STOCKHOLM SCHOOL OF ECONOMICS
Bachelor's Thesis in Accounting and Financial Management

Investing on the risk of company bankruptcy

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Abstract

We investigate the risk-return relationship between bankruptcy risk, measured by Skogsvik (1990)'s probability of firm failure ("pfail"), and stock returns on a refined stock sample on Stockholmsbörsen between 2002 and 2017. Using portfolio analysis and cross sectional regressions inspired by Fama-MacBeth (1973), we find lacking evidence to support a distress risk premium. While investors are better off investing in portfolios with low risk of bankruptcy "*over time*", i.e. when investors are persistently dedicated to the investment strategy for the entire time horizon, we do not find sufficient support for a combined long-short strategy. When instead splitting the time horizon into Pre/during and Post the Global Financial Crisis, we argue that investors have become increasingly risk-averse Post crisis. As a result, the combined long-short strategy can be successfully executed 5 out of 8 years Post crisis, in contrast to 1 out of 7 years Pre/during crisis.

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1. Introduction

1.1 Background

Understanding why some firms are more likely to go bankrupt than others has long been a field of interest for researchers and investors alike. The measurements of financial distress take many shapes, and can be connected to accounting metrics and linked to so called 'bankruptcy prediction models' that seek to predict if a firm should be on the verge of failure. Two forerunners of this approach are Beaver (1966), and Altman (1968) who quantified the risk of firm failure by introducing the Z-score. These were followed by Ohlson (1980)'s O-score, and later by Skogsvik (1990)'s V-score; a study on Swedish industrial firms during 1966-1980.

Linking firms' risk of bankruptcy to their stock market performance soon attracted interest. These studies often investigated whether investors were fairly compensated with a risk-adjusted return for investing in firms with high risk of financial distress, as suggested by asset pricing theory (Campbell, Hilscher and Szilagyi, 2010). However, the results from these studies are broadly polarized. Accounting-based studies like Dichev (1998) show that bankruptcy risk is not rewarded higher returns; a view supported by Abuhamzeh and Malgerud (2015)'s study on the Nordic stock market. Campbell *et al.,* (2008; 2010) reaches the same conclusion when combining accounting and market based metrics. In contrast, Lang and Stulz (1992), Denis, and Denis (1995) found support for bankruptcy risk being related to systematic factors and should thus be rewarded higher returns.

1.2 Purpose

The lack of consensus to justify investing in stocks with different degrees of distress risk inspired us to examine the investment opportunities surrounding this puzzle of distress-risk and return. Prior research tends to focus on the extent to which investors "should" be rewarded premiums in line with firms' distress risk levels. Building on this enquiry, our study instead aims to investigate whether it is possible to capture investment opportunities by going long and short-selling stocks based on their financial distress. Rephrased, we answer the question:

Is it possible to generate excess returns from a long-short investment strategy based on distress risk sorted portfolios on Stockholmsbörsen?

1.3 Scope of investigation

The scope of our investigation is limited to stocks listed on the Stockholm Stock Exchange (OMXS) from April 1, 2002 to March 31, 2017. The time horizon for the study is limited by data availability during this period. The selection of market proxy (here OMX Stockholm All Share Index) is crucial to the calculation of excess returns. Although the index offers a broad coverage of the OMXS, the thesis' results will by nature rely on the precision in determining an appropriate benchmark index. The study will furthermore not consider stocks listed on First North Stockholm as the chosen index excludes these stocks, and for its weaker regulation creating partial comparisons to stocks listed on other markets.

The study will not compare various bankruptcy models' predictive precision and furthermore does not seek to predict specific share prices using bankruptcy prediction. Rather, the thesis examines the share price direction from varying probabilities of bankruptcy and whether this knowledge can be used to build a long-short investing strategy. Note, for the purpose of this thesis, the long-short investing strategy implies either long positions, short positions or combined long-short positions.

1.4 Contribution

Previous studies found on the relationship between distress risk and stock returns mainly interpret investing as "buying" stocks and in a limited extent explore strategies that incorporate the ability to also sell them short. Campbell *et al.,* (2010) and Dichev (1998) considers this opportunity but for U.S. stocks. We believe that too little attention has been paid to examining a twofold investment framework based on distress risk on Stockholmsbörsen. Our study therefore hopes to offer a complementary perspective to such a long-short investing strategy using Skogsvik (1990)'s model for the Swedish stock market. As far as we know, our study differentiates from previous research by using Skogsvik (1990) for investment purposes solely on Swedish data collected from Year-End reports ("Q4"). Our study's dates of investment differ from prior research as we invest closer to the report release. Perhaps most importantly, we spend an additional effort in adjusting the sectors included in the sample to better fit the Skogsvik (1990)'s origination. Finally, we investigate the investment strategy's time-dependent reliability by splitting the sample into two time periods separated by the Global Financial Crisis of 2007-2008.

1.5 Thesis structure

The structure of the study is influenced by Campbell *et al.,* (2010) and Dichev (1998). We will accordingly (1) present a suitable bankruptcy prediction model and (2) use the model's predictions as a framework for sorting firms into portfolios ranked by their distress risk.

(1) The applied bankruptcy prediction model is Skogsvik (1990)'s one-year model, whose V-score is transposed to a "probability of failure" denoted "pfail" obtained from a normal distribution. The measurements of bankruptcy risk are based on the firms' Year-End Reports.

(2) The study makes use of two methods: portfolio analysis and cross sectional regressions inspired by Fama-MacBeth (1973). For the portfolio analysis, we sort the firms in the sample into five portfolios by their pfails each year on April 1. The 1st portfolio is denoted "Low risk" and has the lowest pfail. The pfail rises for each subsequent portfolio, meaning the 5th and final portfolio, denoted "High risk", carries the stocks with the highest pfails. The portfolios' returns will be evaluated against the market index OMX Stockholm All Share Index Cap ("OMXSPI"), a rational choice containing respective listed Large, Mid and Small Cap stocks. The final part of the thesis considers the explanatory power of pfail when jointly considered with the other independent variables using cross sectional regressions.

Potential excess returns, i.e. alphas, are calculated using the Capital Asset Pricing Model ("CAPM"), from here on denoted "CAPM alpha". Positive CAPM alpha are meant to be captured by "buying" safe portfolios, and negative CAPM alpha by "short-selling" distressed portfolios.

2. Theoretical framework and previous research

2.1 Guidance to relevant theory and empirics

Several studies have aimed to find loopholes in the proven financial theories to better explain stock return variations to the risk in the market. The risk represented by firm distress risk has been excessively researched without conclusive evidence to motivate a distress risk premium.

2.2 Efficient Market Hypothesis

One of the most controversial topics in investment management is the question whether active portfolio managers can, through fundamental analysis, outperform passive investment strategies such as buying an index-fund. A central theory in finance related to this topic is the Efficient Market Hypothesis (EMH), which states that: A market is said to be efficient with respect to an information set if the price 'fully reflects' that information set (Fama, 1970); if the price would be unaffected by revealing the information set to all market participants (Malkiel, 1992). The main implication alludes to the extreme difficulty, if not impossibility, in beating the market using an active investment strategy. Jensen (1978) mentions three versions of the EMH (weak, semi-strong and strong) that have been widely discussed regarding their practical usefulness and consistency, whose differences mainly center around the definition of the information set used in those tests. The semi-strong version is the broadly accepted form of the hypothesis most generally referred to when discussing EMH (Jensen, 1978). It follows:

'All publicly available information regarding the prospects of a firm (e.g. annual reports) and historical share price data must already be reflected in the stock price.'

2.3 Modern portfolio theory

According to modern portfolio theory, investors want to be compensated for the risk they take. A centerpiece of modern financial economics related to this topic is the Capital Asset Pricing Model[1] ("CAPM"), developed by Treynor, Sharpe, Lintner, and Mossin in the early 1960s; a

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[1] *The Capital Allocation Pricing Model developed by Sharpe (1964) and Black (1972):*

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

Where,
$E(R_i)$ *equals the expected return on the capital asset*
R_f *equals the risk-free rate of interest such as interest arising from government bonds*
β_i *is referred to as "beta" and equals the sensitivity of the expected excess asset returns to the expected excess market returns*
$E(R_m)$ *equals the expected return of the market*
$E(R_m) - R_f$ *is known as the market premium*
$E(R_i) - R_f$ *is known as the risk premium*

model that has later been refined and is often linked specifically to Sharpe (1964) and Black (1972). The CAPM measures the required rate of return on a security to its systematic risk as measured by the market beta. The EMH thus suggests that it should be impossible to achieve abnormal returns predicted by e.g. CAPM due to mispricing of stocks. However, already in early 1970s, studies were only partially supportive to the original CAPM (Black, Jensen, and Scholes, 1972), and the critics continued. Researchers agreed that the one-dimensional beta somewhat lacked robust explanatory power. Where some viewed the limitations of CAPM as a sign that the reliability of the EMH was in jeopardy, others suggested that the existing models to price assets were the real villains of the stock return inconsistencies (Banz, 1981; Chan, Chen and Hsieh, 1985; and Fama and French, 1992). The likeliness of more precise models to explain stock returns variations in relation to their market risk led to the development of multifactor models that aim to explain a security's return based on several systematic factors.

2.4 Anomalies as additional explanations of risk not captured by CAPM-beta

A leading multi-factor model is Fama and French's three-factor model (1996)[2] that adds firm size and a book-to-market ratio (B/M) to represent proxies for distress risks previously only captured by the CAPM-beta. Accordingly, small firms and/or that have high B/M ratios are more likely to be in financial distress, and have historically achieved abnormal returns. In the context of the EMH, firm characteristics like size and B/M should not matter for stock returns and are anomalies suggesting that the market simply is not efficient (Ball and Brown, 1968).

There are several studies that suggest evidence of anomalies related to distress. Building on Fama and French (1996), Lemmon and Griffins (2002) finds that the B/M effect is largest in small firms with low analyst coverage, where any mispricing is probably a result of information asymmetry. Campbell *et al.,* (2010) suggests that stocks with lower analyst coverage *and* lower institutional holdings have a higher concentration of distress and weak returns. Basu (1983) confirms that stocks with high earnings-to-price (E/P) also have higher risk-adjusted returns than stocks with low E/P; an evident effect even if experimental control is

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[2] *The Fama and French three-factor model (1996):*

$$E(\tilde{R}_i) - R_f = \beta_i[E(\tilde{R}_m) - R_f] + S_i(SMB) + H_i(HMB)$$

Where,
$E(\tilde{R}_i) - R_f$ *equals the expected excess return of asset i*
$[E(\tilde{R}_i) - R_f]$ *equals the expected excess return of the market portfolio*
(SMB) equals the difference in return between a portfolio of small and large stocks respectively
(HMB) equals the difference in return between a portfolio of high and low B/M stocks respectively
β_i, S_i, H_i *equals the sensitivity of the excess return to the various market premium operators*

exercised over differences in firm size. Regarding size, Banz (1981) and Chan, Chen and Hsieh (1985) find that smaller firms' stock returns outperform larger firms' returns ("the size effect").

These studies provide examples where easily accessible financial statistics like book-to-market ratios seem to predict excess returns, albeit imposing challenges to the validity of the second version of the EMH. With that said, there might be a possibility for fundamental analysis to find undervalued stocks and furthermore achieve abnormal stock returns by good stock picking (Ou and Penman, 1989). With aims of systematizing such fundamental analyses, several studies examine the success rate of investing on specific firm characteristics. For instance, Asness, Frazzini, and Pedersen (2014) define stocks as either "quality" or "junk" based on several accounting ratios like profitability, growth, safety and dividend, which creates a quality-minus-junk factor ("QMJ") used to buy "quality" stocks and short-sell "junk" stocks.

To round off, anomalies like the ones above serve as explanatory tools to understand irregularities in the risk-return relationships supported by CAPM, and will be a bridge in this thesis for connecting financial distress to the proposed investment framework.

2.4.1 Financial distress

The width of the term financial distress is both subjective, broad and can be seen through numerous lenses. Chan and Chen (1991) puts financial distress into context of accounting and economic trends by examining the structural characteristics of firm size, whereby a key finding is that small firms, known as "marginal firms", tend to suffer from past misfortunes. These firms are distressed as follows: "They have lost market value because of poor performance, they are inefficient producers, and they are likely to have high financial leverage and cash flow problems. They are marginal in the sense that their prices tend to be more sensitive to changes in the economy, and they are less likely to survive adverse economic conditions". Like so, Fama and French (1996) show that firms that are small and/or with high B/M have persistently produced low earnings, generated little cash and experienced low levels of growth, which contributed to them both becoming proxies for "relative distress" to explain return variations.

Once a firm becomes financially distressed, the ultimate stage is bankruptcy; also known as failure or default. Beaver (1966) uses the textbook example of failure as *"the inability of a firm to pay its financial obligations as they mature"*. Skogsvik (1990) extends this failure perception to take into account firms' voluntary shutdown of the primary production activity, or receipt of a substantial subsidy provided by the state to avoid bankruptcy. Hence, defining when failure has occurred is arguably a difficult task due to a lacking consensus (Ohlson, 1980). In order to make failure more tangible, it has become commonly recognized to view and quantify financial distress through a calculated risk of bankruptcy, which is also the measure used in this thesis as supported by prior research (Dichev, 1998). Two prominent categories of methods are used to predict bankruptcy: accounting-based models that employ financial ratios as explanatory variables (e.g. Smith and Winakor, 1935; Merwin, 1942; Beaver, 1966; Altman, 1968; Ohlson, 1980; and Skogsvik, 1990) and market-based models (e.g. Merton, 1974). Campbell *et al.,* (2008; 2010) combines both accounting and market variables.

2.5 Bankruptcy prediction models based on accounting ratios

Bankruptcy prediction models seek to identify firms' likeliness of default, where using financial ratios is common practice. The various combinations of variables aim to maximize the models' extrapolative power of accounting data (Beaver, 1966). Some of the most acknowledged bankruptcy prediction models from modern literature are chronologically described below, where the last model discussed is Skogsvik (1990).

2.5.1 Beaver (1966), Altman (1968) and Ohlson (1980)

Bankruptcy prediction models focused mostly on univariate analysis until the mid-1960s (Gissel, Giacomino and Akers, 2007). Among these, Beaver (1966) produced a leading study that compares the mean values of 30 ratios of 79 failed and 79 non-failed firms across 38 U.S. industries. Beaver was the first to test a single ratio's ability to predict bankrupt and non-bankrupt firms. Despite a 92% accuracy in the 'Net Income/Total Debt' ratio one year prior to failure, the model suffered from meaningful fallacies. Beaver eventually spurred the research of multiple ratios to be considered simultaneously (Gissel, *et al*., 2007).

Altman (1968) developed a five-factor multivariate discriminant analysis (MDA) model, whose output, the Z-score, organizes firms into two groups: bankrupt or non-bankrupt. Altman (1968) analyzed 66 manufacturing firms; 33 firms defined as healthy, non-bankrupt firms, and 33 firms defined as bankrupt firms. The binomial output of whether or not a firm was considered bankrupt was based on a pre-determined range of Z-scores. Altman's Z-score model for the initial sample one year before failure, had a 95% accuracy. However, the accuracy plunged to 72% two years before failure and was 36% for the final measure of five years before failure (Gissel, *et al*., 2007).

Ohlson (1980) used a logit bankruptcy prediction approach to forecast firm failure from the event of bankruptcy. The model output, O-score, is based on nine independent variables, both financial ratios and dummies, and can be transposed into a bankruptcy probability using normal distribution. Ohlson (1980) used a sample of U.S. listed industrial companies (105 failed and 2,058 non-failed) that stretched over the period 1970-1976. Model restrictions meant that the sectors: financial services, utilities and transportation companies, were excluded. Three models with different time horizon predictions were built. The one-year model arguably attracted the most attention with a 96% prediction accuracy.

2.5.2 Skogsvik (1990)

The bankruptcy prediction model by Skogsvik (1990) uses probit analysis, from which the output, V-score, can be converted to a probability of failure (pfail) using normal distribution. Skogsvik (1990) aimed to evaluate the predictive accuracy of two models developed for: 1) current cost accounting (CCA) and 2) for historical cost accounting (HCA). The two models had strongly analogous prognostic abilities. Skogsvik (1990) used a sample of 379 Swedish manufacturing and mining firms observed over the period 1966-1980, where 51 firms failed, meaning a relatively niched sector model was constructed. Hence, applying the model to other sectors could arguably lead to sample alternations (see section 5.2). Skogsvik (1990) developed various models to predict bankruptcy from one up until six years prior to failure. Like most models, the predictive accuracy shrinks further into the future. The HCA one-year model prior to failure, relevant for the investment horizon of this this study, has an accuracy of 83.3%. The model and its components, where t = year, are described below:

$$R_1 = Return\ on\ assets = \frac{EBIT_t}{\frac{(Total\ Assets_t + Total\ Assets_{t-1})}{2}}$$

$$R_2 = Interest\ rate = \frac{Interest\ Expense_t}{\frac{(Liabilities\ incl.deferred\ tax\ liabilities_t +\ Liabilities\ incl.deferred\ tax\ liabilities_{t-1}}{2}}$$

$$R_3 = Inverted\ inventory\ turnover\ = \frac{\frac{(Inventory_t + Inventory_{t-1})}{2}}{Sales_t}$$

$$R_4 = Shareholder\ equity\ ratio = \frac{Owners\ Equity_t}{Total\ Assets_t}$$

$$R_5 = Changes\ in\ owners'equity = \frac{(Owners\ Equity_t -\ Owners\ Equity_{t-1})}{Total\ Assets_t}$$

$$R_6 = Normalized\ measure\ of\ R_2 = \frac{(R_2 - \bar{\bar{R}}_{2,t-1})}{\left[\frac{\sum_{\tau=1-4}^{t-1}(R_{2,\tau} - \bar{\bar{R}}_{2,t-1})^2}{3}\right]^{0.5}}\ where\ \bar{\bar{R}}_{2,t-1} = \sum_{\tau=t-4}^{t-1}\frac{R_2,\tau}{4}$$

$$\boldsymbol{V_{t+1} = -\ 1.5 -\ 4.3R_1 + 22.6R_2 + 1.6R_3 - 4.5R_4 + 0.2R_5 -\ 0.1R_6}$$

Skogsvik (1990) analyzed a total of 71 HCA ratios and found the 6 ratios above to have the most meaningful ability to predict bankruptcy amongst Swedish manufacturing and mining firms. Overall, the components suggest that firms with weak profitability (ROA), low equity ratios, high interest rates paid and low inventory turnovers, can be considered in the risk-sphere of bankruptcy. That is: the higher the value of V_{t+1}, the higher the estimated risk of bankruptcy (i.e. pfail), vice versa. Note that the '*Normalized measure of* R_2' (R_6) is not considered in this thesis for the sake of simplicity.

2.6 Research on the relationship between stock return and bankruptcy risk

Once bankruptcy risks became quantified by various models, a number of studies aimed to investigate if this was an anomaly that could explain patterns of stock returns (Dichev, 1998). The view was that distress risk puts a figure on firms' financial health and could therefore present an unidentified anomaly in the search of understanding whether taking on additional bankruptcy risk is rewarded by higher stock returns.

2.6.1 Dichev (1998)

Among the earliest studies, Dichev (1998) used portfolio analysis and Fama-MacBeth (1973) regressions to examine whether the risk of bankruptcy was a systematic risk using Altman (1968) and Ohlson (1980). Dichev's view of a "positive association between bankruptcy risk and subsequent realized returns" could be possible "as long as the risk of bankruptcy was systematic". Previous research was divided, but support that bankruptcy risk was related to systematic factors had been found (Lang and Stulz, 1992; and Denis and Denis, 1995). Instead, Dichev concluded that distressed stock portfolios achieve below average returns, suggesting the presence of a distress risk anomaly.

2.6.2 Campbell et al., (2008; 2010)

Campbell, Hilscher, Szilagyi (2008) presents a reformed model to predict corporate failure using a combination of accounting and market-based variables that builds on Shumway (2001) and Chava and Jarrow (2004). Campbell *et al.,* (2008; 2010) sort stocks into portfolios by their distress risk and find results in line with Dichev (1998), where stocks with "high risk of failure tend to deliver anomalously low average returns". Investors were not rewarded for holding distressed stocks, which from the perspective of most leading asset pricing models alludes to such stocks having "negative alphas" (Campbell *et al.*, 2008; 2010). Both studies conclude a distressed stock underperformance and "extreme underperformance" by small firms. The return of their long-short strategy to "long safe, short distressed stocks […] was 145%" in 2008. However, as investors apparently do not realize these gains, they argue that there might be particular reasons that mask the strength of this strategy; otherwise the gains should be exploited until profits were vanished. The authors allude to constraints of short-selling that "cause prices of distressed stocks to stay too high for too long", thereby disturbing the edge of the strategy. Another reason why this long-short strategy has not attracted arbitrage capital could be the difficulty in finding quality information about the "health of distressed stocks", making them hard to short-sell.

2.6.3 Abuhamzeh and Malgerud (2015)

This master thesis, among other objectives, aims to answer the question whether distress risk, as proxied by Skogsvik (1990)'s pfail, is captured in stock returns. Like Dichev (1998), the study makes use of portfolio analysis along with Fama-Macbeth (1973) cross sectional regressions, but for the Nordic stock markets over 2000-2014. In line with conclusions drawn by Dichev (1998) and Campbell *et al.,* (2008), the results suggest a negative relationship between distress risk and excess return. Rather than expecting a higher return premium for holding distressed stocks, investors are willing to pay more for quality firms that have a lower risk of business failure. It is henceforth possible that pfail is another distress risk anomaly.

2.7 Incorporating the probability of failure in company valuation

Skogsvik (2008) merges the Skogsvik (1990)'s pfail into four common equity valuation methods: Residual Income Valuation model, Discounted Cash Flow model, Gordon's Growth model and Economic Value Added model. For illustration, the pfail adjusted Gordon Growth model is as follows:

$$V_0(EK) = \frac{\left(1 - p^*_{fail}\right) * E(Div_1|surv(1))}{r_E - [g^0 * \left(1 - p^*_{fail}\right) - p^*_{fail}]}$$

Where,

$E(Div_1|surv(1))$ *equals the dividend to shareholders given going concern*

p^*_{fail} *equals the probability of firm failure at time = 0*

r_E *equals the required cost of equity*

g^0 *equals the perpetual growth rate*

Skogsvik (2008)'s main conclusion is that the risk of bankruptcy effect on valuation cannot be neglected in the analyzed valuation models. Equity-holders will need to adjust for the risk of not retrieving the full equity amount due to prevailing risk of bankruptcy. Furthermore, if dividends, earnings, or the discount rates are not adjusted for the risk of bankruptcy, the firm valuation could potentially be exaggerated.

Table 1. Equity values affected by pfail in Gordon Growth model

Table 1. illustrates the extent to which the equity value fluctuates with different degrees of growth and pfails.

Growth given going concern	***Pfail***					
g	***0%***	***1%***	***2%***	***3%***	***4%***	***5%***
0%	100	90	81.7	74.6	68.6	63.3
2%	125	109.8	97.6	87.7	79.5	72.5
4%	166.7	140.6	121.3	106.4	94.5	84.4
6%	250	195.7	160.1	135.1	116.5	102.2
8%	500	321.4	235.6	185.1	151.9	128.4

Table 1. is a modified table from Skogsvik (2008), page 175, which implies that a relatively small risk of bankruptcy has significant negative effects on the equity value using Gordon Growth model. While Skogsvik (2008) mentions that financial analysts and shareholders tend not to use the four aforementioned valuation models that take into account the risk of bankruptcy, there is still support for analysts including the risk of failure. For instance, analysts often adjust other components in valuation models, like the cost of capital, to take into account the extra risk premium rather than including a specific pfail component (Skogsvik, 2008). Nevertheless, incorporating pfail into stock valuation should consequently impact share prices.

3. Hypothesis

We investigate if a long-short strategy based on distress risk sorted portfolios as measured by Skogsvik (1990)'s pfail can 'beat the market', i.e. generate CAPM alpha. In other words, we want to test whether it is possible to capitalize upon potentially inefficient assimilation of firms' distress risk and the ability to construct long-short portfolios around such knowledge. Our proposed hypothesis is:

H_0: There is a *positive* relationship between distress risk and stock returns; a *higher (lower)* pfail is associated with a *higher (lower)* average returns.

H_1: There is a *negative* relationship between distress risk and stock returns; a *higher (lower)* pfail is associated with a *lower (higher)* average returns.

The hypothesis tests whether distress risk and associated excess returns systematically follow according to asset pricing theories. For the "buy safe, short-sell distressed stocks" long-short strategy to work, it is evident that safe firms need to be rewarded premiums for their low risk of failure and present a buy opportunity. At the same time, distressed firms' higher risk of failure should make them less attractive for investors to hold from which our strategy can generate CAPM alpha by short-selling these stocks. Thus, the ultimate investment scenario would be the ability to maximize CAPM alphas by longing Low risk and short-selling High risk portfolios simultaneously; a combined long-short strategy.

These stances can further be seen in the light of Skogsvik (2008)'s incorporation of pfail into valuation, where higher pfails imply lower valuation and vice versa. In addition, the strategy takes insight from anomalies arguing in favor of portfolio managers' ability to successfully stock-pick from fundamental analysis. Put differently, the hypothesis lays the foundation for testing whether the market is *efficient* in its incorporation of distress risk into stock returns. However, a long-short strategy that 'beats the market' using this framework should only be possible if the market is *inefficient*. The proposed strategy therefore relies on contradictions to modern asset pricing theory suggesting that a higher pfail should be rewarded higher returns only if the risk is undiversifiable; i.e. systematic, as seen by CAPM.

4. Variables

4.1 Dependent variable

4.1.1 Risk-adjusted returns based on CAPM

CAPM is used to measure the abnormal return of an asset or portfolio over the theoretical expected return predicted by a market model. Long-only portfolio managers strive to find assets with positive alphas, i.e. higher risk-adjusted returns than implied by CAPM. The CAPM is defined as:

$$r_p - r_f = \alpha_p + \beta_m(r_m - r_f) + \varepsilon_{pt}$$

Where,

r_p *equals the return on portfolio p*

r_f *equals the return on the risk-free asset*

α_p *equals the "alpha" term and is assumed to be zero when the EMH holds*

β_m *equals the market beta of portfolio p*

r_m *equals the market return*

ε_{pt} *equals the error term*

CAPM is this thesis' equilibrium model to evaluate whether the portfolios can 'beat the market'; i.e. generate CAPM alpha. This thesis will interpret r_p as the portfolios' monthly CAR returns. The hypothesis will regard the r_m as the market portfolio, which we define as the OMX Stockholm All Share Index Cap. We measure the β_m on a 5-year rolling regression from respective stock's market risk exposure for every trading day throughout the study's time horizon. The r_f is measured as the risk-free return determined by the interest rate on the Swedish 2-year outstanding government bonds collected from the Swedish central bank. The time to maturity of these risk-free assets were chosen to match the investment horizon in the best of our capacity as one-year Swedish bonds are unavailable.

4.2 Independent variables

Table 2. below summarizes the expected relationships between the independent variables and CAPM alpha that are used in this study.

Table 2. Predicted relationships between CAPM alpha and independent variables

Table 2. presents the predicted relationships between each independent variable to CAPM alpha used in this study. The predicted relationship between pfail and CAPM alpha is based on the Efficient Market Hypothesis. We also show a select number of supporting research for the previously discovered expectations with abnormal returns.

Independent variables	***Predicted relationship***	***Supporting research***
Probability of failure	*Positive (+)*	*Dichev (1998) and Campbell et al. (2008; 2010)*
Firm size	*Negative (-)*	*Fama and French (1996) and Chan, Chen and Hsieh (1985)*
Book-to-Market	*Positive (+)*	*Fama and French (1996) and Chen and Zhang (1998*
Earnings' yield	*Positive (+)*	*Basu (1983)*

4.2.1 Probability of failure

Skogsvik (1990)'s pfail is the primary explanatory variable in this thesis. The probability of failure is estimated using the one-year prediction model. Skogsvik (1990) is used for its scope to Swedish firms but also for its dynamic inclusion of both profitability and solidity financial ratios. Furthermore, the one-year prediction model is used for three reasons: investor short-termism in the stock market, the investment horizons of one year, and because of higher model accuracy compared to longer predictive time horizons. Previous studies have also centered on one-year predictions (e.g. Dichev, 1998; and Campbell *et al.,* 2008; 2010). Moreover, our perception is that Skogsvik (1990)'s pfail can be considered broad enough to disregard explanatory variables that consider the same measures as the ones included in the model. Otherwise, there is risk of overweighting the meaning of such variables.

4.2.2 Firm size

This study will use the variable firm size as determined by the stocks' Market Capitalizations ("size") at the time of investment. The inclusion of size is supported by prior research in the theoretical framework, where smaller firms tend to outperform larger firms due to the additional risk from small sizes (Banz, 1981; Chan, Chen and Hsieh, 1985; Fama and French, 1996; and Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015). We incorporate size as there is reason to believe that size could add explanatory power to a firm's risk of failure and excess returns.

4.2.3 B/M

We include B/M due to its common usage in explaining stock return variations, where firms with a high B/M experience a further degree of distress risk that should be rewarded by a higher risk premium. Along with the firm size effect explained above, it is important to consider both size and B/M due to the general perception that high default risk firms tend to be smaller and have higher B/M ratios (Fama and French, 1996; and Chen and Zhang, 1998). B/M is defined as book value of equity divided by market capitalization of equity.

4.2.4 E/P

Basu (1983)'s findings relating to earnings' yield ("E/P") and firm size suggests that stocks with high E/P, defined as earnings per share divided by price per share, also earn higher risk-adjusted returns than stocks with low E/P, even when experimental control was exercised over the size effect. Investors can here be viewed to place an additional value on holding safer stocks with higher earnings' yield, from which the inclusion of Basu (1983) as our final explanatory variable thus adds to the view that stock returns can indeed be explained by choices based on fundamentals such as earnings' yield. Finally, in comparison to both size and B/M, E/P can to a less extent be seen as a proxy for financial distress risk, but could still be viewed as an indicator of "safety" for its link to profitability.

5. Data

5.1 Data collection

Data has been collected for firms publically listed on the Large, Mid and Small Cap indexes on Stockholmsbörsen between the time period April 1, 2002 and March 31, 2017. The firms are included for the years they are listed; the firms need not be listed throughout the time period for inclusion, which is feasible due to events like bankruptcy, acquisitions, de-listings and re-listings. Considering that there are non-Swedish firms listed on Stockholmsbörsen as well, each data point has been collected in the firm's reported currency and converted into SEK using Factset's currency conversion to avoid inconsistencies (see below).

The accounting data has been collected using the Dow Jones Factset database, an acknowledged financial database used by many leading financial institutions, and complemented by the manually overseeing the firms' financial records when Factset lacked data. We have also performed several checks to the accuracy of Factset compared to the actual financial reports, without any findings of misrepresented data. The market data has been collected using Thomson Reuters DataStream.

Collected accounting data points

To calculate Skogsvik (1990)'s pfail equivalent to the one-year bankruptcy prediction model for each year for each firm, the following accounting information has been collected from the firms' Year-End reports: Revenue_t, EBIT_t, Interest Expenses_t, Total Assets_t, Total Assets_{t-1}, Inventory_t, Inventory_{t-1}, Total Liabilities including Deferred Tax Liabilities_t, Total Liabilities including Deferred Tax Liabilities_{t-1}, Shareholder Equity_t, and Shareholder Equity_{t-1}.

Collected market value data points

Adjusted share prices (in SEK) and market capitalization (in MSEK) are collected for each stock listed on the three indices (Large, Mid, and Small) on Stockholmsbörsen. Also, the market price for the benchmark index: OMX Stockholm All Share Index Cap_GI has been collected.

5.2 Data adjustments

Skogsvik (1990)'s model is built for the purpose of Swedish manufacturing and mining firms. Thus we argue that our usage of the model across Stockholmsbörsen requires certain data adjustments. The following structure outlines the sample alterations made in accordance with the model and the portfolio analysis to determine the firm inclusion in the refined sample:

Bankruptcy prediction model

I. The firm must not operate within the following sectors: financial services, real estate or investment firms, due to their reliance on a leveraged financial structure and absence of production operations.

II. The R_3 model component, *'Inverted inventory turnover'*, has been identified as the model's most effective factor to locate firms similar to the manufacturing industry. By examining the inventory-to-average assets levels in entire data sample, we found that a reasonable cut-off for elimination of firms less relevant to this study, is a ratio of < 5%. Without this adjustment, the inventory-efficiency measure would had been redundant for some companies. This adjustment means that service-firms like consultancies have been excluded.

III. Firms must have no missing financial data related to the V-score components. For example, R&D firms that lack revenues are excluded from the sample for those years.

Portfolio analysis

IV. If the firm has more than one share class publically listed (e.g. A and B shares), the most liquid stock for the trading year is used to avoid duplicates and over-weighted portfolios.

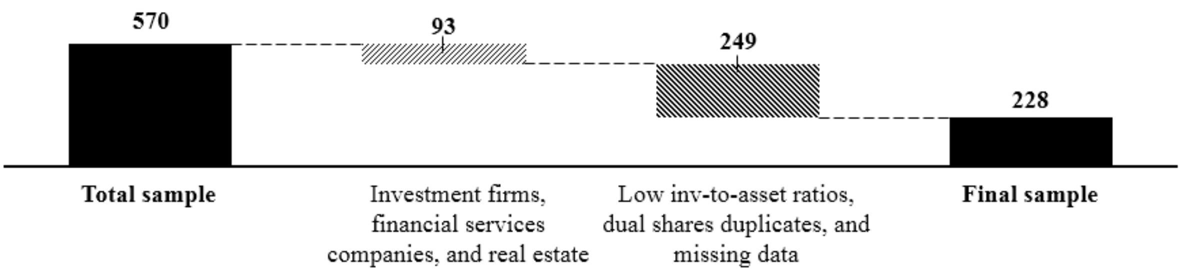
V. Firms with split financial reporting are excluded to avoid date discrepancies as the long-short strategy takes positions set to April 1 every year lasting until March 31 the next year. This will raise the practical application of the proposed investment strategy.

VI. If a firm is delisted or goes bankrupt during a portfolio year, the generated surplus value is invested into the remaining stocks in that particular portfolio to avoid survival bias.

VII. In line with Campbell *et al.,* (2008; 2010) we control for outliers by winsorizing the variables at the 1st and 99th percentile of their distributions.

Graph 1. Sample refinement

Graph 1. presents the refinements made for sample inclusion and covers the criteria: I through IV. The figures presented represent unique companies analyzed in the final sample. Note that the criteria V through VII are adjusted on an intra-year basis.



6. Method

This thesis applies two methods used in prior research: portfolio analysis and cross sectional regressions, to test if a long-short strategy based on pfail-sorted portfolios can generate CAPM alpha on Stockholmsbörsen from April 1, 2002 to March 31, 2017. The portfolio analysis examines the univariate impact of pfail on CAPM alpha and the cross sectional regression examines pfail's explanatory power jointly with the other independent variables.

6.1 Portfolio analysis

Portfolio analysis is the methodology of sorting stocks into portfolios based on some metric, like distress risk, and has appeared useful in prior studies (Dichev, 1998; and Campbell *et al.,* 2008; 2010). The foundation of our portfolio analysis is Skogsvik (1990)'s one-year ahead pfail. We perform two-sided t-tests to assess whether the means of the portfolios are statistically different from each other. We also perform robust OLS regressions for time-dependent considerations on a yearly basis (see Table 6. and Appendix 1.).

Building portfolios

For each year, we sort all firms into 5 portfolios by their degrees of pfail, meaning firms are compared relative to each other. Within each year, each portfolio contains the same number of companies. The 5 portfolios are named by their risk profile: Low risk ("R1"), R2, R3, R4 and High risk ("R5"), where the Low risk portfolio contains the *lowest* pfail stocks and the High risk portfolio contains the *highest* pfail stocks. While prior studies (Dichev, 1998; and Campbell *et al.,* 2008; 2010) have used 10 portfolios, our data is only sufficiently large to motivate the usage of 5 portfolios (Abuhamzeh and Malgerud, 2015).

Portfolio investment horizon

We hold portfolios for a time period of 1 year: April 1 to March 31 the next year; a time length that matches the one-year model pfail prediction similarly to previous research (e.g. Dichev, 1998; and Campbell *et al.,* 2008). Having studied the firms on Stockholmsbörsen in accordance with the sample refinements above, we have found that firms with normal fiscal years have reported their Year-End reports by April 1, which is therefore the normalized investment date for the portfolios in this thesis. Moreover, investing on April 1 removes the ranking distortion and improves the investing realism. The Year-End reports contain all accounting information required to compute pfails, and are particularly interesting as they offer investors the first view to firms' full-year financial accounts and prospects of the coming year.

Weighting portfolio returns

The portfolio returns are calculated using equally-weighted portfolios (Dichev, 1998), meaning each stock carries the same weight in the portfolio. Campbell *et al.,* (2008) and Vassalou and Xing (2004) instead use value-weighted portfolio returns, where the companies' market capitalization determines the portfolio proportions. If pfail can explain CAPM alphas, we argue that the pfail effect should also be present across portfolios that are equally large. Furthermore, considering that our sample refinement by nature removes many smaller stocks, by using equally-weighted portfolios we avoid a 'large company bias'.

Portfolio variables

Building on prior research, the portfolio variables and returns are annually calculated in two steps. The method for creating the portfolio analysis variables is outlined below:

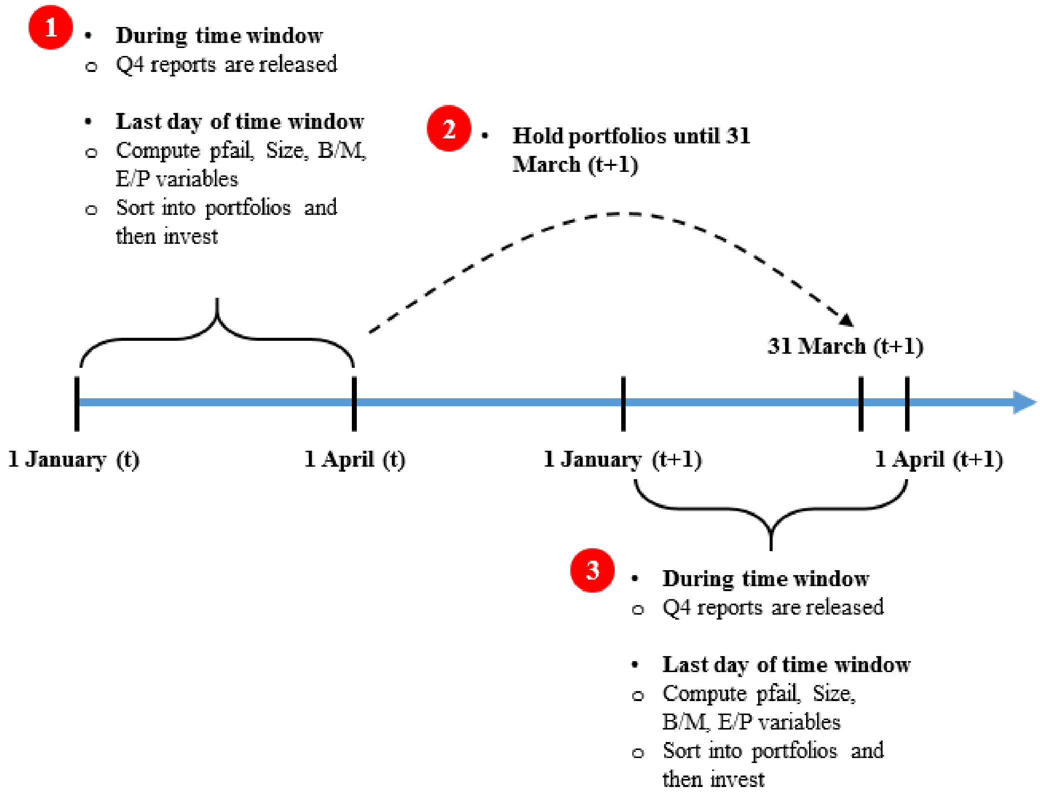
I. Mean returns are calculated for the dependent variable (CAPM alpha) from monthly returns within each year studied per portfolio, starting at April 1 and closing at March 31 the next year. Mean values are calculated for the independent variables (pfail, size, B/M and E/P) for each portfolio, for each year studied, as of April 1. The final result is that each yearly portfolio has one excess return and one value for each independent variable; 5 values per portfolio, per year.

II. The CAPM alphas are averaged across the years studied, giving us one CAPM alpha per portfolio. The same applies for the independent variables. Hence, from April 1, 2002 to March 31, 2017, the final result in the portfolio analysis is 25 averaged values in total; 5 per portfolio.

Portfolio evaluation

To test whether a significant impact of pfail on CAPM alphas exists on the portfolios, we perform two-sided t-tests, and robust OLS regressions. Other studies introduce additional criteria for sorting stocks on financial distress and other variables (e.g. Eisdorfer, Goyal and Zhdanov, 2012). Instead, we aim to shed light on differences in time-dependent predictability. Hence, we split the sample into two time periods with regards to the Global Financial Crisis: April 1, 2002 – March 31, 2009 known as "*Pre/during crisis"* and April 1, 2009 – March 31, 2017 known as *"Post crisis"*. We argue that the crisis could have affected investor's apprehension of bankruptcy risk.

Graph 2: Illustration of portfolio analysis



Alternative method

We considered sorting firms into portfolios using the Δpfails between Skogsvik (1990)'s two-year (at time "0") and one-year (at time "1") prediction models. Mispricing should arise when the one-year model at time "1" failed to generate the same pfail as the two-year model at time "0". However, by nature, the two-year model systematically produced higher pfails, offering no variety to long and short positions.

6.2 Cross sectional regression analysis

Previous research suggest that a wide variety of distress risk variables can explain stock return variations; distress risk proxied by pfail is possibly one but certainly not the only variable. Moreover, portfolio analysis limits the ability to make inferences about certain variables' impact on risk premiums. The statistical tests we use for this purpose are cross sectional regressions inspired by Fama-MacBeth (1973), whereby the sources of return covariation are specified beforehand. The reason for using the same variables to explain returns is to pinpoint each portfolio's returns to this given set of variables, and to add understanding as to whether pfail can explain CAPM alphas through a combination of other risk proxy variables. A gradual inclusion of the independent variables to the univariate, bivariate and multivariate regressions will offer a comprehensive overview of the variables and their potential interdependencies.

The cross sectional regressions performed in this thesis are as follows: firstly, the cross sections of portfolio CAPM alphas are regressed each time period (i.e. yearly from April 1, 2002 to March 31, 2017) on pfail along with size, B/M and E/P for respective portfolio. This procedure obtains the estimates of β_i coefficients of interest to our independent variables. Secondly, the final β_i coefficient estimates are obtained as the average of the first step coefficient estimates in the annual cross sections. The time series standard deviation of β_t is used to estimate the standard error of β_i. These standard errors are corrected for cross sectional correlation but not for time-series autocorrelation (Skoulakis, 2008; and Cochrane, 2005). Equities generally have weak time-series autocorrelations over short periods, but this issue rises as the holding period rises. Thus, we correct these standard errors using Newey-West (1987) with three lags in robust t-statistics (Vassalou and Xing, 2004). Finally, the t-statistics from the regressions equal the coefficient divided by its time-series standard error. The performed regression of portfolio excess returns on the previously explained risk proxies is outlined below:

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_1 pfail_{n,t-1} + \beta_2 size_{n,t-1} + \beta_3 \frac{B}{M}_{n,t-1} + \beta_4 \frac{E}{P}_{n,t-1} + \varepsilon_{pt}$$

Where,

$r_p - r_f$ *equals the portfolios' CAPM alphas*

α_p *equals the constant intercept*

$\beta_{1,2,3,4}$ *equals regression coefficients for respective risk proxy: pfail, size, B/M and E/P*

$size_{n,t-1}$ *equals the firms' logs of market capitalization*

ε_{pt} *equals the error term*

As CAPM is used to measure excess returns, we can exclude market beta as an explanatory variable. Along with Skogsvik (1990)'s pfail, we include size and B/M for their historic importance in explaining stock return (Fama and French, 1992), and consider earnings' yield (E/P) a useful measure of profitability that can justify risk-adjusted returns regardless of firm size (Basu, 1983). Skogsvik (1990) also disregards earnings for EBIT. Finally, the step-wise inclusion of independent variables will enable more careful evaluations of each variable.

7. Results and analysis

Firstly, we present a descriptive overview of the results from the analyzed data in the study. Secondly, we proceed to the portfolio analysis where we analyze the investment strategy (long, short and combined long-short). Lastly, we shed light on a potential distress risk premium through cross sectional regressions where respective explanatory variable is incorporated in a joint variable impact consideration.

7.1 Descriptive results

Table 3. Summary statistics

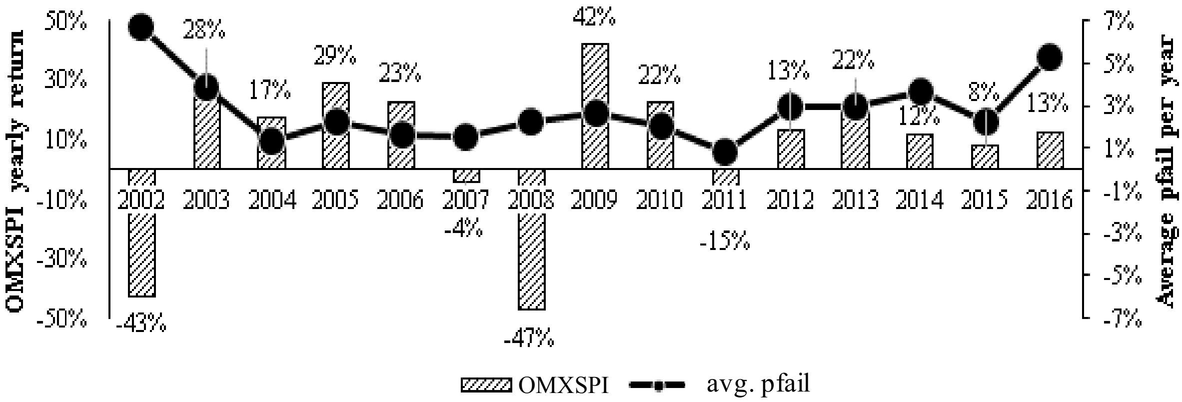
Table 3. presents the descriptive statistics from the data sample used in the evaluation of CAPM alpha linked to pfail. The statistics describe the raw input data used in the study as required by the portfolio analysis. We calculate stock returns from the final firm sample on an annual basis between April 1, 2002 - March 31, 2017. Pfails have been calculated as of April 1 yearly for each stock using Skogsvik (1990). Size is proxied by firms Market Capitilization as of April 1. B/M's book values relate to the firms' Year-End Reports and market values of equity relate to April 1. E/P follows the same structure as B/M. Respective variable is calculated in SEK. We winzorise the values below the 1st percentile and above the 99th percentile. The percentiles are organized from the lowest (left) to highest values (right).

Sample statistics	**Mean**	**StDev**	**P1**	**Median**	**P99**
Final sample: 228 firms					
Return measures					
Stock returns	12.78%	46.60%	-99.71%	12.15%	147.89%
Distress risk measure					
Pfail	2.29%	9.19%	48.40%	0.10%	0.00%
Additional measures of risk					
Size (SEKbn)	21	70	0.09	2	348
B/M	0.654	0.595	3.174	0.482	0.021
E/P	0.015	0.206	-0.848	0.055	0.303
CAPM					
Risk-free rate	2.12%	1.60%	-0.45%	2.33%	5.15%
Beta	0.77	0.31	1.70	0.70	0.41
Risk Premium	0.51%	5.15%	-16.08%	0.91%	12.47%
Observations	***N***				
Accounting data	31 895				
Market data points	975 148				

Results: Table 3. presents the descriptive statistics of the test variables' empirical distributions. We have studied significant amount of accounting and market data points as requested by Skogsvik (1990)'s model and stock return analysis. The sample statistics suggest a strong stock return variation during 2002-2017 for the 228 unique stocks analyzed. This is line with the varying market conditions experienced during the 2000s where the market faced volatility from, in particular, the IT bubble (1995-2001) aftermath and the Global Financial Crisis of 2007-2008. The period has thus seen both booms and recessions, which is important for our ability to test the pfail-sorted portfolios in heterogeneous market conditions. Moreover, pfail is a continuously changing variable, with a high level of variation as seen by the high standard deviation. The median pfail is roughly 0.10%, while the average is sizably higher at 2.29%. The relationship between pfail and market returns is outlined in Graph 3. below. It appears that the sample average pfail has fluctuated non-linearly across the studied time period with the highest probabilities found in the IT bubble aftermath and in 2016.

Graph 3. Relationship between market return and average pfail

Graph 3. illustrates the relationship between annual market returns, OMXSPI, and average pfail calculated from the final sample across the time horizon studied.



Furthermore, the variations in the additional independent variables indicate that a wide range of firms are included in the sample and can suggest a relevant representation of the stock universe. The firms with the highest distress risk are on average smaller, have higher B/M, and lower E/P. The independent variables are further understood from a Pearson correlation matrix.

Table 4. Pearson correlation table 2002 - 2017

Table 4. presents the yearly correlations on 1,953 observations between each variable in the study for the full time period: April 1, 2002 to March 31, 2017, prior to sorting firms into portfolios. The correlation coefficient is presented for each combined independent variable, marked by its corresponding level of significance from the p-value. Significant variables are bolded.

Variables	CAPM-alpha	Pfail	Size	B/M	E/P
CAPM-alpha	1.0000				
Pfail	-0.0355	1.0000			
Size	**-0.0745*****	**-0.0593*****	1.0000		
B/M	**0.0375***	**0.1283*****	**-0.2591*****	1.0000	
E/P	0.0099	**-0.2622*****	**0.2450*****	**-0.0378***	1.0000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 4. presents the results from the Pearson correlation matrix performed on a year-to-year basis for the explanatory variables and offers an initial verification between the independent

variables and CAPM alpha. Prior to sorting the firms into portfolios, there is too much annual variation in pfail against CAPM alpha to establish a significant relationship. While the same is true for E/P, both size and B/M are from a univariate consideration significant at a 1% and 10% significant level, respectively, in line with Fama and French (1992). Conversely, pfail is significantly correlated at a 1% level to the remaining variables and is particularly correlated to E/P. A noteworthy result is that the negative sign for size measured against CAPM alpha means that smaller firms are more likely to fail (Chan and Chen, 1991).

***Analysis**:* the studied correlations prior to the portfolio analysis lack evidence to support a statistically significant relationship between pfail and CAPM alpha. Still, the negative coefficient can indicate that firms with higher pfail earn lower than average CAPM alphas.

7.2. Portfolio analysis

The portfolio analysis examines the univariate relationship between CAPM alpha and pfail. Stocks are sorted into five equally-weighted portfolios by their level of pfail each year on April 1. By nature, this portfolio weighting will exhibit a small firm domination (Campbell *et al.*, 2010), while minimizing the risk of individual stock return disruption (Plyakha *et al.*, 2014). We use intra-year monthly average returns across the years and rebalance the portfolios yearly.

7.2.1 Portfolio analysis: *"over time"*

Table 5. Portfolio relationships between CAPM alpha, pfail and other distress risk proxies

Table 5. presents the key characteristics observed in respective portfolio considered "*over time*" (∞). The pfail-sorted portfolios are built on April 1 each year. The Low risk portfolio includes the firms with the lowest pfail for respective year and the High risk portfolio includes the firms with the highest pfail throughout the study time period. Returns are calculated as intra-yearly monthly means, starting April 1 each year. Size is the market capitalization of equity expressed in SEKbn. B/M is book value of equity divided by the market capitalization of equity. E/P is the earnings divided by the share price. The portfolio gains and losses illustrate the number of years each portfolio generates positive and negative returns, respectively. With a t-stat of -6.87 from the two-sided t-test, we conclude that the average CAPM alpha differs between the pfail-sorted portfolios at a 1% signifiance level and suggest a negative relationship between pfail and CAPM alpha across portfolios over time. (∞) "*over time*" refers to a persistent dedication to the investment strategy for the entire time horizon.

Variables	Low risk	R2	R3	R4	High risk	Low minus High	Sample Mean	t-stat
CAPM alpha	***0.68%***	***0.66%***	***0.47%***	***0.50%***	***0.18%***	***0.50%***	***0.50%***	***-6.87******
Pfail	***0.00%***	***0.02%***	***0.17%***	***0.66%***	***13.36%***	***-13.36%***	***2.84%***	
Size	27.3	23.9	21.7	17.2	12.3	15	20	
B/M	0.56	0.68	0.68	0.70	0.69	-0.13	0.66	
E/P	0.06	0.06	0.05	0.04	-0.10	0.16	0.02	
No. Portfolio gains	*12*	*12*	*9*	*11*	*6*			
No. Portfolio loses	*3*	*3*	*6*	*4*	*9*			

**** p<0.01, ** p<0.05, * p<0.1*

***Results**:* Table 5. shows that all portfolios generate positive CAPM alpha. The Low risk portfolio, with a pfail of <0.00%, has delivered an average monthly CAPM alpha of 0.68% compared to the 0.18% CAPM alpha of the High risk portfolio with an average pfail of 13.36%. The delta CAPM alpha suggests that the Low risk portfolio has outperformed the High risk portfolio by 0.50%, suggesting a negative relationship between pfail and CAPM alpha. However, as found by Dichev (1998), the relationship is not monotonic as there is a disruption between R3 and R4, from which the R4 earns a 0.03% higher CAPM alpha than R3. A closer look shows that the difference in CAPM alpha is marginal between the Low risk portfolio and R2 (<0.02%), but considerably larger between R4 and High risk (0.32%). This can be explained by a greater number of firms having low, rather than high, risk of business failure.

When observing the other explanatory variables, we find a descending trend of size to CAPM alpha. The Low risk portfolio contains the largest firms whereas the High risk portfolio contains the smallest firms. The difference in size between the Low and High risk portfolios is on average SEK 15bn. Hence, pfail can explain the size effect in contrast to previous studies where a weak size effect has been observed on U.S. data during the 1980s and 1990s (Fama and French, 1992; and Roll, 1995). On the other hand, our results suggest that B/M rises from the Low risk towards to the High risk portfolio, although not in an entirely monotonic pattern as the High risk portfolio has lower value than R4. Hence, pfail poorly explains the B/M effect. However, it might be logical that firms with the absolutely highest financial distress also have relatively lower B/M values as firms with financial problems tend to burn through their book value of equity from continuous losses (Dichev, 1998). Campbell *et al.,* (2008) notes this association from which the highest distressed firms show "extreme measures of B/M", although unclear if high or low. In other words, high pfail portfolios can be risky from both the book and market capitalization perspectives. Finally, earnings' yield decreases as pfail increases across portfolios, in line with our interpretation of Basu (1983)'s conclusions. The highest pfail portfolio has the lowest earning's yield, a figure that is negative for the highest pfail.

Our ultimate view of the hypothesis is that the Low risk and High risk portfolios earn positive and negative CAPM alphas, respectively and simultaneously; a crucial relationship for a combined long-short strategy to generate higher returns than a single-sided strategy. Table 5. shows that the Low risk portfolio, as expected, generates positive CAPM alpha 12 out of 15 years, whereas the High risk portfolio generates negative CAPM alphas 9 out of 15 years. What is more, R2 generates positive CAPM alpha an equal number of years as the Low risk portfolio. The marginal difference in CAPM alphas generated between the Low risk and R2 alludes to the fact that a large number of firms exhibit very low pfails as expected. This could indicate that larger sample (allowing more than 5 portfolios) could have generated larger return differentials. The R4 is the black sheep of the portfolio analysis as it disrupts the pattern of higher pfail generating lower CAPM alphas. This exemplifies a limitation of few portfolios.

Analysis*:* there are two primary findings of interest from the above results: firstly, the correlation matrix in the descriptive results suggest a lacking support for a statistically significant negative relationship between CAPM alpha and pfail, i.e. prior to portfolio sorting. This reasonably originates from the fact that correlations were performed on an un-sorted sample on a year-to-year basis. Pfail can thus be concluded to greatly vary on a yearly basis. Secondly, when performing a two-sided t-test on the complete portfolio formations where the yearly differences are averaged away, we can with a 1% significance level conclude that the average CAPM alphas between the pfail-sorted portfolios is different from 0. In fact, we conclude a negative relationship between pfail and CAPM alpha. Our view is that investing on pfail should thus pay-off "*over time*"; i.e. when an investor uses the strategy persistently between 2002 and 2017, as the pfail-sorted portfolios manage to identify relative out-and underperforming portfolios. Our interpretation of these results is that CAPM alpha and pfail produce a significant association only when these variables are considered on an aggregate level throughout the study; not when their relationship is assessed on a year-to-year basis. We note that R2, R3 and R4 generate fairly similar CAPM alphas from rather different pfails. This demonstrates a difficulty to distinguish high from low performers solely based on pfail for the portfolios in the mid-range; other firm characteristics are here potentially more important (Dichev, 1998). To clarify this view, our data shows that the High risk portfolio has experienced almost the same amount of de-listings and bankruptcies as the mid-range portfolios combined. Moreover, in portfolios where pfail is either abnormally small or large, investors seem to place a greater emphasis on differentiating such stocks from each other. But, when the pfail changes marginally between portfolios it seems unlikely to expect a monotonic pattern between CAPM alpha and pfail (Dichev, 1998). As the impact of pfail on CAPM alpha for R2, R3 and R4 can be seen as relatively ambiguous, these portfolios will therefore be given less attention here-on in favor of the Low and High risk portfolios.

The long-short strategy from a rational investor perspective

When evaluating the proposed dichotomous investing strategy linked to the Low and High risk portfolios, it clearly only works as a long-only investing approach. Although the High risk portfolio significantly underperforms the Low risk portfolio, the negative relationship is insufficient to support a short-selling strategy as even the High risk portfolio generates positive CAPM alpha. At this stage, we find it wise to split our views on the proposed investment strategy into two lines of reasoning. The first perspective disregards rational investor behavior, as by mainly analyzing the excess returns from going long the Low risk portfolio and short the High risk portfolio, the positive CAPM alpha from longing the Low risk portfolio covers the loss from short-selling the High risk portfolio. In other words, the combined CAPM alpha is still positive enough to motivate that such a combined long-short strategy *beats the market*. In contrast, rational investors would simply avoid short-selling the High risk portfolio unless the historical relationship had suggested negative CAPM alpha generation, as such an approach would otherwise generate a *relative but unnecessary loss*. The evaluation of the combined long-short strategy thus come down to the stance of determining the rationality of an investor. Hence, we proceed by taking the rational view and cannot therefore yet motivate a realistic combined long-short strategy.

Short-selling constraints

There are numerous reasons that can explain the inability to successfully short-sell the High risk portfolio. Firstly, the large number of low pfail stocks in relation to high pfail stocks means that there is a natural bias against constructing portfolios that could be sold-short. This is evident as 86% of all stocks are considered to be in relatively low risk of bankruptcy with pfails below the sample average. One explanation is therefore that our sample fails to locate enough high pfail stocks to create negative excess return. Hence, the pfail distribution is skewed; it is by nature not an “equal game” between long and short possibilities.

Secondly, the short-selling market on Stockholmsbörsen is arguably restricted. In fact, merely 38 stocks were readily short-able as of 31 Dec, 2016 from the Swedish retail banks. Sorted for our sample inclusion criterion (see section 5.2), only 28 out of those stocks, and out of the 228 stocks in total, are included in this study. While any stock can theoretically be sold short, the relatively constrained market offers a perspective to the distressed portfolios’ positive CAPM alpha. If stocks cannot be easily borrowed for a short, there is limited downwards price pressure, and such short-selling constraints can lead to stock prices of distressed stocks remaining too high for too long (Campbell *et al.*, 2010). In addition, illiquid short-selling markets and low accessibility tend to make short-selling too expensive (Jones and Lamont, 2002). Here, Nagel (2005) claims that stock markets with high levels of institutional ownership can be considered proxies for the stocks available for borrow and short-sell. On Stockholmsbörsen, short-sellers target in particular Large Cap stocks with significant institutional holdings (Celebi and Hakim, 2014). In perspective, we merely find 13 Large Cap stocks among the top 10 yearly most distressed firms throughout the time horizon. This could explain the positive CAPM alpha in the High risk portfolio.

Finally, extremely distressed stocks that ought to be subjects for short-selling often have low or lack institutional owners, along with no analyst coverage, meaning such stocks tend to offer limited access. Hence, it might be difficult to collect enough quality information to assess such firms' financial health and furthermore access stocks for short-selling. On this topic, Celebi and Hakim (2014) finds no evidence to support that market participants engaged in short-selling on Stockholmsbörsen are well informed market participants, again highlighting the problematics of insufficient knowledge. Informational frictions can therefore reasonably explain parts of the distressed stocks' return inconsistencies (Campbell *et al.*, 2010). The key takeaway is that pfail-sorted portfolios seem to locate dissimilar stocks to short-sell than previously research has indicated as typical short-sold stocks on Stockholmsbörsen.

7.2.2 Portfolio analysis: on a yearly basis

The lack of support to motivate a combined long-short strategy led to further, time specific analysis of the data focused to the Low risk and High risk portfolios. We ask the question: *Is there a breaking-point in the time spectrum where the combined long-short strategy finds consistency?* The studied time horizon of 2002 - 2017 arguably represents a historical footprint relating to the financial markets, and we find a shift in pattern relating to the Global Financial Crisis of 2007 – 2008. Like Campbell *et al.,* (2008), we split the time period into two parts: April 1, 2002 – March 31, 2009 ("Pre/during crisis") and April 1, 2009 – March 31, 2017 ("Post crisis").

Results*:* the time split into Pre/during and Post crisis offers insight to the yearly predictive ability of pfail linked to CAPM alpha. When comparing the two periods, the Post crisis achieves an increased number of times for which the Low risk portfolio generates positive CAPM alphas, and the High risk portfolio generates negative CAPM alpha, simultaneously (see Table 6). Furthermore, the High risk portfolio on average only generates negative CAPM alphas Post crisis. When only considering whether the strategy generates abnormal returns, i.e. when the combined long-short strategy is net positive, it succeeds 8 times; 1 time Pre/during crisis and 7 times Post crisis. More importantly, the rational execution of the combined long-short strategy was successful 6 times over the full time horizon; 1 out of 7 times Pre/during crisis and 5 out of 8 times Post crisis.

For the Low and High risk portfolios, we regress pfail against CAPM alpha for each of the three time periods studied using an OLS regression with robust standard errors. The results confirm a negative relationship between pfail and CAPM alpha for the Post crisis period, significant at a 10% level. For verification purposes, the same test is performed on all portfolios using the same time splits, which supports that CAPM alpha and pfail only has a significant negative relationship Post crisis on a yearly basis (see Appendix 1). Hence, we can reject the null hypothesis Post crisis when evaluating CAPM alphas on a yearly basis in addition to the previous findings "*over time*" (see Table 5). Investing on pfail should thus also pay-off on a yearly basis Post crisis.

To our surprise, the Pre/during crisis period instead suggest that pfail carries a weak positive relationship to CAPM alpha. The average CAPM alphas per portfolio confirms this logic for Pre/during crisis as the High risk portfolio generates positive CAPM alpha (0.50%) and even outperforms the Low risk portfolio (0.23%) to the opposite of our proposed strategy. Equally, as seen by the delta between the Low risk and High risk portfolios, the combined long-short CAPM alpha rises from (-0.26%) for Pre/during crisis, to (1.17%) for Post crisis, to (0.50%) for the full time period. Finally, the combined long-short strategy performed on a yearly basis is only successfully when executed Post crisis, as that is the only period when the High risk portfolio on average generates negative CAPM alpha (-0.10%). This is presented in Table 6. below.

Table 6. Time specific portfolio analysis

Table 6. outlines the Low and High risk portfolios on a yearly basis along with the net return from a combined long-short strategy for respective time period considered. CAPM alphas are measured as intra-year monthly average returns. We present the results from the year-on-year OLS regression of pfail against CAPM alpha for respective clustered time periods studied with robust standard errors. The t-stats are presented in parenthesis and show that Post crisis is significant at a 90% confidence interval.

Time horizon	CAPM alphas generated			Combined long-short maximizes returns
	Low risk	*High risk*	*Long-short*	
Apr 1, 2002 - Mar 31, 2003	0.19%	0.36%	-0.17%	*No*
Apr 1, 2003 - Mar 31, 2004	0.51%	2.07%	-1.56%	*No*
Apr 1, 2004- Mar 31, 2005	1.11%	-0.48%	1.59%	***Yes***
Apr 1, 2005 - Mar 31, 2006	0.79%	2.18%	-1.40%	*No*
Apr 1, 2006 - Mar 31, 2007	0.39%	0.76%	-0.36%	*No*
Apr 1, 2007 - Mar 31, 2008	-0.57%	-0.14%	-0.42%	*No*
Apr 1, 2008 - Mar 31, 2009	-0.79%	-1.27%	0.48%	*No*
Apr 1, 2009 - Mar 31, 2010	1.89%	3.17%	-1.28%	*No*
Apr 1, 2010 - Mar 31, 2011	0.24%	-0.22%	0.46%	***Yes***
Apr 1, 2011 - Mar 31, 2012	-0.14%	-1.82%	1.68%	*No*
Apr 1, 2012 - Mar 31, 2013	0.22%	-1.45%	1.67%	***Yes***
Apr 1, 2013 - Mar 31, 2014	1.28%	-0.86%	2.14%	***Yes***
Apr 1, 2014 - Mar 31, 2015	1.35%	-0.16%	1.51%	***Yes***
Apr 1, 2015 - Mar 31, 2016	2.51%	0.61%	1.90%	*No*
Apr 1, 2016 - Mar 31, 2017	1.23%	-0.06%	1.29%	***Yes***
Average full time horizon	**0.68%**	**0.18%**	**0.50%**	**6**
Average Pre/during crisis	**0.23%**	**0.50%**	**-0.26%**	**1**
Average Post crisis	**1.07%**	**-0.10%**	**1.17%**	**5**

Testing Low risk vs High risk	Predicted sign	***Full time horizon*** CAPM alpha	***Pre/during crisis*** CAPM alpha	***Post crisis*** CAPM alpha
Pfail	(+)	-0.04632	0.02617	-0.10657
		(-1.09)	(0.83)	**(-1.78)***
Constant		0.09641	0.1965	0.30102
Balanced		Yes	Yes	Yes
Observations		30	14	16
R-squared		0.0067	0.0243	0.126

**** p<0.01, ** p<0.05, * p<0.1*

Analysis: two possible explanations to the contrasting differences between the combined long-short strategy of Pre/during and Post crisis can be related to the EMH, and biases in pricing selection (Dichev, 1998). Firstly, if pfail is a systematic risk, then there ought to be a positive return association for the EMH to hold; more insolvent firms should exhibit higher risks and on average show higher returns as compared to more solvent firms (Dichev, 1998). As the High risk portfolio outperforms the Low risk portfolio on average Pre/during crisis, this can be seen in the light of support for the EMH. But, these results lack significance. However, the risk-return relationship seems to change Post crisis. The risk of firm failure Post crisis is rewarded to a less extent and reaches negative return territories for the High risk portfolio on average. Hence, it appears that pfail becomes pronounced more as a distress anomaly Post crisis, and can in turn suggest that the market inefficiently assimilates the distress risk information portrayed by pfail. Like most anomalies, we acknowledge that our interpretation could also be explained by incorrectly specified asset pricing models (Keim, 2008). Nonetheless, the evident significance of this changed relationship therefore argue against the EMH Post crisis, and can be further illustrated by the change in coefficient signs from Pre/during crisis (positive) to Post crisis (negative).

Secondly, if the security pricing is persistently biased, one explanation could be that investors are inefficient in their incorporation of the available information on firms' probability of failure. Therefore, the most distressed firms consequently generate lower stock returns first when this negative evidence is eventually embedded in prices (Lakonishok, Shleifer, and Vishny, 1994). While the market tends to use other metrics than pfail to seize the risk of bankruptcy in firm valuation, this could cause share price inconsistencies (Skogsvik, 2008). We argue that investors have possibly become increasingly risk-averse Post crisis, as illustrated by investors "[…] reducing risk exposures, and switching to safer assets" in the Global Financial Crisis aftermath (Papaioannou, Park, Pihlman, and van der Hoorn, 2013). Thus, investors avoid buying highly distressed stocks to a greater extent Post crisis, explaining the mirrored outcomes of returns Post crisis, i.e. Low risk portfolios outperform High risk portfolios. However, the only year in the Post crisis period where the combined long-short strategy generates negative CAPM alpha (-1.28%) is found in the recovery period from the financial crisis: April 1, 2009 – March 31, 2010. As the High risk portfolio strongly *positively* outperforms the Low risk portfolio, this result suggests evidence of the phenomena where rubbish stocks beat the quality stocks as the market recovers from recessions (Skogsvik, 2006). In contrast to Dichev (1998)'s observation of a sizeable change in average bankruptcy risk pre and post 1980 linked to the early 1980s recession in the U.S., our results show that pfail has remained fairly stable over the time horizon studied (see Graph 3). This should strengthen our view that the change in investor behavior is more accurately traced to risk-aversion Post crisis.

Concluding remarks on portfolio analysis

The results from our portfolio analysis are in line with prior studies that examine the relationship between excess return and distress risk. We find that investors on Stockholmsbörsen generate positive relative returns from buying stocks that are considered to be in relatively low risk of failure. This evidence is statistically significant *"over time"* and on a yearly basis Post crisis. Overall, the common risk-return relationship is again not acknowledged as investors are not rewarded additional return premiums from investing in stocks with higher risk of bankruptcy (Dichev, 1998; Campbell *et al.,* 2008, 2010; and Abuhamzeh and Malgerud, 2015). Over the time period studied, it appears that pfail-sorted portfolios can, on average, locate quality stocks for the Low risk portfolio and junk stocks in High risk the portfolio (Asness *et al.,* 2014). The effectiveness of the combined long-short strategy is directly dependent on the time period studied. We argue that investor risk-aversion change Post crisis; a period where investors seem, to a greater extent, prioritize low risk stocks and avoid high risk stocks. This could explain the better performance of the combined long-short strategy Post crisis. The decisions of the hypothesis testing for the portfolio analysis are summarized below.

Table 7. Summary of hypothesis testing

Table 7. below summarizes the results from investigating the relationship between CAPM alpha and pfail for respective time period. We conclude negative relationships between CAPM alpha and pfail "*over time*" and Post crisis. As short-selling is only possible Post crisis, this in turn means that a combined long-short strategy would only maximize returns for the Post crisis period.

Period	**Negative relationship**	**Decision**	***Combined long-short***
"Over time"	**Yes**	**Reject null**	*No*
Yearly evaluations			
Full time horizon	No	Fail to reject null	*No*
Pre/during crisis	No	Fail to reject null	*No*
Post crisis	**Yes**	**Reject null**	***Yes***

7.3 Cross sectional regressions

We perform cross sectional regressions as a way of explaining the evidence from the portfolio analysis with the extension of including the remaining independent variables, and examine if the risk-return relationship can endure over longer time periods. Regressions are performed for the entire time horizon and the Post crisis period to examine whether the negative relationship is again time-dependent. Note that the Pre/during crisis period is excluded for its lack of statistical significance. In a similar structure to Dichev (1998), we regress pfail in gradual combinations with firm size, B/M and E/P, on intra-year monthly CAPM alphas.

***Results**:* The Table 8. outlines the performed regressions with gradual inclusion of variables.

Table 8. Cross sectional regressions

Table 8. shows the results from the cross sectional regressions inspired by Fama-MacBeth (1973) on CAPM alpha, which examines potential distress risk premiums. Regressions are performed for both the full time horizon studied using the 15 yearly cross sections for 2002 - 2017 and for the Post crisis period with 8 yearly cross sections for 2009 - 2017. The coefficients shown from the regressions represent the mean of the yearly cross sectional coefficients. We also present the t-statistic in parentheses calculated as the mean coefficient divided by its time-series standard error using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags. Statistically significant t-scores are bolded. Size is the log value of market capitalization in SEKbn. B/M is book value of equity divided by the market capitalization of equity. E/P is the earnings divided by the share price.

Full time horizon: 2002 - 2017

Univariate regressions

CAPM alpha	=	Pfail	Size	B/M	E/P
Pfail		-0.0425			
		-(1.41)			
Size			-0.0351		
			-(0.18)		
B/M				-0.0147	
				-(1.64)	
E/P					0.0029
					(0.14)

**** p<0.01, ** p<0.05, * p<0.1*

Bivariate regressions

CAPM alpha	=	Pfail	Size	B/M	E/P
Size		-0.0979	-0.0418		
		-(1.96)*	-(1.50)		
B/M		-0.0521		-0.0141	
		-(0.19)		-(1.71)	
E/P		-0.0491			-0.0233
		-(1.84)*			-(0.93)

**** p<0.01, ** p<0.05, * p<0.1*

Multivariate regressions

CAPM alpha	=	Pfail	Size	B/M	E/P
Model (1)		-0.0425			
		-(1.41)			
Model (2)		-0.0979	-0.0418		
		-(1.96)*	-(1.50)		
Model (3)		-0.0508	-0.0683	-0.0757	
		-(0.83)	-(0.19)	-(0.66)	
Model (4)		-0.2537	-0.0118	0.0376	0.0453
		-(0.63)	-(1.34)	(0.82)	(0.23)

**** p<0.01, ** p<0.05, * p<0.1*

Post crisis: 2009 - 2017

Univariate regressions

CAPM alpha	=	Pfail	Size	B/M	E/P
Pfail		-0.0972			
		(2.40)**			
Size			0.0082		
			(0.23)		
B/M				-0.0249	
				(2.93)**	
E/P					-0.0403
					(1.63)

**** p<0.01, ** p<0.05, * p<0.1*

Bivariate regressions

CAPM alpha	=	Pfail	Size	B/M	E/P
Size		-0.0857	-0.0514		
		(2.11)*	-(0.19)		
B/M		-0.0386		-0.0160	
		-(0.99)		**(2.09)***	
E/P		-0.0762			0.0086
		-(2.50)**			(0.39)

**** p<0.01, ** p<0.05, * p<0.1*

Multivariate regressions

CAPM alpha	=	Pfail	Size	B/M	E/P
Model (1)		-0.0972			
		(2.40)**			
Model (2)		-0.0857	-0.0514		
		(2.11)*	-(0.19)		
Model (3)		-0.0231	0.0044	-0.0273	
		-(0.06)	**(1.98)***	**(3.53)*****	
Model (4)		-0.0281	-0.0209	0.0742	0.0446
		-(0.38)	-(1.64)	(1.00)	(0.13)

**** p<0.01, ** p<0.05, * p<0.1*

Univariate: the full time univariate regression generates a negative pfail coefficient but fails to produce a significant relationship between CAPM alpha and pfail. In fact, none of the independent variables are significant. However, for the Post crisis period the relationship between CAPM alpha and pfail is significant at a 95% confidence interval, from which we can reject the null hypothesis. Furthermore, the Post crisis period produces a significantly negative B/M coefficient at a 95% confidence interval suggesting that CAPM alpha drops as B/M rises.

Bivariate: pfail together with size is significant in both time periods at a 90% confidence level. The negative coefficient sign is not a surprising outcome as Chan and Chen (1991) finds that marginal firms tend to be more distressed. What is more, pfail significantly explains CAPM alpha in combination with E/P for both the full time and Post crisis periods with 10% and 5% significance levels, respectively. Note that the E/P coefficient is negative for the full time period in contrast to expectations (Basu, 1983). In addition, the Post crisis period finds that B/M is significant together with pfail at a 90% confidence interval, again with a negative direction.

Multivariate: pfail fails to significantly explain CAPM alpha in both time periods when including respective variables (Models (3) and later (4)). Instead, throughout the regressions, the t-stats decline for pfail as more factors are added to the model, implying that pfail is increasingly subsumed by the other factors, in contrast to previous findings (Dichev, 1998; and Abuhamzeh and Malgerud, 2015). For Model (3) Post crisis, both size and B/M are significant, but as E/P is added through Model (4) these become obsolete in explaining CAPM alpha. Model (4) generates coefficient signs in line with prior studies for both time periods (Dichev, 1998).

Analysis*:* from the regressions we conclude that the univariate relationship between CAPM alpha and pfail is significantly negative for the Post crisis sample only. We interpret the negative pfail coefficients as an indication of a distress anomaly confirmed in the portfolio analysis. In line with previous U.S. studies (Avramov *et al*., 2009; Campbell *et al*., 2008; 2010; and Dichev, 1998) our regression results for the Post crisis period suggest that the anomalous and contradictive risk-return relationship is present on Stockholmsbörsen too. While prior studies have mainly employed the Z-score or O-score as distress risk measures, using pfail seems to reach a similar deduction (Abuhamzeh and Malgerud, 2015). Henceforth, for the Post crisis period, we can again reject the null hypothesis as higher pfail is *not* rewarded a higher premium.

Adding more factors to the regressions Post crisis sheds light on the true casual effect between CAPM alpha and pfail by testing for omitted biasness. Interestingly, pfail loses explanatory power as more independent variables are added. As already indicated by the Pearson correlation matrix (see Table 4), there is a risk that pfail becomes subsumed by the size and B/M factors. The cross sectional regressions confirm this evidence with declining t-stats for pfail when adding size and B/M; both for the bivariate and multivariate regressions. The opposite relationship is true together with E/P where the explanatory power of pfail rises. While size and B/M are acknowledged proxies for financial distress, adding them together with pfail as another measure of financial distress, possibly explains a limited amount of new information. Pfail need not necessarily be viewed as a poor measure of distress. Instead, it becomes increasingly difficult to pinpoint which part of the distress risk that is explained only by pfail using size and B/M jointly. E/P is less of a proxy for distress as much as it is a measure of profitability. Thus, adding E/P to pfail should explain another part of the CAPM alpha relationship reasonably not covered by size and B/M. However, respective variable in Model (4) becomes insignificant as E/P is added. A possible explanation is that, while E/P and B/M have been found to predict equity returns that are consistent with rational pricing of risk when the two variables are positively correlated (Penman and Reggiani, 2008), this predictive ability needs not be true for pricing an anomalous risk relationship between equity returns and distress risk; especially not since our sample contrastingly generates a negative correlation.

For the full time period, the insignificant relationship as shown by the cross sectional regressions between pfail and CAPM alpha can probably be traced to various sources. Most importantly, as the cross sectional regression are run yearly, each year might not produce the anticipated firm characteristics, meaning differences across the time series produce statistically weak regressions. Furthermore, when only using 5 portfolios we create less distinctly defined portfolios at each end of the pfail range. That is, the pfail-sorted portfolios are less fine-cut compared to using a greater number of portfolios made possible from a larger sample. In line with Dichev (1998), our pfail persistently presents negative coefficients, which confirms our directional prediction for pfail on CAPM alpha.

Concluding remarks on the cross sectional regressions

The cross sectional regressions confirm the univariate results as discovered by the portfolio analysis measured on a yearly basis. Again, we only find a significant relationship between CAPM alpha and pfail for the Post crisis period. Moreover, pfail's explanatory power becomes significant to neglect a distress risk premium when adding either size or E/P for both time periods. While the size factor has been previously acknowledged, we interpret the rise of pfail's explanatory power jointly with E/P, as an indication that the variables explain different perspectives of financial distress. Adding size and B/M factors makes pfail increasingly obsolete, which questions pfail as a relevant explanatory variable for predicting CAPM alphas together with other financial distress proxies. Finally, while the multivariate regression is insignificant for both periods, the coefficients again indicate a lack of distress risk premium.

8. Reliability of results

The evaluation of our proposed investment strategy relies on a set of choices including the sample refinement criteria, investment dates, number of portfolios used, and selection of pfail as distress measure. To validate our results and control for these choices, we carry out several robustness tests. A source of weakness that might affect the degree of robustness is the disregard for testing CAPM alphas with alternative bankruptcy prediction models using accounting ratios.

8.1 Robustness tests

Test 1. Excluding the inventory to average assets criterion

To improve the sample fit to Skogsvik (1990), we attempt to exclude non-manufacturers by removing firms with inventory to average assets below the 5% ratio (see section 5.2). We perform a portfolio analysis that ignores this criterion in a way of robustness testing this sample sophistication. Appendix 2. finds a weaker negative relationship between CAPM alpha and pfail "*over time*", and the year-on-year evaluation in Appendix 3. confirm the pattern between CAPM alpha and pfail, but fails to generate significant results. The tests suggest that including the sample refinement adds accuracy to the investment strategy.

Test 2. Investing on July 1

Investing on April 1 assumes that investors can incorporate the prior fiscal year's accounting information containing distress content relatively effectively. As reports are released on various dates depending on firm, the time to assimilate distress risk is reduced the closer the reports are released to April 1. This assumption is tested for robustness by assuming that financial information is available within 6 months of year end (Fama and French, 1992; and Dichev, 1998), and perform the same portfolio analysis by investing on July 1 until June 30 each year. Appendix 4. confirms a negative relationship "*over time*" and Appendix 5. indicates that investors, to some extent, more effectively incorporate the distress risk information from the fact that the t-stat from Post crisis is slightly more significant than previously observed.

Test 3. Number of portfolios

Our proportionately small sample size compared to prior studies allows us to motivate the use of fewer portfolios. With common practice to at least use 20 firms per portfolio, we employed 5 portfolios (Abuhamzeh and Malgerud, 2015). We robustness test the assumption that more portfolios mean a more fine-cut CAPM alpha and pfail association by using 10 portfolios in the portfolio analysis. Average stocks per portfolio drops to 13 stocks, a fallacy that is disregarded for the purpose of this test. Appendix 6. again suggest a negative relationship between CAPM alpha and pfail "*over time*", however in a more non-monotonic pattern (Dichev, 1998). The yearly evaluation in Appendix 7. confirms the previous pattern between the various time periods, and strengthens the view that risk-aversion strongly rose from Pre/during to Post crisis.

8.2 Limitations

Our investigated investment strategy depends on back testing. That is, an examination that relies on analyzing historical patterns of data that are not guaranteed to continue into the future. Nevertheless, investment strategies must be verified somehow.

The original stance taken in this study explains pfail from the perspective of market efficiency; if pfail either is or, to a significant degree, contains systematic risk, then there ought to be a distress risk premium. Prior studies lack consensus in this matter, meaning our established negative relationship between CAPM alpha and pfail can be viewed from the common causality dilemma: "which came first: the chicken or the egg?": is it the fact that pfail cannot be proven to be a systematic risk or that CAPM alpha contains anomalies that do not account for the systematic risk component of pfail? Ergo, believing that pfail is instead an idiosyncratic risk weakens our conclusions as regards to pfail as a measure of distress risk (Opler and Titman, 1994; and Asquith *et al.*, 1994).

9. Conclusions

Portfolio analysis and cross sectional regressions have been used to investigate the possibility of generating CAPM alpha by employing a long-short investment strategy based on Skogsvik (1990)'s pfail for a refined sample on Stockholmsbörsen between 2002 and 2017.

The portfolio analysis finds support for a negative relationship between pfail and CAPM alpha. We thus challenge the acknowledged risk-return relationship as suggested by asset pricing theory, and suggest that a distress risk anomaly in the shape of pfail could exist on Stockholmsbörsen. The finding of a lacking distress risk premium is in line with previous research (Abuhamzeh and Malgerud, 2015; Avramov *et al.*, 2009; Campbell *et al.*, 2008; 2010; Garlappi *et al.*, 2008; and Dichev, 1998). While the Low risk portfolio significantly outperforms the High risk portfolio, we still find it economically unsound to employ a combined long-short strategy "*over time*". Instead, when examining the portfolio performances on a yearly basis, our findings suggest a rise in investor risk aversion – characterized by pfail – in the aftermath of the financial crisis. In fact, the negative relationship Post crisis between CAPM alpha and pfail is pronounced to such an extent that the combined long-short strategy is successful 5 out of 8 years. In contrast, this was only possible 1 out of 7 years Pre/during crisis. We conclude that a distress risk anomaly on a yearly consideration is only present for the Post crisis period.

The conclusions from the portfolio analysis considered yearly are verified by the univariate cross sectional regressions. The explanatory power of pfail fluctuates depending on the added independent variables. Pfail significantly explains the distress risk anomaly together with either size or E/P, but not with B/M. Interestingly, when considering pfail together with both size and B/M – other distress risk proxies – pfail becomes obsolete, from which we question pfail's ability to explain CAPM alphas when jointly examined with other measures of financial distress. Nevertheless, the results again indicate a lack of distress risk premium, which suggests that pfail is not a systematic risk. While this evidence on the possible presence of a pfail anomaly opposes the well-established asset pricing paradigms, we cannot disregard the possibility of having used an improper equilibrium model to correctly price pfail.

9.1 Future research

We have investigated whether pfail, as a measure for distress risk, can be used as an investment criterion from which Low risk portfolios seem to outperform High risk portfolios. Our findings of a potential change in risk aversion post the Global Financial Crisis arguably deserves more attention in the form of investor risk appetite for taking on bankruptcy risk. Evaluating this phenomenon with regards to other stock markets than Stockholmsbörsen should be interesting, but also comparing the change in risk aversion linked to stock returns in relation to other historical financial crises. Finally, we would also suggest investigating our thesis' hypothesis across sectors to examine the accuracy of pfail could improve the accuracy of the investment strategy.

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Appendix

Appendix 1. Time specific portfolio analysis

Appendix 1. outlines the results from the year-on-year OLS regressions with robust standard errors of pfail against CAPM alpha for respective clustered time periods studied. Regressions are performed using respective 5 portfolios. CAPM alphas are measured as intra-year monthly average returns per year. We present pfail's coefficients and the t-stats are shown in parenthesis below. Post crisis is significant at a 90% confidence interval.

Testing all portfolios	Predicted sign	***Full time horizon*** CAPM alpha	***Pre/during crisis*** CAPM alpha	***Post crisis*** CAPM alpha
Pfail	(+)	-0.01471	0.01794	-0.04468
		(-0.75)	(0.65)	**(-1.69)***
Constant		0.05397	0.03523	0.07095
Balanced		Yes	Yes	Yes
Observations		75	35	40
R-squared		0.0065	0.0093	0.0635

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Robustness tests

1. Robustness tests that exclude the inventory/average assets ratio criterion

Appendix 2. Portfolio relationships between CAPM alpha and independent variables excluding the inventory/average assets ratio criteria

Appendix 2. presents the portfolio relationships for the full time period considered when exluding the inventory/average assets criteria imposed as a data refinement for better model fit. Firms are each year on April 1 assigned into five portfolios according to their degree of distress risk measured by their pfail. The Low risk portfolio includes the firms with the lowest pfail for respective year and the High risk portfolio includes the firms with the highest pfail throughout the study time period. Returns are calculated as intra-year monthly average returns, starting April 1 each year. Size is the market capitalization of equity expressed in SEKbn. B/M is book value of equity divided by the market capitalization of equity. E/P is the earnings divided by the share price. The portfolio gains and losses illustrate the amount of years each portfolio generates positive and negative returns, respectively. With a t-stat of -1.74 from the two-sided t-test, we conclude that the average CAPM alpha differs between the pfail-sorted portfolios at a 10% signifiance level and suggest a negative relationship between pfail and CAPM alpha across portfolios over time. (∞) "over time" refers to a persistent dedication to the investment strategy for the entire time horizon.

Variables	Low risk	R2	R3	R4	High risk	Low minus High	Sample Mean	t-stat
CAPM alpha	***0.61%***	***0.78%***	***0.44%***	***0.34%***	***0.38%***	***0.23%***	***0.51%***	***-1.74****
Pfail	***0.00%***	***0.02%***	***0.14%***	***0.59%***	***12.17%***	***-12.17%***	***2.59%***	
Size	25.7	24.4	22.1	15.4	12.7	13	20	
B/M	0.61	0.86	0.79	0.73	0.68	-0.07	0.74	
E/P	0.06	0.06	0.05	0.04	-0.09	0.15	0.02	
No. Portfolio gains	*10*	*12*	*8*	*11*	*8*			
No. Portfolio loses	*5*	*3*	*7*	*4*	*7*			

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Appendix 3. Time specific portfolio analysis excluding inventory/average assets criteria

Appendix 3. outlines the results from the year-on-year OLS regressions of pfail against CAPM alpha for respective clustered time periods studied with robust standard errors. Regressions are performed using all portfolios when exluding the inventory/average assets criteria imposed as a data refinement for better model fit. CAPM alphas are measured as intra-year monthly average returns per year. We present pfail's coefficients and the t-stats are shown in parenthesis below. Post crisis is significant at a 90% confidence interval.

Testing all portfolios	Predicted sign	***Full time horizon*** CAPM alpha	***Pre/during crisis*** CAPM alpha	***Post crisis*** CAPM alpha
Pfail	(+)	-0.02188	0.03916	-0.07462
		(-0.55)	(0.73)	**(-1.35)***
Constant		0.03546	0.06905	0.02043
Balanced		Yes	Yes	Yes
Observations		75	35	40
R-squared		0.0048	0.0128	0.0671

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

2. Robustness tests for investing on July 1 rather than April 1

Appendix 4. Portfolio relationships between CAPM alpha and independent variables investing on July 1

Appendix 4. presents the portfolio relationships for the full time period considered when investing on July 1 rather than April 1. This gives more time for investors to assimilate the distress risk information. Firms are each year on April 1 assigned into five portfolios according to their degree of distress risk measured by their pfail. The Low risk portfolio includes the firms with the lowest pfail for respective year and the High risk portfolio includes the firms with the highest pfail throughout the study time period. Returns are calculated as intra-year monthly average returns, starting July 1 each year. Size is the market capitalization of equity expressed in SEKbn. B/M is book value of equity divided by the market capitalization of equity. E/P is the earnings divided by the share price. The portfolio gains and losses illustrate the amount of years each portfolio generates positive and negative returns, respectively. With a t-stat of -3.83 from the two-sided t-test, we conclude that the average CAPM alpha differs between the pfail-sorted portfolios at a 1% signifiance level and suggest a negative relationship between pfail and CAPM alpha across portfolios over time. (∞) "over time" refers to a persistent dedication to the investment strategy for the entire time horizon.

Variables	Low risk	R2	R3	R4	High risk	Low minus High	Sample Mean	t-stat
CAPM alpha	*0.67%*	*0.66%*	*0.63%*	*0.39%*	*0.36%*	*0.31%*	*0.54%*	*-3.83***
Pfail	*0.00%*	*0.02%*	*0.17%*	*0.68%*	*13.42%*	*-13.42%*	*2.86%*	
Size	25.6	24.4	21.1	16.6	12.8	13	20	
B/M	0.60	0.72	0.76	0.81	0.80	-0.19	0.74	
E/P	0.06	0.06	0.04	0.00	-0.20	0.27	-0.01	
No. Portfolio gains	*13*	*12*	*9*	*10*	*9*			
No. Portfolio loses	*2*	*3*	*6*	*5*	*6*			

**** p<0.01, ** p<0.05, * p<0.1*

Appendix 5. Time specific portfolio analysis when investing on July 1

Appendix 5. outlines the results from the year-on-year OLS regressions of pfail against CAPM alpha for respective clustered time periods studied with robust standard errors when investing on July 1 rather than April 1, and thus holding each portfolio until June 30 each year. Regressions are performed using all portfolios. CAPM alphas are measured as intra-year monthly average returns per year. We present pfail's coefficients and the t-stats are shown in parenthesis below, suggesting that a negative relationship between pfail and CAPM alpha can be established Post crisis with a 90% confidence interval.

Testing all portfolios	Predicted sign	***Full time horizon*** CAPM alpha	***Pre/during crisis*** CAPM alpha	***Post crisis*** CAPM alpha
Pfail	(+)	-0.0283	0.05491	-0.09322
		(-0.72)	(1.02)	**(-1.89)***
Constant		0.03439	0.08296	0.05436
Balanced		Yes	Yes	Yes
Observations		75	35	40
R-squared		0.0074	0.0235	0.0956

**** p<0.01, ** p<0.05, * p<0.1*

3. Robustness tests using 10 portfolios instead of 5 portfolios

Appendix 6. Portfolio relationships between CAPM alpha and independent variables using 10 portfolios

Appendix 6. presents the "*over time*" portfolio relationships for the full time period considered when using 10 portfolios rather than 5 portfolios. Firms are each year on April 1 assigned into five portfolios according to their degree of distress risk measured by their pfail. The Low risk portfolio includes the firms with the lowest pfail for respective year and the High risk portfolio includes the firms with the highest pfail throughout the study time period. Returns are calculated as intra-yearly monthly average returns, starting April 1 each year. Size is the market capitalization of equity expressed in SEKbn. B/M is book value of equity divided by the market capitalization of equity. E/P is the earnings divided by the share price. The portfolio gains and losses illustrate the amount of years each portfolio generates positive and negative returns, respectively. With a t-stat of -5.38 from the two-sided t-test, we conclude that the average CAPM alpha differs between the pfail-sorted portfolios at a 1% signifiance level and suggest a negative relationship between pfail and CAPM alpha across portfolios over time.

Variables	Low risk	R2	R3	R4	R5	R6	R7	R8	R9	High risk	Low minus High	Sample Mean	t-stat
CAPM alpha	***0.51%***	***0.84%***	***0.80%***	***0.58%***	***0.36%***	***0.50%***	***0.45%***	***0.59%***	***0.21%***	***0.18%***	***0.33%***	***0.50%***	*-5.38****
Pfail	***0.00%***	***0.00%***	***0.01%***	***0.04%***	***0.10%***	***0.24%***	***0.44%***	***0.91%***	***2.62%***	***24.77%***	***-24.77%***	***2.91%***	
Size	43.7	10.6	23.6	24.4	21.0	20.7	20.3	15.5	19.2	5.4	38	20	
B/M	0.49	0.62	0.66	0.68	0.69	0.68	0.70	0.71	0.77	0.60	-0.11	0.66	
E/P	0.06	0.06	0.05	0.07	0.05	0.06	0.05	0.02	-0.01	-0.23	0.29	0.02	
No. Portfolio gains	*9*	*12*	*12*	*10*	*9*	*9*	*10*	*11*	*9*	*7*			
No. Portfolio loses	*6*	*3*	*3*	*5*	*6*	*6*	*5*	*4*	*6*	*8*			

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix 7. Time specific portfolio analysis using 10 portfolios

Appendix 7. outlines the results from the year-on-year OLS regressions of pfail against CAPM alpha for respective clustered time periods studied with robust standard errors using 10 portfolios rather than 5. Regressions are performed using all portfolios. CAPM alphas are measured as intra-year monthly average returns per year. We present pfail's coefficients and the t-stats are shown in parenthesis below. Pre/during crisis suggests a positive relationship between CAPM alpha significant at a 99% confidence interval and Post crisis suggests a negative relationship significant at a 95% confidence interval.

Testing all portfolios	Predicted sign	***Full time horizon*** CAPM alpha	***Pre/during crisis*** CAPM alpha	***Post crisis*** CAPM alpha
Pfail	(+)	-0.03317	0.1353	-0.09849
		(-1.10)	**(3.32)*****	**(-2.60)****
Constant		0.02573	0.1265	0.02225
Balanced		Yes	Yes	Yes
Observations		150	70	80
R-squared		0.0093	0.009	0.0984

*** $p<0.01$, ** $p<0.05$, * $p<0.1$