NHH

Is there a Distress Risk Puzzle in the Norwegian Market?

A hazard model approach

Jonas Himberg Sørlie & Snorre Lindseth Nitter

Supervisor: Jørgen Haug

Master thesis, Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

Preface

This thesis was written as part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics (NHH). Our specialization is within Financial Economics, and this thesis is a dive into one of the most fundamental themes in the financial literature; the relationship between risk and return.

It has been rewarding to work on this thesis, and we feel fortunate for the opportunity to indulge ourselves in such an interesting topic.

We would like to thank our supervisor, Jørgen Haug, for valuable guidance, insight and inspiration.

Oslo, December 2018

Abstract

A fundamental principle in the financial literature is that assets with exposure to systematic risk should be compensated with a risk premium in returns. Thus, assuming financial distress risk is systematic, rational investors are expected to demand a premium for holding stocks with exposure to financial distress. However, several academic papers find anomalously low returns for stocks with a high degree of financial distress. This anomaly is referred to as the "distress risk puzzle".

In this paper we explore the relationship between distress risk and stock returns for publicly traded companies in Norway in the period from June 2004 to September 2018. We use default probability as a proxy for financial distress and estimate default probabilities by incorporating Campbell, Hilscher and Szilagyi's (2008) best model. We allocate the stocks into eight different portfolios depending on their level of financial distress and measure the respective returns of the different portfolios. The returns are measured for three months, before the portfolios are re-balanced based on updated default probabilities.

Assuming distress risk is systematic, we would expect the distressed stocks to carry a premium. Thus, our null hypothesis is that investors who hold the most distressed stocks in the market over time will receive a risk premium. However, we find that the portfolio with the most distressed stocks significantly underperforms the portfolio with the least distressed stocks. This finding is also prevalent in risk-adjusted returns, estimated by regressing the portfolio returns on the risk factors in the Fama-French three-factor model. We also find that the most distressed firms on average are smaller in size, have higher market-to-book ratios and a higher degree of leverage.

From the results of our analysis, we can reject the null hypothesis that the most distressed stocks carry a premium. This indicates that there is a distress risk puzzle in the Norwegian market.

Table of Contents

1. Introduction

A fundamental principle in asset pricing theory is that investors should be compensated for bearing systematic risk. That is, investors should be compensated for holding assets with exposure to risk factors that cannot be diversified away. In asset pricing literature, financial distress has been highlighted as one such systematic risk factor (Chan & Chen, 1991; Fama & French, 1993; 1995). However, several academic papers find contradictory results; they find that financially distressed stocks earn anomalously low returns (Dichev, 1998; Griffin & Lemmon, 2002; Garlappi, Shu, & Yan, 2008; Campbell, Hilscher, & Szilagyi, 2008). This anomaly is referred to as the "distress risk puzzle".

The majority of these papers examine the relationship between distress risk and stock returns in the American market, and to the best of our knowledge, no paper conducts a thorough examination on the Norwegian market[1]. Thus, we have found it valuable to research the phenomenon in Norway. As we expect distressed stocks to carry a premium, our null hypothesis is that investors who hold the most distressed stocks in the market over time will receive a risk premium. A potential rejection of the null hypothesis is indicative of a distress risk puzzle in the Norwegian market. In our paper, we use default probability as a proxy for distress risk. That is, a company that is predicted to have a high default probability is assumed to have a high level of financial distress. We allocate stocks into eight different portfolios depending on their level of financial distress, and measure the respective returns of the different portfolios. The returns are measured from the beginning of June 2004 to the beginning of September 2018, and the portfolios are re-balanced every third month based on updated default probabilities.

We find that the portfolio with the most distressed stocks significantly underperforms relative to the portfolio with the least distressed stocks. Moreover, our results indicate that stock performance is negatively correlated with distress risk. We also find that the most distressed firms on average are smaller in size, have higher market-to-book ratios and a higher degree of leverage.

---

[1] Eisdorfer, Goyal and Zhdanov (2018) conducts a global study of which Norway is included, however there is no in-debt analysis of the Norwegian results. We will discuss this in more detail in Chapter 3.

The starting point for the thesis is a discussion regarding the relationship between risk and return in general, building a theoretical framework for understanding risk factors as a source of return premium. In light of this theoretical framework, we discuss the association between distress risk and realized returns. Furthermore, we discuss bankruptcy risk as a proxy for distress risk.

In Chapter 3, we review existing research that is conducted on the relationship between financial distress and stock returns.

Next, in Chapter 4, we start with describing common proxies for distress risk and elaborate on why we found an econometric model for default prediction to be the best proxy for distress risk in Norway. Next, we conduct a literature review on econometric models to further elaborate on why we chose our specific model. After that, we go through our preferred model in more detail, before we end the chapter with discussing the predictive power of the model on Norwegian data.

After that, in Chapter 5, we describe our dataset. We discuss how we collected and processed the data in order to use it as input in the default probability model. In addition, we showcase statistical properties of the final dataset.

In Chapter 6, we analyze the relationship between distress risk and stock returns in the Norwegian market. We begin by describing how the portfolios are formed and re-balanced as well as how we measure the portfolios performance. Next, we perform paired t-tests to compare the returns between the most distressed portfolios against the least distressed portfolios. Subsequently, we turn our attention towards the characteristics of the different distress risk sorted portfolios. In order to strengthen this analysis, we also regress the quarterly returns on the factors in the Fama-French three-factor model. This is to better examine the portfolios characteristics, as well to assess the risk-adjusted returns. The results reveal that the portfolio with the most distressed stocks have high loadings on all the risk factors, and that this portfolio underperforms the other portfolios with a significant negative unexplained return.

Next, in Chapter 7, we discuss potential short-comings of the thesis. This includes a discussion of the time-frame of which we measure returns for the sorted portfolios before they are re-balanced. Furthermore, we discuss realized returns as a proxy for expected returns. We end

this chapter with a discussion regarding the implications of single-sorting on distress risk versus double-sorting on characteristics and distress risk.

Finally, we summarize our findings in a conclusion and utilize the opportunity to elaborate on potential extensions to the thesis.

2. Theory

The first asset pricing model that explained an equity´s expected return based on its exposure to systematic factor risk was the Capital Asset Pricing Model, also known as CAPM (Ang, 2014). In CAPM, there is only one risk factor; the market portfolio. According to CAPM, the expected excess return of a stock is solely decided by the stock´s exposure to the market factor (Ang, 2014). A higher exposure to the market factor should be compensated with higher expected returns.

Since the introduction of CAPM, several studies argue that the model fails to reflect reality (Ang, 2014). However, the model is still valuable as it provides insight into how a stock´s risk premium is determined by its exposure to underlying risk factors. Since CAPM, several multifactor models have been developed to explain the return of a stock based on risk factors.

The most used multifactor models today are variations of the Fama-French three-factor model, which was introduced by Fama and French in 1993. In the three-factor model, a stock´s excess return is explained by its exposure to three factors; the market factor from CAPM, a SMB factor and a HML factor (Fama & French, 1993). The SMB factor is a constructed portfolio that buys stocks with a small market capitalization and sells stocks with a large market capitalization. SMB is adjusted for the variation in book-to-market equity. Thus, the goal is to mimic the cross-sectional variation in returns associated with size (Fama & French, 1993). On the other hand, HML is a portfolio where the goal is to mimic the cross-sectional variation in returns associated with variations in book-to-market equity, corrected for the variation in size (Fama & French, 1993). The HML portfolio buys stocks with a high book-to-market equity ratio and sells stocks with a low book-to-market equity ratio. In other words, the HML portfolio goes long in value stocks and short in growth stocks.

In more recent years, the three-factor model has been extended, and today there exist several different versions that include other factors such as momentum, operating profitability and investment patterns (Carhart, 1997; Fama & French, 2015). We will not discuss these factors in further detail. Instead, we will elaborate on how distress risk, which is the topic of this thesis, can be linked to priced risk factors.

Distress risk is believed to be one of the underlying drivers that can explain the positive returns associated with SMB and HML (Chan & Chen, 1991; Fama & French, 1992). A firm in

financial distress will have trouble paying off its creditors, and the state of financial distress can lead to several costs. The costs often associated with financial distress are increased cost of capital, having to sell off assets at low prices, decreased customer loyalty and having to desist from attractive investment opportunities (Altman, 1984; Andrade & Kaplan, 1998; George & Hwang, 2010). It is reasonable to argue that companies are more likely to incur such costs when the economy is in a low state, and that the cost of distress thus increases the exposure to systematic risk (George & Hwang, 2010). Accordingly, several papers find evidence that the premium observed in the Fama-French risk factors can be explained by exposure to distress risk.

Chan and Chen (1991) argue that small firms carry a value premium over large firms because they tend to have a higher degree of financial distress. They argue that these firms are marginal firms which are more sensitive to changes in the economy and less likely to survive periods of low economic growth (Chan & Chen, 1991). Furthermore, Fama and French (1992; 1995) find evidence of financial distress as a potential explanation of the book-to-market effect[2] captured by the HML factor. They argue that firms with high book-to-market ratios have higher distress risk than their low book-to-market counterparts, and that they experience a risk premium in returns (Fama & French, 1992; 1995). Furthermore, Ferguson and Shockley (2003) argue that relative leverage and relative distress can explain the return premiums associated with exposure to the SMB factor and the HML factor.

These studies indicate that distress risk is a priced systematic factor. However, if distress risk is systematic, stocks with high distress risk should receive a premium in returns relative to stocks with low distress risk. Nevertheless, several academic papers find contradictory results, which is the anomaly referred to as the distress risk puzzle.

We use default probability as a proxy for distress risk and assume that a company's bankruptcy risk is closely related to its distress risk. However, it should be noted that there are conflicting evidence in the financial literature regarding the relationship between default probability and distress risk. George and Hwang (2010) argue that a firm´s probability of default does not necessarily reflect its exposure to distress risk. They argue that firms with high exposure to

---

[2] The book-to-market effect is the phenomenon that firms with high book-to-market ratios tend to outperform firms with low book-to-market ratios (Ang, 2014).

distress risk choose lower leverage, and thus reduce their probability of default. Nevertheless, it is also reasonable to argue that default probability is closely related to distress risk as a company that has a high probability of default is likely to incur costs related to financial distress. Thus, in this paper, we assume that default probability is a good proxy for distress risk. In the next chapter, we will further elaborate on existing research on the relationship between distress risk and return.

3.   Litterature Review

Several papers have investigated the relationship between financial distress and stock returns, but their methods and findings vary.

Dichev (1998) examines the returns of U.S. industrial firms in the period from 1981 to 1995. He uses bankruptcy risk as a proxy for distress risk and estimates bankruptcy risk by using both Altman´s Z-score (1968) and Ohlson´s O-score (1980). The Z-score was developed using a multiple discriminant statistical methodology, while the O-score was developed using a conditional logit specification, and they were both estimated based on financial ratios (Altman, 1968; Ohlson, 1980). These scores are further elaborated in Chapter 4.2. Dichev runs regressions with returns as the dependent variable and bankruptcy risk, market capitalization and book-to-market ratio as independent variables. He finds that the returns of industrial companies decrease with increasing distress risk. That is, his research suggest that financially distressed firms underperform relative to less distressed firms, even when adjusting for the size and book-to-market effects.

Griffin and Lemmon (2002) also uses the Ohlson´s O-score as a proxy for financial distress when they examine U.S. stock returns in the period from July 1965 to June 1996. They find evidence against distress risk as a source of return premium. They group the companies in the dataset based on their book-to-market values and find that for the high book-to-market group, the distressed stocks have approximately similar returns as the stocks with low distress risk. One the other hand, for the low book-to-market group, the distressed stocks receive exceedingly low returns compared to the stocks with low distress risk. Consequently, Griffin and Lemmon argue that Dichev's results largely can be ascribed to the weak performance of low book-to-market stocks.

Vassalou and Xing (2004) uses Merton's (1974) option pricing model[3] to estimate companies likelihood of default, and they use this measure as a proxy for distress risk. They examine the relationship between default risk and equity returns in the U.S. in the period from 1971 to 1999. They find that financially distressed firms outperform firms with less financial distress only to the extent that they have a high book-to-market ratio and small market capitalization

---

[3] Further elaborated in Section 4.1

(Vassalou & Xing, 2004). Furthermore, they point out that the book-to-market effect and the size effect is closely linked to distress risk, as they only find these effects for stocks with high distress risk.

Garlappi et al. (2008) examines the relationship between default risk and stock returns for non-financial U.S. firms in the period from 1969 to 2003. They utilise the Expected Default Frequency measure from Moody´s KMV[4] to estimate the default probability and use this as a proxy for distress risk. This measure of distress risk is very similar to the one used in Vassalou and Xing (2004), as it is based on Merton's option pricing model. They find that default probability and returns, in general, are not positively related (Garlappi et al., 2008)

Campbell et al. (2008) continue the line of research on the return of financially distressed stocks. As will be described in detail later, they develop a logit model to calculate ex-ante default probabilities. They use these default probabilities to allocate stocks into different portfolios and examine the returns for U.S. companies in the period from 1981 to 2003. They find that financially distressed stocks tend to deliver anomalously low returns (Campbell et al., 2008).

George and Hwang (2010) investigate the relationship between financial distress, leverage and returns in the U.S. As part of their study, they use Ohlson´s O-score as a proxy for financial distress and examine the relationship between distress risk and returns from 1966 to 2002. They find that firms with high distress risk earn low returns relative to firms with low distress risk. Furthermore, they find that the distress risk puzzle is more prevalent when the returns are risk adjusted. However, they argue that default probability is a poor measure for capturing systematic distress risk.

Chava and Purnanandam (2010) examine the relationship between stock returns and default risk for U.S. firms in the period from 1953 to 2006. They estimate a hazard model for default probability following Shumway (2001) and others, in addition to a distance to default measure based on Merton's (1974) option pricing model. Both these models are used as proxies for distress risk. In contrast to previous studies, they use the analysts expected returns instead of realized returns, arguing that this better captures the real relationship between financial distress

---

[4] Moody's KMV is a credit risk product developed to estimate default, and the algorithm is based on Merton's option pricing model (Moody's KMV).

and stock returns. In addition, they measure returns for a longer time horizon than previous studies. They find a strong positive correlation between financial distress and expected stock returns for the larger part of their sample period. However, for the period between 1980 and 1990, they find a negative relationship between financial distress and expected stock returns.

Eisdorfer et al. (2018) study the performance of financially distressed companies in the period from 1992 to 2010. They have a global approach, and study companies from 34 different countries using Merton´s distance-to-default model as an estimate of default risk. They find that the distress anomaly is a phenomenon that is prevalent only in developed countries, and not in emerging markets (Eisdorfer et al., 2018). In their study, they report the performance of a long – short portfolio in the Norwegian market that buys the 20% most distressed stocks and sells the 20% least distressed stocks. This portfolio achieves a negative monthly excess return of – 0.43%. The T-statistic is low at -0.83. This is a mild indication of the existence of a distress risk puzzle in the Norwegian market. However, as they conduct a global study, no in-depth analysis is conducted for Norway. We therefore view our research on the Norwegian market as a relevant in depth-study to further examine the existence of a distress risk puzzle in Norway.

As shown in existing literature, there are mixed findings regarding the relationship between distress risk and stock returns, and a range of different measures have been used as proxies for distress risk. There have also been several attempts at explaining the anomaly in returns of distressed stocks, but as yet no consensus has been reached.

4. Distress Risk Model

In this chapter, we will first discuss common proxies for distress risk and explain why we chose an econometric model for default probability as our proxy for distress risk on Norwegian firms. Secondly, we will take the reader through a literature review on the development in econometrically based default probability models, to elaborate on our choice of model. In the third section, we will explain our preferred model, while the last section is a discussion on the predictive power of the model on Norwegian data.

4.1 How to Measure Distress Risk?

In order to do an analysis on the distress risk puzzle, an accurate measure of distress risk is needed. A company's credit rating, the yield on bonds and the probability of default are all proxies that can be used to indicate a company's level of financial distress.

We will start by discussing credit rating as a proxy for distress risk. The U.S. Securities and Exchange Commission (2017) defines credit rating as an assessment of an entity's creditworthiness, that is, an entity's ability to cover its financial obligations. It is the credit rating agencies that perform the credit ratings based on their own analytical models, assumptions and expectations (U.S. Securities and Exchange Comission, 2017). The results typically range from the best rating AAA, to the lowest rating D, of which the latter represents default. Thus, credit rating is closely linked to credit risk; low credit rating implies high credit risk, and hence, high probability of default. Therefore, credit rating can be used as a proxy for distress risk. That is, we can assume that the distress risk increases as credit rating decreases.

However, because of strict regulations in the Norwegian market, the credit rating agencies were unable to supply us with credit ratings on Norwegian firms. In addition, knowing that the agencies use their own analytical models, assumptions and expectations in forming the credit ratings, it is uncertain how extensive the research behind each rating actually is. Furthermore, a credit rating approach implicitly relies on the assumption that all assets within one rating share the same distress risk. In other words, there are several aspects that makes a credit rating approach unsuitable in the Norwegian market.

Next, we would like to discuss the yield of corporate bonds as a proxy for distress risk. The yield of a bond essentially depends on three factors; the risk-free rate, the specifications[5] in the bond contract and the company's default probability (Merton, 1974). Thus, the differences in yield between two corporate bonds with the same specifications will reflect the difference in default probability between the two underlying companies. More generally; the higher the default risk, the higher the spread between the risk-free rate and the bond yield, everything else equal. That is, it would be possible to get a proxy for distress risk by looking at the relative yield spread of the bonds in the market.

In order to do so, a sufficient quantity of liquid corporate bonds must be available to analyze in the market. This immediately limits our potential dataset to companies with corporate bonds that are frequently traded. Only a minority of the companies listed in Norway have corporate bonds that fulfils this requirement. In addition, when taking into consideration that the bonds must be similar in the specifications in order to compare the relative yields, the potential dataset is likely to be insufficient to draw conclusions. In addition, Elton, Gruber, Agrawal and Mann (2001) provide evidence that the spreads of corporate bonds are closely linked to the risk factors accepted for common stocks, and that only a small portion is related to default probability. This suggests that we should adjust for size and book-to-market values for the underlying companies in addition to adjusting for the bond specifications, which will further diminish the possible comparable bonds. With this in mind, we have concluded that using yield spreads as a proxy for distress risk is unfavorable for researching the distress risk puzzle in Norway.

Finally, we will discuss models that are developed to indicate companies likelihood of default. There are two different approaches that we will discuss; the option pricing approach and the econometric approach. The option pricing approach is typically based on the structural default model of Merton (1974), and the idea that a firm's equity can be considered a call option on the underlying value of the firm, with strike price equal to the face value of the debt. The option pricing approach has several advantages. Firstly, this approach depends on a limited set of variables which are easily available. Furthermore, the model incorporates equity values which contain forward-looking information, as equity values reflect the investors future perspectives. It is reasonable to assume that using forward-looking measures is better when

---

[5] Maturity date, seniority in case of default and security in assets etc.

predicting the likelihood of default in the future. However, an option pricing approach relies on several assumptions that are likely not to hold in the real world. It relies on the assumption of a frictionless market, that all firms have issued just one zero-coupon bond and that the underlying value of the firms follow a geometric Brownian motion (Bharath & Shumway, 2008).

The econometric approach, on the other hand, typically uses a logit specification where a bankruptcy indicator[6] is regressed on several accounting and market variables in order to estimate a model for default probability. The advantage of these models is that it does not rely on the assumptions that are present in the option pricing models. In addition, accounting and market data are publicly available for all Norwegian firms listed on Oslo Børs, Oslo Axess and Merkur Markets. Furthermore, as we will elaborate in the next section, econometric models have improved over recent years and have proven to be accurate predictors for default probability (Campbell et al., 2008). Earlier, econometric models were criticized for being backward-looking as they only included variables found in the accounting data published in the quarterly reports (Vassalou & Xing, 2004). The new models, however, have incorporated market data, which means that stock market developments and volatility measures are included as predictors for default probability. Hence, one can argue that the models have developed to incorporate a forward-looking aspect.

In the process of evaluating whether the option pricing approach or the econometric approach is best suited as a proxy for distress risk on Norwegian data, we have emphasized the findings of Campbell et al. (2008) and Bharath and Shumway (2008). Campbell et al. (2008) finds that a distance to default measure based on an option pricing approach adds little explanatory power when included in their best econometric model. Furthermore, they find that the pseudo-R^2 of a pure option pricing model is only half as big as the pseudo-R^2 for their best econometric model when predicting default. Bharath and Shumway (2008) find similar results when they examine the accuracy of Merton's distance to default model against an econometric model. However, they find that econometric logit models perform slightly better when incorporating the Merton's distance to default measure together with other covariates in out-of-sample predictions (Bharath & Shumway, 2008). In addition to the findings from these papers, we

---

[6] 1 if Bankrupt, 0 otherwise

have emphasized the fact that an option pricing approach is based on underlying assumptions that do not hold in the real world.

Thus, after evaluating different opportunities for distress risk proxies on Norwegian data, we have found that an econometric approach, based on an integrated set of accounting and market data, is best suited. However, since there are relatively few listed companies in Norway, the number of bankruptcies are also very limited. Thus, we have chosen to use a model that is developed in the U.S. instead of estimating a model on a limited set of Norwegian data. In order to elaborate on our choice of model, we have conducted a literature review on the development in econometric default probability models in the subsequent section.

4.2 Literature review- Econometric Default Probability Models

The literature review will start with Altman`s Z-score in 1968 and end with Campbell, Hilscher and Szilagyi`s dynamic hazard model in 2008. The latter is our model of choice for predicting distress risk on Norwegian listed companies.

Several studies have been conducted in order to estimate an econometric default probability model. Altman (1968) used a multiple discriminant analysis to study the likelihood of default of publicly traded manufacturing companies. By using financial ratios collected from the companies annual reports, he gave each company a Z-score which could be used to predict bankruptcy within two years (Altman, 1968). Later, Ohlson (1980) developed a logit model for bankruptcy prediction where he extended the research to include a more comprehensive set of companies and found that a wider selection of accounting data significantly improved the predictive power of the default probability model. Shumway (2001) took it further and developed a hazard model to allow for time varying covariates and included both accounting data and market data in the model. Shumway argues that Altman's and Ohlson's models are inappropriate in forecasting bankruptcy because they are what he refers to as static models, which are unable to capture the fact that firm characteristics change from year to year (Shumway, 2001).

In the article "Bankruptcy Prediction with Industry Effects" Chava and Jarrow (2004) validate the superiority of Shumway's dynamic hazard model over previous static models. In addition, Chava and Jarrow improve the research from Shumway by including monthly market data and

quarterly accounting data in their model, which they find to significantly improve the forecasting ability (Chava & Jarrow, 2004). Furthermore, they find that industry effects are statistically significant and that the inclusion of industry effects improves the model's ability to predict default.

Campbell et al. (2008) chose to construct a new empirical measure of financial distress, building on the work from Shumway (2001), Chava and Jarrow (2004) and others. Based on monthly U.S. bankruptcy data from January 1963 to December 1998 and failure data[7] from January 1963 to December 2003, they estimate a hazard logit model of bankruptcy and failure (Campbell et al., 2008). The main difference from Chava and Jarrow's model is that Campbell, Hilscher and Szilagyi found three more variables with explanatory power; market-to-book ratio, share price and corporate cash holdings. In addition, they found that market value of equity had stronger explanatory power than book-value of equity for variables that included total assets. Furthermore, Campbell et al. (2008) added lagged information about profitability and stock returns to capture the fact that a long history of losses or stock decline is a better indicator of default probability than a sudden drop in income or stock prices. Lastly, Campbell et al. (2008) test for industry effects, but they find that the inclusion of these effects does not add explanatory power in their best model.

Campbell, Hilscher and Szilagyi's best model incorporate both market data and quarterly accounting variables, and they show that their best model is better than an option pricing approach in predicting default probability. Thus, we have chosen to use their best model on Norwegian data. The next section will explain the model in more detail.

---

[7] Failure data= Companies with financially driven delisting's and/or companies that receives a D (default) from credit rating agencies

4.3 Model Explanation

Campbell et al. (2008) develop a hazard model that uses logistic regression to estimate probability of default for U.S. listed firms. We use their best model for predicting default one month ahead, which they present in the last column in Table III (Campbell et al., 2008, p. 2910). With inspiration from Li, Lockwood and Miao (2017) we have slightly changed the mathematical notation of Campbell, Hilscher and Szilagyi's model to make it more intuitive. We calculate the default probability (DP) for company i in month t by calculating the probability that the company will fail to meet its financial obligations (Y=1) in the following month[8], as follows:

$$DP_{i,t} = P_{i,t}(Y_{i,t+1} = 1) = \frac{1}{1 + e^{(-z_{i,t})}}$$

Where:

$z_{i,t} = -9.08 - 29.67\ NIMTAAVG_{i,t} + 3.36\ TLMTA_{i,t} - 7.35\ EXRETAVG_{i,t} +$
$1.48\ SIGMA_{i,t} + 0.082\ RSIZE_{i,t} - 2.40\ CASHMTA_{i,t} + 0.054\ MB_{i,t} - 0.937\ PRICE_{i,t}$

And:

NIMTAAVG is a profitability ratio, TLMTA is a debt ratio, EXRETAVG is an excess return measure, SIGMA is a volatility measure, RSIZE is a size measure, CAHMTA is a liquidity measure, MB is a market-to-book ratio and PRICE is a stock price measure.

The coefficients in the model is calculated by Campbell et al. (2008) and are based on U.S. bankruptcy and failure data from 1963-2003. Because of the limited number of Norwegian listed firms and bankruptcies over the timespan of which we have available quarterly accounting data (2004-2018), we have found it best to use their best estimates instead of re-estimating the model ourselves on a limited dataset. The following paragraphs will include an explanation of each of the variables in the model, in addition to a discussion of the sign of the variables with regards to economic intuition. For the variables with a positive coefficient, an

---

[8] Y=1 in the case of default and 0 otherwise

increase in the variable will lead to an increase in default probability, while the opposite applies for the variables with a negative coefficient.

We will start with NIMTA: Net Income to Market value of Total Assets[9]:

$$NIMTA_{i,t} = \frac{Net\ Income_{i,t}}{Firm\ market\ equity_{i,t} + Total\ book\ value\ of\ liabilities_{i,t}}$$

NIMTA is a variable that represents the profitability of the firm for the past quarter, measured as net income divided by the market value of total assets. Campbell, Hilscher and Szilagyi found it better to use market value of total assets instead of the book value of total assets, as equity values are more sensitive to new information. High profitability is indicative of a firm in a good financial state, hence, an increase in NIMTA should lead to a decline in default probability, which is what we observe in our model. However, as the observant reader might have noticed, the model does not incorporate NIMTA directly, but rather the lagged variable NIMTAAVG.

$$NIMTAAVG_{t-1,t-12} = \frac{1 - \theta^3}{1 - \theta^{12}} \left(NIMTA_{t-1,t-3} + \cdots + \theta^9 NIMTA_{t-10,t-12} \right)$$

That is, the historical weighted average of net income over market value of total assets is a preferred measure to NIMTA, which only incorporates the last quarter (Campbell et al. 2008). $\theta = 2^{-\frac{1}{3}}$, which means that the weights are halved each quarter. That is, the most recent quarter has the weight 0.53, while the quarter that is farthest back in time has the weight 0.067. In other words, the most recent quarter is allocated most weight. Obviously, the discussion regarding the sign of the variable still holds, hence an increase in NIMTAAVG leads to a decline in default probability, which is economically intuitive.

The next variable is TLMTA; Total book value of Liabilities over Market value of Total Assets:

$$TLMTA_{i,t} = \frac{Total\ book\ value\ of\ liabilities_{i,t}}{Firm\ market\ equity_{i,t} + Total\ book\ value\ of\ liabilities_{i,t}}$$

---

[9] Market value of total assets is in this thesis defined as market value of equity plus book value of liabilities.

How much leverage a firm holds is correlated with its default probability because financial leverage increases financial risk. A firm with high leverage will have more financial obligations to uphold and thereby the risk of default increases. Lagging TLMTA as done with NIMTA did not enter significantly in the regression analysis of Campbell, Hilscher and Szilagyi, and hence, TLMTA is calculated based on the last quarter. TLMTA enters the model with a positive sign, which implies that an increase in a company's debt ratio will lead to an increase in default probability, which is economically intuitive.

EXRET is the natural logarithm of each firm's excess stock return relative to the OSEBX:

$$EXRET_{i,t} = LN(1 + R_{i,t}) - LN(1 + R_{OSEBX,t})$$

Excess return should be a good indicator of default risk as the measure evaluates the performance of a stock relative to the performance of the OSEBX, which is our benchmark for the Norwegian market. One can argue that the development of a stock price is determined by the available information in the market, and investors' belief about the future prospects for the firm. When a stock performs better than the market for a given period, it implies that the investors believe in better prospects for the firm than for the market as a whole. On the other hand, a stock that underperforms relative to the market, is believed to have less favorable prospects than the market as a whole. EXRET enters the model with negative sign, indicating that a higher excess return will decrease the probability of default, which makes economic sense.

We would like to emphasize that we have used OSEBX as a benchmark instead of the S&P 500 index, which is used in the model of Campbell et al. (2008). Even though we use the coefficients that they have estimated, we use the model on Norwegian data, and thus, want to compare the returns relative to a benchmark reflecting the Norwegian market. The S&P 500 index reflects the U.S. market and incorporating this benchmark for Norwegian stocks will likely inflict a bias as the excess return can vary greatly depending on the development of the Norwegian market relative to the U.S. market.

As we can see from the model, EXRET enters the model as EXRETAVG, which is the monthly lagged EXRET over the past 12 months.

$$EXRETAVG_{t-1,t-12} = \frac{1 - \theta}{1 - \theta^{12}} (EXRET_{t-1} + \cdots + \theta^{11} EXRET_{t-12})$$

That is, a weighted average of excess returns is a preferred measure to EXRET which only incorporate the last month (Campbell et al., 2008). As earlier, $\theta = 2^{-\frac{1}{3}}$, which means that the weights are halved each month, putting most weight on the most recent development.

SIGMA represents the volatility of the stock returns:

$$SIGMA_{i,t-1,t-3} = \left(252 * \frac{1}{N-1} * \sum_{k \in \{t-1, t-2, t-3\}} r_{i,k}^2 \right)^{\frac{1}{2}}$$

SIGMA is a measure of the annualized standard deviation, calculated based on the previous three months daily stock returns (Campbell et al., 2008). It is a measure of the stock's volatility. A stock is volatile in a period if the dispersion of the returns are high in that same period. Intuitively, high volatility, or high SIGMA, should then imply higher default risk, which is the case for our model since SIGMA enters the model with a positive sign.

The next variable is RSIZE, which is the natural logarithm of the firm's market value divided by the combined market capitalization of all the firms in the market:

$$RSIZE_{i,t} = LN \left(\frac{Firm\ Market\ Equity_{i,t}}{Total\ OSE\ Market\ Value_{i,t}} \right)$$

RSIZE is a variable measuring the size of the companies relative to the size of the market. Intuitively, one would expect that larger firms, measured in terms of market capitalization, would have less probability for default than smaller firms. However, several companies with large market capitalization have gone bankrupt over recent years, such as Kodak, Enron and Lehman Brothers, and there is not necessarily a positive relationship between being large and being able to uphold financial obligations. In this model, RSIZE enters with a positive coefficient, indicating that larger companies have a higher risk for default.

The model also includes a measure of liquidity through the variable CASHMTA:

$$CASHMTA_{i,t} = \frac{Cash\ and\ Short\ Term\ Investements_{i,t}}{Firm\ market\ equity_{i,t} + Total\ book\ value\ of\ liabilities_{i,t}}$$

Cash and short-term investments, which is the liquid assets of a company, is divided by the market value of total assets. Companies with a high level of liquid assets should have less

problems covering the interest payments on debt, and thus, the probability of bankruptcy should decrease with increasing CASHMTA ratio. As we can see from the model, CASHMTA enters the model with a negative sign, and thus, an increase in cash and short-term investments over market value of total assets decreases the default probability. Hence, the variable enters the model with the economically intuitive sign.

Market-to-book ratio is the second last variable in our model:

$$MB_{i;t} = \frac{Market\ Value\ of\ Equity_{i,t}}{Book\ Value\ of\ Equity_{i,t}}$$

A high MB ratio indicates that the market interprets the company's prospects as better than what is reflected in the book value of the firm. Hence, a high market-to-book ratio indicates that a company is expected to grow in the future. As MB enters the model with a positive coefficient, a higher market-to-book value indicates more risk and higher default probability. Economically, this makes sense; a company whose equity is worth approximately the same as the net book value of assets should have less risk for a sudden drop in share price, as the share price does not reflect a high growth expectation in the future. However, companies that have a very low MB ratio are most likely firms with negative growth expectations, typically companies with outdated technology or companies that are in a mature segment. One can argue that these companies have a negative future prospect, and therefore should have higher risk for default than companies where the investors believe in high growth potential. On the other hand, our model is predicting default risk for the following month, and as Table II in Campbell et al. (2008, p. 2907) shows, bankrupt companies on average have a higher MB than the average of all companies. Thus, the MB variable seems to be entering the model with the economically intuitive sign. This is also in line with what Dichev (1998) presented in the article "Is the Risk of Bankruptcy a Systematic Risk?". He found that distressed firms generally have low market-to-book ratio, but that the most distressed firms have high market-to-book ratio. This variable will be discussed in more detail in Chapter 6.

Finally, our last variable is PRICE, which is the natural logarithm of the price per share truncated above at 19.2 NOK:

$$PRICE_{it} = LN\big(Stock\ Price_{i,t}\big)$$

The PRICE variable is the least intuitive variable in our model. Including this variable suggests that the price of the stock itself influences the probability of default. Campbell et al. (2008) expect that this variable is relevant for low share prices, arguing that NYSE and NASDAQ tend to delist stocks with a share price below $1 and that reverse stock splits done to prevent the $1 minimum level is a negative sign to the market. PRICE is meant to capture the fact that distressed companies tend to trade at lower share prices (Campbell et al., 2008). Following Campbell, Hilscher and Szilagyi, exploratory analysis suggests that price per share is relevant below $15 and thus, they truncate prize per share at this level before taking the natural logarithm. However, as we are dealing with Norwegian data, we find a suitable measure that is analogous to the $15 relevance area for the Norwegian stock exchanges. We found approximately 19 NOK to be representative for the $15 limit on the Norwegian stock exchanges. We will elaborate on this finding in Chapter 5. The PRICE variable enters the model with a negative sign, which is in line with the idea that distressed firms tend to trade at lower share prices.

In the last section of this chapter we will further elaborate on why we chose to replicate the model. We will also discuss the accuracy of the model on Norwegian data.

4.4 Model Evaluation

The first thing that is important to emphasise is the fact that this model was developed based on historical U.S. data. The most optimal would be to run our own regression on Norwegian data and use Norwegian bankruptcies and company failures as the dependent variable. However, we have concluded that the number of bankruptcies among the listed companies in the period between 2004 and 2018, which is the years we have access to both quarterly data and stock price history, is insufficient in running a logit regression.

If we were to look at all Norwegian companies including those not listed, the dataset would contain enough bankruptcies to run a regression. However, then we would limit the access of data to accounting data from annual reports, which would influence the predictability of our model. In addition, such a model would be backward-looking, since the accounting data only represents what has happened in the past, without indicating anything about the future. Furthermore, such a model would be estimated on all companies, but used only on listed companies, as we are dependent on stock price development to research the distress risk puzzle. Thus, such a model would rely on the assumption that the probability for default is

equal for companies that are listed and those that are not listed. Hence, we have found an approach where we use the coefficients estimated in the model developed by Campbell et al. (2008) to be the best option.

The following paragraphs will evaluate the accuracy of the model on Norwegian data. In order to do this, we examine the model's predictions of default probability for firms in our dataset, and match this with actual bankruptcy data from Norway. Data collection, data processing and the results from the analysis is discussed in later chapters.

The first measure we will conduct is to look at the average predicted default probability for the companies that went bankrupt in the period between 2004 and 2018. In the quarter before the companies went bankrupt, the average default probability was estimated at approximately 30%. This is well above the average default probabilities for the entire dataset. In fact, it is almost three times higher than the average default probability for the five percent most distressed stocks. Looking at the default probability for the companies in the quarter they went bankrupt, the estimated default probability is even higher and above 50%. This indicate that the model is suitable on Norwegian data.

To further validate the model on Norwegian data, we turn our attention to look at how many companies that have high estimated default probabilities, without actually going bankrupt. Of a total of 364 companies in our dataset, 10 companies have default probabilities above 30% in at least one quarter without going bankrupt, and six companies have above 50% default probability in at least one quarter without going bankrupt. Seven of the companies that had more than 30% default probability without officially going bankrupt, had news articles discussing the possibility that the companies would go bankrupt in the near future, and most of these firms conducted restructuring measures during the period in which they had a high default probability. Furthermore, only three companies that actually went bankrupt had less than 30% default probability before they went bankrupt. However, these companies had far higher default probabilities than the average company in the dataset. These findings further confirm that the model is suitable on Norwegian companies.

However, the findings also establish ground for discussing the differences between what is considered bankruptcy in the U.S. versus what is considered bankruptcy in Norway. In the U.S., companies can file for bankruptcy under Chapter 7 or Chapter 11. A Chapter 7 bankruptcy filing imply liquidation of the firm, and is equivalent to the Norwegian bankruptcy

procedure (United States Courts, 2018). The Chapter 11 bankruptcy filing, on the other hand, is known as the reorganization bankruptcy, where the distressed company usually proposes a plan for reorganization to the creditors in order to keep the business alive (United States Courts, 2018). In Norway, there is no equivalent to the Chapter 11 bankruptcy filing. Companies can negotiate terms of the debt obligations and make restructuring plans with their creditors when in financial distress, but these companies will not get a bankruptcy status unless they fail to negotiate with the creditors. As mentioned in the previous paragraph, many of the companies with high default probability did restructuring measures when they were in high distress risk. It is likely that these companies would have been registered as bankrupt in the U.S. under Chapter 11. In Norway however, they will not be registered as bankrupt before the firms are liquidated. Thus, if the same rules did apply, the predictive power of the replicating model would have been even higher. This further validate the predictive power of Campbell et al. (2008) best model on Norwegian data.

After evaluating the accuracy of Campbell, Hilscher and Szilagyi's model on Norwegian data, we feel comfortable in using their default probability measure as a proxy for distress risk on Norwegian data.

5. Data

Chapter 5 will focus on the process of collecting and handling the data that is necessary to estimate default probability for Norwegian firms. In addition, we will showcase and discuss the summary statistics for our final dataset.

5.1 Data Collection & Processing

The first part of this section will explain the dataset that we use for our default probability calculations, that is, which years we research and which stocks we include. Second, we will present the idea of lagging the accounting data to eliminate look-ahead bias[10]. After that, we will look closer into some of the more extensive variables in the model. Next, we will explain the idea behind winsorizing the variables to eliminate outliers, and shorty explain how we did this. In addition, we will elaborate on how we created portfolios based on default probability.

We use Compustat to collect quarterly accounting data on all Norwegian public companies that are, or have been, listed on Oslo Børs, Oslo Axess or Merkur Markets. As quarterly data were available only from 2004 and onwards, our dataset is limited to include data from the first quarter of 2004 to the second quarter of 2018. In order to gather market data, we used Datastream. Stock prices and market capitalization for all listed companies in Norway were collected from the beginning of 2000 until October 2018. That is, data on both active and inactive companies were collected. The collected data were merged and processed using excel, and a few companies were eliminated due to missing values in either accounting or market data. After the first elimination, 11 350 observations[11] per variable, remained in our data set.

Consistent with Campbell et al. (2008) we lag the accounting data by two months. Lagging the accounting data is done to ensure that the last quarterly report is publicly available when the default probabilities are calculated. That is, lagging ensures that the model is tradeable; at any point in time, all information that is necessary for predicting default risk for the following

---

[10] A look ahead bias occurs when estimating models that uses information that is not yet available.

[11] Observation: A datapoint for one variable for one company in a specific quarter

month, is known to the market. Thus, lagging the accounting data by two months eliminates look-ahead bias.

In order to calculate the variable EXRETAVG, we start with calculating EXRET, which is the monthly excess return for a given company over the benchmark index. We selected OSEBX as our benchmark index and used the historical development of the index in order to calculate the monthly excess return. After that, we used EXRET to calculate EXRETAVG. In order to calculate this variable for a given company in a given quarter, 12-month stock price history must be available. This is only a challenge for companies that were listed shortly before or during the period of which we measure default risk (2004-2018). However, a significant number of firms are listed in the period, and so, eliminating all companies with less than 12-month stock history would be a severe loss given the limited number of years we have available data. Therefore, we chose to use a six-month average for the companies with less than 12 months of available data, and a three-month average for the companies with less than six months available data. The companies that had less than three-month stock history for a given quarter was eliminated from the data set. The companies themselves were not eliminated from the model, but excluded until they had more than three months of consecutive returns. In total, 139 observations per variable were eliminated in this action, leaving 11 211 observations.

Similar to EXRETAVG, the variable NIMTAAVG is created based on an underlying variable (NIMTA), and thus also depends on a consecutive history of observations. The NIMTA variable depend on both accounting data and market data, as net income is divided by the market value of total assets. That is, to create the NIMTAAVG variable, we need data on market capitalization, net income and liabilities for the past four quarters. Instead of eliminating all observations that do not fulfill the need for data, we take the average of the last three quarters for the companies that have less than four quarterly observations prior to the time of calculation, and the average of the last two quarters when there is less than three consecutive quarters of observations prior to the calculation date. For the companies that only have available data for the previous quarter, we use NIMTA.

SIGMA is calculated as the annualized standard deviation, computed based on the previous three months daily stock returns. Hence, we are dependent on stock prices for the previous three months in order to calculate this variable. As EXRETAVG is dependent on the same information, we do not need to eliminate any observations when constructing this variable,

nor do we have to collect any new information. For RSIZE, on the other hand, we need to collect some new information in order to calculate the relative size of the companies compared to the market. As no reliable sources were able to supply us with the historical total market capitalization of Oslo Børs, Oslo Axess and Merkur Markets, we constructed this measure ourselves by adding together the market capitalization of all the companies in our dataset each quarter. As our dataset is reasonably complete, this should be a good measure of the value of the total market. We also crosschecked this for some specific years using the Oslo Børs official webpage.

Consistent with Campbell et al. (2008), we adjust book value of equity (BVE) to eliminate outliers by adding 10% of the difference between market value of equity (MVE) and book value of equity to the book value of equity:

$$BVE\ Adjustment\ 1 = BVE + 10\% * (MVE - BVE)$$

After this adjustment, the number of observations with negative book value of equity dropped from 174 observations to 102 observations. That is, less than 1% of the companies had a quarter with negative book value of equity. Campbell et al. (2008) chose to replace these negative values with a $1 positive value. We chose a different strategy; for the companies where the book value of equity was lower than 2.5% of the market value of equity after the first adjustment, we changed the book value of equity to 2.5% of the market value of equity. This limits the MB variable to a maximum of 40, and is done to prevent the MB variable to be too decisive for the final default risk measure. Before doing this preventive measure, the MB variable reached very high levels for some of the observations, leading the default probability to be dependent solely on this single variable.

Another variable, that we have discussed previously, is PRICE. Campbell, Hilscher and Szilagyi truncate PRICE at $15 before taking the natural logarithm, arguing that the share price only is relevant for predicting distress risk under this $15 limit. In order to find a comparable measure for the $15 limit on the Norwegian exchanges, we measure the average percentile of which $15 represents on NYSE and NASDAQ based on stock prices in 2002-

2003[12]. From this analysis we found that a stock price of $15 represents the 45-percentile on NYSE and NASDAQ, when all the stock prices are ranked in ascending order. The 45-percentile stock price on Oslo Børs, Oslo Axess and Merkur Markets for the same period is equivalent to approximately 19 NOK. Thus, we truncated price per share at 19 NOK, meaning that all shares with a share price higher than 19 NOK were adjusted down to 19 NOK, and that all shares with prices below 19 NOK kept their original price.

After creating all the variables needed to predict default probability, we eliminated all company observations were accounting data were missing. In total, 262 observations were missing, leaving the final dataset at 10 949 observations per variable. That is, our final dataset consists of 10 949 estimations of default probability, split between 364 different companies for the period between 2004 and 2018.

Following Campbell et al. (2008), we eliminate outliers for the variables using a method referred to as winsorizing. That is, we eliminate the tails of the distribution for all variables for each company, by changing the values below the 5th percentile to the 5th percentile and the values above the 95th percentile to the 95th percentile. This procedure was carried out accordingly for all the variables except for PRICE and MB. PRICE is not winsorized due to its intrinsic characteristics; it is already truncated above at 19 NOK and low share price is natural for distressed firms. The MB variable was adjusted such that the book value of equity was minimum 2.5% of the market value of equity. That is, we capped the maximum value of the variable to 40. Thus, we chose to only winsorize this variable from below, as we did not want to adjust the highest values. The procedure of winsorizing the variables was conducted using the programming tool R. The same tool was used for sorting the portfolios based on default probability, and for calculating the portfolio returns. The latter will be discussed in Chapter 6.

In this section we have explained the process of collecting and calculating the data necessary for using the model of Campbell et al. (2008) on Norwegian data. We have conducted some

---

[12] We used the period from 2002 to 2003 to avoid look-ahead bias and to be in line with the exploratory analysis conducted in Campbell et al. 2008

minor adjustments on the variables in the model such that they better fit with our Norwegian dataset. The subsequent section summarizes the properties of our eight explanatory variables.

5.2 Summary Statistics

Table I summarizes the eight adjusted explanatory variables which are the input for our default probability model. Instead of looking at NIMTAAVG and EXRETAVG, we examine their building blocks, NIMTA and EXRET. This is in order to keep the format consistent with the other variables. We have separated the summary statistics table into two different panels. Panel A displays summary statistics for all observations in our dataset. As a result, the companies that have a long history as a listed company will have relatively more weight on the descriptive statistics than the companies that have a short history as a listed company. The advantage of measuring the summary statistics across all periods, like in Panel A, is that we capture the total distribution of the dataset. This is particularly important when studying the minimum and maximum values. Panel B, on the other hand, displays summary statistics across the companies in the dataset. We used the programming tool R to take the average of each variable for each company, and then calculate the descriptive statistics based on the companies averages. This method ensures that we avoid the bias of putting too much weight on the companies with many quarterly observations. However, it is important to remember that for the company specific descriptive statistics we don't capture the full spread of observations, thus the minimum and maximum values are pulled closer to the mean. As a result, we have found it best to display both Panel A and Panel B, as both panels have some advantages.

Another aspect that is important to notice is that the variables are equal-weighted[13] instead of value-weighted[14]. That is, firms with a small market capitalization have the same weight as firms with a large market capitalization. We will elaborate on the effect of equal-weighting relative to value-weighting in Chapter 6.3.

---

[13] When calculating the average for an equal-weighted portfolio, each company's observation is assigned the same weight.

[14] When calculating the average for a value-weighted portfolio, each company´s observation is assigned a weight based on their size relative to the other companies. Normally measured as the market capitalization of the company divided by total market capitalization.

Table I, Summary Statistics

Summary Statistics

This table shows the summary statistics for our eight explanatory variables. NIMTA and EXRET are showcased instead of NIMTAAVG and EXRETAVG, as they are the building blocks of the latter variables. Panel A shows the summary statistics for all observations, while Panel B showcases the summary statistics across the companies in the dataset. All values are presented as numbers. Obs. is the number of observations, while Nr.C is the number of companies.

Panel A: Entire Data Set

	NIMTA	TLMTA	EXRET	SIGMA	RSIZE	CASHMTA	MB	PRICE
Mean	-0.004	0.426	-0.026	0.467	-7.253	0.081	2.944	2.476
Median	0.002	0.377	-0.018	0.387	-7.389	0.045	1.885	2.955
Std. Dev.	0.040	0.311	0.158	0.299	1.829	0.120	4.455	0.854
Min	-1.205	0.000	-2.336	0.000	-13.242	0.000	0.044	-3.219
Max	0.154	0.997	1.427	3.148	-0.988	1.541	40.000	2.955
Obs.	10 949	10 949	10 949	10 949	10 949	10 949	10 949	10 949

Panel B: Company Specific

	NIMTA	TLMTA	EXRET	SIGMA	RSIZE	CASHMTA	MB	PRICE
Mean	-0.007	0.391	-0.030	0.472	-7.394	0.080	3.148	2.445
Median	0.001	0.354	-0.019	0.433	-7.599	0.050	2.440	2.819
Std. Dev.	0.023	0.272	0.055	0.214	1.593	0.096	2.904	0.743
Min	-0.166	0.000	-0.373	0.110	-11.178	0.000	0.120	-1.969
Max	0.020	0.990	0.098	1.625	-1.294	1.018	22.976	2.955
Nr.C	364	364	364	364	364	364	364	364

The following section will discuss the descriptive statistics of some of the variables in our dataset. The mean, median and standard deviation will be discussed with basis in Panel B, as we find it more interesting to look at these measures from a company to company perspective. In order to capture the full distribution of the dataset, we use Panel A when discussing the minimum and the maximum values.

NIMTA, which is the profitability measure in our model, have a negative mean of 0.7% per quarter across all companies. That is, the average annual profitability over the market value of total assets is approximately -2.8% when each company is equal-weighted. This is unexpectedly low. However, the impact of the financial crisis in the years of 2008 and 2009 contributes to these low values. In fact, the average NIMTA for the years 2008 and 2009 were significantly lower than the average for the full dataset. However, as the observant reader might have noticed, the median NIMTA is slightly positive at 0.1% per quarter or 0.4% annualized. This indicate a negatively skewed distribution of profitability across the dataset. Looking at the minimum and maximum values we can see that these values vary greatly even after the winsorizing. Especially the minimum value of -120.5% is interesting. This indicates

that the negative net income was even greater than the market value of total assets for that specific company.

The average total liabilities over the market value of total assets is approximately 40% while the median value is a bit lower. The highest observation for this variable has total liabilities that constitutes almost 100% of the total asset value, while on the contrary, some of the companies are completely debt free.

For the variable EXRET, the summary statistics show that the average log excess return over the market benchmark OSEBX is negative at 2.6%[15]. This is a very low value, which likely can be attributed to the fact that the stock returns are equal-weighted while OSEBX is value-weighted. This is in line with the findings of Agustsson and Norang (Cited in Dagens Næringsliv, (2018)). When they analyze stock returns in the Norwegian market in the period from 1985 to 2017, they find that a few companies with a large market capitalization are responsible for the positive index return in the period. Thus, if the companies with large market capitalization drives the positive returns of the index, an equal-weighted approach is likely to result in negative average excess returns.

Another aspect that is important to explain closer is the extremely negative minimum value of approximately -230%. Such high negative values can occur because we use the natural logarithm of the stock return minus the natural logarithm of the market return, which mathematically means that the value declines exponentially with negative returns. For positive stock returns, on the other hand, we see the opposite effect. Since the function is concave for positive returns, the growth diminishes with higher returns, limiting the upside potential for EXRET. This phenomenon also plays a significant role in creating the negative average. The median is a bit higher than the average, but still negative at -1.9%. As for NIMTA, this indicates a negatively skewed distribution of excess returns.

The annual volatility measure, SIGMA, has a mean of 47% and a median of 43%, which imply that the average company have a volatile stock return over the period. The distribution is positively skewed with some very high values.

---

[15] EXRET measure the last month excess return.

The next variable, RSIZE, has a mean of negative 7.4, which implies that the average firm constitutes approximately 0.06% of the market. If we look at the minimum and maximum values, we can understand the extremely large gap between the largest and the smallest companies on the Norwegian exchanges. The largest company at approximately -1 indicates that this company constitutes approximately 30% of the market, while the smallest company at -13 indicates that this company only constitutes approximately 0.0002% of the market. This again clearly indicate large differences between a value-weighted and an equal-weighted approach and helps explain why we see such extreme values for some of the variables.

In the next chapter, we will look at the return of the different distress risk sorted portfolios, in order to evaluate whether there is evidence for a distress risk puzzle in Norway.

6. Results

In this chapter we will examine the different distress risk sorted portfolios. In the first section we will explain how the portfolios are formed and re-balanced, as well as how the returns are calculated. Next, we will focus on the performance of the different portfolios, before ending the chapter with an analysis of the distinguishing characteristics of the different portfolios.

6.1 Portfolio Formation and Return Calculation

We use the model developed by Campbell et al. (2008) to rank the companies on their ex-ante default probability, before sorting the stocks into eight different portfolios. The portfolios consist of stocks from the following percentiles; 0 to 5, 5 to 10, 10 to 30, 30 to 50, 50 to 70, 70 to 90, 90 to 95 and 95 to 100. Lower percentiles imply lower default probability, and thus lower distress risk. We also construct a long-short portfolio that buys stocks in the 0th to 5th percentile range, while selling stocks in the 95th to 100th percentile range. That is, a portfolio that goes long in low distressed stocks and short in high distressed stocks. As the reader might notice, the portfolios are narrower in each tail. This is to better examine the more extreme cases, where the distress premium is assumed to be most prevalent. Each portfolio is equal-weighted and re-balanced every third month in the period from June 2004 to September 2018[16]. For stocks that are delisted during a quarter we hold the proceeds in cash for the rest of the quarter, assuming zero return on cash holdings. Reinvesting proceeds in the remaining portfolio could have inflicted a bias, as the distress risk in the portfolio could have been tilted upwards or downwards, dependent on the stock that were delisted. However, holding the proceeds in cash can also inflict a bias as it can gravitate the portfolio return towards zero. This will, if anything, reduce the differences between the portfolios. As earlier explained; to avoid look-ahead bias, we only use data that is available on the investment date when forming the portfolios.

---

[16] The default probabilities are estimated two months after the end of each calendar quarter. This is also the date where the different distress risk sorted portfolios are re-balanced. The portfolios are then held for three months before they are re-estimated again. This procedure is carried through from the beginning of June 2004 until the beginning of September 2018. The default probabilities are calculated two months after the end of each quarter to make sure that the data from the quarterly reports are publicly available. These lagged dates are also the basis for the calculation of the market variables used in the bankruptcy model.

The returns of the portfolios are calculated as annualized geometric means. To measure this, we calculate the geometric return for each portfolio in each quarter. We use these returns to calculate the accumulated end value of each portfolio by investing a given amount at t = 0, where t = 0 is the beginning of June 2004, and the end date is the beginning of September 2018. The invested amount and the end values are then used to calculate the annualized geometric return.

A geometric mean is preferred because we want to describe the historical performance of the portfolios. In order to explain why, we will go through an example. Imagine giving $100 to an asset manager whom are to invest the money in the stock market. Two years later your account is at $98.8, and the asset manager claims an annualized return of 3%. This can be true if the asset manager uses an arithmetic mean to measure the annualized return. However, if the asset manager used a geometric mean, the annualized return would have been approximately -0.6%, which better reflects the actual monetary loss over the 2-year time horizon.

Another aspect that is important to mention is that the returns are presented as gross returns. When we are comparing the different portfolios, the overarching goal is to examine the hypothesis that distressed stocks carries a premium in the Norwegian stock market, and hence, that there is no distress risk puzzle in Norway. Consequently, it does not add value to compare the excess return of the portfolios. For the same reason, we have not included the brokerage fee in the return calculations. However, in Section 6.3 we will examine how the portfolios perform when we correct for the variation in returns that can be explained by exposure to common risk factors[17].

---

[17]See Section 6.3 for a further explanation of these risk factors.

6.2 Returns of the Distress Risk Sorted Portfolios

In this section we will turn our attention towards the performance of the distress risk sorted portfolios, which is showcased in Table II. Our main finding is that the portfolio with the most distressed stocks (95-100) significantly underperforms the portfolio with the least distressed stocks (0-5). The difference is significant on a 5% level with a t-stat of 2.3. The t-test is showcased in Panel A in Table III. We have used a paired t-test where we compare the geometric mean returns of the portfolios in each of the 57 periods[18]. The least distressed portfolio achieves an annualized positive return of 9.83%, while the most distressed portfolio achieves an annualized negative return of -14.51%. This anomaly is evidence against the null hypothesis that distressed stocks carries a premium, and thus, we can reject the null hypothesis. This indicates that there is a distress risk puzzle in the Norwegian market.

The difference in returns between the second most extreme portfolios in each end of the distribution, however, is not statistically significant, with a t-statistic of 0.3 (see T-test in Table III Panel B). The 5-10 portfolio achieves an annualized positive return of 10.80%, while the 90-95 portfolio achieves an annualized positive return of 4.53%. Even though the difference between these two portfolios is not statistically significant, the results indicate that the least distressed portfolio of the two outperforms the more distressed portfolio.

The return of the portfolios between the 10th and the 90th percentile are rather similar, ranging from 3.66% to 8.00%. However, there is a tendency of declining returns for increasing distress risk. As a result of the significant negative return of the most distressed portfolio relative to the least distressed portfolio, the long – short portfolio performs well with an annualized return of 15.72%.

Turning our attention towards the standard deviations of the distress risk sorted portfolios, we observe that the most distressed portfolios have higher standard deviations than the least distressed portfolios. This imply that the volatility is higher in the most distressed portfolios.

---

[18] 1 period = 3 months

Table II, Returns on Distress Risk Sorted Portfolios

Portfolio Returns and Standard Deviations

This table shows the characteristics of the different distress risk sorted portfolios for the period from June 2004 to September 2018. Portfolio 0-5 contains stocks from the lowest percentile to the fifth percentile, portfolio 5-10 contains stocks from the fifth percentile to the tenth percentile and so on. Portfolio 0-5 contains the least distressed stocks, while portfolio 95-100 contains the most distressed stocks. The Mean Return is the annualized geometric return of the portfolio, the Std. Dev is the annualized standard deviation of the returns and Mean DP is the mean default probability for the stocks in the portfolio. Higher DP implies higher distress risk. Mean N is the average number of firms in the portfolio in each period. Periods are the number of return observations for each portfolio, that is, each portfolio is re-balanced and invested 57 times. The lowest percentile portfolio (0-5) have a slightly lower average number of firms than the high percentile portfolio (95-100). This is because the percentile cut-offs are truncated down to the closest integer when the portfolios are formed. All numbers are in percentage points except for Periods and Mean N. All the means are equal-weighted

| Portfolios	0-5	5-10	10-30	30-50	50-70	70-90	90-95	95-100	L.0-5 S.95-100
Mean Return	9.83	10.80	8.00	3.66	4.98	4.89	4.53	- 14.51	15.72
Std. Dev	24.10	25.33	22.84	22.13	22.96	26.40	36.41	36.18	34.03
Mean DP	0.00043	0.00078	0.00151	0.00345	0.00856	0.03792	0.38215	10.67594	
Periods	57	57	57	57	57	57	57	57	57
Mean N	9	10	38	38	38	38	10	10	

Table III, T-Tests

Panel A

We use paired t-tests to test for the difference in geometric stock returns over the 57 periods of which we form portfolios based on default probability. We perform one T-test to assess whether the period returns of the high distress risk portfolio (95-100) are significantly different from the period returns of the low distress risk portfolio (0-5). The results from this test is showcased in Panel A. The difference between these portfolios is significant on a 5% confidence level (t-stat 2.3). A similar T-test is conducted for the second most distressed portfolio (90-95) against the second least distressed portfolio (5-10). The results from this test is showcased in Panel B. The difference between these two portfolios is not statistically significant (t-stat 0.3). Each return observation in a portfolio has counterparts from the exact same period in the other portfolios. Consequently, a paired t-test is used to examine whether there is a statistical difference in returns.

		Paired T-test 0-5 / 95-100				
Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Confidence Interval]	
0-5	57	0.0303356	0.015961	0.1205031	-0.0016392	0.0623084
95-100	57	-0.0213753	0.0239587	0.1808842	-0.0693703	0.0266198
diff	57	0.0517099	0.0225343	0.1701303	0.0065682	0.0968515

mean (diff) = mean (0-5 – 95-100)   t = 2.2947

H0 : mean (diff) = 0   degrees of freedom = 56

Ha : mean (diff) < 0	Ha : mean (diff) != 0	Ha: mean (diff) > 0
Pr (T < t) = 0.9872	Pr(|T| > |t|) = 0.0255	Pr(T > t) = 0.0128

Panel B

		Paired T-test 5-10 / 90-95				
Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Confidence Interval]	
5-10	57	0.0336977	0.0167753	0.126651	0.0000927	0.0673027
90-95	57	0.02700078	0.0241795	0.1825511	-0.0214295	0.0754451
diff	57	0.0066899	0.0223178	0.1684959	-0.0380181	0.0513979

mean (diff) = mean (5-10 – 90-95)   t = 0.2998

H0 : mean (diff) = 0   degrees of freedom = 56

Ha : mean (diff) < 0	Ha : mean (diff) != 0	Ha: mean (diff) > 0
Pr (T < t) = 0.6173	Pr(|T| > |t|) = 0.7655	Pr(T > t) = 0.3827

In Figure I, presented below, the cumulative returns of the different distress risk sorted portfolios are plotted. The most interesting insight from this analysis is that the portfolios perform differently relative to each other depending on the period we analyze.

Figure I, Cumulative Returns of Distress Risk Sorted Portfolios

This figure plots the cumulative returns for the different distress risk sorted portfolios. Each graph represents the development of 1NOK invested in each portfolio in the beginning of June 2004 and held until the beginning of September 2018. The portfolios are re-balanced every third month during this time period. The cumulative returns are calculated based on the geometric returns that the portfolios achieved in each period.
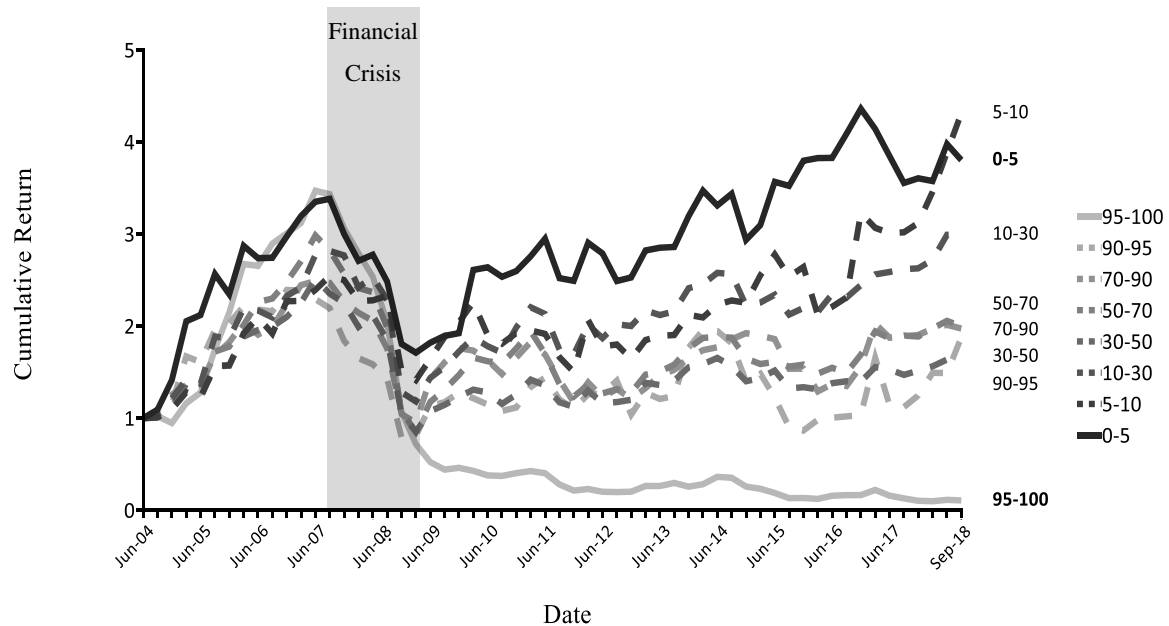
We observe that the portfolios have a rather similar development in the period prior to the financial crisis as well as during the financial crisis[19]. Furthermore, the least distressed portfolio and the most distressed portfolio are in fact the two portfolios with the best performance in the period prior to the crisis. However, the most distressed portfolio plummets during the financial crisis, and it never really recovers. The distress risk puzzle thus seems to be most prevalent in the post-crisis period. In the post-crisis period, there is a tendency of returns decreasing in distress risk. However, the sample period is too short for us to make any precise inference regarding whether the distress risk puzzle is more prevalent in specific time periods.

---

[19] The financial crisis lasted from October 2007 to March 2009 (Estimated based on S&P 500 development, Bloomberg Terminal)

In this section, we have examined the returns and the standard deviations of the distress risk sorted portfolios. The portfolio with the five percent most distressed stocks significantly underperforms the portfolio with the least distressed stocks. This is counterintuitive to fundamental economic theory, which states that a rational investor will demand higher return on stocks that are more exposed to systematic distress risk (Ang, 2014). However, as pointed out, the return patterns are different before and after the crisis, and we encourage further research with a longer time horizon.

Our interpretation of the results builds on the assumption that the probability of default is a good proxy for a firm's exposure to systematic distress risk. As discussed earlier, the firms in the portfolio with the highest default probability are not necessarily the firms with the highest systematic distress risk, which is the type of default risk investors should demand a premium for carrying. Nevertheless, we assume that default probability is a good proxy for distress risk. As a result, the findings from this analysis provide evidence in favor of rejecting the null hypothesis that distressed stocks carry a premium, which again is indicative of the existence of a distress risk puzzle in Norway.

6.3 Portfolio Characteristics and Fama French Regression Loadings

In this section we will focus on the distinguishing characteristics of the different distress risk sorted portfolios. To better understand how the portfolios perform, we correct for the variation in returns that can be explained by exposure to common risk factors. That is, the portfolio returns in excess of the risk-free rate are regressed on the market factor, the SMB factor and the HML factor, which are the factors in the Fama-French three-factor model (Fama & French, 1993).

The market factor is the market return minus the risk-free interest rate. SMB is a constructed portfolio that buys stocks with a small market capitalization and sells stocks with a large market capitalization (Fama & French, 1993). The HML portfolio buys stocks with a high book-to-market equity ratio and sells stocks with a low book-to-market equity ratio (Fama & French, 1993). For the Norwegian market, these factors are constructed and published by Bernt Arne Ødegaard (Ødegaard, 2018). The factors are not updated with data from 2018, thus we regress the portfolio returns on the Fama-French factors from June 2004 to December 2017.

In addition to providing information about how the distress risk sorted portfolios perform when they are adjusted for exposure to risk factors, the regression results also contribute to our understanding of potential trends in firm characteristics across the portfolios. The regression results are reported in Panel A in Table IV.

To further examine the portfolio characteristics, we measure the average size, debt ratio and market-to-book ratio in each portfolio[20]. As a measure of size, we use market capitalization, represented as Mean MCAP. The debt ratio is measured as total liabilities divided by the market value of total assets, represented as Mean TLMTA. The market-to-book ratio is the firms market capitalization divided by the book value of equity, represented as Mean MB. All the variables are showcased in Panel B of Table IV.

To get an understanding of the variation in market capitalization and market-to-book ratio in each portfolio, we also showcase the standard deviations of these variables[21]. To get a better sense of the relative size of the standard deviation we calculate the coefficient of variation, which is the standard deviation divided by the mean. These variables are also presented in Panel B. The standard deviation and the coefficient of variation for market capitalization are presented as Std MCAP and CV MCAP, respectively. Moreover, the standard deviation and the coefficient of variation for the market-to-book ratio are presented as Std MB and CV MB, respectively.

As the reader might notice, we have replaced the variable RSIZE with the more intuitive market capitalization as a measure of size. In addition to being more intuitive, it is also possible to interpret the standard deviation measure of market capitalization. This is not the case for RSIZE, as RSIZE is not linear in size.

We devote time to examine the variation in market capitalization within each portfolio because we want to evaluate the weighting scheme. The weighting scheme is the way the returns and the characteristics for the different portfolios are weighted. When interpreting the portfolio returns, characteristics and regression results, it is important to keep in mind that the portfolios

---

[20] We first calculate the average size, debt ratio and market-to-book ratio for each quarter within each of the distress risk sorted portfolios, and then take the average across time for each portfolio.

[21] We first calculate the standard deviation of size and market-to-book ratio for each quarter within each of the distress risk sorted portfolios, and then take the average across time for each portfolio.

are equal-weighted, as opposed to value-weighted. The lower the variation in size within each portfolio, the less the choice of weighting scheme matters. Just imagine the variation being zero, then the two weighting schemes will produce the same result.

From Panel B in table IV we see that the coefficient of variation for the market capitalization within each portfolio is quite high. This indicates that the returns of the portfolios will differ depending on whether the portfolios are value-weighted or equal-weighted. As we equal-weight the portfolios we implicitly allocate a higher weight to the small companies compared to if the portfolios were value-weighted. An example of the implications of equal-weighting compared to value-weighting is that the coefficient of the SMB factor becomes higher as the returns of small companies are weighted equal to the returns of large companies.

Despite this, we still choose to equal-weight the portfolios as our main goal is to understand whether there is an anomaly in the difference in returns between the stocks with high distress risk and the stocks with low distress risk. When the variation in market capitalization within each portfolio is high, a value-weighted approach will allocate more weight to big firms relative to the small firms. In an extreme case one could imagine one very large company, and several very small companies in a portfolio. The value-weighted portfolio characteristics and returns would then in reality almost solely reflect that one large company. We are equally interested in all of the companies, regardless of size, and have thus adopted an equal-weighting approach.

Table IV, Three-Factor Regression and Portfolio Characteristics

In this table we explore portfolio characteristics. Panel A shows the regression results of the quarterly portfolio returns in excess of the risk-free rate regressed on the factors in the Fama-French three-factor model; the market factor, SMB and HML. The dataset consists of return data from the June 2004 to December 2018[22]. * indicates significance at the 5% level, ** indicates significance at the 1% level and *** indicates significance at the 0.1% level. Portfolio 0-5 contains stocks from the lowest percentile to the fifth percentile, portfolio 5-10 contains stocks from the fifth percentile to the tenth percentile and so on. Portfolio 0-5 contains the least distressed stocks, while portfolio 95-100 contains the most distressed stocks. Panel B shows portfolio characteristics for the different portfolios. The Mean Return (%) is the annualized geometric return of the portfolio, the Mean DP (%) is the mean default probability of the stocks in the portfolio. Mean MCAP is the average market capitalization in each portfolio in million NOK. Std MCAP is the standard deviation of the market capitalization. Mean MB is the average market-to-book ratio and Std MB is the standard deviation of market-to-book ratio. Mean TLMTA (%) is the average debt ratio in each portfolio. Mean N is the average number of companies in each portfolio. All the means are equal-weighted.

Panel A

Three-Factor Regression Coefficients

Portfolios	0-5	5-10	10-30	30-50	50-70	70-90	90-95	95-100	L.0-5 S.95-100
MKT_Excess	1.152***	0.995***	1.130***	1.140***	1.198***	0.992***	1.408***	1.342***	-0.180
	(8.47)	(6.63)	(16.32)	(19.61)	(13.16)	(7.50)	(6.18)	(5.47)	(-0.62)
SMB	1.335***	0.595*	0.609***	0.666***	0.644***	0.184	1.105**	1.422**	-0.0852
	(5.53)	(2.23)	(4.95)	(6.45)	(3.98)	(0.78)	(2.73)	(3.26)	(-0.16)
HML	-0.218	0.153	-0.0573	-0.0152	0.236	0.371	0.295	0.426	-0.643
	(-1.06)	(0.67)	(-0.55)	(-0.17)	(1.71)	(1.85)	(0.85)	(1.14)	(-1.45)
Constant	-0.0216	-0.0133	-0.0201**	-0.0318***	-0.0290**	-0.0185	-0.0409	-0.0866***	0.0590*
	(-1.72)	(-0.96)	(-3.13)	(-5.91)	(-3.44)	(-1.51)	(-1.94)	(-3.81)	(2.18)
Periods	54	54	54	54	54	54	54	54	54

Panel B

Portfolio Characteristics

Portfolios	0-5	5-10	10-30	30-50	50-70	70-90	90-95	95-100	L.0-5 S.95-100
Mean Return	9.83	10.80	8.00	3.66	4.98	4.89	4.53	- 14.51	15.72
Mean DP	0.00043	0.00078	0.00151	0.00345	0.00856	0.03792	0.38215	10.67594	
Mean MCAP	2 554	4 900	13 868	13 995	6 113	3 999	2 568	1 383	
Std MCAP	3 765	6 765	36 210	49 0595	20 468	16 438	5 630	3 181	
CV MCAP	1.47	1.38	2.61	3.51	3.35	4.11	2.22	2.30	
Mean MB	2.85	3.71	3.53	2.84	1.99	1.82	3.04	8.02	
Std MB	1.92	1.91	2.07	1.96	1.86	2.46	4.58	11.19	
CV MB	0.67	0.51	0.59	0.69	0.93	1.35	1.51	1.40	
Mean TLMTA	12.77	14.79	22.22	34.44	54.97	63.35	61.60	60.63	
Mean N	9	10	38	38	38	38	10	10	

---

[22] The portfolios created by Bernt Arne Ødegaard end in 2017, and thus, is not applicable for 2018

The further analysis of the portfolios provides us with several interesting findings. None of the portfolios, except for the long-short portfolio, have positive unexplained returns after adjusting for the exposure to the Fama-French risk factors. The portfolio consisting of the most distressed stocks have significant unexplained negative returns when we adjust for the exposure to the market factor, the SMB factor and the HML factor. The portfolio with the least distressed stocks does not have unexplained returns that is significantly different from zero when we adjust for these factors. Thus, the finding from Section 6.2 that the most distressed stocks underperforms relative to the least distressed stocks is still prevalent in risk adjusted returns.

As expected, all the portfolios have significant positive loadings on the market factor. The loadings are particularly high for the two most distressed portfolios, which display loadings well above one. This is reasonable as one would expect that distressed stocks are sensitive to the general market conditions. A loading above one implies larger fluctuations than the market in each direction, all else equal. Several of the less distressed portfolios also have market loadings above one, which might be ascribed to the fact that the portfolios are equal-weighted.

Furthermore, both the least distressed portfolio and the most distressed portfolio have a high significant loading on the SMB factor. This indicates a strong prevalence of small firms among the most distressed stocks, but also among the least distressed stocks. This finding is confirmed by the average market capitalization in these portfolios. Furthermore, the coefficient of variation for market capitalization is well above one for all portfolios. This indicate that the distribution of market capitalization is right-skewed, and thus, that the majority of the companies have values that are below the mean, but there are some large exceptions.

It is somewhat counterintuitive that the prevalence of small firms is strong in the portfolio with the least distressed stocks. Chan and Chen (1991) argue that small companies on average tend to be small because of poor performance. If this is the case, one would expect a prevalence of large companies in the least distressed portfolio. However, this might be attributed to our measure of default probability. The model predicts bankruptcy in the next month. Consequently, a small firm that recently has had a successful equity issue can have a large amount of cash relative to other assets, and thus a low default probability in the next month. This is an example of an effect that can allocate smaller firms in the least risky portfolio. Nevertheless, except for the portfolio with the least distressed stocks, we find that the average size of the companies decreases with distress risk.

The HML factor does not have a coefficient that is significantly different from zero in any of the portfolios. Consequently, any interpretation should be made with prudence. Nevertheless, we can observe that the loading on the HML factor tend to increase with distress risk. Furthermore, the most distressed portfolio, with the highest loading on HML, experiences the weakest return. This contradicts the work of Fama and French (1992). They find evidence of financial distress as a potential explanation of the positive premium associated with exposure to high book-to-market stocks. If financial distress contributes as a source of the premium to the HML factor, one would expect portfolios with high distress risk to have a high premium. This is further evidence in favor of rejecting our null hypothesis.

Furthermore, we observe that the average market-to-book ratios form a U-shape, with a rapid increase in the MB ratio for the most distressed portfolio. This is consistent with what Dichev found when he examined the returns of U.S. stocks in the period from 1981 to 1995. He found that distressed firms in general have low market-to-book ratios, but that the most distressed firms have high market-to-book ratios (Dichev, 1998). The fact that the portfolio with the highest market-to-book ratio also has the highest loading on HML is somewhat counterintuitive as HML goes long stocks with low market-to-book ratio[23]. However, it should be noted that a more thorough examination of how the cross-sectional returns vary as the market-to-book ratio changes should keep other explanatory variables such as size constant. In addition, we know that the coefficient of the HML factor is not significantly different from zero. We also see from Panel B in table IV that the coefficient of variation for the market-to-book ratios are well above one for the two portfolios with the highest distress risk. This implies that the majority of the market-to-book values in this portfolio are below the mean, and that some companies have market-to-book ratios that are very large.

We can look at the difference in market capitalization and market-to-book ratio between the least distressed portfolio and the most distressed portfolio in order to further interpret the long-short portfolio. As discussed, the long-short portfolio buys the least distressed portfolio and sells the most distressed portfolio. The least distressed portfolio consists of stocks with a large market capitalization relative to the most distressed portfolio. Consequently, we cannot say that the long-short portfolio replicates the SMB factor which goes long in small companies and short in big companies. Furthermore, the least distressed portfolio has a low market-to-

---

[23] A low market-to-book ratio is equivalent to a high book-to-market ratio

book ratio relative to the most distressed portfolio. That is, it has a high book-to-market ratio relative to the most distressed portfolio. Thus, the long-short portfolio does in fact replicate the HML portfolio, as the HML portfolio goes long in high book-to-market stocks and short in low book-to-market stocks. This could explain some of the return of this portfolio. Nevertheless, the portfolio does not have a loading on the HML factor that is significantly different from zero. We also know that the existence of a few large market-to-book ratio stocks in the most distressed portfolio might increase the average ratio substantially, and that the majority of the stocks are likely to have market-to-book ratios that are lower than the mean.

The debt ratio of the companies also varies between the distress risk sorted portfolios. The three portfolios with the lowest distress risk have average debt levels ranging from 13% to 22%, while the three portfolios with the highest distress risk have considerably higher debt levels, ranging from 61% to 63%. This is economically intuitive as companies with high debt ratios have more financial obligations. However, the relationship between debt and financial distress have several aspects, and some studies indicate that firms with high financial distress costs choose low leverage in order to avoid distress (George & Hwang, 2010). Nevertheless, the relationship between debt and financial distress is outside the scope of this paper, and will not be discussed in further detail.

In this section we have seen that the firm characteristics vary across the different portfolios. The most distressed firms are on average smaller, more sensitive to market fluctuations, have higher market-to-book ratios and higher levels of debt. Additionally, our finding from Section 6.2, that the portfolios with the most distressed stocks underperforms relative to the portfolios with the least distressed stocks, still holds in risk adjusted returns. Furthermore, we have seen that many of the portfolios have coefficients of variations for the descriptive statistics that are well above one, indicating large variations within the portfolios.

7. Criticism of Thesis

In this chapter, we discuss potential weaknesses with our analysis. First, we will look at how the length of the periods in which we measure return can affect the results of our analysis. Second, we will discuss the difference between expected returns and realized returns, and the possibility of the distress risk puzzle being an in-sample phenomenon. Lastly, we will discuss the advantages of double sorted portfolios, in order to strengthen the inference of the analysis.

7.1 Length of Return Measures

We use Campbell, Hilscher and Szilagyi's best model to predict companies default probability for the next month, and allocate the stocks into portfolios based on these probabilities. The portfolios are then held for three months before they are re-balanced based on updated default probabilities and re-invested for three new months.

The most distressed portfolio has, by construction, the stocks with the highest probability of default in the next month. Hence, it is likely that some of the stocks in this portfolio will achieve low returns, and even go bankrupt, which will pull down the average return. Thus, for the investors to receive a value premium for holding the most distressed portfolio, some of the stocks have to achieve exceedingly high returns. However, these companies might be allocated into a less distressed portfolio when the portfolios are re-balanced. Thus, potential positive returns from these stocks after the three-month period will come in a different portfolio than the most distressed portfolio. The stocks with a weak performance, on the other hand, will likely stay in the most distressed portfolio, unless they are already bankrupt. This effect can have a negative impact on the return of the most distressed portfolio.

In order to reduce this effect, Chava and Purnanandam (2010) measure the returns over a longer time period when they examine the relationship between returns and financial distress. They find that the portfolio with the most distressed stocks receives a premium in returns. This indicate that we could have achieved different results if we measured the returns over longer time periods. However, it should be noted that Chava and Purnanandam's study differs from ours in other aspects that also can influence the results; for example, that they use expected returns rather than realized returns.

7.2 Expected Returns vs. Realized Returns

Another aspect to be aware of when interpreting the performance of the different distress risk sorted portfolios is that we measure returns as realized returns as opposed to expected returns. We want to examine the actual returns to the different distress risk sorted portfolios, and realized returns is then a natural measure. However, as our sample period is relatively short, the results we obtain can be an in-period phenomenon, attributed by statistical chance. In addition to measuring the returns over a longer period, Chava and Purnanandam (2010), with inspiration from Elton (1999), also use measures of expected return in addition to realized return in their research (Chava & Purnanandam, 2010). Elton (1999) argue that average realized return is a weak proxy for expected returns and refers to the period from 1973-1984 where the stock market in the U.S. on average had lower realized returns than the risk-free rate. In addition, Elton (1999) points out that for the average realized return to be a good proxy for expected returns, the assumption that information surprises cancel each other out must hold. That is, the positive and negative surprises must cancel each other out in order for the realized returns to be equal to the expected returns for a period.

The arguments of Elton (1999) is important to have in mind when interpreting our results. If we were to look at expected returns instead of the actual realized returns, the returns of the different portfolios might have been very different. Thus, the results of our analysis might be attributed to statistical chance; investors might in fact have expected higher returns for the most distressed stocks, but negative information flow for these stocks led to weak returns.

However, the fact is still that the portfolio with the most distressed stocks, measured as default probability, significantly underperform the least distressed stocks in Norway in the period from 2004 to 2018.

7.3 Single Sorts vs. Double Sorts

Lastly, we want to highlight a potential weakness associated with interpreting how the portfolio characteristics vary with distress risk when we use a single-sort approach. As discussed, company characteristics vary greatly within each portfolio, and thus, it is hard to draw conclusions about the relationship between distress risk and returns across the different characteristics. We mention that a more thorough examination of how the characteristics vary across the portfolios should keep other characteristics constant. This could have been achieved

with a double-sort approach. That is, sorting on the characteristic first, and then on default probability.

As our dataset is rather limited, we have chosen a single sorting approach, which is sufficient to analyse tendencies of how the characteristics differ between the portfolios. However, there are quite strong variation within the portfolios, and we view a double-sort strategy as an interesting extension of this study.

8. Conclusion

In this study, we have used default probability as a proxy for distress risk, allocated stocks into distress risk sorted portfolios, and examined the returns. We find that the portfolio consisting of the five percent most distressed stocks underperforms relative to the portfolio consisting of the five percent least distressed stocks in Norway in the period between June 2004 and September 2018. This is contradicting to fundamental asset pricing theory which suggest that there is a positive relationship between distress risk and returns. The results from our analysis are statistically significant, thus we can reject our null hypothesis that investors receive a premium for bearing distress risk. The evidence is further strengthened when we adjust for the risk factors in the Fama-French three-factor model; the most distressed portfolio has significant negative unexplained return, while the least distressed portfolio has no significant unexplained return. Furthermore, we find that companies in the most distressed portfolio tend to have higher leverage, higher market-to-book ratios and smaller market capitalization.

The results from our analysis indicate a distress risk puzzle in Norway in our sample period. However, in order to further strengthen the knowledge within this subject, we have several suggestions for further research. Firstly, we encourage a deeper analysis of the relationship between the probability of default and distress risk. In this paper, we assume that probability of default is a good proxy for distress risk, but there is conflicting evidence on this matter (George & Hwang, 2010).

Furthermore, we encourage future researchers to examine a longer time horizon. We found a model that combined quarterly accounting data with market data to be the best default probability measure. However, this limited our dataset to the period after 2004. When we plot the development of the different portfolios, we see that the distress risk puzzle seems to be most prevalent in the period after the financial crisis. By examining a longer time horizon, it is possible to conduct a more thorough investigation of how the portfolios vary relative to each other under different economic conditions. In addition, a longer dataset will increase the statistical inference, and reduce the probability that the result is an in-period phenomenon.

Lastly, we believe it is interesting to measure the returns of the different distress risk sorted portfolios over a longer time horizon before the portfolios are re-balanced. A distressed company that recovers might be allocated into a less distressed portfolio. Thus, the positive returns associated with the recovery might be achieved when the company is out of the most

distressed portfolio. This issue is particularly present when the returns are measured for a short time horizon.

9. References

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and The Prediction of Corporate Bankruptcy. *The Journal of Finance*, 589-609.

Altman, E. I. (1984). A Further Empirical Investigation of the Bankruptcy Cost Question. *The Journal of Finance*, 1067-1089.

Andrade, G., & Kaplan, S. N. (1998). How Costly is Financial (Not Economic) Distress? Evidence from Highly Leveraged Transactions that Became Distressed. *The Journal of Finance*, 1443-1493.

Ang, A. (2014). Asset Management, A Systematic Approach to Factor Investing. Oxford University Press.

Bharath, S. T., & Shumway, T. (2008). Forcasting Default with Merton Distance to Default Model. *The Review of Financial Studies*, 1339-1369.

Bjerknes, C. (2018, August 7). *Dagens Næringsliv*. Retrieved from Kun tre av syv selskaper på Oslo Børs slår banken: https://www.dn.no/marked/oslo-bors/aksjer/norges-handelshoyskole/kun-tre-av-syv-selskaper-pa-oslo-bors-slar-banken/2-1-385614

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In Search of Distress Risk. *The Journal of Finance*, 2899-2939.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, 57-82.

Chan, K., & Chen, N.-F. (1991). Structural and Return Characteristics of Small and Large Firms. *The Journal of Finance*, 1467-1484.

Chava, S., & Jarrow, R. A. (2004). Bankruptcy Prediction with Industry Effects. *Review of Finance*, 537-569.

Chava, S., & Purnanandam, A. (2010). Is Default Risk Negatively Related to Stock Returns? *The Review of Financial Studies*, 2523-2559.

Dichev, I. D. (1998). Is the Risk of Bankruptcy a Systematic Risk? *The Journal of Finance*, 1131-1147.

Eisdorfer, A., Goyal, A., & Zhdanov, A. (2018). Distress Anomaly and Shareholder Risk: International Evidence. *Finacial Management*, 553-581.

Elton, E. J. (1999). Presidental Address: Expected Return, Realized Return, and Asset Pricing Tests. *The Journal of Finance*, 1199-1220.

Elton, E. J., Gruber, M. J., Agrawal, D., & Mann, C. (2001). Explaining the Rate Spread of Corporate Bonds. *The Journal of Finance* , 247-277.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Reurns. *The Journal of Finance*, 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 3-56.

Fama, E. F., & French, K. R. (1995). Size and Book-to-Market Factors in Earnings and Returns. *The Journal of Finance*, 131-155.

Fama, E. F., & French, K. R. (2015). A Five-Factor Asset Pricing Model. *The Journal of Finance*, 1-22.

Ferguson, M. F., & Shockley, R. L. (2003). Equilibrium "Anomalies". *The Journal of Finance*, 2549-2580.

Garlappi, L., Shu, T., & Yan, H. (2008). Defaul Risk, Shareholder Advantage, and Stock Returns. *The Review of Financial Studies*, 2743-2778.

George, T. J., & Hwang, C.-Y. (2010). A resolution of the distress risk and leverage puzzles in the cross section of stock returns. *Journal of Financial Economics*, 56-79.

Griffin, J. M., & Lemmon, M. L. (2002). Book-to-Market Equity, Distress Risk, and Stock Returns. *The Journal of Finance*, 2317-2336.

Li, K., Lockwood, J., & Miao, H. (2017). Risk-Shifting, Equity Risk, and the Distress Risk Puzzle. *Journal of Corporate Finance*, 275-288.

Merton, R. C. (1974). On The Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance*, 449-470.

Moody's   KMV.   (n.d.).   Retrieved   from   Moody's   KMV   Creditmonitor: https://www.moodys.com/sites/products/ProductAttachments/CreditMonitor_brochur e.pdf

Ødegaard, B. A. (2018, November 15). *UIS*. Retrieved from Asset pricing data as OSE: http://www1.uis.no/ansatt/odegaard/financial_data/ose_asset_pricing_data/index.htm l?fbclid=IwAR3vjysKBXLUaMlpPISrHAZFamoYnarNjgDOVuK-q-dfEEEnMx0xnFDmw40

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 109-131.

Shumway, T. (2001). Forcasting Bankruptcy More Accurately: A Simple Hazard Model. *The Journal of Business*, 101-124.

U.S. Securities and Exchange Comission. (2017, October 12). Retrieved from Investor Alerts and   Bulletins: https://www.sec.gov/oiea/investor-alerts-and-bulletins/ib_creditratings?fbclid=IwAR0MUT_8YHsTc6XmquY80XXCt3mqoMqG TVurrWOR7oeq0CgpVGpreiAOUqE

United   States   Courts.   (2018).   Retrieved   from   Chapter   7-Bankruptcy   Basics: http://www.uscourts.gov/services-forms/bankruptcy/bankruptcy-basics/chapter-7-bankruptcy-basics

United   States   Courts.   (2018).   Retrieved   from   Chapter   11- Bankruptcy   Basics: http://www.uscourts.gov/services-forms/bankruptcy/bankruptcy-basics/chapter-11-bankruptcy-basics

Vassalou, M., & Xing, Y. (2004). Default Risk in Equity Returns. *The Journal of Finance*, 831-868.