Reverse Robin Hood

A Swedish Assessment of the Distress Puzzle

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Abstract

This research adopts some of the most well-known models to predict financial distress to be able to investigate whether firms with higher probability to default and thereby incorporating more risk do provide investors with a higher return in the Swedish market. We create portfolios sorted on the predicted probability of the financial distress and subsequently perform a portfolio analysis to investigate the risk return relationship. Our results show that portfolios consisting of the more financially distressed firms consistently underperform the more stable firms, which results in a financial distress puzzle within the Swedish market.

Keywords: *Financial distress, Z-score, O-score, Portfolio analysis, Distress Puzzle, Asset pricing, Corporate Finance, Distress Risk, Logit analysis*

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1. Introduction & Research Question

This thesis examines the performance of stocks based on their level of financial distress in the Swedish market. An extensive body of research in finance focuses on how to accurately measure a company's expected return. We investigate the effect of a firm's financial distress risk on its returns. Higher probability of experiencing financial distress increases the risk of a firm and in the field of asset pricing it is elucidated that an investment in a riskier firm is assigned with a risk premium (Sharpe 1964). Our research examines if there is a risk premium attributed to investing in firms that are facing financial distress and whether the probability of a firm entering financial distress is priced into the firm's stock value.

Even though studies both within predicting financial distress and asset pricing are extensive, few or none combined research projects can be related to Swedish listed firms. It is true that for larger, publicly traded firms the likelihood of distress is lower but history shows evidence of these firms entering the distress phase (see e.g. Enron in 2001, GM in 2009 and RadioShack in 2015). Studies on performance of financially distressed companies such as Campbell et.al. (2008) are made on US firms, however we argue that it is hard to apply such knowledge to the Swedish market. The legal framework under the Scandinavian law system handling bankruptcy differs from the Anglo-Saxon legal framework. A recent example is the reconstruction of the automotive manufacturer SAAB that filed for bankruptcy in 2012. Even though district court found the company to be bankrupt, the firm was able to apply for corporate reconstruction twice. The same procedure has been done by the media conglomerate Stampen. The latter firm's restructuring was successful and the company managed to stay out of bankruptcy.

Our study uses traditional accounting based models to predict financial distress. We compare and evaluate various models for the Swedish market. We use Altman's Z-score (1968), Ohlson's O-score (1980) and the model by Campbell et.al. (2008). Depending on the predicted probability of experiencing financial distress the firms are then divided into 5 portfolios. We analyse the return on these portfolios using monthly return regressions with factors such as the market return in accordance with Sharpe's (1964) CAPM, the size and value factors provided by Fama and French (1993) and the momentum factor suggested by Carhart (1997). We also evaluate the performance of a Long-Short portfolio, taking a long position in the lowest ranked portfolio on financial distress and a short position in the portfolio that are ranked as most financially distressed.

Our findings on predicting financial distress are not entirely consistent with the findings of Altman, Ohlson, or Campbell with a few variables changing signs on their respective partial effects. However, all models have a good predictive power of financial distress. The portfolio analysis contradicts the theory that investing in riskier firms provides an additional risk-premium. The result shows that the portfolios consisting of firms with the highest probability of financial distress consistently underperform the portfolios with more stable firms. The long-short portfolio that invests in "safe" stocks and goes short on "distressed" stocks provides a positive excess return over the market. These findings are consistent with Dichev (1998) and Campbell et. al (2008). We also argue that this so called "distress puzzle" mostly is of academic importance and that investment strategies leveraging this opportunity should be implemented with caution.

The rest of the thesis is organized as follows. Section two discusses the relevant literature in the financial distress and assets pricing subjects along with our hypothesis. Section three presents the data underlying the research, the models for predicting financial distress and the assets pricing methodology. Section four presents our results and analysis. Section five includes discussion, contributions and further research. Section six concludes.

2. Literature Review & Theoretical Framework

2.1 Financial Distress

Since the main objective of this research is to examine whether financial distress impacts expected returns, it is natural to start with defining the meaning of financial distress.

Financial distress is often characterized as a condition when a company is not able to internally generate funds to pay its current obligations. A company that is in financial distress does not only face the risk of going bankrupt but can also incur costs related to the situation. Direct costs include legal costs and administrative costs, however the larger part of costs tend to be indirect, such as more expensive financing, loss of business and less productive employees (Berk and DeMarzo 2014). If the firm also has outstanding debt (i.e. its assets are partly debt-financed) the company will have a debt overhang problem (Myers 1977), i.e. it will have difficulties raising funds even if they have a positive net present value of possible investments. Thus, it becomes important for the management and shareholders to assess the probability of financial distress.

Rosendal (1908) is one of the first to measure and predict financial distress by focusing on the current ratio to assess a company's creditworthiness. As most firms were debt-financed he states that the assessment of creditworthiness is essential and argues that the current ratio measures the creditworthiness properly. The following early research focuses primarily on qualitative approaches by comparing accounting ratios between firms. Smith and Winakor (1935) conclude that the characteristics of financial ratios of failing firms are significantly different from those of healthier ones.

Horrigan (1965) recognizes the diverse conclusion from previous research and argues that financial ratio analysis might be more complicated than previously presumed by taking into consideration the difficulties to obtain financial statements, the difference in accounting methods and the distributions of the ratios. By Beaver's (1966) paper the inclusion of several ratios are at the time standard. However, he recognizes that further verification of their usefulness is needed to predict failure. Research on financial distress from this time period has been dominated by Altman's (1968) Z-score model (hereafter referred to as "Altman"). The objective of Altman's research is to predict corporate failure with ratio analysis using a set of financial and economic ratios combined into one measure by weighting the different measures, where the weights are determined using multiple discriminant analysis (MDA). To predict financial distress, Altman used five ratios representing the liquidity, profitability, leverage, solvency and activity ratios of each firm, resulting in a 94% accuracy ratio (Altman 1968) and world recognition of the Z-score.

Later research steps away from the MDA prediction model to favor the logit model. As an alternative to the Z-score the O-score developed by Ohlson (1980) is also commonly used as a measure for financial distress (hereafter referred to as "Ohlson"). Using a logit model with additional accounting ratios Ohlson gets both higher accuracy ratio than Altman and more robust results (Ohlson 1980), however Dichev (1998) finds that both models stills hold and provide similar results. The logit model is argued to be more informative and a better tool for predicting financial distress than MDA by Ohlson (1980), Kim and Gu (2006), Piñado et. al. (2006) and Campbell et. al. (2008).

While the actual definition of financial distress as described by Wruck (1990) has been unchallenged, to proxy for it has been debated. Most studies, whether they use accounting based or market based predictors, use bankruptcy filing to measure the point of time when financial distress occurs (see Altman (1968), Opler (1993), Ward (1997), Dichev (1998) and Campbell (2008))**.** On the other hand, Andrade and Kaplan (1997) define their proxy for measuring financial distress when a firm's EBITDA is lower than interest expenses or when a firm applies for debt restructuring. Piñado et. al. (2006) define financial distress as when a firm obtains lower EBITDA than financial expenses for two consecutive years, a definition they argue is adoptable across periods and regions due to differences in legal framework.

Regardless of the definition of financial distress, there are several accounting based studies that obtain robust and accurate results. Ward and Foster (1997) use purely accounting based variables to predict financial distress defined as legal bankruptcy and their model obtain high descriptive power but low significance. Piñado et. al. (2006) who use negative EBITDA as definition of financial distress and has an international sample selection and accounting based variables obtain a pseudo R^2 ratio of approximately 30% across time for both US and international firms. Furthermore their model is also more robust across time than the O-score and Z-score. A more recent model in predicting financial distress is developed by Campbell, Hilscher and Szilagy (2008) who use both accounting and market-based measures to forecast the likelihood of future financial distress (hereafter referred to as Campbell). The mixed model is retested by the authors in 2011 and is once again shown to obtain an accuracy ratio of 95,5 % and pseudo R^2 above 30 % (Campbell et. al. 2011).

Recent research has used a more market-based approach and more elaborate statistical techniques to model probability of bankruptcy. Kealhofer and Kurbat (2001) shows that the Merton distance-to-default formula (derived from the Merton option-valuation formula) better measures probability of financial distress than Moody's credit rating system, which considers both market and accounting based data. Hillgeist et. al. (2004) use the Black-Scholes-Merton (BSM) option valuation technique to predict bankruptcy and also finds that the technique significantly outperforms accounting based techniques (as the Altman and Ohlson techniques). However, Campbell et.al. (2008 and 2011) contradict these results and show that their mixed accounting and market based model better predicts financial distress than a distance-to-default measure.

Another approach is to use credit rating as a summary measure for the risk of future financial distress. Even though far more sophisticated approaches for predicting financial distress exist, the use of credit ratings is designed to capture the creditworthiness of a company. Garlappi and Yan (2010) use credit ratings in their valuation research and conclude that financially distressed stocks (i.e. low credit ratings) provide lower returns than companies with higher ratings. Kisgen (2006) evaluates how companies' credit ratings affect the firms' capital structure. Kisgen's research touches upon the debt overhang problem and finds that firms with low ratings are financed relatively more by equity than with debt since the low ratings prevent these firms to take on new debt. Since the financial crisis in 2008, the major credit rating firms' trustworthiness has been highly discussed and even though credit ratings are used in the entire financial sector to rate firms we will in this research disregard from these since what is underlying these rating is not entirely clear.

2.2 Asset Pricing

In the field of asset pricing there is an extensive body of research suggesting that there exists a risk-reward trade-off. If a risk-averse investor invests in a portfolio of riskier securities over another "safer" portfolio he will demand a higher return. This idea is first outlined by Markowitz

(1952) and serves as the fundamental assumption to asset-pricing models such as the capital asset pricing model, CAPM, developed independently by Treynor (1961), Sharpe (1964) and Lintner (1965). These studies suggest that a security's expected return is higher if there is a higher risk attributed to that security.

Several extensions of the CAPM model exist. Fama and French (1993) extended the CAPM model by developing a three factor model that includes factors of size and value in addition to the market risk factor. Fama and French (1993) argue that the expected return of a stock also depends on the size of the firm and the market-to-book ratio where the returns of small firms outperform the returns of large companies, and the returns of value companies (i.e. companies with high book-to-market ratio) outperform non-value companies. This renewed model of CAPM explains over 90 % of stock returns, whereas the traditional CAPM explains approximately 70 % of stock returns. The three-factor model is extended by Carhart (1997) to a four-factor model where, in addition to the factors used by Fama and French, a momentum factor is included. The motivation for including this factor is to capture the tendency of a stock's price to continue rising if it is going up and continue declining if it is going down and which implies that stock's that earned an above average return the previous year are likely to outperform the market the following year. We are going to use the CAPM, Fama and French and Carhart as benchmark models in our analysis.

Asness, Moskowitz and Pedersen (2013) conduct a more recent research of the Carhart four factor model in eight different markets. Their findings show that value and momentum provide a risk premium of all different markets and that the findings of Sharpe (1964), Fama and French (1993) and Carhart (1997) are still valid. Thereby their paper supports our approach to use these models as benchmarks in the Swedish market.

2.3 The Distress Puzzle

In this paper the intersection between corporate finance research and research in asset pricing becomes interesting. There are numerous studies confirming that, for example, the three-factor model holds and small firms and values stocks outperform large caps and non-value stocks, indicating that the market risk-reward trade-off holds. However, it has also been showed that the compensation received from investing in financially distressed stocks does not match the risk, which is known as the distress puzzle (Dichev 1998). Campbell et. al. (2008 and 2011) repeatedly show that a portfolio of "safe" stocks outperforms a portfolio of "distressed" stocks and that distressed stocks have both higher volatility and beta-values, which is consistent with Dichev’s (1998) evaluation of portfolios sorted on the O-score and Z-score. Griffin and Lemmon (2002) finds the same phenomenon. While defining distress risk as leverage George and Hwang (2010) also find that there is a return premium in "safe" stocks which is inconsistent with the risk-reward trade-off. Similar results are obtained by Opler and Titman (1994) who show that leveraged firms suffer performance drawbacks more severely in industry downturns.

However, research results are not entirely consistent. Vassalou and Xing (2004) who use the market based Merton-model to assess financial distress show that small and value-stocks only earn a return premium if they carry extra default risk, and that the risk-reward trade-off thus holds.

2.4 Hypothesis

The first hypothesis is constructed by testing the accounting based models by Altman (1968), Ohlson (1980) and Campbell et. al. (2008) and we expect that these models have predictive power consistent with research conducted on American companies, and that the more recent Campbell model predicts financial distress best.

Our second hypothesis is that the risk-return trade-off holds and that we will reject the findings of Dichev (1998) and Campbell et. al. (2008). The Swedish market is transparent and has a strong corporate governance code (Lekvell 2014), so we expect to find that distressed firms are traded with a return premium.

3. Data & Methodology

The data needed to construct the measure of financial distress for the Altman, Ohlson and the Campbell model is gathered from several sources since the model use both market and accounting data. The market data that consists of monthly stock prices and market capitalization are collected from the FINBAS database for all listed companies in Sweden for the years 1988-2015. The accounting data used for predicting financial distress are collected from the COMPUSTAT Global database. Annual accounting measures are collected for all the listed Swedish companies for the years 1988-2015. By merging the two extensive datasets including the accounting and market measures and deleting all the financial and real estate firms, due to their different balance sheet structure, the dataset contains 6260 firm-year observations.

To pursue the second step of the research to assess whether financially distressed firms provide investors with a higher expected return, additional data need to be collected. We use the monthly return on a three-month Swedish government bond as the risk-free rate for CAPM. For the monthly market return, we construct an equally weighted index of our sample firms between 1988 and 2015. The Fama and French and Carhart factors for Sweden are retrieved from the AQR library related to the research conducted by Frazzini and Pedersen (2014) who provide monthly returns for the size, value and the momentum factors.

3.1 Models for Predicting Financial Distress

A vital question in predicting bankruptcy is model specification and selection. In this paper we, similar to the study of Campbell, Hilscher and Szilagy (2008), use a logit model to find predicted probabilities of experiencing financial distress. Since the probabilities are constructed to take on values between zero and one when predicting financial distress, the logit model is appropriate. This model will report the signs for each the coefficients' partial effect for each model when estimating financial distress (Wooldrige 2013). We predict the probability of financial distress on one year lagged variables. Explicitly, we use market variables and the income statement at year n-1 to predict the probability for financial distress at year n.

Altman (1968) and Deakin (1972) use a multiple discriminate analysis (MDA) technique, however this model has been shown to be problematic, for predicting financial distress as the assumptions of data normality and equality of covariance matrices are violated (Pervan et.al. 2011). Ohlson (1980) argues that the MDA-model provides an ordinal ranking rather than predictions and more recent literature such as Shumway (2001), Chava and Jarrow (2004) and Kim and Gu (2006) all argue in favor of the logistic probability model. Therefore, we use the logit regression model in the paper.

We assume that the probability of experiencing financial distress, follows a logistic distribution, and just like the original logit model developed by Cox (1958) we specify our model as

$$P_{t-1}(Y_{it} = 1) = \frac{1}{1+\exp(-\alpha-\beta x_{i,t-1})} \qquad \text{(Eq. 1)}$$

where Y_{it} is 1 if the company i experiences financial distress, α is a constant, β a set of coefficient and $x_{i,t-1}$ is a set of one year lagged explanatory variables, i.e. the variables used by Altman (1968), Ohlson (1980) and Campbell et.al. (2008) to predict bankruptcy.

The first issue when doing research on distress risk is the definition of financial distress. Most studies (see Altman (1968), Ohlson (1980), Opler (1994), Hillgeist (2004), and Campbell (2008)) use bankruptcy as proxy, however bankruptcies are not common in all geographical areas. In Sweden, the legal system is Scandinavian Civil Law whereas in the US it is common law which implies some differences. In Sweden, companies file for corporate restruction, even several times before being filing for, or being declared as bankrupt (Tuula-Karlsson 2012) and there are not many companies that have filed for bankruptcy and would be suitable for this study. Thus, we also apply another definition of financial distress, which is used by Pinãdo et.al. (2006) and we find this to be a better proxy for the Swedish market. They use the definition that a firm is in financial distress if it has two consecutive years of EBITDA lower than its financial expenses. We argue that two years of negative consecutive EBITDA alone shows if company is unable to generate organizational funds to pay its financial obligations. By using this definition, we also capture those companies who are facing bankruptcy but are able to refinance their operation by issuing new equity. Selling new equity is seen as a last resource of funding according to the pecking order theory provided by Myers and Majluf (1984) and we think that earlier studies excludes this possibility as a proxy for financial distress. For the EBITDA model Yit is 1 if the company i experiences its second consecutive negative EBITDA for the second year or if the company either has applied for bankruptcy or is unable to pay its debts at year i in the bankruptcy model.

Table 1 reports the total number of firms in our sample along with the number of bankrupt firms and firms with negative EBITDA for two consecutive years. Evidently there is a lack of financially distressed firms prior to the year of 1995 and a low proportion of reported bankruptcies. Notably there are far more reported firms with two consecutive years of negative EBITDA in our sample. Apparent from the table is also that the number of observations is steadily increasing over the years and assuming a normal competitive economic climate the number of distressed firms should proportionally be the same. The EBITDA observations are consistent and will increase the predictive power of the model. However, to be consistent with the literature we also run regressions with the Bankruptcy proxy of financial distress as the dependent variable to evaluate which measure best fits the Swedish market.

Table 1

Financially Distressed Firms by Year

This table displays the number of firms, bankruptcies and firms with two consecutive years of negative EBITDA for the sample firms between 1989 and 2015.

Year	Observations	EBITDA	*As a Percentage*	Bankrupt	*As a Percentage*
1989	38	0	*0%*	0	*0%*
1990	41	0	*0%*	0	*0%*
1991	43	0	*0%*	0	*0%*
1992	46	0	*0%*	0	*0%*
1993	48	0	*0%*	0	*0%*
1994	53	0	*0%*	0	*0%*
1995	57	1	*1,754%*	0	*0%*
1996	109	1	*0,917%*	0	*0%*
1997	164	2	*1,220%*	0	*0%*
1998	193	18	*9,326%*	0	*0%*
1999	213	27	*12,676%*	0	*0%*
2000	243	60	*24,691%*	0	*0%*
2001	244	71	*29,098%*	0	*0%*
2002	247	66	*26,721%*	0	*0%*
2003	240	57	*23,750%*	0	*0%*
2004	266	59	*22,180%*	1	*0,376%*
2005	280	57	*20,357%*	0	*0%*
2006	316	68	*21,519%*	2	*0,633%*
2007	349	87	*24,928%*	2	*0,573%*
2008	351	96	*27,350%*	2	*0,570%*
2009	352	111	*31,534%*	1	*0,284%*
2010	358	108	*30,168%*	4	*1,117%*
2011	360	104	*28,889%*	4	*1,111%*
2012	383	121	*31,593%*	1	*0,261%*
2013	394	120	*30,457%*	3	*0,761%*
2014	417	138	*33,094%*	0	*0%*
2015	455	162	*35,604%*	4	*0,879%*
Total	6260	1534		24	

3.2 Models & Evaluation to Predict Financial Distress

3.2.1 The Altman Model

Altman (1968) uses 5 ratios to predict financial distress, where three are liquidity measures, one is a measure of solvency and one is a profitability measure. In Altman's original model the variables that are used in the model to predict corporate failure are constructed from daily market data and annual accounting data. Equation 2 shows the Altman's Z-score model.

$$Z = \beta_1 WCTA + \beta_2 RETA + \beta_3 \mathrm{EBTA} + \beta_4 \mathrm{MCTL} + \beta_5 \mathrm{SATA} \qquad \text{(Eq. 2)}$$

where:

$WCTA = Working\ capital/Total\ Assets$

$RETA = Retained\ earnings/Total\ Assets$

$EBTA = Earnings\ before\ interest\ and\ taxes/Total\ assets$

$MCTL = Market\ value\ equity/Book\ value\ of\ total\ debt$

$SATA = Sales/Total\ Assets$

We have for consistency over the study adjusted the Total Assets measure, as proposed by Campbell et.al (2008), according to equation 3 for all three models.

$$Total\ Assets_{i,t}^{adj} = Total\ Assets_{i,t} + 0{,}1(Market\ Value\ of\ Equity_{i,t} - Book\ Value\ of\ Equity_{i,t} \qquad \text{(Eq.3)}$$

In the Altman model we were able to retrieve the same accounting measures that Altman uses in his original model, therefore no further deviations are made regarding the variables in the model.

Altman uses a matched dataset consisting of 66 manufacturing firms, 33 that went bankrupt and 33 matched healthy firms with similar characteristics. For accuracy evaluation we apply a similar matching technique, and we expect the coefficients of the model in equation 2 to be negative, i.e. a higher ratio implies lower probability of financial distress.

Table 2 shows the summary statistics for the five explanatory variables included in the Altman model for the entire dataset, for the bankrupt firms and for the firms with negative EBITDA for two consecutive years. Note that all variables in the three models are winsorized at the 5th and 95th percentile to avoid outliers to affect the accuracy of the prediction, which is a technique proposed by Campbell et.al (2008).

Table 2

Summary Statistics of Coefficients for Altman Model

This table reports the relevant summary statistics for all the explanatory variables in the Altman model when the entire dataset, the dataset of the bankrupt firms and when the dataset with the firms with two consecutive years of negative EBITDA is used over the years 1988-2015.

			Entire Data Set		
Variables	RETA	EBTA	MCTL	SATA	WCTA
Mean	-0,0956	-0,0213	5,0450	1,0129	0,1882
Min	-1,8788	-0,5160	0,0786	0,0228	-0,1427
Max	0,4680	0,1882	32,6817	2,3048	0,5761
St. Dev.	0,5776	0,1821	8,2907	0,6277	0,1955
Skewness	-1,9808	-1,3881	2,3866	0,2675	0,2587
Kurtosis	6,2137	4,1798	7,7322	2,2978	2,2941
			Bankrupt Firms		
Mean	-0,7051	-0,2697	1,5767	0,9321	-0,0105
Min	-1,8788	-0,5160	0,0786	0,0228	-0,1427
Max	0,3543	0,0393	10,7003	2,3048	0,5761
St. Dev.	0,7964	0,1868	2,6626	0,7912	0,2039
Skewness	-0,3832	0,1749	2,1600	0,6629	1,7804
Kurtosis	1,4863	1,7515	6,7490	2,0156	4,9604
			EBITDA		
Mean	-0,6396	-0,2619	9,8084	0,5782	0,1918
Min	-1,8788	-0,5160	0,0786	0,0228	-0,1427
Max	0,4680	-0,0023	32,6817	2,3048	0,5761
St. Dev.	0,7503	0,1686	11,4766	0,6217	0,2277
Skewness	-0,5589	-0,3028	1,1060	1,2039	0,2036
Kurtosis	1,9253	1,6914	2,6920	3,4974	1,9407

The RETA variable which describes how much profit over the years the firms have been accumulating in relations to total assets is fairly similar with means of -0,7051 and -0,6396 for the two distressed sets, but is different for the entire sample with a mean of -0,0956. Intuitively, distressed firms rarely make any profits to retain over the years and therefore report a more negative RETA variable. As expected the two distressed subsets report higher risk level in terms of standard deviation. The skewness is lower and negative for the distressed subsets, which indicates a tail longer on the negative side for the distribution of this variable. The SATA and EBTA variables are interpreted in the same fashion since they measure similar accounting characteristics. The distressed sets displays lower means than the entire set. Notably the EBTA variable has a negative mean in our collected sample, however we believe that this variable should be positive if we had data of all public companies. As the variable is a relative in sample constructed variable, we do not think that this will affect the outcome of the regressions. MCTL reports widely different means between the three sets. Low means are reported for the bankrupt subset due to the low number of bankruptcy observations. The argument also applies for the low reported standard deviation for the bankrupt firms which is misleading and better explained by the standard deviation for EBITDA that is higher than the entire set. We see that the firms that filed for bankruptcy has a negative working capital on average while the firms with two years of consecutive negative EBITDA has a working capital to total assets ratio similar to the entire sample.

3.2.2 The Ohlson Model

The second model we assess in this paper is the Ohlson (1980) model. The variables are solely constructed through accounting data to predict financial distress. The Ohlson model uses nine different variables including two liquidity measures, three profitability measures, three solvency measures and one relative size measure. We apply an identical adjustment to Total Assets as in the Altman model according to equation 3.

The nine variables incorporated in Ohlson (1980) model to predict financial distress is shown in the equation 4 below

$$O = \beta_1 SIZE + \beta_2 TLTA + \beta_3 WCTA + \beta_4 CLCA + \beta_5 ONENEG + \beta_6 NITA + \beta_7 FFOTL + \beta_8 INTWO + \beta_9 CHIN \qquad \text{(Eq. 4)}$$

with

$SIZE = log(total\ assets/GNP\ index)$

$TLTA = Total\ liabilities\ /\ total\ assets$

$WCTA = Working\ capital\ divided\ by\ total\ assets$

$CLCA = Current\ liabilities\ divided\ by\ current\ assets$

$ONENEG = One\ if\ total\ liabilities\ exceeds\ total\ assets, zero\ otherwise.$

$NITA = Net\ income\ divided\ by\ total\ assets.$

$FFOTL = Funds\ provided\ by\ operations\ divided\ by\ total\ liabilities$

$INTWO = One\ if\ net\ income\ was\ negative\ for\ the\ last\ two\ years, zero\ otherwise.$

$CHIN = (NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$

where NI_t is net income for the most recent period and NI_{t-1} is the net income in previous period. The denominator acts as a level indicator. The variable is thus intended to measure change in net income.

For the Ohlson model most of the variables could be retrieved except for Net income used in NITA and CHIN. Instead we use Pre-Tax income and argue that this would not change the outcome much since it is only the tax that is not deducted.

Table 3

Summary Statistics of Coefficients for Ohlson Model

This table reports the relevant summary statistics for all the explanatory variables in the Ohlson model when the entire dataset, the dataset of the bankrupt firms and when the dataset with the firms with two consecutive years of negative EBITDA is used over the years 1988-2015.

Variables	WCTA	SIZE	TLTA	CLCA	ONENEG	PITA	FFOTL	INTWO	CHIN
					Entire Data Set				
Mean	0,1882	-8,7369	0,4638	0,6777	0,0155	-0,0376	-0,0126	0,4022	0,0421
Min	-0,1427	-12,6049	0,0776	0,1394	0,0000	-0,5997	-2,4671	0,0000	-1,7608
Max	0,5761	2,4003	0,2164	0,3775	0,1235	0,2038	0,8051	0,4904	0,7742
St. Dev.	0,1955	-4,1405	0,8087	1,5931	1,0000	0,1924	0,9195	1,0000	1,8548
Skewness	0,2587	0,2481	-0,1967	0,7682	7,8455	-1,4328	-1,7585	0,3988	-0,0269
Kurtosis	2,2941	2,1943	1,9958	3,0392	62,5518	4,3218	5,8834	1,1590	3,9782
					Bankrupt Firms				
Mean	-0,0105	-10,6703	0,6713	1,2122	0,2917	-0,3300	-0,2655	1,0000	0,0177
Min	-0,1427	-12,6049	0,1554	0,1394	0,0000	-0,5997	-1,6652	1,0000	-1,0752
Max	0,5761	-8,0190	0,8087	1,5931	1,0000	0,0087	0,9195	1,0000	1,8548
St. Dev.	0,2079	1,6059	0,2090	0,4250	0,4643	0,2159	0,5787	0,0000	0,5778
Skewness	1,7804	0,3717	-1,2282	-0,9188	0,9167	0,1014	-0,7376	N/A	0,9857
Kurtosis	4,9604	1,7765	3,1413	2,9367	1,8403	1,6551	3,8502	N/A	5,7588
					EBITDA				
Mean	0,1918	-10,8788	0,3487	0,6484	0,0404	-0,2864	-0,9018	0,9831	0,0669
Min	-0,1427	-12,6049	0,0776	0,1394	0,0000	-0,5997	-2,4671	0,0000	-1,7608
Max	0,5761	-4,1405	0,8087	1,5931	1,0000	0,1924	0,9195	1,0000	1,8548
St. Dev.	0,2277	1,4558	0,2485	0,4771	0,1970	0,2022	1,0017	0,1291	0,4885
Skewness	0,2036	0,8598	0,5911	0,7724	4,6673	-0,2815	-0,3700	-7,4845	0,0185
Kurtosis	1,9407	3,8245	1,9994	2,3658	22,7841	1,9191	1,9042	57,0172	5,7983

Table 3 reports the summary statistics for the variables included in the Ohlson model. This table shows several interesting findings. The firms' relative sizes are measured in the SIZE variable where the means are similar for the two distressed subsets and lower than for the entire set. We interpret this as larger corporations typically have a lower probability to default. We find that the leverage measures CLCA and TLTA are larger for the bankrupt firms than negative EBITDA firms, which is consistent with the theory of leveraged firms being more risky. However, the EBITDA set shows a lower mean and bankrupt shows a higher mean than the entire set which indicates that for bankrupt firms higher leverage increase the probability of financial distress more than for the firms that have negative EBITDA. In contrast to the other sets EBITDA also report a negative skewness which suggests a longer tail on the negative side than for the other two sets. The results for the ONENEG variable shows that bankrupt firms have a far higher leverage along with a higher risk. INTWO is similar to a financial distress measure and argue that both bankrupt and EBITDA firms are making losses rather than profits. We find the same phenomenon regarding the EBTA variable for the Altman model, that the firms in our sample on average has negative PITA and FFOTL. Again, on average we believe that these numbers should be positive for all public firms, but for our selected sample they are generally negative.

3.2.3 The Campbell Model

The final and most recent model of predicting corporate failure of distress is the Campbell model. To estimate the Campbell model, we use similar measures as provided in the original study, with some modifications. In the Campbell model, there are four market based measures, three accounting based ratios and instead of using book value of total assets we use the market value of total assets. The Campbell model is shown in equation 5.

$$\mathrm{C} = \beta_1 \mathrm{NIMTA} + \beta_2 \mathrm{TLMTA} + \beta_3 \mathrm{EXRET} + \beta_4 \mathrm{SIGMA} + \beta_5 \mathrm{RSIZE} + \beta_6 \mathrm{CASHMTA} + \beta_7 \mathrm{MB} + \beta_8 \mathrm{PRICE} \qquad \text{(Eq. 5)}$$

where:

$NIMTA = Net\ income/Market\ value\ of\ total\ assets.$

$TLMTA = Total\ Liabilities/Market\ value\ of\ total\ assets.$

$EXRET = Excess\ return\ relative\ to\ S\&P\ 500.$

$SIGMA\ =\ Standard\ deviations\ over\ the\ three\ past\ months.$

$RSIZE\ =\ Equity\ capitalization\ relative\ to\ the\ S\&P500$

$CASHMTA\ =\ Shortterm\ liquidity\ /\ Market\ value\ of\ total\ assets.$

$MB\ =\ Market\ Equity/Book\ Equity$

$PRICE\ =\ Log\ of\ the\ stock\ price, which\ is\ capped\ at$ \$15.

As for the Altman and Ohlson models, where Net Income is used we are instead using Pre-tax Income. Since the research is done on the Swedish market excess return is the excess return from the SIX Index for the EXRET variable instead of the excess return of S&P500. PRICE had shown almost no effect and insignificance. However, choose not to cap it at a certain threshold but rather see if there was an overall effect from price. We also adjust the model using the GDP-index of Sweden instead of the value of a market index to obtain a measure of relative size.

The SIGMA variable is calculated as a three-month standard deviation of daily returns, which has been annualized. Equation 6 shows the calculations.

$$SIGMA_{i,t-1,t-3} = \left(252 * \frac{1}{N-1} \sum_{k\epsilon\{t-1,t-2,t-3\}} r_{i,k}^2\right)^{\frac{1}{2}} \qquad \text{(Eq. 6)}$$

Table 4

Summary Statistics of Coefficients for Campbell Model

This table reports the relevant summary statistics for all the explanatory variables in the Campbell model when the entire dataset, the dataset of the bankrupt firms and when the dataset with the firms with two consecutive years of negative EBITDA is used over the years 1988-2015.

Variables	NIMTA	TLMTA	EXRET	SIGMA	RSIZE	CASHMTA	MB	LAST
Entire Data Set								
Mean	-0,0252	0,4035	0,0712	0,1145	4,7514	0,1085	3,3129	62,6784
Min	-0,4453	0,0294	-0,9313	0,0000	0,8411	0,0054	-731	0,0100
Max	0,1458	0,2712	0,5476	0,3036	2,2913	0,1077	18,9294	319
St. Dev.	0,1427	0,9272	0,9600	9,9858	9,1317	0,4003	884	9219
Skewness	-1,5706	0,3921	0,1197	13,4650	0,1856	1,4179	12,2380	19,3063
Kurtosis	4,8674	2,0576	2,2309	303,8262	2,2127	4,1548	1226	450
Bankrupt Firms								
Mean	-0,2603	0,6314	-0,1625	0,1753	2,1993	0,0741	1,8468	5,8985
Min	-0,4453	0,0855	-0,9313	0,0000	0,8411	0,0054	-4,4935	0,0100
Max	0,0026	0,9272	0,9600	1,1434	6,4793	0,4003	15,4769	34,6698
St. Dev.	0,1682	0,2766	0,5678	0,2601	1,4634	0,1006	4,1346	8,8951
Skewness	0,2573	-0,8243	0,2128	2,9169	1,1763	1,8582	1,7318	2,0746
Kurtosis	1,5308	2,3650	2,2060	10,4711	4,0143	5,8330	6,6650	6,4834
EBITDA								
Mean	-0,1876	0,2841	0,0694	0,1641	3,1247	0,1337	4,2857	69,4242
Min	-0,4453	0,0294	-0,9313	0,0000	0,8411	0,0054	-731,1974	0,0100
Max	0,1427	0,9272	0,9600	9,9858	9,1317	0,4003	430,4167	9219,2830
St. Dev.	0,1563	0,2727	0,6831	0,4432	1,5713	0,1272	26,0031	505,1613
Skewness	-0,4990	0,9716	0,0188	12,2033	0,3807	0,9679	-10,2331	14,3141
Kurtosis	2,0151	2,7210	1,5937	211,7738	2,7164	2,6683	490,4143	233,1147

Table 4 reports the summary statistics for the variables in the Campbell model. All the variables incorporated in the Campbell model except for EXRET are consistent with Campbell's (2008) findings in terms of signs. EXRET is negative for the bankrupt subset, which is consistent with Campbell however, it's positive for the two other subsets. If the excess returns would increase the probability of financial distress would increase, by thinking in terms of risk and return a higher return should have a higher risk, i.e., higher probability of financial distress. It can also represent in terms for the bankrupt set that a higher excess returns for these firms do in fact represent a lower default risk due to the firm's performance. Campbell (2008) finds the NIMTA variable to be very close to zero and negatively skewed which is consistent with our findings. We expect this to be the case as the variables are not value-weighted and covers a period of high volatility in earnings.

3.2.4 Model Evaluation

To evaluate the models we compare the adjusted R^2 (hereafter R^2), which tells us, in percentage, how much of the variation of the dependent variable is explained by the models (Wooldrige 2013). To further evaluate the predictive power of the models we calculate an accuracy ratio. To obtain such a ratio we first match each financially distressed firm with an observation of a healthy firm based on year and size. Arguably one could match on size and industry as Altman (1968) however we feel more confident with this matching as we have cleared the data of investment, utilities, financial services and real estate companies. We run the same logit regression as above in the matched sample to obtain a prediction of financial distress. The accuracy ratio is defined in equation 7.

$$Accuracy\ Ratio = \frac{FD_a}{N} + \frac{FH_a}{N} \qquad \text{(Eq. 7)}$$

where FDa is the number of correctly predicted firms in financial distress , FHa is the number of correctly predicted healthy firms and N is the total number of firms in the sample. We set a threshold at a 50% level, i.e. a firm that is predicted with a higher probability than 50% is stated as predicted to be in financial distress. A completely uninformative model would result in an accuracy ratio of 50%.

3.3 Methodology for Performance Evaluation

3.3.1 Portfolio Analysis

To evaluate whether companies in a distressed state perform better or worse than the market, a cross-sectional analysis is used. The method for such an analysis is to rank the companies on predicted probability of financial distress and create five equally sized portfolios, each containing 20% of the available stocks. Portfolio 1 contains companies with the lowest predicted distress probability and portfolio 5 is formed by the companies with the highest predicted probability of distress. The monthly returns are measured and the portfolios are updated yearly. Note that we cut the monthly returns at the 2nd and 98th percentile to adjust for extreme outliers as seen e.g. during the dot-com bubble and crash. We will compare the returns of our equally weighted monthly portfolio returns to our equally weighted market index to assess whether investors actually receive a risk premium by investing in riskier stocks.

The evaluation is based on calculating and comparing average returns over time for the portfolios to see whether returns on portfolio 1 and 5 are significantly different. Cross-sectional analysis will also be done by forming a zero-cost portfolio that goes long portfolio 1 (the "safest" stocks) and short portfolio 5 (the "distressed" stocks). A regression on returns can verify if the zero-cost portfolio delivers a significant alpha and provide additional implications for investors who have the ability to form Long-Short portfolios.

3.3.2 Return Analysis & Model Specifications

To analyse the returns of the portfolios sorted on its predicted probability of financial distress. We calculate the average excess return on a market constant and use the CAPM, the Fama and French (1993) and the Carhart (1997) models. We run time series ordinary least squares (OLS) regressions and we compare the monthly abnormal returns, alpha (α). We collect and compare α-values for the CAPM regression, 3-factor regression and 4-factor regression. For each portfolio, the Beta (β)-coefficients are also obtained for comparative analysis. The CAPM regression is shown in equation 8, the 3-factor regression in equation 9 and the 4-factor regression in equation 10. Original asset pricing equations with descriptions are provided in the appendix.

$$R_{p,t} - R_{f,t} = \alpha + \beta * \left(R_{m,t} - R_{f,t}\right) + \varepsilon_t \qquad \text{(Eq. 8)}$$

$$R_{p,t} - R_{f,t} = \alpha + \beta * \left(R_{m,t} - R_{f,t}\right) + \beta_{SMB} * SMB + \beta_{HML} * HML + \varepsilon_t \qquad \text{(Eq. 9)}$$

$$R_{p,t} - R_f = \alpha + \beta * \left(R_{m,t} - R_{f,t}\right) + \beta_{SMB} * SMB + \beta_{HML} * HML + \beta_{WML} * WML + \varepsilon_t \qquad \text{(Eq. 10)}$$

Where $R_{p,t}-R_{f,t}$ is the monthly portfolio excess-return, $R_{m,t}-R_{f,t}$ is the monthly market excess return, and ε_t is an error term. The size (SMB), value (HML) and momentum (WML) factors for the Swedish stock-market are collected from Frazzini and Pedersen (2014) and are constructed as shown in equation 11, 12 and 13. The factors are denominated as excess return over the monthly return of a 3-month American T-bill, and we correct this by changing the factors to excess returns over the return of a 3-month Swedish T-bill.

Small Minus Big (Eq. 11)

$$SMB = 1/3(Small\ Value + Small\ Neutral + Small\ Growth) - 1/3(Big\ Value + Big\ Neutral + Big\ Growth)$$

High value Minus Low value (Eq. 12)

$$HML\ = 1/2\ (Small\ Value + Big\ Value)\ -\ 1/2\ (Small\ Growth + Big\ Growth)$$

Winners Minus Losers (Eq. 13)

$$WML = 1/2(Small\ High + Big\ High) - 1/2(Small\ Low + Big\ Low)$$

These extensions of CAPM by Fama and French (1993) and Carhart (1997) are applied to our research to conduct an analysis of the portfolio returns as comprehensive as possible. The SMB, HML, and WML, portfolios are rebalanced each calendar month.

4. Results & Analysis

4.1 Predicting Financial Distress

Table 5 reports the results from the logit regression for predicting financial distress for the Altman, Ohlson and Campbell models. In these logit regressions both Bankrupt and negative EBITDA for two consecutive years are used as the dependent variable. Consistent for all three models is that when the negative EBITDA is used as dependent variable the results are significant to a more extent and thereby we will analyse our results from EBITDA. The explanation for that is due to the lack of bankrupt firms in our sample that only represent 24 observations whereas EBITDA represent 1534 observations out of the 6260 total observations.

For the Altman model we find that three of the coefficients are negative, and two are positive. We find that the coefficients for SATA, EBTA and RETA are negative. We interpret the SATA and EBTA variables as higher sales or EBIT or less total assets lowers the probability of financial distress. Sales and EBIT are strong indicators of a firm’s current financial state, thus, higher values should indicate a financially healthier firm. However, if the ratio increases due to a reduction in the asset base it is harder to interpret as the overall asset base rarely stays stable and could fluctuate for a number of reasons. We also find that if the firm's retained earnings over total assets ratio increase, the probability of financial distress decrease. The leverage variables MCTL and WCTA report positive signs which indicated that increased leverage increase the risk of future financial distress.

Our results are consistent with Ohlson’s (1980) findings as the signs on all the variables are the same except for the ONENEG variable, which measures the leverage effect. Our results indicate that for cases when liabilities exceed assets the probability of future financial distress increase and as Ohlson predicts the coefficient to be intermediate our results are realistic. For the eight variables incorporated in the Campbell model six of our variables are consistent with Campbell's findings. The coefficients for the TLMTA and CASHMTA variables reports opposite signs than Campbell (2008). From our results larger liabilities relative to assets indicates a lower probability of financial distress. This could represent the fact of an underlying debt overhang issue that companies that are not financially healthy are not able to carry more debt than financially distressed firms. The CASHMTA variable measures the liquid assets relative to total assets and more liquid assets in our case have barely any effect on the probability of financial distress.

Table 5

Logit Regressions of the Financial Distress Predictors

This table reports the results from the logit regressions for both the bankrupt and negative EBITDA for two consecutive years as the dependent variable. For these regressions all explanatory variables are lagged one year and the dataset is examined for the whole sample from 1988-2015 with robust standard errors. * displays that the variable is significant at a 5% level whereas ** demonstrates a 1% significance.

	Altman		**Ohlson**		**Campbell**	
	Bankrupt	EBITDA	Bankrupt	EBITDA	Bankrupt	EBITDA
RETA	-0,02	-0,2				
EBTA	-6,04**	-14,98**				
MCTL	-0,19*	0,04**				
SATA	-0,07	-1,11**				
WCTA	-0,09	0,81**	-0,06	-0,23		
SIZE			-0,17	-0,32**		
TLTA			0,97	-3,43**		
CLCA			0,02	0,01		
ONENEG			1,13	2,01**		
PITA			0,74*	-2,32**		
FFOTL			0,07	-0,15**		
INTWO			(omitted)	2,56**		
CHIN			0	0*		
NIMTA					-0,48	-7,25**
TLMTA					1,3	-4,61**
EXRET					0,07	-0,1
SIGMA					0,03**	0,02*
RSIZE					-0,33**	-0,42**
CASHMTA					-2,15	0,02
MB					0	0,01
PRICE					0	0**
Observations	5534	5534	2098	5179	4932	4932
Constant	-5,71	-1,52	-5,07	-1,52	-4,69	1,6
Adjusted R^2	0,178	0,621	0,073	0,534	0,113	0,44
Accuracy-Ratio	0,614	0,853	0,545	0,822	0,703	0,812

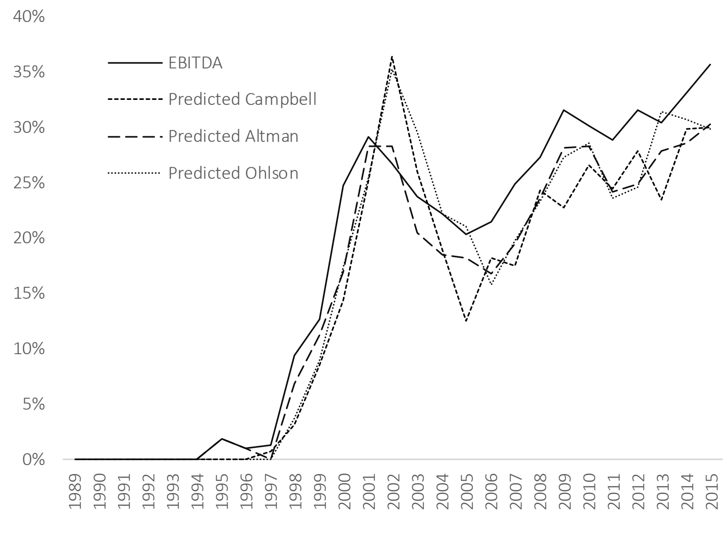
To determine which of the models most accurately predicts financial distress we compare the R^2 and the accuracy ratio for each model. The R^2 shows the variation of the dependent variable that can be explained by the independent variables (Wooldrige 2013). The results of the R^2 for when bankrupt is the dependent variable supports our previous argument that all are poor models when bankrupt is used since the R^2 is low for all three models. By comparing only the R^2 for the models when EBITDA is used it is evident that Altman should be regarded as the best model followed by Ohlson and Campbell.

The second measure to compare the models is the accuracy ratio, which explains how good each model is to accurately predict financial distress. The more detailed calculations for the accuracy ratio can be found in the model evaluation section. Also in terms of this measure Altman is suggested to be the best model. Our findings are consistent with those of Dichev (1998) but contradictory to Campbell et. al. (2008) However, the accuracy ratios for all models are very similar which implies that all three models do a good job when predicting financial distress. It is expected that both market based and accounting based measures affect the health of a company, thus we argue that the Campbell model is a more realistic model and therefore we will continue with this model for portfolio sorting and return analysis. Note however, that we also report the corresponding results for the two other models (Altman and Ohlson) in the Appendix

Graph 1

The Models Predictive Power of Financial Distress

This graph plots the predictive power of financial distress in terms of EBITDA from the Altman, Ohlson and Campbell model over the sample period.

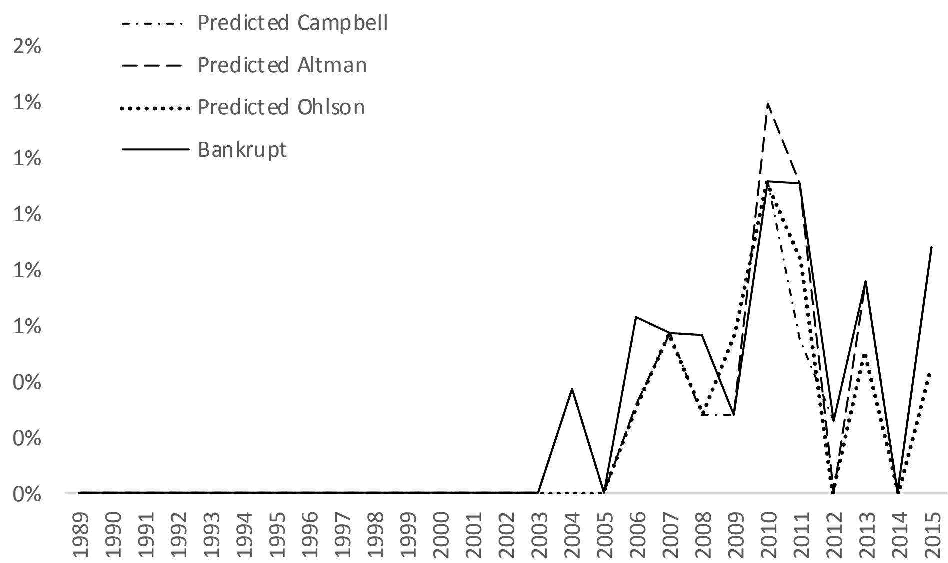


In Graph 1 the ability of predicting financial distress in terms of EBITDA for the three models are illustrated over the sample period. According to previous reasoning along with the graph it's evident that all three models perform similar in predicting financial distress. Evidently the predictions are consistently lower than actual distressed firms as the dataset includes firms that are in financial distress at the first yearly observation, and thus cannot be predicted to be in financial distress until the following year. As the trend of the predictions clearly follows the actual results we believe that all three models are suitable for predicting financial distress. We are unable to prove our first hypothesis that the Campbell model predicts financial distress better than the other models but show that all models predict distress equally well. Graph 2 reports the ability of predicting financial distress in terms of bankrupt e.g. for the three models over the sample period. Although we argue that the bankruptcy definition of financial distress makes the models insufficient due to the small number of bankrupt firms in our sample it is evident that all three models in this case do a similarly good job in predicting financial distress.

Graph 2

The Models Predictive Power of Financial Distress

This graph plots the predictive power of financial distress in terms of Bankrupt from the Altman, Ohlson and Campbell model over the sample period.



4.2 Portfolio Performances

We start by looking at the average performance of 5 portfolios sorted on its predicted probability of financial distress (defined as negative EBITDA for its second consecutive year) for all the models. As shown in table 6 below, the trend is similar regardless of model and contradicting the results of Vassalou and Xing (2004) but affirming the results of Dichev (1998) and Campbell et. al. (2008 & 2011).

Table 6

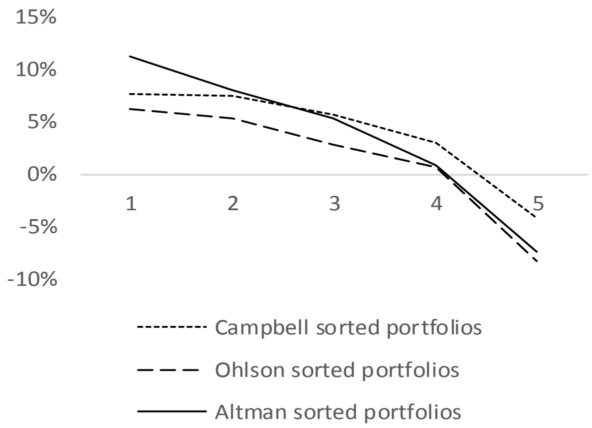
Average Portfolio Excess Returns for the different models

This table displays the average excess return of the 5 portfolios for the entire sample period for the 3 tested models for cut off of outliers at 98th and 2nd percentile.

	Campbell sorted portfolios	Ohlson sorted portfolios	Altman sorted portfolios
Portfolio	Mean return	Mean return	Mean return
1	7,69	6,18	11,30
2	7,48	5,40	8,07
3	5,63	2,83	5,39
4	2,99	0,74	0,81
5	-4,17	-8,28	-7,36

In Graph 3 we see that the annualized average monthly excess return of portfolio 1 is the highest, followed by portfolio 2 and that portfolio 5 yields has the lowest returns for the three different sortings. This clear pattern is also found in table 6. Looking at the average performance we find that regardless of which model we use to predict financial distress, the portfolios perform similarly with a clear trend that portfolio 1 provides the highest average return and portfolio 5 would be the relative worst performing portfolio.

Graph 3
Average Monthly Portfolio Excess Returns
Chart 3 graphically shows the annualized monthly excess return for each portfolio and sorting.



In table 7 we describe the different annualized average excess returns of portfolios sorted on Campbell predicted probability of financial distress. The regression results of the Altman and Ohlson sorted portfolios (see Appendix) displays the same patterns as the ones reported here. The average excess returns show a clear trend in portfolio performances with significant t-statistics indicating that the Campbell (2008 and 2011) findings that safe stocks outperform distressed stocks are also applicable to the Swedish market. Table 7 also shows us that the major part of the difference in returns is attributable to portfolio 5. The difference between portfolio 4 and 5 is larger than the differences between any other two neighbouring portfolios. When looking at the average excess return of the Long-Short portfolio we find a yearly excess return of 7,86%.

Table 7

Financial Distress Risk-Sorted Portfolio Returns

Table 7 describes the annualized returns of the sorted portfolios in percentages. We sort all stocks on their predicted probability of financial distress from the Campbell model, portfolio 1 is the "safest" stocks (the stocks in quintile 00-20) and portfolio 5 is the portfolio with the stocks of highest probability for financial distress. * Denotes significance at 5% level and ** denotes significance at a 1% level. The LS portfolio is a long-short portfolio, taking a long position in portfolio 1 financed by a short position in portfolio 5.

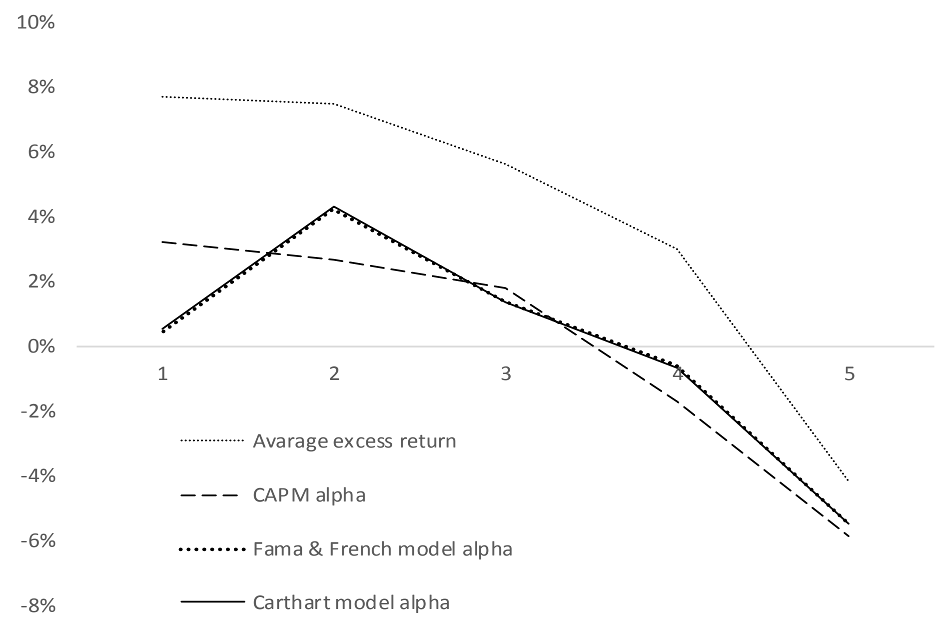
Portfolio	1	2	3	4	5	LS15
Panel A: Portfolio Alpha's						
Avarage excess return	7,69	7,48	5,63	2,99	-4,17	7,86
	(1,95)	(2,02)*	(1,44)	(0,71)	(1,01)	(2,32)*
CAPM alpha	3,23	2,65	1,79	-1,72	-5,89	9,12
	(1,66)	(1,76)	(1,15)	(0,93)	(2,74)**	(2,56)*
Fama & French model alpha	0,48	4,22	1,40	-0,57	-5,48	5,96
	(0,29)	(2,81)**	(0,8)	(0,36)	(2,54)*	(1,8)
Carthart model alpha	0,53	4,30	1,38	-0,67	-5,50	6,04
	(0,33)	(2,92)**	(0,81)	(0,43)	(2,56)*	(1,84)
Panel B: Regression Coefficients in the 4-factor Model						
RM	1,08	0,95	1,05	1,00	0,92	0,160
	(42,84)**	(32,42)**	(30,79)**	(36,5)**	(26,77)**	(3,17)**
SMB	-0,29	0,02	-0,03	0,19	0,11	-0,400
	(7,17)**	(0,47)	(0,71)	(4,5)**	(2,58)**	(5,99)**
HML	0,19	0,13	0,02	-0,19	-0,15	0,340
	(9,04)**	(5,19)**	(0,77)	(7,34)**	(4,57)**	(7,7)**
WML	0,02	0,03	-0,01	-0,03	-0,01	0,03
	(0,64)	(0,98)*	(0,28)	(1,29)*	(0,24)	(0,49)

The CAPM, 3-factor and 4-factor regression alphas show the same trend as the average excess returns. The alpha-values for portfolio 1 are positive but insignificant. As the CAPM-regression captures the dynamics of the market we cannot see a clear trend from portfolio 1 to 3. The differences are small and show that financially healthy firms slightly outperform the sample market over our sample period, which is consistent with Campbell (2008) but inconsistent with Dichev (1998) who find a more linear trend on the Altman and Ohlson sorted portfolios. Portfolio 1, 2 and 3 provide an above average return regardless of the asset pricing model used, whereas correcting for size, value and momentum effects the largest return differences are found between portfolio 4 and 5. Portfolio 5 is also shown over all regression models to have a negative alpha. We also find that the difference between the Fama and French model and the Carhart model is small thus we conclude that momentum effects does not have significant impact on returns, whereas we find that the alpha-values of the portfolios change more when correcting for size- and value effects.

Graph 4

Stock portfolio alphas

This graph plots the annualized average excess return, CAPM alpha, Fama-French alpha and Carthart alpha for each of the five constructed portfolios from 1988-2015.



The abnormal excess returns of the Long-Short portfolio regressed on the market and correcting factors clearly shows that the distress puzzle is evident and reject our hypothesis of financially distressed, i.e. riskier firms provide a higher return in the Swedish market. Graph 4 plots the alpha-values for the different portfolios and we clearly see the downward pattern of returns with respect to predicted financial distress.

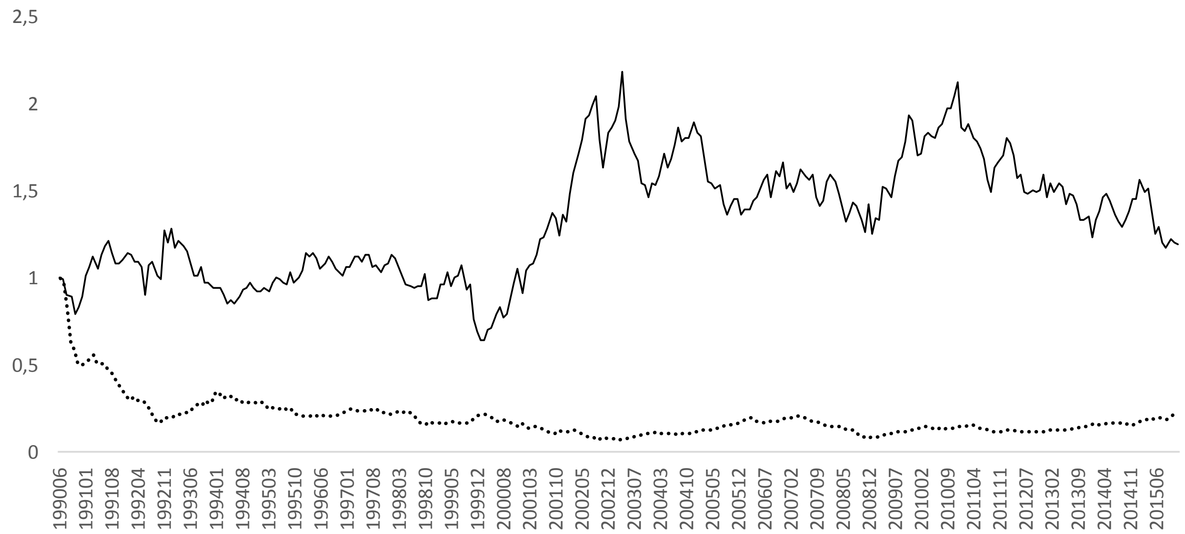
In Panel B of table 7 we also report the coefficients from the 4-factor regression model. As expected we find that the market coefficient (i.e. the CAPM-beta) is close to 1 and significant at a 99% level for all portfolios and close to 0 for the Long-Short portfolio. This indicates that the long portfolios follow the market, and that the Long-Short portfolio is market neutral. We also find that the coefficient of the WML factor is close to 0, but insignificant, indicating that the portfolio does not suffer from momentum bias. The coefficients of the SMB and HML factors are found to be -0,4 and 0,34, both significant at a 1% level. Thus the long-short portfolio tend to follow the returns of large and value stocks. Notably our coefficient results for the Long-Short portfolio differ from those found in Campbell et. al. (2008) whose portfolios are more dependent on market, size and value effects.

As shown in table 7 we find that portfolio 1 has a negative SMB coefficient of -0,29 indicating that the firms in this portfolio are of larger size. Thus we draw the conclusion larger firms are less likely to experience financial distress, and equivalently from the SMB factor in portfolio 4 and 5 we see that smaller firms are less likely to experience financial distress.. All other portfolios reports a SMB coefficient approximated to be 0 and should be independent of the size factor. We also find that no portfolio seems to suffer heavily from a value premium bias.

Graph 5

Cumulative Returns of the Long-Short Portfolio

This graph plots the cumulative return in our constructed Long-Short portfolio and the market excess return for the sample period.



Graph 5 shows the cumulative returns of investing in the Long-Short portfolio compared to investing in the equally weighted market index. As described in table 7 the excess return of the Long-Short portfolio are of positive character, which is visualized in the graph. Over time the investor would be better off investing in the Long-Short portfolio than investing in the market. Notably, the market index we have created looks different than e.g. the SIX index, and our constructed market index displays a negative cumulative excess return. This is mainly due to the fact that very few firms are included in the index in the early years, and it is cleaned from financial services, real estate and utilities companies. The high return of the Swedish 3-month T-bill during the 90´s also negatively affects the excess return of the market. This justifies that the distress puzzle holds under our market conditions, although it should be emphasized due to several reasons discussed in the next chapter that the abnormal returns stems from a non-investable universe. Our hypothesis that the robustness of Swedish corporate governance code should yield efficient pricing of stocks without arbitrage opportunities is rejected over our sample period.

5. Discussions, Contributions & Further Research

5.1 Discussion on the Non-Investable Universe

Several assumptions used by e.g. Sharpe (1964) and Fama and French (1993) is violated in the investable world. An important assumption in the theory of asset pricing is that there is a risk-free asset (which in itself according to us does not exist) of which an investor can invest in, and that the cost of borrowing equals the return of such asset. Thus it is implied that a short position in a stock for instance will carry the cost of capital equal to the rate provided by the risk-free asset. Such assumption would arguably not hold for any investment in the real world. The Long-Short portfolio (where the long position in a portfolio of "safe" stocks is financed by a short position in a portfolio of distressed stocks) would probably carry a high cost of investment. If a stock is predicted to have a negative EBITDA for its second consecutive year it should already be considered a risky asset therefore the cost of borrowing on a risky asset should be higher than the cost of borrowing a risk-free asset. The implication of this violated assumption is crucial. It is clear that the distress puzzle found in our data may not exist or at least, be weaker if it is possible to borrow risky stocks at a risk-free rate, and that the abnormal positive returns in our Long-Short portfolio would be affected by the cost of borrowing.

Furthermore, the portfolio sorting suffers from look-ahead bias. The logit predicted probability of financial distress on which we sort our portfolios stems from an analysis of the whole sample. Whereas in reality we can only analyse data from earlier years. The implications this would have on our portfolio sorting are uncertain, but the portfolio returns would undoubtedly be affected. We believe that the logit regression results of the Altman, Ohlson and Campbell models are robust over time, however one should look further into such bias before investing accordingly with the findings of this study.

5.2 Discussion on the Impact of our Time Period

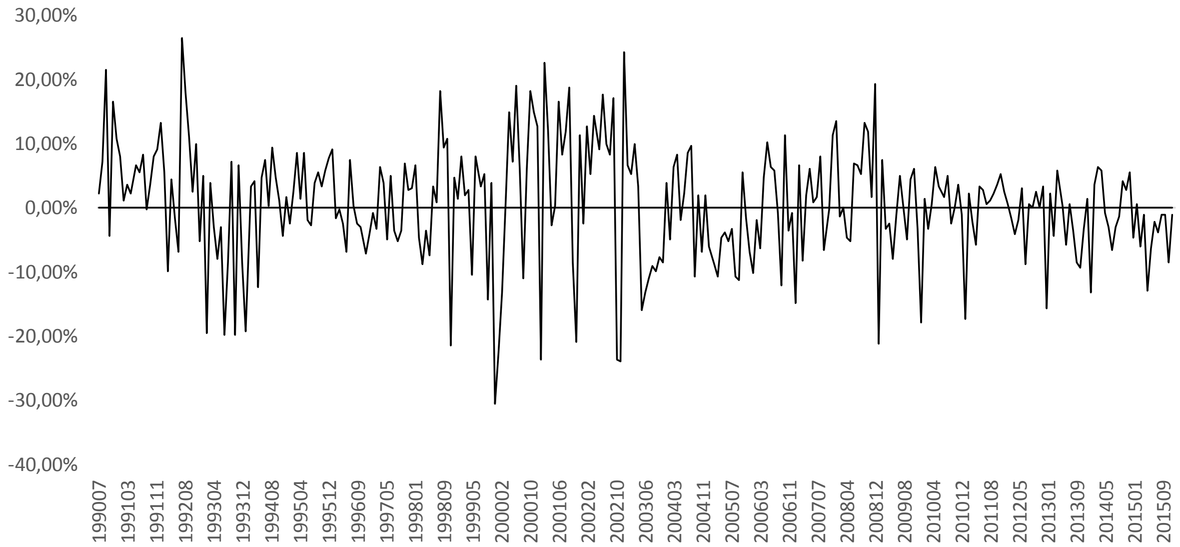
During the nineties Sweden experienced a rather unusual economic environment experiencing a severe bank and real estate crises at the time. This crisis entailed extreme levels of interest rates of up to 500% due to the fixed exchange rate. Thus, the market excess return for this long time period time-period is negative as shown in graph 5. Our portfolios excludes financial services and real estate companies which stocks suffered during this period thus the entire market may be an unfair comparison.

In graph 6 we show the monthly return differences between the market and the Long-Short portfolio and find that there is a cluster of higher than market returns during the time period 2000-2003. Our time-period of returns covers two stock-market crises, the dot-com bubble crash in the beginning of the new millennium and the financial recession starting late 2007. When analysing graph 6 there are some clear diversions between the market return and the Long-Short portfolio. We believe partly that this is due to that portfolio 5 is invested in dot-com stocks which has a high probability of negative EBITDA and collapsed during the years 2000-2003, while the portfolio 1 is invested in larger value companies which performed well during this time period. In graph 6 we find that returns are similar to the market returns after the interest rate crisis until year 2000 where the returns of the Long-Short portfolio climbs.

Graph 6

Monthly return differences

This graph plots the monthly return differences between our constructed Long-Short portfolio and the market between the years 1990-2015.



Stock markets experienced a worldwide downturn during the time period 2007-2009. With the exception of a negative period in 2011 Swedish stocks has been in a bull market, recovering from low levels after the financial crises. Graph 6 also displays that the Long-Short portfolio consistently outperformed the market during the financial crisis period, as there is a cluster of monthly outperformance at this point in time. In bull markets we find no patterns that financially distressed stocks outperform healthy ones, and as shown in graph 6 the performance after 2009 has been similar to the market.

5.3 Robustness of the Study

According to our table 1 there are no bankruptcy or negative EBITDA for two consecutive years events in our data sample prior to 1995. The reason for that could come from several explanations. One of them could be the limitations of our dataset concerning the exclusion of financial and real estate firms and only focusing on listed firms. The economic climate in Sweden in the late 80's and beginning of 90's was relatively stable except the fact that Sweden had a bank, finance and real estate crash the years between 90-94 due to abolished credit market rules. This crises would entail bankruptcies but since it mainly hit the firms that are excluded it could be explained why no bankruptcies are reported for that periods. With this in mind further research could be to drop the years prior to 1995 to evaluate if the results differ. The characteristics of the dataset are similar to the dataset underlying Campbell (2008) research, which supports our approach.

Our data-set has consistently been either winsorized or cut-off at specific levels to capture the trends driving booth the probability of financial distress as well as the portfolio returns. While the winsorization of variables when predicting financial distress nor should change the sign or size of coefficients significantly it should still be recognized that portfolio sorting may differ from a prediction without winsorization. We have shown that the returns of portfolios sorted on the 3 different models, as well as portfolios with returns dropped at different levels follows the same trend. However, if we would have performed the analysis of returns on the full sample we might have found that some of the most distressed firms also provide some of the largest returns and the abnormal returns could have be found to be smaller. Finally, both the portfolios and in-sample market index are constructed as equally weighted, and value-weighting the portfolios could also lower the abnormal returns.

5.4 Contributions

This study deepens the knowledge on performance of distressed stocks and to our knowledge is one of few solely applied in a Swedish context. As we use the two consecutive years of negative EBITDA proxy for financial distress the results of the study can be used as a comparable source for international research on the same subject, whereas if we would have used the bankruptcy proxy approach one would have to consider the bankruptcy laws in the geography evaluated. We would like to highlight that the results are for comparison and not as valid across geographical markets. As our findings are consistent with Opler and Titman (1994), Griffin and Lemmon (2002) and Campbell et. al. (2008 and 2011) we are not able to support academia with much new knowledge rather than affirming what Piñado et. al. (2008) finds; that the distress puzzle is evident across geographical markets. For the Long-Short portfolio investor we suggest to interpret our findings with caution. Even though the cumulative return outperforms the market the cost of a short position in the distressed stocks could overpower the potential benefit. However for the "long only" equity investor we have shown that the historical return on portfolios with high probability of financial distress underperforms "healthy" stocks, thus he might consider the financial health of a company in his investment process.

5.5 Further Research

Our study follows the work by Altman (1968), Ohlson (1980) and Campbell et. al. (2008 and 2011) and the findings are consistent with others who have used accounting based measures such as Opler and Titman (1994), Dichev (1998), Griffin and Lemmon (2002) and George and Hwang (2010). However, ours and the mentioned researchers' results, have been rejected by e.g. Vassalou and Xing (2004) who use a purely market based approach to predict distress. Thus we would suggest studying the performance of portfolios (in Sweden and similar markets) sorted on the Merton probability of financial distress as well as the performance of equity portfolios sorted on credit ratings. Another aspect that we have not considered is to back trade the distress puzzle based on the predicted probability of financial distress. That is, one should estimate the logit model using data up to year n-1 to, sort portfolios at year n-1 and see if there is a significant abnormal outperformance of financially healthy stocks at year n, and repeat the same procedure as n increases throughout the sample. The results of such test might be of more importance to investors.

6. Conclusion

The purpose of this research is to examine if financially distressed companies provide an extra return due to the extra risk they are bearing. This subject is in the intersection of corporate finance and asset pricing to determine whether financially distressed firms provide an additional premium for their investors.

To be able to predict the probability of financial distress three models were used. Two widely renowned models within the subject, the Altman and Ohlson models were complemented with a third one, the Campbell model. The Altman, Ohlson and Campbell models were modified to suit the Swedish context. We tested the models using both bankruptcy and two consecutive years of negative EBITDA as proxy for financial distress and found, in accordance with Piñado et. al. (2006), that the EBITDA proxy is best suitable for our study, partly due to lack of data for listed companies filing for bankruptcy and that the legal framework on organizational restructuring makes actual bankruptcies rare. Our findings imply that all three are good models for predicting financial distress.

After creating portfolios by sorting stocks based on their predicted probability of financial distress we found that the firms with a higher probability of financial distress consistently underperform the safer firms. Therefore the distress puzzle is evident in Sweden and the expected results that riskier companies should have a higher return seems to be false. Throughout our sample period "healthy" firms significantly outperformed "distressed" stocks which is in accordance with studies performed by Dichev (1998), Griffin and Lemon (2002), Campbell et. al. (2008 and 2011) and George and Hwang (2010). Even though there is a significant difference in returns, we cannot state that the market misprice distressed stocks and the divergence of performances could be solely to constraints in taking short positions similar to the equity premium puzzle.

To assess if there are any arbitrage opportunities in the market we evaluate the performance of a Long-Short portfolio. We find that investments in "safe" stocks financed by a short position in "distressed" stocks outperformed the market. We also see that there are clustered performance effects during the dot-com bubble and the recession time-period. The results for these time periods are as expected whereas the result over the entire sample period are unexpected. The reasoning behind the outperformance conclude that the actual cost of borrowing against the "distressed" will make the Long-Short portfolio non-investable and should not be considered as investment advice. Otherwise our results show that the investor should invest opposite to the message of Robin Hood; by putting their money with the financially healthy and not supporting the financially distressed firms.

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Appendix

Asset Pricing Models

The original CAPM model is shown in equation 14

$$E(r_i) = r_f + \beta_i\big(E(r_m) - r_f\big) \qquad \text{(Eq. 14)}$$

where $E(r_i)$ is the expected return on asset i, r_f is the risk-free rate, β_i explains the sensitivity of an asset to the market risk premium, $E(r_m) - r_f$ is the market premium, and following $E(r_i) - r_f$ is the security risk premium.

The Fama and French (1993) model and the Carhart (1997) model are extensions of the CAPM model that try to explain the expected returns on stocks by incorporate additional factors to the CAPM model. Fama and French incorporate size and value factors and are shown in equation 15. Carhart add a momentum factors in addition to Fama French factors to capture the effect of rising or falling stock prices, this model is shown in equation 16.

$$E(r_i) = r_f + \beta_1\big(E(r_m) - r_f\big) + \beta_2 * SMB + \beta_3 * HML \qquad \text{(Eq. 15)}$$

$$E(r_i) = r_f + \beta_1\big(E(r_m) - r_f\big) + \beta_2 * SMB + \beta_3 * HML + \beta_4 * MOM \qquad \text{(Eq.16)}$$

Where β_1 explains the sensitivity of an asset to the market risk premium, β_2 explains the small firm effect, β_3 explains the value-company effect and β_4 explains the effect of previous price movements of the asset.

Statistics for logit regressions & Portfolio returns from Altman and Ohlson

Table 1 Appendix below displays the t-statistics from the logit regressions for the sample between 1988-2015 for the Altman, Ohlson and the Campbell model. Table 2 Appendix and 3 Appendix shows the portfolio returns when the portfolios are sorted on the Ohlson and Altman predicted values of financial distressed respectively.

Table 1 Appendix

T-values of logit predicted coefficients

This table reports the t-statistics is presented for the logit regressions for when both Bankrupt and negative EBITDA for two consecutive years are used as dependent variables. The dataset contains the whole sample between the years 1988-2015 with robust standard errors. * displays and significance level for the variable at a 5% level and ** demonstrates a significance level of 1%.

	Altman		**Ohlson**		**Campbell**	
	Bankrupt	EBITDA	Bankrupt	EBITDA	Bankrupt	EBITDA
RETA	-0,06	-1,57				
EBTA	-5,91**	-18,76**				
MCTL	-1,35*	6,81**				
SATA	-0,2	-9,43**				
WCTA	-0,74	4,94**	-0,11	-0,84		
SIZE			-1,43	-10,34**		
TLTA			2,08*	-9,8**		
CLCA			1,4	0,34		
ONENEG			1,24	4,07**		
PITA			2,53*	-10,11**		
FFOTL			2,19*	-3,32**		
INTWO			(omitted)	-19,32**		
CHIN			0,83	-2,13*		
NIMTA					-1,67	-7,14**
TLMTA					1,64	-17,52**
EXRET					0,31	-1,07
SIGMA					2,62**	2,19*
RSIZE					-4,21**	-12,76**
CASHMTA					-1,09	0,09
MB					-0,05	0,77
PRICE					-0,33	2,69**
Observations	5534	5534	2098	5179	4932	4932
Constant	-10,45**	-12,61**	-12,79**	-6,21**	-6,75**	8,14**
Adjusted R^2	0,178	0,621	0,073	0,534	0,113	0,44

Table 2 Appendix

Financial Distress Risk-Sorted Portfolio Returns

This table describes the yearly returns of the sorted portfolios in percentages. We sort all stocks on its predicted probability of financial distress from the Altman model, portfolio 1 is the "safest" stocks (the stocks in quintile 00-20) and portfolio 5 is the portfolio with the stocks of highest probability for financial distress. * Denotes significance at 5% level and ** denotes significance at a 1% level. The LS portfolio is a long-short portfolio, taking a long position in portfolio 1 financed by a short position in portfolio 5.

Portfolio	1	2	3	4	5	LS15
Panel A: Portfolio Alpha's						
Avarage ex	11,30	8,07	5,39	0,81	-7,36	19,50
	(3,02)**	(2,11)*	(1,43)	(0,2)	(1,78)	(6,12)**
CAPM alph	7,19	4,18	0,09	-1,25	-9,83	17,02
	(4,27)**	(2,8)**	(0,07)	(0,76)	(4,89)**	(5,3)**
Fama & Fr	7,64	4,30	-0,10	-1,79	-9,73	17,37
	(4,39)**	(2,74)**	(0,08)	(1,01)	(4,69)**	(5,24)**
Carthart m	7,92	4,52	-0,04	-2,08	-10,00	17,93
	(4,69)**	(2,95)**	(0,03)	(1,19)	(4,95)**	(5,63)**
Panel B: Regression Coefficients in the 4-factor Model						
RM	0,95	1	1,05	0,98	1,02	-0,07
	(24,14)**	(33,58)**	(37,73)**	(32,26)**	(25,08)**	(1,03)
SMB	-0,01	-0,01	-0,06	0,01	0,06	-0,06
	(0,15)	(0,28)	(1,71)	(0,31)	(0,85)	(0,64)
HML	0,02	0,00	0,07	-0,04	-0,05	0,07
	(0,79)	(0,07)	(2,35)*	(1,57)	(1,43)	(1,43)
WML	0,1	0,08	0,02	-0,1	-0,09	0,19
	(3,66)**	(3,26)**	(1,11)	(4,14)**	(2,98)**	(3,79)**

Table 3 Appendix

Financial Distress Risk-Sorted Portfolio Returns

This table describes the yearly returns of the sorted portfolios in percentages. We sort all stocks on its predicted probability of financial distress from the Ohlson model, portfolio 1 is the "safest" stocks (the stocks in quintile 00-20) and portfolio 5 is the portfolio with the stocks of highest probability for financial distress. * Denotes significance at 5% level and ** denotes significance at a 1% level. The LS portfolio is a long-short portfolio, taking a long position in portfolio 1 financed by a short position in portfolio 5.

Portfolio	1	2	3	4	5	LS15
			Panel A: Portfolio Alpha's			
Avarage ex	6,18	5,40	2,83	0,74	-8,28	15,87
	(1,61)	(1,44)	(0,7)	0,18	(1,96)	(4,21)**
CAPM alph	4,99	3,87	1,28	0,09	-9,68	14,67
	(2,51)*	(2,55)*	(0,91)	(0,05)	(4,36)**	(3,97)**
Fama & Fr	1,12	4,87	1,82	0,62	-8,22	9,33
	(0,65)	(3,2)**	(1,28)	(0,36)	(3,71)**	(2,69)**
Carthart m	0,95	4,65	1,87	0,89	-8,15	9,09
	(0,53)	(3,02)**	(1,29)	(0,52)	(3,65)**	(2,58)*
			Panel B: Regression Coefficients in the 4-factor Model			
RM	1,06	0,97	1,07	0,920	0,96	0,09
	(32,75)**	(32,01)**	(37,4)**	(26,13)**	(22,35)**	(1,34)
SMB	-0,39	0,04	0,03	0,14	0,17	-0,56
	(8,69)**	(1,19)	-0,73	(3,19)**	(3,41)**	(6,88)**
HML	0,14	0,06	0,03	-0,15	-0,1	0,23
	(4,57)**	(2,38)*	(1,4)	(5,79)**	(2,64)**	(4,04)**
WML	0,03	0,04	-0,01	-0,05	-0,01	0,05
	(1,11)	(1,63)	(0,45)	-1,76	(0,39)	(0,8)