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The Relationship between Expected Returns and Financial Distress Risk. Implication for Corporate Valuation

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Abstract

Using portfolio and regression analysis, this study examines the expected returns of European companies for the period 2000-2011 with respect to financial distress risk in order to provide practical implications for corporate valuation. The relationship between realized returns and financial distress risk is found to be negative, in line with the financial distress risk anomaly acknowledged in the existing literature. Based on the empirical evidence that financial distress risk contains systematic components, this anomaly contradicts the fundamental risk-return relationship. On the contrary, the association between the alternative proxy for expected returns - implied cost of equity - and financial distress risk is found to be positive, meaning that investors account for financial distress risk in their *ex ante* expectations. Implied cost of equity is obtained as an internal rate of return from current market prices and analysts' consensus earnings forecasts. Finally, comparing the implied cost of equity and the CAPM based cost of equity it is recommended to use a premium over CAPM based cost of equity of 0.6% to 1.35% for the purpose of valuation of companies with high risk of financial distress.

JEL Classification: G12, G31, G32

Keywords: Financial distress, Implied cost of equity, CAPM, Altman Z-Score, Distance-to-Default

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List of Abbreviations

APV	Adjusted Present Value
Beta	Market beta
BM	Book-to-Market
BV	Book value
CAPM	Capital Asset Pricing Model
CAPM CoE	CAPM based Cost of Equity Capital
CoE	Cost of Equity Capital
DCF	Discounted Cash Flow
DtD	Distance-to-Default value
DtD probability	Distance-to-Default probability
ECB	European Central Bank
EPS	Earnings per Share
EPSFY1	Earnings per Share for Year 1
EPSFY2	Earnings per Share for Year 2
ERP	Equity Risk Premium
FCF	Free Cash Flow
FCFE	Free Cash Flow to Equity
GDP	Gross domestic product
ICoE	Implied Cost of Equity Capital
IRR	Internal Rate of Return
LS	Least Squares
MV	Market value
NPV	Net present value
R&D	Research and Development
RMI	Research Management Institute
TV	Terminal value
Z-Score	Altman Z-Score

1. Introduction

The conceptual framework of asset pricing models and investment decisions originates from the notion that high risk assets should deliver higher expected returns than low risk assets. However, in case of financial distress risk this fundamental risk - expected return trade-off seems to be violated, which in the relevant literature is termed as financial distress anomaly. There exists vast empirical evidence (Da and Gao (2010), George and Hwang (2010), Avramov et al (2009), Breig and Elsas (2009), Campbell et al (2008), Garlappi et al (2008), Griffin and Lemmon (2002), Dichev (1998)) that companies facing high financial distress risk tend to realize lower stock returns than low financial distress risk companies.

These findings drew our attention to the question to what extent this anomalous relationship between risk and realized returns has a spill-over effect on valuation, especially given the fact that expected returns, usually proxied by realized returns, are the main input for the Capital Asset Pricing Model (CAPM) (Sharpe (1964), Lintner (1965)). Firstly, if realized returns contain anomalies, it might also have an undesirable impact on the CAPM cost of equity. Secondly, as noted by Chava and Purnanandam (2010) and Campbell et al (2008), there are additional concerns that CAPM might not fully incorporate the financial distress risk related premium if defaults are correlated with (1) debt securities (Ferguson and Shockley (2003)), (2) declining investment opportunities (Merton (1973)) or (3) hardly measurable components of wealth such as human capital (Fama and French (1996)). Thus, the CAPM based cost of equity capital (CAPM CoE) might be underestimated and, if employed in discounted cash flow (DCF) models, might result in an overestimation of company’s equity value. Our concern is in line with the leading explanation of mispricing for the anomalously negative relationship between bankruptcy risk[3] and subsequently realized returns pointed out by most researchers in this area (Avramov et al (2009), Campbell et al (2008), Griffin and Lemmon (2002), Dichev (1998)). Investors either do not incorporate all available information in their decisions or understate the potential costs of financial distress.

Since investors expect to be rewarded only for non-diversifiable risks, financial distress risk should only be compensated for if it is systematic. Studies investigating if financial distress risk is systematic are scarce and so far largely inconclusive. George and Hwang (2010), Almeida and Philippon (2007), Vassalou and Xing (2004), Denis and Denis (1995), Lang and Stulz (1992) demonstrate that distress risk might be related to systematic risk, while Avramov et al (2009), Asquith and Gertner (1994) note that financial distress is mostly due to idiosyncratic factors and,

[3] Default, insolvency, financial distress and bankruptcy do not have exactly the same meaning as discussed by Altman and Hotchkiss (2006), but in this research we use these terms interchangeably to refer to financial distress as it is also done in other studies (e.g. Dichev (1998)).

thus, unrelated to systematic risk. In general, it seems that at least some components of financial distress risk are systematic and, thus, should be accounted for. In addition as it became evident during the recent financial crisis, the magnitude of financial distress risk should not be ignored[4] and should be accounted for when making investment decisions.

In corporate valuation there are a few methods to account for financial distress risk; however, they are tedious to implement with reasonable precision and to be applied by less sophisticated investors. In this study we examine the possibility to modify the discount rate by adding a positive premium over the CAPM CoE for higher financial distress risk companies. While there are no attempts in empirical studies to quantify a potential premium over CAPM due to financial distress risk, practitioners already recognized this specific need. For example, the U.S. investment bank Duff & Phelps publishes annually a recommended additional premium on CAPM CoE in its "Risk Premium Report" (Duff & Phelps (2012)) for the most distressed companies. The focus of this research is on CAPM, because despite its deficiencies (Fama and French (1992)), CAPM remains the most practical and prevalent way to obtain CoE (Cochrane (2005), Graham and Harvey (2001)). Acknowledging that companies with higher financial distress risk could be incorrectly valued due to underestimated CAPM CoE, we compare CAPM CoE with the implied cost of equity capital (ICoE)[5]. ICoE is backed out from the discounted residual income model as the internal rate of return (IRR) equating current market price with the analysts' consensus earnings forecast. In research, it is increasingly used as an alternative proxy for expected returns (e.g., Lee et al (2009), Pastor et al (2008) and Gebhardt et al (2001)). On the other hand, ICoE could also be seen as an alternative measure of cost of equity (Easton and Sommers (2007)). Our paper attempts to investigate the relationship between expected returns, CoE estimates and financial distress risk in order to provide implications for corporate valuation.

Building on the existing literature, this paper investigates the following research questions:

1) What is the relationship between financial distress risk and realized stock returns?

Hypothesis 1: The relationship between financial distress risk and realized stock returns is negative, but not purely monotonic. This hypothesis is based on the findings of the extensive literature on this topic (Avramov et al (2009), Campbell et al (2008), Garlappi et al (2008) and Dichev (1998) in USA; Breig and Elsas (2009) in Germany).

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[4] Direct costs of financial distress, such as legal fees, occur only in the case of bankruptcy and are relatively small. For example, Warner (1977) and Weiss (1990) estimate these costs to be 3% - 5% of company's value at the time of distress. Meanwhile, indirect costs, such as loss of market share, forgone investment opportunities or higher debt refinancing rates, can have a negative impact on profitability even for a seemingly healthy firm. The estimates of the losses in value due to indirect financial distress costs range 10% - 20% of pre-distress firm value (Andrade and Kaplan (1998), Altman (1984)).

[5] In the literature termed more generally as Implied Cost of Capital (ICC).

2) What is the relationship between financial distress risk and ICoE?

Hypothesis 2: The relationship between financial distress risk and ICoE is positive. This hypothesis is based on the existing findings with respect to ICoE. Chava and Purnanandam (2010) show that default risk and ICoE are positively related. Other researchers (e.g., Pastor et al (2008)) claim that ICoE might better capture the fundamental risk-return relationship. Furthermore, since by construction ICoE is a forward looking measure, it might better account for expectations of investors with respect to financial distress risk.

3) What is the relationship between financial distress risk and CAPM CoE?

Hypothesis 3. The relationship between financial distress risk and CAPM CoE is weakly positive. This hypothesis is formed based on empirical evidence that the market betas of financially distressed companies are higher (Avramov et al (2009), Campbell et al (2008)), but they might not be high enough to fully compensate for higher financial distress risk due to potential estimation biases or anomalies present in realized returns, which is the main input of CAPM.

4) Is there a difference between ICoE and CAPM CoE?

Hypothesis 4: There is a difference between ICoE and CAPM CoE for companies with high financial distress risk. This hypothesis is justified based on *Hypothesis 2* and *Hypothesis 3*. We expect the spread between ICoE and CAPM CoE to be more pronounced for higher financial distress risk companies as ICoE might better incorporate this risk in investors' expectations.

To investigate these research questions, data from a sample of 501 listed European firms over the period from December 1999 to January 2011 is used. The sample is limited to the companies listed in countries[6] within the Euro-zone because of the same currency and similar level of economic development, which assures a homogenous sample. The sample of European companies was also chosen because there is ample research in the area relating to financial distress on the U.S. data, while it is scarce on European data (except for the study of Breig and Elsas (2009)).

The first part of this paper concerns the analysis of the relationship between expected returns and financial distress risk. In asset pricing theory, expected returns are defined as the probability weighted average of the possible outcomes (Bodie et al (2011)). Since expected returns are unobservable, different proxies for them can be used. In research, usually expected returns are proxied by *ex post* realized returns (Avramov et al (2009), Campbell et al (2008), Dichev (1998)). ICoE represents an alternative *ex ante* proxy for expected returns. It has an important advantage over realized returns by being a forward looking measure and by possibly being a

[6] Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Netherlands, Portugal, Spain.

better measure in uncovering inter-temporal risk-return relations (Pastor et al (2008)). However, it also relies on the critical assumption that the consensus forecast is a good estimator of investors' expectations. Following Chava and Purnanandam (2010), the relationship of financial distress risk will be compared to both, realized returns and ICoE.

Financial distress risk in this study is defined as an intermediate state between solvency and insolvency rather than direct bankruptcy, which is in line with Altman (1984), who claims that any company can suffer from indirect costs of financial distress and not necessarily only the ones which go bankrupt. Financial distress risk can be well proxied by bankruptcy risk indicators (Dichev (1998)). Default risk measures mostly used in the research on distress premium could be divided into two groups: (1) accounting data based: Altman (1968) Z-Score or Ohlson (1980) O-Score[7] and (2) market data based: Distance-to-Default (DtD)[8]. In this study we will use one measure from each of these groups – Altman Z-Score and DtD. Due to differences in their predictive methodology and input variables, which are reflected in a positive but not perfect correlation, these two measures are expected to complement each other well.

First of all, to uncover the relationship between financial distress risk and expected returns, we group stocks into 10 portfolios based on one of the financial distress risk measures (Altman Z-Score and DtD) and test if portfolios with different default risk characteristics provide significantly different returns. This portfolio analysis is beneficial to study potential non-linearity in the relation between distress risk measures and returns. Chava and Purnanandam (2010), Avramov et al (2009), Campbell et al (2008), Vassalou and Xing (2004), Dichev (1998) use a similar method. Secondly, in order to confirm the evidence from the univariate portfolio analysis, regression analysis is used. We employ Fama-MacBeth (1973) cross-sectional regressions of monthly individual stock returns on a financial distress risk measure in line with Avramov et al (2009), Vassalou and Xing (2004) and Dichev (1998). Based on portfolio and regression analysis we find, in line with our expectations, that the relationship between realized returns and financial distress risk is negative, while the relation between ICoE and financial distress risk is positive.

The second part of this paper is devoted to the comparison of the CAPM CoE with ICoE including a particular emphasis on the difference between them depending on different levels of financial distress risk. The comparison between CAPM CoE and ICoE is valid because both are comparable methods of obtaining CoE (Ballwieser and Wiese (2010)). As expected we find that

[7] Used by George and Hwang (2010), Ferguson and Shockley (2003), Griffin and Lemmon (2002), Dichev (1998).
[8] Used by Garlappi and Yan (2011), Chava and Purnanandam (2010), Garlappi et al (2008), Da and Gao (2008), Vassalou and Xing (2004).

indeed ICoE is higher than CAPM CoE for the most distressed companies, which justifies a premium over CAPM CoE in the range of 0.6% to 1.35%.

The investigation of financial distress impact on returns and possible consequences to European corporate valuation processes are interesting to practitioners and important contributions to the exiting literature, which focuses mainly on the U.S. data. Most importantly, there are no empirical studies relating evidence from the relationship between realized returns and financial distress risk to valuation. Thus, our results are beneficial to both investors and valuation specialists as the obtained premium over CAPM CoE of 0.6% - 1.35% could be easily applied in practice. Secondly, we provide a contribution by comparing the impact on returns by two different financial distress measures. Similar research usually focuses on one default indicator (Avramov et al (2009), Campbell et al (2008), Vassalou and Xing (2004)) or compares two indicators from the same category – either both measures are accounting based (Griffin and Lemmon (2002), Dichev (1998)) or both measures are market based (Chava and Purnanandam (2010)). Thus, it is relevant to see how the results are compatible for differently constructed default measures. Third, a few researchers (Chava and Purnanandam (2010), Campbell et al (2008)) claim that the financial distress anomaly could only be present in their particular sample, but is not valid out of sample. Therefore, using a European setting and newer data might provide additional evidence for the validity of this explanation.

The remainder of the paper is organized as follows. Section II reviews the literature related to the relationship between financial distress risk and expected returns. Section III describes the data used and provides summary statistics. Section IV outlines the methodology employed to estimate financial distress measures, ICoE and CAPM CoE and to establish the relationship between financial distress risk, expected returns and CoE. Section V presents the obtained results and discusses their implications. Section VI concludes the analysis, outlines the main limitations of our study and provides directions for further research in this area.

2. Literature Review

2.1. Financial Distress Measures

In this study financial distress does not indicate outright insolvency; it is rather defined as an intermediate state between solvency and insolvency. This is in line with Altman (1984), who claims that any company can suffer from indirect costs of financial distress, but not necessarily only the ones which go bankrupt. Purnanandam (2008) distinguishes between three main sources of financial distress costs. Firstly, companies in financial distress might lose important suppliers, key employees and customers. Secondly, companies in financial distress might need to cut on R&D and reject positive NPV projects due to costly external financing (Altman (1984)). Thirdly, a financially distressed company is more likely not to fulfill financial obligations, which would have a negative impact through resources tied up in negotiations with creditors (Altman (1984)) or trough financial penalties. Thus, financial distress affects corporate performance negatively and has adverse cash flow effects.

According to Dichev (1998), bankruptcy risk is a reasonable proxy for financial distress meaning that with increased bankruptcy risk, higher indirect financial distress costs are expected to occur. Financial distress risk measures mostly used in research could be divided into two groups: (1) accounting data based distress risk indices as Altman (1968) Z-Score or Ohlson (1980) O-Score and (2) market data based Distance-to-Default (DtD) measure developed in line with Black and Scholes (1973) and Merton (1974) option pricing methodology. Other approaches to measure financial distress risk (a different version of default predictors combining market and accounting data[9], bond ratings[10] or simply the leverage ratio[11]) are either expected to be biased or are rarely applied in research and practice and, therefore, hard to verify.

The main advantage of accounting based measures is that they are extensively used in empirical research and in practice. In this paper Altman (1968) Z-Score will be used as an indicator of financial distress risk as it is a wide-spread and understood measure of bankruptcy, which is easy to implement, represents a relatively accurate predictor of bankruptcy[12] and was used in similar research (Purnanandam (2008), Ferguson and Shockley (2003), Griffin and Lemmon (2002), Dichev (1998)). However, accounting data based models also have considerable disadvantages. Firstly, they use information derived from financial statements, so by construction they are backward looking and cannot be updated frequently (Vassalou and Xing (2004)). Secondly, these indicators do not incorporate the volatility of firm's assets, which implies that firms with

[9] Campbell et al (2008)
[10] Avramov et al (2009), Dichev and Piotroski (2001)
[11] Chava and Purnanandam (2010), Ferguson and Shockley (2003)
[12] 75% - 84% of investigated companies were classified correctly as healthy or bankrupting in different samples over different time periods: 1969-1975, 1976-1995, 1997-1999 (Altman (2002)).

similar financial ratios have a similar probability of default, which might not always be the case (Vassalou and Xing (2004), Hillegeist et al (2004)). Third, accounting data might be biased due to different compilation methods employed (Breig and Elsas (2009)).

Regarding market based distress measures, the most popular bankruptcy risk indicator is the DtD, which views the firm's equity as a call option on its assets. Since shareholders are residual claimants, in the case of bankruptcy they would be rewarded only after debt claims are paid off. Thus, the strike price of this call option is the face value of company's liabilities. DtD could be seen as a measure of the number of standard deviations between the firm's current value and its bankruptcy threshold, i.e. promised debt repayment (Crosbie and Bohn (2003)). Some researchers (Garlappi and Yan (2011), Garlappi et al (2008)) obtain the DtD measure directly from Moody's KMV (Kealhofer, McQuown and Vasicek) database. Other researchers (Da and Gao (2010), Chava and Purnanandam (2010), Breig and Elsas (2009), Vassalou and Xing (2004), Hillegeist et al (2004)) calculate their own versions of DtD. Moody's provides DtD indicators with corresponding default probabilities estimated based on a historical default rate for given levels of DtD (Crosbie and Bohn (2003)). Researchers not using Moody's DtD indicator obtain the corresponding default probabilities by applying a theoretical distribution (mostly normal distribution consistently with Merton (1974)) of the default rate. This transformation of DtD measures to probabilities is irrelevant to our results as the DtD value itself is used to investigate the relation between equity returns and financial distress risk, and the corresponding default probabilities are shown only for illustrative purposes.

The main advantage of the DtD measure is its forward looking perspective. Secondly, DtD takes into account the volatility of firm's assets, which has an effect on the likelihood of default. Compared to credit ratings, DtD is superior as credit ratings rely on strong assumptions that all firms within a particular rating category have the same default risk, default risk is equal to historical average default risk, and default risk of a firm changes only if its rating changes. However, a firm can experience a surge in its default risk already before the change of a rating (Vassalou and Xing (2004)). Further, DtD uses market price information which is updated more frequently than accounting data based financial distress measures or ratings. There are studies claiming that the DtD as a market based measure provides significantly more information than accounting based indicators and is more adequate for empirical studies (Hillegeist et al (2004)).

The emphasis in this paper will be put on well documented in relevant literature and practically approved bankruptcy risk indicators - Altman (1968) Z-Score and DtD measure. Since both, accounting data based and market data based indicators have their advantages and disadvantages we will use one indicator from each category, which will also serve as a robustness check.

2.2. Return Anomaly with Respect to Financial Distress

Research investigating the relationship between financial distress risk and expected stock returns consistently finds that high financial distress risk stocks deliver low returns (Da and Gao (2010), George and Hwang (2010), Avramov et al (2009), Breig and Elsas (2009), Campbell et al (2008), Garlappi et al (2008), Griffin and Lemmon (2002), Dichev (1998)). This finding contradicts the fundamental risk-return relationship in the finance theory and is termed as distress anomaly.

Studies investigating the financial distress risk – expected returns relationship usually use two approaches building on each other. The first method is portfolio analysis, where firms are ranked by their corresponding financial distress risk measure and the average returns of portfolios with different level of distress are compared. The second approach is regression analysis using Fama and MacBeth (1973) approach where the dependent variable is return and the independent variable is a financial distress risk measure. Usually other explanatory variables as size, book-to-market (BM) or leverage are also included.

Using Ohlson (1980) O-Score and Altman (1968) Z-Score as proxies for default risk, Dichev (1998) finds that firms with high financial distress risk yield lower than average returns. Griffin and Lemmon (2002) confirm the negative relationship found by Dichev (1998). Campbell et al (2008) use their own constructed hazard model to obtain a measure of default probability. They find that financially distressed firms have higher market betas and high loadings on value and size factors, but deliver anomalously low average returns. Avramov et al (2009) using credit ratings as proxies for financial status present very similar findings to Campbell et al (2008). However, the difference in returns persists only during the limited period of three months before and after a credit rating downgrade for the worst rated companies. In general, studies examining the effect of rating upgrades and downgrades on equity returns find that bond downgrades are followed by negative stock returns (e.g., Dichev and Piotroski (2001)). Using the market based DtD measure provided by Moody's KMV as a measure of financial distress risk, Garlappi et al (2008) also find that the relationship between expected returns and default probability is in general negative. While all other mentioned researchers focus on the U.S. market, the study of Breig and Elsas (2009) is the only one comparing the impact of default risk on equity returns in USA and Germany. They find that higher default risk is associated with lower equity returns in both markets.

On the contrary to the above mentioned research, Vassalou and Xing (2004) find that higher financial distress risk stocks yield higher returns than low financial distress risk firms, but only if they are small in size and/or have a high book-to-market ratio. Da and Gao (2010) state that the returns of distressed stocks in the research of Vassalou and Xing (2004) are biased upwards and this bias is driven by short-term returns reversals. Consistently with Da and Gao (2010), George and Hwang (2010) replicate the research using Vassalou and Xing (2004) data and show that the positive relationship reverses when stocks with prices below 5$ are excluded from the sample.

2.2.1. The Relation between Size, BM and Financial Distress

The reason behind underperformance in terms of returns of financially distressed firms could not only be financial distress, but also other firm characteristics, e.g. extremely small stocks. Some researchers (Chan and Chen (1991), Fama and French (1992), Fama and French (1996)) claim that size and/or value (BM) factors might be proxying for financial distress risk or fully capturing its effects. However, there are contradicting findings that financial distress has implications beyond size and value factors and contains additional information.

Dichev (1998) finds that the relation between bankruptcy risk and BM is not monotonic, i.e. in general distressed firms have high BM, but the most distressed companies have lower BM. Dichev (1998) also finds that the size effect is virtually gone since 1980 (in line with Fama and French (1992)). Campbell et al (2008) show that high financial distress risk stocks underperform in all quintiles of value and size distributions. Avramov et al (2009) claim that the financial distress risk effect is an independent anomaly not related to size and BM effects. The results of Vassalou and Xing (2004) indicate that size and BM effects contain some default related information, but they also contain some important information unrelated to financial distress risk, which helps to explain cross-section of returns. Vassalou and Xing (2004) also claim that "default is a variable worth considering in asset-pricing tests, above and beyond size and BM".

In summary, even if size and value factors proxy for financial distress risk, they might not fully capture it. Further, to account for at least part of financial distress risk, investors should always use Fama and French (1996) Three Factor Model (including size and BM factors) to get a less biased market beta, which in practice is not always the case since CAPM remains the most widely used model to calculate discount rates (Cochrane (2005), Graham and Harvey (2001)).

2.2.2. Is Default Risk Systematic?

According to finance theory, riskier assets should offer higher expected returns so that investors hold them or, in the same vein, riskier assets should trade for lower prices to induce investors to hold them. But only the systematic part, i.e. not diversifiable risk, of any payoff is priced (Cochrane (2005)). If default risk is systematic, then investors should demand a positive risk premium for undertaking this risk, i.e. there should be a positive relation between financial distress risk and subsequent realized returns. If financial distress risk is not systematic, it should be no significant difference between returns due to financial distress risk, which also contradicts findings in this area. There is not much evidence on the relation between bankruptcy risk and systematic risk and the existing studies are often contradicting each other. In this section different opinions on this issue are presented.

Systematic risk could be defined as covariance or sensitivity of stock's returns with market wide news (Berk and DeMarzo (2011)). Therefore, financial distress risk is systematic only if returns of distressed companies are more sensitive to unexpected changes of macroeconomic factors. It seems reasonable that the performance of more distressed companies could be more sensitive to recessions and economic upturns. Dichev (1998) claims that the fact that more firms get bankrupt during economic downturns is not a sufficient condition to conclude that financial distress risk is systematic because in recessions the probability of failure is higher for all firms. Avramov et al (2009) do not find any evidence that the credit risk effect has a systematic component. Asquith and Gertner (1994) provide evidence that bankruptcy occurs mostly due to idiosyncratic factors (e.g. inefficient debt structures), so bankruptcy might not be related to systematic risk.

On the other hand, there is evidence that financial distress risk contains systematic components, which is also why research relating to distress anomaly intensified in recent years. Denis and Denis (1995) investigate the reasons of financial distress in a sample of 29 leveraged recapitalizations. They find that default risk is related to economic conditions rather than firm specific characteristics implying that default risk could be positively related to systematic risk. George and Hwang (2010) claim that the occurrence of low asset payoff states is at least partly systematic. Thus, financial distress costs realizing in these low payoff states should contribute to priced risk. Almeida and Philippon (2007) claim that default risk has a systematic component and presents a method to quantify the present value of financial distress costs, which takes into account this systematic component in the risk of distress.

Since Vassalou and Xing (2004) find a positive relationship between financial distress risk and returns, they claim that financial distress risk is systematic and positively priced into returns. In addition, they claim that bankruptcy of one firm might have spillover effects on other firms, which implies a systematic component in default risk. Lang and Stulz (1992) examine the effect of company's default on its competitors and find that it has a significant negative effect on the market value of competitors suggesting that financial distress risk is contagious. Chan and Chen (1991) state that the stock prices of companies facing higher distress risk tend to be more sensitive to changes in economic conditions and are more likely to fail during prolonged adverse economic conditions if compared to healthy firms. Fama and French (1996) also note that firm and investor behavior could be cross-sectionally correlated due to changes in economic conditions. Campbell et al (2008) admits that the performance of financially distressed companies is correlated and this risk might be hard to diversify. Chan-Lau (2006) notes that financial distress risk measured by default rates is highly economic cycle dependent. Thus, he advocates that there is a systematic component of default risk, which should be priced in equity returns.

There is also empirical evidence that higher default risk is associated with lower systematic risk. Garlappi et al (2008) state that due to shareholder advantage, i.e. magnitude of the possibility to buy firm's assets or output at lower prices during renegotiation with creditors, the equity risk decreases when the probability of financial distress gets very low. However, if the shareholder advantage is low, then returns increase with higher default risk, which is an indication that default risk is systematic.

Balancing all these differing views, our study is based on the assumption that financial distress risk has not only idiosyncratic, but also systematic components, which should be accounted for.

2.2.3. Potential Explanations for Return Anomaly

The majority of the researchers agree that the risk-return relationship fails to explain the financial distress risk anomaly. The leading explanation is mispricing, i.e. investors incorrectly value financial distress stocks (Avramov et al (2009), Campbell et al (2008), Griffin and Lemmon (2002), Dichev (1998)). This mispricing sustains for longer time periods and is not arbitraged away potentially due to lower liquidity, lack of information as distressed stocks are usually less covered by analysts or constraints on short-selling because less institutional investors hold distressed assets. In this part the main explanations for the return anomaly are discussed.

One of the alternative explanations is that the negative financial distress risk – return relationship might only be valid in the particular sample, but might not necessarily be true out of sample. According to Campbell et al (2008), underperformance could be due to worse macroeconomic news or an unexpected shift of equity ownership from individuals to institutions during the period of analysis. The findings of Chava and Purnanandam (2010), George and Hwang (2010) and Dichev (1998) go in line with the explanation that the results might be time period dependent as they find that the financial distress anomaly is less pronounced in samples prior 1980s.

Secondly, Lundblad (2007) and Elton (1999) claim that a very long sample of realized returns is needed to establish a positive relation between risk and returns. Chava and Purnanandam (2010) also note that the sample size might be too small to detect a true relationship between financial distress risk and realized returns.

There could also be special features of distressed stocks which induce rational investors to hold them even if they provide low average returns. Campbell et al (2008) point out that increased opportunities to extract private benefits of control could be a reason as the owners of distressed stocks might expect to purchase the company's assets or output at bargain prices. It might pay off to wait if a company has a very low probability to survive and hold these distressed stocks instead of selling them at distressed prices (von Kalckreuth (2005)). Similarly, Garlappi and Yan (2011) and Garlappi et al (2008) find that the relationship between the financial distress risk and returns depend on the magnitude of shareholder advantage (i.e. the ability of distressed firms shareholders to get benefits during renegotiations with creditors).

Most researchers agree that investors misprice high financial distress risk stocks by making valuation errors. Campbell et al (2008) claim that investors might not fully understand that the variables comprising financial distress measures indicate failure risk. Consequently, they might not discount the expected cash flows of high financial distress risk stocks sufficiently to offset their financial problems. Further, Campbell et al (2008) show that investors perceive cross-sectional differences in financial distress risk, but might underestimate their importance. Avramov et al (2009) claim that mispricing is generated by retail investors as high financial distress stocks are mainly bought by individual investors. These stocks are usually followed by few analysts and individual investors employing simple tools and strategies in their trading might not realize how overpriced financially distressed stocks are. Basing on the finding that investors assign similarly high multiples to poorly performing firms as to healthy ones, Griffin and Lemmon (2002) state that investors might underestimate the importance of current financial data and overestimate the payoffs from future growth opportunities. According to Dichev (1998), there could be persistent biases in the pricing of securities, which means that the market does not fully incorporate the available financial distress related information. Consequently, the most insolvent firms earn lower returns throughout the process of finally incorporating negative information in pricing decisions.

2.3. Cost of Equity Estimation

It seems that the market is underpricing higher financial distress risk stocks, but there is evidence that financial distress risk should still be considered for valuation and investment purposes due to the systematic components it contains. The most prominent way is to subtract expected indirect financial distress costs from the estimated value of a firm (Damodaran (2010)). To calculate expected financial distress costs two components are needed: the dollar amount of financial distress costs and the probability of them occurring. There are complex academic methods to calculate these terms suggested by e.g., Almeida and Philippon (2007). However, they might be tedious to implement and apply for less sophisticated investors. Scenario analysis is also used in this case, but the limitations are similar: it might be hard to quantify different outcomes and there is sizeable uncertainty. In this paper the main focus is put on how discount rates are affected in the presence of heightened financial distress risk. Since the required risk-adjusted rate of return on invested equity by investors is not observable, different models[13] are used to calculate it (Ballwieser and Wiese (2010)). This study focuses on CAPM and ICoE.

2.3.1. CAPM based Approach

Despite its documented deficiencies, such as its strong restrictive assumptions or questionable empirical validity (e.g., Fama and French (1996)), the CAPM (Sharpe (1964), Lintner (1965)) remains the most used method to estimate the cost of equity capital both in academia and among practitioners (Ballwieser and Wiese (2010), Cochrane (2005), Graham and Harvey (2001)). CAPM advantages are the usage of market data, solid theoretical basis, simplicity of applying and interpreting (Ballwieser and Wiese (2010)). The hypothesis in this paper is that the cost of equity capital might be underestimated in the presence of financial distress risk due two main reasons. First, returns of financially distressed companies are anomalously low. Even though there is evidence that higher default risk stocks have higher betas (Avramov et al (2009), Campbell et al (2008)), the betas obtained using realized returns with inherent anomalies might still be biased downwards. Secondly, as noted by Chava and Purnanandam (2010) and Campbell et al (2008) there is evidence that single-beta CAPM might not fully incorporate financial distress risk related premium if defaults are correlated with (1) debt securities (Ferguson and Shockley (2003)), (2) declining investment opportunities (Merton (1973)) or (3) hardly quantifiable components of wealth such as human capital (Fama and French (1996)).

By construction, CAPM implies that beta measures the variability of a stock to wealth portfolio returns (Cochrane (2005)). This portfolio should include not only stocks, but also bonds, real estate, human capital among other wealth forms. Cochrane (2005) and Fama and French (1996)

[13] CAPM, Implied Cost of Equity Capital (ICoE), the Fama-French Three-Factor Model, the Arbitrage Pricing Theory (APT), various Build-Up models.

note that commonly used various stock indices to measure returns to total wealth might be poor proxies. Ferguson and Shockley (2003) argue that companies' equity betas estimated against market portfolio equity proxy might be understated because market portfolio proxy does not include the economy's debt claims. These understatement errors would increase with the firm's leverage and distress risk if the firm's equity returns co-vary positively with the debt claims omitted from the market portfolio proxy. This effect is found to be nonlinear, so the under-measurement of beta will be higher for mostly distressed stocks. Due to these concerns that CAPM CoE might not be fully risk adjusted we intend to compare it with ICoE which is hypothesized to better capture financial distress related risks.

2.3.2. Implied Cost of Equity Capital Approach

There are a few different models to obtain ICoE, but their theoretical basis originates from dividend discount model, where the current price of an asset is defined as the present value of future dividends (Ballwieser and Wiese (2010)). Due to different construction of ICoE and CAPM CoE, these two models are interesting to compare with respect to financial distress risk over time. ICoE method is not new[14], but only recently it attracts increasing attention from researchers as a possible alternative proxy of unobservable expected returns.

Apart from findings of Vassalou and Xing (2004), the empirical evidence shows that higher distress risk stocks yield lower returns. This finding is robust to different measures of financial distress risk, but it does not seem to be robust to the usage of different proxies for expected returns. All researchers who found a negative relationship between financial distress risk and expected returns used realized returns observable *ex post* as a proxy for expected returns. However, Chava and Purnanandam (2010), Lee et al (2009), Pastor et al (2008), Gebhardt et al (2001) and Elton (1999)[15] admit that realized returns are noisy and, thus, a poor proxy for the expected returns. In general, realized returns as an *ex post* proxy for expected returns delivered disappointing results in asset pricing research, which has serious implications for valuation purposes as the estimated cost of equity might be biased[16]. Thus, there is an increasing demand for *ex ante* expected returns.

[14] It was mentioned already in 1956 by Gordon and Shapiro.

[15] Elton (1999): "When I first entered the profession, anyone using realized returns as expected returns made the argument that in the long run we should get what we expect. Even this weak defense is no longer used and researchers generally treat realized returns as expected returns in their tests without any qualifications. The purpose of this article is to convince the reader (…) that it is worth our collective efforts to think about alternative ways to estimate expected returns".

[16] Fama and French (1997) claim that the cost of capital estimated based on average realized returns are "unavoidably imprecise".

In response to the failure of asset pricing models to estimate the cost of equity capital for firm valuation (Pastor and Stambaugh (1999), Elton (1999), Fama and French (1997)), ICoE[17] was used as an alternative proxy for expected returns. It is found as an internal rate of return (IRR) equating the current market stock price with the present value of future free cash flows to equity holders, which are obtained from analysts' consensus forecasts. ICoE has been already used in different contexts relating risk and returns in literature (Chava and Purnanandam (2010), Lee et al (2009), Pastor et al (2008), Gebhardt et al (2001)). While researchers are using slightly different valuation models as a base for the ICoE estimation, in all cases ICoE is calculated as IRR. ICoE is an *ex ante* measure and therefore might better capture the expectations of investors. Pastor et al (2008), based on their ICoE calculations, claim that under certain assumptions the ICoE is a better proxy for expected returns.

Gebhardt et al (2001) find a set of variables, which can predict ICoE without incorporating the current stock price. They demonstrate that there are solid alternatives to estimate CoE, which does not depend on realized returns or even a firm's current stock price. Pastor et al (2008) use the ICoE approach to investigate the relationship between market-wide returns and volatility in G7 countries. Lee et al (2009) use the ICoE as firm-level expected returns to test international asset pricing models in G7 countries. They conclude that using ICoE provides a more accurate view on economic relationships than using noisy realized returns.

According to our extensive literature review only Chava and Purnanandam (2010) relate financial distress risk and ICoE. They found a positive cross-sectional relationship between stock returns and default risk. However, when they use realized returns, the relationship between the expected returns and financial distress risk in line with other researchers is found to be negative.

Despite its advantages, ICoE also has considerable weaknesses, most prominently, the dependence on analysts' forecasts. There is empirical evidence that analysts' forecasts might be slowly updated or too optimistic (Pratt and Grabowski (2008), Easton and Sommers (2007), Claus and Thomas (2001), Dechow et al (1999), Rajan and Servaes (1997)). The fact that despite these disadvantages ICoE is still widely used in research and that currently there are no superior alternatives validate our usage of ICoE and implicit assumption that analysts' forecasts are a good measure of investors' expectations. In addition, Chava and Purnanandam (2010) test the analyst forecasts used in many different ways and conclude that any potential bias in consensus forecasts do not have significant influence on results.

[17] In the literature termed more generally as Implied Cost of Capital (ICC).

3. Data

3.1. Sample Selection

The sample selection starts from a universe of more than 8000 listed companies which are registered in the Eurozone[18]. These 11 countries comprising the Eurozone were chosen because they are on a similar level with regard to economic development, accounting standards and monetary policy (in particular, the common currency). Thus, no further adjustments, e.g., with respect to exchange rates, are required. The sample of companies was reduced to the ones which have financial information available in the intersection of Worldscope, Datastream, Institutional Brokers Estimates System (I/B/E/S) and the database provided by the Risk Management Institute of the National University of Singapore (RMI). Return data is based on Datastream price information. Most accounting data required as input for the calculation of Z-Score is taken from Worldscope. The alternative distress measure, DtD is obtained directly from the extensive RMI database. Consensus analysts' forecasts for the ICoE calculation are obtained from I/B/E/S.[19] About 4000 companies have data points in all the mentioned databases. The availability of reliable analyst estimations in I/B/E/S as well as the start of the Eurozone limits the starting point of the time series to December 31st 1999. The monthly time series ends after 11 years, at December 31st 2011.

Besides the limitation on availability of data from these databases, the calculation of distress measures (Z-Score and DtD) as well as of alternative expected returns/CoE (ICoE and CAPM based CoE) impose additional data limitations and leads to a further reduction of the number of companies in the sample.

In line with other studies (Chava and Purnanandam (2010)) we exclude firms in the financial and utility sectors. We choose to go even a step further and exclude service companies, since the Z-Score has been initially estimated for publicly held manufacturing companies.[20] The focus on manufacturing companies is driven by the goal to achieve homogenous measures which allow a relative comparison among individual companies due to different Z-Score specification and interpretation for service companies (Dichev (1998)).

Further, for an unbiased calculation of ICoE the firms in the sample are required to have at least three estimations of EPS 1 and 2 years ahead (EPSFY1, EPSFY2) in order to provide reliable

[18] Germany, Portugal, France, Spain, Italy, Belgium, Netherlands, Austria, Finland, Ireland and Luxemburg (see Appendix I for more details about the number of firms per country).
[19] These estimates are widely used in research relating to financial distress (Chava and Purnanandam (2010), Altman (1984)), to market expectations (Elton et al (1981)) or to establishing the relationship between risk and returns (Pastor et al (2008)) and to ICoE (Pastor et al (2008), Gebhardt et al (2001)).
[20] We distinguish between manufacturing and service companies according to the breakdown provided by Datastream (Datastream AFO sample sheet "Z-Score Bankruptcy Predictions").

analysts' consensus estimates (Elton et al (1981)). Consensus estimates obtained from less than three analysts could be idiosyncratic and not representative of market expectations. This method has been chosen to balance the need for high analyst coverage underlying consensus estimates and the potential selection bias towards less distressed companies as analyst coverage is typically lower for companies with higher financial risk (Campbell et al (2008)). Other reasons for excluding companies are continuous stock prices below 1€ or missing accounting data for several points in time. Other researchers (Chava and Purnanandam (2010), Avramov et al. (2009), Campbell et al. (2008)) remove all penny stocks (definition varies from below 1$ to 5$), however, to avoid further sample reduction we exclude only companies having stock prices below the threshold for a prolonged time period.[21]

After conducting the described adjustments the sample consists of 501 companies over 11 years with 145 monthly observations. Due to the nature of the research, the number of companies is varying, either because they were not listed before or because of delisting.[22] A company can be delisted not only because it is bankrupt, but also due to different reasons as too low price or violation of data filing requirements (Dichev (1998)). Since Datastream does not differentiate between delistings depending on the cause of delisting, we assumed that all delisted companies defaulted[23]. This assumption seems reasonable as delisted firms in most cases experienced financial or operational difficulties. All bankrupted companies, in line with Vassalou and Xing (2004), were assigned delisting returns of -100% assuming that shareholders on average do not recover anything from their investment. While delisting returns of -100% is rather pessimistic as shareholders might still get some bankruptcy proceeds, this negative effect is reduced by winsorizing returns. In general, in order to avoid a bias from outliers in the sample all main variables (realized returns, ICoE, CAPM based CoE, Z-Score, DtD, size, BM, leverage) have been winsorized at 1% and 99% over the entire panel for the economic analysis (in line with Chava and Purnanandam (2010), Dichev (1998)).

[21] Removing all stocks with prices below 1$ at least in one point of time seemed to lead to a potential bias of excluding financially distressed companies, so that we allowed companies to have prices below 1€ but removed the ones which were over longer time periods below this threshold.

[22] Other studies, e.g. Campbell et al (2008), Garlappi et al (2008) and Gebhardt et al (2001) also allow for new companies to enter the sample.

[23] Datastream does not provide the exact reason of delisting in case it is too low price or some requirements violations, but it provides information if a company was taken over or merged. Naturally, merged or taken over companies were not considered as bankrupted in our sample. However, this distinction between defaulted, merged or acquired companies in Datastream was introduced only over time, so it might be that some companies were treated as bankrupted even though they were actually taken over or merged.

Table 1: Number of Firms

This table lists the average number of firms each year and the number of bankrupted firms for all years of our sample period. Over the entire sample period 68 firms bankrupted. Further, the table displays the average number of firms which could be classified as "distressed" according to the distress measures: Z-Score <1.81 and DtD probability of default ≤ 4%.

Year	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Total	390	399	419	425	421	413	417	429	443	441	422	406	390
Bankrupted	0	0	0	4	5	12	6	6	8	8	8	3	8
Distressed (Z-Score)	74	87	87	88	88	90	90	92	92	92	95	98	97
% of total	*19%*	*22%*	*21%*	*21%*	*21%*	*22%*	*22%*	*21%*	*21%*	*21%*	*23%*	*24%*	*25%*
Distressed (DtD)[24]	32	63	62	63	64	68	71	72	73	76	87	88	84
% of total	*8%*	*16%*	*15%*	*15%*	*15%*	*16%*	*17%*	*17%*	*16%*	*17%*	*21%*	*22%*	*22%*

Other researchers calculating ICoE based on analyst forecasts usually exclude firms with negative EPS forecast FY1 and FY2 (e.g., Lee et al (2009), Elton et al (1981)) in order to avoid computation errors when solving the polynomial present value of future cash flows equation for the return on equity. However, since we focus on companies with high risk of financial distress risk, the most distressed companies would fall out from our sample and the results of our analysis would be biased. Thus, we found a solution which allows us to keep some of the most distress companies and at the same time eliminates computational errors. In particular, we set negative values of EPS forecast FY2 to a low positive value of 0.01€ while keeping negative EPS FY1 estimations.[25]

Subsample. Being aware of potential biases of the ICoE in our sample, we form a subsample, consisting only of companies which have positive EPS forecasts FY1 and FY2. This subsample serves as a robustness check of our results to erroneous ICoE values. Descriptive statistics indicate that the distress measures Z-Score and DtD are higher in the subsample than in the main sample, showing that overall the risk of financial distress is lower in the subsample.

[24] Firms with a Moody's Rating of CCC and lower are assumed to be distressed. According to Crosbie and Bohn (2003), a CCC-rated firm has a probability of default of 4% or higher.

[25] This becomes necessary as the ICoE is the IRR that equals the future free cash flows to equity holders to the current stock price. In the case of positive cash flows followed by negative ones and then by positive ones the equation can give several solutions (Hazen (2003)).

Table 2: Summary Statistics

This table presents summary statistics for the main sample (Panel A) and for the subsample (Panel B). For the latter we excluded all firms with negative EPS consensus estimates for year 2. Besides the realized returns which are calculated from observable stock market prices, it includes summary statistics for the different distress measures (the default probability according to DtD is proxied assuming a normal distribution of financial distress). For realized returns, DtD and Z-Score values below the 1st percentile are replaced by the 1st percentile and values above the 99th percentile are replaced by the 99th percentile. The table lists the input variables required for the calculation of the CAPM CoE as well as for the calculation of ICoE, the number of observations, mean, standard deviation and selected percentiles. Further, additional variables used in the regression analysis to test potential effects on equity returns are displayed. Summary statistics are reported for all observations for which realized returns indicate the listing of a company and values could be obtained. Please refer to Appendix II for summary statistics of ICoE and CAPM CoE and Appendix VI for sources and definitions of all variables employed in our analysis.
* Realized Returns p.a. are 12 times monthly returns for illustration purposes. Knowing that the multiplication of monthly returns might be a poor estimate for realized annual returns, we follow the procedure of Fama and French (1997).
** Summary statistics for EPS Year 2 are before assigning 0.01€ for values of 0 and below. In the subsample this adjustment was not necessary as it includes only firms with positive EPSFY2 estimates.
*** Summary statistics for EPS long-term growth are displayed after assigning a growth rate of 2% for values below and 100% for values above this threshold.

Variables	**N**	**Mean**	**StD**	**p1**	**p50**	**p99**
Panel A - Main Sample (501 firms)						
Realized Returns (monthly)	60689	0.35%	11.45%	-33.33%	0.00%	38.87%
*Realized Returns (p.a.) **	*60689*	*4.22%*	*137.43%*	*-400.00%*	*0.00%*	*466.42%*
<u>Distress Measures</u>						
Distance-to-Default	60614	4.28	2.46	-0.03	3.90	12.00
Distance-to-Default (Prob.)	60614	3.00%	9.00%	51.00%	0.00%	0.00%
Altman Z-Score	66531	3.16	2.68	-1.02	2.48	16.70
<u>CAPM CoE</u>						
Beta	54991	1.12	0.71	-0.06	1.02	3.39
Equity Risk Premium	60689	5.42%	1.27%	4.50%	5.00%	13.01%
Risk-free rate (LT)	60689	4.30%	1.26%	2.30%	4.18%	8.75%
<u>ICoE</u>						
EPS Year 1	60687	1.52	4.31	-1.80	0.89	10.96
EPS Year 2 **	60687	1.95	5.59	-0.16	1.10	11.97
EPS LT growth ***	60675	19.00%	23.00%	2.00%	12.00%	100.00%
<u>Additional Variables</u>						
Size (in bn €)	66531	3.17	10.20	0.01	0.48	54.83
Book-to-Market	66531	0.71	0.88	0.02	0.58	3.52
Leverage	66537	2.04	6.04	-0.03	1.33	11.13
Panel B - Subsample (294 firms)						
Realized Returns (monthly)	34388	0.65%	9.71%	-27.67%	0.39%	31.18%
*Realized Returns (p.a.) **	*34388*	*7.80%*	*116.52%*	*-332.04%*	*4.68%*	*374.16%*
<u>Distress Measures</u>						
Distance-to-Default	34350	4.90	2.52	0.35	4.54	12.78
Distance-to-Default (Prob.)	34350	1.39%	5.23%	0.00%	0.00%	36.36%
Altman Z-Score	34388	3.42	2.80	0.60	2.60	17.54
<u>CAPM CoE</u>						
Beta	31124	0.94	0.57	-0.09	0.88	2.59
Equity Risk Premium	34388	5.38%	1.18%	4.50%	5.00%	13.01%
Risk-free rate (LT)	34388	4.35%	1.30%	2.35%	4.20%	9.63%
<u>ICoE</u>						
EPS Year 1	34388	1.81	2.26	0.08	1.20	10.06
EPS Year 2	34386	2.03	2.44	0.10	1.37	10.56
EPS LT growth ***	34383	15.97%	17.57%	2.00%	11.03%	100.00%
<u>Additional Variables</u>						
Size (in bn €)	34388	4.21	12.58	0.03	0.68	64.66
Book-to-Market	34388	0.66	0.52	0.06	0.53	2.63
Leverage	34388	1.81	2.78	0.14	1.35	8.54

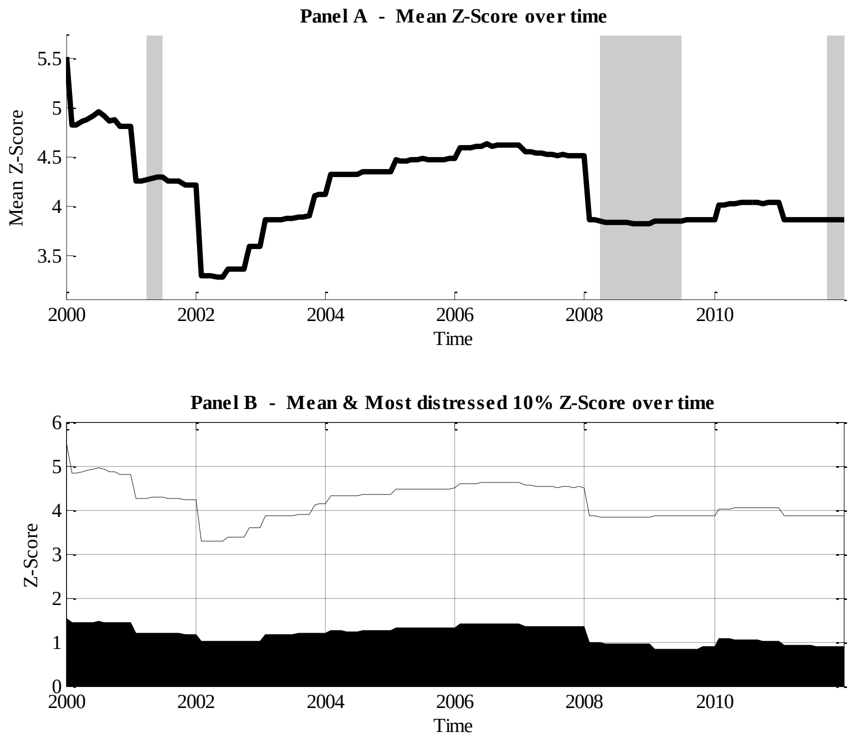
3.2. Financial Distress Measures

For the analysis of returns behavior with respect to different levels of financial distress we match each monthly return observation with a corresponding distress measure value (DtD and Z-Score).

Z-Score. The construction of Z-Score requires monthly observations of the following accounting measures: Total Assets (TA), Working Capital (WC), Earnings before Interest and Taxes (EBIT), Retained Earnings (RE), Market Capitalization and Book value of Liabilities. These values are obtained on a yearly basis as of year-end from the Worldscope database and then used for all monthly observations of this year.[26] In line with the initial specification of the Altman's (1968) bankruptcy prediction model, we use also for Market Capitalization the year-end value although one might argue that the current share price times the number of shares outstanding are known at every point in time. Since the accounting based bankruptcy models have been estimated using discriminant analysis it is essential that the variables used are consistent with the original model specification. Z-Score in the studies of Dichev (1998) and Ferguson and Shockley (2003) is calculated in the same "static" way as done in our research.

Graph 1: Z-Score over Time

Panel A displays the mean Z-Score over all firms at each point in time. The grey areas indicate periods of recession. Instead of the aggregate Eurozone GDP, a quarter is marked as recessionary if more than 1 country in our sample experiences negative quarterly GDP growth rates.
Panel B shows in addition to the mean Z-Score the aggregate of the lowest 10% of Z-Score at each monthly observation (area filled in black).

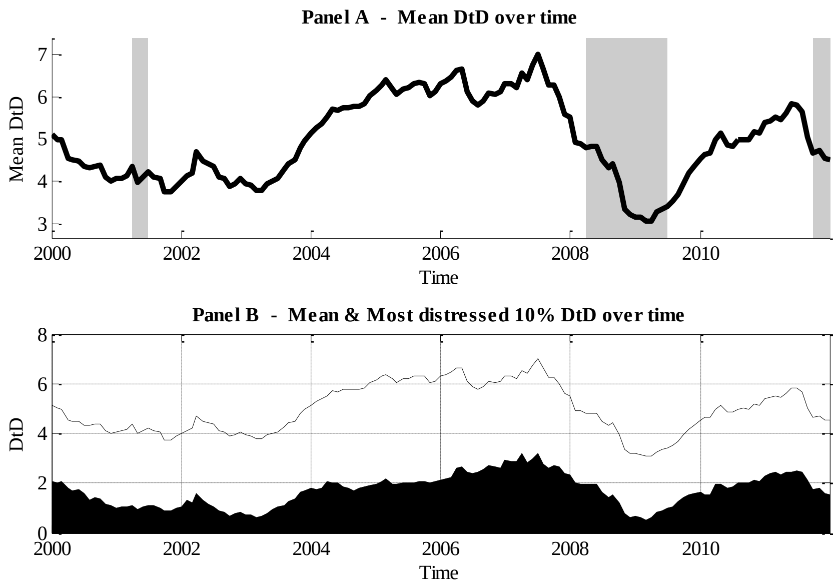


[26] The choice of yearly observations is based on two factors. First, Z-Score has been estimated on year-end figures and, secondly, year-end figures are more reliable than quarterly reported results (Dichev (1998)).

Distance-to-Default. The DtD measure, based on Merton's model (1974) and employed by Moody's KMV (Crosbie and Bohn (2003)) and in slightly adjusted versions calculated by many researchers (e.g., Chava and Purnanandam (2010), Vassalou and Xing (2004)) has been directly obtained from the RMI database. This Credit Research Initiative aims to provide credit ratings as a publicly available good. The RMI hereby provides individual company's probability of default for around 60,400 listed firms (including the ones which have been delisted) in about 106 economies worldwide.[27] The database provides historical time series of an individual DtD indicator for the prediction of corporate defaults (Duan and Wang (2012)). The DtD values for each individual company are available on a monthly basis. For illustrative purposes the DtD value has been transformed into default probabilities assuming that the default rate is normally distributed.

Graph 2: DtD over Time

Panel A displays the mean DtD over all firms at each month end. The grey areas indicate periods of recession. Instead of the aggregate Eurozone GDP, a quarter is marked as recessionary if more than 1 country in our sample experiences negative quarterly GDP growth rates.
Panel B shows in addition to the mean DtD the aggregate of the lowest 10% of DtD at each monthly observation (area filled in black).



As can be seen from Graph 1 and Graph 2, both distress measures are varying over time and it becomes apparent from the mean over the 501 firms as well as from the mean of the 10% most distressed firms that the Z-Score and DtD are lower (and hence the corresponding probability of default higher) in recession periods. Graphical illustrations and the construction of the distress measures also provide an indication that the variation over time in the DtD is higher than in the Z-Score.

[27] The database is strongly research oriented and encourages academics to use their measures in academic research (www.rmicri.org).

In line with the consensus of several studies (Dichev (1998), Griffin and Lemmon (2002) for Z-Score and Vassalou and Xing (2004) for default measures similar to Moody's KMV), these financial distress risk measures are powerful in predicting firm defaults. Therefore, it is expected that both measures are positively correlated. Table 3 shows that the Pearson correlation coefficient between the Z-Score and the DtD is 0.45. This justifies our approach of testing the relationship of returns to both distress measures, since both measures capture similar factors of financial distress, but also contain different independent financial distress related information.[28]

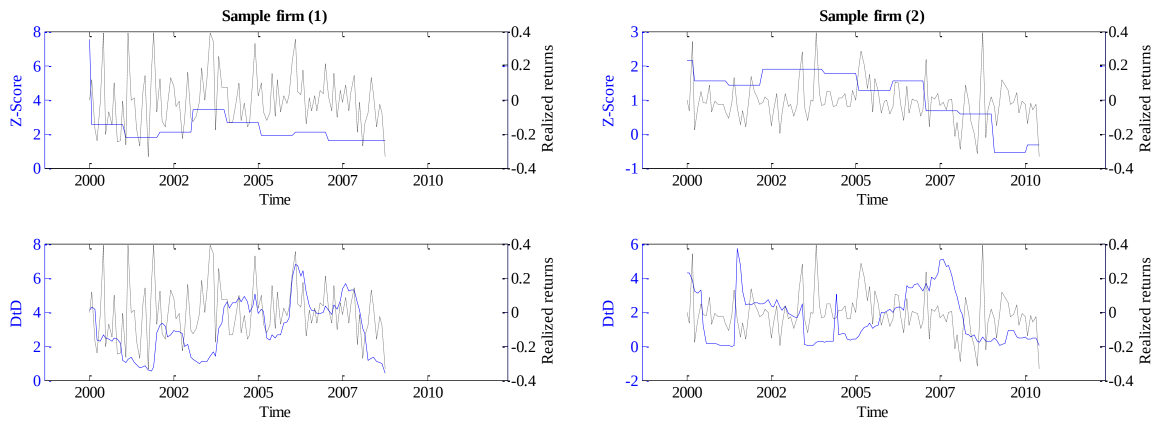
Table 3: Pearson Correlation Coefficients

Variables	**Z-Score**	**DtD**	**DtD (prob.)**	**Size**	**BM**
Z-Score	1				
DtD	0.45	1			
DtD (prob.)	-0.22	-0.49	1		
Size	-0.03	0.18	-0.11	1	
BM	-0.21	-0.29	0.08	-0.12	1

While there is empirical evidence on the significant default prediction ability of Z-Score and DtD for U.S. companies, there is not much evidence justifying the application of these financial distress measures for European companies. As it could be observed from Graph 1 and Graph 2, DtD and Z-Score seem to move in line with the economic cycle in the Eurozone, i.e. financial distress risk measures are lower (probabilities of default higher) in recession periods. Further, we estimated that for bankrupted firms in our sample the Z-Score indicated that a company has financial difficulties in 69% of cases, and the DtD in 77% of cases. This rationalizes our usage of these distress measures for European data. In Graph 3 we provide evidence of two sample firms showing how DtD and Z-Score move over time in case a company approaches bankruptcy.

Graph 3: Sample Bankrupted Firms

The figure consisting of 4 subplots displays the Z-Score and the DtD for two exemplary bankrupted firms in our sample. Further realized monthly returns are displayed at each point in time for illustrative purposes.



[28] Chava and Purnanandam (2010) compare two market based distress measures and report correlation between them of 77%. Naturally, accounting and market based measures could be expected to be less correlated.

3.3. Implied Cost of Equity Capital

The data required for the calculation of ICoE consists of three components. First, mean consensus estimates on Earnings per Share (EPS) for one and two years ahead and the long-term growth are required. Secondly, the input which is normally not explicitly forecasted by equity analysts, the plowback ratio, is obtained as last reported $1 - payout\ ratio$. Similarly, the last reported EPS is obtained from I/B/E/S to fill potential gaps in the inputs of the ICoE calculation. Third, we retrieve the yearly real Gross Domestic Product (GDP) and inflation data from the Worldbank database[29] on a country level and compute the nominal GDP for each country and each year.

3.4. CAPM Cost of Equity Capital

In order to estimate CAPM CoE the main inputs needed are long term risk-free rate, equity risk premium (ERP) and market beta. The long term risk-free rate (based on government debt issues with 10 years maturity) is retrieved from the European Central Bank (ECB)[30]. ERP on a year and country basis is obtained from Damodaran's website[31]. ERP estimated by Damodaran is chosen because of its wide practical usage. Fernandez et al (2013) show that Damodaran's country ERP is the most used source in the financial community to justify individual ERP estimates. As it could be seen from Table 2, the mean ERP is around 5%, which goes in line with the general consensus to use an ERP of 4-6%. The market beta measuring the market risk of individual companies is estimated for each point in time using a 36 month rolling window regression. Therefore, realized returns starting 3 years before the general time series are required. The short-term risk free rate (1 month EURIBOR) was obtained from ECB and EUROSTOXX 600 proxying for the market return was obtained from Datastream (see Appendix VI for detailed description of variables and sources used).

[29] http://data.worldbank.org/indicator (retrieved April 10th 2013)
[30] http://www.ecb.europa.eu/stats (retrieved April 10th 2013)
[31] The ERP provided by Damodaran is based on U.S. implied equity risk premium and contains country premium for different European countries (http://people.stern.nyu.edu/adamodar/).

4. Methodology

4.1. Financial Distress Risk Measures

4.1.1. Altman Z-Score

Altman (1968) developed a multivariate model to predict financial distress using balance sheet and income statement information based ratios. Altman Z-Score for publicly held manufacturing companies is defined as follows (1968, 2002):

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \tag{1}$$

$$\begin{aligned}
&where:\\
&X1 \;=\; Working\ capital\ /\ Total\ assets\\
&X2 \;=\; Retained\ earnings\ /\ Total\ assets\\
&X3 \;=\; Earnings\ before\ interest\ and\ taxes\ /\ Total\ assets\\
&X4 \;=\; Market\ value\ of\ equity\ /\ Book\ value\ of\ total\ debt\\
&X5 \;=\; Sales\ /\ Total\ assets\\
&Z \;=\; overall\ score
\end{aligned}$$

From a set of 22 accounting ratios Altman (1968) found these 5 ratios to have the highest predictive power. Z-Score is a good predictor of bankruptcy up to two years prior to insolvency, but the accuracy decreases as the time of the lead increases (Altman (1968)). Z-Score cannot be transformed directly into a default probability, but it provides an indication of a high probability of failure as soon as the Z-Score falls below a certain level. In particular, companies with a Z-Score of higher than 2.99 are classified as “non-bankrupt”, and companies with a Z-Score lower than 1.81 are classified as “bankrupt”. The interval from 1.81 to 2.99 is defined as “gray area” or “zone of ignorance” as most of the misclassification occurs in this zone. Thus, companies with these Z-Score values could not be classified into one or the other group (Altman (1968)). As it was mentioned in Section 3 describing our data sample, the specification of Z-Score and the cut-offs indicating if a company is in a bankruptcy zone or not are slightly different for listed non-manufacturing companies[32]. To avoid biases arising from different interpretation of Z-Score for service companies, we focus only on manufacturing companies. This approach also makes our sample more homogenous.

Despite its criticism, Altman Z-Score is said to be the most popular model of bankruptcy prediction in practice and academia (e.g., Dichev (1998)). When interpreting its results it is especially important to keep in mind that the model was estimated on U.S. manufacturing firms over the time period of 1946 to 1965. Hence, bias can be introduced due to different accounting

[32] The Z-Score definition for non-manufacturing companies (Altman (2000)) is:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

where X_1, X_2, X_3 are the same ratios as above. X_4 is now defined as Book value of equity / Book value of total debt. X_5 is excluded from Z’’-score estimation to minimize the potential industry effect. Z’’-scores below 1.10 signal a highly distressed state.

standards across countries and over time. Z-Score is criticized for being "static" as it incorporates only ratios of one particular financial statement. However, bankruptcy models including several years financial statement history don't have a higher predictive power than the Z-Score.[33]

4.1.2. Distance-to-Default

The calculation of the DtD measure is beyond the scope of this paper. Thus, it is directly obtained from the RMI database. It is calculated based on the option pricing methodology (Merton (1974)), where equity is considered as an option on firm's value. According to the researchers of the RMI (Duan and Wang (2012)), their DtD is defined as follows:

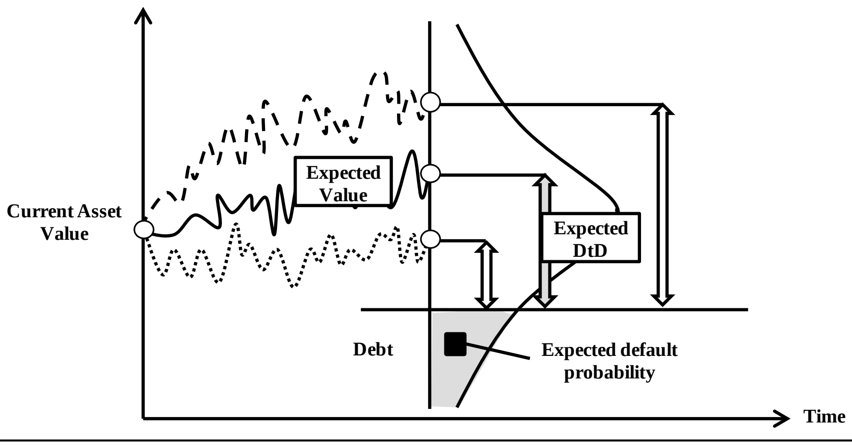
$$DtD_t = \frac{ln(V_{A,t}/X_t)+(\mu-\frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}} \quad (2)$$

$where$:
$V_{A,t}$ $is\ the\ asset\ value\ of\ a\ firm\ at\ time\ t,$
X_t $is\ the\ book\ value\ of\ the\ debt\ at\ time\ t\ with\ maturity\ of\ T$
μ $is\ instantaneous\ drift\ of\ the\ asset\ value$
σ_A $is\ volatility\ of\ assets$

As shown symbolically in Graph 4, the DtD indicates the distance between firm's current value and its bankruptcy threshold (Chava and Purnanandam (2010), Vassalou and Xing (2004)). Using the simplification of $P_{def} = N(-DtD)$, we are able to approximate default probabilities. Since the underlying default rate might not be normally distributed[34], the default probabilities are used only for illustrative purposes. Therefore, absolute DtD values are used throughout our analysis.

Graph 4: Graphical Illustration of DtD

In line with Bessis (2010, page 606), the graph illustrates simplified calculation of the expected DtD. It also shows how under the assumption that the default rate follows a normal distribution, the DtD value can be transformed into a default probability.



[33] Alternatives for Altman Z-Score in Europe could be the Skogsvik Bankruptcy model (1988) or Z-Score version re-estimated for UK (Taffler (1983)). However, these two models are less known and used in practice.
[34] The default probabilities provided by KMV are based on the empirical distribution of defaults (Crosbie and Bohn (2003)).

4.2. Implied Cost of Equity Capital

There are several approaches to estimate the ICoE (Ohlson and Juettner-Nauroth (2005), Easton (2004), Claus and Thomas (2001), Gebhardt et al (2001)). The ICoE used in our analysis is calculated closely following Lee et al (2009), Pastor et al (2008) and Gebhardt et al (2001), who use a discounted residual income model. This methodology was also applied by Chava and Purnanandam (2010) in their study comparing ICoE and financial distress risk. Not only is this approach widely used in research, it is also conceptually appealing for practical applications.

ICoE is usually calculated from a discounted free cash flow model of equity valuation. The expected return on a stock is calculated as an internal rate of return (IRR), where the current market value is equated to the present value of free cash flows to equity holders (FCFE). Following Lee et al (2009), Pastor et al (2008) and Gebhardt et al (2001), the stock price $P_{i,t}$ of a firm i at time t is could be expressed as:

$$P_{i,t} = \sum_{k=1}^{k=\infty} \frac{E_t(FCFE_{i,t+k})}{(1+r_{i,e})^k} \tag{4}$$

$where$:
$FCFE_{i,t+k} is\ the\ free\ cash\ flow\ to\ equity\ in\ year\ t{+}k\ of\ a\ firm\ i$
$E_t\ is\ the\ expectation\ operator\ conditional\ on\ the\ information\ at\ time\ t$
$r_{i,e}\ is\ the\ ICoE\ based\ on\ the\ information\ set\ at\ time\ t$

All variables are expressed in nominal terms and the present value formula implies the inherent assumption that the term structure of discount rates is flat. FCFE captures the total cash flow available to shareholders after excluding stock repurchases and new equity issues. The formula above hints to infinite cash flows, but in our practical application a finite time period is defined. Consistently with the existing research, FCFE is forecasted over 15 years and the remaining FCF is captured in the terminal value (Chava and Purnanandam (2010), Lee et al (2009), Pastor et al (2008))[35]. Thus, the value of a firm is calculated in two steps. First, the present value of FCFE up to the terminal period $t{+}T$ is obtained. Secondly, the present value of FCFE beyond the terminal period is added. FCFE up to year $t{+}T{+}1$ is computed:

$$E_t(FCFE_{i,t+k}) = FE_{i,t+k}(1 - b_{i,t+k}) \tag{5}$$

$where$:
$FE_{t+k} is\ the\ forecast\ of\ earnings$
$b_{t+k}\ is\ the\ forecast\ of\ plowback\ rate\ for\ year\ t + k$

[35] Gebhardt et al (2001) use a finite period of 12 years, but the results obtained using 6, 9, 15, 18 or 21 years are very similar. As a robustness check, Lee et al (2009) uses a period of 10 and 20 years and Chava and Purnanandam (2010) uses 10 years and find that the results are essentially unchanged. Meanwhile, Pastor et al (2008) conducting the same robustness check find that the choice of forecasting horizon affects the level of the ICoE.

The plowback rate is the part of earnings that is reinvested in a firm, which is equivalent to one minus payout ratio. Therefore, the FCFE is net income after excluding net new equity investment (Pastor et al (2008)).

The first three years ($t+1$ to $t+3$) of earnings forecasts are based on analysts' consensus forecasts obtained from I/B/E/S, which are assumed to be equal to average market expectations. Three years are used as a cut-off for an explicit earnings forecast by Pastor et al (2008) and Gebhardt et al (2001) since further forecasts are not available for all firms at the I/B/E/S database. Already the 3-year-ahead EPS consensus estimates are scarcer, so that EPSFY2 and the long term growth rate of earnings (Ltg) are used instead for the calculation of EPSFY3 ($FE_{t+3} = FE_{t+2}(1 + Ltg)$). In line with Chava and Purnanandam (2010) and Pastor et al (2008), long term growth rates above 100% are assigned to 100% and rates lower than 2% are assigned to 2% since negative or extremely high growth rates are not sustainable in the long run.

The forecasts for the following years ($t+4$ to $t+T+1$) are obtained by mean-reverting the $t+3$ earnings growth rate to its steady-state value by year $t+T+2$. The steady state growth rate g starting in year $t+T+2$, in line with Lee et al (2009) and Pastor et al (2008), is assumed to be the long-run nominal GDP growth rate, which is estimated by adding the long-run real GDP growth rate (a rolling average of annual real GDP growth) and the long-run average rate of inflation. It is a strong assumption that all firms will grow at the same GDP rate in perpetuity, but there are no credible alternatives. Gebhardt et al (2001) advocates using the median industry ROE as a steady-state growth rate, but it is hard to implement empirically and it is also likely to contain measurement errors.

Lee et al (2009) and Pastor et al (2008) impose an exponential rate of decline to mean-revert the year $t+3$ growth rate to the steady state growth rate. The rate of decline is chosen to be exponential in line with the existing empirical evidence that growth rates of earnings mean-revert fast (e.g., Chan et al. (2003)). This rapid mean reversion minimizes any biases in the short-term forecasts of analysts on long-term growth rates or the estimated ICoE (Lee et al (2009), Pastor et al (2008)). Earnings growth rates and earnings forecasts for years $t+4$ to $t+T+1$ ($k = 4, \ldots, T+1$) are calculated using the following expressions:

$$g_{i,t+k} = g_{i,t+k-1} * exp[log(g/g_{i,t+3})/(T-1)] \tag{6}$$

$$FE_{i,t+k} = FE_{i,t+k-1} * (1 + g_{i,t+k}) \tag{7}$$

The procedure of forecasting plowback rate is slightly different. It is explicitly forecasted for the first two years ($t+1$ and $t+2$). Afterwards the plowback rates between $t+2$ and $t+T+1$ are linearly mean-reverted to a steady state value. In line with Lee et al (2009) and Pastor et al (2008), a linear decline in the plowback rate is chosen because empirically plowback rates mean-revert slower than earnings growth rates. A steady state value of the plowback rate is computed using the sustainable growth rate formula (Brealey and Myers (2003)), which implies that the steady-state growth rate could be obtained by multiplying the steady-state return on new investments (*ROI*) and the steady-state plowback rate: $g = ROI * b$.

ROI is set equal to r_e assuming that the competition would diminish returns on investments to the cost of equity (Lee et al (2009), Pastor et al (2008)). Thus, the steady-state plowback ratio b from the sustainable growth rate formula is solved as $b = g/r_e$.

Since in the steady state equilibrium (all new investments are NPV = 0) the ROI is equal to r_e (Lee et al (2009)) a non-growth perpetuity formula is applied.[36].

The finite horizon FCF model and the terminal value can then be equated to the stock price:

$$P_{i,t} = \sum_{k=1}^{T} \frac{FE_{i,t+k}(1-b_{i,t+k})}{(1+r_{i,e})^k} + \frac{FE_{i,t+T+1}}{r_{i,e}(1+r_{i,e})^T} \quad (8)$$

Since all other variables except $r_{i,e}$ are given in the equation above, it can be solved for the ICoE. In line with Pastor et al (2008), 1% of the top and the bottom values of ICoE will be winsorized.

The main advantages of using ICoE instead of realized returns as a proxy of expected returns are that by construction ICoE is a forward looking measure (consensus forecasts are assumed to be representative of investors' expectations) and hence does not rely on noisy realized returns (Pastor et al (2008)). The main concern, raised in the increasing research using ICoE, is that ICoE could be systematically biased due to its strong dependence on analysts' forecasts (Pratt and Grabowski (2008), Easton and Sommers (2007), Claus and Thomas (2001)) and due to its high sensitivity to assumptions in the estimation model. In particular, we assume that a company is going concern, meanwhile in our sample we have some companies bankrupting over the estimation period. On the other hand, Chava and Purnanandam (2010) check for the possible bias by accounting for the possibility of default and conclude that the impact is not significant on results.

Further, the numerical solution of equation (8) for $r_{i,e}$ (equivalent to IRR) may have multiple values if positive cash flows are followed by negative ones and then by positive ones (for example, $+ + - - - +$). Therefore, other researchers (e.g., Lee et al (2009), Elton et al (1981))

[36] The non-growth perpetuity formula is the Gordon growth model used for the terminal value in DCF calculations, but with zero growth.

eliminate observations with negative earnings forecasts. This could lead to a substantial bias of the ICoE towards less distressed companies. Since it is fundamental for our analysis not to exclude companies with higher risk of financial distress, we do not adopt the approach of excluding companies with at least one negative EPS observation. Instead we assign a very low value (0.01 €) for negative EPSFY2 estimates. To test the robustness of our results using this approach differing from other researchers we form a subsample containing companies with only positive EPS forecasts as described in section 3.1.

The application of ICoE not only as implied expected return, but also as an alternative measure of cost of equity depends on the assumptions that market prices are efficient and that analysts' consensus forecasts represent well the expectations of the market (Easton and Sommers (2007)). Since this involves forward looking components, we hypothesize that ICoE might be a better measure of CoE than CAPM CoE especially with respect to financial distress risk.

4.3. Rolling Window Market Beta Estimation

Following the most popular and the most widely used model in asset pricing and valuation to obtain the cost of equity capital from historical returns, we use the CAPM (Sharpe (1964), Lintner (1965)). In order to estimate market betas the following specification in line with Cochrane (2005) was used:

$$R_i - R_f = \alpha_i + \beta_i(R_M - R_f) + \varepsilon_{it} \tag{9}$$

$where$:
R_i $is\ a\ monthly\ return\ on\ stock\ i$
R_f $is\ short - term\ riskfree\ interest\ rate$
R_M $is\ return\ on\ market\ portfolio$
β_i $is\ market\ beta$

We calculate betas on a company level using rolling window regressions for time series. There is evidence (Fama and French (1992), Elton et al (1981), Fama and MacBeth (1973)) that the estimates of market betas are more precise using the regressions on a portfolio level where stocks are grouped according to a particular characteristic related to average returns (e.g. size, BM, industry). However, the approach of running a company level regression is more suitable in our case. First, if market betas are estimated on a portfolio basis, then each stock in one portfolio would be assigned the same market beta in a particular time period, which would reduce variability. Most importantly, since the focus of this paper is to draw conclusions for practical valuation purposes, analysts or investors would not be willing to estimate betas on portfolios of similar companies, but rather assess the market risk of individual companies, which they attempt to value.

We use 36 monthly observations of returns up to and including the month when the valuation is performed. Monthly observations for the estimation of betas are chosen in line with the majority of the studies (e.g., Gebhardt et al (2001), Fama and French (1992), Elton et al (1981)). Most researchers use 60 monthly observations to obtain betas (Gebhardt et al (2001), Chan and Chen (1991), Fama and MacBeth (1973)). Depending on data availability Fama and French (1992) estimate market betas on 24 to 60 monthly returns. Due to data limitations we chose to estimate betas using 36 months in line with Lin and Zhang (2013). The requirement that each company has returns for at least 60 months would have further reduced our sample. After market betas were obtained for each company, we calculated the cost of equity:

$$CoE_i^{CAPM} = E(R_i) = r_f + \hat{\beta}_i * ERP_i \tag{10}$$

$where$:
CoE_i^{CAPM} $is\ the\ cost\ of\ equity\ capital\ based\ on\ CAPM$
r_f $is\ the\ long - term\ riskfree\ interest\ rate$
$\hat{\beta}_i$ $is\ the\ market\ beta\ obtained\ from\ the\ rolling\ window\ estimation$
ERP_i $is\ equity\ risk\ premium$

In contrast to the rolling window beta estimation, we now use the long-term risk-free interest rate to calculate the CAPM CoE to reflect the long time-horizon of cash flow in a valuation context. Since an estimation of the ERP would exceed the scope of our work, we based our calculation on the ERP provided by Damodaran[37], which is widely used among researchers and practitioners (Fernandez et al (2013)).

4.4. Relationship between Expected Returns and Financial Distress Risk

4.4.1. Portfolio Analysis

Portfolio analysis, i.e. ranking stocks into different groups based on a financial distress risk measure, is very popular among researchers in this area. Portfolio analysis is beneficial as it allows to see economic significance of results and to spot potential non-linearity in the relation between distress risk measures, cost of equity and returns. Each month companies are assigned into decile portfolios based on their distress measure. Companies are ranked relative to each other. Firstly, they are ranked from the least distressed to the most distressed and then they are divided into ten portfolios containing the same number of companies. Afterwards the mean of distress indicators and subsequently the variables which we want to analyze (realized returns, ICoE and CAPM CoE) are calculated across the firms of each portfolio for each month and then they are averaged throughout the years. The t-test is conducted to see if portfolios with different default risk characteristics differ significantly with respect to the variables of interest.

[37] http://people.stern.nyu.edu/adamodar/

The same portfolio analysis methodology was used by Chava and Purnanandam (2010), Avramov et al (2009), Garlappi et al (2008), Vassalou and Xing (2004) and Dichev (1998). However, Campbell et al (2008) form 10 portfolios not according to deciles, but slightly asymmetrically emphasizing the tails of the distribution.[38] They claim that the distress premium could be relevant only for the most distressed companies. We believe that if the financial distress effect is present it should also be detected using equal size portfolios and, thus, we follow the methodology of the majority of researchers in this area.

In line with Avramov (2009) and Dichev (1998) portfolio returns will be calculated only equally weighted. While some researchers also analyze value weighted results (e.g. Campbell et al (2008), Vassalou and Xing (2004)), we think that weighting returns according to their size is not meaningful in our study. Our data sample is already biased towards larger companies due to the fact that companies only followed by minimum three analysts are included.

For comparison and robustness check purposes two different distress measures (Z-Score and DtD) will be used to rank firms on their level of distress. Similar research usually focuses on one default indicator (Avramov et al (2009), Campbell et al (2008), Vassalou and Xing (2004)) or compare two indicators from the same category – either both measures are accounting based (Griffin and Lemmon (2002), Dichev (1998)) or both measures are market based (Chava and Purnanandam (2010)). We decided that it would be interesting to check the sensitivity of results when using one accounting data based and one market based indicator. Due to the differences in their predictive methodology and variables used, these two measures are expected to complement each other well, underlined by the correlation of around 0.45 in our sample (see Table 3).

When returns or cost of equity capital will be matched with Z-Score, it will be lagged by 4 months. According to disclosure requirements on the Frankfurt stock exchange (Frankfurt Stock Exchange Regulations and Rules § 51.5), listed companies have to publish their financial statements information by the end of May, end of August and end of November.[39] The implicit assumption is made that four months after year-end or two month after quarter-end, financial information should be available to investors. Z-Score is used (as initially estimated by Altman (1968)) on an annual base, however, it is assumed that investors can already calculate an approximate Z-Score for the whole year after the information is published for the first quarter of

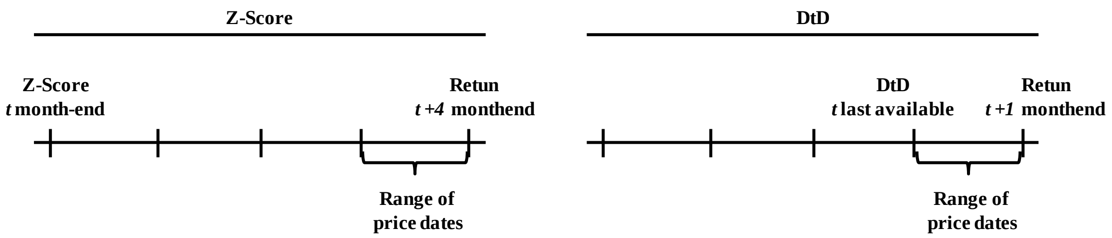
[38] 0-5, 5-10, 10-20, 20-40, 40-60, 60-80, 80-90, 90-95, 95-99, 99-100 percentiles.

[39] Although the International Accounting Standards (IAS 34.1) do not specify specific reporting deadlines for interim reports, the major stock exchanges require the listed companies to report quarterly financial statements. We assume that rules between the major stock exchange in the Eurozone (Frankfurt) and other financial marketplaces in the Eurozone do not differ substantially.

the year. This assumption is made due to data limitations as there is no reliable quarterly financial information available. Even if quarterly information would be available, Z-Score is mostly estimated using yearly data, so further adjustments would be required. The alternative in our case would be to use a lag of 1 year and 4 months (similarly to Dichev (1998)), i.e. at least 16 months. However, it is unreasonable that investors do not have any indication about the Z-Score for such a long period of time and it is expected that the potential effect of Z-Score would have been faded away.

Graph 5: Timing of Distress Measures and Returns

The graph shows how expected returns and CoE estimates are matched with the corresponding distress measure. It also illustrates the composition of the monthly returns.



Regarding the DtD measure, in line with Vassalou and Xing (2004) monthly returns were matched with the most recent DtD measure. This means an implicit lag of less than a month. Since DtD is a market based measure, using a longer lag is not meaningful as any effect on returns fades away very fast.

4.4.2. Regression Analysis

Using portfolio analysis, the relationship between default risk measures and expected returns is established at univariate level. However, some of the difference in returns could come not only from the differing financial distress risk, but also from other characteristics not necessarily related to default risk. To establish the relationship in multivariate tests expected returns will be regressed on firm's financial distress risk measure and step-wise including other widely documented significant determinants of equity returns.

First of all, in line with other researchers (Chava and Purnanandam (2010), Avramov et al (2009), Vassalou and Xing (2004), Dichev (1998)), when examining the relationship between realized returns and default risk, size and BM will be included as they are the most widely known additional variables potentially affecting equity returns (Fama and French (1992), Chan and Chen (1991), Rosenberg et al (1985), Banz (1981)). It is very important to consider these variables because there are hypothesis that high default risk firms tend to be smaller and have higher BM ratios (Fama and French (1992), Chan and Chen (1991)). Consistently with Avramov et al (2009), Dichev (1998), Fama and French (1992) and Banz (1981) size is defined as logarithm of market value of equity. BM is defined as book value of equity divided by market value of equity. While Fama and French (1992) use a logarithm of the BM ratio in their regressions, we will use the simple ratio because some companies have a negative book value (in line with Dichev (1998)). As companies having a negative BM ratio are very likely to be distressed excluding these observations does not seem appropriate given the focus of this study.

Secondly, our result will be controlled for leverage and one-month lagged stock returns for robustness check purposes as they are also expected to have an impact on equity returns (Jegadeesh and Titman (1993), Bhandari (1988)). The hypothesis is that the default risk measure will retain its significance in the cross-sectional regressions even after controlling for other stock characteristics. The following regressions step-wise including independent variables will be run[40]:

$$R_{it} = a_1 + b_1 Zscore_{it-4} + b_2 Size_{it-1} + b_3 BM_{it-1} + \varepsilon_{it} \tag{11}$$

$$R_{it} = a_1 + b_1 DtD_{it-1} + b_2 Size_{it-1} + b_3 BM_{it-1} + \varepsilon_{it} \tag{12}$$

$where$:
R_{it} $is\ a\ monthly\ return\ on\ stock\ i\ at\ time\ t$
a_1 $is\ a\ constant$
$b_{1,2,3}$ $are\ regression\ coefficients\ for\ the\ respective\ independent\ variable$
ε_{it} $is\ the\ error\ term$

As reported in Table 3, there is some correlation between Z-Score, DtD, size and BM since they all in some way include MV of equity. However, they also contain considerable independent information and can be simultaneously used as regressors without raising multicollinearity issues (Vassalou and Xing (2004)). The same independent variables will be used in regressions testing the relationship between ICoE and distress risk as well as the relationship between CAPM CoE and distress risk. Gebhardt et al. (2001) find a positive relationship between BM and ICoE. Lee et al (2009) show that size, BM and leverage have a significant relation to expected returns.

In line with similar research (Chava and Purnanandam (2010), George and Hwang (2010), Avramov et al. (2009), Garlappi et al (2008), Vassalou and Xing (2004), Ferguson and Shockley (2003), Dichev (1998)), the regressions will be estimated using the Fama-MacBeth (1973) approach. The basic idea behind the Fama and MacBeth (1973) approach is that first cross-sectional regressions are run at each time period to obtain the estimates of coefficients of interest. Secondly, the time series of $\hat{b}$ coefficients are used to get final estimates of the coefficients. The time series standard deviation of $\widehat{b_t}$ is used to estimate the standard error of $\hat{b}$. This method accounts for time variation in coefficients and produces standard errors corrected

[40] We also run regressions including market beta as an explanatory variable. The results regarding the influence of Z-Score and DtD on returns remain the same.

for cross-sectional correlation (Skoulakis (2008), Cochrane (2005)). In line with other researchers (Chava and Purnanandam (2010), Vassalou and Xing (2004)), robust t-statistics will be computed using Newey-West (1987) heteroskedasticity and autocorrelation adjusted standard errors with three lags, which proved to produce reliable t-statistics (Skoulakis (2008)). To ensure the validity of our results panel Least Squares (LS) regressions will be also conducted as a robustness check.

While there is contradicting evidence if distressed factors are priced in realized returns, we do not examine this. We want to determine the relationship between returns and distress measure as well as assess if it is in line with a traditionally postulated risk-return relationship. A mere indication that the traditional risk-return relationship does not hold justifies our intention to extend the analysis to the CoE obtained using different methods (CAPM CoE and ICoE) as *distress anomaly* might also be present in CoE calculated from realized returns.

4.5. Quantifying the Difference between ICoE and CAPM based CoE

Based on the existing research, our hypothesis is that ICoE might better capture distress risk than CAPM CoE, where market betas were obtained from realized returns. As it was pointed out in previous sections, since market prices might not be efficient or analysts' forecasts might not be fully representative of market expectations, we define ICoE as an IRR implied by current market prices, analysts' consensus earnings forecasts and accounting information. Defined in this way ICoE is still expected to better capture risks due to its forward looking components. Thus, we attempt to quantify the difference between ICoE and CAPM CoE for different levels of financial distress risk.

To capture the different levels of distress in a way, which could be easily understood and applied in practice, we generated three dummies for the Z-Score according to the original Altman (1968) cut-offs indicating if a company is bankrupt or not. *Z1* is equal to 1 if a company has a Z-Score higher than 2.99, *Z2* is equal to 1 if a company has a Z-Score between 2.99 and 1.81, *Z3* is equal to 1 if a company has a Z-Score lower than 1.81. In the same manner we generated three dummies for DtD according to the different levels of default risk. There is no formal cut-off as in the case of Z-Score, so we determined the cut-offs corresponding to percentiles of Z-Score. Consequently, *DtD1* is 1 if a company has DtD measure of more than 4.51, *DtD2* is 1 if DtD is between 4.51 and 2.97, *DtD3* is 1 if DtD is lower than 2.97. The following regressions will be run to quantify the difference:

$$ICoE_{it} - CoE_{it}^{CAPM} = b_1 Z1_{it-4} + b_2 Z2_{it-4} + b_3 Z3_{it-4} + \varepsilon_{it} \qquad (13)$$

$$ICoE_{it} - CoE_{it}^{CAPM} = b_1 DtD1_{it-1} + b_2 DtD2_{it-1} + b_3 DtD3_{it-1} + \varepsilon_{it} \quad (14)$$

$where$:

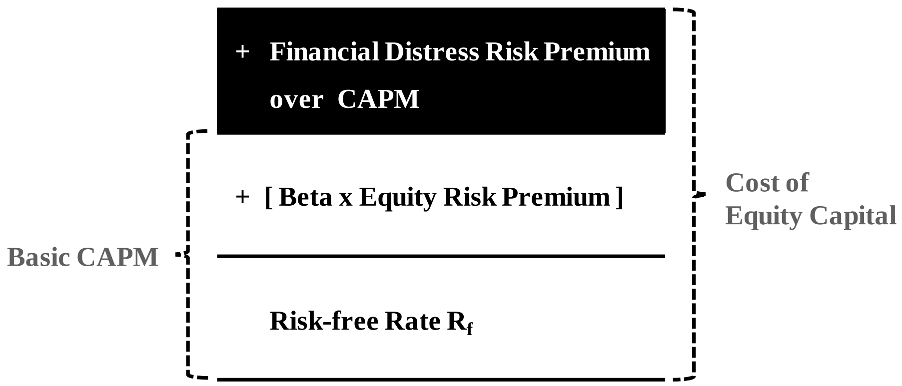
$ICoE_{it} - CoE_{it}^{CAPM}$ $is\ the\ difference\ between\ lCoE\ and\ CoE\ obtained\ from\ CAPM$

The constant term is not reported in regressions (13) and (14) to point out that we are aware of the "dummy variable trap". In this part we will run Fama-MacBeth (1973) regressions and panel LS regressions will be conducted for robustness check purposes.

If we find that there is a difference between ICoE and CAPM CoE for the most distressed companies, the practical implication is to use a premium over CAPM (Duff & Phelps (2012)) for firms with high risk of financial distress as portrayed in Graph 6.

Graph 6: Financial Distress Risk Premium over CAPM

In line with Duff & Phelps (2012) this graph displays the components of CAPM as it is used in its basic specification. It illustrates the premium over CAPM which could be added on the basic CAPM CoE to account for the high financial distress risk of a firm.



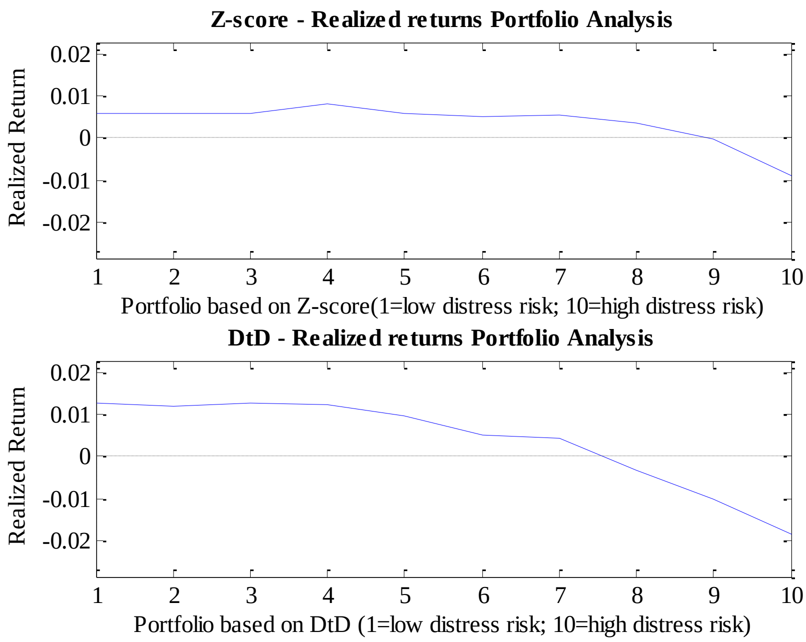
5. Results

5.1. Relationship between Realized Returns and Financial Distress Risk

Portfolio analysis. The monthly portfolio formation based on the distress measures Z-Score and DtD reveals that the monthly stock returns of companies falling into the most distressed portfolio is on average negative: -0.89% sorted according to Z-Score and -1.85% sorted according to DtD (see Table 4). The difference in monthly returns between the least distressed and the most distressed decile is 1.48% for Z-Score and 3.12% for DtD (statistically significant at 10% and 1%, respectively).

Graph 7: Portfolio Analysis - Realized Returns

The graph plots the mean value of realized returns for each portfolio. The portfolios are deciles, formed each month according to the distress measures, and sorted from the least distressed to the most distressed. For the mean value of realized returns the mean realized return per portfolio is calculated at each point of time across all firms in the sample. Subsequently the time-series mean for each portfolio is calculated. Realized returns are displayed in absolute terms per month (e.g. 0.01 corresponds to 1%).



Graph 7 shows that the relationship of both distress measures to monthly stock returns is not monotonic, meaning that returns are much lower for the most distressed companies (portfolios 8-10). The line describing the relationship of realized return and a distress measure has a clear trend downwards and is steeper for portfolios below the “bankruptcy” threshold (i.e. Z-Score of less than 1.81) as defined by Altman (1968). The relationship in case of Z-Score is almost identical to the one observed by Dichev (1998). There seems to be less variation in returns for the safer portfolios (especially for portfolios 1 – 4, with a hump in returns for portfolio 4 in case of Z-Score and stable returns for DtD). This is reasonable because for safer companies also the probability of bankruptcy is close to 0, while it increases rapidly after portfolio 5, so more variability in returns is expected due to increasing default risk. Portfolios 5 – 7 fall in a “grey zone" as their Z-Score ranges 2.99 – 1.81 and it could be seen that these companies have slightly lower returns.

Table 4: Portfolio Analysis – Realized Returns

The table provides for each portfolio mean values across firms and over time. The portfolios are sorted monthly according to the distress measures (Z-Score and DtD). At each point in time the mean of the realized returns, size and BM are calculated. The mean over the time-series is displayed in this table for each portfolio. Realized returns are in % per month. With t-statistics of 1.8 for Z-Score and 4.6 for DtD we can reject the Null-Hypothesis that the mean of realized returns of portfolio 1 minus the mean of realized returns of portfolio 10 is 0 at 10% and 1% significance level, respectively. Size is the market value of equity expressed in bn €. BM is book value of equity divided by the market value of equity.

Portfolio	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**t-test**
Z-Score	**9.41**	**4.86**	**3.72**	**3.10**	**2.67**	**2.32**	**2.01**	**1.71**	**1.38**	**0.53**	
Returns	0.58	0.59	0.60	0.80	0.59	0.51	0.53	0.34	-0.04	-0.89	1.8^{*}
Size	3.64	2.07	2.53	4.43	4.25	3.26	2.73	2.69	3.23	2.81	
BM	0.30	0.46	0.58	0.61	0.69	0.75	0.82	0.97	1.08	0.81	
DtD	**8.71**	**6.47**	**5.49**	**4.82**	**4.26**	**3.77**	**3.31**	**2.80**	**2.14**	**0.97**	
DtD Prob.	0.00%	0.00%	0.01%	0.04%	0.11%	0.27%	0.62%	1.48%	4.23%	21.83%	
Returns	1.27	1.18	1.27	1.23	0.97	0.52	0.43	-0.31	-1.02	-1.85	4.6^{***}
Size	5.05	6.16	4.66	3.51	2.62	2.41	2.67	2.25	1.87	2.10	
BM	0.42	0.52	0.59	0.63	0.71	0.75	0.80	0.87	0.99	0.96	

[* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

Although the size of companies with the highest financial distress risk seems to be lower than of companies with the lowest financial distress risk, size varies across different portfolios without a clear negative trend especially in the case of Z-Score. Consistently with the explanation of Fama and French (1992) that higher BM ratio might be indicating financial distress, we see that the BM ratio increases with the risk of financial distress (also observed by Vassalou and Xing (2004)). However, this relationship is not entirely monotonic as the BM ratio decreases for the most distressed portfolio 10 compared to portfolios 7-9 in case of Z-Score and to portfolio 9 in case of DtD. This finding was also presented in the study of Dichev (1998) on U.S. firms. The fact that BM is lower for the most distressed companies makes sense as substantial financial problems are expected to be reflected in low or even negative book value of equity.

Regression results. The regression results confirm the evidence from the portfolio analysis that more distressed companies deliver lower returns, which contradicts the fundamental risk – expected return relationship. The economic interpretation of the regressions is the same for both distress measures: the estimated coefficient on both Z-Score and DtD is positive and significant at 1% level meaning that realized returns are lower with deteriorating financial health of a company. The magnitude of the coefficient and the significance level remain robust also for the step-wise inclusion of size and BM. The coefficient on financial distress measures as well as t-statistics even slightly increase when BM is included (increase in the coefficient and t-statistics when size is included is observed only in the case of DtD). This is line with the findings of Dichev (1998) and might indicate that the common variation between Z-Score and BM is not much related to realized returns.

Table 5: Regression - Realized Returns on Financial Distress Measures

The results below show the effect of independent variables – financial distress risk measures Z-Score and DtD (with a lag of 4 month for Z-Score and 1 month for DtD), size and BM - on realized monthly returns. The base regression (1) consists only of the distress measure as independent variable. Control variables Size and BM are step-wise included in regressions (2) and (3). Size is the market value of equity, BM is book value of equity divided by market value of equity. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score			**Panel B: DtD**		
	(1) Realized returns	(2) Realized returns	(3) Realized returns	(1) Realized returns	(2) Realized returns	(3) Realized returns
Distress Measure	0.00114***	0.00110***	0.00160***	0.00407***	0.00434***	0.00473***
	(2.88)	(2.77)	(4.08)	(5.23)	(5.63)	(5.89)
Size		-0.00206***	-0.000986*		-0.00297***	-0.00180***
		(-3.97)	(-1.95)		(-6.42)	(-3.97)
BM			0.00461***			0.00531***
			(8.14)			(9.89)
Constant	-0.000128	0.0264**	0.00594	-0.0119	0.0254**	0.00280
	(-0.02)	(2.32)	(0.53)	(-1.44)	(2.25)	(0.23)
N	58575	58575	58575	60614	60400	58515
R^2	0.011	0.022	0.030	0.028	0.040	0.048

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

In line with previous studies, we find that size has a significant negative impact on returns (Fama and French (1992), Banz (1981)) and the BM ratio has a significant positive effect on returns (Dichev (1998), Fama and French (1992), Rosenberg et al (1985)). The BM effect seems to be slightly stronger in terms of significance compared to the size influence in case of Z-Score. Dichev (1998) and Fama and French (1992) noted that the size effect diminished or even vanished after 1980 in USA, which might be to some extent the case in Europe as well. As an additional robustness check, including book leverage and past returns did not change the results (see Appendix III.1). Thus, the influence of financial distress risk indicators seems to be significant above and beyond other determinants of returns. Results also remain robust when controlling for country (see Appendix III.2) or using different regression estimation technique, Panel LS regressions[41].

However, the results seem to be sensitive to the time period, which is assumed to be enough for the market to incorporate the financial distress information in pricing decisions. When 6 months is assumed to be needed to incorporate the accounting information, size and BM impact remain significant, but the estimate of the Z-Score coefficient is significant at 1% level in only 2 out of 4 regression specifications, the DtD loses significance in all regressions if a longer lag is used (see

[41] Since it is recommended to cross-check the results of two similar regression estimation techniques (Skoulakis (2008)), to prove the validity of our results we conducted all regressions also using Panel LS regressions. While the magnitude of coefficient estimates and t-statistics slightly vary, the qualitative interpretations remain the same. In general, all robustness check results not provided in Appendix are available upon request.

Appendix III.4.). The results for the subsample of 294 companies are also not so strong: the positive relationship is significant at 1% only in the case of DtD.

Discussion. Based on univariate and multivariate analysis we fail to reject the *Hypothesis 1* of our research, that the relationship between financial distress risk and realized returns is negative and non-monotonic, which seems to contradict the fundamental risk-return trade-off in finance theory. In line with Avramov et al (2009), Campbell et al (2008), Garlappi et al (2008), Dichev (1998), who examine U.S. data, we find this anomalous relationship to be present also in Europe. Qualitatively the result is the same for both distress measures even though the magnitude of their influence on returns is slightly different, which is to some extent expected because Z-Score and DtD convey considerable independent information as indicated by their correlation of 45%. While our finding is also robust to the inclusion of additional explanatory variables, the relationship almost loses its significance if a longer time period is allowed between the release of financial distress related information and the estimation of returns. This indicates that the anomalously negative relationship in returns might not persist over longer time periods.

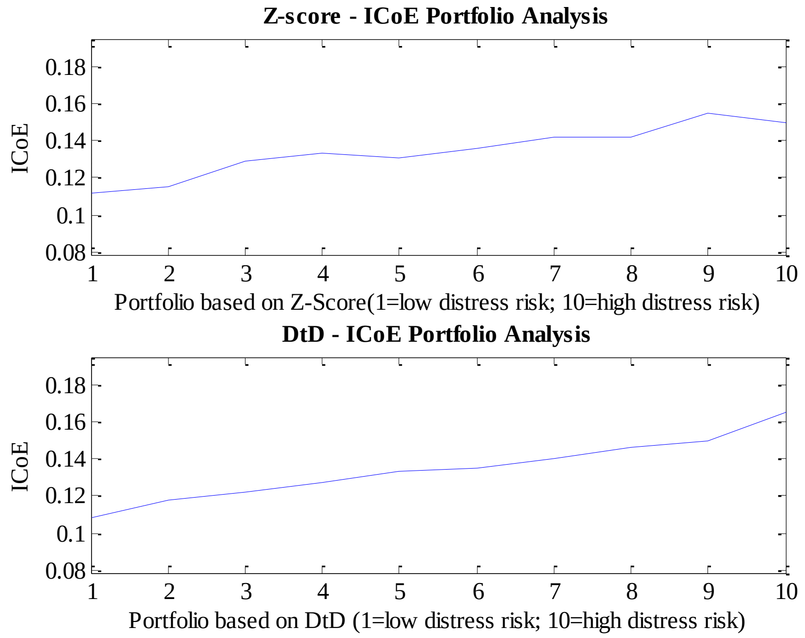
If financial distress risk is systematic, then the relationship to returns should be on average positive. If financial distress risk is not systematic, then the return differential should not be significant. The negative relationship, thus, seems puzzling. As advocated by Garlappi et al (2008) and von Kalckreuth (2005), financial distress might imply lower systematic risk due to high shareholder advantage and possible gains in case of bankruptcy. Dichev (1998) observing the same negative relationship states that due to the presence of this negative relationship financial distress risk is not likely to be a systematic risk priced into returns. We believe that due to evidence that default risk might contain systematic components (George and Hwang (2010), Almeida and Philippon (2007), Vassalou and Xing (2004), Denis and Denis (1995), Lang and Stulz (1992)), higher financial distress firms might be simply mispriced because investors fail to incorporate the distress related information in their valuation or are not aware of financial distress, but underestimate its negative costs. This interpretation hinges on the very important assumption that financial distress risk is at least partly systematic. In any case, the observed anomalous relationship confirms our concern that this might have a negative impact on CoE obtained from realized returns. We continue our analysis with investigating the relationship between financial distress risk and an alternative proxy for expected returns – the *ex ante* ICoE.

5.2. Relationship between ICoE and Financial Distress Risk

Portfolio analysis. First of all, using the methodology described in Section 4.2., the implied cost of equity capital (ICoE) is estimated (see Appendix II for summary statistics). In this section we compare the mean of the ICoE across the portfolios formed according to distress measures. The evidence in Graph 8 shows that in contrast to findings with realized monthly returns, the alternative proxy of expected returns ICoE is higher for companies with higher risk of financial distress and vice versa, which is in line with findings of Chava and Purnanandam (2010). This holds for both distress measures, the market-based DtD and the accounting-based Z-Score.

Graph 8: Portfolio Analysis – ICoE

The graph plots the mean value of ICoE for each portfolio. The portfolios are deciles, formed each month according to the distress measures, and sorted from the least distressed to the most distressed. For the mean value of ICoE the mean per portfolio is calculated at each point of time across all firms in the sample. Subsequently the time-series mean for each portfolio is calculated. The ICoE is expressed in absolute value per annum (e.g. 0.1 corresponds to 10% p.a.).



The ICoE differential between the riskiest and the safest portfolio is 3.76% for the Z-Score and 5.61% for the DtD measure, both statistically significant at 1% level (see Table 6). Even though the evidence for the most distressed 10th portfolio is slightly different comparing Z-score and DtD, the upwards sloping trend in ICoE from portfolio 1 to 10 seems to be very strong. This leads to the interpretation that investors in firms with higher risk of financial distress require *ex ante* a higher return than for less risky firms.

Table 6: Portfolio Analysis – ICoE

The table provides for each portfolio mean values across firms and over time. The portfolios are sorted monthly according to the distress measures (Z-Score and DtD). At each point in time the mean of the ICoE is calculated. The mean over the time-series is displayed in this table for each portfolio. ICoE is displayed in % p.a. With t-statistic of -12.5 for Z-Score and -17.6 for DtD we can at 1% significance level reject the Null-Hypothesis that ICoE differential between the most and the least distressed portfolios is 0.

Portfolio	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**t-test**
Z-Score	**9.41**	**4.86**	**3.72**	**3.10**	**2.67**	**2.32**	**2.01**	**1.71**	**1.38**	**0.53**	
ICoE	11.16	11.47	12.86	13.35	13.07	13.54	14.16	14.17	15.44	14.92	-12.5***
DtD	**8.71**	**6.47**	**5.49**	**4.82**	**4.26**	**3.77**	**3.31**	**2.80**	**2.14**	**0.97**	
DtD Prob.	0.00%	0.00%	0.01%	0.04%	0.11%	0.27%	0.62%	1.48%	4.23%	21.83%	
ICoE	10.85	11.80	12.19	12.72	13.30	13.49	13.97	14.64	14.99	16.46	-17.6***

[* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

Regression analysis. The regression results confirm the main conclusion of the portfolio analysis that higher distressed companies seem to be expected to deliver higher returns as measured by ICoE. This is strongly contradicting the results obtained with realized returns. The impact on ICoE of both financial distress measures is significant at 1% level. Consistently with the findings for realized returns, the impact on ICoE is more pronounced when the DtD indicator is used.

Table 7: Regression - ICoE on Financial Distress Measures

The results below show the effect of independent variables – financial distress risk measures Z-Score and DtD (with a lag of 4 month for Z-Score and 1 month for DtD), size and BM - on ICoE. The base regression (1) consists only of the distress measure as independent variable. Control variables Size and BM are step-wise included in regressions (2) and (3) as for the previous regression in Table 4. Size is the market value of equity, BM is book value of equity divided by the market value of equity. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score			**Panel B: DtD**		
	(1) ICoE	(2) ICoE	(3) ICoE	(1) ICoE	(2) ICoE	(3) ICoE
Distress Measure	-0.00454***	-0.00466***	-0.00449***	-0.00730***	-0.00686***	-0.00660***
	(-10.85)	(-11.28)	(-11.16)	(-12.17)	(-11.99)	(-11.32)
Size		-0.00564***	-0.00571***		-0.00429***	-0.00423***
		(-11.56)	(-11.71)		(-9.83)	(-9.38)
BM			0.00208			0.00229*
			(1.45)			(1.77)
Constant	0.149***	0.223***	0.222***	0.164***	0.218***	0.214***
	(42.68)	(25.18)	(24.51)	(43.14)	(27.42)	(25.62)
N	58559	58559	58559	60592	60381	58499
R^2	0.020	0.034	0.040	0.030	0.039	0.045

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

The impact of the financial distress measure remains robust for the step-wise inclusion of size and BM variables. Consistently with the findings of Lee et al (2009), the impact of size is negative and highly significant at 1% level meaning that bigger companies as measured by market capitalization are expected to deliver lower returns. Differently from realized returns, the significance of BM on ICoE diminished. BM remains significant only in the case of DtD. Since the evidence regarding BM is different using both distress measures, it is hard to conclude about the significance of BM importance for ICoE. The evidence on this matter in the existing literature is also mixed. Lee et al (2009) and Gebhardt et al (2001) find that BM is important determinant of ICoE, but they did not control for financial distress in their regressions. Meanwhile, Chava and Purnanandam (2010) controlling for financial distress with a measure similar to our DtD find that the effect of BM is not significant. The inclusion of leverage or country variable did not change the results (see Appendix IV and IV.2, respectively). Results are also robust for a longer time lag between the estimation of financial distress measure and ICoE (see Appendix IV.4.) as well as for Panel LS regressions instead of Fama-MacBeth (1973) approach. Compared to realized returns, lower sensitivity to the time lag of ICoE could be due to the fact that analysts' earnings forecasts are less volatile and might be to some extent sluggish as each analyst does not publish new estimates each month, but rather a few times per year. Thus, the consensus forecast is influenced by new forecasts coming every month, but at the same time they still contain older, not yet updated forecasts. The results described in this section remain very similar also for the sub-sample of 294 firms, which indicates the reliability of our ICoE estimates.

Discussion. With a clear positive trend between financial distress risk and expected rate of return as measured by ICoE and highly significant coefficients in regressions, we fail to reject our *Hypothesis 2* that financial distress risk and ICoE are positively related. This finding is in line with Chava and Purnanandam (2010)) who show that the relationship is negative between realized returns and distress measures, but positive between ICoE and market-based distress measures. It seems that *ex ante* investors account for financial distress risk in their investment decisions and require/expect a higher rate of return. This might further imply that a change in distress risk of a firm would therefore (all other parameters including the expected earnings kept constant) lead to a lower stock price, since investors would attribute a higher CoE to the firm. Given these findings we believe that ICoE might better capture expectations about financial distress risk than realized returns.

While this finding is robust to inclusion of additional variables and changing the time period between matching returns with financial distress risk measures, it might be biased due to assumptions we made in a valuation model or especially because of systematic biases in analysts' consensus earnings forecasts. The main concern in the similar research is that analysts' forecasts tend to be overoptimistic (Pratt and Grabowski (2008), Easton and Sommers (2007)), which means that our ICoE is overestimated. Additional overestimation effect might come from the fact that all negative EPSFY2 forecasts were replaced with slightly positive values to reduce estimation errors. While we recognize that our results might be erroneous, the expected return differential of 3.76% in case of Z-Score and 5.61% in case of DtD seems too sizeable to be purely driven by potential biases[42]. Also the positive upwards sloping trend is almost monotonic with both financial distress measures suggesting that even ICoE is overestimated, the upward trend should still remain.

We understand that ICoE could be treated as cost of equity only if market prices are efficient and analysts' earnings forecasts are representative of market expectations, which might not be the case (Easton and Sommers (2007)). In general, ICoE could be defined as IRR implied by current prices on the market, available accounting information and analysts' earnings forecasts, and therefore represents a good alternative to compare with CAPM CoE with respect to financial distress risk.

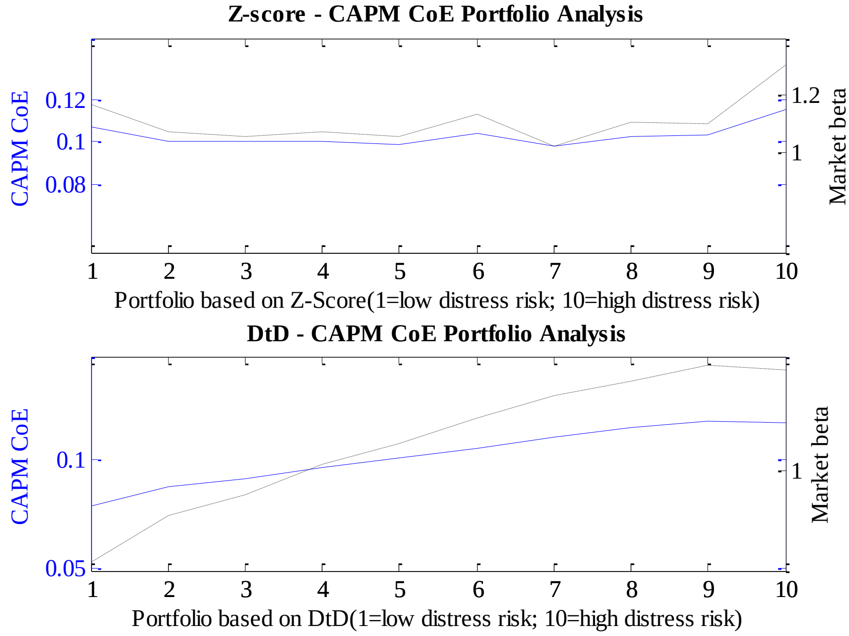
5.3. Relationship between CAPM CoE and Financial Distress Risk

Portfolio analysis. CAPM CoE is estimated using the methodology described in Section 4.3. (see Appendix II for summary statistics). Building on the results presented in section 5.1 and section 0 regarding the sensitivity of alternative proxies of expected returns (realized returns and ICoE) to financial distress risk, we intend to provide practical implications for corporate valuation. In particular, it is of interest how the market betas of stocks obtained from realized returns and the consequent CAPM CoE are related to financial distress and if the negative risk-return relationship found for realized returns might influence the cost of equity. Comparing the market betas across firms with different financial distress risk (see Graph 9), our analysis indicates that betas might be higher for companies with high financial risk than for companies with low financial risk (in line with findings of Campbell et al (2008) and Avramov et al (2009)).

[42] Easton and Sommers (2007) quantify the bias in ICoE due to analysts' over-optimism to be around 2.84%.

Graph 9: Portfolio Analysis - CAPM CoE

On the left hand scale (solid blue line), the graph plots the mean value of CAPM CoE for each portfolio. The portfolios are deciles, formed each month according to the distress measures, and sorted from the least distressed to the most distressed. The mean value of CoE per portfolio is calculated at each point of time across all firms in the sample. Subsequently the time-series mean for each portfolio is calculated. CAPM CoE are displayed in absolute values per annum (i.e. 0.1 corresponds to 10% p.a.). On the right hand scale (dashed black line), the graph contains the mean of firm specific market betas for each portfolio.



The patterns of market beta and consequent CAPM CoE are different across the portfolios formed using Z-Score and DtD. The portfolio analysis according to Z-Score allows us neither to conclude that on average CAPM CoE or beta increases with financial distress nor vice versa although the most distressed companies in portfolio 10 are clearly regarded as riskier. The DtD reveals a monotonic positive relationship between CAPM CoE, beta and financial distress risk, which shows that the market beta and, hence, the CAPM CoE account to a certain extent for the risk of financial distress. However, it is not clear if the observed compensation is sufficient for financial distress risk. We emphasize in particular on the relationship of market beta and distress risk measure, since the CAPM CoE might be further influenced by country specific risk (risk free-rate and ERP).

Table 8: Portfolio Analysis – CAPM CoE

The table provides for each portfolio mean values of CAPM CoE and market betas across firms and over time. The portfolios are sorted monthly according to the distress measures (Z-Score and DtD). At each point in time the mean of the firm specific CAPM CoE or market beta is calculated. The mean over the time-series is displayed in this table for each portfolio. CAPM CoE is displayed in % p.a. High t-statistics indicate that the differential between CAPM CoE and market betas for the most and least distressed portfolios is statistically significant from 0 at 1% level.

Portfolio	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**t-test**
Z-Score	**9.41**	**4.86**	**3.72**	**3.10**	**2.67**	**2.32**	**2.01**	**1.71**	**1.38**	**0.53**	
CAPM CoE	10.70	10.03	10.06	10.00	9.90	10.37	9.81	10.28	10.29	11.53	-5.3^{***}
Beta	1.16	1.07	1.06	1.07	1.05	1.13	1.02	1.11	1.10	1.30	-6.0^{***}
DtD	**8.71**	**6.47**	**5.49**	**4.82**	**4.26**	**3.77**	**3.31**	**2.80**	**2.14**	**0.97**	
DtD Prob.	*0.00%*	*0.00%*	*0.01%*	*0.04%*	*0.11%*	*0.27%*	*0.62%*	*1.48%*	*4.23%*	*21.83%*	
CAPM CoE	7.85	8.76	9.16	9.69	10.13	10.58	11.08	11.49	11.83	11.72	-29.4^{***}
Beta	0.69	0.85	0.92	1.02	1.10	1.18	1.26	1.31	1.36	1.34	-28.6^{***}

[* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

Regression analysis. Regression analysis results are consistent with the evidence from portfolio analysis. In case of Z-score, none of explanatory variables seem to have a significant impact on CAPM CoE. In case of DtD, the result is totally different: all explanatory variables are significant. In particular, the DtD measure is negatively related to CAPM CoE meaning that cash flows of more distressed companies would be discounted with higher cost of equity. Size and BM seem to have an opposite effect compared with ICoE and realized returns, which is quite surprising. However, their effect seems to be small in magnitude. In general, since by construction CAPM is country dependent, the results might be driven a lot by a country level variables (see Appendix V.1). The results remain very similar if an additional leverage variable (see Appendix V.1) is included in regressions, if a different lag is allowed between the estimation of CAPM CoE and financial distress measures (see Appendix V.2) or if Panel LS regressions instead of Fama-MacBeth (1973) approach are used. Very similar results are also obtained in the subsample of 294 firms.

Table 9: Regression - CAPM CoE on Financial Distress Measures

The results below show the effect of independent variables – financial distress risk measures Z-Score and DtD (with a lag of 4 month for Z-Score and 1 month for DtD), size and BM - on CAPM CoE. The base regression (1) consists only of CAPM CoE as independent variable. Control variables Size and BM are step-wise included in regressions (2) and (3) as for the previous regressions. Size is the market value of equity; BM is book value of equity divided by the market value of equity. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score			**Panel B: DtD**		
	(1) CAPM CoE	(2) CAPM CoE	(3) CAPM CoE	(1) CAPM CoE	(2) CAPM CoE	(3) CAPM CoE
Distress Measure	-0.000349	-0.000246	-0.000297	-0.00572***	-0.00587***	-0.00609***
	(-1.06)	(-0.81)	(-1.16)	(-15.86)	(-16.38)	(-18.53)
Size		0.000431	0.000173		0.00160***	0.00103***
		(1.40)	(0.51)		(6.22)	(3.49)
BM			-0.000347			-0.00191***
			(-0.50)			(-3.65)
Constant	0.104***	0.0975***	0.101***	0.126***	0.105***	0.116***
	(54.46)	(18.25)	(17.57)	(49.58)	(21.16)	(20.32)
N	53775	52953	52953	54015	53949	52874
R^2	0.017	0.030	0.042	0.116	0.136	0.149

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

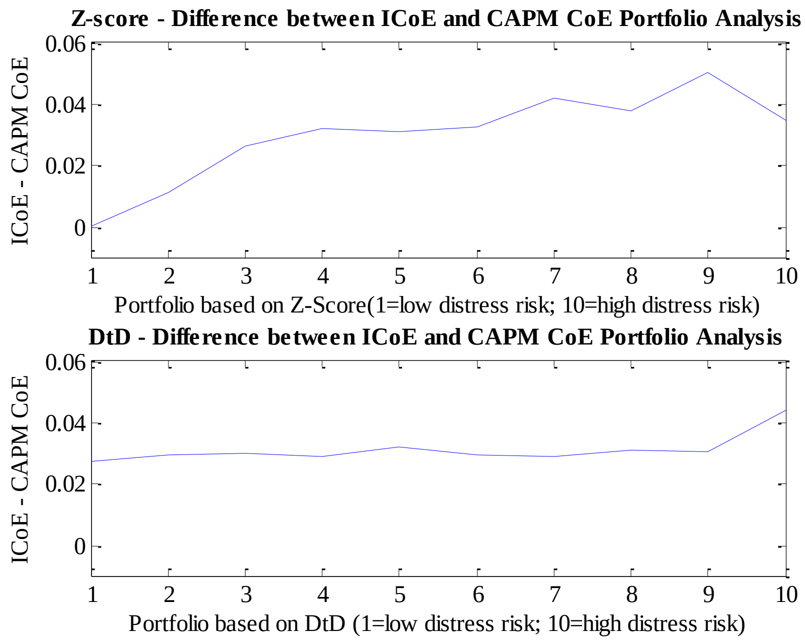
Discussion. Based on portfolio and regression analysis results we fail to reject our *Hypothesis 3*. In line with findings of Avramov et al (2009) and Campbell et al (2008) market betas are highest for the most distressed companies, but this difference is mostly pronounced in the case of DtD. Even the relationship between Z-Score and CAPM CoE is not significant in regressions, taking into account also portfolio analysis results, we conclude that the relationship between CAPM CoE and financial distress risk is positive meaning that riskier companies are discounted with higher cost of equity. However, this discount rate might not be enough to compensate for the inherent risks and potential costs of financial distress. In general, the results in this section might also be driven by country specific conditions.

5.4. Comparing CAPM based CoE with ICoE

Portfolio analysis. The results from the portfolio and regression analysis in previous sections signal that there is a difference between CAPM CoE and ICoE and their sensitivity to financial distress risk. In this part we aim to obtain an indication to what extent the spread between the ICoE and the CAPM CoE is influenced by the financial distress risk of a firm and how practitioners might be able to adjust their CoE estimation to better account for the higher risk of financially distressed companies. Graph 10 illustrates the average difference between ICoE and CAPM CoE sorted according to financial distress.

Graph 10: Portfolio Analysis - Difference ICoE and CAPM CoE

The graph plots the average difference between ICoE and CAPM CoE for each portfolio. The portfolios are deciles, formed each month according to the distress measures, and sorted from the least distressed to the most distressed. For the average difference the mean per portfolio is calculated at each point of time across all firms in the sample. Subsequently the time-series mean for each portfolio is calculated. The spread is expressed in absolute value per annum (e.g. 0.01 corresponds to 1% p.a.).



The results based on the Z-Score indicate that the spread is almost monotonically increasing with higher financial distress risk of a firm. The average spread for the least distressed companies is only 0.09% which is in line with our expectation that safer companies are easier to price and that different methods should give similar results. The evidence from the portfolios formed according to DtD suggests that the difference between ICoE and CAPM CoE is almost evenly distributed over the entire sample, with a slightly higher spread for the most risky portfolio (see Table 10).

Table 10: Portfolio Analysis - Difference ICoE and CAPM CoE

The table provides for each portfolio the average difference between ICoE and CAPM CoE across firms and over time. The portfolios are sorted monthly according to the distress measures (Z-Score and DtD). At each point in time spread is calculated and displayed in % p.a. The mean over the time-series is displayed in this table for each portfolio. High t-statistics indicate that the differential between the difference ICoE and CAPM CoE for the most and least distressed portfolios is statistically significant from 0 at 1% level.

Portfolio	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**t-test**
Z-Score	**9.41**	**4.86**	**3.72**	**3.10**	**2.67**	**2.32**	**2.01**	**1.71**	**1.38**	**0.53**	
ICoE - CAPM CoE	0.09	1.05	2.36	2.89	2.68	2.78	3.76	3.28	4.27	2.96	-8.6^{***}
DtD	**8.71**	**6.47**	**5.49**	**4.82**	**4.26**	**3.77**	**3.31**	**2.80**	**2.14**	**0.97**	
DtD Prob.	0.00%	0.00%	0.01%	0.04%	0.11%	0.27%	0.62%	1.48%	4.23%	21.83%	
ICoE - CAPM CoE	2.56	2.79	2.78	2.57	2.85	2.48	2.50	2.69	2.72	3.91	-3.7^{***}

[$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$]

The interpretation of the difference between ICoE and CAPM CoE is not very conclusive, since both distress measures do not draw an entirely coherent picture with regard to the spread between CAPM CoE and ICoE. However, similar trends in this analysis suggest that assuming that the ICoE captures the risk of financial distress better than the CAPM CoE, one could carefully derive a range of premium over CAPM CoE depending on the distress level.

However, it is important to notice that this premium over CAPM CoE is based on the strong assumption that the ICoE is not biased and represents a better proxy for expected returns. Further this spread could also be attributable to other factors, such as size, BM, or leverage.

Regression analysis. Table 11 reports the regression results regarding the difference between ICoE and CAPM CoE depending on the distress level. In this case the results with both estimation techniques – Fama-MacBeth (1973) and Panel LS regressions – are reported for the robustness check and interpretation purposes. The significance and magnitude of obtained results seem to be very similar for both estimation techniques and both distress measures Z-Score and DtD. The third dummy indicating the most distressed companies is in all cases highly significant, which is in line with portfolio results. The additional premium for safest companies ranges from 1.73% to 3.05%, for companies in the “grey zone” the range is 2.83% - 3.47% and for the most distressed companies the range is 3.49% - 4.19%. As expected the premium over CAPM is increasing with financial distress risk level. In this case it is especially useful to have evidence based on two financial distress risk measures because both of them contain independent information and, thus, the true result might be somewhere in between the outcomes dictated by Z-Score and DtD.

Table 11: Regression - Difference ICoE and CAPM CoE on Distress Measures

The results below show the effect of independent dummy variables, classifying the companies into three groups, from distressed over "grey zone" to safe, (with a lag of 4 month for Z-Score and 1 month for DtD) on the difference between ICoE and CAPM CoE. The regression (1) uses the Fama-MacBeth (1973) approach with a constant. The regression (2) is a LS regression without a constant. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score		**Panel B: DtD**	
	(1) Difference ICoE - CAPM CoE	(2) Difference ICoE - CAPM CoE	(1) Difference ICoE - CAPM CoE	(2) Difference ICoE - CAPM CoE
Safe Zone	-0.0174***	0.0178***	-0.00200	0.0222***
(Dummy Z1)	(-8.87)	(5.25)	(-0.98)	(7.65)
Grey Zone	0.00182	0.0339***	-0.00108	0.0283***
(Dummy Z2)	(0.76)	(10.11)	(-0.98)	(9.50)
Bankrupt Zone	0.00723***	0.0363***	0.00441***	0.0374***
(Dummy Z3)	(3.24)	(6.61)	(2.72)	(9.64)
Constant	0.0347***		0.0305***	
	(9.98)		(8.38)	
N	52998	52998	54047	54047
R^2	0.019		0.009	

[* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

The spread between ICoE and CAPM CoE could also be due to various other factors, e.g. size, BM, leverage or a specific industry a company operates in. The estimates of the coefficients in front of all financial distress risk related dummies remain robust to the inclusion of size and BM effects. The results are also similar for the subsample of 294 companies.

Discussion. Given portfolio and regression analysis results, we fail to reject our *Hypothesis 4* and conclude that there is a material difference between ICoE and CAPM CoE, which is higher for companies with higher financial distress risk. However, the identified „add-on“ is subject to many concerns and it should be treated only as a general indication that it might be important to account for financial distress risk in corporate valuation. Even though we chose the methodology the closest possible to practical implementation of CAPM, obtained CAPM CoE might be biased due to market beta estimation imprecisions or ERP choice and the direction of bias is hard to identify. Estimation of ICoE also involves many assumptions, but most importantly it might be biased due to overoptimistic analysts' earnings forecasts (Pratt and Grabowski (2008), Easton and Sommers (2007), Rajan and Servaes (1997)).

The quantification of the magnitude of overestimation is beyond the scope of this paper, but existing evidence from U.S. suggests that overestimation in ICoE due to overoptimistic analysts' forecasts tend to be around 2.84% (Easton and Sommers (2007)). While our sample period and countries are different, it seems that overestimation of around 3% is very likely. This is in line with the surprising result that the difference between ICoE and CAPM CoE even for safe companies ranges 1.73% - 3.05% as we would expect that both methods provide very similar results for safe companies. Thus, from our regressions estimates for additional financial distress risk premium we net out the suspected overestimation of 2.84%. This leaves with a recommended premium over the estimated cost of equity from CAPM of up to 0.2% for the healthiest companies with the Z-Score above 2.99 or as measured by DtD above 4.5. It might be the case that companies approaching the “grey zone” border of 2.99 already experience indirect financial distress costs, which should be accounted for. The premium over CAPM for companies in the “grey area”, i.e. with Z-Score 1.81 – 2.99 or with DtD 3 – 4.5, is up to 0.6%. Finally, the highest premium of up to 1.35% is suggested for the most distressed companies, i.e. with Z-Score below 1.81 or DtD below 3.

The use of this “add-on” is limited since it is derived from historical data over the relatively short time period of 11 years and in the future the trends might be different. It could also be driven by development only in particular countries, but using, e.g., only German data would limit our sample even further. In general, our overall results indicate that the ICoE might better capture default risk related expectations. This leads to implication for corporate valuation with respect to using CAPM. While CAPM seems to work quite well in estimating cost of equity for healthy companies, it should be adjusted upwards for higher financial distress risk companies.

6. Conclusions

Using portfolio and regression analysis, this study investigates the relationship between financial distress risk and expected returns for European companies in the period of 2000 - 2011 and draws corresponding implications for corporate valuation.

Graph 11: Conclusion

Hypothesis I	Hypothesis II	Hypothesis III	Hypothesis IV
The relationship between financial distress risk and realized stock returns is negative, but not purely monotonic.	*The relationship between financial distress risk and ICoE is positive.*	*The relationship between financial distress risk and CAPM CoE is weakly positive.*	*There is a difference between ICoE and CAPM CoE for companies with high financial distress risk.*
✓	✓	✓	✓

Consistently with our *Hypothesis 1*, we find that the relation between financial distress risk and realized stock returns is negative. This contradicts the fundamental risk-return relationship and signals that the *financial distress anomaly* might be also present among European companies. Our finding is in line with the previous studies in this area for Germany (Breig and Elsas (2009)) and for USA (Da and Gao (2010), George and Hwang (2010), Avramov et al (2009), Campbell et al (2008), Garlappi et al (2008), Griffin and Lemmon (2002) and Dichev (1998)). In line with Dichev (1998), we show that the negative relation is especially pronounced among the highest financial risk companies, i.e. the ones having a Z-Score below 1.81 or a Distance-to-Default indicator below 3. Compared to other studies, our result is especially robust because we use two different financial distress measures – Z-Score and Distance-to-Default, while other studies concentrated only on one indicator.

In accordance with *Hypothesis 2*, our second important finding is that the financial distress risk and expected return relationship reverses and becomes positive if expected returns are measured as forward looking ICoE rather than historical realized returns. This confirms the concerns of asset pricing researchers (Pastor and Stambaugh (1999), Elton (1999), Fama and French (1997)) that realized returns might be a poor proxy for expected returns. It is also in line with the result of Chava and Purnanandam (2010), which is the only paper investigating the relationship between ICoE and financial distress risk. This shows that on average the market expects and implicitly requires to be rewarded with higher returns for holding stocks with higher financial distress risk.

Further, we relate the contradicting findings from the default risk and expected return relationship to corporate valuation using the cost of equity obtained from CAPM. In line with

Avramov et al (2009) and Campbell et al (2008), we find that market betas are higher for more distressed companies. The relationship between CAPM CoE and financial distress measures is found to be weakly positive as expressed in *Hypothesis 3*. Since realized returns are shown to potentially possess anomalous trends with respect to financial distress risk, we conclude that the market betas obtained using these returns might not be high enough and, thus, CAPM CoE might be underestimated.

We demonstrate this by comparing CoE measures of two kinds – ICoE and CAPM CoE. As articulated in *Hypothesis 4*, the CAPM CoE seems to be on average significantly lower than the ICoE for higher financial distress risk companies, i.e. the ones with Z-Score below the “grey zone” limit of 2.99 or below 4.5 in case of Distance-to-Default measure. This difference might be driven due to many different reasons, but our finding is that at least part of this spread is driven by financial distress risk. In particular, we find that the premium over CAPM CoE is 0.6% - 1.35% depending on the distress level. If due to uncertain parameters a range of CoE for a DCF valuation is obtained, it would be advisable based on our findings to choose the CoE for a firm with high financial distress risk on the upper end of the range. Consequently, we confirm the concern of practitioners (e.g., Duff & Phelps) that financial distress risk should be accounted for in discount rates. While we acknowledge that the assumptions employed in our methodology could be challenged in different ways, it still provides an indication and illustrates general trends of returns with respect to financial distress risk.

6.1. Limitations

The results of this study have to be viewed taking into consideration a wide range of limitations.

Most importantly, our study hinges on the assumption that financial distress risk contains systematic components, which should be compensated for. However, there is no solid consensus that financial distress risk is really partly systematic. Hence, our identified financial distress risk and realized returns relationship suffers from the “chicken-egg” syndrome, i.e. what comes first - the fact that financial distress risk is not systematic or that realized returns contain anomalies and do not account for the systematic component of financial distress risk? If one believes that systematic risk is purely idiosyncratic, then our study loses relevance with respect to financial distress. However, the finding that the difference between ICoE and CAPM CoE is significantly different should stimulate further methods to improve the accuracy of a central variable – cost of equity - in corporate valuation.

An important restriction concerns the sample selection. In particular, the data availability for European firms is significantly worse compared to U.S., on which most of the related studies are based upon. Data constraints limit our sample to the time period 2000-2011, characterized by two highly pronounced economic crises, which might affect the results of our research. Thus, our results might be only valid for the time period employed in this study. Further, a certain sample selection bias may exist due to the requirement that at least three analysts cover a firm. Griffin and Lemmon (2002), Campbell et al (2008) claim that the distress anomaly is mostly pronounced among high financial distress risk stocks not followed or less followed by analysts. These stocks are more difficult to value for investors, since they are associated with larger information asymmetries. Hence, our restriction to only include companies which are followed by at least three analysts might have resulted in a bias towards larger and less distressed companies, so that the extent of the negative relationship between a financial distress risk measure and realized returns we find might be underestimated.

Despite our efforts to mitigate potential biases due to the selection of a distress measure by conducting exactly the same analysis using both the accounting-based Z-Score and the market-based DtD, the following weaknesses have to be acknowledged. Our sample differs from the original sample on which Altman (1968) estimated his Z-Score with respect to the country (the accounting standards in the U.S. and in Europe differ in various ways) and with respect to time (the original model has been estimated in the 50s and 60s of the last century).[43] The DtD has been obtained directly and without further adjustments from the research oriented RMI. Since it exists only for a few years, it does not have any track record in other academic studies or in a practical context, so that its reliability cannot be entirely proven. The robustness checks have also shown that the conclusion about the relationship between realized returns and financial distress risk measure from our research is sensitive to the assumptions made with regard to the lag between the observation of the distress measure and the expected returns (see section 4.4).

ICoE based on different valuation models or differently justified assumptions might lead to slightly different results. All models attempt to find a trade-off between modeling real life coherences and simplicity. Important assumption we make is that all firms arrive at a steady-state at the same time (e.g., after 15 years). However, it could be that this period is too long for mature companies and too short for growth companies (Lee et al (2009), Gebhardt et al (2001)). If this is the case, ICoE would be underestimated for growth firms and overestimated for mature companies. Independent from differing valuation models, the analysts' consensus forecasts (which all ICoE models are based upon) have to be treated with caution, since they could be biased in various ways (Pratt and Grabowski (2008), Easton and Sommers (2007), Claus and Thomas (2001), Dechow et al (1999), Rajan and Servaes (1997)). Even if the popularity of ICoE

[43] Although Altman confirms in his study in 2002 that his model still works good, it is questionable if the specification of his ratios have not changed significantly over time and have no impact on the accuracy of the model.

in research increases, studies investigating the validity of firm level estimates of ICoE claim that they might be subject to severe estimation errors and unreliable (Botosan and Plumlee (2005), Easton and Monahan (2005)). In addition, even if analysts' estimates are not biased upwards, we have replaced negative EPSFY2 forecasts with small positive values in order to avoid multiple ICoE values and a negative mean reversion, which could lead to overestimation of ICoE. Our approach to cross-check the results with a smaller sample, including only companies with positive EPS is not able to mitigate this bias, but allows confirming that the ICoE obtained for the entire sample is on average correct.

In order to bridge from the analysis of expected returns to implications for valuation purposes, we use the CAPM, which is widely used (Ballwieser and Wiese (2010), Cochrane (2005), Graham and Harvey (2001)), but is also subject to various criticism (e.g., Fama and French (1996)). Our CAPM CoE estimates could be biased because the market beta was estimated using the monthly realized returns of the last three years, which might be a too short period; ERP from Damodaran webpage was used because of its wide practical usage (Fernandez et al (2013)), but this choice might be subject to criticism.

The comparison of ICoE and CAPM CoE is valid only under assumption that ICoE is a better measure of cost of equity and expected returns. In general, ICoE could be termed as cost of equity only under conditions that market prices are efficient and the analysts' earnings forecasts are representative of market expectations (Easton and Sommers (2007)). Since this might not be the case, we define ICoE as an IRR implied by current market prices, analysts' consensus earnings forecasts and accounting information. Since some forward looking information is incorporated in the construction of ICoE it is still expected to be a better measure of CoE than CAPM CoE especially if realized returns are really suffering from anomalies.

The transferability of our results to non-listed companies or especially to non-manufacturing firms is limited, hence, the results of our analysis can initiate practitioners only to think more carefully about the influence of financial distress on the discount rates used in their discounted cash flow models.

6.2. Suggestions for Future Research

Regarding further research in the area of corporate valuation with respect to financial distress risk, it would be useful to try to introduce time variation into discount rates. However, higher accuracy might come at a cost of higher complexity, which might prevent it from practical application. Further, in a discounted residual income model to obtain ICoE different forecast horizons before the terminal period for different firms depending on the growth cycle or industry could be used (as currently the same horizon of 15 years was used for all companies). Finally, since there are alternative Z-Score specifications for service and non-traded companies, our analysis could be extended beyond manufacturing companies.

Our research shows that within the finance literature there are only few attempts to build a bridge between asset pricing and corporate valuation. The numerous tests of asset pricing models rarely lead to practically viable adjustments for corporate valuation models. The fact that the CAPM is still the most used model to calculate CoE, although more risk factors have been shown to be priced by the market, illustrates this gap well.

Many researchers have already focused on describing the relationship between financial distress risk and realized returns. However, the academic research on this relationship with alternative measures of expected returns, such as ICoE, is still in its early stages of development.[44] Chava and Purnanandam (2010) made a start using an ICoE calculation method adapted with little variation from other renowned researchers (Lee et al (2009), Pastor et al (2008), Gebhardt et al (2001)) to relate it to financial distress risk. For comparability of future research on ICoE further efforts should be put to standardize ICoE calculation models.

In order to strengthen the view that financial distress risk has a systematic component adopted in our paper, we suggest further researchers to examine the spillover effects of financial distress risk and differentiate between the idiosyncratic and systematic components of financial distress risk.

[44] Pratt and Grabowski (2008) mention information received from prices of stock options as a further alternative measure of expectations.

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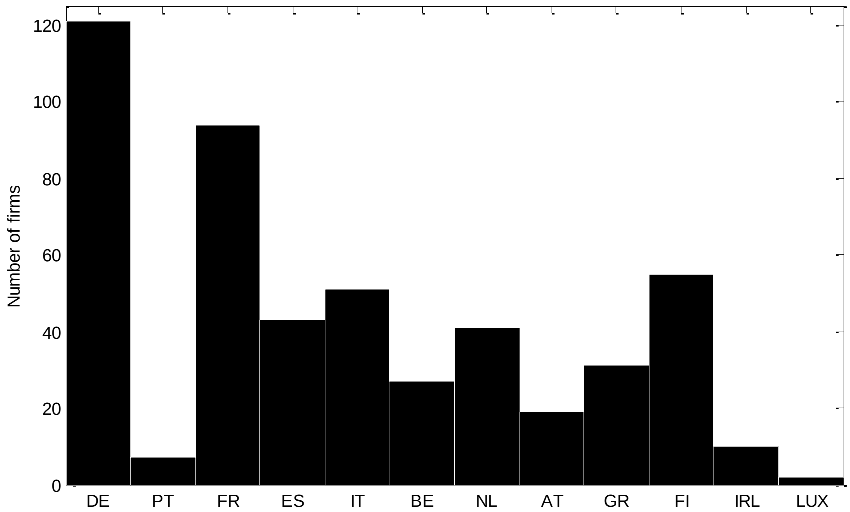
Appendix

I. Number of Firms per Country

The graph displays the regional composition of our sample. In total 501 firms are in the sample. The countries below have been chosen as they belong to the homogenous Eurozone.



II. Summary Statistics Output Variables

This table presents summary statistics for the main sample (Panel A) and for the subsample (Panel B). For the latter we excluded all firms with negative EPS consensus estimates for year 2. Besides the ICoE which is calculated from stock prices and analysts' consensus estimates, it includes summary statistics for the CoE calculated with CAPM. Both variables have been winsorized for the analysis, meaning that values below the 1st percentile are replaced by the 1st percentile and values above the 99th percentile are replaced by the 99th percentile. Please refer to Table 2 for summary statistics of the input variables.

Variables	N	Mean	StD	p1	p50	p99
			Panel A - Main Sample (501 firms)			
ICoE	60667	13.43%	10.29%	-30.01%	12.08%	56.27%
CAPM CoE	54991	10.30%	4.10%	3.81%	9.53%	25.83%
			Panel B - Subsample (294 firms)			
ICoE	34379	13.37%	6.09%	5.77%	11.89%	41.80%
CAPM CoE	31124	9.37%	3.38%	3.78%	8.77%	22.29%

III. Robustness Check for the Relationship between Realized Returns and Financial Distress Measures

III.1. Leverage ratio and past returns

The results below are displaying robustness checks for the regression results displayed in Table 5, of realized returns on financial distress measures, for the inclusion of leverage and past returns. The control variables Size and logarithm of BM are included in Panel A and B as well. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score	**Panel B: DtD**
	Realized Returns	Realized Returns
Distress Measure	0.00238***	0.00610***
	(6.25)	(6.29)
Size	-0.00119**	-0.00253***
	(-2.43)	(-5.92)
BM	0.00449***	0.00503***
	(7.90)	(9.85)
Leverage ratio	0.00430***	0.00711***
	(4.06)	(5.20)
Past Returns	-0.00878	-0.0218**
	(-0.84)	(-2.24)
Constant	0.00462	0.00394
	(0.42)	(0.33)
N	58158	58098
R^2	0.053	0.075

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

III.2. Country fixed effects

The results below are displaying robustness checks for the regression results displayed in Table 5, of realized returns on financial distress measures, for the inclusion of country fixed effects. The control variables Size, BM, Leverage and past returns are included stepwise. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score				**Panel B: DtD**			
	(1) Realized Returns	(2) Realized Returns	(3) Realized Returns	(4) Realized Returns	(1) Realized Returns	(2) Realized Returns	(3) Realized Returns	(4) Realized Returns
Distress Measure	0.001***	0.00109***	0.00159***	0.00235***	0.00408***	0.00437***	0.00476***	0.00612***
	(2.85)	(2.75)	(4.05)	(6.20)	(5.36)	(5.80)	(6.07)	(6.41)
Country	-0.00033	-0.000391	-0.000372	-0.000280	-0.00054**	-0.00065**	-0.00053**	-0.000446*
	(-1.23)	(-1.48)	(-1.42)	(-1.08)	(-2.03)	(-2.49)	(-2.21)	(-1.84)
Size		-0.002***	-0.001**	-0.001**		-0.003***	-0.002***	-0.003***
		(-4.01)	(-2.01)	(-2.47)		(-6.52)	(-4.08)	(-6.01)
BM			0.0046***	0.0044***			0.0053***	0.005***
			(8.04)	(7.73)			(9.78)	(9.67)
Le-verage				0.0043***				0.0072***
				(4.02)				(5.23)
Past Returns				-0.00843				-0.0214**
				(-0.83)				(-2.25)
Constant	0.00145	0.0286**	0.00828	0.00644	-0.00939	0.0290**	0.00602	0.00660
	(0.22)	(2.49)	(0.72)	(0.57)	(-1.14)	(2.56)	(0.50)	(0.56)
N	58575	58575	58575	58158	60614	60400	58515	58098
R^2	0.022	0.032	0.041	0.063	0.038	0.049	0.058	0.084

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

III.3. Increased time lag

The results below are displaying robustness checks for the regression results displayed in Table 5, of realized returns on financial distress measures, for the regression on further lagged distress measures. Z-Score in Panel A is used with a lag of 6 instead of 4 months and DtD in Panel B with a lag of 2 months instead of 1 month. The control variables (with the respective lag) Size, BM, Leverage and past returns will be included stepwise. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score				**Panel B: DtD**			
	(1) Realized Returns	(2) Realized Returns	(3) Realized Returns	(4) Realized Returns	(1) Realized Returns	(2) Realized Returns	(3) Realized Returns	(4) Realized Returns
Distress Measure (long lag)	0.000721	0.000681	0.00115***	0.00179***	0.000108	0.000354	0.000572	0.000551
	(1.65)	(1.56)	(2.67)	(4.30)	(0.15)	(0.50)	(0.83)	(0.64)
Size (long lag)		-0.002***	-0.00108**	-0.00121**		-0.0024***	-0.0014***	-0.0014***
		(-3.89)	(-2.13)	(-2.47)		(-4.96)	(-2.97)	(-3.15)
BM (long lag)			0.00418***	0.00414***			0.00398***	0.00360***
			(7.36)	(7.20)			(8.46)	(8.56)
Le-verage (long lag)				0.00353***				0.000893
				(3.72)				(0.60)
Mo-mentum				-0.00747				-0.0104
				(-0.70)				(-1.07)
Constant	0.00133	0.0276**	0.00915	0.00750	0.00226	0.0322***	0.0132	0.0133
	(0.20)	(2.40)	(0.81)	(0.67)	(0.28)	(2.83)	(1.12)	(1.16)
N	57573	57573	57573	57164	60119	60115	58520	58103
R^2	0.011	0.022	0.029	0.052	0.018	0.029	0.037	0.061

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

IV. Robustness Check for the Relationship between ICoE and Financial Distress Measures

IV.1. Leverage ratio and past returns

The results below are displaying robustness checks for the regression results displayed in Table 7, of ICoE on financial distress measures, for the inclusion of leverage and past returns. The control variables Size and logarithm of BM are included in Panel A and B as well. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score	**Panel B: DtD**
	ICoE	ICoE
Distress Measure	-0.00124**	-0.00414***
	(-2.42)	(-6.57)
Size	-0.00675***	-0.00581***
	(-13.64)	(-12.19)
BM	0.00236	0.00171
	(1.62)	(1.32)
Leverage ratio	0.0155***	0.0131***
	(8.25)	(7.96)
Past returns	0.221***	0.222***
	(23.43)	(25.27)
	58143	58083
Constant	0.057	0.061
	-0.00124**	-0.00414***
N	(-2.42)	(-6.57)
R^2		

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

IV.2. Country fixed effects

The results below are displaying robustness checks for the regression results displayed in Table 7, of ICoE on financial distress measures, for the inclusion of country fixed effects. The control variables Size, BM, Leverage and past returns are included stepwise. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score				**Panel B: DtD**			
	(1)	(2)	(3)	(4)	(1)	(1)	(1)	(1)
	ICoE	ICoE	ICoE	ICoE	ICoE	ICoE	ICoE	ICoE
Distress Measure	-0.0046***	-0.0048***	-0.0046***	-0.0012**	-0.0076***	-0.0072***	-0.007***	-0.0045***
	(-11.32)	(-11.71)	(-11.45)	(-2.39)	(-13.19)	(-13.01)	(-12.25)	(-7.15)
Country	0.0033***	0.0031***	0.0031***	0.003***	0.0035***	0.0033***	0.0033***	0.0031***
	(14.93)	(13.73)	(13.42)	(11.95)	(18.31)	(16.51)	(15.79)	(13.72)
Size		-0.0053***	-0.0054***	-0.006***		-0.0039***	-0.0038***	-0.0054***
		(-11.09)	(-11.02)	(-12.96)		(-8.93)	(-8.36)	(-11.12)
BM			0.00217	0.00248*			0.00236*	0.00177
			(1.55)	(1.73)			(1.88)	(1.39)
Leverage				0.016***				0.0132***
				(8.58)				(7.97)
Constant	0.133***	0.204***	0.203***	0.202***	0.148***	0.198***	0.194***	0.202***
	(32.82)	(22.28)	(21.12)	(20.02)	(36.99)	(24.17)	(22.07)	(21.69)
N	58559	58559	58559	58143	60592	60381	58499	58083
***R*²**	0.035	0.047	0.053	0.070	0.045	0.053	0.059	0.075

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

IV.3. Increased time lag

The results below are displaying robustness checks for the regression results displayed in Table 7, of ICoE returns on financial distress measures, for the regression further on lagged distress measures. Z-Score in Panel A is used with a lag of 6 instead of 4 months and DtD in Panel B with a lag of 2 months instead of 1 month. The control variables (with the respective lag) Size, BM, Leverage and past returns are included stepwise. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score				**Panel B: DtD**			
	(1)	(2)	(3)	(4)	(1)	(1)	(1)	(1)
	ICoE	ICoE	ICoE	ICoE	ICoE	ICoE	ICoE	ICoE
Distress Measure (long lag)	-0.004***	-0.0045***	-0.0044***	-0.00095*	-0.007***	-0.006***	-0.0063***	-0.0037***
	(-10.39)	(-10.77)	(-10.62)	(-1.90)	(-12.28)	(-12.09)	(-11.47)	(-6.28)
Size (long lag)		-0.0056***	-0.0057***	-0.0068***		-0.004***	-0.0042***	-0.0059***
		(-11.37)	(-11.51)	(-13.16)		(-9.82)	(-9.43)	(-12.34)
BM (long lag)			0.00208	0.00243			0.00234*	0.00178
			(1.42)	(1.61)			(1.81)	(1.36)
Leverage (long lag)				0.0161***				0.0136***
				(8.64)				(8.31)
Constant	0.148***	0.222***	0.221***	0.220***	0.163***	0.217***	0.213***	0.221***
	(42.33)	(24.74)	(24.11)	(22.90)	(42.03)	(27.20)	(25.65)	(25.25)
N	57557	57557	57557	57149	60101	60099	58504	58088
***R*²**	0.018	0.031	0.037	0.055	0.028	0.037	0.043	0.059

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

V. Robustness Check for the Relationship between CAPM CoE and Financial Distress Measures

V.1. Country fixed effects

The results below are displaying robustness checks for the regression results displayed in Table 9, of CAPM CoE on financial distress measures, for the inclusion of country fixed effects. The control variables Size, BM, Leverage and past returns are included stepwise. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score				**Panel B: DtD**			
	(1) CAPM CoE	(2) CAPM CoE	(3) CAPM CoE	(4) CAPM CoE	(1) CAPM CoE	(2) CAPM CoE	(3) CAPM CoE	(4) CAPM CoE
Distress Measure	-0.000216	-0.000127	-0.000193	-0.00057*	-0.000216	-0.000127	-0.000193	-0.000506*
	(-0.64)	(-0.40)	(-0.73)	(-1.82)	(-0.64)	(-0.40)	(-0.73)	(-1.82)
Country	-0.00111**	-0.00116**	-0.00119**	-0.0012**	-0.00111**	-0.00116**	-0.00119**	-0.00119**
	(-2.07)	(-2.21)	(-2.27)	(-2.25)	(-2.07)	(-2.21)	(-2.27)	(-2.25)
Size		0.000367	0.0000865	0.000161		0.000367	0.0000865	0.000161
		(1.18)	(0.24)	(0.48)		(1.18)	(0.24)	(0.48)
BM			-0.000488	-0.000213			-0.000488	-0.000213
			(-0.72)	(-0.30)			(-0.72)	(-0.30)
Le-verage				-0.00177				-0.00177
				(-1.62)				(-1.62)
Constant	0.109***	0.104***	0.108***	0.108***	0.109***	0.104***	0.108***	0.108***
	(34.19)	(16.30)	(13.88)	(13.51)	(34.19)	(16.30)	(13.88)	(13.51)
N	53775	52953	52953	52554	53775	52953	52953	52554
R^2	0.062	0.074	0.086	0.096	0.062	0.074	0.086	0.096

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

V.2. Increased time lag

The results below are displaying robustness checks for the regression results displayed in Table 9, of CAPM CoE returns on financial distress measures, for the regression on further lagged distress measures. Z-Score in Panel A is used with a lag of 6 instead of 4 months and DtD in Panel B with a lag of 2 months instead of 1 month. The control variables (with the respective lag) Size, BM, Leverage and past returns are included stepwise. Regressions are estimated using Fama-MacBeth (1973) procedure. The t-values in parentheses are calculated using Newey-West (1987) standard errors adjusted for heteroskedasticity and autocorrelation up to three lags.

	Panel A: Z-Score				**Panel B: DtD**			
	(1) CAPM CoE	(2) CAPM CoE	(3) CAPM CoE	(4) CAPM CoE	(1) CAPM CoE	(2) CAPM CoE	(3) CAPM CoE	(4) CAPM CoE
Distress Measure	-0.000346	-0.000246	-0.000303	-0.000482	-0.006***	-0.006***	-0.0062***	-0.008***
(long lag)	(-1.01)	(-0.78)	(-1.13)	(-1.58)	(-15.79)	(-16.43)	(-17.92)	(-17.09)
Size		0.000367	0.000106	0.000177		0.00162***	0.00104***	0.00219***
(long lag)		(1.22)	(0.32)	(0.57)		(6.28)	(3.53)	(9.11)
BM			-0.000395	-0.0000945			-0.0019***	-0.0016***
(long lag)			(-0.55)	(-0.13)			(-3.61)	(-3.49)
Le-Verage				-0.00121				-0.0105***
(long lag)				(-1.18)				(-8.91)
Constant	0.104***	0.0984***	0.102***	0.102***	0.126***	0.106***	0.116***	0.112***
	(52.86)	(18.46)	(17.78)	(17.66)	(49.25)	(20.99)	(20.19)	(21.60)
N	53240	52418	52418	52024	53791	53790	52912	52513
R^2	0.018	0.029	0.041	0.051	0.118	0.138	0.150	0.190

t statistics in parentheses [* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$]

VI. Definition and Sources of Input Variables

Variables	Data Source	Definition	Frequency
Market Data			
Realized Returns	Datastream (P)	Monthly returns from month-end stock prices	Monthly
Number of shares outstanding	Datastream (NOSH)	Total number of ordinary shares that represent the capital of the company	Monthly
Market Return (EUROSTOXX600)	Datastream (DJSTOXX(PI))	*Price Index* Weighted by market value and calculated using a representative list of shares.	Monthly
Risk-free rate (short-term)	ECB (EURIBOR 1M)	Interest rate at which Euro interbank deposits for 1 month are offered among prime banks within the Eurozone.	Monthly
Risk-free rate (long-term)	ECB	Long-term interest rate for convergence purposes, 10 years debt securities issued	Monthly
Distance-to-Default	National University of Singapore, Risk Management Institute, CRI database	DtD based on the Merton-Model (1974) and Moody's KMV according to Duan and Wang (2012)	Monthly
Accounting Data			
Working Capital	Worldscope (WC03151)	The difference between current assets and current liabilities	Yearly
Total Assets	Worldscope (WC02999)	The sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets	Yearly
Retained Earnings	Worldscope (WC03495)	The accumulated after tax earnings of the company which have not been distributed as dividends to shareholders	Yearly
EBIT	Worldscope (WC18191)	The earnings of a company before interest expense and income taxes. It is calculated by taking the pretax income and adding back interest expense on debt and subtracting interest capitalized.	Yearly
Market Capitalization	Worldscope (WC08001)	Market Price-Year End * Common Shares Outstanding For companies with more than one type of common/ordinary share, market capitalization represents the total market value of the company.	Yearly
Book Value of Liabilities (Total Liabilities)	Worldscope (WC03351)	All short and long term obligations expected to be satisfied by the company	Yearly
Net Sales / Revenues	Worldscope (WC01001)	Gross sales and other operating revenue less discounts, returns and allowances.	Yearly
Plowback ratio (1- Payout ratio)	Worldscope (WC09502)	*Payout ratio:* Dividends Per Share / Earnings Per Share * 100	Yearly
Book Value of Equity (Common Equity)	Worldscope (WC03501)	common shareholders' investment in a company (including retained earnings)	Yearly

Variables	Data Source	Definition	Frequency
Economic Data			
Nominal GDP growth (Real GDP growth – GDP deflator)	Worldbank	*Real GDP* Annual percentage growth rate of GDP at market prices based on constant local currency *GDP deflator* GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency.	Yearly
Equity Risk Premium	Damodaran	ERP is estimated based upon a simple 2-stage Dividend discount model and reflects the risk premium which would justify they current level of the index, given the dividend yield, expected growth in earnings and the level of the long term bond rate.	
Recession periods	OECD	GDP growth rate compared to previous quarter, seasonally adjusted	Quarterly
ICC			
EPS Last reported	I/B/E/S (F0EPS)	Reported annual EPS for the last fiscal year (FY0)	Monthly
EPS Year 1	I/B/E/S (F1EPS)	Mean earnings per share for FY1 (next fiscal year end to be reported)	Monthly
EPS Year 2	I/B/E/S (F2EPS)	Mean earnings per share for FY2 (2 years after fiscal year end to be reported)	Monthly
EPS LT growth	I/B/E/S (LTMN)	Mean long term growth estimate. The mean of all long term growth estimates, expressed as a percentage.	Monthly