Distress Risk – Quality or Junk?
- Nordic evidence on the ability of distress risk to explain variations in stock returns

Parham Abuhamzeh♠

Stockholm School of Economics

Axel Malgerud♣

Stockholm School of Economics

Master's Thesis

Stockholm School of Economics

Department of Accounting and Financial Management

Tutor: Kenth Skogsvik

December 2015

Abstract: The risk-return paradigm suggests there should be a positive association between distress risk (i.e. the probability of firm failure) and subsequent excess stock returns. However, we present puzzling evidence suggesting investors are not compensated for taking on additional distress risk. To the contrary, we find that junk stocks (i.e. stocks with high levels of distress) earn lower than average returns during 2000 – 2014. In other words, results point to the absence of a distress premium, suggesting distress risk is not to be considered systematic. Stock price reactions following changes in distress offer one potential explanation to the anomalous findings. We find that the market tends to re-price stocks whose distress risk has increased (decreased) with a negative (positive) stock price adjustment. What is more, results point to a drift in stock prices following changes in distress risk. It is hence not unlikely that the absence of a distress premium observed in our results is driven by abnormal returns following periods of credit downgrades.

Keywords: Distress Anomaly, Probability of Failure, Cross Section, Asset Pricing Models, Stock Price Reaction

---

The authors would like to extend their gratitude to Professor Kenth Skogsvik, PhD at the Department of Accounting and Financial Management at the Stockholm School of Economics for guidance throughout the writing process, as well as key insights on the application of his research.

♠ **40708@student.hhs.se**

♣ **22658@student.hhs.se**

Table of Contents

1 Introduction

A distressed firm that has a high likelihood of failing would be expected to deliver relatively higher returns to its shareholders to compensate for the increased risk. Although this view appeals to the intuitive trade-off between risk and return, some researchers have found a negative relationship between distress risk and stock returns (Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008; Avramov, Chordia, Jostova and Philipov, 2009). The findings are puzzling considering existing theories of capital asset pricing.

Research examining the behavior of stock returns and risks build on the theories of Markowitz (1952) and Ross (1976), who suggested that only systematic risk factors influence the returns of diversified portfolios of assets. In addition, individual asset returns can also be affected by unsystematic risk factors. In other words, investors are thus mainly exposed to a risk component that cannot be diversified. Dichev (1998) highlights how the theory relates to distress risk as follows:

"The risk of bankruptcy is systematic only if it is undiversifiable…Thus, bankruptcy risk is systematic only if the returns of distressed firms are more sensitive to unexpected changes in relevant economy-wide factors."

The quantification of risk in the domain of capital markets is important, particularly as it is a pre-requisite for allowing available capital to flow to investments in the economy. As a result, the topic remains actively debated; particularly in the context of academia. While representations of risk in the form of factors deployed in multifactor asset pricing models constitute the leading attempts to capture variations in asset returns, consensus is yet to be reached (Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015; Fama and French, 2015).

Early asset pricing models seeking to encompass all types of risks in a single factor (Sharpe, 1964; Black, 1972) have been preceded by various studies using multiple factors, of which some have sought to capture distress risk in different ways, e.g. through the use of credit ratings (Avramov, Chordia, Jostova and Philipov, 2009). Others have sought to capture distress risk by means of incorporating several traditional bankruptcy prediction models with various other measures in attempts to explain stock returns (Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008; Asness, Frazzini and Pedersen, 2014).

This paper aims to answer the question of whether distress risk, i.e. the risk of business failure, is captured in stock returns.

We extend previous literature by: i) adding additional evidence to the debate surrounding the existence of a distress anomaly, ii) using an alternative definition of distress risk to explain variations in stock returns, iii) making use of an alternative data set. The use of Nordic data offers a new angle to previous studies seeking to explain variations in stock returns, given that most of them are based on US-data (Dichev, 1998; Fama and French 1992, 1995, 1996 and 2015). With the study, we also hope to highlight the overlap of a wide range of accounting ratios commonly used to capture risks driving stock returns.

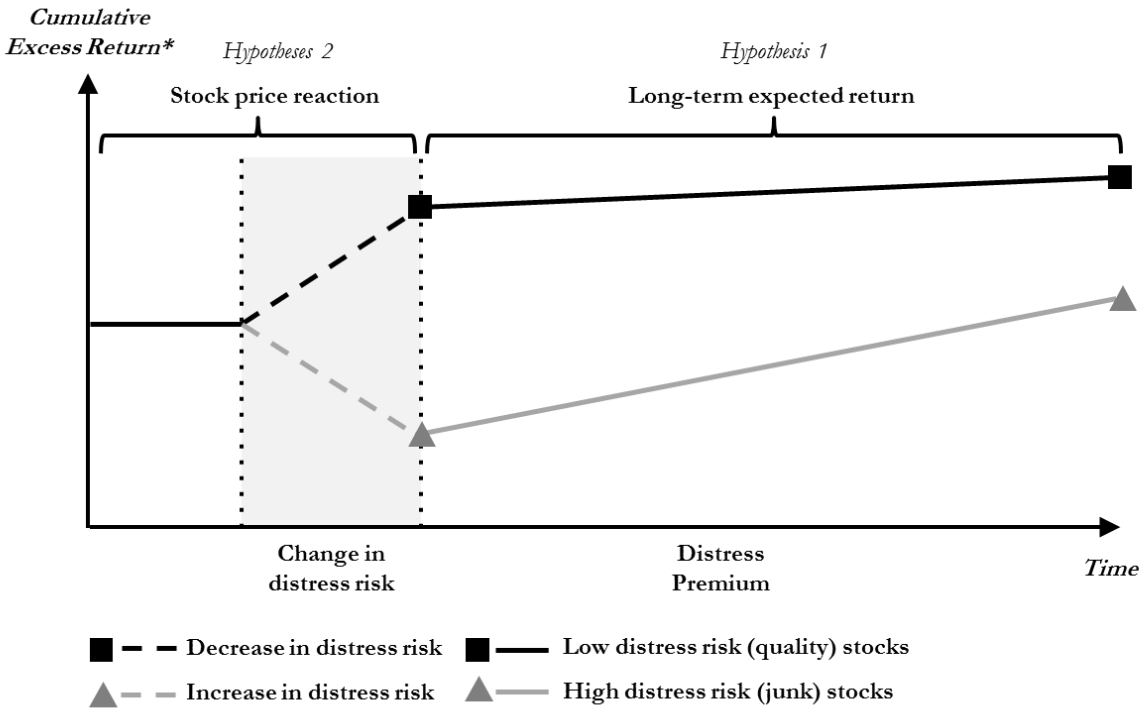
As part of our study, we perform portfolio analysis, cross sectional regression analysis and an event study on a data set containing 926 firms currently or previously listed on the four major Nordic exchanges. Outcomes support evidence presented by similar studies suggesting the market does not reward higher return to stocks with higher distress risk (junk stocks) over time (Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008). Rather, results suggest firms with lower levels of distress risk (quality stocks) tend to outperform junk stocks over time (Asness, Frazzini and Pedersen, 2014). Finally, we do however find strong evidence suggesting that the market re-prices stocks whose distress risk has increased or decreased beyond expectation as information becomes publically available (Dichev and Piotroski, 2001).

2 Hypotheses

This thesis seeks to study whether the risk of business failure is captured in the return variations of stocks. In other words, we are interested in understanding to what extent the market has priced in the probability of failure into firm valuation. We present several hypotheses to study the relationship between the risk of business failure and stock returns to guide the thesis as follows:

> **1)** Firms with a higher risk of business failure will deliver higher stock returns, on average, than firms with lower risk of business failure.
>
> **2 a)** As new information regarding the risk of business failure of a particular firm becomes publically available; the market will re-price stocks whose distress risk has changed beyond market expectations.
>
> **2 b)** The direction of the stock price reaction will correspond to the direction of the change in distress risk. An increase in distress risk will lead to a negative stock price reaction, and vice versa.
>
> **2 c)** The magnitude of the stock price reaction will correspond to the magnitude of the change in distress risk. A large change in distress risk will correspond to a large stock price reaction, and vice versa.

Figure 1: Overview of expected stock market behavior implied by the hypotheses. The figure presents the anticipations underlying this paper's hypotheses. At the event of a change in distress risk, we expect to see firms with an increase (decrease) in distress risk to display a negative (positive) stock price reaction. Finally, we expect junk stocks to outperform quality stocks over time, to compensate for the heightened distress risk. *Excess Return is assumed to have been adjusted for co-variance (market beta) risk, size, value, profitability and investment, but not for distress risk (see Data Section 4 and Method Section 5 for more information).



For the sake of clarity, the first hypothesis seeks to establish whether the market rewards stocks with higher levels of distress risk with higher returns. In other words, the first hypothesis tests whether distress risk is a systematic risk. The traditional risk-return paradigm would suggest that the rational investor expects to earn higher returns for taking on additional risk in the form of distress, and leads us to expect junk stocks should outperform quality stocks over time (Markowitz, 1952). As this relationship is reviewed over time, it will be tested by means of a portfolio analysis, as well as a cross sectional multiple regression analysis.

The second hypothesis seeks to establish whether the market correctly re-prices stocks whose distress risk has increased or decreased beyond expectation. If we consider once more traditional theories of risk and return, a rational investor would demand a lower price for a stock whose distress risk has increased while its expected flow to equity remains constant. Similarly, the same investor would be willing to pay a higher price for a stock whose distress risk has decreased while expected flow to equity remains constant (Markowitz, 1952; Skogsvik, 2006). As this relationship is reviewed by looking at stock price developments around the publication of information surrounding distress risk, it will be tested by means of an event study.

The approach adopted in this thesis is not to isolate all independent sources of common variation in stock returns. Rather, we will use an observable proxy for distress in the form of the probability of failure, and measure whether it is capable of explaining part of the variation in stock returns. The construction of data variables is described in section 4 and methodology is described in section 5.

3 Previous Research

3.1 Introduction to Previous Research

Building on modern portfolio theory, previous research has sought to explain asset pricing and returns using different proxies for risk; shaped by the capital asset pricing model ("*CAPM*") developed by Sharpe (1964) and Black (1972). Patterns of stock return have later been identified that are not properly explained by the CAPM and the market beta, commonly referred to as market anomalies. Anomalies have in turn been scrutinized and debated heavily in search for an appropriate measure of risk, a debate that is still on-going where the academic community is yet to reach an agreement.

Studies led by Fama and French (1992, 1995, and 1996) sought to capture anomalies by introducing additional representations of risk in multi-factor models. The studies of Fama and French highlight the importance of our research area as they attribute stock return to fundamental performance variables such as earnings and financial leverage. More recently, studies led by Asness, Frazzini, Israel, Moskowitz and Pedersen (2015) seek to reconcile empirical irregularities by quantifying risk as the relative level of quality or the inverse ("junk") of stocks and the returns associated with each (Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015).

At the same time, a separate set of studies have sought to empirically identify firms likely to experience business failure by making use of accounting information expressed as ratios reflecting financial performance (Skogsvik and Skogsvik, 2013). By means of probit/logit analysis, bankruptcy prediction models such as that of Skogsvik (1990) have been specified, capable of implying a probabilistic association between accounting numbers and business failure. Notably, some studies have made use of one or several bankruptcy prediction models to test whether distress risk explains the variation in stock returns (Dichev, 1998; Griffin and Lemmon, 2002; Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015).

The following sections describe different representations of risk used in previous literature, including those used in conventional bankruptcy prediction models. The last part covers the methods used by previous research. Readers may find Appendix 1,2 and 3, containing outlines of common asset pricing models and the various representations of risk in each, to be helpful when looking to grasp the general theoretical background to capital asset pricing (see Section 9.1).

3.2 Relationship between Risk and Return

The trade-off between risk and return is based on the notion that a rational investor would demand higher returns from an investment that has higher risks and vice versa. In other words, an investor, assumed to be risk averse, would only accept higher risk if compensated with higher returns. By using the standard deviation of returns as a proxy for risk, Markowitz (1952) demonstrated how a portfolio of assets can generate the same returns as individual assets while having a lower risk. According to the theory, so long as individual asset returns are not perfectly correlated, unsystematic risk (i.e. risk related to individual assets) can be diversified. Conversely, systematic risks (i.e. risks common to all assets) cannot be diversified.

Building on portfolio theory, Sharpe (1964) and Black (1972) developed a model used to explain asset-level returns rather than that of the market portfolio. Widely recognized and applied in practice, the CAPM continues to be used to describe the expected return of capital assets in market equilibrium by means of a univariate linear relationship. According to the model, risk is captured solely by the market beta factor β_i, intended to explain the variations in stock returns using the sensitivity of each individual asset's return to that of the overall market portfolio. In other words, the CAPM states that the required return of an asset is linked only to systematic, non-diversifiable risks as opposed to the stand-alone risk of individual assets. While being consistent with the theories of Markowitz (1952), most applications of the CAPM have identified empirical irregularities suggesting the market beta factor does not fully capture the risks explaining variations in stock returns.

3.3 Anomalies

After its inception, researchers began identifying various stock return patterns that could not be explained by the CAPM. In practice, such patterns presented anomalies of a certain group of stocks producing excess returns over and above returns adjusted for risk using the market beta in the CAPM. The emergence of anomalies sparked an academic debate regarding the choice of an appropriate risk measure used to explain variations in stock returns, as well as arguments questioning the efficiency of modern stock markets (Ball and Brown, 1986). Anomalies are important in the context of this thesis as they may suggest there is room for alternative representations of risk to explain stock returns.

The relationship between firm size (market capitalization) and returns (i.e. that smaller firms tend to outperform larger firms) is one of the anomalies that emerged when using the CAPM to explain stock returns. The relationship was initially studied by Banz (1981) and subsequently re-visited in various academic studies (Chan, Chen and Hsieh, 1985; Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015). In his study of returns on stocks quoted on the NYSE between 1926 and 1975, Banz presented empirical evidence suggesting smaller firms have higher risk-adjusted returns, on average, than larger firms ("the size effect"). Banz (1981) argued that the size effect is evidence of the misspecification of the initial model developed by Sharpe (1964) and

Black (1972). Subsequent studies led by Fama and French (1992), argue that the size effect could be a proxy for other unidentified risks that typically characterize smaller firms. Such an interpretation would suggest that traditional asset pricing models such as the CAPM require empirically determined risk variables other than the market beta defined above to explain the variations in stock returns.

Similar to the size effect, Basu (1983) noted a systematic difference in returns between stocks with high earnings' yield and stocks with low earnings' yield. His empirical findings suggest that stocks with high earnings' yield earn, on average, higher risk-adjusted returns than stocks with low earnings' yield. This is referred to as the earnings-to-price (E/P) effect. The anomaly persists even after controlling for firm size. Basu concludes that the E/P effect is, much like firm size, likely to be a proxy for more fundamental determinants of expected returns.

Rosenberg, Reid and Lanstein (1985) found statistically significant abnormal returns when following a strategy that buys stocks with high book-to-market (B/M) ratios and sells stocks with low B/M ratios. In their study, they control for several representations of fundamental firm characteristics such as financial leverage, dividend yield, growth, size as well as the market beta. Fama and French (1992) later cite their findings as evidence of a value premium.

In another study on US firms, Bhandari (1988) found that the debt-to-equity ratio (defined as the book value of assets less the book value of equity divided by the market value of equity) is positively associated with stock returns, having controlled for firm size and the market beta factor. The study suggests that the empirical results are a reflection of the fact that a firm with a higher debt-to-equity ratio experiences "*an increased risk to its common equity*", and that this risk is in turn captured in stock returns.

The notion that firms would generate excess risk-adjusted returns, i.e. that anomalies such as those mentioned are not reflected in the market beta, has several implications that vary depending on how results are interpreted. One interpretation considers anomalies as evidence of market inefficiencies and could be used to dismiss the efficient market hypothesis (Ball and Brown, 1968). An alternative interpretation suggests that traditional asset-pricing models are misspecified (Banz, 1981; Fama and French, 1992; Chan, Chen and Hsieh 1985). The latter interpretation implies there may be other, more accurate representations of risk to use instead or in combination with the market risk captured by the CAPM.

3.4 Representations of Risk

The CAPM attempts to capture risk by measuring an asset's correlation to a single factor; the excess returns of the market portfolio. According to the CAPM, residual risk is not awarded any return. However, anomalies suggest some unspecified risks are not captured by the market portfolio and may be represented by means of other factors. The Arbitrage-pricing theory (APT) suggests asset returns can be modelled linearly by making use of more than one factor (Ross, 1976).[1]

The APT assumes markets are perfectly competitive and frictionless (i.e. that there are no transaction costs), much like the CAPM. However, the APT differs in that it models stock returns on several macroeconomic factors rather than an efficient portfolio of assets. The model hence seeks to attribute variations in stock returns to fundamental risks faced by a firm by including multiple representations of risk into the asset pricing model.

Following the emergence of market anomalies, research primary led by Fama and French (1992, 1995 and 1996), sought to explain stock returns using multivariate models. In addition to the CAPM market beta factor, other risk factors were included to capture the risk-return patterns of anomalies. Common examples of additional representations of risk include firm size, value, leverage, growth and earnings yield; intended to serve as proxies for unidentifiable risks.

Chan, Chen and Hsieh's (1985) study sought to explain the size effect by identifying alternative factors for which size could be a proxy. In their study, they hypothesize that stock prices react primarily to changes in the economic environment. To test their hypothesis, they use a set of economic risk factors to explain stock returns and study whether the size effect persists when taking these risks into account. The economic risk factors used include real growth in industrial production, unanticipated inflation, term risk (captured by the difference in short term vs. long-term rates) and a risk premium. Chan, Chen and Hsieh (1985) choose to define the risk premium as the high yield corporate bond spread, i.e. the difference in returns between a portfolio of high yield bonds and a portfolio of long-term government bonds. They argue that their empirical findings (that a substantial portion of the size effect is explained by the risk premium alone) are further evidence that firm size is really a proxy for other unidentified risks.

The use of bond spreads as a proxy for risk and its explanatory power is important in the context of this paper. Although described as being meant to capture business risk and business cycles, the inherent element of credit risk in such a measure could be used to support the notion of using bankruptcy prediction models to explain variations in stock returns.

---

[1] The Arbitrage Pricing Theory multifactor model developed by Ross (1976) is specified as follows:

$$E(\tilde{R}_i) = R_f + \beta_{i1}RP_1 + \beta_{i2}RP_2 \dots + \beta_{in}RP_n$$

Where,

$E(\quad) = expected\ operator$

$\tilde{R}_i = return\ on\ asset\ i\ for\ the\ period$

$R_f = return\ on\ a\ riskless\ asset\ for\ the\ period$

$RP_n = risk\ premium\ ascribed\ to\ a\ macroeconomic\ factor$

In their 1996 study, Fama and French argue that factors used to reflect the size effect and the value premium are proxies for 'relative distress'[2]. For example, they note that firms with higher B/M ratios (i.e. those whose returns load positively to the HML factor) are firms that have persistently produced low earnings, generated little cash and experienced low levels of growth. In the same way, firms that are smaller tend to generate higher risk-adjusted returns (i.e. those whose returns load positively to the SMB factor). The use of the word 'distress' is again no coincidence and implicitly points to the characterization of risk as that of the inability of a firm to pay dividends (i.e. deliver return) to its shareholders and ultimately the risk of business failure. Despite attributing the behavior of various risk factors partially to distress risk, Fama and French (1996) do not include explicit measures of distress into the multi-factor model they specify. Although their model makes use of accounting ratios somewhat different to those predominantly used in bankruptcy prediction models (the main difference being the use of market-based measures which may give rise to correlation to stock return variations) there is merit in understanding the usefulness of bankruptcy prediction models in explaining excess stock return.

Dichev's (1998) study presents one of the earliest attempts at making use of existing bankruptcy prediction models to test whether distress risk is captured in stock returns. By adding a distress factor using either Altman's Z-Score (1968) or Ohlson's O-Score (1980) to a cross sectional multiple regression including a size and value factor[3], his study seeks to establish whether distress risk is indeed a systematic risk as theories of risk and return would suggest. The findings of his study point to the contrary; firms with higher risk of failing are not rewarded with higher returns, but actually earn lower-than-average returns. This anomalous and surprising evidence is confirmed by Campbell, Hilscher and Szilagyi (2008) who employ similar methodology to test variations in stock returns, albeit with a separate bankruptcy prediction model specified as part of their study.

In a more recent study including a multivariate asset pricing model, Asness, Frazzini, Israel, Moskowitz and Pedersen (2015) respond to the multiple challenges made to the size effect in recent years that suggest it is; i) weak when using other measures than market capitalization, ii) weak internationally, iii) concentrated around the smallest stocks and iv) primarily resides in

[2] The Fama and French three-factor model (1996) is specified as follows:

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

Where,

$E(\tilde{R}_i) - R_f = expected\ excess\ return\ of\ asset\ i$

$[E(\tilde{R}_m) - R_f] = expected\ excess\ return\ on\ the\ market\ portfolio$

$(SMB) = the\ difference\ in\ return\ between\ a\ portfolio\ of\ small\ and\ large\ stocks\ respectively$

$(HML) = the\ difference\ in\ return\ between\ a\ portfolio\ of\ high\ and\ low\ book-to-market\ stocks$

$\beta_i, S_i, H_i = sensitivity\ of\ the\ excess\ return\ to\ the\ various\ market\ premium\ operators$

[3] The model used by Dichev (1998) including the Z and O factors respectively, is specified as follows:

$Rets = \beta_1 + \beta_2(Z\ or\ O) + \beta_3(MV) + \beta_4(B/M)$

January. Their study makes use of an alternative measure of distress they denote "junk" (or the inverse of quality) by means of constructing a factor based on a wide range of accounting ratios reflecting a firm's profitability, growth, safety and payout respectively (Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015). The factor, called quality-minus-junk ("QMJ"), is constructed by going long high-quality stocks and short junk stocks. The QMJ factor produces significantly positive returns, having controlled for risk using four other risk factors (market beta, size, value and momentum[4]) taken from previous research. While the results are puzzling in the sense that higher risk (defined here as lower quality) is not compensated with higher returns, Asness, Frazzini and Pedersen (2014) suggest the results could be consistent with the mispricing of risk. An alternative explanation provided is that results point to a flight to quality, given the strong performance of the QMJ factor during market downturns. Notably, Altman's Z-Score and Ohlson's O-Score are amongst the variables used to construct the factor within the 'safety' category. The use of such scores adds to the relevance of bankruptcy prediction factors used in the context of explaining stock returns (Asness, Frazzini and Pedersen, 2014)[5].

In an attempt to evaluate common representations of risk and their relationship to bankruptcy prediction models, the following sections review theory and empirics related to different representations of risk.

3.4.1 Size

Theory

Small firms are often associated with experiencing higher levels of risk than larger firms. Empirical studies of the size effect generally recognize size as a proxy for other fundamental risks to performance (Fama, 1976, as cited in Berk, 1995; Fama and French, 1992). For example, Chan, Chen and Hsieh (1985) argue that small firms are more exposed to risks in their production. Similarly, Chan and Chen (1991) argue that the performance of smaller firms (and hence their earnings prospects) is more sensitive to economic downturns than that of larger firms. According to their study, small size may in turn be the result of poor fundamental performance:

"…in a competitive economy with continuing technological changes, firms that become relatively inefficient or have higher costs will decrease in relative size. While a more efficiently run firm may do well and even prosper if the aggregate economy is growing slowly, a less efficiently run firm may not survive a low growth rate for very long."

[4] Investing in past winners, i.e. stocks that have experienced positive returns recently.

[5] The model used by Asness et al. (2015) including the QMJ factor is specified as follows:

$E(\tilde{R}_i) - R_f = \beta_i[E(\tilde{R}_m) - R_f] + S_i(SMB) + H_i(HML) + U_i(UMD) + ST_i(STREV) + Q_i(QMJ)$ Where,

$(UMD) = the\ difference\ in\ return\ between\ a\ portfolio\ of\ previous\ winner\ and\ loser\ stocks$

$(STREV) = as\ with\ the\ UMD\ factor\ but\ for\ just\ the\ most\ recent\ month\ rather\ than\ t-12\ to\ t-2$

$(QMJ) = quality\ minus\ junk\ factor\ based\ on\ ratios\ of\ profitability, growth, safety\ and\ payout$

$U_i, ST_i, Q_i = sensitivity\ of\ the\ excess\ return\ to\ the\ various\ market\ premium\ operators$

Similarly, firm size may have implications on access to (and hence the cost of) capital, where smaller firms are often associated with more restricted access to credit relative to larger firms. Furthermore, smaller firms may be disadvantaged by a relatively shorter history of operating performance and relatively weaker bargaining power with its partners. Investors may find that small firms disclose less information and have less liquid securities.

Empirics

Research on asset pricing including a risk factor for size tend to measure size using market capitalization (Fama and French, 1992). In his critique of the size anomaly, Berk (1995) argues the use of the measure is problematic given its direct relationship to riskiness in cashflows. He does however agree it is suitable for predicting stock returns for the very same reason:

"Assume that all firms in the economy are exactly the same size; that is, assume that the expected value of every firm's end-of-period cashflows is the same. Since the riskiness of each firm's cashflows is different, the market value of each firm must also differ...riskier firms will have lower market values and so, by definition, will have higher expected returns."

Asness, Frazzini, Israel, Moskowitz and Pedersen (2015) revisit the size effect and find that a significant size premium remains when using non-price measures for size (e.g. book value of assets, equity, PP&E or sales) when controlling for the relative quality of the firm. By introducing the QMJ as a distress factor, their study distinguishes between factor loadings relating to size and distress risk respectively. Their findings highlight the importance of distress risk in the context of stock returns.

A distinguishing feature of bankruptcy prediction models in the context of size is that they tend to exclude an explicit categorization of size altogether (Bellovary, Giacomino, and Akers, 2007). Rather, they tend to make use of financial performance indicators that can be comparable across firms regardless of size. Fundamental risks associated with smaller firms may arguably be captured in the other measures used in bankruptcy prediction models.

3.4.2 Value

Theory

Value stocks are those that trade at a price lower than their fundamental value. As a result, expected returns on value stocks are likely to be higher than stocks priced at or above fundamental value. Given the relationship between risk and return, this may imply that value stocks carry higher risk. As such, representations of value may be used as a proxy for other unidentifiable risks not captured in the market portfolio. This view is held by authors that argue the returns in value stocks are warranted by higher fundamental risk in such firms, reflected through poor earnings, poor earnings prospects and high financial leverage (Chen and Zhang, 1998; Fama and French, 1992). Other authors however, argue that investor behavior and contrarian investment strategies[6] explain the value stock premium and that this is in fact not a representation of risk (Lakonishok, Shleifer and Vishny, 1994).

Measuring value involves the use of both market-based and accounting-based measures, where the former is often used to reflect firm value as ascribed by the market, while the latter is used to reflect fundamentals (for example in the B/M ratio). While both types reflect financial performance, the relationship between these two types of measures is a source of academic debate (Gentry and Shen, 2010). Some authors argue the measures differ in the sense that the former reflects future financial performance while the latter reflects past financial performance. Others argue that market-based measures carry an implicit assumption of efficient markets (i.e. that market value is equal to the present value of the expected cash flows accruing from the firm). This relationship is important in the context of this thesis when considering factors that operationalize value risk.

Empirics

Previous literature commonly operationalizes characteristics of value by means of factors reflecting a relationship between fundamental firm value and/or performance and market value. The multifactor asset pricing model of Fama and French (1992) uses the B/M factor; relating the book value of a firm to its market value. Other examples include the earnings-to-price factor (Basu, 1983) relating the earnings of a firm to its market value, or similarly the cashflow-to-market factor (Nai-Fu and Zhang, 1998).

Other proxies may be used to reflect value. For example, Asness, Frazzini and Pedersen (2014) demonstrate how Gordon's growth model can be used as a framework for developing relevant measures to reflect value. By re-writing the model to reflect the B/M ratio, they identify separate components that can be used to reflect similar risk. As such, measures of distributions made by the firm such as equity and debt payout ratios are examples of alternative representations of value.

Market-based measures such as share price and market capitalization are not widely used in bankruptcy prediction models that tend to rely on accounting numbers (Bellovary, Giacomino, and Akers, 2007; Skogsvik, 1990; Altman, 1968). The absence of market-based measures in bankruptcy prediction models could be interpreted as support for B/M ratios capturing distress risk. Consider a scenario where an investor seeks to ascribe value to the assets of a distressed firm. A rational investor would not be willing to ascribe a market value that is substantially higher than the book value of the assets if the firm is distressed. This would result in a relatively high B/M ratio. The example illustrates how distress risk could be captured in the B/M ratio.

[6] Investing in past losers, i.e. stocks that have experienced negative returns recently.

3.4.3 Leverage

Theory

The level of indebtedness of a firm has several implications on risk and return. A firm funded with debt is obliged to deliver return and repayment to debt holders prior to equity holders, putting pressure on core earnings, thus reducing cash flows available for dividend payments (Penman, 2009). Debt repayment may also reduce the ability of a firm to make investments in growth opportunities. Furthermore, an indebted firm becomes directly exposed to interest rate risk.

Conversely, leverage can also generate additional value to shareholders. For example, debt can prove to be a relatively cheap source of funding and may allow firms to invest at a faster pace in the short run. Furthermore, Miller and Modigliani (1963) showed in their theorem that when taking taxes into consideration, debt funding can generate value through the tax-deductibility of interest. However, the same theorem suggests higher levels of debt in relation to equity funding increases required return on equity, given the higher risk involved for shareholders in a firm with debt.

Empirics

Despite its relationship to risk and shareholder returns, research seeking to explain the variation in stock returns has historically made limited use of risk factors directly representing firm indebtedness. Examples of earlier attempts to capture indebtedness by means of proxy variables include the use of high yield bond spreads by Chan, Chen and Hsieh (1985).

Recent studies make important contributions by using proxies for leverage as risk factors to explain variations in stock returns. Avramov, Chordia, Jostova and Philipov (2009) make use of conventional credit ratings issued by Moody's as a proxy for credit risk. Their study provides puzzling evidence suggesting that firms with low credit risk (i.e. higher credit ratings) generate higher stock returns than firms with high credit risk (i.e. lower credit ratings). Their results remain even after having controlled for firm size, value and momentum. Avramov, Chordia, Jostova and Philipov (2009) suggest results are explained by the fact that their study centres on the event of credit downgrades. Hence, the study becomes crucially dependent on credit cycles where stocks with receiving ratings downgrades experience large, negative returns reflected in the cross section.

Another important aspect of their study is the use accounting ratios to control for fundamental firm performance, where interest coverage ratios are used to capture the risk of high levels of indebtedness. They find that firms experiencing ratings downgrades tend to display deteriorating fundamental performance. As such, the results of their study suggest downgrades may have already been anticipated and priced into stock returns (Avramov, Chordia, Jostova and Philipov, 2009).

The construction of the QMJ factor by Asness, Frazzini and Pedersen (2014) is another important example of a recent study using several proxies for leverage to describe stock returns. Their study defines junk stocks as those displaying weak fundamentals as outlined by the Gordon Growth Model, and makes use of several proxies for leverage within the 'safety' dimension (see Appendix 2). Leverage is defined as total debt including minority interests and preferred shares over total assets. The factor also makes use of the Altman Z-Score and the Ohlson O-Score, indirectly including the abovementioned proxies for indebtedness through the two bankruptcy prediction models. The QMJ factor is particularly important in the context of this thesis, as it is an example of a study that makes use of bankruptcy prediction scores to describe stock returns.

Bankruptcy prediction models typically make frequent use of various measures reflecting the indebtedness of a firm to predict business failure. This is less surprising given the relationship between high levels of leverage and the risk of a firm not being able to meet its obligations. In their review of various bankruptcy prediction models, Bellovary, Giacomino, and Akers (2007) highlight examples of key ratios used across various models. Common financial ratios include Net Worth to Debt, Current Ratio, Working Capital to Total Assets and Net Income to Total Debt. The latter ratio was found by Beaver (1966) to have 92% accuracy in predicting corporate failure one year prior to failure. Other examples include Altman's (1968) use of an inverse debt-to-equity ratio (Market Capitalization / Book Value of Total Debt) and Ohlson's (1980) use of liability ratios reflecting both gearing and cash coverage (Total Liabilities / Total Assets; Funds from Operations / Total Liabilities). Skogsvik (1990) captures the risk of indebtedness by reflecting both the cost of liabilities and gearing through separate ratios (Interest Expense / Total Liabilities; Equity / Total Assets). The model also includes a normalized measure of the cost of liabilities, using data on interest expense over four historical periods.

Finally, Campbell, Hilscher and Szilagyi (2008), who specify their own bankruptcy prediction model to explain the pricing of financially distressed stocks, make use of several accounting ratios designed to reflect the risk of high levels of indebtedness. One example is the Total Liabilities / Market Capitalization + Total Liabilities ratio. Similarly to Ohlson (1980), they also use the Total Liabilities / Total Assets ratio. An important difference of their study includes the adjustment of Total Assets in all measures by adding a fraction of the difference between the market value and the book value to total assets. The adjustment is meant to capture asset-light firms.

3.4.4 Earnings

Theory

The variability of earnings presents a key risk to shareholders, given its direct impact on the firms' ability to deliver returns to its shareholders. Earnings, particularly those generated by core operations, thus presents a key driver of firm value (Penman, 2009). Re-organizing the dividend discount model offers an appealing mathematical relationship between firm value and expected future earnings[7] that the theoretical-minded reader may find appealing. The relationship shows that a firm that has higher future expected earnings should, all else equal, have a higher market value (Fama and French, 2015). In other words, investors and creditors to firms with higher risk to their future earnings will demand higher returns. Alternatively, firms with higher risk to their earnings bear a higher risk of becoming distressed.

The empirical challenge of the theoretical implications of future earnings on current stock price lies in finding a suitable proxy for future earnings. Parsimonious models of forecasting commonly use historical accounting earnings information to forecast future earnings (Ball and Brown, 1968; Skogsvik, 2008). Thus, different measures reflecting current profitability are likely candidates for proxies for future earnings.

Empirics

Following the findings of Basu (1983), researchers seeking to describe stock returns have historically focused on capturing earnings yield (i.e. earnings in relation to price) rather than earnings alone as factors in asset pricing models. Note that this measure captures the relative cheapness of a stock rather than its future expected earnings. However, recent models have appeared that make use of explicit measures of profitability as a proxy for future earnings in order to capture earnings risk. For example, the QMJ factor by Asness, Frazzini and Pedersen (2014) includes profitability measures such as Gross Margin, pre-tax ROA and after-tax ROE. Similarly, Fama and French (2015) found that their original three-factor model performs better when including a profitability factor, operationalized as pre-tax ROE[8].

Earnings risk and profitability is commonly reflected by means of different accounting ratios in many conventional bankruptcy prediction models (Bellovary, Giacomino, and Akers, 2007). The most common proxies for profitability include pre- and post-tax ROA, ROE and Net Margin and are utilized by several studies to capture earnings risk (Altman, 1968; Ohlson, 1980; Skogsvik, 1990). The recent study by Campbell, Hilscher and Szilagyi (2008) that seek to capture distress risk in stock returns also chooses to include a profitability measure (post-tax ROA) in the bankruptcy prediction model constructed as part of the study.

[7] Please refer to the re-organized version of the dividend discount model on page 2 (formula (3)) offered in the recent paper by Fama and French (2015)

[8] The five-factor model of Fama and French (2015) including the ROE factor is specified as follows:

$$E(\tilde{R}_i) - R_f = \beta_i[E(\tilde{R}_m) - R_f] + S_i(SMB) + H_i(HML) + R_i(RMW) + C_i(CMA)$$

Where,

$$(RMW) = difference\ between\ returns\ on\ robust\ vs.weak\ stocks\ ranked\ by\ operating\ profitability$$

$$Operating\ Profitability = \frac{Rev_t - Cogs_t - SG\&A_t - Interest_t}{Book\ Value\ of\ Equiy_{t-1}}$$

$$(CMA) = difference\ between\ returns\ on\ high\ (aggressive) and\ low\ (conservative)\ investing\ firms$$

$$Investment = \frac{Total\ Assets_{t-1} - Total\ Assets_t}{TotaL\ Assets_{t-1}}$$

Comparing proxies for future earnings in asset pricing models and bankruptcy prediction models respectively highlights an important relationship between earnings, distress risk and firm valuation. As suggested by Asness, Frazzini and Pedersen (2014), a firm with high future earnings is a high quality firm, and is as such expected to command a high price for its stock. At the same time however, a firm with high earnings is also characterized as a safe firm (i.e. the opposite of distressed) in many bankruptcy prediction models seeking to quantify distress (Altman, 1968; Ohlson, 1980; Skogsvik, 1990). In other words, strong earnings prospects is considered an indicator of low levels of distress risk, and firms with lower levels of risk should not prompt higher returns according to the traditional risk-return paradigm. While this observation may in itself seem counter-intuitive, consider the implications of distress risk on future earnings. A firm with higher levels of distress has a higher risk of seeing its forecast earnings falling short of expectations. A firm with identical earnings prospect and lower levels of distress should, all else equal, be awarded a higher valuation. Fundamental valuation models that take distress risk into account offer a theoretical explanation to this intuition (See Section 3.4.6).

3.4.5 Growth

Theory

A firm's ability to grow revenues, increase margins and ultimately earnings is a critical driver of valuation and hence, a firm's ability to deliver shareholder returns. Penman (2009) defines a growth firm as one that "grows residual earnings – that is, has abnormal earnings growth", emphasizing that growth is only value accretive when increasing earnings over and above the required return on the book value of equity. As growth requires investment, which in turn requires financing (that may include more or less leverage), it becomes clear that there are many ways to represent risks related to growth.

Empirics

Research studying stock return patterns has tended to identify risks in growth stocks by comparing them to value stocks. For example, Fama and French (1992) define growth stocks as the inverse of value stocks by using the B/M and E/P ratios as proxies. Their study suggests that firms with low B/M ratios and low E/P ratios are typical of growth stocks.

More recent research has sought to include explicit measures of growth to describe stock returns. For example, growth is one of the four dimensions used to define the QMJ factor (Asness, Frazzini and Pedersen, 2014). Their study makes use of five different accounting ratios that are all various representations of growth in profitability. Examples include growth in return on equity and gross margin growth. Fama and French (2015) find that their model performs better when adding a factor capturing the levels of investment made by a firm, where growth in the book value of assets is used as a proxy.

Bankruptcy prediction models commonly use different indicators of growth to reflect fundamental business risks. Ohlson (1980) measures growth through earnings by using a scaled measure for change in Net Income. Skogsvik (1990) looks at growth in the book value of equity, capturing both earnings growth and changes in capital structure over time. Laitinen (1991) captures growth by calculating growth in assets.

3.4.6 Distress

Theory

In line with previous research, we consider distress as a continuous state during which a firm is approaching insolvency (see Section 3.7.2). Firms in distress are subject to various effects likely to have an adverse impact on their ability to generate cashflows (i.e. returns) to their shareholders. These effects are directly or indirectly caused by the limited access to funds that a firm approaching insolvency will, by definition, have. For example, a distressed firm risks losing suppliers (customers) who fear to deliver (take delivery) of goods or services produced by the firm, particularly by means of credit. Similarly, a distressed firm may be forced to forego NPV-accretive investment opportunities. Furthermore, a distressed firm is likely to experience an increase in funding costs of both equity and debt, putting further pressure on access to funding.

Penman (2009) highlights how such effects can be captured in various accounting ratios that in one way or another result in a reduction of future residual earnings. Examples include declining sales, margin deterioration, and inventory build-up and reduced return on investment. The difference between the underlying cause of such financial deterioration and its effects is often unclear, as one enforces the other. Penman (2009) describes how different forces interact to cause distress:

"*A fall in sales reduces net operating asset growth and asset turnovers. The fall in asset turnover reduces return on net operating assets, which reduces the operating spread. Operating creditors may reduce credit, reducing operating liability leverage, and borrowing costs may increase because of lower profitability. These effects compound to reduce residual earnings and the compounding effect can cause considerable distress, or even failure.*"

Distress is thus likely to be caused by the intercommunion of several risk factors facing businesses, continuously reinforcing one another.

The impact of distress risk on equity returns may be less intuitive, as shareholders (unlike creditors) have no pre-determined returns to expect and are, by definition, residual claimants (Vassalou and Xing, 2004). Fundamental valuation models that incorporate the risk of business failure may offer theoretical foundations for such intuition. Skogsvik (2006) illustrates how valuation models can be adjusted to accommodate for probabilities of business failure.

A numerator approach allows for period-specific failure probabilities to be incorporated into flow to equity valuations. Expected flow to equity, being conditioned on firm survival, can be treated with the relevant probability of failure for the period in question to become unconditional. We find that treating expected flow to equity with the probability of failure causes a reduction in cashflows and hence, in firm valuation, offering an intuition that appeals to the traditional risk-return paradigm. In other words, a rational investor will be willing to pay less to acquire a firm whose expected flow to equity are exposed to a higher probability of failure in order to achieve the same required return. Alternatively, all else equal, the value of a firm would increase (decrease), should the probability of failure turn out to be lower (higher) than what was initially expected. Skogsvik (2006) illustrates the mathematical relationship by means of a fundamental PVED valuation, where net dividends are unconditional on firm survival as follows (assuming a recovery rate of zero in the case of failure):

$$V_0 = \sum_{t=1}^{T} \frac{\left(1 - p_{fail}\right)^t * E_0(NDIV_t^*)}{(1 + r_E)^t} + \frac{\frac{(1 - p_{fail})^T * E_0(NDIV_T^*)}{r_E - g_{ss}}}{(1 + r_E)^T}$$

Where,

$NDIV_t^* = D_t + R_t - N_t$, conditioned on firm survival

$D_t = Dividends\ paid\ at\ date\ t$

$R_t = Repurchase\ of\ own\ shares\ made\ at\ date\ t$

$N_t = New\ equity\ issues\ made\ at\ date\ t$

$r_E = required\ rate\ of\ return\ for\ an\ equity\ investment$

$g_{ss} = earnings\ growth\ in\ steady\ state$

A denominator approach calls for adjusting the rate with which expected flow to equity are discounted to accommodate for the probability of business failure. This approach lends itself well to how risk is considered in cash flow based models where the discount rate (often operationalized as a weighted average cost of capital where equity cost of capital is priced using the CAPM) captures risk to equity holders by means of an equity risk premium (Sharpe, 1964; Black, 1972). While this method presents a limitation in that it assumes a constant probability of business failure, it offers parsimonious application as follows:

$$V_0 = \sum_{t=1}^{T} \frac{E_0(NDIV_t)}{(1 + r_E^*)^t} + \frac{\frac{E_0(NDIV_T)}{r_E^* - g_{SS}^*}}{(1 + r_E)^T}$$

Where,

$r_E^* = \frac{r_E + p_{fail}}{(1 - p_{fail})}$ is the failure-adjusted required rate of return for an equity investment

and,

$NDIV_t = D_t + R_t - N_t$

$D_t = Dividends\ paid\ at\ date\ t$

$R_t = Repurchase\ of\ own\ shares\ made\ at\ date\ t$

$N_t = New\ equity\ issues\ made\ at\ date\ t$

$g_{SS}^* = earnings\ growth\ in\ steady\ state$

Skogsvik (2006) illustrates how both applications can be made to the present-value-of-expected-dividends (PVED) valuation model, as well as the residual-income-valuation (RIV) model, amongst others[9]. Fundamental valuation models incorporating probabilistic business failure predictions offer intuitive reasoning as to why investors should demand higher returns, over time, from firms whose cashflows are exposed to higher levels of distress risk, and vice versa.

Empirics

Accounting-based distress measures are well-established and tend to be parsimonious in their application. The use of such measures is frequent in studies looking to test whether distress risk is captured in the variation of stock returns. For example, Dichev (1998) makes use of Altman's Z-Score (1968) and Ohlson's O-Score (1980) to act as a proxy for distress. Similarly, Griffin and Lemmon (2002) make use of Ohlson's O-Score. Campbell, Hilscher and Szilagyi (2008) specify their own accounting-based bankruptcy prediction model using a set of financial ratios similar to those used in previously established bankruptcy prediction models.[10]

The frequent use of accounting-based distress measures suggest they serve their purpose well. However, the reliance of such measures on leverage ratios presents a notable limitation they have in common. This is because leverage ratios are often not applicable on businesses that rely heavily on leverage as part of their business models; e.g. financial or real estate firms. Furthermore, accounting-based measures do not capture the volatility of a firm's assets when estimating default, which some research cites as a limitation (Vassalou and Xing, 2004). Market-based measures of distress tend to overcome such limitations.

[9] Readers interested in more detailed illustrations of how to incorporate probabilistic business failure predictions into discounted cash flow valuations will find Skogsvik's working paper "Probabilistic Business Failure Prediction in Discounted Cash Flow Bond and Equity Valuation" contains many examples of practical applications. The paper is available as part of a working paper series issued by the Stockholm School of Economics.

[10] The ratios used by Campbell, Hilscher and Szilagyi (2008) to predict bankruptcy include:
Net Income to Market-valued Total Assets (NIMTA), Net Income to Total Assets (NITA), Total Liabilities to Market-valued Total Assets (TLMTA), Total Liabilities to Total Assets (TLTA), Cash and Short-term Assets to Market-valued Total Assets (CASHMTA), Market-to-Book (MB), Monthly log excess return on firm equity relative to the S&P 500 (EXRET), Standard deviation of stock returns over the previous 3-months (SIGMA), log market capitalization relative to log capitalization of the S&P 500 (RSIZE) and log price per share truncated above $15 (PRICE).

Merton (1973) made use of the put-call parity relationship present in fundamental option pricing models to develop an alternative market-based methodology for measuring distress risk. The method assumes that the value of firm equity equals the value of a European call option on the firm's assets. Default is in turn defined as the moment when asset value falls below the face value of debt (i.e. equity value becomes negative). With option-pricing methodology, the model can back solve expected asset value and compare it to firm debt. The Distance-to-Default measure ascribes a probability of failure to a firm by measuring the number of standard deviations the firm's value is away from default. Notably, Vassalou and Xing (2004) find that the measure can be used to establish a positive relationship between the risk of default and stock returns, arguing that default risk is indeed to be considered systematic.

Alternative methods for calculating distress risk are available in the bond market. Bond ratings or credit spreads are frequently used as a proxy for the risk of business failure (Dichev and Piotroski, 2001; Vassalou and Xing, 2004; Avramov, Chordia, Jostova and Philipov, 2009).

As a final remark, we recognize that the explicit use of an accounting-based measure to reflect distress risk may be highlighted as a key limitation of this study. We consider the use of alternative measures of distress as one of several areas suggested for further research (see Section 7).

3.5 How different risk factors are related

Albeit useful to the reader, the separation of the different representations of risk outlined above is misleading. They are more likely to be overlapping representations of other unspecified risks. Previous research, including studies of market anomalies, highlights such interrelatedness. For example, Banz (1981) suggests the E/P effect is obsolete when controlling for size, thus concluding it can be considered a proxy for size. Similarly, Fama and French (1992, 1995) note that firms with low B/M ratios tend to have poor earnings. Chan, Chen and Hsieh (1985) find that small firms are more likely to be distressed. Nai-fu and Zhen (1998) not only use both size and B/M to identify value stocks, but suggest that different levels of financial distress, leverage and earnings uncertainty are all representations of value. Chan and Chen (1991) highlight that smaller firms tend to have more levered capital structures as a result of being the product of past poor performance. More recently, Vassalou and Xing (2004) conclude that the size anomaly is a distress-anomaly as it only exists within firms that have the highest level of distress risk.

What the different representations have in common is that they in one way or another reflect various fundamental value drivers of a firm. If we consider future earnings as one such fundamental value driver, some measures can be thought of as reflecting a firm's ability (or lack thereof) to meet its financial obligations, e.g. its operating expenses or financing costs. If we follow this logic, it is likely that one or several of the measures capture different dimensions of distress risk (Fama and French, 1992; Vassalou and Xing, 2004).

3.6 Information and Stock Price Behavior

Up until this point, we have to a greater extent considered risk factors that are likely to drive the behavior of stock prices. However, we have to a lesser extent considered whether information on such risks is appropriately reflected, accessed and acted upon across capital markets. Fama (1970) highlights the relationship between information and stock prices in his review of efficient capital markets:

"A market in which prices always 'fully reflect' available information is called 'efficient'."

In other words, if markets are "fully efficient", we would expect stock prices to increase (decrease) immediately, and with the appropriate magnitude, when new positive (negative) information surrounding a firm is made public. Collectively called the Efficient Market Hypothesis, the hypothesis that markets are efficient and securities are priced according to their fundamental value underpins (and is either implicitly or explicitly assumed) much of modern asset pricing literature (Fama, 1970)[11]. Investors can, and are assumed to, act on changes in risk when they are informed of them. This notion begs to question how information is defined and what type of information is likely to impact stock prices. In his study on the information content of earnings announcements, Beaver (1968) posits:

"A firm's earnings report is said to have information content if it leads to a change in investors' assessment of the probability distribution of future returns, such that there is a change in equilibrium value of the current market price."

Thus, only information that changes investor's perception of the future performance of the firm is likely to prompt a price response. The reaction of stock prices to information disclosures of different kinds has been researched extensively. Ball and Brown (1968) examined how investors react to accounting earnings information. They find that while accounting information is useful, its information content is limited by the time of its announcement, as much of its impact occurs prior to announcement. Bernard and Thomas (1989) offer further evidence suggesting stock prices continue to drift post-earnings announcement. Bartov, Lindahl and Ricks (1998) look at the announcement of negative information in the form of write-offs and find that the event is generally both preceded and followed by large stock price declines. Haugen (2002) conducted several studies criticizing the efficient market hypothesis and existing asset pricing models. Haugen's argument builds on the earlier findings of De Bondt and Thaler (1985), suggesting that the market tends to overreact to past performance by pricing stocks of successful firms too high and pricing stocks of unsuccessful firms too low. The argument offers an alternative explanation to the behavior of stock prices of different types of firms. Relatively cheap (value) stocks outperform not because they are risky, but because the market corrects its initial overreaction to

[11] Fama (1970) classified three degrees of market efficiency. Strong form efficiency hypothesizes that prices reflect all public and private information. Semi-strong form efficiency implies that only public information is reflected in stock prices. Finally, weak form efficiency describes a market where stock prices are based on historical prices alone.

its performance, causing investors to become pleasantly surprised, and vice versa (Haugen, 2002). Finally, Skogsvik (2008) found that a zero-net trading strategy that goes long stocks with a predicted increase in future ROE and goes short stocks with a predicted decrease in future ROE generates significant positive abnormal returns. Skogsvik's findings confirm previous research asserting that accounting information is useful when determining stock prices (Skogsvik, 2008).

We note that the direction of stock price reactions to different informational disclosures rests on whether investors perceive the information to be positive or negative (Beaver, 1968). In other words, the anticipation of stock price reactions relies on expectations of certain investor behavior. Recall that traditional portfolio theory assumes investors to be risk-averse, meaning that given two investments with the same expected return, a rational investor will seek the less risky one. Conversely, an investor will only take on further risk with the promise of higher expected returns (Markowitz, 1952). If we follow this logic, rational investors receiving information that the risk of a firm has increased would, all else equal, attribute a lower value to the firm. In other words, an increase in distress risk, assuming unchanged projected flow to equity, ought to be perceived as negative information by the rational investor. This logic underpins hypothesis 2 a), b) and c) in Section 2.

Evidence brought forward by Holthausen and Leftwich (1986) supports the abovementioned logic, suggesting that the announcement of bond rating downgrades is associated with negative abnormal stock returns. However, they also find that the negative abnormal returns remain in the quarter following the announcement, which may indicate a drift rather than a reversal in the post-event period. Dichev and Piotroski (2001) find similar results for bond rating downgrades, but add evidence of abnormally low returns up to 3 years after downgrade announcements. Glascock, Davidson and Henderson (1987) also find a negative stock price reaction around the announcement of bond rating downgrades. However, in line with what we anticipate in hypothesis 2, they find a significant return reversal in the quarter after the announcement.

3.7 Methods of Previous Research

3.7.1 Stock Performance

Why Reduce Risk into Factors?

At this stage it might be interesting to elaborate further on why one should search for different representations of risk that can explain variations in stock returns. A simple way to address risk would be to take into account the covariance matrix as dictated by Markowitz (1952). However, there are benefits to adopting risk through a limited number of factors, since an asset's sensitivity to a specific risk factor may be more stable than its sensitivity to the return of the market portfolio. Thus, one can control an asset's risk more reliably by handling its exposure to these risk factors. Furthermore, by narrowing down the number of risk parameters to take into consideration, it may become simpler to improve returns as one can focus on estimating fewer risk parameters (Kritzman, 1993).

Portfolio Analysis

Several studies exploring the relationship between distress risk and stock return perform similar versions of portfolio analysis (Dichev, 1998; Griffin and Lemmon, 2002; Campbell, Hilscher and Szilagyi, 2008). The method involves sorting firms into portfolios based on the value of the independent variable (risk factor) subject to investigation and calculating mean returns of each portfolio. The method has gained widespread popularity as it illustrates economic significance and can reveal potential nonlinearities between the dependent and independent variable (Dichev, 1998). The estimation of portfolio means may also reveal relationships between the test variable and other independent (control) variables. The method can be refined by conducting a second sorting criterion within the initially constructed portfolios, also known as two-sorts (Vassalou and Xing, 2003).

Factor Analysis vs. Cross Sectional Regression Analysis

Kritzman (1993) distinguishes between two different approaches of isolating risk factors in the search for common sources of return variation. The first approach is called factor analysis and enables isolation of factors by observing common variations in stock returns. Factor analysis shows the covariation in returns and is appropriate when the goal is to identify all the different sources of this covariation. It involves grouping stocks into portfolios and testing to determine whether these portfolios can partly be explained by a set of common factors. However, even if such factors are found, it is not certain that they are definable and can be interpreted. Factors may reflect a mixture of perhaps even offsetting influences, that are specific to the sample and time period of study. Hence, factors resulting from factor analysis may not be persistent over time and/or across different samples. To conclude, even if we can account for almost all of a sample's common variation in return through factor analysis, we might not be able to say as much about the meaning of the identified factors (Kritzman, 1993).

The second approach is called cross sectional regression analysis. In contrast to factor analysis, where the goal is to identify all sources of return covariation, it instead requires the sources of return covariation to be pre-specified, and subsequently tests whether these sources explain differences in return. In other words, cross sectional regression analysis is appropriate when the goal is to determine the amount of return variation that a set of independent risk factors can explain. Based on intuition and previous research, one hypothesizes attributes that are believed to explain variations in stock returns. An attribute is a measure of sensitivity to some underlying factor. Once attributes are determined, the stock returns are regressed against the attribute values for one time period. Then this regression is repeated over all the time periods of study. If the coefficients of the attribute values are nonzero and a sufficiently high number of the regressions are significant, it can be concluded that the variation in stock returns are related to the variation in their attribute values. In order to test if a coefficient is significant in a certain regression one can calculate the coefficient's t-statistic, which equals the value of the coefficient divided by its standard error (Kritzman, 1993).

The Fama-MacBeth Cross Sectional Regression Methodology

One particular method that has been used within the area of cross sectional regression analysis is the Fama-MacBeth (1973) approach (Fama and French, 1992; Carhart, 1997; Dichev, 1998). It is important to distinguish between the Fama-MacBeth cross sectional regression and the Fama-MacBeth two-step regression. The latter includes a set of time-series regressions for each asset or portfolio prior to that of the cross sectional regressions. The two-step regression methodology, however, is only applied when factor-mimicking portfolios are constructed (Fama and French, 1992). What the Fama-MacBeth cross sectional regression analysis does is to determine the risk premium rewarded by the market for different types of risks. Similar to the coefficients of the attribute values in the cross sectional regression analysis (in the previous section), these risk premiums suggest that the investigated risks explain variation in stock returns. A requirement for that suggestion is that the risk premiums are significantly different from zero.

Event Study

An alternative way of testing the relationship between risk and return is to form an event when information of a firm's specific risk status becomes publically available. By doing so, one can investigate whether a certain event is associated with stock price reaction, as well as the informational content of the news surrounding the event. Among previous studies that have adopted this methodology Ball and Brown (1968) is frequently cited. They show how the announcement of firms' earnings is related to stock price reactions. The explanatory power, and hence usefulness, of such studies is dependent on how significant the abnormal returns are for a firm's stock around the event (Kothari, Lewellen and Warner, 2006). Studies commonly include a pre- and post-event period, since the stock price reaction to the announcement of new information might not be immediate and correct as suggested by Bernard and Tomas (1989) as well as Bartov, Lindahl and Ricks (1998).

MacKinlay (1997) investigates various types of event studies and highlights a number of important steps to consider when conducting one. Key considerations include the definition of an event, portfolio construction, choice of abnormal return metric, cross sectional aggregation of abnormal return, and time series aggregation of abnormal return. When defining an event, it is often the case that the event window is larger than the event itself. This enables exploration of price effects around the event as well. Even though the importance of aligning the portfolio construction with the question of research is not to be underemphasized, these first two considerations are relatively straight forward compared to the other three. Alternative ways of handling them will be elaborated on in the remainder of this section.

Abnormal return is widely recognized as the difference between realized return and expected return. As there are different ways of measuring expected return, it is important that the model used to calculate expected returns is correctly specified. Additionally, conclusions about market efficiency might be sensitive to the choice of abnormal return metric (Skogsvik, 2008). Hence, it is important to be aware of potential implications of a certain metric.

MacKinlay (1997) distinguishes between economic and statistical models in the context of calculating expected returns. The former is however not absent from statistical assumptions, and include models such as the CAPM and the Market-adjusted Return Model, which in contrast to the CAPM also controls for additional firm characteristics such as size and value. The Constant Mean Return Model and the Market Model are two of the most widespread statistical models (MacKinlay, 1997). These models are absent from economic restrictions and are solely based on statistical assumptions. Economic models are preferable when data availability is limited or a pre-event estimation period is not possible. Without an estimation period, the model coefficients must be pre-specified. MacKinlay (1997) suggests that such models are only to be applied when necessary, as the pre-specified model coefficients may cause biases. Among the statistical models, the Constant Mean Return Model is the simplest model. Even so, Brown and Warner (1980) argue that it often gives similar results as more sophisticated models. However, MacKinlay (1997) argues that the Market Model is preferable, as it eliminates the amount of return that is related to the variation in market return. The Market Model is another example of a univariate statistical factor model. Additional factors could potentially be included in the Market Model; however, the gain of doing so is limited. This is based on the fact that the marginal explanatory power of additional factors to that of the market is small (MacKinlay, 1997). Hence, the reduction in variance of abnormal returns is small.

The cross sectional aggregation of abnormal returns involves the calculation of means at each point in time. This implies that each time period may contain different amounts of observations. For an event that lasts for one time period, the significance of that time period's average abnormal return is the foundation for the event's explanatory power (Kothari and Warner, 2006). However, an event may stretch for longer than one time period and there might be suspicion regarding the presence of a lag or lead in the stock price reaction, why a pre-event and post-event period may be included. Consequently, a time series aggregation of the average abnormal returns may be useful. A more frequently used method for doing this is calculating cumulative abnormal returns (MacKinlay, 1997). However, an alternative method is to form an abnormal performance index (Ball and Brown, 1968). This latter method makes it easier to compare how different portfolios perform over time, since they begin from a joint starting point.

3.7.2 Bankruptcy Prediction

Definition of failure

Defining business failure is important in the context of seeking to capture distress risk. Research on bankruptcy prediction models tend to specify different, albeit related definitions of failure. According to Beaver (1966) failure is defined as:

"the inability of a firm to pay its financial obligations as they mature", continues;

"…*operationally, a firm is said to have failed when any of the following events have occurred: bankruptcy, bond default, an overdrawn bank account, or non-payment of a preferred stock dividend"*

Campbell, Hislcher and Szilagyi (2008) make an explicit separation between bankruptcy and failure when defining distress in their own specification of a bankruptcy prediction model. Similarly, Vassalou and Xing (2004) define distress risk explicitly as the risk of a firm defaulting on its debt. While these definitions capture many indicators of distress, they are by no means exhaustive. Skogsvik (1990) adopts a different definition of failure in his study. In addition to i) legal bankruptcy and/or a composition agreement, he defines failure as ii) the voluntary shut-down of the primary production activity of a firm, as well as iii) the receipt of a substantial subsidy provided by the state. The expanded definition is explained by the sample used in the study (Swedish manufacturing firms) and that government subsidies were common during the time period of study. What the definitions have in common is that they seek to capture a state of insolvency of a firm. In line with Skogsvik (1990), we will adopt a wider definition of failure and consider distress as a state where a firm is approaching any of the abovementioned types of insolvency.

Dichev (1998) highlights the practical implications of bankruptcy for firms whose shares are publicly listed. A listed firm filing for bankruptcy may never delist its shares from an exchange; or do so substantially later than its bankruptcy filing date. Conversely, a delisting can occur for several reasons other than bankruptcy. The definition of failure adopted by Skogsvik (1990) suggests its model is not likely to run into classification problems based on a firms' listing status and is as such considered suitable for the purposes of this study.

Bankruptcy prediction models

Bankruptcy prediction models seek to identify firms likely to enter into any of the defining events of failure outlined above by measuring their financial performance. Most studies make use of financial ratios to measure firm performance. By so doing, research on bankruptcy prediction seek to provide an empirical verification of the usefulness (i.e. predictive ability) of accounting data (i.e. financial statements), in line with what Beaver (1966) argues in his study. As summarized by Bellovary, Giacomino and Akers (2007), a wide range of bankruptcy prediction models have quite high predictive abilities.

The Bureau of Business Research attempted in 1930 to find common characteristics of failing firms, as they studied 29 firms using 24 accounting ratios. Each firm's ratios were compared to the average ratios of all 29 firms that were investigated. The study found that some 8 ratios were good indicators of a firm's "growing weakness"[12]. Two years later FitzPatrick (1932) made a comparison of ratios in successful and failed firms. His findings suggested that successful firms displayed better financial performance relative to failed firms when comparing a set of standard ratios (FitzPatrick, 1932). Up until 1966 most research on bankruptcy prediction looked quite similar to that of FitzPatrick's (1932) study, including some investigation of accounting ratios for a set of firms and highlighting how the ratios differed between successful and failed firms respectively. Firms were often compared within the same industry.

Beaver (1966) conducted a study including 30 ratios and 158 firms (of which 50 % were firms that fail) across 38 industries. Similar to previous research, he compared the average ratios between the failed and successful firms. However, in contrast to previous research, he also investigated the ratios' ability to predict whether a firm would fail or not. His study was a univariate discriminant analysis (UDA), meaning that the financial ratios were tested separately after which a cut-off point was determined for each ratio in order to maximize the number of correct classifications for the specific sample. The proportion of incorrect classifications suffered from two limitations. The first involved the probability of misclassifying a failed firm (Type 1 error). The second involved the probability of misclassifying a non-failed firm (Type 2 error). These errors are general for bankruptcy prediction models and are important to keep distinct due to the fact that the probability of failure for the population might differ from that of the sample. As a result, Beaver argues that a comparison of total errors (i.e. Type 1 and Type 2 errors aggregated) is not very meaningful.

Altman (1968) picked up on what Beaver (1966) left as suggestions for future research, namely multi-ratio analysis; where more than one ratio is used simultaneously to predict failure. Altman developed a five-factor bankruptcy prediction model using multivariate discriminant analysis (MDA). The output, or Z-Score, in Altman's model predicted the probability of failure for a firm given that the Z-Score fell within a certain range. This is similar to the cut-off point used in Beaver's UDA. Classifications are made by observing whether the score falls within the pre-determined cut-off points established on the basis of the initial sample, where the cut-off points ($Z<1.81$, the "distress zone" and $Z>2.99$, the "safe zone") are those that best separate failed from non-failed firms. Due to the importance of distinguishing Type 1 and Type 2 errors, Altman established a range of outputs ($1.81 < Z < 2.99$, the "zone of ignorance") where users ought to proceed with caution, as prediction errors may frequently occur within that range (Altman, 1968).

[12] *The ratios were Working Capital/Total Assets, Surplus and Reserves/Total Assets, Net Worth/Fixed Assets, Fixed Assets/Total Assets, Current Ratio, Net Worth/Total Assets, Sales/Total Assets and Cash/Total Assets*

Following Altman (1968), a number of studies using MDA were made during the 1970's, e.g. Blum (1974). Ohlson (1980) noted problems with previous bankruptcy prediction models that his study could address by means of using logit analysis. Firstly, he argued that using matched samples based on common firm characteristics was problematic. For example, discriminant analysis often uses samples that pairs failed and surviving firms according to size and industry. Ohlson (1980) argues that such characteristics could rather be viewed as predicting variables of failure. This argument is in line with multi-factor asset pricing models including size as a proxy for unidentifiable risks. Furthermore, the argument supports findings in studies that suggest firm size may be a proxy for distress (Fama and French, 1995, 1996; Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015). Secondly, Ohlson (1980) criticizes the necessity of making assumptions regarding prior probabilities of failure and for the distributional properties of the predictors. He argued that his logit model addresses the abovementioned issues with discriminant analysis.

More recently, Skogsvik (1990) specified a bankruptcy prediction model using probit analysis. The sample used was based on Swedish manufacturing firms and showed that the predictive ability of current cost accounting (CCA) ratios was very similar to that of historical cost accounting (HCA) ratios. Skogsvik's study is relevant for this paper, considering its use of a data set containing Nordic firms.

Similar to logit analysis, probit analysis considers a firm's probability of going bankrupt. Both methods use similar statistical methods that apply a non-linear s-shaped curve (rather than the straight line used for simple regressions) to produce statistical relationships and generate similar results. A distinguishing factor (and arguably a strength) of bankruptcy prediction models specified using probit/logit analysis is their ability to infer a probabilistic association between the independent variables and the outcome variable. Previous methods discussed (i.e. UDA and MDA) on the other hand; do not offer estimations of bankruptcy probabilities (Ohlson, 1980).

4 Data and Variables

4.1 Data Acquisition

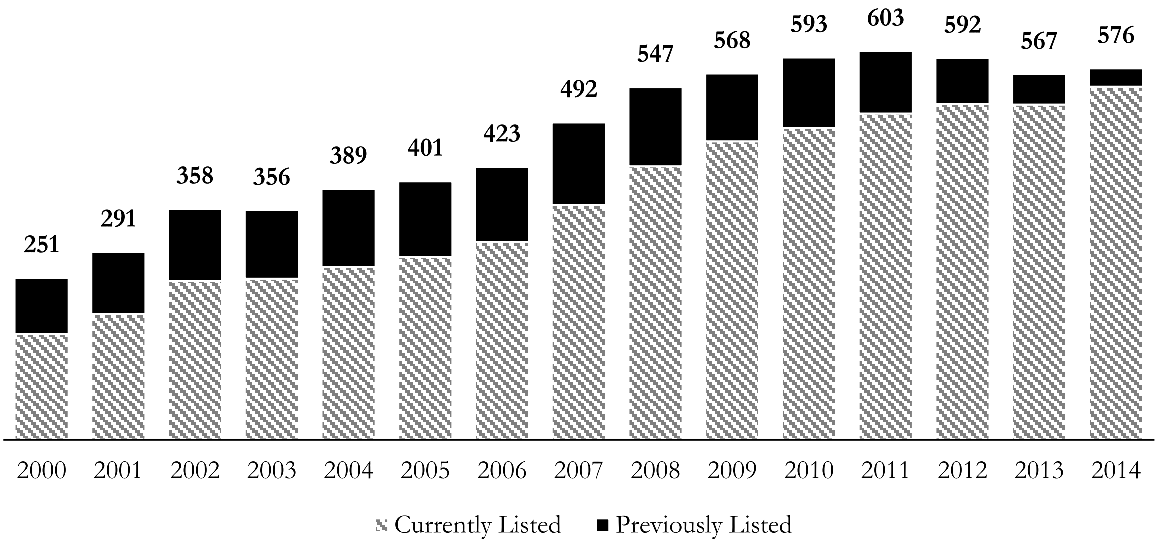
To test the hypotheses, data on 926 firms across four Nordic exchanges is acquired. The exchanges are Nasdaq OMX Stockholm (Sweden), Oslo Bors (Norway), Nasdaq OMX Copenhagen (Denmark) and Nasdaq OMX Helsinki (Finland). Data availability limits the time period of study, which extends from 2000 through 2014. Due to time matching criteria, requiring the independent variables to be publically known before the dependent variable, data is assembled from December 31, 1999 through June 30, 2015. Out of the total sample of firms, 640 are currently listed, while 286 firms have previously been listed during part of the time period covered by the sample. Important to note is that previously listed firms include those that have been delisted by means of choice (i.e. a take-private) or by means of being an acquisition target. Firms that have gone bankrupt are included in this group of firms as well.

Limiting the data set to Nordic firms is supported by several factors. Firstly, the data set is unique in the context of previous literature seeking to use distress risk in order to explain variation in stock returns. Secondly, the data set benefits from the Nordic region housing stock markets with a long history and many market actors, where trading is liquid in relation to many other European Exchanges. Thirdly, the data set is suitable for the use of bankruptcy prediction models other than the traditional models of Altman (1968) and Ohlson (1980) that are based on data sets of US firms. The Skogsvik (1990) probit model, based on Swedish manufacturing firms, is likely to be particularly suitable for the chosen data set.

Information on the firms for the final set of events is acquired from the S&P Capital IQ database, which pools data and analytical capabilities across over 50,000 firms globally. We use an excel interface of the database that allow us to download data directly into spreadsheets and update as needed. While S&P Capital IQ constitutes the primary source of data, the sample is complemented using the Thomson Reuters DataStream database. The use of an additional database is justified by the availability of a list of previously listed firms, something that Capital IQ does not provide. However, the list of previously listed firms is then used in Capital IQ, where the actual data on the previously listed firms is available. This may help us avoid potential discrepancies between acquiring the same variables from different databases. The previously listed firms included in the data set are important given that some of the firms that may have gone bankrupt are part of this group.

Data required to test the hypotheses consists of i) key line items from financial statements used to calculate relevant ratios ii) monthly and yearly stock prices to determine return for firms and the markets, and iii) other country-specific data such as government debt rates. The cross section of stocks in the final sample contains a total of 7,007 observations. The number of firms and hence observations increase over time as follows:

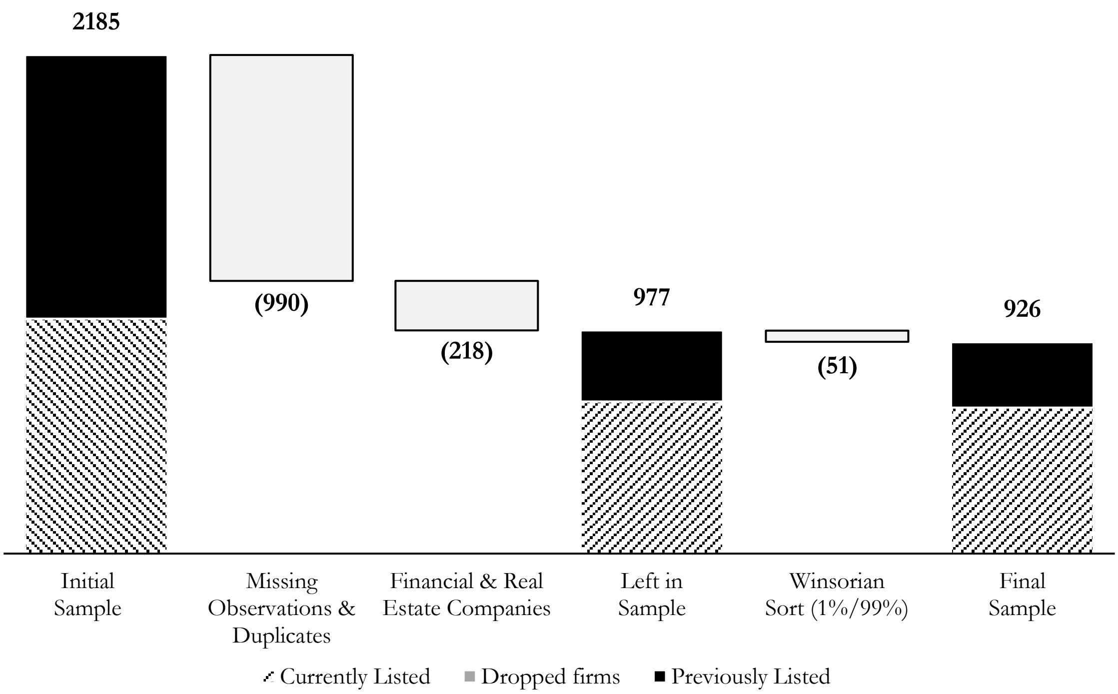
Figure 2: Number of observations by year and listing status. The figure presents descriptive statistics that illustrate the distribution of observations during the years 2000 – 2014 split by listing status. The total amount of observations is 7,007, which constitutes the final sample.



All yearly financial statement items gathered are the latest available at the end of each year. The yearly market-based measures, i.e. market beta and market capitalization, are collected at the end of June each year. This has to do with matching purposes in the portfolio and regression analysis, which will be gone through more thoroughly further on in this paper. For the monthly observations, relevant for the event study, data is obtained by the end of each month.

The final sample of 926 firms is a result of a number of sample limitations. The initial sample included 2,185 securities across the four exchanges. The first limitation of the sample involved removing duplicate securities and missing observations. This incorporates removing securities where the full set of accounting data required to perform the tests in this paper is not available. The second limitation involved the scope of the applied bankruptcy prediction model of this paper, i.e. Skogsvik's (1990) pfail. Why it is not applicable on all industries will be elaborated on in section 4.3.1, but as a consequence of its limited scope, financial and real estate firms are removed from the sample. The third and final limitation involves winsorizing the investigated variables at the 1% and 99% level over the entire panel. Due to some extreme observations causing irregularities when analyzing average values, this last sorting step is necessary.

Figure 3: Refining of data set. The figure illustrates the process of refining the whole data set, starting from the initial sample of 2,185 firms and ending up at the final sample of 926 firms. In the first refining step, duplicates refer to firms that have class A shares and class B shares. Missing observations refers to firms where insufficient information is available to fill all test variables needed in the cross section.



4.2 Dependent Variable and Definition of Excess Return

This paper looks to explain the variations of excess stock returns in the cross section. In line with Fama and French (1996) we define excess return as:

$$E(\widetilde{R_i}) - R_f$$

Where,

$E(\widetilde{R_i}) = actual\ returns\ of\ stock\ i\ in\ the\ cross\ section\ over\ period\ t \rightarrow t + 1$

$R_f = risk\ free\ rate, the\ average\ \ treasury\ bill\ rate\ of\ relevant\ country\ during\ period\ t$

To test our first hypothesis, we measure yearly stock returns stretching from July 1 through June 30 the following year. These are analyzed in the portfolio and regression analysis, which are explained in the method section. To test our second hypotheses, we measure monthly stock returns based on end of month prices.

The risk free rate used to express excess returns is defined here as the rate of the government issued Treasury bill for each country of the respective exchanges covered in the data set. The period (1-month and 12-month respectively) represents a reasonable holding period for equity investments and matches the duration of the stock returns measured in each test. Government debt rates are frequently used as a proxy for risk-free rates in similar studies (Fama and French, 1995, 2015). Data on government rates is acquired through the central bureau of statistics or the central bank of each respective country represented in the data set. Given the relative maturity of the Swedish capital markets in the Nordic region, data on Swedish rates span the furthest back. For data missing on the early years of some of the other Nordic markets, the Swedish rate has been used as a Nordic proxy.

4.3 Independent Variables and Explanatory Factors of Risk

4.3.1 Distress Risk

Skogsvik (1990) developed a probit model to predict the probability of a firm failing a certain year using balance sheet and income statement based ratios. The model can be used to predict failure up to six years prior to failure. However, the accuracy decreases as the time of the lead increases. The Skogsvik V-score one year prior to failure is defined as follows:

$$V = -1.5 - 4.3 \cdot R_1 + 22.6 \cdot R_2 + 1.6 \cdot R_3 - 4.5 \cdot R_4 + 0.2 \cdot R_5 - R_6$$

Where,

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

$$R_2 = \frac{Interest\ Expense_t}{(Liabilities\ \&\ Deferred\ Taxes_t + Liabilities\ \&\ Deferred\ Taxes_{t-1}) \div 2}$$

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

$$R_4 = \frac{Owners\ Equity_t}{Total\ Assets_t}$$

$$R_5 = \frac{(Owners\ Equity_t - Owners\ Equity_{t-1})}{Total\ Assets_t}$$

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

and, $\bar{\bar{R}}_{2,t-1} = \sum_{\tau=t-4}^{t-1} R_{2,\tau} \div 4$

$t = year$

From a broad set of 71 historical cost accounting ratios, Skogsvik (1990) found that the above ratios have the highest predictive ability of distress. Mainly, two notions support the use of this bankruptcy prediction model in front of other more frequently used ones such as the Altman Z-Score and Ohlson O-Score (Dichev, 1998). First, the V-score can be converted directly into a probability of failure in contrast to the Altman Z-Score, which rather provides an indication of high probability of failure when the Z-Score falls below a certain level. This is due to the fact that the Skogsvik's (1990) study is based on a probit model, while Altman's (1968) study is based on a

MDA. Second, the Z-Score and O-Score are estimated on US data, while the V-score is estimated on Swedish data. As Skogsvik's (1990) model represents the only bankruptcy prediction model conducted on Swedish data, we consider it more appropriate for our Nordic data set, considering that OMX Stockholm is largest among the four stock exchanges that constitute our sample. A bankruptcy prediction model based on Norwegian or Danish data is yet to come (Bellovary, Giacomino and Akers, 2007). Skogsvik's (1990) study was also estimated solely on manufacturing firms. Since leverage is an important part in the determination of the V-score, Skogsvik's model is not applicable on firms where leverage is a central part of the business model. Hence, financial and real estate firms are excluded from our sample.

Even though there are benefits with using Skogsvik's prediction model, there are important aspects to take into account before interpreting the results. The model was estimated over the time period 1966 to 1979 on Swedish data. Hence, a potential bias might be present due to different accounting standards over time and across the countries included in this study.

4.3.2 Market Beta

The market beta measuring individual firms' market risk is estimated for each point in time using a 52-week rolling window regression. The inclusion of market beta in the regression analysis allows both for testing its relationship with distress risk, but more importantly allows for the study to determine whether the probability of business failure has explanatory power over and above that of conventional market beta. The market beta is defined:

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

Where,

$\beta_i = Market\ exposure\ of\ stock\ i$
$R_i = Excess\ return\ for\ stock\ i$
$R_m = Return\ for\ market$

4.3.3 Value

In their studies of stock price behavior and returns, Fama and French (1992, 1995) find that a book-to-market ratio BE_{t-1}/ME_{t-1} captures part of the cross section of average stock returns with statistical significance. Furthermore, their study explains the previously unidentified risk captured by the B/M ratio reflected in varying stock returns. Their findings, that high B/M ratios signals low earnings and that low B/M stocks typically are more profitable provides a relationship between the ratio and fundamental performance, supporting rational pricing theories. Therefore, we choose to include the B/M ratio as a separate factor in the regression sought to explain excess stock return. The inclusion is justified by the ratio's predictive ability, its relationship with earnings as well as its potential to increase the robustness of the pfail factor we primarily look to test in this paper.

4.3.4 Size

Based on the findings of Banz (1981), various studies have identified a relationship between firm size and returns as a market anomaly, potentially representative of a different, unidentified source of risk commonly present in smaller firms (Chan, Chen and Hsieh, 1985; Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015). As such, the definition of a relevant proxy variable for size will be important when testing for the predictive ability of pfail. This study defines size as the market capitalization of each stock, $MCAP_{t-1}$, in line with similar studies (Fama and French, 1996; Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008). Albeit commonly used, this measure must be used with care given its implicit relationship to stock return. Asness, Frazzini, Israel, Moskowitz and Pedersen (2015) highlight the findings of Berk (1995) that caution any misspecification of the traditional asset pricing model will be captured in a size measure reflected using market capitalization as a result of this relationship. Consequently, Berk makes use of other common non-price measures as his proxies for size. Such measures include book value of assets and sales (Berk, 1997). However, this paper seeks to remain consistent with the findings of Asness, Frazzini, Israel, Moskowitz and Pedersen (2015) that shows that size, defined as market capitalization, remains an unidentified proxy for risk when controlling for the relative distress risk of the firm in question.

4.3.5 Additional Explanatory Factors

We argue there is further merit to test the predictive ability of other individual accounting ratios in the cross section. While Skogsvik's probit model makes a non-linear association of such ratios to assess the probability of failure, ratios can be added to a linear regression used to explain stock return as additional factors. The inclusion of such ratios may also reveal potential interdependencies with Skogsvik's pfail. Recent studies have made similar use of ratios in different ways. Campbell and Thompson (2008) showed that various accounting ratios reflecting profitability, payout and financing could be used to predict stock returns on US firms using out-of-sample approach and restricted regressions. Fama and French (2015) found that adding accounting ratios representing profitability and investment to their multivariate factor model, the explanatory power improved compared to their original three-factor model. Asness, Frazzini, Israel, Moskowitz and Pedersen (2015) made use of their QMJ factor in a multi-factor model seeking to explain stock return, where the factor, based on Gordon's growth model, makes use of numerous accounting ratios designed to reflect quality characteristics.

Building on the approach of the abovementioned research, we will add two ratios to the previously mentioned three risk factors. These two ratios, supported by Fama and French (2015) five-factor model, help us capture profitability and investment in our analysis.

Proxy for profitability, ROE_{t-1} defined as $\frac{Net\ Income_t}{(Owners\ Equity_t + Owners\ Equity_{t-1}) \div 2}$

Proxy for investment, growth in Total Assets, defined as $\frac{Total\ Assets_{t-1} - Total\ Assets_t}{TotaL\ Assets_{t-1}}$

Notably, our definition of profitability differs slightly from that of Fama and French (2015) in that it uses Net Income to reflect profitability rather than using operating profitability defined as revenues less cost of goods sold, selling general and administrative expenses, and interest expense. The use of a single accounting metric in the denominator simplifies the process of data acquisition but may give rise to slightly biased coefficient estimates.

5 Method

In order to investigate whether distress risk can explain variations in stock returns, we choose to follow two methodologies of previous research, namely portfolio analysis and Fama-Macbeth (1973) cross sectional regressions, in line with Dichev's (1998) study. In addition, we will conduct an event study to test whether a change in distress risk gives rise to a stock price reaction, similar to that of Ball and Brown's (1968) study. Finally, we perform a number of robustness tests with the hope to strengthen the validity of our results.

5.1 Portfolio Analysis

Portfolio analysis is conducted to highlight the economic significance of the results and reveal potential nonlinearities between stock return and distress risk. Here, firms are split into portfolios each year based on their probability of failure. Firms are ranked relative to one another each year, from the firm with the lowest to the highest probability of failure. Then, firms are split into quintiles each year with an equal amount of firms. Thenceforward, we calculate portfolio means in two steps. First, we calculate mean values for each portfolio and each year for both the dependent and independent variables; yearly excess return, market beta, market capitalization, book-to-market ratio, return on equity, asset growth and probability of failure. This gives one value for each portfolio for every variable and time period. Second, the yearly means are averaged throughout all the time periods, which ultimately give us one mean value for each portfolio and variable.

By introducing second sorting criteria for other independent variables we may also reveal interrelationships between such variables and distress risk. Something that differentiates our study from previous studies is the use of fewer portfolios (Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008). This is motivated by the fact that similar studies conducted tend to investigate larger samples[13]. If we were to use the same amount of portfolios as such studies, the amount of firms in each portfolio would be too small to produce reliable results. Rather, our results would likely be biased due to the impact of more extreme observations on portfolio means. Campbell,

[13] Avramov, Chordia, Jostova and Philipov (2009) have 434,746 monthly observations. Dichev (1998) investigates two samples including 237,628 and 262,304 monthly observations respectively. Campbell, Hilscher and Szilagyi (2008) have a total of 1,695,036 monthly observations.

Hilscher and Szilagyi (2008) form decile portfolios in their study, in line with Dichev (1998) and Avramov, Chordia, Jostova and Philipov (2009).

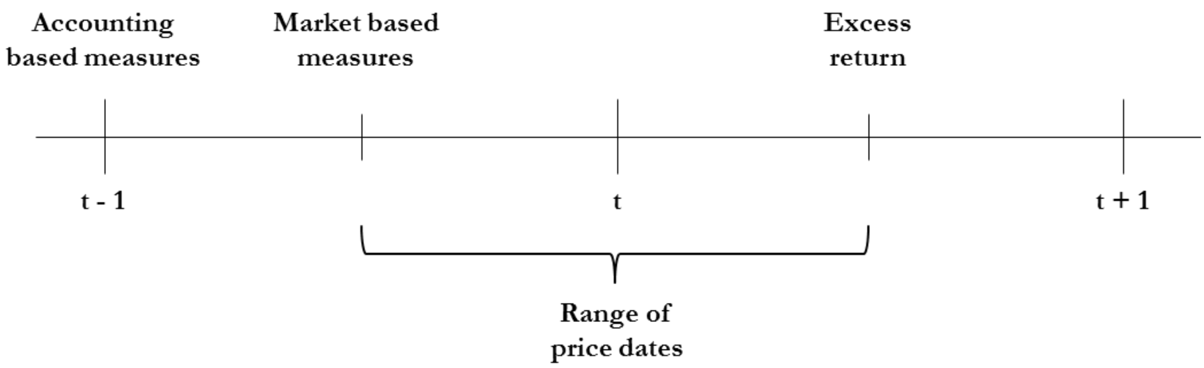
Furthermore, the portfolio formation of Campbell, Hilscher and Szilagyi (2008) somewhat asymmetrically emphasizes the tails of the distribution[14], since they claim that the distress premium might only be related to the most distressed firms. Another distinction between the methodology of previous research is how the portfolio returns are calculated. Avramov, Chordia, Jostova and Philipov (2009) and Dichev (1998) use equally weighted returns, while Campbell, Hilscher and Szilagyi (2008) use value weighted returns.

We will calculate equally weighted portfolio returns and form five symmetrical portfolios. We believe that if distress risk really has an effect on stock returns it should also be recognized when using equally large portfolios. The use of equally weighted portfolio returns is further supported by the notion that we do not wish to emphasize market-based measures, since the focus of this paper surrounds accounting-based measures.

The timing of the dependent and independent variables, which concerns both the portfolio analysis and the cross sectional regression analysis, is as follows. Assume a firm with fiscal year-end December 31, 2000. The accounting-based independent variables are gathered from the financial statements as of that date and will match the calculated yearly excess returns extending from July 1, 2001 through June 30, 2002. The market-based independent variables (e.g. market beta and market capitalization) as of June 30, 2001 will match the abovementioned excess return interval. Some previous research (Basu, 1983) presumes that accounting information is available within three months after the fiscal year ends. However, this is frequently shown not to be true (Fama and French, 1992). Thus, to ensure that the accounting-based variables are known before the excess return interval that they are meant to explain, we assume that financial statements are publically available within 6 months after each fiscal year ends. This is in line with previous research using accounting information to explain stock returns (Fama and French, 1992; Dichev, 1998).

[14] *Percentiles: 0-5, 5-10, 10-20, 20-40, 40-60, 60-80, 80-90, 90-95, 95-99, 99-100.*

Figure 4: Timing of test variables. The figure presents the timing of the dependent and independent variables used in the portfolio analysis and cross sectional regression analysis. Accounting based measures include probability of failure, book-to-market ratio, return on equity, asset growth and Z-Score. Market based measures include market beta and market capitalization. Excess return is calculated as the return of each stock less the risk free rate.



5.2 Cross Sectional Regression Analysis

In the portfolio analysis, the relationship between probability of failure and excess return is pronounced on a univariate level. However, other firm characteristics, perhaps not related to probability of failure, may also explain the variation in stock returns (Fama and French, 1992). In order to establish the relationship on a multivariate level, excess return is regressed on probability of failure and other firm characteristics that are expected to explain the variation in stock returns. By comparing results from multivariate regressions and univariate regressions of the independent variables, suggestions can be made regarding the interdependencies among them. The inclusion of variables will be done in a step-wise manner to facilitate more precise conclusions.

The statistical tests used are Fama-MacBeth (1973) cross sectional regressions; a methodology that has gained widespread popularity for its practical way of testing whether a chosen number of firm characteristics can help explain stock returns[15] (Dichev, 1998). The cross section of realized stock returns is regressed yearly on pfail, market beta, market capitalization (log), book-to-market, return on equity, and asset growth. The complete theoretical model we want to test is the following:

$$ER_{i,n,t} = \alpha_t + \beta_{1,t}Pfail_{n,t-1} + \beta_{2,t}Beta_{n,t-1} + \beta_{3,t}Mcap_{n,t-1} + \beta_{4,t}B/M_{n,t-1} + \beta_{5,t}ROE_{n,t-1} + \beta_{6,t}AG_{n,t-1} + \varepsilon_t$$

Where,

$ER_{n,t} = Excess\ stock\ return\ for\ security\ i\ at\ time\ t$

$\beta = Beta - coefficient$

[15] *Studies that construct factor mimicking portfolios perform a set of time series regressions prior to the cross sectional regressions. However, this is not the case for this study.*

$n = Number\ of\ firms\ included\ in\ the\ regression\ at\ year\ t$

A regression coefficient as reported in the tables represents the average of the coefficients in the yearly cross sections. Each coefficient's t-statistic, which determines the formal test of statistical significance, is calculated as the coefficient divided by its time-series standard error.

A considerable amount of previous research attempting to explain the variation in stock returns have performed monthly cross sectional regressions (Fama and French, 1992; Dichev, 1998; Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015). However, as this study investigates whether the estimated 1-year pfail can explain the variation in stock returns we deem it more intuitive to perform the regressions on an annual basis. Additionally, most of the firm characteristics tested are based on accounting information that for a substantial amount of firms in our sample is only obtainable once a year from their respective Annual Reports.

5.3 Event Study

In the portfolio and regression analysis, the relationship between probability of failure and excess stock return is established on a univariate and multivariate level respectively. These tests sought to establish whether firms with higher distress risk earn, on average, higher returns over time. We are also interested in establishing whether a change in distress risk beyond market expectations would prompt the market to re-price stocks to reflect fundamental value, as traditional theories of risk and return would suggest. More precisely, an increase in distress risk should cause stock prices to fall to reflect the increased risk an investor would have to bear to hold the stock, and vice versa.

In order to examine whether there is a stock price effect associated with the announcement of accounting information surrounding distress risk, we conduct an event study (MacKinlay, 1997). Following is a description of the event study methodology pursued to test hypothesis 2 a), b) and c).

In this paper, the event investigated is a change in distress risk, which is defined as the difference between the current and preceding year's estimated 1-year pfail, as derived through Skogsvik's (1990) bankruptcy prediction model. We define the event of a decrease in pfail (i.e. strengthened credit quality) as "good news". Conversely the event of an increase in pfail (i.e. worsened credit quality) will be denoted as "bad news". Hence, in line with our hypothesis, we would expect a decrease in distress risk to be associated with a positive stock price reaction, as investors gain the same expected flow to equity while carrying lower risk. The event window will last from the beginning of February until the end of April, since firm's Annual Reports typically become publically available within that time period. The use of an event window is a consequence of the fact that the exact release dates of the Annual Reports of each firm is unknown to us. This may be a potential limitation to our study, since it becomes more difficult to identify abnormal returns when the event date is not restricted to a single day.

2-quantile, 5-quantile (quintile) and 10-quantile (decile) portfolios are formed in the month of January each year, based on the magnitude and direction of the change in pfail. This will help us observe the magnitude of the stock price effect in the more extreme portfolios, as well as test the informative content of a change in distress risk.

In order to determine whether the event has any effect on stock returns, abnormal returns are calculated for each firm and month around the announcement of accounting information necessary to calculate pfail. There are different ways of estimating a firm's expected return. We choose to apply the market model for two reasons. Firstly, we have the opportunity to estimate the model coefficients through a statistical model. Hence, we can avoid potential biases arising from using predetermined coefficients, which may be the case when using economic models. Secondly, the other most widespread statistical model, the constant mean return model, does not eliminate the amount of return that is related to the variation in the market's return.

In a market model, the return of each stock is regressed against the return of the market. By estimating how each stock would normally perform in the absence of the event and comparing it with actual return, it signalizes how the market perceives the event. Thus, using the market model to measure expected return; abnormal returns are calculated as follows:

$$AR_{it} = R_{it} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{mt}\right)$$

Where,

$AR_{it} = Abnormal\ return\ for\ stock\ i\ at\ month\ t$

$R_{it} = Actual\ return\ for\ stock\ i\ at\ month\ t$

$\hat{\alpha}_i = Intercept\ for\ stock\ i$

$\hat{\beta}_i = By\ what\ factor\ stock\ i\ is\ exposed\ to\ the\ market\ return$

$R_{mt} = Actual\ return\ for\ market\ at\ month\ t$

The estimation period for the market model β is set so that the event window is not included in the estimation. This ensures that the event does not affect the estimated βs, something that could potentially have biased the estimates and consequently led to an over- or underestimation of abnormal returns. Each firm's specific monthly β is estimated on the most recent year's weekly observations of stock and market returns. By using a rolling estimation period for the monthly βs it also ensures that the event is included in the estimation period when estimating expected return after the event window. This is important considering the fact that the event may actually impact stock prices and thereby influence what is expected to be the normal return for a stock after the event has taken place. The βs are obtained through the Capital IQ database.

The estimation period for the αs in our study includes part of the post-event period for each stock. Ball and Brown (1968) also faces this issue in their estimation of expected return coefficients. It is not entirely uncommon that a pre-event period contains irregularities. Therefore, including a post-event period in the estimation window is a plausible alternative (MacKinlay, 1997). The αs are generally relatively low values and therefore the potential bias in the α estimates are not expected to be of any greater significance.

Abnormal Performance Index

After the abnormal return for each firm's monthly observation is computed and firms are split up in different portfolios, an abnormal performance index (API) is constructed. The API is used to illustrate how different portfolios of firms perform over time. In line with Ball and Brown (1968), the equation used to calculate the API is as follows:

$$API_t = \sum_{i=1}^{N_t} \left[\prod_{t=-1}^{t} (1 + AR_{it}) \right] \frac{1}{N_t}$$

Where,

$API_t = Abnormal\ performance\ index\ at\ month\ t$

$N_t = Number\ of\ stocks\ in\ the\ portfolio\ at\ month\ t$

$AR_{it} = Abnormal\ return\ for\ firm\ i\ at\ month\ t$

The cross sectional aggregation of each firm's abnormal return is calculated each month. Consequently, to observe how the stock price effect takes place over time, a time series aggregation of the monthly average abnormal returns is calculated. This is done through the API calculation. By including both pre-event and post-event periods in the time series aggregation, we can also analyze potential market reactions before and after the event takes place. Hence, suppositions can be made regarding the efficiency of the market.

The API spans across the period February – December. The reason for excluding January from the API is that our sample includes a significant January effect (De Bondt and Thaler, 1985; Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015), which may hinder the interpretation of results. We include the anomaly as part of a robustness test in Appendix 15 (see Section 9.2.4, robustness test 4).

5.4 Robustness Tests

During the process of preparing and performing our tests, we have strived to find support in previous research regarding the methods we have chosen. However, different studies might have different conditions, why some subjectivity may be necessary. Thus, we perform a number of robustness tests in areas where assumptions and limitations in our methodology may have impact on our results. These tests can be found in Appendix 9.2.

In the context of accounting-based bankruptcy prediction models used as a proxy for distress risk, the Altman Z-Score is a commonly used alternative (Dichev, 1998). To assure that the use of Skogsvik's probability of failure is valid, we replace it with Z-Score in all three of our tests.

Another area of potential scrutiny surrounds the relatively low number of portfolios used in the portfolio analysis compared to previous research (Vassalou and Xing, 2003; Campbell, Hilscher and Szilagyi, 2008). Even though this is supported by the fact that each portfolio requires a sufficiently high number of observations, we construct decile portfolios as a robustness test for our portfolio results, as well as our event study results.

6 Results

This section will present and analyze the findings of empirical tests performed as part of the study. Section 6.1 seeks to give the reader a better understanding of the characteristics of the data set by presenting descriptive statistics. Section 6.2 covers results from portfolios of stocks ranked into groups on the basis of their level of financial distress. Section 6.3 presents findings from the Fama-Macbeth cross sectional regressions. Finally, Section 6.4 presents results from an event study examining stock price reactions of portfolios of stocks ranked into groups on the basis of their relative increase or decrease in distress risk.

6.1 Descriptive Statistics

Our sample, consisting of 926 firms, contains data over the period 2000 to 2014. The period is characterized by events with substantial impact on global financial markets. The years following the turn of the 21st century and the burst of the 'dot-com' bubble, as well as the mass-default of US collateralized debt securities in 2008 marked the beginning of global financial crises. In both instances, the stocks in our sample return -19 percent and -34 percent, on average, respectively.

The inclusion of periods with positive and negative stock return, respectively, is likely to be suitable for the purpose of our tests. For example, a time-series examination of pfail reveals that the average distress risk of firms in our sample increases around both events, as one would expect. Similarly, average firm size, profitability and level of investment of firms in our sample all decrease following both crises.

Figure 5: Relationship between sample returns and market returns. The figure presents descriptive statistics that illustrate the relationship between annual stock returns from the final sample and annual market returns during the period 2000 – 2014. Sample returns are calculated as the mean of all stocks' annual returns each year. Market returns are calculated as the mean of the four Nordic exchanges' annual returns each year.

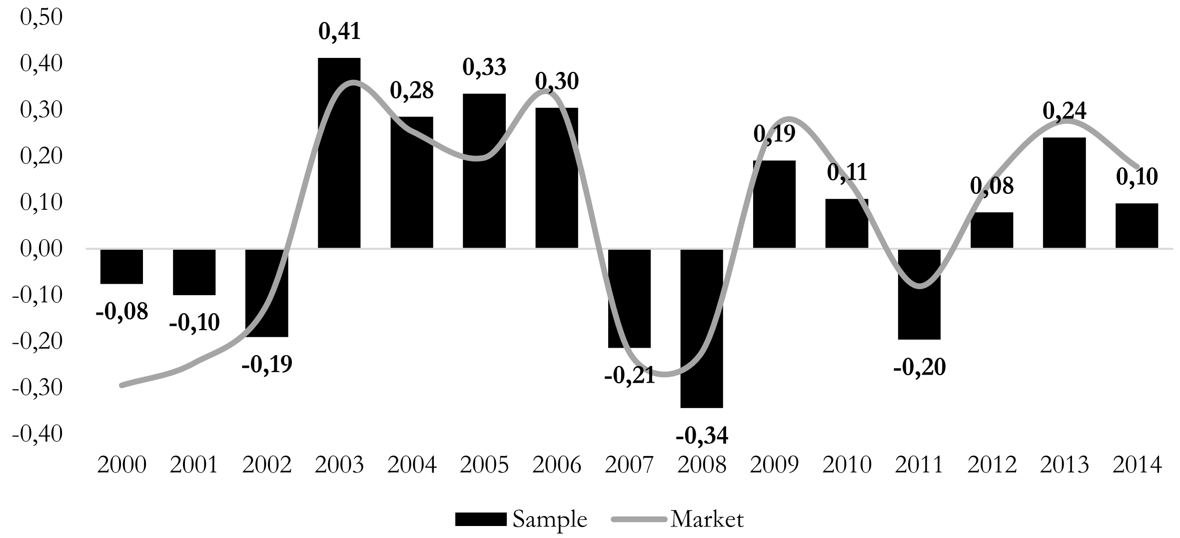


Table 1 contains descriptive statistics for the test variables. Drawing parallels to Dichev's (1998) study, sample distributions are very similar. A key difference of our sample is a lower mean and standard deviation of Z-Score (equivalent to a higher mean pfail), possibly explained by the difference in the time period covered by our study and that of Dichev's, (1981 – 1995).

Table 1: Descriptive statistics for the test variables during 2000 to 2014. The table presents descriptive statistics that illustrate the test variables' empirical dispersals. E. Returns are yearly excess returns for the final sample of firms including firms from all four of the major Nordic stock exchanges investigated in this paper. Beta is the measure of stocks' exposure to the market. MCAP is the market capitalization, in million USD, based on the end-of-June. B/M is the book-to-market ratio based on the fiscal-year-end book value of common equity and market capitalization. ROE is the return on equity and AG is the growth in total assets. Pfail is the primary measure of distress risk from Skogsvik (1990), while ZScore is the secondary measure of distress risk from Altman (1968) used in robustness tests.

Sample Statistics	Mean	StdD	P5	P25	P50	P75	P95
E. Returns	**0.04**	0.48	-0.65	-0.28	-0.01	0.29	0.88
Beta	**0.59**	0.53	-0.19	0.24	0.54	0.88	1.54
MCAP	**1094**	3028	6	34	126	646	5733
B/M	**0.76**	0.69	0.13	0.31	0.56	0.97	2.06
ROE	**0.03**	0.37	-0.62	-0.05	0.09	0.20	0.44
AG	**0.13**	0.40	-0.27	-0.06	0.05	0.19	0.81
Pfail	**0.0239**	0.0996	2.79E-08	1.49E-05	0.0006	0.0059	0.1014
Zscore	**2.29**	3.03	-0.80	1.21	2.05	3.08	5.86

Correlation coefficients provide a number of interesting observations, suggesting there is a relationship between several of the independent variables (see Table 2). Pfail displays the highest level of correlation with ROE (-0.4878, $p < 0.0000$). The observation is less surprising, given that ROE is one of the ratios used to determine pfail. Nevertheless, the observation is important as we would expect firms with high levels of distress to be less profitable.

Furthermore, we find that pfail is negatively correlated to size (-0.2011, $p < 0.0000$). This is also to be expected, given arguments presented by previous research suggesting that the size effect is revived when taking distress into account (Asness, Frazzini, Israel, Moskowitz and Pedersen, 2015). Finally, we include the Altman's (1968) bankruptcy measure for firms in our sample as a robustness test and observe a negative correlation between pfail and Z-Score (-0.1981, $p < 0.0000$). This result is comforting, as a high Z-Score is ascribed to firms with low risk of bankruptcy, and vice-versa.

Looking at pairwise correlations of the independent variables and excess return, we find that several risk factors load significantly onto the dependent variable. Value and profitability both correlate positively to excess return (0.0742, $p < 0.0000$ and 0.0591, $p < 0.0000$) within a confidence interval of 99%. The level of investment, measured as asset growth, loads negatively onto excess returns (-0.1271, $p < 0.000$), in line with evidence presented by Fama and French (2015), suggesting that firms with conservative investment spend earn higher returns, on average, than firms with aggressive investment spending. Furthermore, we find that distress risk, measured as the probability of business failure, loads up negatively to excess return (-0.0262, $p < 0.0000$). This result suggests that relatively safer quality firms with a lower probability of failing earn higher returns, on average, than riskier junk firms with a higher probability of failing. In other words, distress risk is not likely to be a systematic risk. This result suggests hypothesis 1 should be rejected.

Table 2: Pearson Correlation table for test variables during 2000 to 2014. The table presents a Pearson correlation matrix for all test variables, including Z-Score used in robustness tests. The numbers in the parentheses are the P-values for each regression coefficient. For more detailed explanations of the test variables, view Table 1.

Variable	E. Returns	Beta	MCAP	B / M	ROE	AG	Pfail	ZScore
E. Returns	1.0000							
Beta	-0.0562	1.0000						
	(0.0000)***							
MCAP	0.0040	0.2608	1.0000					
	(0.7348)	**(0.0000)*****						
B / M	0.0742	-0.0567	-0.2442	1.0000				
	(0.0000)***	**(0.0000)*****	**(0.0000)*****					
ROE	0.0591	-0.0233	0.3487	-0.1749	1.0000			
	(0.0000)***	**(0.0515)***	**(0.0000)*****	**(0.0000)*****				
AG	-0.1271	0.0231	0.0172	-0.1659	0.0703	1.0000		
	(0.0000)***	**(0.0532)***	(0.1488)	**(0.0000)*****	**(0.0000)*****			
Pfail	-0.0262	-0.0072	-0.2011	0.0145	-0.4878	-0.0136	1.0000	
	(0.0281)**	(0.5491)	**(0.0000)*****	(0.2264)	**(0.0000)*****	(0.2563)		
ZScore	0.0121	0.0100	0.1386	-0.1761	0.3875	0.1062	-0.1981	1.0000
	(0.3124)	(0.4022)	**(0.0000)*****	**(0.0000)*****	**(0.0000)*****	**(0.0000)*****	**(0.0000)*****	

*[* $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$]*

Analysis

Interpreting these findings, we conclude them to be inconsistent with the relationship between risk and return, as they point to a negative relationship between distress risk and excess return. In other words, results suggest higher returns are rewarded to firms with lower levels of distress, i.e. investors are willing to pay more for quality firms that have a lower likelihood of failing. Results could be interpreted as in line with the recent findings of Asness, Frazzini and Pedersen (2014) who find that stocks of high quality firms earn higher returns, on average, than low quality firms.

Furthermore, results add support to the idea that the distress- and size-effects could be related (Chan, Chen and Hsieh, 1985). The negative correlation between size and the probability of failure suggests smaller firms have a higher probability of failing, and vice versa.

Similarly, we find support for evidence presented in the research of Fama and French (1996, 2015) suggesting value and profitability both explain variations in stock returns. In other words, firms whose market value is low in relation to their book value are expected to generate higher returns, on average, than firms whose market value is high in relation to their book value.

Similarly, firms with higher levels of profitability are expected to earn higher returns, on average, than firms with lower levels of profitability.

6.2 Portfolio Analysis

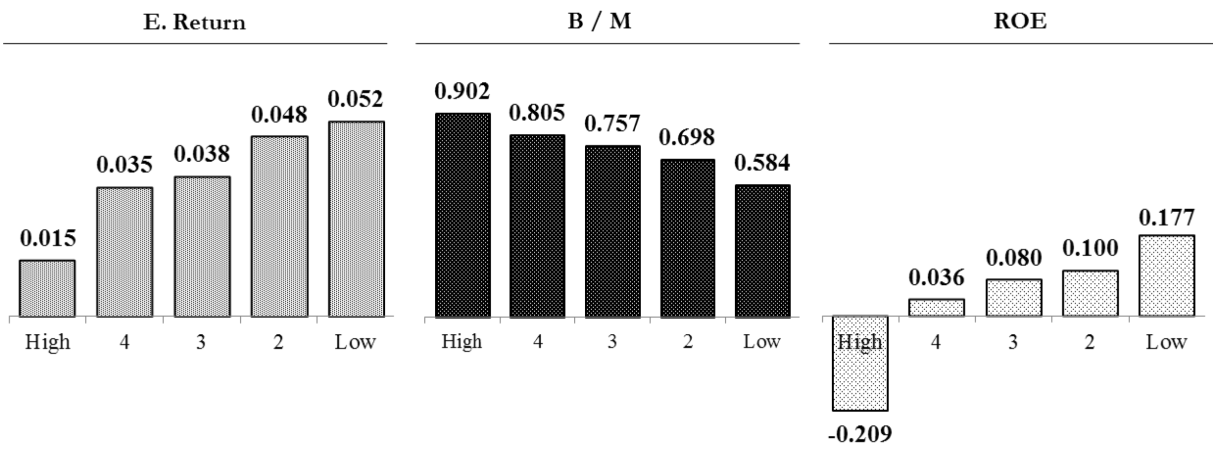
Distress-sorted portfolios

Portfolio analysis reveals a negative relationship between distress risk and excess return. Portfolio quintiles with high levels of distress risk (i.e. high probability of failure) earn lower than average returns. Conversely, quintiles with low levels of distress risk earn higher than average returns. Firms with the highest distress risk in the top quintile earn, on average, 3.7 percent less than the safest firms with the lowest distress risk in the bottom quintile. The relationship appears to be non-linear in the sense that the difference in average return across quintiles is higher among the two quintiles with the highest average probability of failure. We note that this negative relationship between distress risk and returns is in line with the Pearson's correlation presented in section 6.1.

Table 3: Relation between pfail and other test variables during 2000-2014. The table presents portfolio results, where firms are assigned yearly into quintile portfolios based on the magnitude of their probability of failure. High represents the quintile portfolio including firms with the highest pfail. Low represents the quintile portfolio including firms with the lowest pfail. For more detailed explanations of the test variables, view Table 1.

Portfolio	High	4	3	2	Low	High - Low	Sample Mean
Pfail	0.1097	0.0045	0.0007	0.0001	0.0000	0.1097	0.0239
E. Return	0.015	0.035	0.038	0.048	0.052	-0.037	0.036
Beta	0.565	0.599	0.623	0.563	0.593	-0.028	0.589
MCAP	635	1378	1592	977	818	-183	1094
B / M	0.902	0.805	0.757	0.698	0.584	0.318	0.762
ROE	-0.209	0.036	0.080	0.100	0.177	-0.386	0.032
AG	0.135	0.119	0.125	0.132	0.151	-0.016	0.127
Z-Score	1.111	1.912	2.304	2.642	3.606	-2.495	2.294

Figure 6: Pfail's relation to excess return, B/M ratio and ROE during 2000 to 2014. The figure presents portfolio results that illustrate mean annual excess return, B/M and ROE across pfail quintiles in descending order. Firms are assigned into quintile portfolios annually based on the magnitude of their pfail. High represents the quintile portfolio including firms with the highest pfail. Low represents the quintile portfolio including firms with the lowest pfail.



Sorting stocks according to their probability of failure further reveals common characteristics of firms across quintiles. Results suggest there is a positive relationship between value and distress, as firms with the highest level of distress risk in the top quintile have B/M ratios that are 0.318 points higher, on average, than firms in the bottom quintile. Similarly, sorting stocks into quintiles gives rise to a negative relationship between distress risk and profitability. We find that firms in the top quintile earn, on average 38.6 percent less on their book value of equity than firms in the bottom quintile. In other words, firms with low levels of distress risk have considerably higher ROE, on average, than firms with high levels of distress risk. Again, we note that the negative relationship between distress risk and profitability observed in the portfolio analysis is in line with results presented in the Pearson's correlation test in section 6.1.

Finally, we measure the average Z-Score of each portfolio as part of our robustness testing of the choice of proxy for distress. Portfolio results show that average Z-Score is higher in quintiles with lower levels of distress. This result is to be expected, since Z-Score is a measure of financial strength; higher Z-Score means lower level of distress (Dichev, 1998).

Distress risk controlled by value effect

In line with Vassalou and Xing (2004), we perform two-way portfolio sorts to examine the behavior of stocks with high and low B/M ratios within each distress-sorted portfolio and evaluate the extent to which value and distress risk may be related.

Table 4 suggests that the value anomaly is present, albeit in different magnitudes across all quintiles sorted on levels of distress. Notice that in every quintile, stocks with high B/M earn, on average, higher returns than stocks with low B/M. Perhaps more interesting is the observation that the negative relationship between distress and excess return (i.e. that firms with low levels of distress earn, on average, higher returns) is prevalent to a much larger extent within high risk stocks that display high B/M ratios. The difference in return between stocks in the top and bottom distress quintile that have high B/M ratios is -5.46 percent, while the difference in return between stocks in the top and bottom distress quintile that have low B/M ratios is 1.99 percent. This compares to the sample as a whole where the difference in returns of the top and bottom distress quintile is -3.73 percent. In other words, the phenomenon that quality stocks outperform riskier junk stocks is more pronounced among value stocks than growth stocks. Similarly, we find that the difference in the book-to-market ratio of high B/M and low B/M stocks is higher in the top distress quintile (0.99 points) than in the lowest distress quintile (0.68 points).

Looking at firm characteristics, there is no immediate trend to be observed across the distress-sorted quintiles. Within each quintile however, we find that stocks with high B/M tend to be smaller in size, less profitable and invest more aggressively than stocks with low B/M, in line with results presented in previous tests.

Table 4: Distress risk controlled by value effect during 2000 to 2014. The table presents portfolio results, where firms are assigned yearly into quintile portfolios based on the magnitude of their probability of failure as well as all the other test variables respectively. Within each portfolio, firms are then sorted into two B/M portfolios, based on their previous year's B/M ratio.

Portfolio	**High**	**4**	**3**	**2**	**Low**	**High - Low**
			E. Return			
High B/M	0.032	0.041	0.057	0.071	0.087	-0.055
Low B/M	-0.002	0.028	0.019	0.025	0.018	-0.020
Whole Sample	0.015	0.035	0.038	0.048	0.052	-0.037
			Beta			
High B/M	0.486	0.513	0.573	0.511	0.565	-0.079
Low B/M	0.644	0.686	0.671	0.615	0.620	0.024
Whole Sample	0.565	0.599	0.623	0.563	0.593	-0.028
			MCAP			
High B/M	398	964	1225	828	468	-70
Low B/M	870	1786	1956	1125	1165	-295
Whole Sample	635	1378	1592	977	818	-183
			B / M			
High B/M	1.405	1.212	1.158	1.068	0.923	0.481
Low B/M	0.405	0.402	0.361	0.331	0.248	0.157
Whole Sample	0.902	0.805	0.757	0.698	0.584	0.318
			Pfail			
High B/M	0.082	0.005	0.001	0.000	0.000	0.082
Low B/M	0.137	0.004	0.001	0.000	0.000	0.137
Whole Sample	0.110	0.004	0.001	0.000	0.000	0.110
			ROE			
High B/M	-0.146	0.000	0.023	0.042	0.098	-0.245
Low B/M	-0.271	0.072	0.136	0.157	0.255	-0.527
Whole Sample	-0.209	0.036	0.080	0.100	0.177	-0.386
			AG			
High B/M	0.078	0.085	0.070	0.067	0.103	-0.025
Low B/M	0.190	0.152	0.180	0.196	0.198	-0.007
Whole Sample	0.135	0.119	0.125	0.132	0.151	-0.016
			Z-Score			
High B/M	1.348	1.758	1.784	2.085	2.580	-1.232
Low B/M	0.877	2.065	2.817	3.194	4.623	-3.747
Whole Sample	1.111	1.912	2.304	2.642	3.606	-2.495

Distress risk controlled by earnings

In the following we show a two-way portfolio sort examining the behavior of stocks with high and low profitability within each distress-sorted portfolio. This is to evaluate the extent to which profitability and distress risk may be related.

Table 5 suggests a profitability effect is present in all quintiles apart from that with the lowest distress risk, albeit in different quantities. Notice that stocks with high ROE earn, on average, higher returns than stocks with low ROE across quintiles two through five. Perhaps more important is the observation that the negative relationship between distress and excess return is pronounced, in particular, among firms with low profitability. The difference in return between stocks in the top and bottom distress quintile that have high ROE is negligible at -0.09 percent, while the difference in return between stocks in the top and bottom distress quintile that have low ROE is -7.36 percent. In other words, the phenomenon that quality stocks outperform riskier junk stocks is more pronounced among firms with low profitability than firms with higher profitability. Similarly, we find that the difference in the average return on equity of more profitable and less profitable stocks is higher in the top distress quintile (0.70 points) than in the lowest distress quintile (0.30 points).

Finally, results on average firm characteristics across the distress quintiles suggest that stocks with high profitability tend to be larger in size, have lower B/M ratios and lower probability of failure than firms with low profitability.

Table 5: Distress risk controlled by earnings effect during 2000 to 2014. The table presents portfolio results, where firms are assigned yearly into quintile portfolios based on the magnitude of their probability of failure as well as all the other test variables respectively. Within each portfolio, firms are then sorted into two ROE portfolios, based on their previous year's ROE.

Portfolio	**High**	**4**	**3**	**2**	**Low**	**High - Low**
			E. Return			
High ROE	0.049	0.093	0.061	0.072	0.050	-0.001
Low ROE	-0.019	-0.023	0.014	0.025	0.055	-0.074
Whole Sample	0.015	0.035	0.038	0.048	0.052	-0.037
			Beta			
High ROE	0.519	0.614	0.616	0.546	0.600	-0.080
Low ROE	0.611	0.586	0.629	0.581	0.587	0.024
Whole Sample	0.565	0.599	0.623	0.563	0.593	-0.028
			MCAP			
High ROE	997	1889	2193	1150	1268	-270
Low ROE	276	871	999	807	371	-96
Whole Sample	635	1378	1592	977	818	-183
			B / M			
High ROE	0.866	0.621	0.555	0.505	0.402	0.464
Low ROE	0.938	0.987	0.956	0.889	0.764	0.174
Whole Sample	0.902	0.805	0.757	0.698	0.584	0.318
			Pfail			
High ROE	0.047	0.004	0.001	0.000	0.000	0.047
Low ROE	0.172	0.005	0.001	0.000	0.000	0.172
Whole Sample	0.110	0.004	0.001	0.000	0.000	0.110
			ROE			
High ROE	0.141	0.216	0.252	0.257	0.328	-0.187
Low ROE	-0.556	-0.142	-0.091	-0.055	0.028	-0.584
Whole Sample	-0.209	0.036	0.080	0.100	0.177	-0.386
			AG			
High ROE	0.189	0.160	0.169	0.184	0.204	-0.015
Low ROE	0.081	0.078	0.083	0.080	0.098	-0.017
Whole Sample	0.135	0.119	0.125	0.132	0.151	-0.016
			Z-Score			
High ROE	1.958	2.320	2.942	3.336	4.508	-2.550
Low ROE	0.273	1.510	1.676	1.954	2.713	-2.440
Whole Sample	1.111	1.912	2.304	2.642	3.606	-2.495

Analysis

The results from the portfolio analysis are in line with previous research, suggesting that distress risk is not priced into returns and is hence not a systematic risk (Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008; Avramov, Chordia, Jostova and Philipov, 2009). Contrary to what is to be expected given the intuitive relationship between risk and return, results suggest investors in firms with higher risk of failing are not rewarded for taking on additional risks. In other words, we find that high quality stocks with lower probability of failure outperform low-quality junk stocks with higher probability of failure. Results are in line with the findings of Asness, Frazzini and Pedersen (2014) and the performance of the QMJ factor.

Furthermore, we observe results similar to that of Dichev (1998) as the portfolios with high probabilities of failure tend to have, on average, high B/M ratios. While it is tempting to conclude results support the findings of the Fama and French (1992), suggesting the B/M factor is capturing fundamental risks related to distress, the common variation in distress risk and value risk in our sample has little relation to returns. In other words, while distress risk and value risk seem to be related, distress risk is unlikely to account for the B/M effect (Dichev, 1998).

What is more, we find that the negative relationship between distress risk and returns is prevalent to a larger extent among value stocks. In other words, investors seem to reward quality (i.e. lower levels of distress) particularly within the category of value stocks as opposed to growth stocks. Similarly, we also observe that firms with low B/M underperform firms with high B/M to a large extent in the quintiles with high levels of distress. One potential explanation to this phenomenon in line with the findings of Dichev (1998) is offered by Griffin and Lemmon (2002), who claim that the risk inherent in growth stocks with high levels of distress is largely diversifiable, and hence not awarded with higher excess returns as the traditional risk-return paradigm would suggest.

Interestingly, portfolio results provide further evidence on the profitability premium observed by Fama and French (2015). As would be expected, we find that portfolios with high distress risk tend to have lower profitability and vice versa. In other words, average ROE increases as average pfail decreases, suggesting that safer firms with higher profitability earn a higher return and vice versa. Particularly interesting perhaps is the observation that firms in the quintile with the highest level of distress earn, on average, a negative return on equity. Looking at the two-sort portfolio's, the counter-intuitive behavior of firms with high probability of failure is once more pronounced in the category of stocks with the highest risk (i.e. firms with low ROE). In other words, investors seem to reward quality (i.e. lower levels of distress) particularly within the category of firms with low profitability rather than firms with high profitability. This pattern is intuitively satisfying and lends to one of the explanations offered by Asness, Frazzini and Pedersen (2014) that suggests they point to a 'flight to quality' where investors put increasing emphasis on rewarding stocks that are safe with higher prices. Such an emphasis may be particularly relevant among the segment of stocks which is relatively more risky.

6.3 Cross Sectional Regression Analysis

The reasoning behind performing a cross sectional regression is to establish whether distress risk can explain the variation in stock returns while taking other documented risk proxies into account. Emphasis is placed on examining the explanatory power of pfail over and above additional factors used. We perform univariate, bivariate and multivariate regressions to test whether any explanatory power observed on pfail is not subsumed by other factors. A cross sectional regression will also give an indication as to whether any observed risk premiums are likely to persist over time.

Cross sectional regression results presented in Tables 6, 7 and 8 suggest there is no significant relationship between the level of distress risk of a firm and excess return. The univariate cross sectional regressions find that only the size factor (-0.02448, t-stat = -2.0210) and the value factor (0.04490, t-stat = 2.4534) significantly explain variations in stock returns with 90% and 95% confidence respectively. The performance of the size factor and the value factor is less surprising and support the findings of Fama and French (1992, 1995, and 1996). Bivariate cross sectional regressions produce similar results. Finally, multivariate regressions find that the size factor becomes obsolete when introducing the profitability factor into the regression model. The value factor consistently loads positively to excess returns (0.0392, t-stat = 2.2311) while the profitability factor seems to capture similar risks to that of the size factor, also loading positively to excess returns (0.0356, t-stat = 2.2103) in a six-factor regression within a 95 percent confidence interval. The distress factor does not generate any patterns in any of the cross sectional regression models that are significant. However, we do observe a positive co-efficient to the distress factor. What is more, significance levels rise as we add more factors to the regression, as the distress factor has the highest explanatory power in the six-factor model (0.1624, t-stat = 1.3318).

Table 6: Univariate regression results during 2000 to 2014. The table presents regression results for univariate Fama-MacBeth (1973) regressions with 15 yearly cross sections. A coefficient in these regressions represents the mean of the yearly cross sectional coefficients. A t-statistic (in parentheses) is calculated as the mean coefficient divided by its time-series standard error.

Regression Results - Univariate							
	Re - Rf	= *Pfail*	+ *Beta*	+ *MCAP*	+ *B / M*	+ *ROE*	+ *AG*
Pfail		0.08171					
		(0.5061)					
Beta			-0.00669				
			-(0.1895)				
MCAP				-0.02448			
				-(2.0210)*			
B / M					0.04490		
					(2.4534)**		
ROE						0.01325	
						(0.9064)	
AG							-0.01614
							-(0.4225)

*[* p < 0.10, ** p < 0.5, *** p < 0.01]*

Table 7: Bivariate regression results during 2000 to 2014. The table presents regression results for bivariate Fama-MacBeth (1973) regressions with 15 yearly cross sections. A coefficient in these regressions represents the mean of the yearly cross sectional coefficients. A t-statistic (in parentheses) is calculated as the mean coefficient divided by its time-series standard error.

Regression Results - Bivariate							
	Re - Rf	= *Pfail*	+ *Beta*	+ *MCAP*	+ *B / M*	+ *ROE*	+ *AG*
Beta		0.07820	-0.00200				
		(0.5165)	-(0.0578)				
MCAP		-0.01263		-(0.0256)			
		-(0.0748)		**-(2.0203)***			
B / M		0.09062			0.04694		
		(0.5848)			**(2.5315)****		
ROE		0.09616				-0.00416	
		(0.5167)				-(0.1617)	
AG		0.10540					-0.01651
		(0.6824)					-(0.4698)

*[* p < 0.10, ** p < 0.5, *** p < 0.01]*

Table 8: Multivariate regression results during 2000 to 2014. The table presents regression results for multivariate Fama-MacBeth (1973) regressions with 15 yearly cross sections. A coefficient in these regressions represents the mean of the yearly cross sectional coefficients. A t-statistic (in parentheses) is calculated as the mean coefficient divided by its time-series standard error.

Regression Results - Multivariate						
Re - Rf	= *Pfail*	+ *Beta*	+ *MCAP*	+ *B / M*	+ *ROE*	+ *AG*
Predicted	(+)	(+)	(-)	(+)	(+)	(-)
1	0.0817					
	(0.5061)					
2	0.0782	-0.0020				
	(0.5165)	-(0.0578)				
3	-0.0230	0.0255	-0.0270			
	-(0.1358)	(0.5075)	-(1.7391)			
4	0.0724	-0.0228	-0.0066	0.0413		
	(0.5862)	-(0.8172)	-(0.7675)	**(2.3485)****		
5	0.1438	-0.0211	-0.0086	0.0410	0.0364	
	(1.1565)	-(0.7658)	-(1.0614)	**(2.3324)****	**(2.1494)****	
6	0.1624	-0.0224	-0.0083	0.0392	0.0356	-0.0238
	(1.3318)	-(0.8372)	-(1.0240)	**(2.2311)****	**(2.2103)****	-(1.2505)

*[* p < 0.10, ** p < 0.5, *** p < 0.01]*

In other words, the results suggest hypothesis 1 should be rejected, as they do not support the significant existence of a distress premium. Finally, the results do not find support for the negative relationship between distress risk and excess returns that we find in our Pearson's correlation test and portfolio analysis, as well as that which has been documented by several studies in the field (Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008; Avramov, Chordia, Jostova and Philipov, 2009).

Analysis

Results offer further evidence on the explanatory power of distress risk, as well as other risk factors and their relationship to stock returns. We note that while distress risk does not generate significant factor loadings in the regression analysis, tests do provide positive factor loadings. The lack of significance is likely to be caused by insufficient evidence of a relationship within each year in the data set, as a cross sectional regression would demand, rather than looking at patterns across the whole 15-year period. Alternatively, results could be interpreted as pointing towards the existence of a distress premium, but with small magnitude only pertaining to certain years. Theory suggests that junk stocks should outperform during times of stock market uplift, while the opposite is true for times of market downturn (Skogsvik, 2006). Thus, the lack of strong results in this test may be a result of stock market dynamics during the time period covered by the sample (2000 – 2014).

More interesting perhaps is the interaction of the different risk factors observed in the results, particularly the redundancy of the size factor in a multi-factor model that takes profitability into account. The relationship between profitability and excess returns is in line with results of previous tests, suggesting that firms that are more profitable earn, on average, higher returns than firms that are less profitable (Fama and French, 2015). However, the introduction of the profitability factor also seems to capture the increased risk in smaller firms. Taking into consideration the negative correlation observed between profitability and size (i.e. that smaller firms tend to be less profitable and vice versa), one may suggest that the negative factor loadings in the size factor are really reflecting poor earnings generation in such firms. The findings support evidence relating small size (measured as market capitalization) to poor earnings (Chan, Chen and Hsieh, 1985; Chan and Chen, 1991). If we also consider the relationship between profitability and distress (i.e. that profitable firms are less likely to fail and vice versa), results may be interpreted as the market rewarding a premium for safe, high quality stocks rather than less profitable stocks that are more likely to fail. This line of reasoning would be in line with evidence presented by Asness, Frazzini and Pedersen (2014) who find that a portfolio going long high-quality stocks (defined in part as having relatively higher levels of profitability) and short low-quality stocks earns significant risk-adjusted returns.

6.4 Event Study

Rather than categorizing firms according to their relative probability of failing and observing patterns of variations in return, the event study aims to evaluate the extent to which a change in the probability of failure (i.e. a change in distress risk) is followed by a stock price reaction in a direction and magnitude that is in line with what fundamental valuation would lead one to expect.

Results suggest a decrease in pfail (i.e. improving credit quality) is significantly associated with a positive stock price reaction. Likewise, an increase in pfail (i.e. deteriorating credit quality) is significantly associated with a negative stock price reaction.

Figure 7: Abnormal performance indexes for good and bad news portfolios (quantiles). The figure presents event study results for the period 2000 to 2014. Abnormal performance indexes are calculated for the entire sample, as well as for good and bad news portfolios. The good news portfolio includes all firms that have experienced a decrease in pfail. The bad news portfolio includes all firms that have experienced an increase in pfail. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of February and ends at the end of December.

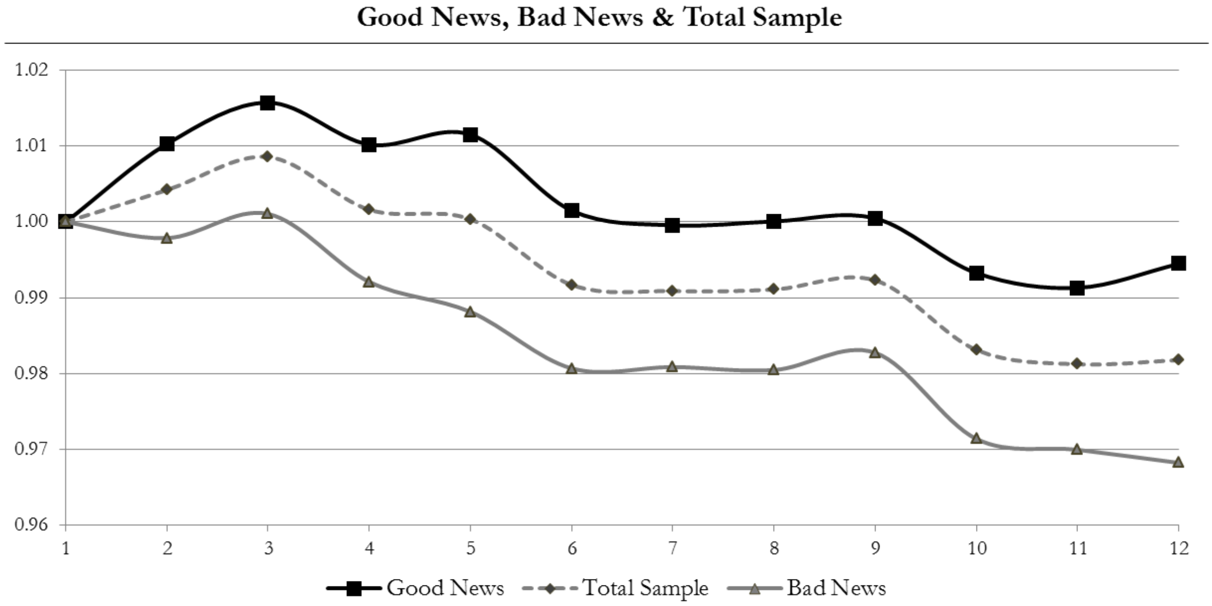


Figure 8: Difference between good and bad news portfolios. The figure presents the difference in the abnormal performance index between the good and bad news portfolios for the period 2000 to 2014. The good news portfolio includes all firms that have experienced a decrease in pfail. The bad news portfolio includes all firms that have experienced an increase in pfail. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of February and ends at the end of December.

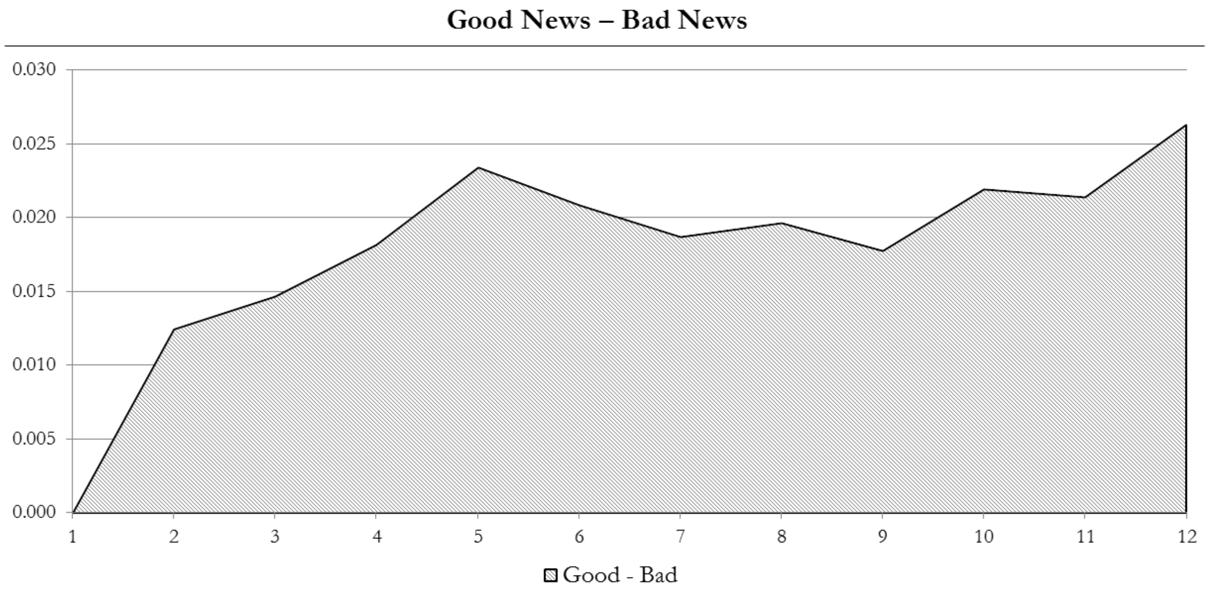


Figure 7 and 8 compare API's for two groups of firms (2-quantiles) depending on whether they have experienced an increase or decrease in pfail, respectively. We observe that firms in the sample who experience a decrease in pfail earn, on average 1.95 percent higher abnormal monthly returns, than firms with the largest increase in pfail over the period spanning February to December month (t-stat = 16.6912). Firms in the sample whose distress risk has decreased outperform the total sample by 0.092 percent over the same period (t-stat = 16.6808). Similarly, firms in the sample whose distress risk has increased underperform the total sample by -1.03 percent over the same period (t-stat = -16.5408). Results are significant within a confidence interval of 99 percent. In other words, we find strong evidence that the market re-prices stocks whose distress risk has changed beyond market expectations, and hence we fail to reject hypothesis 2a. What is more, we find the direction of the stock price reaction to consistently be positive for good news firms and negative for bad news firms, respectively, and hence we fail to reject hypothesis 2b.

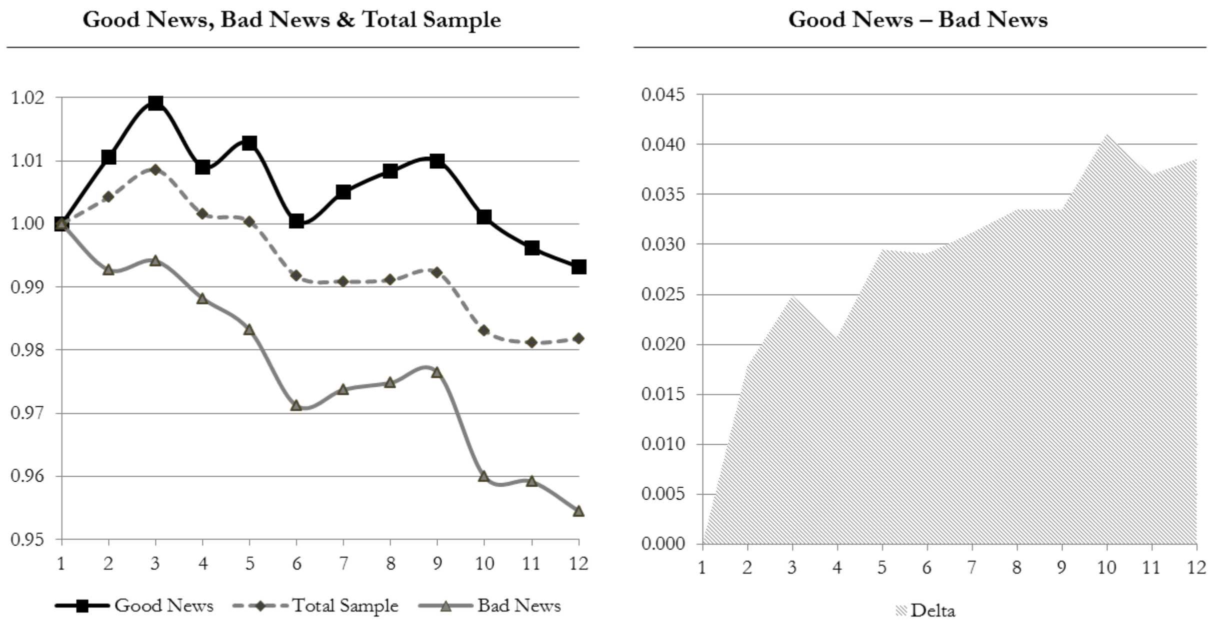
Table 9: Test of significance for good and bad news portfolios during 2000 to 2014 (quantiles). The table presents the level of significance of the event study with various lengths of the post-event window included. Good – Bad shows the formal test of statistical significance. The Good – Total Sample and Bad – Total Sample shows the magnitude of the event's relative effect on aggregated abnormal returns for good and bad news portfolios respectively. T-statistics are calculated as the mean coefficient divided by its time-series standard error.

Event Study Results - Quantiles										
Time		**Good - Bad**			**Good - Total Sample**			**Bad - Total Sample**		
Start	**End**	**Mean**	**StD**	**t-stat**	**Mean**	**StD**	**t-stat**	**Mean**	**StD**	**t-stat**
-1	+1	0.0151	0.0029	9.0849	0.0073	0.0013	10.0047	-0.0078	0.0016	-8.3552
-1	+2	0.0172	0.0048	7.1836	0.0083	0.0022	7.4977	-0.0089	0.0026	-6.9084
-1	+3	0.0179	0.0044	8.9907	0.0086	0.0020	9.4437	-0.0093	0.0024	-8.5983
-1	+4	0.0180	0.0040	11.0562	0.0086	0.0018	11.5873	-0.0094	0.0022	-10.5713
-1	+5	0.0182	0.0037	13.0709	0.0086	0.0017	13.7444	-0.0096	0.0020	-12.4241
-1	+6	0.0182	0.0034	15.0199	0.0086	0.0015	15.6775	-0.0096	0.0019	-14.3368
-1	+7	0.0186	0.0034	16.2498	0.0088	0.0015	17.0624	-0.0098	0.0019	-15.4537
-1	+8	0.0189	0.0034	17.7971	0.0089	0.0015	18.6076	-0.0100	0.0019	-16.9898
-1	+9	0.0195	0.0039	16.6912	0.0092	0.0018	16.6808	-0.0103	0.0021	-16.5408

Furthermore, results from the 2-quantile sort suggest most of the observed difference in stock returns between the two groups of firms emerges in the event window starting in the month of February. During this period, firms receiving good news earn, on average, 1.51 percent higher abnormal returns, than firms receiving bad news (t-stat = 9.0849). Results are significant within a 95 percent confidence interval. The event window signifies the period when relevant accounting information from the previous calendar year is assumed to be published. Accounting information is in turn required, we assume, to determine change in distress risk. Likewise, this observation could be interpreted as the market anticipating information contained in financial reports prior to them being published, as some firms publish reports later (Ball and Brown, 1968).

Figure 9 compares API's for the subset of firms with the largest and lowest changes in distress risk, respectively, when the sample is divided into five equally numerous subsets (quintiles).

Figure 9: Abnormal performance indexes for good and bad news portfolios (quintiles). The left figure presents event study results for the period 2000 to 2014. Abnormal performance indexes are calculated for the entire sample, as well as for good and bad news portfolios. The good news portfolio represents the quintile portfolio with the largest decrease in pfail. The bad news portfolio represents the quintile portfolio with the largest increase in pfail. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of February and ends at the end of December. The right figure presents the difference in the abnormal performance index between the good and bad news portfolios.



We observe that firms in the quintile experiencing the largest decrease in pfail earn, on average 3.07 percent higher abnormal monthly returns, than firms in the quintile with the largest increase in pfail over the period spanning February to December month (t-stat = 14.0210). Firms in the subset whose distress risk has decreased outperform the total sample by 1.26 percent over the same period (t-stat = 10.1277). Similarly, firms in the subset whose distress risk has increased underperform the total sample by -1.81 percent over the same period (t-stat = -12.7693). Results are significant within a 99 percent confidence interval.

Looking at the stock price reactions of quintiles with moderate changes in pfail (see Appendix 9), we note that the API's of these subsets line up closer to the sample mean, i.e. within the two groups sorted on the most extreme changes in pfail. In other words, the magnitude of the stock price reaction following a change in distress risk seems to be related to the corresponding magnitude of the change in risk. This evidence leads us to suggest hypothesis 2c cannot be rejected.

While we note that the stock price reaction emerges in the event window, quintiles reveal what appears to be a delayed price response to changes in distress risk, as suggested by the increasing difference between the API of good news and bad news following the release of relevant accounting information. Looking at Table 10, note that the mean abnormal return difference between good news and bad news firms increases from 2.12 (t-stat = 10.2771) percent over the event window, to the 3.07 percent achieved, on average, over a twelve month period. In other words, results point to a post-publication[16] drift in stock prices, where riskier junk stocks continue to underperform safer quality stocks over a twelve month period, in line with the findings of Holthausen and Leftwich (1985). What is more, we find that the drift is significantly higher when forming ten equally numerous subsets (deciles) and observing the stock price reactions for the subsets with the highest and lowest change in distress risk (see Section 9.6.2, robustness test 6).

As a final remark, we note that the API computed on all firms in the sample drifts downwards over the twelve month period. This mean negative abnormal return is less surprising, and is likely to be caused by the high number of monthly observations in our sample occurring during years of financial crises.

[16] Post-publication period refers to periods following the publication of relevant financial statements required to determine the level of distress risk. Similar studies commonly refer to this as a 'post-announcement period'. However, as the event investigated in our study does not entail an announcement per se, we denote the period as the 'post-publication period' (Ball & Brown, 1968)

Table 10: Test of significance for good and bad news portfolios (quintiles) during 2000 to 2014. The table presents the level of significance of the event study with various lengths of the post-event window included. Good – Bad shows the formal test of statistical significance. The Good – Total Sample and Bad – Total Sample shows the magnitude of the event's relative effect on aggregated abnormal returns for good and bad news portfolios respectively. T-statistics are calculated as the mean coefficient divided by its time-series standard error.

Event Study Results - Quintiles										
Time		Good - Bad			Good - Total Sample			Bad - Total Sample		
Start	End	Mean	StD	t-stat	Mean	StD	t-stat	Mean	StD	t-stat
-1	+1	0.0212	0.0036	10.2771	0.0081	0.0022	6.4766	-0.0131	0.0015	-15.1625
-1	+2	0.0233	0.0051	9.1480	0.0092	0.0028	6.6060	-0.0141	0.0024	-11.9074
-1	+3	0.0245	0.0051	10.6622	0.0091	0.0024	8.4013	-0.0154	0.0035	-9.8110
-1	+4	0.0256	0.0054	11.6973	0.0099	0.0030	8.1235	-0.0157	0.0032	-11.9454
-1	+5	0.0268	0.0057	12.3401	0.0110	0.0039	7.4670	-0.0158	0.0029	-14.1692
-1	+6	0.0276	0.0058	13.3938	0.0118	0.0043	7.7466	-0.0158	0.0027	-16.3699
-1	+7	0.0291	0.0071	12.3388	0.0125	0.0045	8.2873	-0.0166	0.0035	-14.0414
-1	+8	0.0299	0.0071	13.2651	0.0128	0.0043	9.2928	-0.0171	0.0038	-14.4205
-1	+9	0.0307	0.0073	14.0210	0.0126	0.0041	10.1277	-0.0181	0.0047	-12.7693

Analysis

The statistically significant stock price reactions observed during the event window confirms the usefulness of the information content in accounting numbers used to evaluate distress (Ball and Brown, 1968). In line with what was expected, results suggest the market revalues firms experiencing an improvement in credit quality, all else equal, to a higher value upon the publication of relevant financial statements. Likewise, the market seems to revalue firms experiencing a deteriorating credit quality, all else equal, to a lower value. In other words, results are in line with the intuitive risk-return relationship.

More surprising however is what appears to be a post-publication drift in stock prices for stocks with the highest change in distress risk as observed in the quintile and decile portfolios. Rather than observing a distress premium following the stock price correction, we find evidence that stock prices of junk firms with higher levels of distress risk continue to drift downward. In other words, junk stocks consistently underperform quality stocks beyond the event window. The trend supports evidence found by previous research (Holthausen and Leftwich, 1985). What is more, we also find the opposite to be true; stock prices of quality firms with lower levels of distress risk continue to drift upward following the initial stock price reaction. The evidence surrounding firms with improving credit quality is in contrast to the results of previous research who find no significant positive stock market reaction to credit rating upgrades (Dichev and Piotroski, 2001).

We recognize that one potential explanation of our results may be that changes in distress risk are correlated to corresponding changes in earnings. In other words, the results we observe could very well be post-earnings-announcement surprises, in line with the findings of Bernard and Thomas (1989). While this is certainly a possibility, robustness tests including the use of an alternative measure of distress as well as an increased number of portfolios producing very similar results, we hope, will offer readers some comfort (see Section 9.2). Furthermore, similar studies performing tests conditional on earnings surprises find that the post-announcement effect surrounding changes in distress risk remains significant (Dichev and Piotroski, 2001).

The findings of Dichev and Piotroski's (2001) study on long-run post-announcement returns; that the underperformance of firms receiving a credit downgrade persists for a period of three years following the downgrade, bears similarities to the findings presented here. With compelling evidence, they also suggest firms with deteriorating credit quality experience significant deterioration in earnings in future periods. As a result, they argue the post-announcement drift in stock returns of firms receiving downgrades may be caused by the market's failure to anticipate deteriorating performance, causing continuous disappointment to future earnings announcements.

Similar to this line of reasoning, the post-publication drift in stock prices may also be the result of the markets' lack of ability to re-price stocks by the appropriate magnitude. In other words, the outperformance (underperformance) of quality (junk) stocks could be driven by the market's inability to apply an appropriate premium (discount) to stock prices following the publication of relevant information on distress risk. This explanation is in line with the argument that distress risk is not a systematic risk.

We suggest the post-publication drift may partly explain the previously documented distress anomaly and is thus in line with previous research (Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008). In other words, it is not unlikely that the distress anomaly (i.e. that firms with low distress risk realize higher returns, on average, than firms with high distress risk) is crucially dependent on the presence of time periods containing credit downgrades. The effect, combined with findings that suggest distressed firms experience a substantial deterioration in operating and financial performance during times of distress, entertains the idea that investors (perhaps large institutional ones in particular) remain net sellers of junk stocks causing substantial price drops, and vice versa (Avramov, Chordia, Jostova and Philipov, 2009).

Finally, we recognize that our results may be caused by informational disclosures and announcements other than those intended to be tested, and that an exhaustive list of disclosures currently absent would be required to control for this effect.

7 Conclusions

We have used three methods to test whether distress risk can explain variations in stock returns. The purpose of the study has been to search for a distress premium, and to establish whether the market correctly re-prices stocks whose distress risk has changed in an accurate and timely manner. Distress has been defined as the probability of business failure, and operationalized by means of an established bankruptcy prediction model using accounting information from the financial statements of public firms (Skogsvik, 1990).

Results support the notion that distress risk is not a systematic risk. In other words, investing in stocks of firms with higher levels of distress risk does not justify earning a higher return, on average, than investing in stocks of firms with lower levels of distress risk. Hence, this study adds to evidence provided by previous research pointing to the absence of a distress premium (Dichev, 1998; Campbell, Hilscher and Szilagyi, 2008).

What is more, the performance of stocks with varying degrees of distress risk in our sample is puzzling. We find that quality stocks, defined as those with low distress risk, outperform junk stocks with high distress risk. In other words, our results point to a slight risk aversion in the market. We also note that this tendency of risk aversion is more pronounced among value stocks and firms with low profitability, respectively. That is to say, results suggest investors tend to display risk averseness by prioritizing stocks with low distress risk, in particular, amongst groups of stocks defined as high risk by means of the B/M ratio and ROE, respectively.

One potential explanation to the findings is that the asset pricing model used in this study, based on previous research, is misspecified (Fama and French, 1992). This view suggests the model fails to accurately capture different dimensions of risk, giving rise to the distress anomaly. Perhaps more appealing is the explanation offered by Asness, Frazzini and Pedersen (2014), who attribute the premium (discount) placed on quality (junk) stocks to the flight to quality that has characterized capital flows in the post-crisis era of the early 21st century. Regardless of interpretation, the lack of distress premium and the unwarranted underperformance of junk stocks pose a challenge to traditional capital asset pricing models based on the risk-return paradigm.

Looking at stock price reactions to changes in distress, we find additional possible explanations to the anomalous behavior of quality and junk stocks, respectively. We present strong evidence suggesting a change in distress risk is significantly associated with a stock market reaction. Following the publication of annual financial statements, the market seems to punish (reward) stocks whose distress risk has increased (decreased) with a negative (positive) stock price reaction. The direction of the re-pricing is in line with what the traditional risk-return paradigm would suggest. Results support previous research claiming the usefulness of accounting information (Ball and Brown, 1968; Skogsvik, 2008).

Contrary to what the efficient market hypothesis would lead us to expect however, results point to a post-publication drift in stock prices following changes in distress risk, similar to what previous research has found (Holthausen and Leftwich, 1985). The effect is particularly visible among stocks with the highest degree of change in distress risk. In other words, stocks whose distress risk has increased continue to underperform stocks whose distress risk has decreased beyond the period when new information is received by the market, perhaps over several years[17].

Dichev and Piotroski (2001) attribute such anomalous stock price behavior to what they find is an increased likelihood of deteriorating earnings following an increase in distress risk. The markets' lack of ability to fully anticipate such change in future earnings, they argue, is cause for additional stock price decline in subsequent periods. Their argument lines up well with our findings and may explain the post-publication drift in stock prices observed.

Alternatively, the magnitude of the stock price reaction observed following the publication of new information, albeit significant, may not have fully reflected the change in distress risk for quality and junk stocks respectively. In other words, evidence suggests the market underreacts to changes in distress risk, causing quality stocks to continue to outperform and junk stocks to continue to underperform over time.

Finally, the observed post-publication drift in stock prices, we suggest, may serve as an explanation for the distress anomaly. The lack of sufficient reversals following stock price corrections caused by changes in distress risk seems to result in the prolonged underperformance of junk stocks. It is hence not unlikely that the absence of a distress premium observed in our results is crucially dependent on periods of credit downgrades. In other words, stock returns during periods of deteriorating or improving credit quality may account for the anomalous outperformance of quality stocks and underperformance of junk stocks, respectively, over time (Avramov, Chordia, Jostova and Philipov, 2009).

By way of concluding, we identify areas for further research based on the findings of previous research as well as that of this study. Firstly, the notion that the market is risk averse in its assessment of distress risk has interesting implications on investor behavior, and offers an opportunity to complement studies of distress risk with theories of behavioral finance. Secondly, the reliance on accounting-based measures of distress in this study could be considered a limitation, and could be complemented by testing market-based measures on a similar sample. Lastly, our findings prompt further investigation into the spill-over effects of stock price reactions following credit downgrades into the long-term performance of stocks with varying degrees of distress risk.

[17] Note that while the event study conducted as part of this paper does not examine abnormal returns beyond a twelve month period, the cross-sectional regressions and the portfolio analysis examine the returns of stocks with varying levels of distress risk over a 15-year period.

8 References

Altman, Edward I., 1968, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, The Journal of Finance, Vol. 23, No. 4, pp. 589 – 609

Asness, Clifford S., Frazzini, Andrea and Pedersen, Lasse H., 2014, Quality Minus Junk, Working paper, AQR Capital Management, pp.1 – 65

Asness, Clifford S., Frazzini, Andrea, Israel, Ronen, Moskowitz, Tobias and Pedersen, Lasse H., 2015, Size Matters, if You Control Your Junk, Working paper, AQR Capital Management, pp.1 – 59

Avramov, Doron, Chordia, Tarun, Jostova, Gergana, Philipov, Alexander, 2009, Credit Ratings and the Cross-Section of Stock Returns, Journal of Financial Markets Vol. 12, No.3, pp. 469 – 499

Ball, Ray and Brown, Philip, 1968, An Empirical Evaluation of Accounting Income Numbers, Journal of Accounting Research, pp.159 – 178

Bartov, Eli, Lindahl, Frederick W., Ricks, William E., 1998, Stock Price Behavior Around Announcements of Write-Offs, Review of Accounting Studies, Vol. 3, pp. 327 – 346

Basu, Sanjoy, 1983, The relationship between earnings' yield, market value and returns for NYSE common stocks, Journal of Financial Economics, Vol. 12, pp. 129 – 156

Beaver, William H., 1966, Financial Ratios as Predictors of Failure, Journal of Accounting Research, Vol. 4, Empirical Research in Accounting: Selected Studies, pp. 71 – 111

Beaver, William H., 1968, The Information Content of Annual Earnings Announcements, Journal of Accounting Research, Vol. 6, pp. 67 – 92

Bellovary, Jodi L., Giacomino, Don E., Akers, Michael D., 2007, A Review of Bankruptcy Prediction Studies: 1930 to Present, Journal of Financial Education, Vol. 33, pp. 1 – 42

Berk, Jonathan, 1995, A Critique of Size-Related Anomalies, Review of Financial Studies, Vol. 8, No. 2, pp. 275 – 286

Berk, Jonathan, 1997, "Does Size Really Matter?" Financial Analysts Journal, Vol. 53, No. 5, pp. 12 – 18

Bernard, Victor L. and Thomas, Jacob K., 1989, Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?, Journal of Accounting Research, Vol 27, pp. 1 – 36

Bhandari, Laxmi Chand, 1988, Debt to Equity Ratio and Expected Common Stock Returns: Empirical Evidence, The Journal of Finance, Vol. 43, No. 2, pp. 507 – 528

Black, Fischer, 1972, Capital Market Equilibrium with Restricted Borrowing, The Journal of Business, Vol. 45, No. 3, pp. 444 – 455

Brown, Stephen J., Warner, Jerold B., 1980, Measuring security price performance, Journal of Financial Economics, Vol. 8, pp. 205 – 258

Campbell, Y. John, Thompson, B. Samuel, 2008, Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average?, Oxford University Press; The Review of Financial Studies, Vol. 21, No. 4, pp. 1509 – 1531

Campbell, John Y., Hilscher, Jens and Szilagyi, Jan, 2008, In Search of Distress Risk, Journal of Finance, Vol. 63, pp. 2,899 – 2939

Carhart, Mark M., 1997, On persistence in Mutual Fund Performance, the Journal of Finance, Vol. LII, No. 1, pp. 57 – 82

Chan, K.C., Chen, Nai-fu and Hsieh, David, 1985, An exploratory investigation of the firm size effect, the Journal of Financial Economics No. 14, pp. 451 – 471

Chan, K.C. and Chen, Nai-fu, 1991, Structural and Return Characteristics of Small and Large Firms, The Journal of Finance, Vol. 46, No. 4, pp. 1,467 – 1,484

Dambolena, Ismael G., Shulman, Joel M., 1988, A Primary Rule For Detecting Bankruptcy: Watch The Cash, Financial Analysts Journal, Vol. 44, No. 5, pp. 74 – 78

De Bondt, Werner F. M. and Thaler, Richard, 1985, Does the Stock Market Overreact?, The Journal of Finance, Vol. 40, No. 3, pp. 793 – 805

Dichev, Ilia D., 1998, Is the Risk of Bankruptcy a Systematic Risk, The Journal of Finance, Vol. 53, No. 3, pp. 1131 – 1147

Dichev, Ilia D. and Piotroski, Joseph D., 2001, The Long-Run Stock Returns Following Bond Ratings Changes, Journal of Finance, Vol. 5, pp. 173 – 203

Fama, Eugene F., 1970, Efficient Capital Markets: A Review of Theory and Empirical Work, The Journal of Finance, Vol. 25, No. 2, pp. 383 – 417

Fama, Eugene F. and MacBeth, James D., Risk, Return, and Equilibrium: Empirical Tests, 1973, The Journal of Political Economy, Vol 81, No. 13, pp. 607 – 636

Fama, Eugene F., and French, Kenneth R., The Cross-Section of Expected Stock Returns, 1992, The Journal of Finance, Vol XLVII, No. 2, pp. 427 – 465

Fama, Eugene F. and French, Kenneth R., 1996, Multifactor Explanations of Asset Pricing Anomalies, The Journal of Finance, Vol Li, No.1, pp. 55 – 84

Fama, Eugene F. and French, Kenneth R., 2015, A five-factor asset pricing model, The Journal of Financial Economics, Vol. 116, pp. 1 – 22

FitzPatrick, P., 1932, A comparison of ratios of successful industrial enterprises with those of failed companies, The Certified Public Accountant (October, November, December), pp. 598 – 605, 656 – 662, and 727 – 731

Gentry, Richard J. and Shen, Wei, 2010, The Relationship between Accounting and Market Measures of Firm Financial Performance: How Strong Is It, Journal of Managerial Issues, Vol. 22, No. 4, pp. 514 – 530

Griffin, John M. and Lemmon, Michael L., 2002, Book-to-Market Equity, Distress Risk and Stock Returns, The Journal of Finance, Vol. 57, No. 2, pp. 2317 – 2336

Haugen, Robert A., 2002, The Inefficient Stock Market – Second Edition, Prentice Hall

Holthausen, Robert W. and Leftwich, Richard W., 1986, The effect of bond rating changes on common stock prices, Journal of Financial Economics, Vol. 17, No. 1, pp. 57 – 89

Jegadeesh, Narasimham, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, Journal of Finance Vol. 48, pp. 65 – 91

Kothari, S. P., Lewellen, Jonathan and Warner, Jerold B., 2006, Stock returns, aggregate earnings surprises and behavioral finance, Journal of Financial Economics, Vol. 79, pp. 537 – 568

Lakonishok, Josef, Shleifer, Andrei and Vishny, Robert W., 1994, Contrarian Investment, Extrapolation, and Risk, The Journal of Finance, Vol. 49, No. 5, pp. 1,541 – 1,578

Laitinen, Erkki, K., 1991, Financial Ratios and Different Failure Processes, The Journal of Business Finance & Accounting, Vol. 18, No. 5, pp. 649 – 673

Lintner, John, 1965, The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, Vol. 47, No.1, pp. 13 – 37

Markowitz, Harry, 1952, Portfolio Selection, The Journal of Finance, Vol. 7, No. 1, pp. 77 – 91

Merton, C. Robert, 1973, On the Pricing of Corporate Debt: the Risk Structure of Interest Rates, Journal of Finance, Vol. 29, pp. 449 – 470

Miller, Merton H. & Modigliani, Franco, 1963, Corporate income taxes and the cost of capital: a correction, American Economic Review, Vol. 53, No. 3, pp. 433 – 443

Nai-fu, Chen & Zang, Feng, 1998, Risk and Return of Value Stocks, The Journal of Business, Vol. 71, No. 4, pp. 501 – 535

Ohlson, James A., 1980, Financial Ratios and the Probabilistic Prediction of Bankruptcy, Journal of Accounting Research, Vol. 18, No. 1, pp. 109 – 131

Penman, Stephen H., 2009, Financial Statement Analysis and Security Valuation, McGraw Hill

Rosenberg, Barr, Reid, Kenneth and Lanstein, Ronald, 1985, Persuasive Evidence of Market Inefficiency, The Journal of Portfolio Management, Vol. 9, pp. 9 – 16

Ross, Stephen, The Arbitrage Theory of Capital Asset Pricing, 1976, The Journal of Economic Theory, Vol. 13, pp. 341 – 360

Sharpe, William F., 1964, Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk, No. 3, Vol. XIX, pp. 425 – 442

Skogsvik, Kenth, 1990, Current cost accounting ratios as predictors of business failure: the Swedish case, Journal of Business and Finance, Vol. 17, No. 1, pp. 137 – 160

Skogsvik, Stina, 2008, Financial Statement Information, the Prediction of Book Return on Owners' Equity and Market Efficiency: The Swedish Case, Journal of Business, Finance and Accounting, Vol 35. No. 7-8, pp. 795 – 817

Skogsvik, Kenth, 2006, Probabilistic Business Failure Prediction in Discounted Cash Flow Bond and Equity Valuation, SSE/EFI Working Paper Series in Business Administration, No. 5, pp. 2 – 29

Skogsvik, Kenth and Skogsvik, Stina, 2013, On the choice based sample bias in probabilistic bankruptcy prediction, Investment Management and Financial Innovations, Vol. 10, Issue 1, pp. 29 – 37

Vassalou, Maria and Xing, Yuhang, 2003, Equity Returns Following Changes in Default Risk: New Insights into the Informational Content of Credit Ratings, EFA 2003 Annual Conference Paper No. 326, pp. 1 – 50

Vassalou, Maria and Xing, Yuhang, 2004, Default Risk in Equity Returns, Journal of Finance, Vol. 59, No. 2, pp. 831 – 869

Zmijewski, Mark E., 1984, Methodological Issues Related to the Estimation of Financial Distress Prediction Models, Journal of Accounting Research, Vol. 22, Supplement: Studies on Current Econometric Issues in Accounting Research, pp. 59 – 82

9 Appendix

Section 9.1 contains additional exhibits not included in the text, but that may be of interest to the detail-oriented reader. Section 9.2 contains results from a total of six robustness tests carried out with the hope to strengthen the validity of results presented in Section 6.

9.1 Exhibits

Appendix 1: Summary of key stock performance literature with an emphasis on distress risk. The table summarizes the name of each constituent variable used in the asset pricing models of the main stock performance studies focusing on distress risk. The table deliberates further on key metrics used in each variable.

Dichev (1998)		Dichev and Piotroski (2001)		Vassalou and Xing (2003, 2004)		Campbell, Hilscher and Szilagyi (2008)	
Variable	***Metric(s)***	***Variable***	***Metric(s)***	***Variable***	***Metric(s)***	***Variable***	***Metric(s)***
O	*Ohlson's O-Score*	**UP--GRADE**	*Credit Rating upgrade (debt)*	**DLI**	*Default-likelihood-indicator Merton (1974)*	**NIMTA**	$\frac{Net\ Income}{Market\ Value\ of\ Total\ Assets}$
Z	*Altman's Z-Score*	**DOWN-GRADE**	*Credit Rating downgrade (debt)*	**CDLI***	*Change in DLI (change in rating)*	**NITA**	$\frac{Net\ Income}{Book\ Value\ of\ Total\ Assets}$
MV	*Market Value (Market Capitalization)*	**MV**	*Market Value (MCAP)*	**EMKT**	*F&F Market Factor*	**TLMTA**	$\frac{Total\ Liabilities}{Market\ Value\ of\ Total\ Assets}$
B / M	*Book-to-Market (Book Value of Equity / Market Value of Equity)*	**B / M**	*Book Value of Equity / Market Value of Equity*	**SMB**	*F&F Small-Minus-Big Factor*	**TLTA**	$\frac{Total\ Liabilities}{Book\ Value\ of\ Total\ Assets}$
				HML	*F&F High-Minus-Low Factor*	**CASH -MTA**	$\frac{Cash\ \&\ ST\ Assets}{Market\ Value\ of\ Total\ Assets}$
						MB	$\frac{MV\ of\ Equity}{BV\ of\ Equity}$
						EXRET	$[E(\tilde{R}_i) - R_f] - [E(\tilde{R}_{S\&P500}) - R_f]$
						SIGMA	$\partial(\tilde{R}_i)\ for\ the\ last\ 3-months$
						RSIZE & PRICE	*Log(MCAP of stock) / Log (MCAP of S&P)*

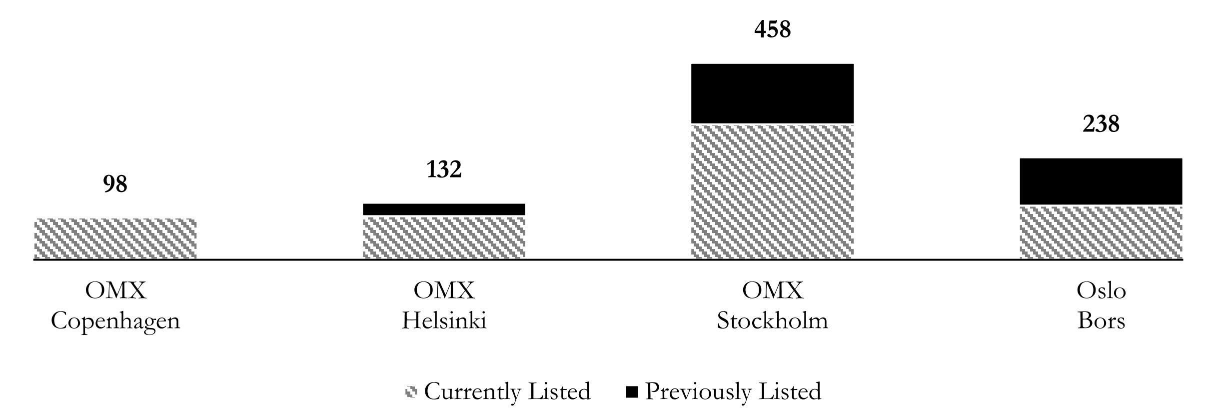
Appendix 2: Summary of key stock performance literature. The table summarizes the name of each constituent variable used in the asset pricing models of the main stock performance studies cited in this thesis. The table deliberates further on key metrics used in each variable.

Chan, Chen and Hsieh (1985)		Fama and French (1996)		Avramov, Chordia, Jostova and Philipov (2009)		Asness, Frazzini and Pedersen (2014)		Fama and French (2015)	
Variable	*Metric(s)*	*Variable*	*Metric(s)*	*Variable*	*Metric(s)*	*Variable*	*Metric(s)*	*Variable*	*Metric(s)*
EWNY	*Equally weighted NYSE index*	***MKT***	$E(\tilde{R}_m) - R_f$	***Sales Growth***	$\frac{Sales_{Qt} - Sales_{Qt-1}}{Sales_{Qt}}$	***Profitability***	*Gross Profit / Assets* *Net Income / Equity* *EBIT / Assets* *Cash Flow / Assets* *Gross Profit / Sales*	***MKT***	*As in 1996*
IPISA	$Industrial\ Production\ (IP)$ $log\frac{IP_{t+1}}{IP_t}$	***SMB***	*⅓ (Small Value + Small Neutral + Small Growth) - ⅓ (Big Value + Big Neutral + Big Growth)*	***Profit Margin***	$\frac{Net\ Income}{Sales}$	***Growth***	*⊿ Gross Profit / Assets* *⊿ Net Income / Equity* *⊿ EBIT / Assets* *⊿ Cash Flow / Assets* *⊿ Gross Profit / Sales*	***SMB***	*As in 1996*
UITB	$CPI_t -$ $Expected\ Inclation\ (EI)_t$	***HML***	*½ (Small Value + Big Value) - ½ (Small Growth + Big Growth)*	***Net Cash Flow***	$Net\ Income + Standardized\ Dep$	***Safety***	*Betting against Beta (BAB)* *Idiosyncratic vol. (IVOL)* *Leverage (LEV)* *Ohlson O-Score* *Altman Z-Score* *ROE volatility (EVOL)*	***HML***	*As in 1996*
DEI	$EI_{t+1} - EI_t$			***Interest Coverage***	$\frac{EBT + Int.Exp.}{Int.Expense}$	***Payout***	*Equity net issuance (EISS)* *Debt net issuance (DISS)* *Net Payout / Profit (NPOP)*	***RMW***	*[(SR - SW) + (BR - BW)] / 2*
UTS	$LT\ Gov\ Bond_t - T - Bill_t$			***Asset Turnover***	$\frac{Sales}{Tot.Assets}$			***CMA***	*[(SC - SA) + (BC - BA)] / 2*
PREM	$< Baa\ Bonds_t - LT\ Gov\ Bond_t$								

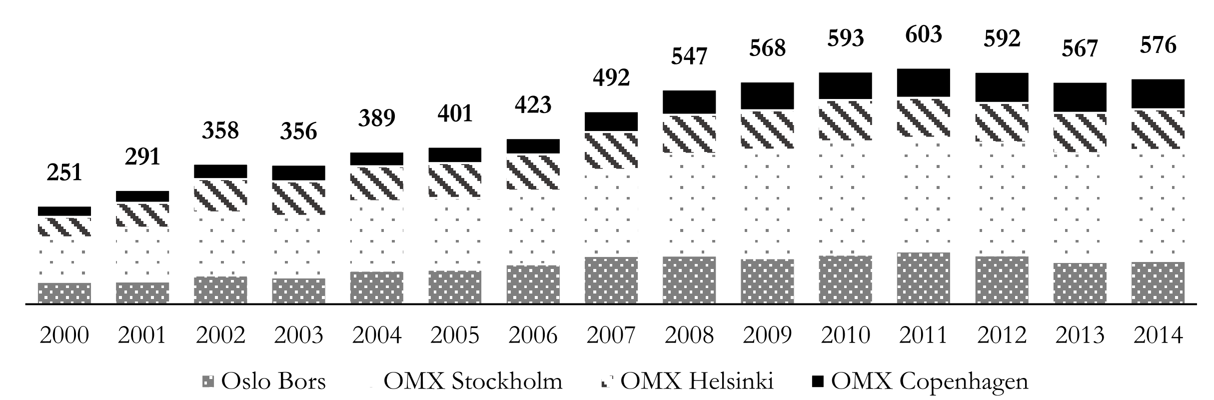
Appendix 3: Summary of literature on bankruptcy prediction models. The table summarizes the name of each constituent variable used in the bankruptcy prediction models of key studies cited in this thesis. The table deliberates further on key metrics used in each variable.

Beaver (1966)		Altman (1968)		Ohlson (1980)		Skogsvik (1990)		Laitinen (1991)	
Variable	*Metric(s)*	*Variable*	*Metric(s)*	*Variable*	*Metric(s)*	*Variable*	*Metric(s)*	*Variable*	*Metric(s)*
Group I: CF Ratios	*CF / Sales* *CF / Assets* *CF / NW* *CF / Debt*	X_1	$\frac{Working\ Cap.}{Tot.Assets}$	**SIZE**	$\log \frac{Tot.Assets}{GNP\ price - inde}$	R_L	$\frac{Int.Exp.}{Av.Tot.Liab.}$	**ROI**	$\frac{Sales - Exp}{Tot.Assets}$
Group II: NI Ratios	*NI / Sales* *NI / Assets* *NI / NW* *NI / Debt*	X_2	$\frac{Ret.Earnings}{Tot.Assets}$	**TLTA**	$\frac{Tot.Liabilities}{Tot.Assets}$	E'	$\frac{\Delta\ Equity}{OB\ Equity}$	**GTA**	$\frac{\Delta\ Tot.Assets}{Tot.Assets}$
Group III: Liab. Ratios	*CL / Assets* *LTL / Assets* *CLTL / Assets* *CLTPS / Assets*	X_3	$\frac{EBIT}{Tot.Assets}$	**WCTA**	$\frac{Working\ Cap.}{Tot.Assets}$	R_A	$\frac{EBIT}{Av.Tot.Assets}$	**NSA**	$\frac{Net\ Sales}{Tot.Assets}$
Group IV: Liq. Ratios	*Cash / Assets* *QA / Assets* *CA / Assets* *WC / Assets*	X_4	$\frac{Mkt.Cap}{BV\ of\ Tot.Debt}$	**CLCA**	$\frac{Curr.Liabilities}{Curr.Assets}$	**ER**	$\frac{Equity}{Tot.Assets}$	**CFR**	$\frac{Cash\ Flow}{Net\ Sales}$
Group V: Liq. (CL) Ratios	*Cash / CL* *QA / CL* *CA / CL*	X_5	$\frac{Sales}{Tot.Assets}$	**OENEG**	$If\ TLTA > 1, 1$ $If\ TLTA < 1, 0$	**TIV**	$\frac{Av.Inventory}{Sales}$	**DAR**	$\frac{Tot.Debt}{Tot.Assets}$
Group VI: Turnover Ratios	*Cash / Sales* *AR / Sales* *Inventory / Sales* *QA / Sales* *CA / Sales* *WC / Sales* *NW / Sales* *Assets / Sales* *Cash / FEFO* *DA / FEFO* *(DA - CA) / FEFO*			**NITA**	$\frac{Net\ Income}{Tot.Assets}$			**CUR**	$\frac{Curr.Assets}{Curr.Liabilities}$
				FUTL	$\frac{FFO}{Tot.Liabilities}$				
				INTWO	$If\ NI_{t-2} < 0, 1$ $If\ NI_{t-2} > 0, 0$				
				CHIN	$\frac{NI_t - NI_{t-1}}{\lvert NI_t \rvert - \lvert NI_{t-1} \rvert}$				

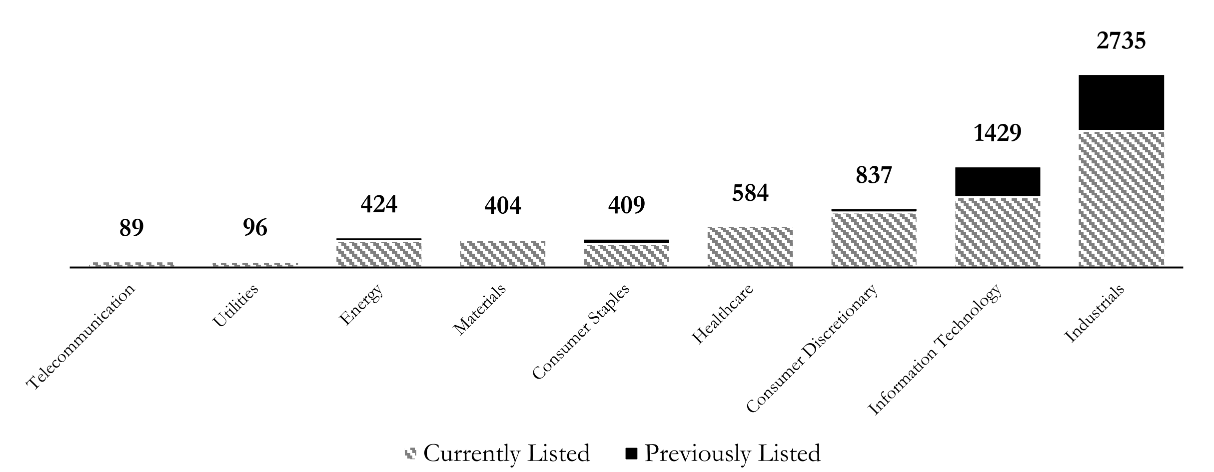
Appendix 4: Number of firms by stock exchange. The figure presents descriptive statistics that illustrate the distribution of firms between the four Nordic exchanges split by listing status. The total number of firms is 926, which constitutes the final sample.



Appendix 5: Number of observations by year and stock exchange. The figure presents descriptive statistics that illustrate the distribution of observations during the years 2000 – 2014 split by exchange. The total number of observations is 7,007, which constitutes the final sample.



Appendix 6: Number of observations by industry. The figure presents descriptive statistics that illustrate the distribution of observations across different industries split by listing status. The total amount of observations is 7,007, which constitutes the final sample.



Appendix 7: Yearly mean values for test variables. The table presents descriptive statistics for the independent variables. Mean values are calculated for each independent variable and year. The total amount of observations is 7,007, which constitutes the final sample.

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
# observations	*251*	*291*	*358*	*356*	*389*	*401*	*423*	*492*	*547*	*568*	*593*	*603*	*592*	*567*	*576*
Beta	0.513	0.511	0.809	0.683	0.640	0.434	0.533	0.622	0.732	0.603	0.506	0.639	0.653	0.499	0.453
MCAP	1177	902	775	749	1052	1162	1292	1391	1251	721	1056	1150	1092	1187	1256
B / M	0.617	0.757	0.852	1.013	0.684	0.551	0.432	0.400	0.514	1.216	0.817	0.737	0.998	0.918	0.733
ROE	0.111	0.066	-0.013	-0.019	-0.009	0.088	0.126	0.110	0.097	0.043	-0.015	-0.018	0.013	-0.004	-0.022
Ag	0.212	0.276	0.068	-0.004	0.016	0.128	0.233	0.272	0.305	0.135	0.009	0.111	0.085	0.056	0.081
Pfail	0.016	0.018	0.023	0.033	0.018	0.012	0.010	0.016	0.017	0.028	0.027	0.032	0.026	0.037	0.031
ZScore	2.40	2.60	2.27	2.18	2.06	2.37	2.61	2.75	2.99	2.45	1.65	1.91	2.31	2.05	2.14

Appendix 8: Abnormal performance indexes for good and bad news portfolios (quantiles). The table presents event study results for the period 2000 to 2014. Abnormal performance indexes are calculated for the entire sample, as well as for good and bad news portfolios. The good news portfolio includes all firms that have experienced a decrease in pfail. The bad news portfolio includes all firms that have experienced an increase in pfail. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of February and ends at the end of December.

Month	Good News	Bad News	Good - Bad	Total Sample	Good - Total Sample	Bad - Total Sample
1	1.0000	1.0000	0.0000	1.0000	0.0000	0.0000
2	1.0103	0.9979	0.0124	1.0042	0.0061	-0.0063
3	1.0158	1.0011	0.0147	1.0086	0.0072	-0.0075
4	1.0102	0.9921	0.0181	1.0016	0.0086	-0.0095
5	1.0115	0.9881	0.0234	1.0004	0.0112	-0.0122
6	1.0015	0.9807	0.0208	0.9917	0.0098	-0.0110
7	0.9996	0.9809	0.0187	0.9909	0.0087	-0.0100
8	1.0001	0.9805	0.0196	0.9911	0.0090	-0.0106
9	1.0005	0.9827	0.0177	0.9923	0.0082	-0.0096
10	0.9933	0.9714	0.0219	0.9831	0.0102	-0.0117
11	0.9913	0.9699	0.0214	0.9812	0.0101	-0.0113
12	0.9945	0.9682	0.0263	0.9818	0.0127	-0.0136

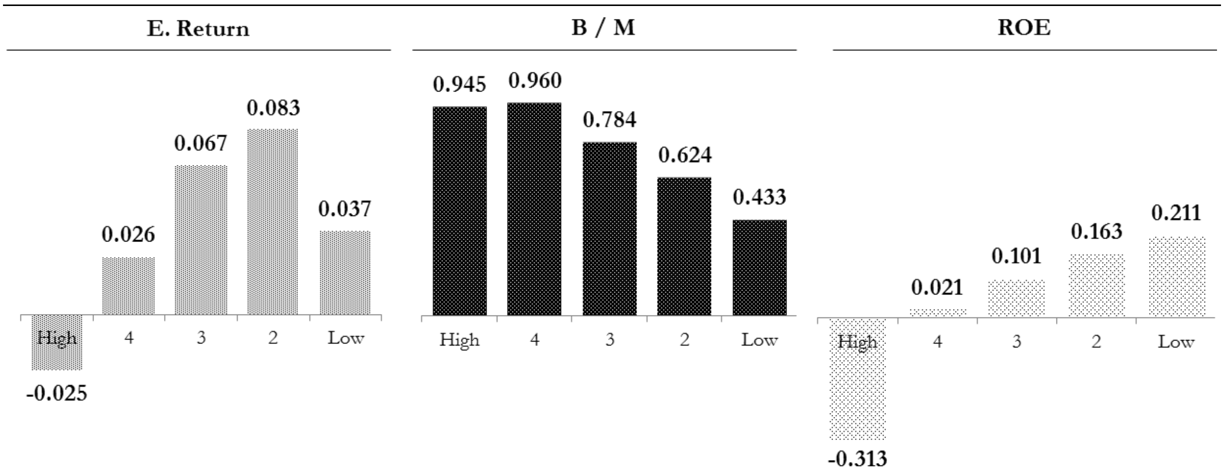
Appendix 9: Abnormal performance indexes for good and bad news portfolios (quintiles). The table presents event study results for the period 2000 to 2014. Abnormal performance indexes are calculated for the entire sample, as well as for good and bad news portfolios. The good news portfolio represents the quintile portfolio with the largest decrease in pfail. The bad news portfolio represents the quintile portfolio with the largest increase in pfail. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of February and ends at the end of December.

Month	Good News	2	3	4	Bad News	Good - Bad	Total Sample	Good - Total Sample	Bad - Total Sample
1	1.0000	1.0000	1.0000	1.0000	1.0000	0.0000	1.0000	0.0000	0.0000
2	1.0106	1.0108	1.0056	1.0016	0.9927	0.0179	1.0042	0.0064	-0.0115
3	1.0191	1.0123	1.0139	1.0034	0.9941	0.0250	1.0086	0.0105	-0.0144
4	1.0091	1.0109	1.0067	0.9932	0.9882	0.0209	1.0016	0.0074	-0.0134
5	1.0128	1.0148	0.9997	0.9914	0.9832	0.0296	1.0004	0.0124	-0.0172
6	1.0004	1.0081	0.9941	0.9850	0.9712	0.0292	0.9917	0.0087	-0.0205
7	1.0051	1.0050	0.9850	0.9864	0.9738	0.0313	0.9909	0.0142	-0.0171
8	1.0084	1.0018	0.9831	0.9881	0.9748	0.0335	0.9911	0.0173	-0.0163
9	1.0100	1.0009	0.9874	0.9873	0.9764	0.0336	0.9923	0.0177	-0.0158
10	1.0011	0.9954	0.9835	0.9765	0.9599	0.0411	0.9831	0.0180	-0.0232
11	0.9962	0.9934	0.9856	0.9724	0.9592	0.0370	0.9812	0.0150	-0.0220
12	0.9932	0.9999	0.9905	0.9723	0.9545	0.0387	0.9818	0.0114	-0.0273

9.2 Robustness Tests

9.2.1 Robustness Test 1: Portfolio Analysis with alternative measure of distress

Appendix 10: Z-Score's relation to excess return, B/M ratio and ROE during 2000 to 2014. The figure presents portfolio results that illustrate how excess return, B/M and ROE is affected as Z-Score increases. Firms are assigned yearly into quintile portfolios based on the magnitude of their Z-Score. High represents the quintile portfolio including firms with the highest distress risk (i.e. lowest Z-Score). Low represents the quintile portfolio including firms with the lowest distress risk (i.e. highest Z-Score).

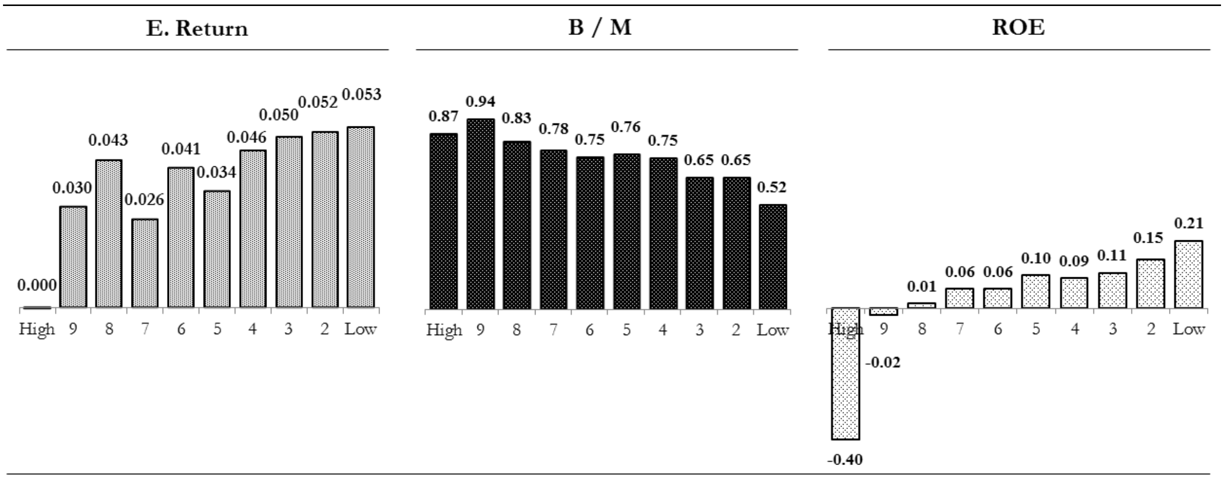


Appendix 11: Relation between Z-Score and other test variables during 2000-2014. The table presents portfolio results, where firms are assigned yearly into quintile portfolios based on the magnitude of their Z-Score. High represents the quintile portfolio including firms with the highest distress risk (i.e. lowest Z-Score). Low represents the quintile portfolio including firms with the lowest distress risk (i.e. highest Z-Score).

Portfolio	High	4	3	2	Low	High - Low	Sample Mean
Z-Score	-0.394	1.409	2.089	2.833	5.645	-6.038	2.294
E. Return	-0.025	0.026	0.067	0.083	0.037	-0.062	0.036
Beta	0.637	0.598	0.592	0.549	0.568	0.068	0.589
MCAP	460	1472	1445	1099	922	-463	1094
B / M	0.945	0.960	0.784	0.624	0.433	0.512	0.762
ROE	-0.313	0.021	0.101	0.163	0.211	-0.524	0.032
AG	0.087	0.091	0.109	0.138	0.236	-0.149	0.127
Pfail	0.075	0.020	0.010	0.005	0.005	0.071	0.024

9.2.2 Robustness Test 2: Portfolio Analysis with increased number of portfolios

Appendix 12: Pfail's relation to excess return, B/M ratio and ROE during 2000 to 2014. The figure presents portfolio results that illustrate how excess return, B/M and ROE is affected as pfail decreases. Firms are assigned yearly into decile portfolios based on the magnitude of their probability of failure. High represents the decile portfolio including firms with the highest pfail. Low represents the decile portfolio including firms with the lowest pfail.



Appendix 13: Relation between Pfail and other test variables during 2000-2014. The table presents portfolio results, where firms are assigned yearly into decile portfolios based on the magnitude of their probability of failure. High represents the decile portfolio including firms with the highest pfail. Low represents the quintile portfolio including firms with the lowest pfail.

Portfolio	High	9	8	7	6	5	4	3	2	Low	High - Low	Sample Mean
Pfail	0.2016	0.0188	0.0064	0.0025	0.0010	0.0004	0.0001	1.98E-05	2.32E-06	8.55E-08	0.2016	0.0239
E. Return	0.000	0.030	0.043	0.026	0.041	0.034	0.046	0.050	0.052	0.053	-0.053	0.036
Beta	0.575	0.557	0.618	0.581	0.637	0.609	0.531	0.595	0.587	0.600	-0.025	0.589
MCAP	280	988	1431	1323	1855	1335	1217	738	667	970	-691	1094
B / M	0.868	0.936	0.826	0.783	0.750	0.763	0.747	0.650	0.650	0.517	0.351	0.762
ROE	-0.401	-0.019	0.014	0.059	0.059	0.100	0.091	0.109	0.148	0.206	-0.607	0.032
AG	0.137	0.134	0.123	0.114	0.134	0.117	0.130	0.133	0.132	0.169	-0.033	0.127
Z-Score	0.596	1.620	1.783	2.042	2.210	2.397	2.511	2.772	3.098	4.119	-3.523	2.294

9.2.3 Robustness Test 3: Cross Sectional Regression with alternative measure of distress

Appendix 14: Multivariate regression results during 2000 to 2014. The table presents regression results for multivariate Fama-MacBeth (1973) regressions with 15 yearly cross sections. A coefficient in these regressions represents the mean of the yearly cross sectional coefficients. A t-statistic (in parentheses) is calculated as the mean coefficient divided by its time-series standard error. For more detailed explanations of the test variables, view Table 1.

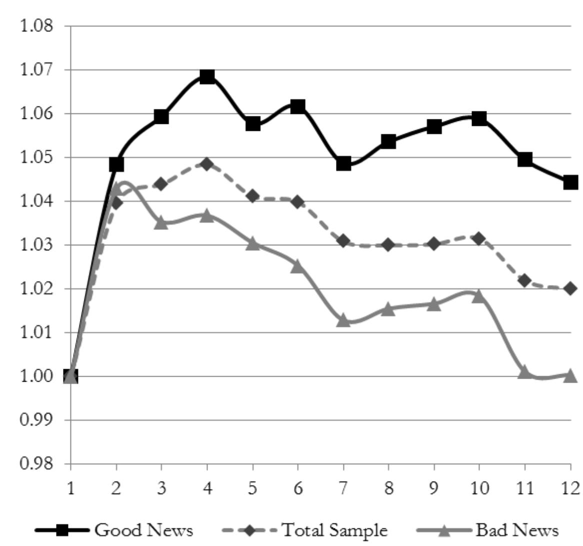
Regression Results - Multivariate						
Re - Rf	= *Zscore*	+ *Beta*	+ *MCAP*	+ *B / M*	+ *ROE*	+ *AG*
Predicted	(-)	(+)	(-)	(+)	(+)	(-)
1	-0.0045					
	-(0.8647)					
2	-0.0043	-0.0087				
	-(0.8585)	-(0.2503)				
3	-0.0005	0.0151	-0.0251			
	-(0.1551)	(0.3230)	**-(1.8422)***			
4	0.0012	-0.0284	-0.0078	0.0380		
	(0.3623)	-(0.9936)	-(0.8102)	**(2.1939)****		
5	-0.0004	-0.0260	-0.0105	0.0384	0.0394	
	-(0.1138)	-(0.9156)	-(1.1453)	**(2.2071)****	**(2.3529)****	
6	0.0000	-0.0272	-0.0104	0.0367	0.0374	-0.0269
	(0.0115)	-(0.9918)	-(1.1418)	**(2.1024)***	**(2.3932)****	-(1.3660)

*[* p < 0.10, ** p < 0.5, *** p < 0.01]*

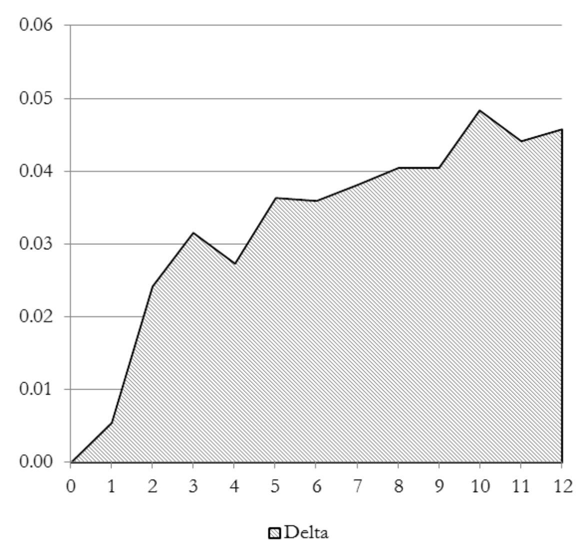
9.2.4 Robustness Test 4: Event Study including the January effect

Appendix 15: Abnormal performance indexes for good and bad news portfolios (quintiles). The left figure presents event study results for the period 2000 to 2014. Abnormal performance indexes are calculated for the entire sample, as well as for good and bad news portfolios. The good news portfolio represents the quintile portfolio with the largest decrease in pfail. The bad news portfolio represents the quintile portfolio with the largest increase in pfail. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of January and ends at the end of December. The right figure presents the difference in the abnormal performance index between the good and bad news portfolios.

Good News, Bad News & Total Sample



Good News – Bad News



Appendix 16: Test of significance for good and bad news portfolios (quintiles) during 2000 to 2014

The table presents the level of significance of the event study with various lengths of the post-event window included. Good – Bad shows the formal test of statistical significance. The Good – Total Sample and Bad – Total Sample shows the magnitude of the event's relative effect on aggregated abnormal returns for good and bad news portfolios respectively. T-statistics are calculated as the mean coefficient divided by its time-series standard error.

Event Study Results - Including January

Time		Good - Bad			Good - Total Sample			Bad - Total Sample		
Start	End	Mean	StD	t-stat	Mean	StD	t-stat	Mean	StD	t-stat
-1	+1	0.0204	0.0135	2.6227	0.0082	0.0078	1.8065	-0.0017	0.0062	-0.4791
-1	+2	0.0221	0.0115	3.8386	0.0111	0.0087	2.5529	-0.0042	0.0071	-1.1843
-1	+3	0.0250	0.0118	4.7137	0.0122	0.0079	3.4431	-0.0055	0.0067	-1.8085
-1	+4	0.0268	0.0115	5.7084	0.0138	0.0081	4.1729	-0.0070	0.0071	-2.4113
-1	+5	0.0284	0.0113	6.6320	0.0144	0.0076	5.0376	-0.0085	0.0077	-2.9397
-1	+6	0.0299	0.0113	7.4713	0.0156	0.0077	5.6964	-0.0093	0.0074	-3.5387
-1	+7	0.0311	0.0112	8.3534	0.0168	0.0082	6.1900	-0.0098	0.0071	-4.1318
-1	+8	0.0328	0.0119	8.7504	0.0179	0.0084	6.7479	-0.0101	0.0068	-4.7194
-1	+9	0.0338	0.0118	9.5511	0.0188	0.0085	7.3485	-0.0111	0.0072	-5.1097

Appendix 17: Abnormal performance indexes for good and bad news portfolios (quintile)

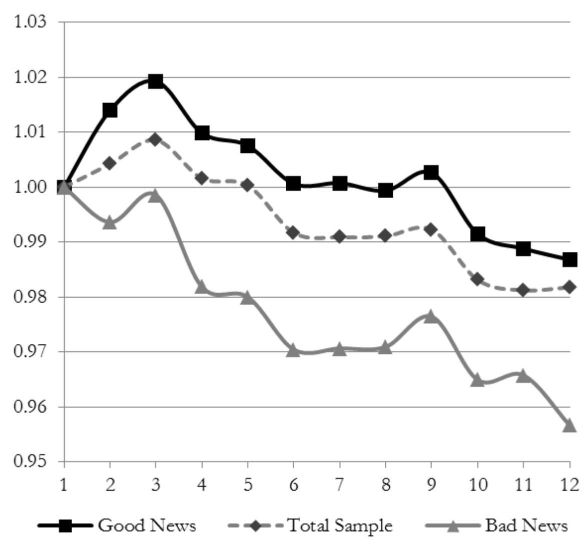
The table presents event study results for the period 2000 to 2014. Abnormal performance indexes are calculated for the entire sample, as well as for good and bad news portfolios. The good news portfolio represents the quantile portfolio with the largest decrease in pfail. The bad news portfolio represents the quantile portfolio with the largest increase in pfail. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of January and ends at the end of December.

Month	Good News	2	3	4	Bad News	Good - Bad	Total Sample	Good - Total Sample	Bad - Total Sample
0	1.0000	1.0000	1.0000	1.0000	1.0000	0.0000	1.0000	0.0000	0.0000
1	1.0484	1.0394	1.0355	1.0315	1.0429	0.0055	1.0395	0.0089	0.0034
2	1.0595	1.0507	1.0414	1.0332	1.0354	0.0241	1.0439	0.0156	-0.0085
3	1.0684	1.0522	1.0500	1.0350	1.0368	0.0316	1.0484	0.0200	-0.0116
4	1.0579	1.0507	1.0425	1.0245	1.0306	0.0273	1.0412	0.0167	-0.0106
5	1.0618	1.0548	1.0352	1.0226	1.0254	0.0364	1.0399	0.0219	-0.0145
6	1.0488	1.0478	1.0294	1.0160	1.0129	0.0359	1.0309	0.0179	-0.0180
7	1.0537	1.0446	1.0200	1.0175	1.0156	0.0381	1.0300	0.0237	-0.0145
8	1.0572	1.0413	1.0180	1.0192	1.0167	0.0405	1.0303	0.0269	-0.0136
9	1.0589	1.0403	1.0225	1.0184	1.0184	0.0405	1.0315	0.0274	-0.0131
10	1.0495	1.0346	1.0184	1.0072	1.0011	0.0484	1.0220	0.0276	-0.0208
11	1.0444	1.0325	1.0206	1.0030	1.0004	0.0441	1.0200	0.0244	-0.0196
12	1.0413	1.0393	1.0257	1.0029	0.9955	0.0458	1.0206	0.0207	-0.0251

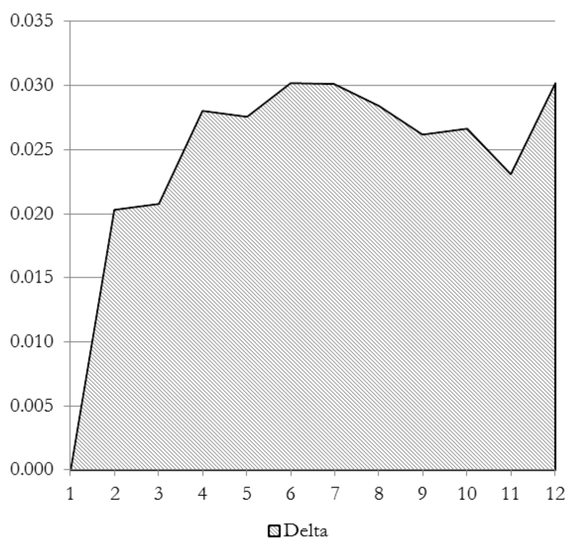
9.2.5 Robustness Test 5: Event Study with alternative measure of distress

Appendix 18: Abnormal performance indexes for good and bad news portfolios (quintiles). The left figure presents event study results for the period 2000 to 2014. Abnormal performance indexes are calculated for the entire sample, as well as for good and bad news portfolios. The good news portfolio represents the quantile portfolio with the largest increase in Z-Score. The bad news portfolio represents the quantile portfolio with the largest decrease in Z-Score. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of February and ends at the end of December. The right figure presents the difference in the abnormal performance index between the good and bad news portfolios.

Good News, Bad News & Total Sample



Good News – Bad News



Appendix 19: Test of significance for good and bad news portfolios (quintiles) during 2000 to 2014. The table presents the level of significance of the event study with various lengths of the post-event window included. Good – Bad (here based on Z-Score) shows the formal test of statistical significance. The Good – Total Sample and Bad – Total Sample shows the magnitude of the event's relative effect on aggregated abnormal returns for good and bad news portfolios respectively. T-statistics are calculated as the mean coefficient divided by its time-series standard error.

Event Study Results

Time		API			Good - Total Sample			Bad - Total Sample		
Start	**End**	**Mean**	**StD**	**t-stat**	**Mean**	**StD**	**t-stat**	**Mean**	**StD**	**t-stat**
-1	+1	0.0230	0.0043	9.1948	0.0049	0.0069	1.2247	-0.0053	0.0075	-1.2247
-1	+2	0.0242	0.0042	11.4763	0.0068	0.0059	2.3016	-0.0069	0.0059	-2.3068
-1	+3	0.0254	0.0045	12.5100	0.0072	0.0049	3.2821	-0.0101	0.0081	-2.7929
-1	+4	0.0262	0.0045	14.2551	0.0072	0.0042	4.1560	-0.0121	0.0084	-3.5539
-1	+5	0.0265	0.0042	16.7109	0.0075	0.0039	5.1318	-0.0137	0.0084	-4.3232
-1	+6	0.0264	0.0039	19.2604	0.0078	0.0036	6.0865	-0.0146	0.0080	-5.1450
-1	+7	0.0265	0.0036	21.8509	0.0079	0.0034	7.0158	-0.0153	0.0077	-5.9695
-1	+8	0.0261	0.0036	23.0143	0.0081	0.0033	7.9193	-0.0154	0.0072	-6.7523
-1	+9	0.0265	0.0036	24.2895	0.0082	0.0031	8.8323	-0.0156	0.0068	-7.5842

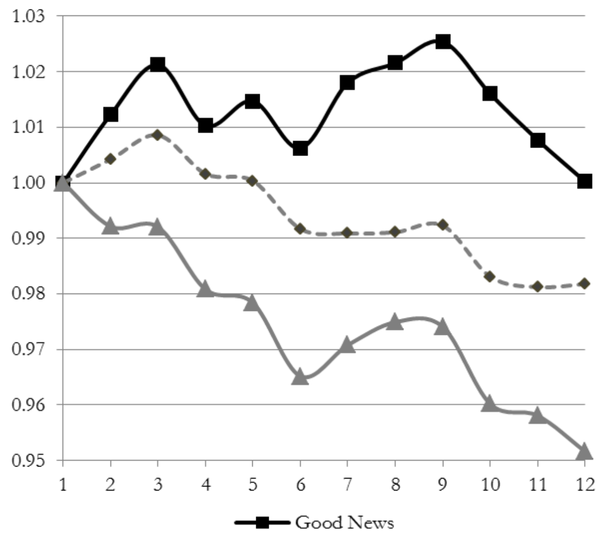
Appendix 20: Abnormal performance indexes for good and bad news portfolios (quintiles). The table presents event study results for the period 2000 to 2014. Abnormal performance indexes are calculated for the entire sample, as well as for good and bad news portfolios. The good news portfolio represents the quantile portfolio with the largest increase in Z-Score. The bad news portfolio represents the quantile portfolio with the largest decrease in Z-Score. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of February and ends at the end of December.

Month	Good News	2	3	4	Bad News	Good - Bad	Total Sample	Good - Total Sample	Bad - Total Sample
1	1.0000	1.0000	1.0000	1.0000	1.0000	0.0000	1.0000	0.0000	0.0000
2	1.0140	1.0117	1.0073	0.9955	0.9936	0.0203	1.0042	0.0097	-0.0106
3	1.0193	1.0176	1.0072	1.0012	0.9986	0.0207	1.0086	0.0107	-0.0100
4	1.0099	1.0171	1.0041	0.9966	0.9819	0.0280	1.0016	0.0083	-0.0198
5	1.0076	1.0172	1.0029	0.9956	0.9800	0.0276	1.0004	0.0072	-0.0204
6	1.0006	1.0096	0.9955	0.9841	0.9704	0.0302	0.9917	0.0089	-0.0213
7	1.0008	1.0074	0.9940	0.9833	0.9707	0.0301	0.9909	0.0099	-0.0202
8	0.9994	1.0066	0.9943	0.9856	0.9709	0.0284	0.9911	0.0083	-0.0202
9	1.0026	1.0047	0.9935	0.9854	0.9764	0.0262	0.9923	0.0103	-0.0159
10	0.9915	0.9952	0.9895	0.9750	0.9649	0.0266	0.9831	0.0084	-0.0182
11	0.9888	0.9948	0.9865	0.9709	0.9657	0.0231	0.9812	0.0076	-0.0155
12	0.9868	1.0011	0.9897	0.9752	0.9567	0.0302	0.9818	0.0050	-0.0251

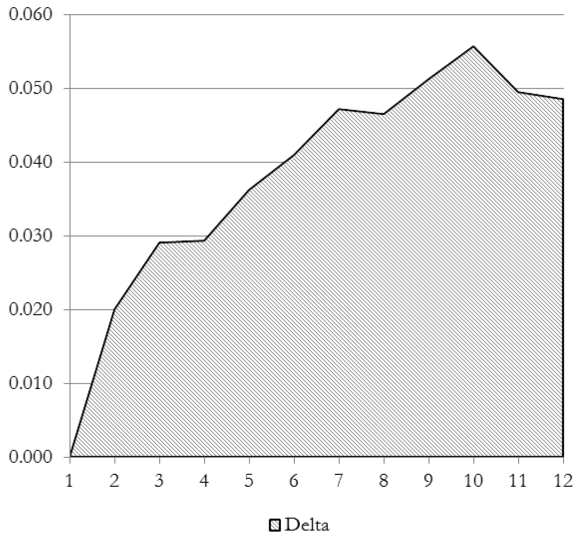
9.2.6 Robustness Test 6: Event Study with increased number of portfolios

Appendix 21: Abnormal performance indexes for good and bad news portfolios (deciles). The left figure presents event study results for the period 2000 to 2014. Abnormal performance indexes are calculated for the entire sample, as well as for good and bad news portfolios. The good news portfolio represents the decile portfolio with the largest decrease in pfail. The bad news portfolio represents the decile portfolio with the largest increase in pfail. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of February and ends at the end of December. The right figure presents the difference in the abnormal performance index between the good and bad news portfolios.

Good News, Bad News & Total Sample



Good News – Bad News



Appendix 22: Test of significance for good and bad news portfolios (deciles) during 2000 to 2014. The table presents the level of significance of the event study with various lengths of the post-event window included. Good – Bad shows the formal test of statistical significance. The Good – Total Sample and Bad – Total Sample shows the magnitude of the event's relative effect on aggregated abnormal returns for good and bad news portfolios respectively. T-statistics are calculated as the mean coefficient divided by its time-series standard error.

Event Study Results - Deciles

Time		Good - Bad			Good - Total Sample			Bad - Total Sample		
Start	End	Mean	StD	t-stat	Mean	StD	t-stat	Mean	StD	t-stat
-1	+1	0.0263	0.0053	8.5259	0.0098	0.0025	6.7588	-0.0165	0.0044	-6.5254
-1	+2	0.0288	0.0067	8.6405	0.0109	0.0031	7.1331	-0.0178	0.0045	-7.9116
-1	+3	0.0312	0.0080	8.7701	0.0117	0.0031	8.3919	-0.0196	0.0055	-7.9521
-1	+4	0.0339	0.0097	8.5943	0.0142	0.0069	5.0544	-0.0197	0.0049	-9.7733
-1	+5	0.0357	0.0100	9.4062	0.0166	0.0088	4.9841	-0.0192	0.0047	-10.8173
-1	+6	0.0377	0.0108	9.8541	0.0186	0.0100	5.2575	-0.0190	0.0044	-12.3773
-1	+7	0.0397	0.0118	10.1036	0.0202	0.0105	5.7682	-0.0195	0.0043	-13.6830
-1	+8	0.0407	0.0115	11.1412	0.0208	0.0101	6.5197	-0.0198	0.0042	-14.9777
-1	+9	0.0414	0.0112	12.2474	0.0206	0.0096	7.1127	-0.0208	0.0050	-13.6593

Appendix 23: Abnormal performance indexes for good and bad news portfolios (decile). The table presents event study results for the period 2000 to 2014. Abnormal performance indexes are calculated for the entire sample, as well as for good and bad news portfolios. The good news portfolio represents the decile portfolio with the largest decrease in pfail. The bad news portfolio represents the decile portfolio with the largest increase in pfail. The abnormal performance index, which aggregates average monthly abnormal returns, starts in the beginning of February and ends at the end of December.

Month	Good News	2	3	4	5	6	7	8	9	Bad News	Good - Bad	Total Sample	Good - Total Sample	Bad - Total Sample
1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.0000	1.0000	0.0000	0.0000
2	1.0123	1.0089	1.0081	1.0136	1.0073	1.0037	1.0027	1.0006	0.9928	0.9922	0.0201	1.0042	0.0080	-0.0121
3	1.0213	1.0171	1.0072	1.0174	1.0136	1.0140	1.0047	1.0023	0.9963	0.9920	0.0292	1.0086	0.0127	-0.0165
4	1.0103	1.0079	1.0047	1.0170	1.0095	1.0038	0.9896	0.9972	0.9963	0.9808	0.0295	1.0016	0.0087	-0.0208
5	1.0147	1.0109	1.0070	1.0225	1.0033	0.9960	0.9883	0.9948	0.9884	0.9784	0.0363	1.0004	0.0144	-0.0220
6	1.0062	0.9946	1.0016	1.0144	0.9984	0.9896	0.9767	0.9936	0.9769	0.9652	0.0411	0.9917	0.0145	-0.0265
7	1.0180	0.9921	0.9991	1.0109	0.9908	0.9791	0.9760	0.9972	0.9744	0.9708	0.0472	0.9909	0.0271	-0.0201
8	1.0216	0.9953	0.9947	1.0088	0.9905	0.9754	0.9819	0.9946	0.9726	0.9749	0.0466	0.9911	0.0305	-0.0162
9	1.0254	0.9946	0.9900	1.0117	0.9929	0.9816	0.9827	0.9922	0.9757	0.9741	0.0513	0.9923	0.0331	-0.0182
10	1.0160	0.9863	0.9870	1.0036	0.9864	0.9804	0.9771	0.9762	0.9569	0.9602	0.0558	0.9831	0.0329	-0.0229
11	1.0077	0.9848	0.9890	0.9976	0.9873	0.9837	0.9727	0.9722	0.9581	0.9581	0.0496	0.9812	0.0265	-0.0231
12	1.0002	0.9863	0.9955	1.0041	0.9951	0.9857	0.9727	0.9722	0.9549	0.9516	0.0486	0.9818	0.0185	-0.0302