	0.0002	-0.0008	-0.0066 ***	-0.0086			0.03
	(1.74)	(0.49)	(-0.92)	(-4.80)	(-1.41)			
4)	0.0351 **	0.0003	-0.0016 *	-0.0082 ***		0.0231 ***		0.03
	(2.25)	(0.67)	(-1.88)	(-5.80)		(4.75)		
5)	0.0240	0.0002	-0.0013	-0.0083 ***	0.0156 ***	0.0303 ***		0.03
	(1.59)	(0.32)	(-1.55)	(-5.86)	(2.76)	(5.90)		
6)	0.0239	0.0002	-0.0013	-0.0083 ***	0.0161 ***	0.0320 ***	-0.0036	0.03
	(1.54)	(0.36)	(-1.58)	(-5.61)	(2.67)	(3.21)	(-0.26)	
7)	0.0161 ***	0.0003			-0.0078			0.01
	(3.56)	(0.69)			(-1.13)			
8)	0.0126 **	0.0003				0.0168 ***		0.01
	(2.14)	(0.66)				(3.08)		
9)	0.0083	0.0003			0.0107 *	0.0222 ***		0.01
	(1.62)	(0.50)			(1.83)	(4.17)		
10)	0.0009	-0.0001		-0.0071 ***	0.0171 ***	0.0279 ***		0.02
	(0.18)	(-0.12)		(-5.02)	(2.89)	(5.10)		
11)	0.0022	0.0002	0.0003		0.0128 **	0.0229 ***		0.03
	(0.15)	(0.36)	(0.42)		(2.29)	(4.49)		
12)	0.0026				0.0224 ***	0.0453 ***	-0.0318 ***	0.02
	(0.47)				(3.81)	(4.51)	(-2.55)	

*** Significant at 0.01 level
** Significant at 0.05 level
* Significant at 0.10 level

5.6.4 Asset Pricing Tests: Summary Result and Conclusion

The descriptive statistics (5.6.1), the correlation tests (5.6.2) and the Fama-MacBeth (1973) cross-sectional regression tests (5.6.3) lead to the following results:

The descriptive statistics of table 5.6.1.1 show that on average, highly distressed stocks do underperform non-distressed stocks. Distress deciles with probability of failure larger than 0.50 show a strong shortfall in mean excess returns when comparing to the group of non-bankrupt firms at 8th distress decile but also when benchmarking with the lowest distress risk portfolios (Figure 5.6.1.1) This finding is consistent with Dichev (1998), Campbell, Hilscher and Szilagyi (2008) as well as Agarwal and Taffler (2008). Given the descriptive test results I conclude that hypothesis $H2_A a)$ as shown in alternative form below cannot be rejected.

$H2_A a)$ Distressed stocks underperform on average non-distressed stocks.

The results (section 5.6.2) of the Pearson correlation tests performed on a portfolio by portfolio as well as on an individual stock basis clearly indicate that bankruptcy risk is independent from both the Size and B/M factors. Also, this study reveals that the B/M factor follows an inverted u-shape along the distress risk deciles axis (section 5.6.1, figure 5.6.1.4) which means that highly distressed stocks are found in the low B/M quartile in contrast to Fama and French's (1992) distress factor proposition which would expect to have high distressed stocks to be linked to high B/M values. This non-linear relationship with the distress risk factor derived from a bankruptcy prediction model supports the results of the Pearson correlation tests. The Fama-MacBeth (1973) cross-sectional regressions show that a five-factor analysis consisting of Fama and French (1992) three-factors plus Distress risk and profitability (OPCF) improve the B/M and Size factors' significance level as reflected by related t-statistics. If B/M or Size were capturing the distress factor, the inclusion of this study's distress factor should have weakened either the B/M and Size factors' explanatory power or rejected the distress risk factor by its low t-statistics. Furthermore, the addition of these two highly significant variables improved the models' overall explanatory power (higher adjusted R^2). The intercepts of this excess return model remained economically and statistically indifferent from zero. Assuming that the bankruptcy prediction model's probability of failure serves as a valid proxy for the relative distress risk I can conclude that both Fama and French factors (1992) do not capture bankruptcy risk. Given the descriptive (5.6.1, 5.6.2) and inferential statistics' (5.6.3) test results I conclude that hypothesis *$H2_A$b)* as shown in alternative form below cannot be rejected.

$H2_A$b): The Fama-French (1992, 1993) distress factor hypothesis where both size and B/M factors proxy distress risk does not hold.

The descriptive statistics (5.6.1) of Tables 5.6.1.1, 5.6.1.6 and in particular Figure 5.6.1.33 show that on average only highly distressed stock that is profitable may overperform non-distressed stocks. Highly distressed but non-profitable portfolios as reflected by negative OPCF earn on average lower stock returns.

The cross-sectional regressions as shown by Table 5.6.3.4 show that model 10) with proxy factors for the risk based rational pricing proposition (distress factor) and the earnings levels to returns proposition (OPCF) dominates the Fama-French (1992) three factor model in describing excess returns as reflected by its slightly higher adjusted R^2. The B/M factor shows an improved t-statistics by the inclusion of the statistically significant distress risk and profitability factors. Both, distress risk and profitability (OPCF) have positive slopes and are in joint settings statistically significant as shown by Fama-MacBeth t-statistics, hence confirming the two theoretical propositions of risk based rational pricing and the positive relationship between earnings levels and stock returns as well as the result of descriptive statistics. The separate testing of the interaction variable distress risk and profitability confirms the conditional relationship between the two factors. Given the descriptive (5.6.1) and inferential statistics' (5.6.3) test results above and the non-rejection of *$H2_A$a), $H2_A$b)* I conclude that hypothesis *$H2_A$c)* as shown in alternative form below cannot be rejected.

$H2_A$c): The anomalous market underperformance of distressed stock can be explained by a parallel analysis of risk based rational pricing and profitability/earnings levels to returns propositions.

Overall, I conclude that an anomalous underperformance of distressed stocks can be explained by the parallel application of risk based rational pricing and profitability levels to return propositions .

On average, distressed stocks earn lower returns than non-distressed ones, a finding which is consistent with Dichev (1998), Campbell, Hilscher, Szilagyi (2006) and Agarwal and Taffler (2008). However, once the conditional relationship with profitability is taken into account, the distress risk is rewarded by a continuous positive return hence priced appropriately. Two-thirds of the highly distressed companies have low or negative excess returns associated with negative profitability strength. The other third of distressed companies is profitable and earn on average superior returns compared to a) their non-distressed counterparts and b) distressed but non-profitable companies. Profitability (OPCF) is also found to be positively associated with stock returns hence in line with the earnings levels to returns relationship proposition.

Besides the joint pricing of relative distress risk and profitability levels (OPCF), the study makes clear that the distress factor hypothesis as proposed by Fama and French (1992) does not hold. Highly distressed companies have a similar low B/M profile as low distress firms do hence it cannot support a linear relationship to relative distress risk derived from a bankruptcy prediction model. However, the B/M factor's inverted u-shape actually mirrors the excess stock returns along the distress deciles quite well. That is why it is technically speaking highly significant in explaining stock returns.

CHAPTER 6: CONCLUSION

6.1 Conclusion

The main purpose of this study is to find out if the anomalous market underperformance of distressed stock can be explained by a parallel analysis of risk based pricing and profitability/(earnings) levels to returns relationship propositions. When the conditional relationship with profitability is taken into account, the distress risk is rewarded by a continuous positive return hence priced appropriately. In addition, the distress risk factor is derived from a cash flow based bankruptcy prediction model. In this study I aim to show that a cash flow based hazard model predicts bankruptcies at higher accuracy rates than its benchmark, the Altman's Z-score model.

6.1.1 Contribution to Knowledge

Two main contributions are made to the literature of prediction and pricing of relative distress risk.

First, for the pricing of the distress risk and profitability factors various portfolios have been formed and factors calculated on an equal-weighted basis. The portfolios are rebalanced on a quarterly basis using only publicly available data at the formation date assuming a three-month reporting lag. The descriptive statistics emerged from the portfolio formation and factor calculations based on time-series averages over 204 months (1990 – 2006) have been provided on a portfolio by portfolio basis. In addition, Pearson correlation tests have been conducted to check for multicollinearity and to obtain results in connection with the distress factor hypothesis. Last but not least, Fama-MacBeth (1973) cross-sectional regressions have been run on various sets of portfolios to obtain t-statistics and adj. R^2 for different types of models such as CAPM, Fama-French (1992) three-factor model and augmentations. This also included the four-factor model with beta, B/M, the relative distress risk and profitability strength (OPCF) factors to perform the parallel analysis of the two propositions as mentioned above. In addition, I have also tested for a potential conditionality between the two factors.

First, I can show that the anomalous underperformance of distressed stocks in the US computer and electronics industry can be explained by the parallel analysis of the risk based rational pricing and the profitability levels to returns relationship propositions. There is evidence that distressed stocks earn a positive continuous distress risk premium and that they are appropriately priced once the conditionality with profitability is taken into account.

Second, a cash flow based hazard model which predicts bankruptcies at higher accuracy rates than Altman's (1968) Z-score, as evidenced by a ROC benchmark model, has been developed. This industry specific model uses in contrast to many other studies non-arbitrarily selected cash flow variables derived from Lawson' cash flow identity (1971). This econometric model is constructed on the grounds of one of the more recent developments in this field by employing a hazard model (Shumway, 2001; Beaver, McNichols and Rhie, 2004; Campbell, Hilscher and Szilagyi, 2008). The model's prediction outcomes are validated by confirmative out-of-sample and favourable benchmark test results and can be considered to be robust. This model, a Cox proportional hazard model, not only predicts corporate failure, but also produces the probabilities of failure for each firm on quarterly basis which serve as a proxy for the continuous relative distress risk factor to be included in asset pricing tests as mentioned before.

Besides the joint pricing of relative distress risk and current profitability levels the study shows that the distress factor hypothesis as proposed by Fama and French (1992) does not hold. Highly distressed companies have a similarly low B/M profile as low distress firms. The inverted u-shape of B/M values along the distress risk deciles axis is in line with Dichev's (1998) finding. As result, it cannot support a linear relationship to the relative distress risk derived from a bankruptcy prediction model. The B/M and/or Size factors may capture something else with or without an involvement of relative distress risk.

6.1.2 Limitations

Bankruptcy prediction models are widely used in practice and in the literature but they lack a coherent theoretical basis. Jones (1987) argues that the prediction of firms' bankruptcies in temporal and economic settings different from then when the models are developed makes it rather difficult to ascertain whether such procedure is appropriate. Like other models, the one in this study measures bankruptcy risks with errors.

Although, there is a lack of bankruptcy theory, these empirical findings may contribute to the knowledge of better understanding the phenomenon of bankruptcy by providing economic interpretations.

There are also limitations given from a time and industry perspective. The data used for the asset pricing tests cover the period from 1990 to 2006. The financial data to be used for the calculation of the probabilities of failure is drawn from a statement of cash flows as required by Statement of Financial Accounting Standards (SFAS) No. 95. This Statement has been effective for firms reporting annual financial statements for fiscal years ending after July 15, 1988. The bankruptcy prediction model requires four quarters' rolling cash flow data so that the first probability of failure is obtained for the second quarter in 1989.

In order to avoid a look-ahead bias in asset pricing tests a three-month lag between quarter or year end and reporting of financial statements is assumed. The earliest availability of historical data would have been at beginning of the 4th quarter in 1989. For simplicity and completeness reasons the first month used for asset pricing tests in this study is January 1990. An expansion of prior periods would require a different approach in calculating the needed cash flow variables. The bankruptcy prediction model as well as the asset pricing models' test results are limited to the computer and electronics industry (NAICS code 334). Therefore, drawing statistical inferences from these models outside this specific industry is rather prohibitive but it could be an area for future research.

The cross-sectional regression results of the asset pricing tests are subject to several known limitations. First, the market return used for the calculation of market beta is the S&P 500 index which itself cannot be considered to be the entire "true" market portfolio. Therefore, CAPM's inability to describe returns in this study cannot automatically lead to a rejection of the model (Roll, 1977). Kothari, Shanken and Sloan (1995) argue that annual betas are more appropriate than monthly ones since the investment horizon for a typical investor is probably closer to a year. The beta could be estimated using a different convention than applied in this study and consequently could have produced higher significance in explaining stock returns. Multi-factor models such as Fama and French (1992, 1993) which are able to describe monthly stock returns successfully may be the result of data snooping (Black, 1993; MacKinlay, 1995). The study has been designed to counter this accusation.

The asset pricing models are tested for an association measurement between financial statements' derived factors and stock returns. Investors have access to many more information sources about a company's distress risk and cash flow generating ability. The Statement of Financial Accounting Standards (SFAS) No. 95 has been used to calculate distress risk and operating cash flow strengths for companies in the US computer and electronics industry and can be considered to be a proxy or substitute for investors' available information at hand when making their investment decisions. Nevertheless, as Kothari (2001) points out, there is no causal connection between such accounting information and stock prices and their movements to be inferred.

Haugen and Baker (1996) see two different groups of explaining differentials in stock returns. The first one supports a risk based rational pricing hypothesis (Fama and French, 1992, 1993, 1996; Ball, Kothari and Shanken, 1995) and the second group view these differentials in predicted returns as surprise to investors as result of market over- and underreactions related factors (Chopra, Lakonishok and Ritter, 1992; Lakonishok, Shleifer, Vishny, 1994; Haugen, 1995; and others). They find it rather difficult to link an underperformance of distressed stock to a rational asset pricing explanation as in their studies distressed stocks showing conflicting but expected characteristics of higher beta, higher B/M and smaller size. So, this group rather believes in a pricing bias hypothesis.

I provide a parallel analysis of two propositions, the risk based rational pricing and the positive relationship between profitability/earnings levels and returns, which can explain the underperformance of highly distressed stocks once the conditional relationship with profitability levels is taken into account. The study shows that distressed stocks are appropriately priced. However, the question remains why and under what rational or irrational assumptions investors would get involved in highly distressed and loss making investments. This is a topic for further research.

APPENDIX A: DESCRIPTIVE STATISTICS OF PORTFOLIOS

Table 5.6.1.2: Descriptive Statistics across OPCF Quartiles and Distress Quintiles

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently ranked on OPCF quartiles and independently ranked on Distress by probability of failure quintiles. 20 portfolios are then formed at intersections of OPCF quartiles and Distress quintiles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, ln(B/E) and ln(Size) are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. Distress risk and OPCF factor values are obtained from the bankruptcy prediction model. Monthly mean excess return is the time-series average of the difference between monthly stock returns and the one-month t-bill rate at the beginning of each month. Mean betas of portfolios are estimated at the portfolio formation date. For the final month of a firm's life, delisting returns provided by CRSP are included and if not available the last reported full-month return instead (very rare). Mean ln(Size), mean ln(B/M), mean Distress probability and mean OPCF are the time-series averages over a 204-month period of the respective factor's regression coefficients obtained on a monthly basis. On average, 520 NYSE, NASDAQ or AMEX listed companies from the computer and electronics industry are included on a monthly basis. Comments on the descriptive statistics below are provided in connection with figures 5.6.1.7 to 5.6.1.10.

A. Monthly Mean Excess Return

OPCF/Prob		Low	2	3	4	High	Avg
	High	0.018	0.022	0.024	0.028	0.028	0.024
	2	0.008	0.016	0.015	0.023	0.018	0.016
	3	0.006	0.005	0.012	0.014	0.012	0.010
	Low	0.010	0.001	0.007	0.013	0.007	0.008
Avg		0.010	0.011	0.015	0.020	0.016	0.014

B. Mean Beta

OPCF/Prob		Low	2	3	4	High	Avg
	High	1.46	1.50	1.68	1.69	1.62	1.59
	2	1.41	1.48	1.67	1.71	1.70	1.59
	3	1.42	1.40	1.63	1.68	1.72	1.57
	Low	1.19	1.38	1.55	1.59	1.73	1.49
Avg		1.37	1.44	1.63	1.67	1.69	1.56

C. Mean ln(Size)

OPCF/Prob		Low	2	3	4	High	Avg
	High	19.6	19.6	18.8	17.9	18.2	18.8
	2	19.0	19.3	18.9	18.1	18.0	18.6
	3	18.4	18.6	18.6	18.0	17.7	18.3
	Low	18.0	18.0	17.9	17.6	17.5	17.8
Avg		18.7	18.9	18.6	17.9	17.8	18.4

D. Mean ln(B/M)

OPCF/Prob		Low	2	3	4	High	Avg
	High	-1.12	-0.87	-0.85	-0.91	-0.82	-0.91
	2	-0.76	-0.60	-0.60	-0.66	-0.54	-0.63
	3	-0.62	-0.50	-0.49	-0.62	-0.45	-0.54
	Low	-0.78	-0.49	-0.67	-0.79	-1.12	-0.77
Avg		-0.82	-0.62	-0.65	-0.74	-0.73	-0.71

E. Mean Distress Probability

OPCF/Prob		Low	2	3	4	High	Avg
	High	0.14	0.29	0.40	0.45	0.62	0.38
	2	0.10	0.24	0.41	0.47	0.58	0.36
	3	0.14	0.29	0.42	0.48	0.58	0.38
	Low	0.14	0.30	0.43	0.51	0.60	0.40
Avg		0.13	0.28	0.41	0.48	0.60	0.38

F. Mean OPCF

OPCF/Prob		Low	2	3	4	High	Avg
	High	0.305	0.262	0.265	0.269	0.288	0.278
	2	0.151	0.145	0.141	0.137	0.139	0.143
	3	0.054	0.053	0.048	0.039	0.037	0.046
	Low	-0.118	-0.094	-0.121	-0.143	-0.393	-0.174
Avg		0.098	0.092	0.083	0.075	0.018	0.073

G. Average Size - Market Cap in $ m

OPCF/Prob		Low	2	3	4	High	Avg
	High	4'480	4'620	1'500	1'240	2'910	2'950
	2	880	1'980	1'250	724	877	1'142
	3	453	717	941	619	420	630
	Low	211	237	230	189	125	198
Avg		1'506	1'889	980	693	1'083	1'230

H. Average Number of Stocks (per month)

OPCF/Prob		Low	2	3	4	High	Avg
	High	69	28	18	10	6	26
	2	25	42	33	20	10	26
	3	9	27	36	40	19	26
	Low	2	7	17	34	70	26
Avg		26	26	26	26	26	26

Figures 5.6.1.7 to 5.6.1.10 derived from Table 5.6.1.2

The figures below depict the mean statistics

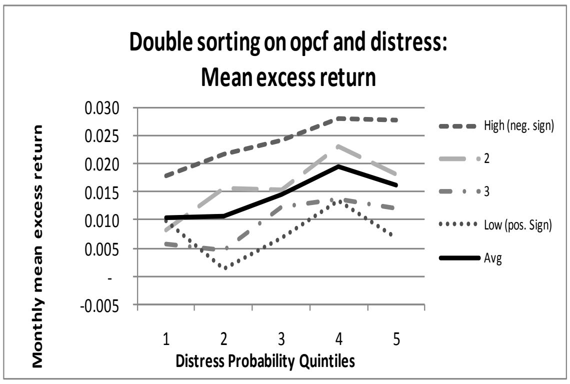


Figure 5.6.1.7. Monthly Excess Returns by OPCF and Distress. The figure plots the monthly excess mean returns by distress and OPCF sorted portfolios. Returns increase up to 4th quintile. With exception of high OPCF returns fall at highest distress levels of $p > 0.5$. Risk premium at highest distress level is maintained only by companies producing high operating cash flows.

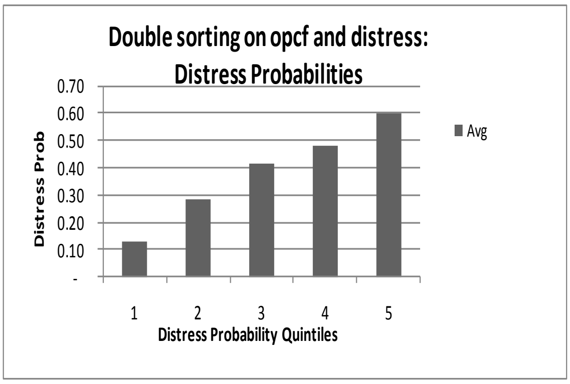


Figure 5.6.1.8. Mean Probability of Failure by OPCF and Distress. The figure plots the monthly mean probability of failure by distress and OPCF sorted portfolios. The 4th quintile depicts a mean probability of failure 0.48 and the 5th 0.60.

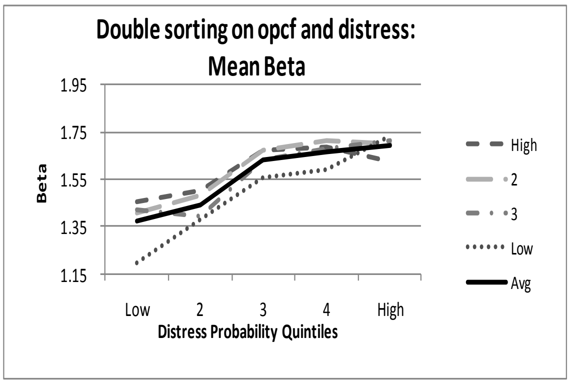


Figure 5.6.1.9. Mean Beta by OPCF and Distress. The figure plots the mean betas by distress and OPCF sorted portfolios.

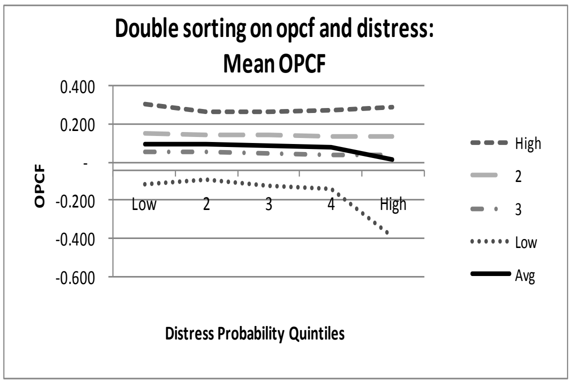


Figure 5.6.1.10. Mean OPCF by OPCF and distress. The figure plots the monthly mean OPCF by distress and OPCF sorted portfolios.

Table 5.6.1.3: Descriptive Statistics across Size Quartiles and Distress Quintiles

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently ranked on Size quartiles and independently ranked on Distress by probability of failure quintiles. 20 portfolios are then formed at intersections of Size quartiles and Distress quintiles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, ln(B/E) and ln(Size) are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. Distress risk and OPCF factor values are obtained from the bankruptcy prediction model. Monthly mean excess return is the time-series average of the difference between monthly stock returns and the one-month t-bill rate at the beginning of each month. Mean betas of portfolios are estimated at the portfolio formation date. For the final month of a firm's life, delisting returns provided by CRSP are included and if not available the last reported full-month return instead (very rare). Mean ln(Size), mean ln(B/M), mean Distress probability and mean OPCF are the time-series averages over a 204-month period of the respective factor's regression coefficients obtained on a monthly basis. On average, 520 NYSE, NASDAQ or AMEX listed companies from the computer and electronics industry are included on a monthly basis. Comments on the descriptive statistics below are provided in connection with figures 5.6.1.11 to 5.6.1.16.

A. Monthly Mean Excess Return

Size/Prob	Low	2	3	4	High	Avg
Small	0.009	0.011	0.013	0.019	0.007	0.012
2	0.012	0.009	0.016	0.017	0.010	0.013
3	0.014	0.013	0.015	0.014	0.013	0.014
Big	0.017	0.017	0.017	0.018	0.018	0.017
Avg	0.013	0.013	0.015	0.017	0.012	0.014

B. Mean Beta

Size/Prob	Low	2	3	4	High	Avg
Small	1.14	1.01	1.21	1.22	1.48	1.21
2	1.20	1.29	1.45	1.73	1.79	1.49
3	1.48	1.53	1.82	2.05	2.01	1.78
Big	1.61	1.70	1.95	2.17	2.10	1.91
Avg	1.36	1.39	1.61	1.79	1.84	1.60

C. Mean ln(Size)

Size/Prob	Low	2	3	4	High	Avg
Small	16.4	16.4	16.3	16.1	16.2	16.3
2	17.8	17.8	17.7	17.8	17.7	17.8
3	19.0	19.0	19.0	18.9	18.9	19.0
Big	21.2	21.2	20.9	20.8	20.6	21.0
Avg	18.6	18.6	18.5	18.4	18.4	18.5

D. Mean ln(B/M)

Size/Prob	Low	2	3	4	High	Avg
Small	-0.30	-0.11	-0.16	-0.35	-0.55	-0.29
2	-0.65	-0.38	-0.54	-0.73	-1.09	-0.68
3	-0.94	-0.67	-0.72	-1.02	-1.29	-0.93
Big	-1.39	-1.04	-0.95	-1.04	-1.35	-1.15
Avg	-0.82	-0.55	-0.59	-0.79	-1.07	-0.76

E Mean Distress Probability

Size/Prob	Low	2	3	4	High	Avg
Small	0.07	0.27	0.42	0.49	0.60	0.37
2	0.07	0.27	0.42	0.49	0.61	0.37
3	0.07	0.25	0.41	0.48	0.59	0.36
Big	0.06	0.24	0.39	0.47	0.58	0.35
Avg	0.07	0.26	0.41	0.48	0.60	0.36

F. Mean OPCF

Size/Prob	Low	2	3	4	High	Avg
Small	0.220	0.117	0.066	0.014	-0.269	0.030
2	0.221	0.108	0.064	0.002	-0.283	0.022
3	0.231	0.132	0.082	0.018	-0.187	0.055
Big	0.262	0.162	0.119	0.075	-0.033	0.117
Avg	0.233	0.130	0.083	0.027	-0.193	0.056

G. Average Size - Market Cap in $ m

Size/Prob	Low	2	3	4	High	Avg
Small	18	17	17	16	16	17
2	70	71	68	69	66	69
3	255	247	257	232	233	245
Big	8'020	6'340	3'300	3'260	3'560	4'896
Avg	2'091	1'669	910	894	969	1'307

H. Average Number of Stocks (per month)

Size/Prob	Low	2	3	4	High	Avg
Small	13	16	23	37	41	26
2	21	23	25	29	32	26
3	29	29	28	23	21	26
Big	41	36	29	14	10	26
Avg	26	26	26	26	26	26

Figures 5.6.1.11 to 5.6.1.16 derived from Table 5.6.1.3

The figures below depict the mean statistics

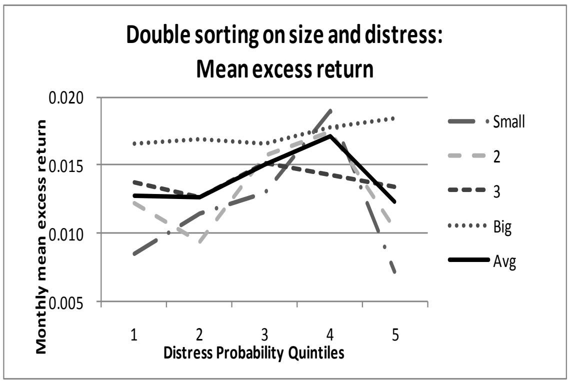


Figure 5.6.1.11. Monthly Excess Returns by Size Distress. The figure plots the monthly excess mean returns by size distress portfolios. On average, returns increase up to 4th quintile and sharply fall at highest distress levels of p > 0.5 except big companies which maintain a positive distress premium at 5th quintile. These are the ones generating positive operating cash flows also at highest distress level – see figure 5.6.1.16

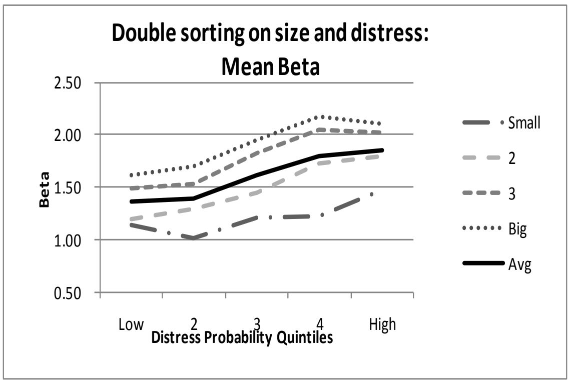


Figure 5.6.1.12. Mean Beta by Size Distress. The figure plots the mean betas by size and distress sorted portfolios. The mean betas increase in line with distress risk, but do not drop at 5th quintile with p > 0.5. Beta cannot grasp the deterioration of returns of highly distressed stocks with negative operating cash flows. But distress risk proxied by probabilities of failure appear to mirror the market risk factor from an average point of view.

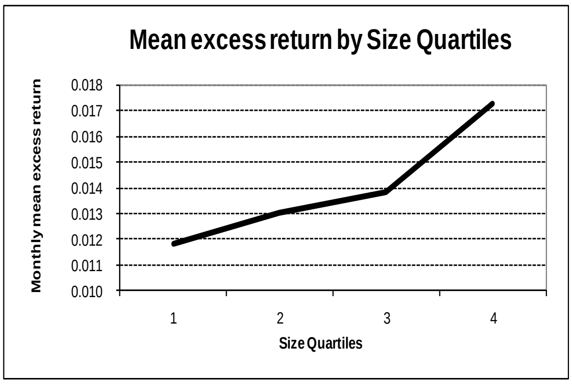


Figure 5.6.1.13. Mean ln(Size). The figure plots the monthly mean ln(size) factor effect (Fama & French, 1992). In contrast to Fama & French (1992) larger companies yield on average higher returns than small sized companies. This is also supported by a higher beta of big companies (Figure 5.6.1.12) and positive operating cash flow (Figure 5.6.1.16).

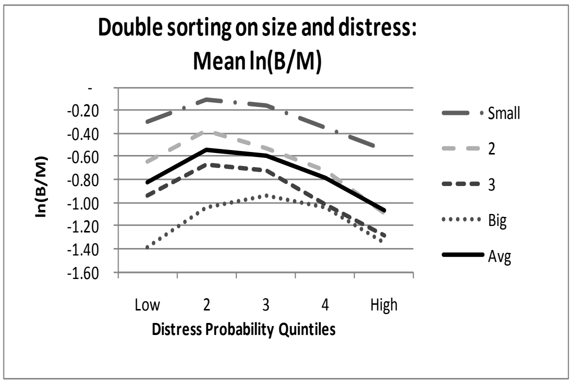


Figure 5.6.1.14. Mean ln(B/M) by Size Distress. The figure plots the mean ln(B/M) factor (Fama & French, 1992) by size and distress sorted portfolios. The mean B/M increases in line with distress risk and drops at 2th quintile or a probability of failure > 0.26. This shortfall speaks against a strong correlation between distress risk and B/M. It is close to an inverted u-shape as identified by Dichev (1998).

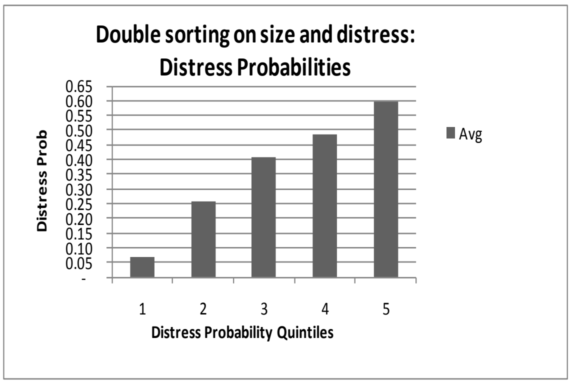


Figure 5.6.1.15. Mean Probability of Failure by Size Distress. The figure plots the monthly mean probability of failure by size and distress sorted portfolios. The 4th quintile depicts a mean probability of failure 0.48 and the 5th 0.60.

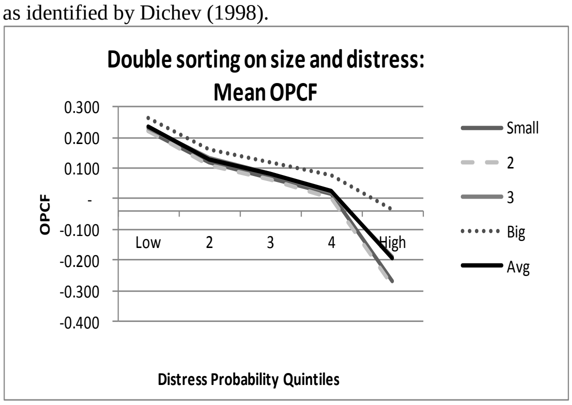


Figure 5.6.1.16. Mean OPCF by Size Distress. On average at 5h quintile, all except big companies produce negative operating cash flows.

Table 5.6.1.4: Descriptive Statistics across B/M Quartiles and Distress Quintiles

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently ranked on B/M quartiles and independently ranked on Distress by probability of failure quintiles. 20 portfolios are then formed at intersections of B/M quartiles and Distress quintiles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, ln(B/E) and ln(Size) are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. Distress risk and OPCF factor values are obtained from the bankruptcy prediction model. Monthly mean excess return is the time-series average of the difference between monthly stock returns and the one-month t-bill rate at the beginning of each month. Mean betas of portfolios are estimated at the portfolio formation date. For the final month of a firm's life, delisting returns provided by CRSP are included and if not available the last reported full-month return instead (very rare). Mean ln(Size), mean ln(B/M), mean Distress probability and mean OPCF are the time-series averages over a 204-month period of the respective factor's regression coefficients obtained on a monthly basis. On average, 520 NYSE, NASDAQ or AMEX listed companies from the computer and electronics industry are included on a monthly basis. Comments on the descriptive statistics below are provided in connection with figures 5.6.1.17 to 5.6.1.22.

A. Monthly Mean Excess Return

BM/Prob	Low	2	3	4	High	Avg
Low	0.023	0.025	0.027	0.026	0.014	0.023
2	0.013	0.016	0.017	0.017	0.008	0.014
3	0.007	0.011	0.013	0.015	0.010	0.011
High	0.007	0.006	0.007	0.012	0.004	0.007
Avg	0.013	0.014	0.016	0.018	0.009	0.014

B. Mean Beta

BM/Prob	Low	2	3	4	High	Avg
Low	1.54	1.61	1.73	1.77	1.78	1.69
2	1.45	1.56	1.75	1.72	1.77	1.65
3	1.38	1.45	1.67	1.70	1.76	1.59
High	1.26	1.27	1.47	1.48	1.58	1.41
Avg	1.40	1.47	1.66	1.67	1.72	1.58

C. Mean ln(Size)

BM/Prob	Low	2	3	4	High	Avg
Low	20.5	20.3	19.4	18.5	18.1	19.4
2	19.4	19.8	19.2	18.2	17.9	18.9
3	18.4	18.9	18.7	17.9	17.6	18.3
High	17.5	17.7	17.7	17.1	16.9	17.4
Avg	19.0	19.2	18.8	17.9	17.6	18.5

D. Mean ln(B/M)

BM/Prob	Low	2	3	4	High	Avg
Low	-1.77	-1.70	-1.84	-1.92	-2.06	-1.86
2	-0.98	-0.97	-0.96	-0.97	-0.98	-0.97
3	-0.47	-0.46	-0.46	-0.46	-0.46	-0.46
High	0.10	0.15	0.19	0.25	0.27	0.19
Avg	-0.78	-0.74	-0.77	-0.78	-0.81	-0.78

E. Mean Distress Probability

BM/Prob	Low	2	3	4	High	Avg
Low	0.05	0.24	0.40	0.49	0.63	0.36
2	0.07	0.25	0.40	0.48	0.59	0.36
3	0.08	0.26	0.41	0.49	0.59	0.36
High	0.09	0.27	0.41	0.49	0.58	0.37
Avg	0.07	0.25	0.41	0.49	0.60	0.36

F. Mean OPCF

BM/Prob	Low	2	3	4	High	Avg
Low	0.286	0.171	0.094	-0.001	-0.434	0.023
2	0.238	0.145	0.096	0.032	-0.185	0.065
3	0.213	0.125	0.087	0.031	-0.112	0.069
High	0.172	0.111	0.071	0.021	-0.097	0.056
Avg	0.227	0.138	0.087	0.021	-0.207	0.053

G. Average Size - Market Cap in $ m

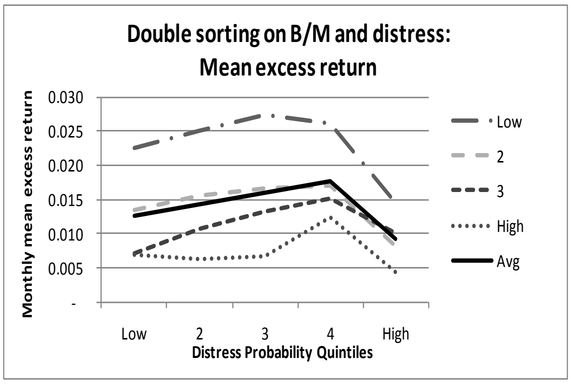
BM/Prob	Low	2	3	4	High	Avg
Low	7'930	6'700	2'090	1'150	135	3'601
2	1'920	2'610	1'300	530	706	1'413
3	427	991	805	446	652	664
High	173	303	323	154	278	246
Avg	2'613	2'651	1'130	570	443	1'481

H. Average Number of Stocks (per month)

BM/Prob	Low	2	3	4	High	Avg
Low	34	18	18	25	35	26
2	33	27	25	22	22	26
3	25	31	29	26	20	26
High	13	28	32	31	27	26
Avg	26	26	26	26	26	26

Figures 5.6.1.17 to 5.6.1.22 derived from Table 5.6.1.4

The figures below depict the mean statistics



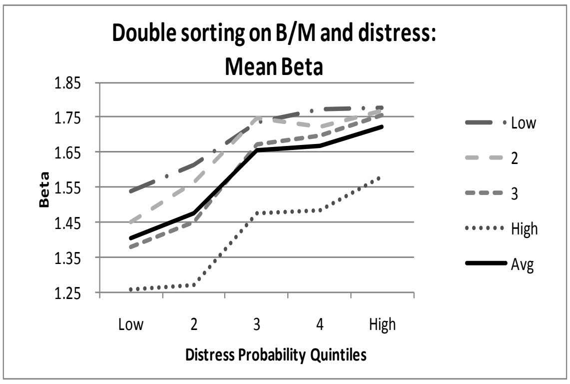
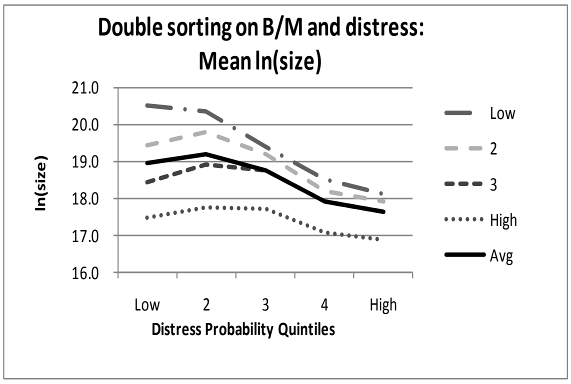


Figure 5.6.1.17. Monthly Excess Returns by B/M Distress. The figure plots the monthly excess mean returns by B/M distress portfolios. On average, returns increase up to 4th quintile and sharply fall at highest distress quintile with p > 0.5 hence distressed stocks underperform non-distressed ones. In contrast to Fama and French (1992, 1993) growth company earn a higher return than value stock.

Figure 5.6.1.18. Mean Beta by B/M Distress. The figure plots the mean betas by B/M and distress sorted portfolios. The mean betas increase in line with distress risk. On average, the CAPM appears to grasp distress risk somewhat, but it may not be able to explain the average underperformance of distressed stocks as shown in figure 5.6.1.17.



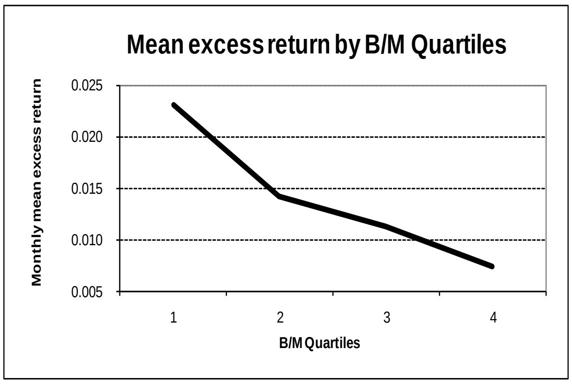
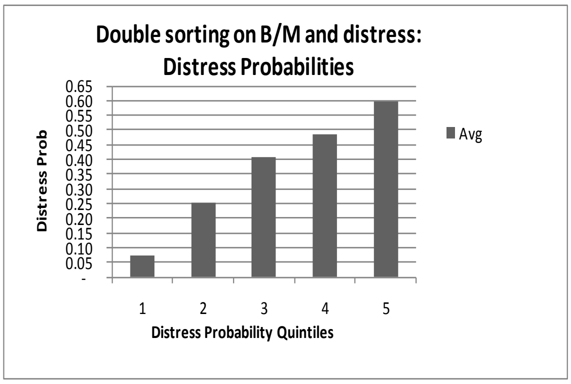


Figure 5.6.1.19. Mean ln(Size) by B/M Distress. The figure plots the monthly mean ln(size) factor effect (Fama & French, 1992) by B/M and distress sorted portfolios. Small firms are on average at higher risk compared to the large cap.

Figure 5.6.1.20. Mean ln(B/M). The figure plots the mean ln(B/M) factor (Fama & French, 1992). High B/M or value stock portfolio as reflected with the 4th quartile yields in lower monthly mean excess returns than low B/M or growth stock portfolio as reflected by the 1st quartile.



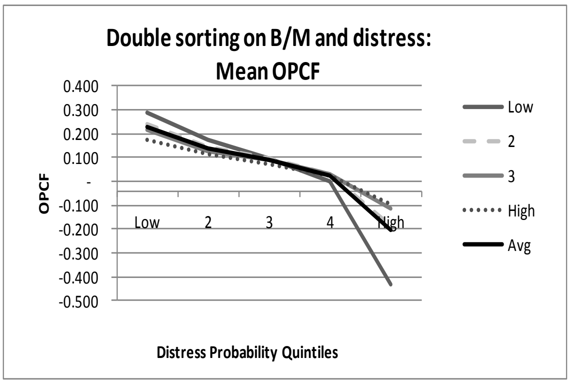


Figure 5.6.1.21. Mean Probability of Failure by B/M Distress. The figure plots the monthly mean probability of failure by B/M and distress sorted portfolios. The 4th quintile depicts a mean probability of failure 0.49 and the 5th 0.60.

Figure 5.6.1.22. Mean OPCF by B/M Distress. On average at 5h quintile, all companies produce negative operating cash flows. Portfolios with p > 0.50 show deterioration of excess stock returns as shown in figure 5.6.1.17.

Table 5.6.1.5: Descriptive Statistics across Size and B/M Quartiles

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently ranked on Size quartiles and independently ranked on B/M quartiles. 16 portfolios are then formed at intersections of Size quartiles and B/M quartiles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, ln(B/E) and ln(Size) are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. Distress risk and OPCF factor values are obtained from the bankruptcy prediction model. Monthly mean excess return is the time-series average of the difference between monthly stock returns and the one-month t-bill rate at the beginning of each month. Mean betas of portfolios are estimated at the portfolio formation date. For the final month of a firm's life, delisting returns provided by CRSP are included and if not available the last reported full-month return instead (very rare). Mean ln(Size), mean ln(B/M), mean Distress probability and mean OPCF are the time-series averages over a 204-month period of the respective factor's regression coefficients obtained on a monthly basis. On average, 520 NYSE, NASDAQ or AMEX listed companies from the computer and electronics industry are included on a monthly basis. Comments on the descriptive statistics below are provided in connection with figures 5.6.1.23 to 5.6.1.28.

A. Monthly Mean Excess Return

BM/Size	Small	2	3	Large	Avg
Low	0.009	0.022	0.023	0.025	0.020
2	0.013	0.019	0.015	0.012	0.014
3	0.016	0.013	0.006	0.012	0.012
High	0.010	0.005	0.005	0.010	0.008
Avg	0.012	0.015	0.012	0.015	0.013

B. Mean Beta

BM/Size	Small	2	3	Large	Avg
Low	1.33	1.62	1.81	1.76	1.63
2	1.27	1.53	1.73	1.78	1.58
3	1.28	1.51	1.70	1.86	1.59
High	1.25	1.51	1.79	1.91	1.61
Avg	1.28	1.54	1.76	1.83	1.60

C. Mean ln(Size)

BM/Size	Small	2	3	Large	Avg
Low	16.5	17.8	19.0	21.2	18.6
2	16.4	17.8	19.0	21.0	18.6
3	16.3	17.8	19.0	20.8	18.5
High	16.1	17.7	18.9	21.5	18.5
Avg	16.3	17.8	19.0	21.1	18.5

D. Mean ln(B/M)

BM/Size	Small	2	3	Large	Avg
Low	-1.87	-1.93	-1.87	-1.84	-1.88
2	-0.95	-0.96	-0.97	-0.99	-0.97
3	-0.44	-0.45	-0.47	-0.49	-0.46
High	0.31	0.16	0.05	0.05	0.14
Avg	-0.74	-0.80	-0.82	-0.82	-0.79

E. Mean Distress Probability

BM/Size	Small	2	3	Large	Avg
Low	0.56	0.50	0.38	0.26	0.42
2	0.46	0.38	0.31	0.23	0.34
3	0.42	0.36	0.32	0.32	0.35
High	0.43	0.39	0.36	0.38	0.39
Avg	0.47	0.41	0.34	0.30	0.38

F. Mean OPCF

BM/Size	Small	2	3	Large	Avg
Low	-0.321	-0.208	-0.008	0.192	-0.086
2	-0.063	0.028	0.110	0.160	0.059
3	0.019	0.061	0.104	0.131	0.079
High	0.018	0.042	0.073	0.100	0.058
Avg	-0.087	-0.019	0.070	0.146	0.027

G. Average Size - Market Cap in $ m

BM/Size	Small	2	3	Large	Avg
Low	21	69	243	8'260	2'148
2	18	73	256	4'340	1'172
3	17	69	243	2'700	757
High	15	64	230	2'220	632
Avg	18	69	243	4'380	1'177

H. Average Number of Stocks (per month)

BM/Size	Small	2	3	Large	Avg
Low	17	28	34	52	32
2	20	29	39	42	33
3	31	36	36	27	33
High	66	42	25	19	38
Avg	33	33	34	35	34

Figures 5.6.1.23 to 5.6.1.28 derived from Table 5.6.1.5

The figures below depict the mean statistics

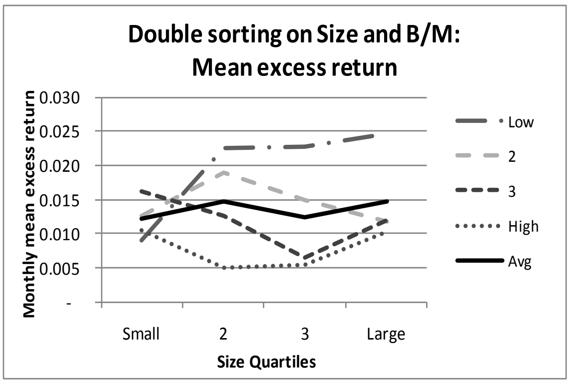


Figure 5.6.1.23. Monthly Excess Returns by Size . The figure plots the monthly excess mean returns by size and B/M sorted portfolios. On average, high B/M (value) portfolios achieve lower returns compared to low B/M (growth) portfolios.

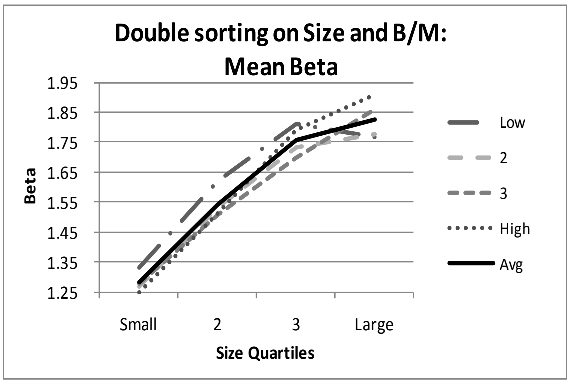


Figure 5.6.1.24. Mean Beta by Size B/M. The figure plots the mean betas by Size and B/M sorted portfolios. The mean betas increase in line with size and appear to be independent from the B/M factor.

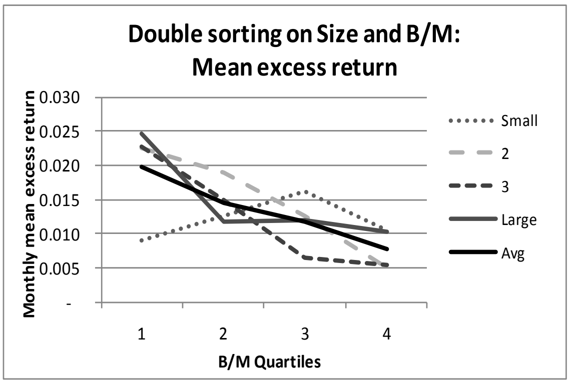


Figure 5.6.1.25. Monthly Excess Returns by B/M. The figure plots the monthly excess mean returns controlled by B/M. With exception of small companies, a low B/M (1st quartile) yields on average in higher returns compared to high B/M portfolio (4th quartile). The small stocks in the 1st quartile include highly distressed underperforming cash burning stocks.

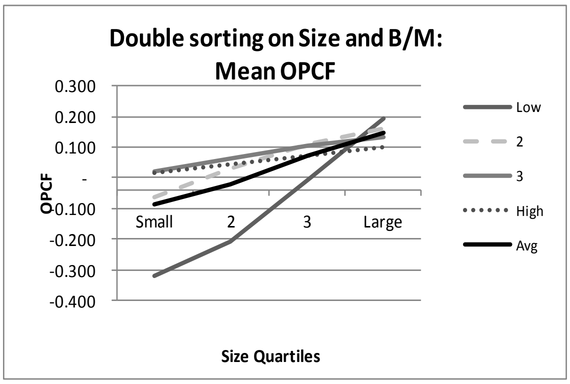
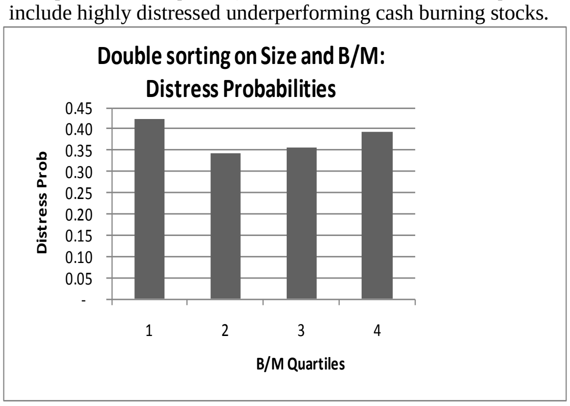


Figure 5.6.1.26. Mean OPCF by Size B/M. The figure plots the mean OPCF by size and B/M sorted portfolios. On average, positive operating cash flows are achieved by large companies. The 1st size quartile shows that a majority of small companies produce negative operating cash flows.



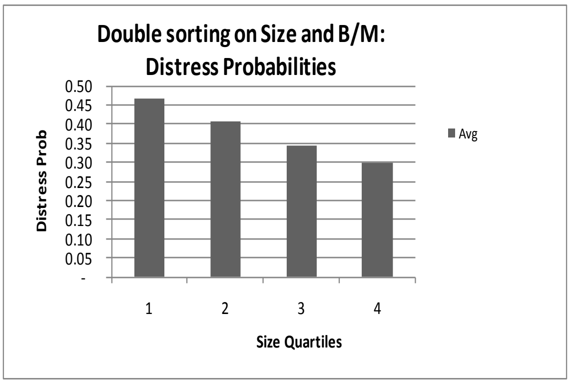


Figure 5.6.1.27. Mean Probability of Failure by B/M. High B/M stock (4th B/M quartile) have a higher distress risk than 2nd and 3rd quartile B/M stock.

Figure 5.6.1.28. Mean Probability of Failure by Size. On average, large companies have a lower distress risk than the small ones.

APPENDIX B: PEARSON PRODUCT-MOMENT CORRELATIONS

	Beta	Size	B/M	Distress	OPCF	Dis*OPCF
Beta	1					
Size	0.1316	1				
B/M	-0.0547	-0.2837	1			
Distress	0.0633	-0.3365	0.0436	1		
OPCF	-0.0264	0.2698	0.1046	-0.6314	1	
Dis*OPCF	-0.0102	0.1569	0.2013	-0.3620	0.8880	1

Table 5.6.2.1 Pearson correlations – single firm observations. The above table shows weak correlations among independent variables. The only exception noted is the interaction variable Dis*OPCF showing some very strong correlation with OPCF.

	Beta	Size	B/M	Distress	OPCF	Dis*OPCF
Beta	1					
Size	0.0458	1				
B/M	-0.0602	-0.2690	1			
Distress	0.2182	-0.5577	0.1183	1		
OPCF	0.0166	0.4605	-0.0289	-0.3424	1	
Dis*OPCF	0.0287	0.2168	0.1780	-0.0528	0.8705	1

Table 5.6.2.2 Pearson correlations - OPCF and Distress sorted portfolios. The above table shows weak correlations among independent variables. The only exception noted is the interaction variable Dis*OPCF showing some very strong correlation with OPCF.

	Beta	Size	B/M	Distress	OPCF	Dis*OPCF
Beta	1					
Size	0.5324	1				
B/M	-0.5122	-0.6966	1			
Distress	0.3712	-0.0928	-0.1406	1		
OPCF	-0.2244	0.2403	0.1735	-0.8275	1	
Dis*OPCF	-0.0897	0.2330	0.2696	-0.4734	0.8440	1

Table 5.6.2.3 Pearson correlations - Size and Distress sorted portfolios. The above table shows weak correlations among independent variables. The only exceptions noted are the interaction variable Dis*OPCF showing some strong correlation with OPCF and a strong correlation between OPCF and Distress.

	Beta	Size	B/M	Distress	OPCF	Dis*OPCF
Beta	1					
Size	0.1163	1				
B/M	-0.2884	-0.6115	1			
Distress	0.3357	-0.5109	-0.0026	1		
OPCF	-0.2650	0.4886	0.1218	-0.8252	1	
Dis*OPCF	-0.1742	0.2556	0.2810	-0.4649	0.8421	1

Table 5.6.2.5 Pearson correlations - B/M and Distress sorted portfolios. The above table shows weak correlations among independent variables. The only exceptions noted are the interaction variable Dis*OPCF showing some strong correlation with OPCF and a strong correlation between OPCF and Distress.

The Pearson correlation tests are performed on a monthly basis. The correlation coefficients are the time-series average of 204 months.

APPENDIX C: PORTFOLIO REGRESSIONS

Table 5.6.3.1: OPCF (4) x Distress (5) - 20-Portfolio Regression

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently ranked on OPCF quartiles and independently ranked on Distress by probability of failure quintiles. 20 portfolios are then formed at intersections of OPCF quartiles and Distress quintiles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. β_{it-1} is the beta of portfolio *i* estimated at the portfolio formation date. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, $\ln(B/E)_{it-1}$ and $\ln(Size)_{it-1}$, are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. $Distress_{it-1}$ and $OPCF_{it-1}$ as well as the interaction variable $distress*OPCF_{it-1}$ are obtained from the bankruptcy prediction model. R_{it} is the equally weighted return on portfolio *i* during month *t*. R_{Ft} is the risk free rate proxied by the one-month t-bill rate at the beginning of each month *t*. Values being lower than the 1st or higher than the 99th percentile are set equal to next largest or smallest values of the ratios (0.01 and 0.99 fractiles) in order to eliminate the influence of extreme outliers. The Fama-MacBeth (1973) or FM cross-sectional regression estimates are obtained for the CAPM, the 3-Factor Fama & French (1992) and other multi-factor models related to distress and OPCF as shown below for each of the 204 months from January 1990 to December 2006. The average slopes are the time-series averages of the equal-weighted monthly regression estimates and figures shown in brackets are the respective FM t-statistics.

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}(distress_{it-1}) + \gamma_{5t}(OPCF_{it-1}) + \gamma_{6t}(distress*OPCF_{it-1})$$

	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	adj R^2
A. CAPM								
1)	0.0116	0.0019						0.04
	(1.65)	(0.69)						
B. FF - 3-Factor								
2)	-0.0001	0.0024	0.0005	0.0006				0.13
	(-0.00)	(0.89)	(0.28)	(0.16)				
C. Multi-Factor								
3)	-0.0152	0.0020	0.0013	0.0005	0.0074			0.16
	(-0.37)	(0.68)	(0.59)	(0.13)	(0.87)			
4)	0.0399	0.0027	-0.0020	-0.0026		0.0318 ***		0.19
	(1.08)	(0.99)	(-0.99)	(-0.69)		(3.89)		
5)	0.0007	0.0013	-0.0001	-0.0030	0.0197 **	0.0364 ***		0.23
	(0.02)	(0.45)	(-0.04)	(-0.76)	(2.22)	(4.24)		
6)	-0.0248	-0.0012	0.0014	-0.0034	0.0249 **	0.0357	-0.0050	0.27
	(-0.61)	(-0.42)	(0.65)	(-0.65)	(2.27)	(1.46)	(-0.12)	
7)	0.0107	0.0009			0.0067			0.08
	(1.65)	(0.32)			(0.89)			
8)	0.0084	0.0021				0.0323 ***		0.10
	(1.16)	(0.76)				(4.42)		
9)	0.0027	0.0003			0.0215 **	0.0403 ***		0.16
	(0.39)	(0.09)			(2.58)	(4.74)		
10)	-0.0031	0.0009		-0.0065 *	0.0221 **	0.0401 ***		0.19
	(-0.43)	(0.28)		(-1.76)	(2.57)	(4.70)		
11)	0.0077	0.0007	-0.0003		0.0190 **	0.0373 ***		0.21
	(0.21)	(0.23)	(-0.14)		(2.21)	(4.37)		
12)	0.0006				0.0258 **	0.0562 **	-0.0334 *	0.14
	(0.08)				(2.36)	(2.63)	(-1.84)	

*** Significant at 0.01 level
** Significant at 0.05 level
* Significant at 0.10 level

Table 5.6.3.2: Size (4) x Distress (5) - 20-Portfolio Regression

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently ranked on Size quartiles and independently ranked on Distress by probability of failure quintiles. 20 portfolios are then formed at intersections of Size quartiles and Distress quintiles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. β_{it-1} is the beta of portfolio *i* estimated at the portfolio formation date. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, $\ln(B/E)_{it-1}$ and $\ln(Size)_{it-1}$, are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. $Distress_{it-1}$ and $OPCF_{it-1}$ as well as the interaction variable $distress*OPCF_{it-1}$ are obtained from the bankruptcy prediction model. R_{it} is the equally weighted return on portfolio *i* during month *t*. R_{Ft} is the risk free rate proxied by the one-month t-bill rate at the beginning of each month *t*. Values being lower than the 1st or higher than the 99th percentile are set equal to next largest or smallest values of the ratios (0.01 and 0.99 fractiles) in order to eliminate the influence of extreme outliers. The Fama-MacBeth (1973) or FM cross-sectional regression estimates are obtained for the CAPM, the 3-Factor Fama & French (1992) and other multi-factor models related to distress and OPCF as shown below for each of the 204 months from January 1990 to December 2006. The average slopes are the time-series averages of the equal-weighted monthly regression estimates and figures shown in brackets are the respective FM t-statistics.

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}(distress_{it-1}) + \gamma_{5t}(OPCF_{it-1}) + \gamma_{6t}(distress*OPCF_{it-1})$$

	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	adj R^2
A. CAPM								
1)	0.0095 *	0.0025						0.09
	(1.83)	(0.85)						
B. FF - 3-Factor								
2)	-0.0031	-0.0010	0.0010	-0.0017				0.22
	(-0.14)	(-0.42)	(0.80)	(-0.53)				
C. Multi-Factor								
3)	-0.0014	-0.0022	0.0009	-0.0016	0.0051			0.29
	(-0.07)	(-0.83)	(0.82)	(-0.59)	(0.73)			
4)	0.0106	-0.0008	0.0001	-0.0041		0.0022		0.27
	(0.54)	(-0.31)	(0.09)	(-1.50)		(0.28)		
5)	0.0156	-0.0026	-0.0007	-0.0076 **	0.0242 **	0.0316 ***		0.29
	(0.80)	(-1.00)	(-0.61)	(-2.61)	(2.76)	(3.05)		
6)	0.0314	-0.0035	-0.0010	-0.0104 **	0.0060	-0.0148	0.0730	0.31
	(1.36)	(-1.30)	(-0.86)	(-2.81)	(0.37)	(-0.44)	(1.51)	
7)	0.0093 *	0.0020			0.0022			0.18
	(2.00)	(0.63)			(0.30)			
8)	0.0097	0.0025				0.0021		0.19
	(1.54)	(0.80)				(0.26)		
9)	0.0042	0.0019			0.0147 *	0.0171 *		0.20
	(0.69)	(0.59)			(1.75)	(1.73)		
10)	0.0046	-0.0021		-0.0050 *	0.0218 **	0.0263 **		0.26
	(0.73)	(-0.80)		(-1.77)	(2.41)	(2.41)		
11)	-0.0100	-0.0020	0.0011		0.0183 **	0.0177 *		0.29
	(-0.63)	(-0.78)	(1.19)		(2.30)	(1.91)		
13)	0.0013				0.0286	0.0375	-0.0164	0.12
	(0.16)				(1.67)	(1.14)	(-0.41)	

*** Significant at 0.01 level
** Significant at 0.05 level
* Significant at 0.10 level

Table 5.6.3.3: B/M (4) x Distress (5) - 20-Portfolio Regression

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently ranked on B/M quartiles and independently ranked on Distress by probability of failure quintiles. 20 portfolios are then formed at intersections of B/M quartiles and Distress quintiles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. β_{it-1} is the beta of portfolio *i* estimated at the portfolio formation date. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, $\ln(B/E)_{it-1}$ and $\ln(Size)_{it-1}$, are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. $Distress_{it-1}$ and $OPCF_{it-1}$ as well as the interaction variable $distress*OPCF_{it-1}$ are obtained from the bankruptcy prediction model. R_{it} is the equally weighted return on portfolio *i* during month *t*. R_{Ft} is the risk free rate proxied by the one-month t-bill rate at the beginning of each month *t*. Values being lower than the 1st or higher than the 99th percentile are set equal to next largest or smallest values of the ratios (0.01 and 0.99 fractiles) in order to eliminate the influence of extreme outliers. The Fama-MacBeth (1973) or FM cross-sectional regression estimates are obtained for the CAPM, the 3-Factor Fama & French (1992) and other multi-factor models related to distress and OPCF as shown below for each of the 204 months from January 1990 to December 2006. The average slopes are the time-series averages of the equal-weighted monthly regression estimates and figures shown in brackets are the respective FM t-statistics.

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}(distress_{it-1}) + \gamma_{5t}(OPCF_{it-1}) + \gamma_{6t}(distress*OPCF_{it-1})$$

	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	adj R^2
A. CAPM								
1)	0.0063	0.0047						0.03
	(1.28)	(1.67)						
B. FF - 3-Factor								
2)	-0.0104	0.0003	0.0011	-0.0056 **				0.22
	(-0.37)	(0.12)	(0.70)	(-2.78)				
C. Multi-Factor								
3)	-0.0175	-0.0002	0.0015	-0.0051 ***	0.0030			0.25
	(-0.68)	(-0.10)	(1.04)	(-2.92)	(0.44)			
4)	0.0316	0.0014	-0.0015	-0.0082 ***		0.0172 **		0.25
	(1.24)	(0.62)	(-1.00)	(-4.04)		(2.15)		
5)	0.0235	-0.0009	-0.0014	-0.0093 ***	0.0251 ***	0.0434 ***		0.27
	(0.90)	(-0.38)	(-0.96)	(-4.26)	(3.09)	(4.63)		
6)	0.0164	-0.0003	-0.0008	-0.0091 ***	0.0142	0.0119	0.0380	0.27
	(0.60)	(-0.14)	(-0.51)	(-4.02)	(1.06)	(0.48)	(1.18)	
7)	0.0060	0.0056 **			-0.0031			0.12
	(1.35)	(2.15)			(-0.43)			
8)	0.0047	0.0057 *				0.0057		0.12
	(0.80)	(2.13)				(0.72)		
9)	0.0005	0.0057 **			0.0090	0.0175 **		0.13
	(0.10)	(2.16)			(1.20)	(2.10)		
10)	-0.0017	-0.0006		-0.0076 ***	0.0236 ***	0.0352 ***		0.25
	(-0.32)	(-0.25)		(-4.48)	(2.89)	(3.99)		
11)	-0.0737 ***	-0.0001	0.0043 ***		0.0233 ***	0.0164 **		0.22
	(-3.23)	(-0.02)	(3.32)		(3.02)	(2.11)		
12)	-0.0077				0.0436 **	0.0824 **	-0.0858 **	0.12
	(-1.07)				(2.66)	(2.73)	(-2.31)	

*** Significant at 0.01 level
** Significant at 0.05 level
* Significant at 0.10 level

Table 5.6.3.5: Size (4) x B/M (4) - 16-Portfolio Regression

At the beginning of each quarter starting in 1990 and ending in 2006, all stocks are independently ranked on Size and B/M quartiles. 16 portfolios are then formed at intersections of Size quartiles and B/M quartiles and rebalanced on a quarterly basis. A three-month reporting lag is applied on financial statement information used to avoid any look-ahead bias. β_{it-1} is the beta of portfolio *i* estimated at the portfolio formation date. B/E is the book value of common equity plus balance-sheet deferred taxes divided by the average market equity t-1. Negative B/M observations are excluded. Size is the average market capitalization of equity t-1. Both, $\ln(B/E)_{it-1}$ and $\ln(Size)_{it-1}$, are the result of transformation by natural logarithm on the average B/E and Size ratios of stocks in portfolio *i* at the portfolio formation date. $Distress_{it-1}$ and $OPCF_{it-1}$ as well as the interaction variable $distress*OPCF_{it-1}$ are obtained from the bankruptcy prediction model. R_{it} is the equally weighted return on portfolio *i* during month *t*. R_{Ft} is the risk free rate proxied by the one-month t-bill rate at the beginning of each month *t*. Values being lower than the 1st or higher than the 99th percentile are set equal to next largest or smallest values of the ratios (0.01 and 0.99 fractiles) in order to eliminate the influence of extreme outliers. The Fama-MacBeth (1973) or FM cross-sectional regression estimates are obtained for the CAPM, the 3-Factor Fama & French (1992) and other multi-factor models related to distress and OPCF as shown below for each of the 204 months from January 1990 to December 2006. The average slopes are the time-series averages of the equal-weighted monthly regression estimates and figures shown in brackets are the respective FM t-statistics.

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}(distress_{it-1}) + \gamma_{5t}(OPCF_{it-1}) + \gamma_{6t}(distress*OPCF_{it-1})$$

	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	adj R^2
A. CAPM								
1)	0.0081	0.0034						0.06
	(1.14)	(1.04)						
B. FF - 3-Factor								
2)	0.0056	0.0009	0.0002	-0.0052 ***				0.26
	(0.32)	(0.29)	(0.17)	(-3.59)				
C. Multi-Factor								
3)	0.0160	-0.0007	0.0002	-0.0079 ***	-0.0288 *			0.29
	(0.96)	(-0.24)	(0.19)	(-4.05)	(-1.98)			
4)	0.0115	-0.0005	-0.0002	-0.0074 ***		0.0220 *		0.30
	(0.69)	(-0.15)	(-0.24)	(-4.17)		(2.07)		
5)	0.0180	-0.0012	-0.0004	-0.0081 ***	0.0065	0.0213		0.31
	(1.03)	(-0.36)	(-0.42)	(-4.05)	(0.25)	(1.26)		
6)	0.0400	-0.0019	-0.0009	-0.0082 ***	-0.0297	-0.0412	0.0902	0.32
	(1.65)	(-0.52)	(-0.79)	(-4.06)	(-0.98)	(-0.89)	(1.32)	
7)	0.0011	0.0038			0.0175			0.11
	(0.16)	(1.12)			(1.41)			
8)	0.0062	0.0046				-0.0042		0.13
	(0.88)	(1.36)				(-0.43)		
9)	0.0016	0.0034			0.0213	0.0140		0.15
	(0.15)	(1.07)			(0.92)	(0.72)		
10)	0.0118	-0.0004		-0.0072 ***	-0.0097	0.0194		0.20
	(1.01)	(-0.13)		(-3.60)	(-0.36)	(0.99)		
11)	0.0056	0.0022	-0.0003		0.0268	0.0169		0.25
	(0.34)	(0.72)	(-0.29)		(1.12)	(0.98)		
12)	0.0122				0.0130	-0.0148	0.0324	0.14
	(0.88)				(0.47)	(-0.32)	(0.49)	

*** Significant at 0.01 level
** Significant at 0.05 level
* Significant at 0.10 level

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