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# Bankruptcy Risk Prediction and Pricing: Unravelling the Negative Distress Risk Premium

Cranfield School of Management

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**Supervisor**
**Dr. Vineet Agarwal**

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## ABSTRACT

In sharp contrast to the basic risk-return assumption of theoretical finance, the empirical evidence shows that distressed firms underperform non-distressed firms (e.g. Dichev, 1998; Agarwal and Taffler, 2008b). Existing literature argues that a shareholder advantage effect (Garlappi and Yan, 2011), limits of arbitrage (Shleifer and Vishny, 1997) or gambling retail investor (Kumar, 2009) could drive the underperformance. Herein, I test these potential explanations and explore the drivers of distress risk. In order to do so, I require a clean measure of distress risk. Measures of distress risk have usually been accounting-based, market-based or hybrids using both information sources. I provide the first comprehensive study that employs a variety of performance tests on different prediction models.

My tests are based on all UK non-financial firms listed in the Main market segment of the London Stock Exchange (LSE) between September 1985 and October 2010. It includes 22,217 observations with 2,428 unique firms of which 202 went bankrupt.

I find that hybrid models clearly outperform the accounting-based z-score (Taffler, 1983) and the market-based model of Bharath and Shumway (2008) (BS). Hybrid models forecast bankruptcies more accurately and they subsume the bankruptcy related information of z-score and BS. While there is little to distinguish between the hybrids in forecasting accuracy, tests of differential misclassification costs show that the highest economic value is delivered by the most parsimonious hybrid model of

Shumway (2001) (Shum). The forecasting accuracy between z-score and BS depends on the sample period while both carry complementary bankruptcy related information.

My study provides confirmatory evidence on the puzzling negative distress risk premium. Moreover, my tests show that the distress risk premium is independent of the distress risk proxy (Shum, z-score or BS). Remarkably, z-score –the weakest bankruptcy prediction model - subsumes the return related information of Shum and BS in cross-sectional tests suggesting that it might not be distress risk *per se* that is priced.

My results provide no evidence that the potential explanations in the existing literature are able to account for the distress puzzle. As such, I find no confirmation for the shareholder advantage effect. Although the characteristics of firms with high limits of arbitrage and gambling features are shared by distressed firms, tests provide no evidence for their pricing relevance or their impact on the distress risk premium.

This is the first study that deconstructs the distress measures into their component parts to unravel the distress risk premium and shows that the profitability components of Shum and z-score drive the premium. The composite measure without the information carried by profitability is insignificant in the pricing tests. In time-series regressions, I show that the pricing information carried by a profitability factor is able to reduce the distress risk premium. Portfolio analysis identifies low distress risk-high profitability firms as the key driver of the mispricing. The distress anomaly is not driven by distress risk but by profitability. Another major contribution is the use of the three approaches to assess distress risk. Together with the full range of major performance measures, I provide the first comprehensive test of the competing approaches. This study has important implications for the future research agenda on both, how we measure distress risk and the pricing of distress risk.

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# Table of Contents

# Table of Contents

# Table of Contents

## Table of Contents

# Table of Contents

# List of Tables

# List of Tables

# List of Figures

# CHAPTER 1: INTRODUCTION

## Introduction

One of the central tenets in theoretical finance is that higher systematic risk is rewarded with higher returns. If financial distress risk is systematic, then investors expect a positive premium for bearing distress risk.[1] Campbell, Hilscher and Szilagyi (2008) and Chava and Purnanandam (2010) note that distress risk should be captured by standard asset pricing models unless firm failures correlate with deteriorating investment opportunities (Merton, 1973), unmeasured components of wealth such as human capital (Fama and French, 1996) or debt securities (Ferguson and Shockley, 2003). Chan and Chen (1991) and Fama and French (1992) argue that some empirical violations of the risk-return relationship are explained by relative financial distress risk. Following this argument, distress risk would result in the positive return patterns related to size and value as argued by Fama and French (1992).[2]

There are few empirical studies that find a positive distress risk-return relation. While Vassalou and Xing (2004) find a positive distress risk premium using realised returns, Chava and Purnanandam (2010) find expected returns to be higher for distressed firms. On the other hand, in the majority of literature a negative relation between distress risk and realised stock returns is found (e.g. Dichev, 1998; Agarwal and Taffler, 2008b; Da and Gao, 2010). This is in sharp contradiction to the risk-reward assumption of theoretical finance, as well as rejecting the distress hypothesis proposed by Chan and Chen (1991) and Fama and French (1992).

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[1] Following Agarwal and Taffler (2008b), the terms financial distress and bankruptcy risk are used interchangeably throughout this thesis.

[2] Fama and French (1992) propose the argument for the first time while they confirm it in subsequent studies. Important contributions include the model in Fama and French (1993) as well as the often referred Fama and French Model in Fama and French (1996).

There are several potential explanations for the underperformance of distressed firms. Garlappi and Yan (2011) provide a risk-based explanation and argue that shareholders of highly distressed firms have an advantage as they can choose to strategically default at the cost of debt holders. Hence, equity risk decreases with high levels of distress risk: stocks of highly distressed firms are expected to earn low returns. An alternative explanation for the negative distress risk premium is that distressed stocks have characteristics that are associated with both limits of arbitrage and gambling retail investors (e.g. Coelho, Taffler and John, 2010). Limits of arbitrage hinder institutional investors' ability to correct mispriced stocks (Shleifer and Vishny, 1997) while the priority of gambling retail investors is not on profit maximisation (Han and Kumar, 2011). As such, distressed firms could be mispriced because sophisticated investors are unable to correct the mispricing or because their lottery features attract gamblers.

Exploring the pricing of distress risk requires models to proxy for the level of distress risk. The approaches to assess the risk that individual firms will go bankrupt differ in their information basis. Traditional models are predominantly based on either accounting information (e.g. Altman, 1968; Taffler, 1983) or market information (e.g. Vassalou and Xing, 2004). More recent literature provides hybrids using both data sources (e.g. Shumway, 2001).

While some of the models are argued to be superior due to their conceptual nature (e.g. Shumway, 2001), the empirical performance is what really matters. The empirical literature provides performance tests of the three approaches using the (i) receiver operating characteristics (ROC) curves (Hanley and McNeil, 1982; Sobehart and Keenan, 2001), (ii) information content tests (Hillegeist, Keating, Cram and Lundstedt, 2004), and (iii) test of differential misclassification costs (Stein, 2005; Blöchlinger and Leippold, 2006). However, existing literature does not provide clean evidence on the usefulness of competing approaches as (i) the studies fail to cover all three approaches in their tests (e.g. Vassalou and Xing, 2004; Reisz and Perlich, 2007), and (ii) none of the studies, except Agarwal and Taffler (2008a), use all three available tests to assess the empirical performance.

**Main Objectives of Thesis**

1. To identify the best bankruptcy prediction approach using the three different measures that test for forecasting accuracy, bankruptcy related information and economic value under differential misclassification costs.
2. To review existing evidence on the underperformance of distressed firms controlling for the common risk factors and to test whether the underperformance is dependent on the distress risk proxy.
3. To test empirically the potential explanations for the underperformance of distressed firms.
4. To explore the drivers of the distress risk premium.

I conduct the tests using all UK non-financial firms listed in the Main market segment of the London Stock Exchange (LSE) anytime between 1985 and 2010. The tests involve different methodologies. First, I use all three available bankruptcy prediction approaches, i.e. the accounting-based z-score model of Taffler (1983), the market-based model of Bharath and Shumway (2008) and three hybrid specifications (Shumway, 2001; Campbell et al., 2008; Christidis and Gregory, 2010). I test three dimensions of relative performance of the bankruptcy prediction models: forecasting accuracy using receiver operating characteristics curve, bankruptcy related information using information content tests, and the economic value of models under differential misclassification costs. Second, in the pricing analysis I use individual securities as well as different portfolio formation methods and employ cross-sectional regressions (Fama and MacBeth, 1973) and time-series regressions (Fama and French, 1996; Carhart, 1997).

**Main Findings**

1. Hybrid models clearly outperform the accounting-based z-score (Taffler, 1983) and the market-based model of Bharath and Shumway (2008) (BS). Hybrid models have a higher forecasting accuracy and they subsume the bankruptcy related information carried by z-score and BS. The forecasting accuracy between the hybrid models does not differ statistically. However, accounting for differential misclassification costs shows that Shum results in a higher economic value than the alternative hybrids. Results on the forecasting accuracy between z-score and BS are mixed but they both contain significant and complementary bankruptcy related information.
2. The stocks of distressed firms underperform those of non-distressed firms independent of whether distress is proxied by Shum, z-score or BS. These findings are robust to time-series regressions and cross-sectional regressions. However, the cross-sectional regressions also show that z-score subsumes the bankruptcy related pricing information carried by Shum and BS.
3. The potential explanations proposed in the literature cannot capture the negative distress risk premium. The predictions of Garlappi and Yan (2011) do not hold in the UK market. The characteristics and the areas under ROC curve of stocks

with limits of arbitrage and lottery features are similar to those of distressed firms. But surprisingly, they are not significant in subsequent stock returns and they have no impact on the negative distress risk premium.

4. Profitability drives the distress risk premium. Cross-sectional tests show that net income over total assets (component of Shum) and profit before tax over current liabilities (component of z-score) are the components that drive the significance of Shum and z-score respectively. Using time-series regressions, I show that the pricing information carried by a profitability factor is able to reduce the distress risk premium. The distress effect is driven by the high returns of profitable firms.

**Structure of Thesis**

The rest of the thesis is organised as follows: the next Chapter 2 reviews the literature on bankruptcy prediction models and the pricing of distress risk, Chapter 3 states the research questions and research propositions. Chapter 4 describes the data and methods applied in the empirical analysis. Chapter 5 tests the three bankruptcy prediction approaches using different performance tests. Chapter 6 tests for the distress risk premium employing the three approaches for bankruptcy prediction using time-series and cross-sectional regression tests. Chapter 7 tests whether the shareholder advantage theory, the limits of arbitrage, and the gambling retail investors account for the negative distress risk premium using time-series and cross-sectional regressions. Chapter 8 unravels the negative distress risk premium. Chapter 9 draws conclusions from the analysis, describes limitations, and indicates potential for future research.

# CHAPTER 2: LITERATURE REVIEW

## 2.1 Introduction

This thesis is anchored within the pricing of distress risk. As such, the literature review encompasses two major fields: distress risk modelling and asset pricing.

My literature review is organised as follows. First, I review the different approaches of bankruptcy prediction and highlight their main advantages and disadvantages. I also discuss studies that compare the different approaches. Then I review the literature on the pricing of distress risk while in the last part, I review literature on potential explanations for the return behaviour of distressed stocks.

## 2.2 Distress Risk Models

The approaches to bankruptcy prediction can be separated by the information basis they use. Traditional bankruptcy prediction models use accounting information (e.g. Altman, 1968). Alternatively, there are theoretically-sound contingent claims models that draw information from market data (e.g. Vassalou and Xing, 2004). More recent literature, however, argues that bankruptcy prediction is most powerful when the two information sources are combined (e.g. Shumway, 2001).

### 2.2.1 Accounting-Based Models

**Literature Review**

It is self-explanatory that annual accounts are one of the first sources when judging the financial health of a company. As such, there is a broad range of bankruptcy prediction models using accounting data. In fact, one can argue that financial analysis, and thus (informal) bankruptcy risk assessment, is as old as accounting data itself.[3] The more recent literature can be classified into simple accounting ratio-based prediction, multiple discriminant models and conditional probability models.

Simple accounting ratio-based prediction employs univariate analysis. Beaver (1966) analyses the predictive ability of individual accounting ratios in a bankruptcy context using a matched sample of 79 non-failed and 79 failed US firms listed between 1954 and 1962. By selecting 30 ratios and grouping them by their information content (i.e. cash flow, net income, leverage, working capital and turnover), he compares the change over time up to five years before failure. He finds that while the ratios of non-failed firms are fairly stable, those of failed firms had deteriorated approaching failure. Further, while all the chosen ratios predicted failure, the cash flow-to-total debt ratio was the best in discriminating between failures and non-failures. The finding of Beaver (1966) that accounting ratios are able to predict failures built the basis for future accounting ratio-based research.

Altman (1968) criticises the use of individual accounting ratios for their potential to give conflicting signals. He argues for a multi-ratio model to allow a more comprehensive assessment of potential failure. Using a matched sample of 33 non-failed and 33 failed US firms listed between 1946 and 1965, he applies multiple discriminant analysis to choose from a basket of 22 ratios and finds five ratios that distinguish best between non-failure and failure. The resulting z-score model

[3] For instance, several studies refer to Rosendal (1908), and Beaver, Correia and McNichols (2010) note that the financial statements have been used for more than 100 years to assess financial distress likelihood.

incorporates ratios representing working capital, retained earnings, profitability, market-to-book equity and sales.[4]

Conditional probabilities models were introduced by Ohlson (1980). He criticises the multiple discriminant analysis as it employs matched samples that involve arbitrary choice and lead to an oversampling of bankrupt firms. Using all available failed and non-failed firms from 1970 to 1976 with most of them listed on New York Stock Exchange (NYSE) and American Stock Exchange (AMSE), his sample does not require any matching procedure and thus, represents a more realistic failure rate. He suggests a logit model that, in contrast to the multiple discriminant analysis, returns a default probability. The variables included in the model are market capitalisation, leverage, profitability, and measures of current liquidity. However, while the model uses better sample features, it is still pooling the data and thus, does not account for time-variations in distress risk.

There have been a number of studies providing alternative accounting-based models by both refining existing models and applying different methodologies. However, the multiple discriminant analysis has dominated the failure prediction literature for several years. For instance, Deakin (1972) applies the discriminant analysis using the variables in Beaver (1966) while Blum (1974) develops the failing firms model and shows that a regular update of the model does not improve forecasting accuracy. Altman, Haldeman

[4] Strictly speaking, the z-score model of Altman (1968) is not a pure accounting-based bankruptcy prediction model as one of the five ratios contains market value of equity and thus, the model could be listed under hybrid models. However, I still classify z-score as an accounting-based model since its focus is primarily on accounting ratios. Also, at that time the intention of bankruptcy prediction research was not on researching the competing arguments of accounting-based and market-based models. In fact, market-based bankruptcy prediction models, and thus hybrid models, evolved much later.

and Narayanam (1977) provide the proprietary Zeta™ model and Taffler (1983) offers an alternative accounting-based z-score model specifically developed for the UK market. His z-score model includes four ratios representing profitability, working capital, financial risk, and liquidity with the corresponding coefficients being first published in Agarwal and Taffler (2007). A conditional probability model using a cumulative normal distribution is provided by Zmijewski (1984).[5]

**Advantages of Accounting-Based Models**

Altman (1968) underlines the value of accounting information and argues that financial ratios should not be regarded as too simplistic. Taffler (1983) describes the information in financial statements to be distinct and fundamental and highlights its value when considered in multi-ratio models.

Importantly, accounting information such as leverage or liquidity ultimately builds the decision basis for a bankruptcy filing. Legal decisions in relation to the bankruptcy event are based on accounting information and not on market data such as market volatility, for example.

Financial statements have structural advantages: they are audited (annual) accounts and thus, can be regarded as being a valid information source. The double entry bookkeeping introduces automatic checks and balances making window dressing harder

[5] Besides the main approaches described here, there are a number of alternatives. Balcan and Ooghe (2006) summarise them as survival analysis, machine-learning decision trees, expert systems and neural networks.

(e.g. realising sales early increases the receivables).[6] Legal requirements prescribe a frequent and timely publication of the information and thus, ensure the availability of financial information.

**Disadvantages of Accounting-Based Models**

Hillegeist, Keating, Cram and Lundstedt (2004) argue that accounting statements are prepared on a going-concern assumption and thus, by design limited in predicting bankruptcy. Agarwal and Taffler (2008a) point out some further structural disadvantages of financial statements in bankruptcy prediction (p. 1542): "(i) accounting statements present past performance of a firm and may or may not be informative in predicting the future, (ii) conservatism and historical cost accounting mean that the true asset values may be very different from the recorded book values, (iii) accounting numbers are subject to manipulation by management." Apart from that, accounting data is subject to different accounting policies e.g. complicating a comparison of accounting ratios of different companies.

Although listed firms are required to publish their accounts in a timely manner, it is also well-known that some firms (especially distressed firms) are prone to publish their accounts late or not at all (Keasey and Watson, 1988). This can lead to an imprecise or out-dated bankruptcy probability assessment, especially for the firms in the most critical position.

[6] Window dressing is "the deceptive practice of using accounting tricks to make a company's balance sheet and income statement appear better than they really are" (See: www.investorwords.com, accessed 5th February 2012). However, window dressing is substantially different to outright fraud (e.g. Enron, Worldcom).

Empirical literature also documents a change in accounting ratios over time. However, the static and time-independent approach of discriminant analysis is unable to account for it (Mensah, 1984). The change in accounting ratios is also neglected due to the pooling of sample firms (matched firms approach). Further, Begley, Ming and Watts (1996) show that updating the coefficients alone is not enough and the models have to be periodically re-developed (see as well Hillegeist et al., 2004; Agarwal and Taffler, 2007).

Besides the conceptual shortcomings, Hillegeist et al. (2004) criticise accounting-based models for not including a measure of asset volatility that captures the likelihood that the value of total assets will be lower than the value of liabilities.

### 2.2.2 Market-Based Models

**Literature Review**

An alternative approach for modelling bankruptcy risk draws from contingent claims. Since the contingent claims approach is based on market information, I refer to such models as market-based models. In implementation, market-based models follow the definition that a firm is bankrupt if the value of total assets is lower than the value of liabilities.

The set-up of market-based models is given by the option pricing approach of Black and Scholes (1973) and the derivative pricing model of Merton (1973) (BSM). Market-based models regard firm equity as a call option on the value of the firm's assets with a strike price that equals the face value of liabilities. The firm is bankrupt when the call option expires worthless. It follows that the probability of bankruptcy is the probability of a worthless option i.e. that the value of assets is less than the face value of liabilities at the end of the holding period. McDonald (2002) defines the probability using a standard normal cumulative distribution as

$$P = N\left(-\frac{\ln(V_A/X) + (\mu - \delta - 0.5\sigma_A^2)T}{\sigma_A\sqrt{T}}\right) \tag{1}$$

where P is the probability of default, $N(\cdot)$ is the cumulative normal density function, $V_A$ is the value of assets, X is the face value of debt (i.e. total liabilities), $\mu$ is the expected return, $\delta$ is the dividend rate, $\sigma_A$ the asset volatility, and T is time to maturity. It follows that the measurement of default probability requires three unobservable variables: $V_A$, $\mu$ and $\sigma_A$. Empirical studies implementing the option pricing framework differ in the way they infer the unobservable variables. Generally, $V_A$ and $\sigma_A$ are obtained by an iterative process that is initiated by setting $V_A$ equal to the sum of the market value of equity and total liabilities and $\sigma_A$ equal to the equity volatility.

There are a number of empirically studies that apply the BSM approach. Vassalou and Xing (2004) apply the BSM to the US data available on the database of The Center for Research in Security Prices (CRSP) that covers (among others) stocks listed on New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ) from 1971 to 1999. They define the face value of debt as the sum of debt with a maturity of one year or less plus half of the long-term debt and calculate the equity volatility over the prior twelve months using daily returns. The expected return is proxied by the risk-free rate and the model is not adjusted for expected dividends.

Hillegeist et al. (2004) use US stocks available on CRSP between 1980 and 2000 and infer the value of total assets by starting the iterative process with the proxy of market value of equity and total liabilities. Expected returns are estimated by taking the change in market value of total assets adjusted for expected dividends.

Campbell et al. (2008) employ the BSM framework to the US market (CRSP, 1963 to 2003). They use a debt proxy similar to that of Vassalou and Xing (2004) and infer asset volatility from equity volatility using the optimal hedge equation while they calculate equity volatility over the prior three months using daily returns. To proxy expected returns, they take the sum of the equity premium and risk-free rate. Dividends are not considered.

Crosbie and Bohn (2003) differ in determining the default probability. Instead of using a cumulative normal distribution, they use actual default probabilities drawing from the Moody's KMV database with over 250,000 company-years and over 4,700 bankruptcies. As such, they calculate the default score and take the number of actual failures to derive the expected default frequency. Literature often refers to the model in Crosbie and Bohn (2003) as Moody's KMV model.

An alternative is offered by Bharath and Shumway (2008) who employ US market data on CRSP between 1980 and 2003. They argue that the benefit of the traditional market-based model lies in its functional form rather than in the complex calculation. As such, Bharath and Shumway (2008) provide a naïve version of the market-based model to calculate the default score. They define asset volatility as the weighted average of equity volatility and debt volatility while debt volatility is defined as a linear function of equity volatility. Expected returns are proxied by the prior-year stock return. Importantly, they find their naïve distance to default measure to be superior to the standard market approach in a hazard model and out-of-sample tests. Similar results are provided in Agarwal and Taffler (2008a) who apply the model in Hillegeist et al. (2004) and Bharath and Shumway (2008) on the UK market.

While the previous studies differ in terms of their calculation of the unobserved parameters or the bankruptcy probability assessment, Brockman and Turtle (2003) argue that the vanilla call option does not appropriately reflect reality because the debt holders can force bankruptcy before the expiry of the equity holders' call option as soon as the asset value falls below the face value of debt. Similarly, Reisz and Perlich (2007) claim that this early bankruptcy option with the debt holders implies that the equity holders have a down-and-out barrier call option rather than a vanilla call option.[7] They apply the down-and-out barrier call option framework using a sample of 5,784 US industrial firms listed between 1988 and 2002.

**Advantages of Market-Based Models**

The primary advantage of the market-based models is their sound theoretical grounding. However, there are a number of other advantages that are of particular interest when compared to accounting-based models. Agarwal and Taffler (2008a: p. 1542) summarise them as follows: (i) in efficient markets, stock prices will reflect all the information contained in accounting statements and will also contain information not in the accounting statements, (ii) market variables are unlikely to be influenced by firm

[7] A further implication of viewing equity as a call is that managers (if they are acting in the best interests of the shareholders) should increase the firm's riskiness without bound. However, we do not observer this in practice and down-and-out framework shows that option value does not increase with volatility after a certain barrier.

accounting policies, (iii) market prices reflect future expected cash flows, and hence should be more appropriate for prediction purposes, and (iv) the output of such models is not time or sample dependent.

While accounting-based models have high data requirements, market-based models are less limited since the general market-based model requires only market return data and book value of debt. This is important for empirical studies because it allows for a greater sample size. Also, market data is available with a much higher frequency.

**Disadvantages of Market-Based Models**

Saunders and Allen (2002) argue that market-based models assume normally distributed stock returns. They also assume that the input variables are observable. Since especially asset volatility is not directly observable, market-based models eventually only offer an approximation of the real inputs. Moreover, the reliability of market data could be questioned due to several empirical findings that conflict with the assumption of efficient markets and that especially distressed assets are subject to e.g. market liquidity constraints (Avramov, Chordia, Jostova and Philipov, 2010).

Further, the BSM framework assumes a single zero-coupon bond maturing at the end of the forecasting horizon (one year). However, most firms have more complex capital structures with several coupon bearing loans with different maturities. Agarwal and Taffler (2008a) also argue that the BSM framework assumes costless bankruptcy, no safety covenants, and, unless the down-and-out barrier option framework is applied, default is triggered only at maturity without taking into account that the company can default earlier.

### 2.2.3 Hybrid Models

**Literature Review**

The two approaches described above base their predictive ability on either accounting or market information. Beaver (1968) notes that financial ratios and market prices are neither mutually-exclusive nor competing predictors of failure. While accounting data can be seen as a subset of market information, recent research similarly argues that both data sources could be complementary (Pope, 2010). For the purpose of increasing the explanatory power of bankruptcy prediction models, recent studies implement hybrid models that use both accounting and market information.

Shumway (2001) uses hazard models on a sample of US industrial firms listed between 1963 and 1992 (NYSE and AMEX). He claims that many of the previously applied accounting ratios have little statistical significance. On the other hand, he finds firm size, past stock returns and idiosyncratic stock return variability to be statistically highly significant. Combining these market-based variables with the accounting-based profitability and leverage, Shumway (2001) proposes the first hybrid model. Apart from that, he highlights the statistical advantages of his hybrid model over existing linear and conditional probability accounting-based models. He notes that hazard models allow for time-varying covariates and that they reduce sample selection biases as they do not employ matched samples.

In line with the model of Shumway (2001) there are a number of studies. Chava and Jarrow (2004) further refine the hazard model including different variables and adjusting for industry effects. Beaver, McNichols and Rhie (2005) and Beaver, Correia and McNichols (2010) examine the predictive power of accounting-based and market-based variables. Campbell et al. (2008) test the model in Shumway (2001) and alternative hybrid model specifications. Especially, they find the variables in Shumway (2001) to be more meaningful when adjusted by a market-based denominator, i.e. market value of total assets (book value of debt plus market value of equity) instead of book value of total assets. They also add two variables to the Shumway (2001) specification (book-to-market equity and share price). Anginer and Yildizhan (2010) apply the model in comparison with corporate credit spreads (CDS) and argue that CDS are more accurate. However, the results of Anginer and Yildizhan (2010) are less robust as no formal performance test is actually applied.[8] Also, their sample (US market data) ranging between 5,175 and 8,069 firms (43 and 94 failures) is quite small and thus, might impede the results.

Recent hybrid models have also been applied to the UK market. For instance, Charalambakis, Espenlaub and Garret (2009) provide a hazard model similar to the one in Shumway (2001). Christidis and Gregory (2010) provide a range of specifications arguing that the inclusion of macro-economic variables increases the explanatory power of existing hybrid models.

**Advantages of Hybrid Models**

The competing arguments in accounting-based and market-based bankruptcy prediction enforce a trend in the literature that argues for combining the two information sources. Sloan (1996) finds that market prices do not accurately reflect the information from company accounts and hence, accounting data can be used to complement market data.

[8] They apply simple hazard models but not information content tests. Additional tests, neither with sorts nor ROC curve analysis is provided.

Hybrid models use hazard models that are time-independent and thus, allow a bankruptcy risk assessment at each point in time. Since hazard models include all healthy and distressed firms, the trend of bankruptcy risk can be observed. In addition, hybrid models allow for the inclusion of macro-economic variables that affect the general bankruptcy risk of firms.

**Disadvantages of Hybrid Models**

Due to the inclusion of various variables and the fact that all of the variables are able to predict bankruptcy, hybrid models are prone to suffer from multicollinearity. As McLeay and Omar (2000) argue, the independent variables do not necessarily have to be normally distributed while extreme non-normality can adversely affect results.

Ideally, market data reflects all available information. Including accounting data should therefore add no explanatory power unless market prices do not fully incorporate accounting data. As such, the combination of accounting and market data is a very practical approach and motivated by an increase in explanatory power.

### 2.2.4 Empirical Tests

There are different approaches to assess the performance of bankruptcy prediction models. Early tests mainly focus on simple performance indicators such as portfolio sorts or cut-off points (Beaver, 1966; Beaver, 1968) and a classification matrix of type I and type II errors (Altman, 1968). More sophisticated approaches have become available in recent years: (i) the receiver operating characteristics (ROC) curves (Hanley and McNeil, 1982; Sobehart and Keenan, 2001) to test for forecasting accuracy, (ii) information content tests (Hillegeist et al., 2004) to test for bankruptcy related information carried by the prediction model, and (iii) evaluation of the economic value with differential misclassification costs (Stein, 2005; Blöchlinger and Leippold, 2006). The latter one is of great importance because, in contrast to ROC curve analysis and relative information content tests, it takes into account differential misclassification costs. Agarwal and Taffler (2007; 2008a) adjust the approach to assess the profitability of each model in an illustrative credit market.

In the literature review above I describe the three basic approaches to assess bankruptcy risk using accounting and/or market information. Literature often highlights the principal advantages of the respective approaches (e.g. Shumway, 2001; Vassalou and Xing, 2004). However, the advantages of each approach do not *per se* imply better forecasting predictions. In the end, what really matters is empirical performance.

In the following, I present the studies that analyse the performance of (i) accounting-based vs. market-based models, (ii) hybrid vs. accounting-based models, and (iii) hybrid vs. market-based models.

**Accounting-Based vs. Market-Based Models**

Brockman and Turtle (2003) compare their down-and-out call option approach with the z-score using a sample of industrial firms on CRSP between 1989 and 1998. In simple distress risk sorts, the market approach outperforms z-score. Using information content tests, they find that both approaches have significant and incremental bankruptcy related information over a one-year prediction horizon. Reisz and Perlich (2007) use two accounting-based measures, i.e. z-score and z''-score (Altman, 1968; Altman and Hotchkiss, 2006), and two market-based approaches, i.e. call option and down-and-out call option, to test for discriminatory power using 5,784 US industrial firms (CRSP) listed between 1988 and 2002. They choose ROC curve analysis to test for forecasting accuracy. For the one-year prediction horizon, they find that the accounting-based z-score model outperforms the market approaches. Unsurprisingly, the longer the time horizons, the worse is the forecasting accuracy of the models while the relative performance of the market-based models increases.

Hillegeist et al. (2004) compare the market approach with the z-score and o-score model. They also provide updated versions of the two accounting-based models by employing the variables in a hazard model and assess the relative performance by information content tests. They find that the market approach carries significantly more bankruptcy related information than any of the accounting-based measures. The outperformance is robust to the use of z-score or o-score (original and updated) as well as to industry adjustments.

Agarwal and Taffler (2008a) compare the Taffler (1983) z-score with the market-based approaches of Hillegeist et al. (2004) and Bharath and Shumway (2008) on the UK market using firms listed in the Main market segment anytime between 1985 and 2001 using ROC curve analysis and information content tests. They also assess the differential misclassification costs of the bankruptcy prediction models in an illustrative loan market. Using ROC, they find that z-score has higher predictive accuracy than both market-based models but the outperformance over the Bharath and Shumway (2008) model is insignificant. Using relative information content tests they find both the accounting- and the market-based models to be significant and argue that both approaches carry incremental bankruptcy related information. Allowing for different misclassification costs in an illustrative loan market, they find that z-score has greater economic value than the model of Bharath and Shumway (2008) because a bank using z-score has a greater market share and a lower share of loans defaulting, resulting in both higher profits and profitability.

**Hybrid vs. Accounting-based models**

Shumway (2001) uses US industrial firms listed between 1963 and 1992 (NYSE and AMEX) to compare the predictive power of hybrid and accounting-based bankruptcy prediction models. In order to do so, he uses hazard functions and employs the variables of his hybrid model and the accounting ratios of Altman (1968), Begley et al. (1996) and Zmijewski (1984). Alternatively, he includes the original coefficients of the accounting-based models in the hazard functions and tests forecasting accuracy using portfolio sorts. His results show that the hybrid specification has higher forecasting accuracy than the accounting-based models (both original and hazard coefficients).

Beaver et al. (2005) test for changes in the forecasting ability of accounting-based and market-based ratios for two sub-periods (1962 to 1993 and 1994 to 2002) and industrial firms listed on NYSE and AMEX. Simple performance tests are applied using hazard models and predictive ability by decile portfolios. They find that the predictive ability of financial ratios is offset by the forecasting ability of the market variables. Combining the accounting-based and market-based model, the hybrid model outperforms the accounting-based model. Similar results are obtained in Beaver, Correia and McNichols (2011).

Charalambakis et al. (2009) use a sample of UK firms listed between 1980 and 2006 on London Stock Exchange. They employ z-score (Taffler, 1983) as well as its components to compare it with variables similar to Shumway (2001) using hazard functions. They show that the coefficients for z-score are insignificant when combined with the

Shumway (2001) variables in a hazard function. Also, the hybrid model allocates more failures to the high risk decile portfolio.

Chava and Jarrow (2004) use a sample of US firms listed between 1962 and 1999 and available on CRSP. They make use of the variables from the accounting-based Altman (1968) and Zmijewski (1984) model and compare it with the Shumway (2001) model. They apply simple performance comparisons as well as ROC curve analysis. Chava and Jarrow (2004) confirm the outperformance of the Shumway (2001) model over both accounting-based models. Moreover, they also show that a model that is only based on market value, i.e. prior-returns and idiosyncratic volatility, is nearly as good as Shumway (2001) arguing that (i) the accounting-based models do not contribute much to the predictive ability of the Shumway (2001) model and (ii) the three market-based measures perform better than the two accounting-based models.

**Hybrid vs. Market-Based Models**

While there were only few studies testing hybrid models against accounting-based models, there is even less evidence on the performance of hybrid vs. market-based models. Campbell et al. (2008) is the only paper that compares their hybrid model with the market approach using a sample of CRSP firms listed between 1963 and 2003. They use hazard functions (in-sample tests) and information content tests (out-of-sample tests). Unfortunately, the results presentation is very brief and it does not provide the coefficients with the respective significance for the out-of-sample tests (Table V, p. 2916). Their in-sample tests show that the market-based model carries significant bankruptcy related information when included in a univariate regression and when controlled for the variables of the Campbell et al. (2008) model, i.e. the market-based model carries bankruptcy related information incremental to the control variables. However, the significance of the control variables is not provided. The results on out-of-sample tests only show that the pseudo $R^2$ is higher for the hybrid than for the market-based model. As such, the evidence is non-transparent on the performance of the two bankruptcy prediction approaches and only suggests that both carry significant information in out-of-sample tests.

### 2.2.5 Summary Distress Risk Models

The literature presented above can be summarised as follows:

1. There are three major approaches to assess bankruptcy risk. They differ in the information basis they use. The traditional approach is accounting ratio-based. The second alternative is market-based employing the BSM. The third approach consists of hazard models that combine accounting ratios and market information.
2. Besides simple tests that use hazard functions and risk sorting, there are three performance tests provided. The two most frequently used are ROC curve analysis for testing forecasting accuracy and the relative bankruptcy information content tests. However, both assume that the costs of erroneous misclassification are the same. The method of Stein (2005) and Blöchlinger and Leippold (2006) account for the economic impact of differential misclassification costs.

3. The evidence on empirical performance of accounting-based and market-based models is mixed. Reisz and Perlich (2007) find evidence in favour of the z-score while Hillegeist et al. (2004) argue in favour of the market-based approach. The results in Agarwal and Taffler (2008a) suggest a higher economic value of the z-score when differential misclassification costs are taken into account.
4. Hybrid models outperform accounting-based models. Chava and Jarrow (2004) find that hybrid models carry more bankruptcy related information while others find hazard models to have higher predictive power (Shumway, 2001; Beaver et al., 2005; Charalambakis et al., 2009; Beaver et al., 2010).
5. Indicative evidence of the performance of hybrid models vs. market-based models is only available in Campbell et al. (2008). Their out-of-sample results are non-transparent and indicatively suggest that both approaches carry significant bankruptcy related information in information content tests.
6. None of the existing studies considers ROC, information content tests, and differential misclassification costs to test the bankruptcy prediction models, except for Agarwal and Taffler (2008a) who compare the market and accounting approaches.[9]
7. None of the present studies compares the accounting, market and hybrid approach in a unified test.

[9] Agarwal and Taffler (2007) apply all three tests to examine the performance of the z-score model against profit before tax but with binary rather than continuous measures.

## 2.3 Negative Distress Risk Premium

### 2.3.1 Positive Distress Risk Premium

The Capital Asset Pricing Model (CAPM, Sharpe, 1964; Lintner, 1965; Mossin, 1966) predicts that only the systematic risk measure BETA is a complete measure of risk of each security i.[10] However, early tests of the CAPM provide evidence on the forecasting ability of characteristics in addition to BETA. Seminal contributions are provided by:

- Basu (1977) using a sample of US industrial firms listed on NYSE between 1956 and 1971 finding that stocks with low price-earnings-ratios (PE) outperform stocks with high PE,
- Banz (1981) using a sample of US firms listed on NYSE between 1926 and 1975 finding that stocks with low market capitalisation outperform stocks with high market capitalisation (size effect),
- Rosenberg, Reid and Lanstein (1985) using a sample of US listed firms between 1980 and 1984 finding that stocks with high book-to-market ratio (BM) outperform stocks with low BM,
- and Bhandari (1988) using a sample of US firms listed on NYSE between 1948 to 1979 finding that high leverage firms outperform low leverage firms.

Chan and Chen (1991) examine why small stocks outperform large stocks using a sample of US firms listed on NYSE and NASDAQ (1956 to 1985). They use proxies for marginal firms (substantial dividend cut and high leverage) which have poor future

[10] BETA is the covariance of return of security i and market return divided by the variance of the market return.

prospects and find that the returns of the marginal firms explain the size effect. Fama and French (1992) study the size and the BM effect on a sample of industrial firms listed on NYSE, AMEX, and NASDAQ between 1962 and 1989. They show that market capitalisation and BM are able to subsume the return patterns associated with PE and leverage. Similar to Chan and Chen (1991), they argue that the returns of high BM stocks are associated with poor prospects firms that are in relative distress. Motivated by these findings, Fama and French (1996) adjust CAPM for the two factors SMB and HML to mimic the returns earned by small stock and high BM stocks respectively.[11] The literature often refers to the two studies as they postulate the "distress hypothesis" in explaining the size and BM effect: relative to non-distressed firms, distressed firms earn high returns due to the high loadings on SMB and HML.

The probability of bankruptcy is a natural proxy for the distress risk factor. Several studies make use of the accounting-based, market-based and hybrid models introduced in the previous sub-chapter. Vassalou and Xing (2004) are the first to employ the market-based approach using BSM in the context of stock returns (US data on CRSP with a sample period from 1971 to 1999). First, in line with the distress hypothesis, they use simple sorts on the BSM score and find a weak but positive distress risk premium (present for equally but not for value-weighted portfolio sorts). Second, they use sequentially-formed portfolios sorted on distress risk then on size (or BM) and show that the size (BM) effect is only present in the highest (highest two) distress risk quintiles. They reverse the order of their sorts finding distress risk to be positive and

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[11] SMB is Small Minus Big and represents the return of a portfolio that is long on small stocks and short on big stocks. HML is High Minus Low and represents the return of a portfolio that is long on high BM stocks and short on low BM stocks.

significant only in the small (high BM) quintile. They argue that the size and BM effect are largely a distress effect though, there is additional return predictability covered by SMB and HML. Using a measure of aggregate distress risk, they further claim that distress risk is indeed a systematic risk factor.

However, the results of Vassalou and Xing (2004) are less robust. First, the positive distress risk premium in their Table III (p. 845) is weak as it depends on the weighting-scheme applied. Robustness tests are not provided. Tables VI and VII (p. 852 and 854) do not provide the H-L premium for the whole sample on the distress sort, but remarkably, it is presented for all other sorts (Tables IV and V). Second, the objective of sorting is to control for a certain variable. It is doubtful whether this is possible using sequential sorts. For instance, Table IV Panel C (p. 847), the argued size effect in the high DLI portfolio can also be driven by distress risk: DLI reduces from 27.45 in the small to 14.30 in the big portfolio. A similar problem occurs in Tables V to VII.

Da and Gao (2010) also raise significant concerns with the findings in Vassalou and Xing (2004). In replicating the analysis using US firms on CRSP (1983-1999), they show that the positive distress risk premium is (i) only apparent in the first month after portfolio formation, and (ii) it is confined to a small subset of stocks with similar default likelihoods. In addition, they find that these stocks experienced heavy recent losses leading to the conclusion that the positive return premium is due to a short-term return reversal.

Chava and Purnanandam (2010) offer an alternative study using a hybrid model similar to Shumway (2001) and an expected default frequency based on a market-based model. They use a sample of US firms (excluding financial and utility firms) listed on AMEX, NYSE, or NASDAQ during 1963–2005. In contrast to most empirical stock market studies, they employ expected returns (sample period 1980 to 2005) instead of realised returns arguing that realised returns are a noisy estimate of expected returns (see as well Elton, 1999). They calculate expected return by the implied cost of capital, i.e. the discount rate at which the expected cash flows equal the current price. Using consensus estimates from the Institutional Brokers Estimate System (I/B/E/S) to estimate expected returns, they find that expected returns are positively associated with distress risk using sorts on both the hybrid and the market-based model. Further, their cross-sectional regressions show that distress dummy variables (derived from decile portfolios) have a positive and significant loading. In sharp contrast to that, they find a negative distress risk-return relation when they use realised returns instead of expected returns. They attribute this contrary finding to investors who were not able to anticipate the risk because of unexpectedly high default rates, unexpectedly low cash flows of distressed firms and the large negative forecast errors of analysts during the 1980s.

However, a substantial drawback of studies deriving expected returns using analyst forecasts is the low sample size. Although Chava and Purnanandam (2010) are unclear about the actual size of their analyst forecast sample, it can be reasonably suspected that the analyst coverage is quite low, especially for high distress risk firms as they are usually small and not followed by analysts. Several studies provide evidence for this assumption (Diether, Malloy and Scherbina, 2002; Taffler, Lu and Kausar, 2004; Da and Gao, 2010). As such, while the use of analyst forecasts avoids some drawbacks of realised returns, it imposes high limitations on researching expected returns on distressed firms.

Although the findings in Vassalou and Xing (2004) and Chava and Purnanandam (2010) could be argued to be in line with the distress hypothesis, the results are not robust as described above. There is no further evidence suggesting a positive distress risk-return relation.

### 2.3.2 Negative Distress Risk Premium

Dichev (1998) is the first to research the pricing impact of a distress risk measure using Altman's (1968) z-score and Ohlson's (1980) o-score on US industrial firms listed at NYSE, AMEX and NASDAQ between 1981 and 1995. He finds that for the firms listed on NYSE and AMEX, there is a negative distress risk premium for both z-score and o-score (decile portfolios). However, for NASDAQ stocks there is only a significant distress risk-return relationship for o-score; the return relation in z-score is hump-shaped. He also shows time-series returns long on non-distressed and short on distressed firms that earn significant positive returns over the observation period.

Dichev (1998) also argues that size and BM are not proxying for distress. While distressed firms (both z-score and o-score) generally tend to be small and have high BM, the most distressed firms do not have the highest BM ratios. As such, in contrast to Vassalou and Xing (2004), Dichev (1998) finds a hump-shaped rather than a monotonic relation between BM and distress risk (see also Garlappi and Yan, 2011). Further rejecting the distress hypothesis, cross-sectional regressions show that size is insignificant independent of distress and BM is significant independent of distress. However, Dichev (1998) fails to account for the systematic CAPM risk factor beta or additional risk-adjustments following Fama and French (1993).

Griffin and Lemmon (2002) use Ohlson's (1980) o-score to analyse the relationship between distress, BM and returns for US non-financial firms listed on NYSE, AMEX, and NASDAQ between 1965 and 1996. They find an underperformance of high distress risk firms that is only present for low BM stocks; the returns of high distress risk stocks with high BM are twice as large.[12] In contrast to the distress hypothesis, risk-adjusted returns using the Fama and French (1993) model still exhibit a large underperformance of the high distress risk-low BM stocks although they load high on SMB and HML. High distress risk firms have characteristics that have a greater chance of being mispriced. As such, they find distressed firms to have large return reversals around earnings announcements, small market capitalisation and low analyst coverage.

Ferguson and Shockley (2003) offer a theoretical argument for the risk factors in the Fama and French (1993) model and thus for the outperformance over CAPM. They argue that the equity only beta, i.e. a beta that is solely derived from an equity only index, underestimates systematic risk. Factors related to leverage and distress are expected to improve the explanatory power of the CAPM. Since SMB and HML are correlated with distress and leverage, the Fama and French (1993) model outperforms CAPM. However, their empirical tests using US firms available on CRSP between 1964 and 2000 show that there is actually a negative distress risk-return relation.

Although the theoretical explanation of Ferguson and Shockley (2003) is appealing, Agarwal and Poshakwale (2010) point out two major empirical problems with their study. While the theoretical propositions of Ferguson and Shockley (2003) argue for a

[12] These results are further confirmed using z-score (Altman, 1968).

positive distress risk premium, their empirical results (US data) show the opposite. Agarwal and Poshakwale (2010) test the implications of the Ferguson and Shockley (2003) model using UK non-financial firms listed in the Main market segment of London Stock Exchange (LSE) between 1979 and 2006 and further confirm that (i) CAPM (equity only) betas systematically underestimate risk for distressed and levered firms while distress (z-score) and leverage factors are correlated with SMB and HML, and (ii) there is no outperformance of the Ferguson and Shockley (2003) model over the Fama and French (1993) model and that the negative distress risk premium leads to large pricing errors.

These findings cast doubt on the ability of the Fama and French (1993) model to account for the distress risk premium. Apart from the underperformance of distressed firms, the literature focused on anomalies has identified a robust stock return momentum. Jegadeesh (1990) conducts tests using US firms on CRSP (1929-1987) and finds stocks that earned high (low) returns in the last three to twelve months earn high (low) returns in the following three to twelve months (see as well Jegadeesh and Titman, 1993; 2001). Due to its robustness Fama and French (1998: p. 1653) admit that momentum is the "premier anomaly". Similarly, Lewellen (2002) finds momentum to be robust to the Fama and French (1993) SMB and HML premia. Carhart (1997) recognises as well the importance of the momentum factor and proposes an extension of the Fama and French (1993) model to include the momentum factor WML accounting for return continuation.[13] As such, there is an additional benchmark model for distress

[13] WML is Winner Minus Loser and represents the return of a portfolio that is long on prior-winners and short on prior-losers.

risk pricing. However, as the following two studies show, the distress risk premium is also robust to the WML factor.

Campbell et al. (2008) use a hybrid model to assess bankruptcy risk for listed US firms (CRSP) between 1981 and 2003. They report a negative relation between distress risk and risk-adjusted returns, independent of whether CAPM, the Fama and French (1993) model or the Carhart (1997) model is applied. Even more puzzlingly, the loadings on the explanatory factors of the alternative models are positively related to distress risk. Testing the distress risk premium across size and BM quintiles, Campbell et al. (2008) find that the distress anomaly is more pronounced within small or growth stocks but generally robust and independent of size and BM.

Agarwal and Taffler (2008b) establish a link between returns and financial distress risk measured by the UK accounting-based z-score model for non-financial firms listed in the Main market of LSE between 1979 and 2002. They find that distressed stocks underperform although they load high on risk factors i.e. distressed firms have high betas and high loadings on SMB and HML. Agarwal and Taffler (2008b) also find that distress risk is related to return momentum since the market is likely not to anticipate the bad news associated with distress risk. This leads to continuing underperformance of distressed firms and drives the medium-term return continuation. In fact, distress risk largely subsumes return momentum. Avramov, Chordia, Jostova and Philipov (2007) study credit ratings and the momentum effect of US firms on CRSP from 1985 to 2003. Similar to Agarwal and Taffler (2008b), they argue that the momentum effect is mainly driven by low-graded firms.

The above cited studies use available approaches to measure distress risk. However, none of the studies actually combines the accounting-based, market-based, and hybrid approach to examine the relationship between distress risk and stock returns with the benefit of a consistent methodology. Since previous literature shows mixed results while using the same distress risk measure (e.g. Vassalou and Xing, 2004; Chava and Purnanandam, 2010), it seems important to provide definite and robust evidence.

Beside the use of distress risk measure, there are a number of studies that use more direct distress risk indicators. For instance, Lamont, Polk, Saá-Requejo (2001) construct a financial constraints index for US manufacturing firms on CRSP between 1968 and 1997. They show that constrained firms earn low average stock returns (after risk-adjustment for beta, size, BM and momentum). Moreover, Lamont et al. (2001) argue that the returns of financially-constraint firms tend to move together supporting the view that constrained firms are subject to common shocks. Alternatively, Avramov, Chordia, Jostova and Philipov (2009) analyse stock returns and credit ratings for US firms on CRSP from 1985 to 2007. They document low average returns for low-graded firms (after risk-adjustment for beta, size, BM and momentum). More specifically, Avramov et al. (2009) observe that the underperformance is substantial in the three months prior and subsequent to credit rating downgrades. Anginer and Yildizhan (2010) provide a return analysis using credit spreads for industrial US firms on CRSP listed from 1980 to 2006. Consistent with related studies, they argue that returns of firms with higher credit spreads are anomalously low (after risk-adjustment for BETA, SIZE, BM and momentum). In addition, they argue that the distress anomaly does not stand on its own but is an amalgamation of anomalies associated with leverage, volatility and profitability. However, as described earlier, the use of sequential sorts is less robust.

### 2.3.3 Summary Negative Distress Risk Premium

1. Chan and Chen (1991) and Fama and French (1992) provide a distress related explanation for the high returns earned by small and high BM stocks. Motivated by these findings, Fama and French (1992) suggest a model that adjusts the CAPM by the factors SMB and HML that account for the size and BM effect. The distress hypothesis is: relative to non-distressed firms, distressed firms earn high returns due to their high loadings on SMB and HML. In addition to that, Carhart (1997) suggests a further extension to account for return momentum.
2. Vassalou and Xing (2004) and Chava and Purnanandam (2010) find general evidence for the distress hypothesis as they find distress risk to be positively associated with subsequent returns. However, the results are limited and not confirmed in similar studies (Da and Gao, 2010).
3. Majority of studies find a negative distress risk premium (e.g. Dichev, 1998; Agarwal and Taffler, 2008b). Even more puzzlingly, distressed firms score high on the usual risk measures as they show high loadings on the risk factors (e.g. Campbell et al., 2008; Avramov et al., 2010).
4. Although there is substantial evidence for the negative distress risk premium using different distress risk proxies, none of the studies actually tested the price impact of all three available approaches to measure distress risk in a unified test. This could provide additional reliability in the pricing of distress risk.

## 2.4 Explaining the Negative Distress Risk Premium

### 2.4.1 Introduction

While there is little and weak evidence on a positive distress risk-return relation (Vassalou and Xing, 2004; Chava and Purnanandam, 2010), the majority of studies find a negative distress risk premium (e.g. Dichev, 1998; Griffin and Lemmon, 2002; Agarwal and Taffler, 2008b). Although this seems to be at odds with the traditional finance paradigm, there are studies seeking an explanation of the distress puzzle. In the following, I review and summarise the literature on the risk-based shareholder advantage explanation, the limits of arbitrage, and the gambling retail investors.

### 2.4.2 Shareholder Advantage

Zhang (2012: p. 225) provides a definition of shareholder advantage: "When liquidation upon default results in a significant amount of losses in firm values, creditors may forgive some of the debt if doing so gives debt holders more than the recovery rate they would otherwise obtain from a complete liquidation. This creates incentives for shareholders to default opportunistically." The definition implies that shareholders strategically default on debt to enforce a firm restructuring at cost of debt holders. This advantage of shareholders becomes more valuable with increasing distress risk and thus, changes equity risk fundamentally. Garlappi, Shu and Yan (2008) and Garlappi and Yan (2011) recognise the effect of shareholder recovery in their valuation model that explicitly accounts for leverage (BM) and distress risk. They argue that at low levels of default probability, higher leverage increases equity beta. At high levels of default probability, the shareholder advantage de-levers the equity risk. As such, they predict a hump-shaped relation of equity beta and expected returns in distress risk.

The shareholder advantage theory provides three main testable implications. First, it provides a direct explanation for the distress risk premium: since equity beta is hump-shaped in distress risk, stock returns are expected to decrease for high distress risk firms. As such, the relative low returns earned by distressed firms are actually in line with the equity risk once strategic default is taken into account. The empirical analysis of Garlappi and Yan (2011) is based on a sample of US non-financial firms on CRSP for the years 1969 to 2007. Using CAPM and Dimson (1979) portfolio betas (both equally- and value-weighted) and decile distress risk portfolios, Garlappi and Yan (2011) find a hump-shaped relation between beta and distress risk. Consistent with their predictions, beta increases up to the 7$^{th}$ decile and drops in the highest distress risk deciles (p. 809).

Second, the theory predicts that the value premium (i.e. stocks long on high BM, short on low BM) is also hump-shaped in distress risk: the relation between BM and stock returns depends on the level of distress risk. Since returns on distress risk are hump-shaped, the value premium is also expected to be hump-shaped. For low levels of distress risk, the value premium is positive while for high levels of distress risk the value premium is negative. Garlappi and Yan (2011) use independent sorts on distress risk (deciles) and BM (terciles) to show that the value premium increases with distress risk up to the 8$^{th}$ distress risk decile and drops for the high distress risk portfolios (p. 811). The findings are robust to equal- and value-weighting as well as risk-adjusted value premia using CAPM, the Fama and French (1993) model, the Carhart (1997) model and the model of Pástor and Stambaugh (2003).

Third, the theory predicts that momentum profits are more pronounced in high distress risk firms: for low levels of default risk, negative price shocks increase both distress risk and expected returns. Thus, there is a negative autocorrelation. For high levels of risk, a negative price shock increases distress risk but, due to the shareholder advantage effect, it lowers both equity risk and expected return. Thus, there is a positive autocorrelation. Garlappi and Yan (2011) use quintile distress risk portfolios and quintile prior-return portfolios (resulting in a 5x5 return matrix) in two way sorts to examine the relation between distress risk and momentum (p. 817). They find that momentum profits increase with distress risk. In an additional analysis including proxies for shareholder recovery (size of total assets, R&D expenditures, industry concentration), they show that momentum profits are most pronounced in high distress risk-high shareholder recovery portfolios (p. 815).[14]

However, the results in Garlappi and Yan (2011) are less transparent on critical issues. For instance, they argue that equity risk and expected stock returns are hump-shaped in distress risk but in Table II (p. 809) they only report beta, not returns. As such, they miss the definite evidence for a hump-shaped relation of distress risk and returns which is the basis for all predictions. The results presented in Garlappi et al. (2008) are similarly inconclusive. The scepticism on the return pattern also applies to the use of a market-based measure as distress risk proxy. As the literature review in the previous sub-chapter shows, the evidence on the stock price impact of market-based measures is mixed (Vassalou and Xing, 2004; Chava and Purnanandam, 2010). As such, clarity on

[14] Garlappi et al. (2008) provide similar results while including the size of tangible assets as an additional proxy.

the returns is required as well as additional robustness by using alternatives to the market-based distress risk measures.

In addition to that, their theoretical model assumes that the resolution of distress risk is costless and frictionless. Zhang (2012) tests the predictions in Garlappi and Yan (2011) using US non-financial firms on CRSP between 1975 and 2006. He uses bondholder and shareholder dispersion as well as short-term debt as proxies for renegotiation frictions. However, he finds that the shareholder advantage effect on returns is only present where renegotiation frictions are less distinct or where the shareholder advantage effect is particularly strong. Though, the effect is observed for firms with private debt only. This limits the explanatory power of the theoretical framework of shareholder advantage.

On the other hand, there is indicative and supporting evidence for the predictions and results in Garlappi and Yan (2011). Hackbarth, Haselmann and Schönherr (2011) argue that the 1978 Bankruptcy Reform Act (BRA) unexpectedly augmented shareholders' bargaining power. For instance, they claim that violations of the absolute priority rule increased as a consequence of the introduction of the BRA. Examining the returns of US firms on CRSP from 1972 to 1984, they find that the positive distress risk premium found before the introduction of BRA turns negative after the introduction of the BRA. Hackbarth et al. (2011) deduce that the sign change in distress risk premium is due to the shareholders' bargaining power and thus, the lower risk exposure of shareholders of highly distressed firms.

Besides the empirical proof of Garlappi and Yan (2011) and the indicative evidence of Zhang (2012) and Hackbarth et al. (2011), there is no study that tests the empirical predictions of the shareholder advantage theory. The very basic predictions related to equity risk, returns, value premium, and return momentum in distress risk are uncontested in literature. Moreover, Garlappi and Yan (2011) use a market-based distress risk measure which has mixed return impact in previous studies (e.g. Vassalou and Xing, 2004; Campbell et al., 2008). As such, their results lack robustness. Although Garlappi and Yan (2011) downplay the importance of violations of the absolute priority rule, the theory has to be tested in different bankruptcy regimes since the legal settings might restrict violations of the absolute priority rule or resolutions of financial distress.

The literature on shareholder advantage can be summarised as follows:

1. Shareholders are able to derive some recovery value from the resolution of financial distress (shareholder advantage). As this becomes more likely the closer the firm is to bankruptcy, the shareholder advantage effect de-levers distress risk and equity risk decreases for high levels of distress risk. Thus, equity risk and returns are hump-shaped in distress risk.
2. The valuation model of Garlappi et al. (2008) and Garlappi and Yan (2011) accounts for leverage and shareholder advantage and predicts a hump-shape of equity risk and returns in distress risk, a positive value premium for low distress risk firms, a negative value premium for high distress risk firms, and a more distinct momentum effect for high distress risk firms.

3. Empirical tests are limited in literature. Zhang (2012) provides first evidence and shows that the shareholder advantage affect is restricted to private debt firms. Hackbarth et al. (2011) provide indicative supporting evidence.
4. None of the studies examines the robustness of the very basic predictions in relation to different distress risk measures and bankruptcy regime.

### 2.4.3 Limits of Arbitrage

Modern portfolio theory assumes that market prices fully reflect all available information (Fama, 1970; Fama, 1991). However, the existence of stock market anomalies is often referred to be due to investor's inability to assess the value of a firm according to its underlying risk (Barberis and Thaler, 2003).[15] La Porta, Lakonishok, Shleifer and Vishny (1996) argue that a significant portion of the value premium is due to earnings surprises, that is, investors underestimate (overestimate) the future earnings of high (low) BM securities. As investors slowly acknowledge the underlying risk of the security, prices gradually drift towards their fair values. Similarly, Dichev and Piotroski (2001) find that stocks earn significant negative abnormal returns in the first year following rating downgrades. Since this is not found for rating upgrades, they claim that investors underreact to bad news (see as well Hong, Lim and Stein, 2000). In a similar vein, Taffler et al. (2004) find a significant market underreaction to UK firms disclosing going-concern audit reports. Although behavioural-based asset pricing models deliberately account for such misjudgements (Subrahmanyam, 2008), the question still is why these profit opportunities persist without being exploited by arbitrageurs.

[15] Barberis and Thaler (2003) summarise the irrational behaviour as people form beliefs due to investor overconfidence, optimism and wishful thinking, representativeness, conservatism, belief perseverance, and anchoring.

Shleifer and Vishny (1997) argue that for mispricings to persist in the presence of sophisticated investors there must be some limits of arbitrage. They claim that in real world arbitrageurs face some long run fundamental risks and their pay offs are not certain.

Lesmond, Schill and Zhou (2004) and Pontiff (2006) argue that arbitrage is not costless. For instance, Pontiff (1996) analyses the market values of 52 close-end funds between 1965 and 1985 and finds that investors are unable to trade opportunistically on the discounts of close-end funds due to high arbitrage costs (proxied by price and market value). Taffler et al. (2004) analyse the return of first-time going concern modified (GCM) audit reports of 108 non-financial UK firms listed on LSE and the Unlisted Securities Market (USM) between 1995 and 2000 and find a robust underperformance of -24% to -31% in the year following the GCM audit report. In spite of this substantial underperformance, they show that an illustrative arbitrage trading strategy is unprofitable due to high implementation costs (proxied by bid-ask spread, shorting and trading commission costs). Kausar, Taffler and Tan (2009) reach similar conclusions using a US sample of non-financial, non-utility firms with 1,293 GCM audit reports between 1993 and 2005. As such, the studies show that high transaction costs impede the observed profit opportunities.

Ali, Hwang and Trombley (2003) use a sample of US firms listed on NYSE and AMEX between 1976 and 1997 to examine the returns on the BM anomaly (Rosenberg et al., 1985). Besides a range of proxies for arbitrage costs (e.g. bid-ask spread, price, and volume), investor sophistication, and firm size, they use as well idiosyncratic volatility (arbitrage risk) to explore the impact on BM returns. While all limits of arbitrage proxies are associated with a higher predictability of the BM returns, it is strongly and most consistently related to idiosyncratic volatility. As such, they show that it is not only transaction costs that limits arbitrage activity but as well arbitrage risk. These findings are consistent with Shleifer and Vishny (1997) who argue that arbitrage risk deters arbitrage activity.

Mendenhall (2004) examines the post-earnings announcement drift for US firms available on CRSP between 1991 and 2000. He applies several proxies for arbitrage costs (price and volume), arbitrage risk (idiosyncratic volatility following Wurgler and Zhuravskaya (2002)) and investor sophistication (institutional ownership and analysts following). Using cross-sectional tests, he finds that the magnitude of post-earnings announcement drift is strongly decreasing with trading volume and strongly increasing with idiosyncratic volatility. Mashruwala, Rajgopal and Shevlin (2006) use similar proxies and transaction costs (price, volume, size) to study the accruals and cash flow anomaly (Sloan, 1996). Employing a sample of US industrial firms between 1975 and 2000 and cross-sectional tests, they find that the anomaly is more pronounced for low priced/low volume stocks and abnormal returns are higher for high idiosyncratic risk firms. Thus, both Mendenhall (2004) and Mashruwala et al. (2006) further confirm that the existence of the respective anomaly is due to both arbitrage costs and arbitrage risk.

Pontiff (1996) argues that even without arbitrage costs or arbitrage risks involved in exploiting arbitrage opportunities, the existence of sophisticated investors does not guarantee that prices will reflect fundamental values due to the institutional environment. Almazan, Brown, Carlson and Chapman (2004) examine US funds' SEC filings from 1994 to 2000 and find that while 31% have investment policies allowing them to short sell, only 10% of those eligible to short sell actually do. Moreover, Nagel (2005), using US firms on CRSP between 1980 and 2003, highlights problems in implementing short selling strategies. He argues that the main stock suppliers for short trades are institutional investors. Since institutional holdings in overpriced firms are typically low, there is no stock supply for a short trade strategy. Indeed, his empirical tests show that return predictability of stock returns is more pronounced in stocks with low institutional ownership. Similarly, D'Avolio (2002) analyses proprietary data of a US security lender between April 2000 to September 2001 and finds that 16% of the stocks in CRSP are potentially impossible to borrow (and hence, to sell short).

As with other underreaction anomalies, it is possible that the distress anomaly is also driven by arbitrage costs and arbitrage risk. Campbell e t al. (2008: p. 2935) close their study with "The limits to arbitrage help us to understand how the distress anomaly has persisted into the 21st century." Given this request, it is surprising that none of the present studies explicitly tests for the limits of arbitrage using different distress risk measures.

The literature review on limits of arbitrage can be summarised as stated below:

1. Arbitrage is subject to trading costs and volatility. Market mispricing is more pronounced for stocks that have high transactions costs (e.g. high bid-ask spread, low price, low volume, stock borrowing costs, trading commissions) and high volatility.

2. Against the textbook descriptions, institutional investors make very little use of the perceived arbitrage opportunities. They either do not short sell (e.g. due to their investment charter) or they are unable to implement their strategy due to a paucity of stock supply.
3. Present studies fail to assess the potential of limits of arbitrage to explain the negative distress risk premium using different distress risk proxies.

### 2.4.4 Lottery Stocks

Friedman and Savage (1948) as well as Markowitz (1952) incorporate the option of buying lottery tickets as opposed to insurances in defining the utility from investments. Both studies note that utility is not a constant function and that the level of income or socio-economic class of the investor determines the willingness to gamble. Statman (2002) explains the phenomena of lottery playing by arguing that some people see buying lotteries or equivalently, trading on the stock market, as the only option to increase social status. Barberis and Huang (2008) model this preference to gamble by introducing a model of cumulative prospect theory using transformed rather than objective probabilities. This involves people's preference for positively skewed returns leading to an overpricing of such stocks.

Kumar (2009) uses socioeconomic characteristics to infer gambling preferences for stock investment decisions. This requires a definition of both the socioeconomic characteristics and lottery-type socks. For the socioeconomic characteristics, Kumar (2009) draws on the evidence on state lotteries that finds the propensity to play the lottery to be higher for poor, young, and relatively poorly educated single men, who live in urban areas and belong to minorities and religious groups. To identify investors with these characteristics, Kumar (2009) uses a proprietary dataset of a US discount brokerage house that contains investor information (e.g. age income, location) from 1991 to 1996. In addition to that, he attributes racial and ethnic characteristics from various databases (e.g. US Census) to the investor by his location (assumption: people in zip-code area 1 are more educated so investors in zip-code 1 are educated). Lottery-type stocks are defined following Markowitz (1952: p. 1555): "Lotteries have large chances of a small loss for a small chance for a large gain." As such, Kumar (2009) identifies lottery-type stocks by their low prices, high volatility and high skewness. He uses firms available on CRSP from 1980 to 2005.

First, consistent with the research on state lotteries, Kumar (2009) finds that the salient socioeconomic factors that are associated with higher expenditures in lottery stocks are also associated with higher investments in lottery-type stocks. While individual investors exhibit a distinct preference for lottery-type stocks, institutional investors avoid them. In a subsequent study, Han and Kumar (2011) use US stock market data between 1983 and 2000 and show that the retail trading proportion (defined as the monthly dollar value of trades with a volume smaller than $ 5,000 divided by the total monthly trading volume) is higher for lottery-type stocks. They conclude that speculation in lottery-type stocks is not only conducted by gamblers but by retail investors in general. Importantly, institutional investors are found to underweight those stocks.

Second, Kumar (2009) observes low average returns for investments in lottery-type stocks. Han and Kumar (2011) argue that lottery-type stocks are held by retail investors and thus, they generalise the findings as they document an underperformance of stocks with high retail trading proportion. Similarly, Statman (2002) argues that stock gambling, as opposed to stock holding, leads to negative returns. Previous studies also have examined the impact of characteristics that are associated with lottery-type stocks. For instance, Ang, Hodrick, Xing and Zhang (2006; 2009) provide US and international evidence that stocks with high idiosyncratic volatility earn low subsequent stock returns. Similarly, Bali, Cakici and Whitelaw (2011) examine the impact of highly skewed returns (i.e. maximum daily return in the prior-month) using US market data (CRSP) between 1962 and 2005. They show that individual investors are willing to pay more for stocks with an extreme positive historical daily return leading to low future returns. However, they also show that the negative return relation with idiosyncratic risk found in Ang et al. (2006; 2009) is reversed once they control for the lottery feature of extreme past return. As such, literature provides evidence that lottery-type characteristics such as idiosyncratic volatility and high daily past month returns have a negative relation with subsequent stock returns as well as that the lottery-type characteristics might be related to each other.

Instead of filtering lottery-type stocks by certain characteristics, Coelho et al. (2010) take a sample of 351 non-finance, non-utility industry Chapter 11 firms between 1979 and 2005 that remain listed on NYSE, AMEX or NASDAQ.[16] Indeed, they argue that consistent with Markowitz (1952) definition of a lottery, Chapter 11 firms trade at a few cents while offering a low probability of a huge future reward but very high probability of a small loss. In line with the other lottery-stock studies, they find that, on average,

[16] The study of Coelho and Taffler (2009) is assumed to be an earlier version of the paper.

individual investors own 90% of firms under Chapter 11. Also, those firms earn a negative return of -28% over the year following the Chapter 11 filing.

Coelho et al. (2010) is the only study that explores the connection between lottery characteristics and bankruptcies, i.e. Chapter 11. The potential power of lottery-type stocks to explain the overpricing of distressed stocks before the Chapter 11 filing, i.e. using distress risk measures, is not yet explored in literature.

Before summarising the literature on lottery-type stocks, please note that the lottery stock literature shares some commonalities with the limits of arbitrage literature. On a general basis, the limits of arbitrage literature employs proxies mostly identical to those of lottery-type stocks. For instance, studies on limits of arbitrage usually apply share price, idiosyncratic volatility, idiosyncratic skewness, bid-ask spread, institutional ownership, low analyst coverage (Shleifer and Vishny, 1997; Wurgler and Zhuravskaya, 2002; Ali et al., 2003). More specifically, Mendenhall (2004) and Mashruwala et al. (2006) use the identifiers of lottery-type stocks, i.e. low price, high volatility and high skewness, to proxy for limits of arbitrage. As such, there is high commonality in the variables that are used to proxy for limits of arbitrage and lottery-type stocks.

Further, the literature provides direct evidence for the connection between limits of arbitrage and lottery-stocks. Han and Kumar (2011) note that lottery-type stocks face high limits of arbitrage as they tend to have a very low market capitalisation, low price, high idiosyncratic volatility, low institutional ownership and low analyst coverage. Bali et al. (2011) argue that the stocks they define as lottery-type stocks are also the ones that are hard to arbitrage. Coelho et al. (2010) conclude that the post-Chapter 11 filing drift is caused by both gambling retail investors and limits of arbitrage. Thus, one can argue that lottery-type characteristics describe the market frictions associated with limits of arbitrage or *vice versa.*

My literature review on lottery stocks can be summarised as follows:

1. Typical lottery-type stocks are low-priced, have high volatility and highly skewed stock returns. Literature finds that lottery-type stocks are primarily traded by retail investors.
2. Lottery-type stocks underperform.
3. Chapter 11 firms have lottery-type characteristics, they are traded by retail investors and they underperform after the Chapter 11 filing.
4. There is a high commonality with limits of arbitrage. Especially, share price and volatility are frequently used for proxying for implementation costs and risk of arbitrage.
5. Existing studies have not yet analysed the impact of lottery characteristics on the negative distress risk pricing using distress risk measures.

In the next chapter I define my research questions and research propositions that address the gaps in the literature described in this chapter.

# CHAPTER 3: RESEARCH QUESTIONS AND PROPOSITIONS

## 3.1 Which of the alternative approaches to predict bankruptcies is the best?

Bankruptcy prediction measures differ in their information basis. There are accounting-based models (e.g. Altman, 1968), market-based models (e.g. Vassalou and Xing, 2004), and hybrid models (e.g. Shumway, 2001). The performance of bankruptcy prediction models can be assessed by their forecasting accuracy using ROC curve analysis (Hanley and McNeil, 1982; Sobehart and Stein, 2000), by their bankruptcy related information using information content tests (Hillegeist et al., 2004), and by their economic value under differential misclassification costs using an illustrative credit loan market following Stein (2005) and Blöchlinger and Leippold (2006). Existing literature fails to provide a comprehensive test that compares the three different approaches with the full range of performance tests. I establish the following propositions:

*P1: The three different bankruptcy prediction measures have different predictive ability.*

*P2: All three measures carry bankruptcy related information incremental to each other.*

*P3: There is a difference in performance once misclassification costs are taken into account.*

## 3.2 Is there a distress risk premium and does it depend on the distress risk measure?

While Vassalou and Xing (2004) and Chava and Purnanandam (2010) report a positive distress risk-return relation, the majority of studies find a puzzling underperformance of distressed firms (e.g. Dichev, 1998; Griffin and Lemmon, 2002; Agarwal and Taffler, 2008b). However, none of the present studies compares the influence on subsequent stock returns using the three alternative distress risk measures. I thus review existing evidence and test the following research propositions:

*P4: There is a distress risk premium in stock returns.*

*P5: The distress risk premium depends on the proxy for distress risk.*

## 3.3 Can shareholder advantage, gambling retail investors or limits of arbitrage explain the negative distress risk premium?

Literature provides several potential explanations to explain the empirically found underperformance of distressed firms. These include shareholder advantage (Garlappi et al., 2008; Garlappi and Yan, 2011), limits of arbitrage (Shleifer and Vishny, 1997), and gambling retail investors (Kumar, 2009; Han and Kumar, 2011).

**Shareholder advantage**

Within their valuation framework that explains the low returns of distressed firms, Garlappi et al. (2008) and Garlappi and Yan (2011) predict that beta and the value premium are hump-shaped in distress risk. I therefore test the following proposition:

*P6: There is a hump-shaped relation between BETA and distress risk as well as between the value premium and distress risk.*

**Limits of arbitrage**

Shleifer and Vishny (1997) argue that due to the existence of sophisticated investors, there must be limits of arbitrage for mispricings to persist. Distressed firms have characteristics that are usually associated with limits of arbitrage (Taffler et al., 2004; Kausar et al., 2009). Thus, my research proposition is:

*P7: Limits of arbitrage hinder sophisticated investors' ability to correct the overpricing of distressed firms.*

**Gambling Retail Investors**

Kumar (2009) argues that the priority of retail investors is on gambling, not on profit-maximisation. Coelho et al. (2010) find that Chapter 11 firms have lottery-type characteristics. As such, the demand for lottery-type stocks like distressed firms could lead to their overpricing. I test the following proposition:

*P8: Gambling retail investors drive the overpricing of distressed firms.*

## 3.4 Does one of the components of the distress risk measures drive the returns or is it the composite?

The research questions and research propositions above aim to test explanations of the negative distress risk premium. An alternative is to unravel the negative distress risk premium by exploring the drivers of it. Distress risk measures are composite measures drawing their explanatory power from accounting- and/or market-based variables. Since the composite distress risk measures are found to be significant in subsequent stock returns, one or more of its components must be significant in subsequent stock returns. Therefore, I test the following proposition:

*P9: One or more of the components of the distress risk measures drive the observed distress risk premium.*

# CHAPTER 4: DATA AND METHOD

## 4.1 Sample Selection

### 4.1.1 Selection Criteria and Data Sources

The sample contains all UK non-financial firms listed in the Main market segment of the London Stock Exchange (LSE). In the following, I outline the selection process and the data sources used.

The primary data source is the London Share Price Database (LSPD) with a total number of over 20,000 firms. Stepwise, I discard firms irrelevant for this research or where market or accounting data is not (sufficiently) available. First, I exclude secondary and non-equity listings, non-UK companies, companies not denominated in £, and financial industry firms (e.g. banks, insurance companies, trusts and investment companies).

Second, the LSPD sample is matched with Datastream, the source of market data i.e. the sample is limited to the firms that have market data available in Datastream. I further exclude companies that Datastream classifies as secondary and non-equity listings, non-UK/£ companies, or financial industry firms.

Third, the market data sample is then checked for available accounting data on Datastream. I also match the sample (by e.g. company name, SEDOL, ISIN) with other accounting data sources such as Exstat and Company Analysis. For some failed firms I use hand-collected data from Fame (Bureau van Dijk) and the London Business School Library (LBS). Exstat is the primary accounting data source for the early sample years while Datastream and Company Analysis have good coverage in more recent years. The following order is generally used when accounting data is available from multiple sources: Datastream, Exstat then Company Analysis.

### 4.1.2 Market Segments and Empirical Studies

London Stock Exchange (LSE) offers primarily two market segments for equity listings, the Main market and the Alternative Investment Market (AIM).[17] There are a number of structural differences between the two segments:

- As with other prime standards in the EU, Main market is regulated by EU law. In contrast, AIM is privately operated by LSE, implements less strict trading rules, and falls under the classification of the Multilateral Trading Facility (MTF).
- Main-listed firms require a minimum free-float of 25% and a minimum market capitalisation of £ 700k. In contrast, AIM rules do not prescribe such minimum liquidity requirements.
- AIM firms are required to have a nominated advisor that is responsible for all transactions and liaises with AIM regulation to confirm that admission criteria and AIM rules are met.
- Main-listed firms must provide financial information in a more frequent and timely manner than AIM-listed firms. For instance, annual and half-year accounts are required to be published within four months after the financial closing date (for AIM it is six months). Interim management statements must only be provided for Main-listed firms.

[17] The Unlisted Securities Market (USM) was closed shortly after the introduction of AIM.

- International Financial Accounting Standards were introduced for Main-listed firms from January 2005 while for AIM firms from January 2007.
- Main market firms have to conform with the corporate governance rules of the Financial Service Authority (FSA) while for AIM firms there is no official requirement (expected market practice).
- AIM firms are eligible for tax benefits schemes (e.g. Venture Capital Tax relief) that are designed to encourage investment in small-high risk firms (HM Revenue & Customs).

These arguments illustrate that Main and AIM have fundamental differences in their listing requirements. The effect is illustrated by the following two examples. The average failure rate of Main is 0.91% compared to an average failure rate of 2.80% at AIM (not tabulated) implying that AIM firms are more risky than Main firms. Further, firm characteristics are significantly different between the two segments. As of January 2012, 884 UK firms were listed on Main while approximately the same number of firms was listed on AIM (902). However, UK Main firms have about 97.49% of the total market capitalisation.[18] I apply the selection process described above as well to firms listed on AIM or Unlisted Securities Market (USM) and compare the market capitalisation (median) of the sample with Main firms (from portfolio year 1981). Figure 1 illustrates that there is a substantial difference in annual market capitalisation especially for the more recent years. Based on the differences in listing requirements (e.g. minimum liquidity requirements, introduction of IFRS) and firm characteristics I

[18] Trading Summary Statistics January 2012, London Stock Exchange, See: London Stock Exchange, http://www.londonstockexchange.com/statistics/home/statistics.htm (accessed 10th Feb 2012).

argue that studies have to differentiate between market segments and that combining firms of different market segments in the same analysis leads to less robust results.

My sample is limited to firms listed on the Main market segment of London Stock Exchange.

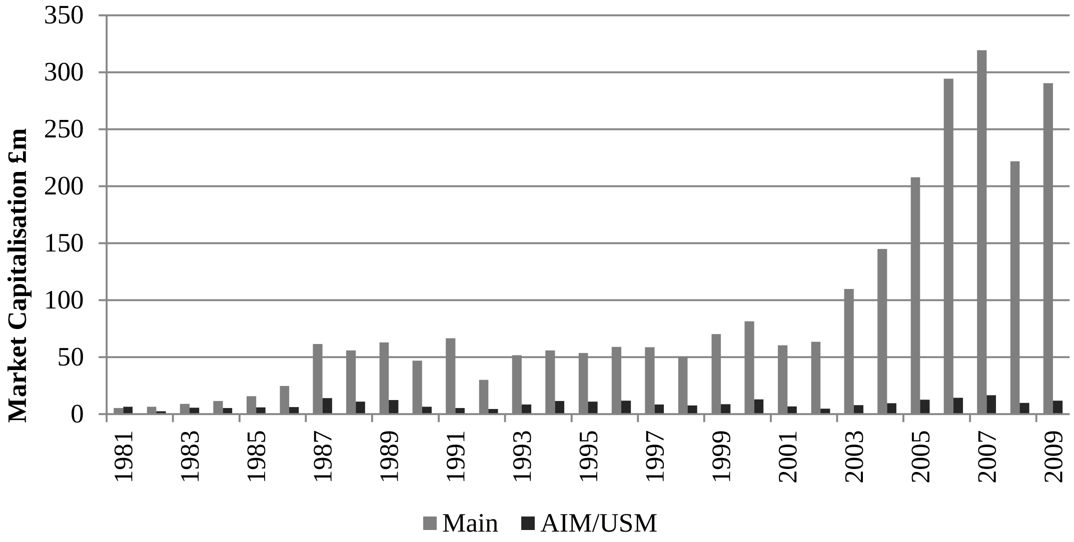


**Figure 1 Market Capitalisation Main and AIM/USM**
This figure shows the median market capitalisation of UK non-financial firms listed in the Main, AIM and USM segment of the London Stock Exchange. Market capitalisation is taken at the end of each September between 1981 and 2009.

### 4.1.3 Key Dates and Time-Subscripts

Empirical studies on stock markets use information cut-off dates where data is available or assumed to be available. This cut-off date is the portfolio formation date (PFD). US studies usually choose the PFD to be at the end of June. It is assumed that most firms have their financial year-ends at the end of December and thus, with a time-lag of six months accounting data is made public by the end of June latest.[19]

Agarwal and Taffler (2008b) find that for the UK, financial year-ends are more distributed in the calendar year. In their sample, 37% of the firms have financial year-ends in December while about the same number of firms have year-ends between January and April with approximately 22% of firms having March year-ends. Agarwal and Taffler (2008b) choose the PFD to be at the end of September. I indicatively check the financial year-ends of my sample and make a similar observation as Agarwal and Taffler (2008b). Figure 2 reports that 39% of the companies have a financial year-end in December and 22% in March. The line shows the average age of the accounting data using a time-lag of five months allowing for accounting data to made public.[20] It shows that the most up-to-date accounting numbers are available using a PFD at the end of August (average age 8.8 months). However, for UK studies it became standard to use a portfolio formation date at the end of September (e.g. Agarwal and Taffler, 2008b; Christidis and Gregory, 2010) and thus, I follow their approach and set the PFD to the end of September/beginning of October. In fact, Figure 2 shows that the average age of accounting data at the end of September (9.0 months) is only marginally higher than at the end of August.

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[19] This stems from listing requirements. Today, firms listed at NYSE Amex are required to submit their annual reports to shareholders and to the exchange not later than four months after the close of the last preceding fiscal year of the company (NYSE Amex LLC Company, § 611 TIME OF PUBLICATION).

[20] Similar to NYSE, UK Main market (LSE) firms are obliged to submit their annual reports no later than four months after the close of the last preceding fiscal year of the company. See: London Stock Exchange, http://www.londonstockexchange.com/companies-and-advisors/Main market/documents/brochures/Main market-continuing-obligations.pdf (accessed 20th Oct 2011).

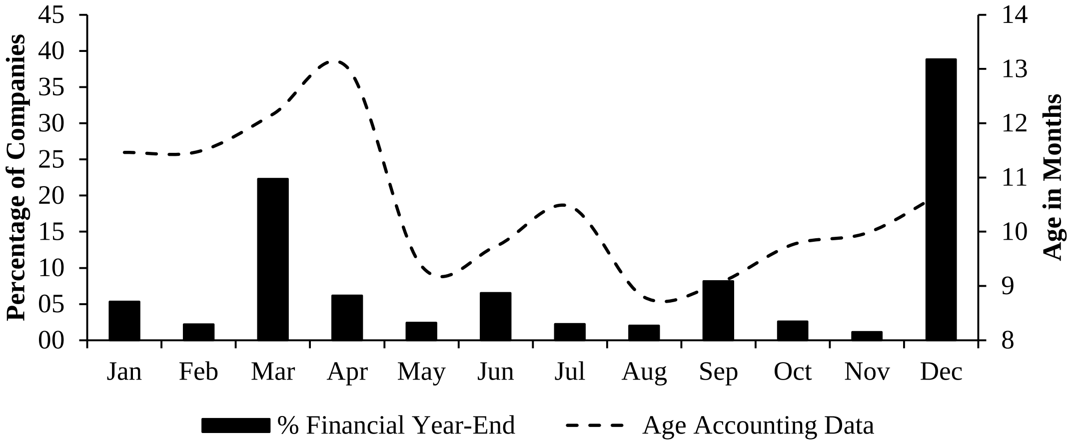


**Figure 2 Financial Year-Ends 1979 to 2009**
This figure shows indicative information on financial year-ends of the sample from 1979 to 2009. The sample includes UK non-financial firms listed in the Main market segment of the London Stock Exchange. Financial Year-End presents the Percentage of Companies in the sample with financial year-ends in the respective month averaged across years. Average Age Accounting Data is the average time from the financial year-end month until the respective month. The average is weighted by the share of financial year-end and includes a five month time lag.

This study uses annual data intervals. A portfolio year is thus defined as the twelve months from October to September. Throughout this document, subscript t denotes the beginning of each portfolio year (i.e. October). Subscript m is an integer between 1 and 12 and denotes the month-ends of the portfolio year from October to September. As such, t denotes the beginning of October in portfolio year t, t+1 is the end of October in portfolio year t, t+2 the end of November,…, t+12 is the end of September in portfolio year t. Likewise, t-1 denotes the previous portfolio year.

To be included in the sample, companies must be listed for at least 12 months. While market data is taken at the end of September, while accounting data is used with a lag of five months i.e. to be included at t, companies must have the fiscal year-ends between May t-1 and April t. I relax this restriction for failed firms: in the portfolio year of failure I use the most recent accounting data with fiscal years ending between May t-2 and April t.

### 4.1.4 Bankrupt Firms

An important part of this study is to identify firms that went bankrupt. However, neither bankruptcy nor failure is a strictly defined term. Karels and Prakash (1987) identify this problem and clearly illustrate it with a summary of terms that have been used (Table 1 page 576, Karels and Prakash (1987)). To have a clean definition of economic failure, I identify it by equating it with one of the following failure-terminology: liquidation, administration/ receivership or valueless company.[21] The following sources are used to identify and cross-check the sample of failed firms.

First, I use the death codes given in LSPD. Death codes 16 (receiver appointed/liquidation, probably valueless, but not yet certain) and 20 (in administration/administrative receivership) are included according to the failure-terminology. Firms with codes 7 (liquidation, usually valueless, but there may be liquidation payments) and 21 (cancelled and assumed valueless) are included unless shareholders received any terminal payment. In contrast to Christidis and Gregory (2010), I exclude all other cases of cancellations or suspensions. Second, I manually complement the sample with the failures provided by the Capital Gains Tax Book/HM Revenue & Customs (companies in receivership and/or liquidation or companies of negligible value). Third, I use Factiva (primary source is Regulatory News Service) to

[21] As Agarwal and Taffler (2007) point out, in the UK the term bankruptcy applies only to persons. To conform to other studies, I use it interchangeably with failure or liquidation/receivership and valueless companies.

manually complement and cross-check all failures (receivership or administration announcements).

The failure date is given by the last trading day of the failed company. It is found in the Regulatory News Service, LSPD or Datastream (in that order). The failure date is generally found to be identical across the sources.

Following Agarwal and Taffler (2008b), the monthly return is set to -100.0% in the month of failure.

#### 4.1.5 Final Sample

Table 1 reports the observation and failures per portfolio year. The total sample covers the portfolio years 1979 to 2009 (2,748 unique firms of which 274 failed and in total 28,804 firm years/observations). There are usually not many failures per portfolio year but to be calibrated, the logit regressions of the hybrid bankruptcy prediction models require a certain amount of failures to be calibrated. I use the first six years for calibration (portfolio years 1979 to 1984) and the remaining portfolio years for my analysis (portfolio years 1985 to 2009).

The final sample contains the 300 months from October 1985 to September 2010 and is represented by portfolio years 1985 to 2009. It includes 2,428 unique firms of which 202 failed and a total of 22,217 firm years/observations. The average failure rate is 0.91%.

## Table 1 Observations in Sample

This table gives an overview of my sample based on all UK non-financial firms listed in the Main market segment of the London Stock Exchange. A Portfolio Year is the twelve month period starting with October each year from 1979 to 2009. No. Observations is the number of sample firms. No. Failures is the number of failed firms during the portfolio year. Failure Rate is failures over observations. Failures are from LSPD (death codes 7, 16, 20 and 21), the Capital Gains Tax Book (receivership and/or liquidation, negligible value) and the Regulatory News Service from Factiva (receivership, administration).

| **Portfolio Year** | **No. Observations** | **No. Failures** | **Failure Rate** |
|---|---:|---:|---:|
| 1979 | 1,067 | 8 | 0.75 |
| 1980 | 1,141 | 13 | 1.14 |
| 1981 | 1,132 | 20 | 1.77 |
| 1982 | 1,108 | 8 | 0.72 |
| 1983 | 1,089 | 13 | 1.19 |
| 1984 | 1,050 | 10 | 0.95 |
| 1985 | 1,018 | 4 | 0.39 |
| 1986 | 954 | 1 | 0.10 |
| 1987 | 907 | 2 | 0.22 |
| 1988 | 866 | 1 | 0.12 |
| 1989 | 841 | 9 | 1.07 |
| 1990 | 811 | 19 | 2.34 |
| 1991 | 824 | 17 | 2.06 |
| 1992 | 1,011 | 8 | 0.79 |
| 1993 | 1,015 | 4 | 0.39 |
| 1994 | 1,064 | 6 | 0.56 |
| 1995 | 1,213 | 7 | 0.58 |
| 1996 | 1,265 | 9 | 0.71 |
| 1997 | 1,280 | 14 | 1.09 |
| 1998 | 1,235 | 13 | 1.05 |
| 1999 | 1,111 | 10 | 0.90 |
| 2000 | 987 | 9 | 0.91 |
| 2001 | 916 | 20 | 2.18 |
| 2002 | 843 | 12 | 1.42 |
| 2003 | 747 | 7 | 0.94 |
| 2004 | 669 | 6 | 0.90 |
| 2005 | 606 | 1 | 0.17 |
| 2006 | 559 | 2 | 0.36 |
| 2007 | 510 | 9 | 1.76 |
| 2008 | 493 | 8 | 1.62 |
| 2009 | 472 | 4 | 0.85 |
| **Total Sample** | **28,804** | **274** | **0.95** |
| Firms | 2,748 | | |
| **Final Sample 1985 to 2009** | **22,217** | **202** | **0.91** |
| Firms | 2,428 | | |
| Obs/Firm | 9.15 | | |

## 4.2 Distress Risk Models

There are a number of bankruptcy prediction models (distress risk measures) available in literature. In the following, I describe the models I employ in my study starting with the hybrid approach and followed by the accounting-based and market-based approaches with a description of the required input variables (see Table 2A on page 91 for a summary of the key variables).

### 4.2.1 Hybrid Model

**Model**

Hybrid models are defined as models that use both accounting and market data to assess the risk of a firm going bankrupt. In the literature, hybrid models frequently take on the functional form of discrete hazard models using logistic regression functions. Shumway (2001) introduces a discrete hazard model of the basic form to estimate bankruptcy risk:

$$P_{i,t} = \frac{e^{\alpha_t + \boldsymbol{\beta}\mathbf{X}_{i,t}}}{1 + e^{\alpha_t + \boldsymbol{\beta}\mathbf{X}_{i,t}}} = \frac{1}{1 + e^{-\alpha_t - \boldsymbol{\beta}\mathbf{X}_{i,t}}} \qquad (2)$$

where $P_{i,t}$ is the probability at time t that firm i will go bankrupt in t+m, $\boldsymbol{\beta}$ is the coefficient vector and $\mathbf{X}$ is the explanatory variables matrix. This study uses annual data to assess each year the risk that a firm will go bankrupt in the next twelve months. I apply an expanding window approach with a fixed start date and annual observations.

**Dependent Variable**

The probability of default for firm i at time t is conditional on survival until t. The dependent variable is of binary form i.e. survival or failure in t+m. Following Chava and Jarrow (2004) and Campbell et al. (2008) I specify the discrete probability of failure at time t as

$$P_{i,t}\left(Y_{i,t+m}=1 \middle| Y_{i,t+m}=0\right)=\frac{1}{1+e^{-\alpha_t-\boldsymbol{\beta}\mathbf{X}_{i,t}}} \tag{3}$$

where $Y_{i,t+m}$ is coded 1 if the company failed (0 if not) in t+m and $\mathbf{X}_{i,t}$ is the vector of the time varying covariates known at time t and with its coefficients given by $\boldsymbol{\beta}$.

**Independent Variable**

At the beginning of each portfolio year t, I take the independent variables for each firm. The analysis tests the basic model of Shumway (2001) (Shum) and the specifications in Campbell, Hilscher and Szilagyi (2008) (CHS) and Christidis and Gregory (2010) (CG). In the following, I introduce the variables required for the hybrid models. They are classified as accounting variables, market variables and macro-economic and other variables.

**Accounting Variables**

Accounting variables are taken at t with a minimum time-lag of five months between the fiscal year-end and PFD.

- TA is book value of total assets.
- BV is book value of shareholders' equity less preference shares and minorities.
- TL is the difference between TA and BV. All obligations except those attributable to common equity holders are treated as liabilities.

- MTA is the market alternative to TA. It is the sum of market value of common equity (SIZE) and book value of total liabilities (TL).
- NITA and NIMTA are profitability ratios. It is net income - after minorities and preference shares - over TA or MTA.
- TLTA and TLMTA represent the leverage of the firm from a shareholder perspective. It is TL over TA or MTA.
- CASHMTA and NCASHMTA is cash or net cash over MTA. Cash consists of cash and cash equivalents. For net cash (NCASH), I deduct bank overdrafts (i.e. short-term debt).
- BM is the commonly used book-to-market equity ratio i.e. BV over SIZE.
- CFMTA is cash flow over market value of total assets. For cash flow I take net income and add back depreciation and amortisation and deduct (add) the change in current assets excluding cash (current liabilities excluding short-term debt).

**Market Variables**

Market variables are taken at t.

- SIZE is the market value of common equity.
- RSIZE is a relative size measure. It is the natural log of the firm's SIZE over the aggregate market value of the FTSE All Share index.
- PRICE is the unadjusted or raw stock price.
- EXRET is the company's log excess return over the FTSE All Share over the prior twelve months ($EXRET = \log(1+R_{i,12m}) - \log(1+R_{FTSE\ All,12m})$)

- SIGMA is the annualised standard deviation of daily returns over the three months prior to t.[22] I follow Campbell et al. (2008) and use the cross-sectional average for companies that have less than five non-zero observations in the three-month window. There are on average 3.3% observations (with a maximum of 8.8% in 1995 and a minimum of 0.4% in 1986) and 30 failures with less than five non-zero observations in my study.

**Macro-Economic Variables**

Since hybrid models contain market prices or market-based variables, one would expect hybrid models to take account of macro-economic information. However, Christidis and Gregory (2010) find several macro-economic variables to be significant in their bankruptcy prediction models. Based on their results, I incorporate similar macro-economic variables. I follow their argument that the deflated one-month Treasury Bill rate (DEFTBR) will affect the firm's financing. As such, a secure financing strengthens the solvency of a company and reduces the risk of going bankrupt. Further, I include the term structure premium (LONGSHT) which is the yield difference between the long-term government bond and the one-month Treasury Bill rate. A negative term structure (short-term yield is higher than long-term yield) is generally perceived as a recession indicator. Since failure rates are higher in recessions (Campbell et al., 2008), I test as well for significance of LONGSHT. For the same reasons, I test whether the change in the UK industrial production index (INDPROD) is significant in bankruptcy prediction. All macro-economic variables are taken at t.

[22] For calculation details see Campbell et al. (2008: p. 2936).

### 4.2.2 Accounting-Based Model

Z-score is the seminal accounting-based model. It was originally introduced by Altman (1968) and is a widely used benchmark in bankruptcy prediction literature. With the use of multiple discriminant analysis, Altman (1968) chooses from different ratios the linear combination that best differentiates between non-failure and failure. Taffler (1983) uses a similar approach to introduce a UK-version of the model. The full z-score model is published in Agarwal and Taffler (2007):

$$\text{z-score} = 3.2 + 12.18x_1 + 2.50x_2 - 10.68x_3 + 0.029x_4 \tag{4}$$

where

- $x_1$ measures profitability by taking profit before tax over current liabilities (PBTCL).
- $x_2$ is a working capital ratio and defined as current assets over total liabilities (CATL).
- $x_3$ represents financial risk and is current liabilities over total assets (CLTA).
- $x_4$ is the No-Credit Interval (NCI) and measures the degree of liquidity. NCI is calculated as:

$$\text{NCI} = \frac{\text{quick assets-current liabilities}}{\frac{\text{sales-profit before tax-depreciation}}{365}} \tag{5}$$

Variables are defined as above or directly taken from the balance sheets. Agarwal and Taffler (2008a) note that the model was constructed in 1977 and thus, it is completely out-of-sample.

Please note that a higher z-score is associated with lower default risk. Following Hillegeist et al. (2004) I change the sign of z-score for the correlation analysis, the cross-sectional and logit regressions (information content tests) to conform to the other alternative hybrid and market-based bankruptcy prediction models that associated a higher score with higher default risk. This has no effect on the results but makes the coefficients more comparable and easier to interpret jointly.

### 4.2.3 Market-Based Model

The third default prediction model is a market-based approach. Traditional market-based models apply the derivative pricing model of Merton (1973) and the option pricing approach of Black and Scholes (1973) (BSM) and derive the distance to default that is implemented in a cumulative density function. The use of the option pricing formula requires two assumptions: the total firm value follows a Brownian motion and total debt is a single discount bond with time T to maturity. Equity value is then defined by the option pricing formula:

$$MV = AN(d_1) - e^{-r_f T}\, MTL\, N(d_2) \tag{6}$$

where MV is the value of equity, A the value of the firm, $r_f$ is the risk-free rate, MTL the market value of total liabilities and $N(\cdot)$ describes the cumulative standard normal distribution. $d_1$ is given by

$$d_1 = \frac{\ln\left(\frac{A}{MTL}\right) + \left(r_f + 0.5\sigma_A^2\right) T}{\sigma_A T} \tag{7}$$

And $d_2$ is given by

$$d_2 = d_1 - \sigma_A\sqrt{T}. \tag{8}$$

where $\sigma_A$ is the firm volatility and defined as:

$$\sigma_A = \frac{\left(\frac{A}{MV}\right)N(d_1)}{\sigma_E} \tag{9}$$

where $\sigma_E$ is equity volatility. McDonald (2002) shows that distance to default is calculated and implemented in a cumulative density function as

$$P_{BSM} = N(-DD_{BSM}) = N\left(-\frac{\ln\left(\frac{A}{MTL}\right) + \left(\mu - 0.5\sigma_A^2\right)T}{\sigma_A\sqrt{T}}\right) \tag{10}$$

where μ is the expected return over the forecasting period.

The calculation of the BSM function requires solving Eq. (6) and Eq. (9) simultaneously. However, Bharath and Shumway (2008) offer a less sophisticated version of the distance to default measure.

Bharath and Shumway (2008) separate the informational benefit of the BSM framework. Their empirical results suggest that the value of traditional market-based models lies in the functional form rather than in solving the BSM function. As such, their naïve distance to default measure retains the functional form of the option pricing model but bypasses the simultaneous calculation of unobservable parameters.

According to Bharath and Shumway (2008), firm volatility can be written as the weighted average of equity and debt volatility:

$$\sigma_{A,\text{naïve}} = \frac{\text{MV}}{\text{MTA}}\sigma_{E} + \frac{\text{TL}}{\text{MTA}}\sigma_{D} \tag{11}$$

Note that Eq. (11) uses TL (book value of total liabilities) as an indicator for the market value of total liabilities. Debt volatility is estimated by:

$$\sigma_{D,\text{naïve}} = 0.05 + 0.25\sigma_{E}. \tag{12}$$

Bharath and Shumway (2008) use the five percentage points to represent the term structure and allow for a variation of 25.0% of the equity volatility.

With these variables Bharath and Shumway (2008) (BS) define their naïve distance to default measure and probability of default as:

$$P_{\text{naïve}} = N(-DD_{\text{naïve}}) = N\left(-\frac{\ln\left(\frac{\text{MTA}}{\text{TL}}\right) + \left(\text{ER1y} - 0.5\sigma^{2}_{A,\text{naïve}}\right)T}{\sigma_{A,\text{naïve}}\sqrt{T}}\right) \tag{13}$$

where $P_{\text{naïve}}$ is the probability of default for the BS model, $N(\cdot)$ describes the cumulative standard normal distribution, ER1y is the return over the previous year. The strike price is TL that is assumed to be a single discount bond maturing at $T$. T is set to one year since this study uses a one-year prediction horizon.

The data requirement for the BS contingent claims model is:

- MTA, the market value of total assets measured as the current market value of common equity (SIZE) and the market value of total debt (i.e. strike price) proxied by TL.
- Equity volatility $\sigma_E$ is SIGMA
- ER1y is the return over the previous twelve months.

Bharath and Shumway (2008) find that their naïve approach performs slightly better than the BSM approach while Agarwal and Taffler (2008a) show that there is no difference between the two. As such, the naïve BS measure is a validated alternative to the more sophisticated BSM function.

### 4.2.4 Data Winsorisation

Empirical studies in finance manipulate the data to remove outliers from the sample. The data in this study is manipulated as well because I winsorise all variables or ratios at the 5.0% level across all firm year observations. That is, I rank the sample on each variable or ratio and replace the lowest (highest) 5.0% with the 0.05 (0.95) fractile of each variable. Similar to Hillegeist et al. (2004), I truncate distress risk scores at ±18.4207. This equals a default probability of 0.00000001 and 0.99999999.

In contrast to other studies, there are no further data manipulations. For instance, Campbell et al. (2008) winsorise share price above \$ 15 without providing a clear rationale for doing so.[23] Campbell et al. (2008) and Christidis and Gregory (2010) add 10.0% of the difference between market and book equity to total assets. They adjust the book value of equity in a similar manner. The adjustment is argued to be valid since ‘it corrects book values that are probably mis-measured’ (Campbell et al., 2008: p. 2905). On this basis, I find it hard to judge on mis-measurement and whether this adjustment actually captures the mis-measurement. In fact, I argue that it fails to identify the mis-measurement since the market value of total asset-ratios (containing the book value of total liabilities and market value of equity) might still carry the assumed ‘mis-measurement’.

## 4.3 Evaluating Distress Risk Models

Studies testing the performance of distress risk measures use the receiver operating characteristics curves to test for forecasting accuracy, information content tests to test the bankruptcy related information carried by the distress risk measures, and the test of economic value with differential misclassification costs. In the following, I present the method of each.

### 4.3.1 Receiver Operating Characteristics

Receiver Operating Characteristics (ROC) curves is a method to assess the appropriateness of prediction parameters. It has been widely used in the field of

[23] Campbell et al. (2008: p. 2912): ‘Exploratory analysis suggests that price per share is relevant below \$15, and so we winsorise price per share at this level before taking the log.’

medicine (Hanley and McNeil, 1982). Today it is as well an established tool to validate bankruptcy prediction models (Sobehart and Keenan, 2001; Chava and Jarrow, 2004; Agarwal and Taffler, 2008a).

Vassalou and Xing (2004) provide a precise description: Let θ be the percentage of firms that default $\left(\theta=\frac{\text{Failures}}{\text{N}}\right)$. Let λ be an integer between 1 and 100. λ represents the λ% of firms with highest default risk known at time t $\left(\lambda=\frac{\text{Firms}}{\text{N}}\right)$. For each λ at time t, the firms that fail in t+m are counted. Let $f(\lambda)$ be a function of λ that divides the number of failures in the λ% by the total number of failures. It follows:

$$f(\lambda) = \frac{\lambda}{\theta} \text{ for } \lambda<\theta \text{ and} \tag{14}$$

$$f(\lambda) = 1 \text{ for } \lambda\geq\theta \tag{15}$$

A perfect bankruptcy prediction model - that is the ranking on default probability at time t is equal to the ranking of failures at time t+m – would be able to capture all defaults for each integer λ. The function $f(\lambda)$ would take the value of 1. If we were to plot the ROC curve – that is the plot of integer λ against $f(\lambda)$ – the graph would be at 1 for each λ. See Figure 3.

A random bankruptcy prediction model – that is the ranking at time t is not correlated with the ranking of failures at time t+m – would have the same percentage of failures across each integer λ. The function $f(\lambda)$ would take the value of λ. The ROC curve corresponds to a 45° line between the integer λ and $f(\lambda)$. See Figure 3.

For each other model, the function $f(\lambda)$ would take the value $\frac{\lambda}{\theta}$. Since we expect a bankruptcy prediction model to be better than a random model, the ROC curve is expected to be between the perfect and the random model.

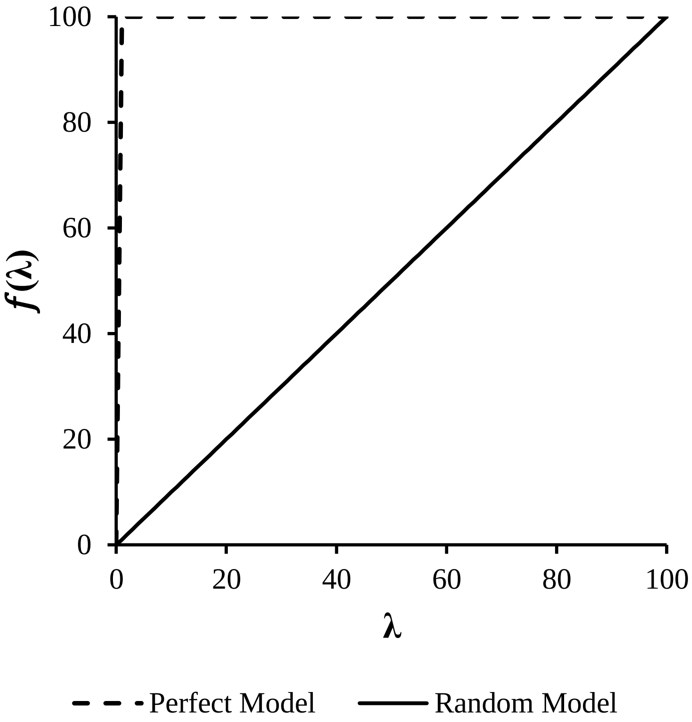


**Figure 3 Receiver Operating Characteristics Curve**

The figure illustrates the receiver operating characteristics curves for a perfect and random bankruptcy prediction model. $\lambda$ is an integer between 0 and 100 and describes the $\lambda$% of the highest bankruptcy risk firms. $\boldsymbol{f}(\lambda)$ is a function of $\lambda$ that divides the number of failures in the highest $\lambda$% of default risk by the total number of failures.

To compare the predictive ability of two models one has to calculate the area under the ROC curve (AUC). Sobehart and Keenan (2001) argue that the AUC is the decisive indicator of a model's predictive ability. I calculate AUC using the Wilcoxon statistic (Hanley and McNeil, 1982). Sobehart and Keenan (2001) further show that the standard error of the AUC is given by

$$\mathrm{SE(A)}=\sqrt{\frac{\mathrm{AUC(1\text{-}AUC)}+(\mathrm{n_F}\text{-}1)(\mathrm{n_F}\text{-}\mathrm{AUC}^2)+(\mathrm{n_{NF}}\text{-}1)(\mathrm{Q_2}\text{-}\mathrm{AUC}^2)}{\mathrm{n_F n_{NF}}}}. \tag{16}$$

where AUC is the area under the ROC curve, $\mathrm{n_F}$ the number of failed firms and $\mathrm{n_{NF}}$ the number of non-failed firms. $\mathrm{Q_1}$ is defined as $\frac{\mathrm{AUC}}{(2\text{-}\mathrm{AUC})}$ and $\mathrm{Q_2}$ is defined as $\frac{2\mathrm{AUC}^2}{(1+\mathrm{AUC})}$.

The test-statistic to compare the area under the curves of two different models follows a normal distribution and is suggest by Hanley and McNeil (1983):

$$\mathrm{z}=\frac{\mathrm{AUC_1\text{-}AUC_2}}{\sqrt{\left(\mathrm{SE(AUC_1)}\right)^2+\left(\mathrm{SE(AUC_2)}\right)^2\text{-}2\mathrm{rSE(AUC_1)SE(AUC_2)}}} \tag{17}$$

where SE is the standard error and r the Pearson correlation between the two areas.

Engelmann, Hayden and Tasche (2003) put the ROC curve into the context of the cumulative accuracy ratio (AR) and show that the AUC contains the same information as the AR. They find that AR is just a linear transformation of the area below the ROC curve. To compare the AUC of two models AR is defined as

$$\mathrm{AR}=2(\mathrm{AUC_1\text{-}AUC_2}) \tag{18}$$

### 4.3.2 Information Content Test

**Model**

I use information content tests to examine bankruptcy prediction models. Information content tests reveal whether bankruptcy prediction models carry more information than another set of variables. They complement the ROC curve analysis since Hillegeist et al. (2004) argue that (i) ROC curve analysis leaves users with a dichotomous option but in reality users are not faced with such a decision. Moreover, users of bankruptcy prediction models are likely to determine credit terms. (ii) ROC curve analysis is based on type I and type II errors that are context specific and thus do not give information about the associated error costs. As such, Hillegeist et al. (2004) propose a hazard model of the following form:

$$P_{i,t+m}=\frac{e^{\alpha_t+\boldsymbol{\beta}\mathbf{X}_{i,t}}}{1+e^{\alpha_t+\boldsymbol{\beta}\mathbf{X}_{i,t}}}=\frac{1}{1+e^{-\alpha_t-\boldsymbol{\beta}\mathbf{X}_{i,t}}} \tag{19}$$

where $P_{i,t+m}$ is the actual failure probability of firm i at time t+m. $\alpha_t$ is the baseline hazard rate (proxied by the trailing one-year failure rate), $\mathbf{X}_{i,t}$ is a matrix of independent variables and $\boldsymbol{\beta}$ is a column vector of estimated coefficients.

**Dependent Variable**

$P_{i,t+m}$ is the actual failure probability. As such, the actual probability is of binary form and takes the value of 1 if the company failed and 0 if not.

**Independent Variable**

The difference to the hazard model in Eq. (2) lies in the independent variables and their timing. First, Eq. (19) includes the baseline hazard rate $\alpha_t$. Second, the independent variables $\mathbf{X}_{i,t}$ are taken at t. Since I use scores from the hybrid, accounting-based and market-based models and to avoid look-ahead bias, these have to be estimated over the previous months in order to be known at t.[24] To be consistent with the underlying assumptions of the logit model, I follow Hillegeist et al. (2004) and transform the default probabilities from the market and hybrid model into logit scores:

$$\text{score} = \ln\left(\frac{p}{1-p}\right) \tag{20}$$

The scores are truncated at ±18.4207 i.e. I winsorise the probabilities to be between 0.00000001 and 0.99999999.

[24] For robustness, I include as well established risk factors in the vector $\mathbf{X}_{i,t}$.

### 4.3.3 Economic Value of Distress Risk Measures

Agarwal and Taffler (2008a) argue that while the ROC curve analysis assumes equal costs for lending to a firm that subsequently fails and not lending to a firm that does not fail, in practice, the costs associated with the two misclassifications are different. While refusal to lend to a subsequently non-failed firm simply leads to the loss of extra revenue, lending to a firm that subsequently fails can lead to substantial losses. I follow the approach of Agarwal and Taffler (2008a) to assess the economic impact of using different models in a competitive market. I use the loan pricing model of Stein (2005) and Blöchlinger and Leippold (2006) to derive the credit spread as a function of the credit score (S) by:

$$R=\frac{p(Y=1|S=t)}{p(Y=0|S=t)}LGD+k \tag{21}$$

where R is the credit spread, p(Y=1|S=t) is the conditional probability of failure for a score of t, p(Y=0|S=t) is the conditional probability of non-failure for a score of t, LGD is the loss in loan value given default, and k is the credit spread for the highest quality loan.

I closely follow the method in Agarwal and Taffler (2008a) and assume a simple loan market worth £ 100.0 billion with banks competing for business each using a different bankruptcy prediction model. To keep the analysis tractable and objective, I assume all loans are of same size and have same LGD. The banks reject customers that fall in the bottom 5.0% according to their respective models and quote a spread as defined in Eq. (21) for all the other customers. The customer chooses the bank which quotes the lower spread. If the quoted spreads are equal, the customer randomly chooses one of the banks (or equivalently, the business is split equally between the banks). For each year, I independently sort my sample firms on their probability of failure based on different bankruptcy prediction models and group them into 100 categories for each of the models.

Due to the number of defaults and the 100 categories, I recognise that some of the categories are sparsely populated with failures. In extreme cases, this could lead to a lower default probability for the next higher risk category and thus, to a lower credit spread although failure risk is higher. In order to have a monotonic increase in credit spread with credit risk, I apply the method described in Burgt (2007) to smooth default probabilities of the categories.

To assess the economic value of using different models for mixed regime loan pricing, I use two measures to evaluate bank profitability, return on assets (ROA) and return on risk-weighted assets (RORWA):

$$\text{ROA} = \frac{\text{Profit}}{\text{Assets lent}} \tag{22}$$

and

$$\text{RORWA} = \frac{\text{Profit}}{\text{risk-weighted assets}} \tag{23}$$

Unlike ROA, which ignores the inherent riskiness of profits, RORWA considers the risk of the outstanding loans and hence, is a more suitable performance measure. Similar to Agarwal and Taffler (2008a), I use the Basel III Foundation Internal Ratings-Based

Approach to derive the value of risk-weighted assets (Basel Committee, 2011). The details are in the appendix to this chapter.

## 4.4 Pricing Distress Risk

### 4.4.1 Cross-Sectional Regression Tests

**Model**

Following Fama and MacBeth (1973), I conduct cross-sectional regression tests on individual stock level using annual independent variables:

$$R_{i,t+m}\text{-}R_{f,t+m}=\alpha_{i,t+m}+\gamma_{1,t+m}BETA_t+\gamma_{2,t+m}LN(SIZE)_t+\gamma_{3,t+m}LN(BM)_t+\gamma_{4,t+m}PYR_t \qquad (24)$$

where subscript t denotes the portfolio year starting at the beginning of October each year from 1985 to 2009 and t+m for integer m = 1 to 12 denotes the month-ends of the portfolio year.

**Dependent Variable**

The dependent variable is excess returns of individual securities. $R_{i,t+m}$ is the return of firm i in month m (integer 1 to 12) in portfolio year t, $R_{f,t+m}$ the one-month UK Treasury Bill rate during month t+m. As such, the dependent variable is the return of firm i at time t+m in excess of the risk-free rate.

**Independent Variable**

Independent variables are taken for each firm at t. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months with a one month time-lag. In cross-sectional regressions, SIZE and BM are included as the natural log.

PYR represents the 11-month return prior to t excluding September (i.e. 11-months period from October t-1 to August t). I also run specifications of this model while including the score of one of the distress risk measures (Shum, z-score and BS), the individual variables of the default measures (e.g. NITA or PBTCL) or distress risk measures orthogonalised by NITA (Shum) and by PBTCL and NCI (z-score).

### 4.4.2 Times-Series Regression Tests

**Model**

In this study, I use the Fama and French (1993) model and the augmented version of Carhart (1997) which includes the momentum factor to measure risk-adjusted returns. While the models are originally developed using US data, it has been used for risk-adjustment in the UK as well (Agarwal and Taffler, 2008b).

Michou, Mouselli and Stark (2010) show that there is no standard approach for estimating the factors in the UK and conclude that the results can be sensitive to the manner in which the factors are constructed. They thus argue that researchers should be aware of the level of robustness of the estimates of abnormal returns. In a similar study, Gregory, Tharyan and Huang (2009) suggest the use of characteristics-matched portfolios to measure abnormal returns in the UK. Both Gregory et al. (2009) and Michou et al. (2010), however, fail to provide evidence that the alternative methods produce estimates that are superior to that of Agarwal and Taffler (2008b). Further, my results show that the Fama and French (1993) and Carhart (1997) models are superior to the CAPM in explaining stock returns; e.g. Tables 15 (Shum), 17 (z-score) and 19 (BS) show that the average adjusted $R^2$ of the factor models is between 83 % and 85% while for CAPM the average adjusted $R^2$ is only between 62 % and 69 % (not tabulated). This shows indeed the empirical value of the models and that the different risk factors are priced in the UK.

Since the Fama and French (1993) model (RmRf, SMB and HML) is a reduced version of the Carhart (1997) model (RmRf, SMB, HML and WML), I only present the Carhart (1997) model here:

$$R_{i,t+m}\text{-}R_{f,t+m}=\beta_1+\beta_{MKT}RmRf_{t+m}+\beta_{SMB}SMB_{t+m}+\beta_{HML}HML_{t+m}+\beta_{WML}WML_{t+m}+\varepsilon_{i,t+m} \quad (25)$$

where $R_{i,t+m}$ is the return on portfolio i during month m (integer 1 to 12) in portfolio year t, $R_{f,t+m}$ the one-month UK Treasury Bill rate at the beginning of month t+m, $RmRf_{t+m}$ the return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate during month t+m, $SMB_{t+m}$ the return on the mimicking portfolio for the size factor, $HML_{t+m}$ the return on the mimicking portfolio for the BM factor, $WML_{t+m}$ the return on the mimicking portfolio for the return momentum factor during month t+m, and $\varepsilon_{i,t+m}$ is the error term.

**Dependent Variable**

Test assets for time-series regressions are monthly portfolio excess returns (value-weighted or equally-weighted).

**Independent Variable**

Factors are formed following Fama and French (1993): (i) at the end of each September from 1985 to 2009, I rank all stocks on market capitalisation and sort them into two equally populated portfolios using median. (ii.i) For SMB and HML, I independently rank the stocks on BM and sort them into three portfolios using the 30$^{th}$ and 70$^{th}$

percentile. Six portfolios are then formed at the intersections of the break-points i.e. small-low BM, small-medium BM,…, large-high BM. I calculate value-weighted monthly portfolio excess returns for the subsequent twelve months (t+m). SMB is the difference between average returns of the three small and the three large portfolios (equally-weighted). HML is the difference between average returns of the two high and the two low BM portfolios (equally-weighted). (ii.ii) For WML, I independently rank the stocks on PYR and sort them into three portfolios using the 30$^{th}$ and 70$^{th}$ percentile. Six portfolios are then formed at the intersections of the break-points i.e. small-low PYR, small-medium PYR,…, large-high PYR. I calculate value-weighted monthly portfolio excess returns for the subsequent twelve months (t+m). WML is the difference between average returns of the two high and the two low PYR portfolios (equally-weighted).

## 4.5 Explanations Negative Distress Risk Premium

### 4.5.1 Shareholder Advantage

Garlappi and Yan (2011) predict a hump-shaped relation of BETA, returns, and value premium with distress risk. As such, I form portfolios on the distress risk proxies (hybrid, accounting-based, and market-based) and test whether portfolio BETA and returns (value-weighted and equally-weighted) are hump-shaped with distress risk. In order to do so, I use decile portfolios. That is at the end of each September, I rank the sample firms on default probability and sort into equally populated decile portfolios.

To test the relation of distress risk and the value premium, I independently split all firms into low and high BM using median at the end of each September. I form 20 portfolios at the intersections of the decile distress risk sort and the median BM sort and calculate the value premium for each distress risk portfolio, i.e. the return on a portfolio that is long on high BM stocks and short on low BM stocks in the respective decile distress risk portfolio. Similar to Garlappi and Yan (2011), the value premia (value-weighted and equally-weighted) are risk-adjusted using time-series regressions following Carhart (1997) and as defined in Eq. (25).

### 4.5.2 Limits of Arbitrage and Lottery Stocks

My literature review finds that the proxies for limits of arbitrage are identical to the proxies of lottery-type stocks. As such, my tests are designed to explore whether these characteristics are relevant in pricing distress risk. I follow closely the method of Han and Kumar (2011) to construct a lottery index (LOTT) for each security in my sample. LOTT consists of share price (PRICE), idiosyncratic volatility (IVOL) and idiosyncratic skewness (ISKEW). IVOL and ISKEW are derived as follows: at the end of each September from 1985 to 2009 for each security, I run the regression using the Carhart (1997) model as defined in Eq. (25) over the previous 24 months and collect the residual terms per firm. IVOL is the variance of the residual terms and ISKEW the skewness of the residual terms. I then construct each security's LOTT as follows: at the end of each September from 1985 to 2009, I rank the sample firms on PRICE and form virgintile portfolios. I repeat that for IVOL and ISKEW. LOTT is the sum of each security's virgintile assignments for the sort on PRICE, IVOL and ISKEW divided by 60:

$$\mathrm{LOTT_i} = \frac{\mathrm{P_{i,\,PRICE}} + \mathrm{P_{i,\,IVOL}} + \mathrm{P_{i,\,ISKEW}}}{60} \tag{26}$$

where LOTT is the lottery-index for security i, $P_{i,\,PRICE}$ the assignment to the virgintile portfolios formed on PRICE, $P_{i,\,IVOL}$ the assignment to the virgintile portfolios formed on IVOL, and $P_{i,\,ISKEW}$ the assignment to the virgintile portfolios formed on ISKEW.

For summary statistics and time-series regression tests I form decile portfolios on LOTT at the end of each September from 1985 to 2009. For cross-sectional tests, I employ LOTT and its individual components PRICE, IVOL and ISKEW.

## 4.6 Unravelling the Negative Distress Risk Premium

### 4.6.1 Cross-Sectional Regressions

In Chapter 8 I explore the pricing impacts of the individual variables of the distress risk measures. In order to do so, I break each distress risk measure (Shum, z-score and BS) down into its individual variables and test for relevance in subsequent stock returns using the regression of Fama and MacBeth (1973) as defined in Eq. (24).

In order to remove the impact on subsequent stock returns of a chosen individual variable of the composite distress risk measure, I employ orthogonalised composite measures. That is, at the end of September of each year, I run the following cross-sectional regression with the composite measure as dependent variable and the chosen variable as independent variable:

$$\text{Score}_t = a_t + b_t \text{Variable}_t + \varepsilon_t \tag{27}$$

I then collect the intercept and the error terms, i.e. the part of the composite distress risk measure that is unexplained by the chosen variable.

where $Score_t$ is the score of the distress risk measure at portfolio year t and $a_t$ the regression intercept, $b_t$ the coefficient of $Variable_t$, and $\varepsilon_t$ is the error term. In my analysis I employ four orthogonalised distress risk scores: I orthogonalise (i) the score of Shumway (2001) by NITA, (ii) the z-score (Taffler, 1983) by PBTCL, (iii) the z-score (Taffler, 1983) by NCI, and (iv) the z-score (Taffler, 1983) by PBTCL and NCI.

### 4.6.2 Time-Series Regressions

To test for the impact of profitability on distress risk I use portfolios sorts on profitability (distress) to conduct time-series regressions. I employ the standard asset pricing models as defined in Eq. (25). Similar to Novy-Marx (2010), I also use a profitability factor and add it to the Carhart (1997) model as defined in Eq. (28). The profitability factor is formed in the same way as SMB, HML and WML following Fama and French (1993). At the end of each September from 1985 to 2009, I rank all stocks on market capitalisation and sort them into two equally populated portfolios using median. I independently rank the stocks on PBTCL and sort them into three portfolios using the 30$^{th}$ and 70$^{th}$ percentile. Six portfolios are then formed at the intersections of the break-points i.e. small-low PBTCL, small-medium PBTCL,…, large-high PBTCL. I calculate value-weighted monthly portfolio excess returns for the subsequent twelve months (t+m). PMU is the difference between average returns of the two high and the two low PBTCL portfolios (equally-weighted). As such, the factor is labelled PMU ("Profitable-Minus-Unprofitable") as it represents the return of a portfolio long on profitable firms and short on unprofitable firms. The five factor profitability model therefore is:

$$
\begin{aligned}
R_{i,t+m}\text{-}R_{f,t+m} &= \beta_1+\beta_{MKT}RmRf_{t+m}+\beta_{SMB}SMB_{t+m}+\beta_{HML}HML_{t+m} \\
&\quad +\beta_{WML}WML_{t+m}+\beta_{PMU}PMU_{t+m}+\varepsilon_{i,t+m}
\end{aligned}
\tag{28}
$$

where $R_{i,t+m}$ is the return on portfolio i during month m (integer 1 to 12) in portfolio year t, $R_{f,t+m}$ the one-month UK Treasury Bill rate at the beginning of month t+m, $RmRf_{t+m}$ the return difference of the FTSE All Share Index and the one-month UK

Treasury Bill rate during month t+m, $SMB_{t+m}$ the return on the mimicking portfolio for the size factor during month m in portfolio year t, $HML_{t+m}$ the return on the mimicking portfolio for the BM factor, $WML_{t+m}$ the return on the mimicking portfolio for return momentum, $PMU_{i,t+m}$ is the return on the mimicking portfolio for the profitability effect, and $\varepsilon_{i,t+m}$ is the error term.

In order to test whether the information carried by PMU is already covered by the common risk factors, I run the following time-series regression:

$$PMU_{t+m} = \beta_1 + \beta_{MKT} RmRf_{t+m} + \beta_{SMB} SMB_{t+m} + \beta_{HML} HML_{t+m} + \beta_{WML} WML_{t+m} + \varepsilon_{i,t+m} \quad (29)$$

where $PMU_{t+m}$ is the return on the mimicking portfolio for the profitability effect during month m of portfolio year t. All other variables are as defined above.

## 4.7 Appendix

**Table 2A Key Variables and Definitions**

| **Variable** | **Description** |
|---|---|
| BETA | Beta factor calculated according to Dimson (1979) over the previous 24 months with a ± 1 month lag |
| BM | Book value of shareholders' equity less preference shares and minorities over market value of common equity (BV / MV) |
| BV | Book value of shareholders' equity less preference shares and minorities |
| CASH | Cash and cash equivalents |
| CASHMTA | Cash and cash equivalents over market value of total assets (CASH / MTA) |
| CATL | Current assets over total liabilities (TL) |
| CF | Net income plus depreciation and amortisation plus (minus) change in current assets excluding cash (current liabilities excl. short-term debt) |
| CFMTA | Operating cash flow over market value of total assets (CF / MTA) |
| CLTA | Current liabilities over total assets (TA) |
| DEFLTBR | Deflated one-month Treasury Bill rate |
| ER1y | Return over the previous year |
| EXRET | Log excess return over the FTSE All Share Index over the prior 12-months (EXRET = $\log(1+R_{i,12m}) - \log(1+R_{FTSE\ All,12m})$) |
| INDPROD | Change in UK industrial production index |
| LONGSHT | Difference between the long-term government bond and one-month Treasury Bill rate |
| MTA | Market value of total assets (TL + MV) |
| NCASH | Cash and cash equivalents minus bank overdrafts (i.e. short-term debt) |
| NCI | No-credit interval: (quick assets – current liabilities) / ((sales – profit before tax – depreciation) / 365) |
| NI | Net income after minorities and preference shares |
| NIMTA | Net income over market value of total assets (NI / MTA) |
| NITA | Net income over total assets (NI / TA) |
| PBTCL | Profit before tax over current liabilities |
| PRICE | Unadjusted or raw stock price |
| PYR | 11-month return for the period from October t-1 to August t |
| RSIZE | Log of market value of security i over the market value of the FTSE All Share Index |
| SIGMA | Annualised standard deviation of daily returns for the prior 3-months following Campbell et al. (2008) |
| SIZE (MV) | Market value of common equity |
| TA | Book value of total assets |
| TL | Book value of total liabilities (TA - BV) |
| TLMTA | Total liabilities over market value of total assets (TL / MTA) |
| TLTA | Total liabilities over total assets (TL / TA) |

**Basel Committee (2011): Risk-weighted assets**

According to the latest version of the International Convergence of Capital Measurement and Capital Standards document prepared by the Basel Committee on Banking Supervision (2011), for obligations not already in default, risk-weighted assets are computed as follows:

$$\text{Correlation (R)}=\left[0.12\,\frac{1\text{-}e^{-50PD}}{1\text{-}e^{-50}}\right]+\left[0.24\left(1\text{-}\frac{1\text{-}e^{-50PD}}{1\text{-}e^{-50}}\right)\right] \tag{30}$$

$$\text{Maturity adjustment (b)}=[0.11852\text{-}0.05478*\ln(PD)]^2 \tag{31}$$

$$\text{Capital requirement (K)}= \tag{32}$$

$$[LGD*N((1\text{-}R)\text{^}(\text{-}0.5)*G(PD)+(R/(1\text{-}r))\text{^}0.5*G(0.999))\text{-}PD*LGD]*$$

$$(1\text{-}1.5*b)\text{^}(\text{-}1)*(1+(M\text{-}2.5)*b)$$

$$\text{Risk-weighted assets (RWA)}=K*12.5*EAD \tag{33}$$

**where:**

PD = probability of default (at least 0.03%),

LGD = loss given default,

N(·) = cumulative normal density function,

G(·) = inverse cumulative normal density function,

M = effective maturity, and

EAD = exposure at default.

# CHAPTER 5: EVALUATING DISTRESS RISK MODELS

## 5.1 Introduction

The risk of going bankrupt is of major interest to shareholders, creditors, and employees of a firm. There is a vast body of literature on assessing the risk that individual firms will go bankrupt. There are three main approaches in the literature: (i) traditional models predominantly based on accounting information (e.g. Altman, 1968), (ii) contingent claims based models that view equity as a call option on assets (e.g. Vassalou and Xing, 2004), and (iii) more recent hybrid models that assess bankruptcy risk using both accounting and market data (e.g. Shumway, 2001).

While some of the models are argued to be superior due to their theoretical grounding (e.g. Vassalou and Xing, 2004), eventually, the empirical performance of the approaches is what really matters. Literature provides three methods of testing the empirical performance of bankruptcy prediction models. (i) The receiver operating characteristics (ROC) curve testing forecasting accuracy (Hanley and McNeil, 1982; Sobehart and Stein, 2000), (ii) information content tests testing whether measures contain bankruptcy related information (Hillegeist et al., 2004), and (iii) the illustrative credit loan market testing for economic value when misclassification costs differ (Stein, 2005; Blöchlinger and Leippold, 2006).

However, the existing literature does not provide clean evidence on the usefulness of competing approaches. First, existing literature is incomplete in the use of bankruptcy prediction models. Current tests contain single bankruptcy prediction models (e.g. Vassalou and Xing, 2004; Bharath and Shumway, 2008) or two of the three available approaches (e.g. Hillegeist et al. (2004) use accounting- and market-based models, Chava and Jarrow (2004) use hybrid and accounting-based models, Campbell et al.

(2008) use hybrid and market-based models). Second, existing literature is incomplete in the use of the performance tests. The majority of studies apply (in sample) information content tests (e.g. Hillegeist et al., 2004) or ROC curve analysis (e.g. Chava and Jarrow, 2004). In fact, the only study that tests for differential misclassification costs, in addition to information content and ROC curve, is Agarwal and Taffler (2008a). However, they only compare accounting- and market-based models but do not include hybrid models. This chapter extends the framework of existing studies and that of Agarwal and Taffler (2008a) while comparing all three available bankruptcy prediction approaches using all three available performance tests.

The remainder of this chapter is organised as follows: in sub-chapter 2 I present the research question and research propositions. In sub-chapter 3 I briefly describe the data and method used. Sub-chapter 4 describes the hybrid models by presenting the variables and summary statistics from the logit regressions using different specifications. Sub-chapter 5 provides comprehensive tests including hybrid, accounting-based and market-based models. Sub-chapter 6 concludes.

## 5.2 Research Question

In this chapter I will examine the following research question and the corresponding research propositions to test for the difference in performance of the three bankruptcy prediction approaches.

**Which of the alternative approaches to predict bankruptcies is the best?**

*P1: The three different bankruptcy prediction measures have different predictive ability.*

*P2: All three measures carry bankruptcy related information incremental to each other.*

*P3: There is a difference in performance once misclassification costs are taken into account.*

## 5.3 Data and Methodology

My sample consists of UK non-financial firms listed in the Main market segment of the London Stock Exchange between October 1979 and September 2010.

I apply the specifications of hybrid models presented in Shumway (2001) (Shum), Campbell, Hilscher and Szilagyi (2008) (CHS) and Christidis and Gregory (2010) (CG) using rolling logit regressions. In addition, I apply the accounting-based z-score of Taffler (1983) and the market-based model of Bharath and Shumway (2008) (BS). The different test methodologies are receiver operating characteristics (ROC) curves, information content tests, and economic value with differential misclassification costs.

In order to derive the coefficients for the hybrid models I use the total sample period from October 1979 to September 2010 (i.e. portfolio years 1979 to 2009) consisting of 28,804 observations (2,748 unique firms of which 274 failed). To avoid look-ahead bias, I use an annually expanding regression window with a fixed start date in October 1979. To assess the bankruptcy risk each year, I use the coefficients estimated at the end of September in that year.

## 5.4 Hybrid Models

### 5.4.1 Summary Statistics

Table 3 presents the summary statistics of accounting and market variables used in the hybrid models of Shumway (2001), Campbell et al. (2008) and Christidis and Gregory (2010).

Panel A in Table 3 documents the summary statistics for all sample firms. NITA and NIMTA show that the sample firms are in general profitable (mean 3.83% for NITA and 2.28% for NIMTA). The operating cash flow ratio CFMTA demonstrates that firms are also profitable on a cash flow basis (mean 4.26%). CASHMTA shows that 6.33% (mean) of the market value of total assets consists of cash and cash equivalents. The net cash ratio NCASHMTA, however, shows that these cash holdings just cover the short-term commitments of the sample firms as it is close to zero (mean 0.56%). Book leverage TLTA reveals that approximately half of the balance sheet consists of liabilities (mean 55.22%) while market leverage TLMTA is 42.19% and slightly lower due to the use of market equity. The reason why TLMTA (NIMTA) is lower than TLTA (NITA) is explained by BM. BM is smaller than one (mean 0.75), i.e. book value of equity is smaller than the market value of equity, leading to smaller ratios based on MTA than on TA. RSIZE puts the market value of equity into context with the FTSE All Share Index (natural log mean -9.23). PRICE is heavily skewed with a low mean of £ 2.27 and median of £ 1.67. A similar observation can be made for the market value of equity (not reported). EXRET is the log one-year excess return over the FTSE All Share

Index and shows a negative average return of -5.98% (mean).[25] SIGMA, i.e. the annualised standard deviation of daily returns over the three months prior to portfolio formation, displays a volatility measure for the total sample of 0.46 (mean).

Panel B in Table 3 gives the summary statistics for the non-failed sub-sample. As they contain the majority of observations (22,015 out of 22,217) I find no significant deviation from the total sample group: NITA and NIMTA are still positive with a mean of 3.92% and 2.35% respectively. The operating cash flow ratio CFMTA remains at a mean of 4.25%, CASHMTA is slightly higher with a mean of 6.34%. The net cash ratio NCASHMTA is still close to zero (mean 0.65%). TLTA and TLMTA are 55.08% and 41.98% respectively (both mean) while BM remains at 0.74 (mean). The natural log of RSIZE increases little to -9.21 (mean) while PRICE hardly changed (mean £ 2.29). EXRET is higher for non-failed firms (mean -5.54%) while SIGMA is still at 0.46 (mean).

The focus of Table 3 is on Panel C as it illustrates the summary statistics of failed firms. It also reports the mean differences to the non-failed group, thus providing first indication if the variables are related to future bankruptcy. Failed firms are loss makers on average as the profitability ratios NITA and NIMTA are both negative (mean -5.51% and -4.67% respectively). As expected, the difference to non-failed firms is highly significant ($t = 13.91$ and 12.58 respectively). Interestingly, CFMTA measuring the operating cash flows of failed firms has a mean of 4.29% that is similar to the mean of non-failed firms ($t = 0.03$). Marginally significant ($t = 1.93$) is the difference in the

[25] The negative average excess return over the FTSE All Share Index is only observed for continuously compounded returns (log excess returns).

CASHMTA ratio between failed and non-failed firms (mean of failed firms 5.39%). However, highly significant is the difference in NCASHMTA (mean -9.00 and t = 9.70) leading to the conclusion that failed firms have significantly higher short-term borrowings. Moreover, this effect is also observed for total liabilities as the mean of TLTA and TLMTA (71.49% and 66.03% respectively) are significantly higher when compared to non-failed firms (t = 13.07 and 16.05 respectively). BM demonstrates the very low market values of failed firms as the BM ratio for failed firms is with 1.18 (mean) above one (t = 5.87). Also, RSIZE shows that the relative size of failed firms decreased significantly (t = 18.30) to a mean of -10.96. Similarly, PRICE of failed firms is £ 0.52 and less than a quarter of the PRICE of the non-failed group (t = 30.08). EXRET shows that failed firms are prior-year losers as the natural log (mean) is -46.11% (t = 14.66). SIGMA is two times higher for failed firms than for non-failed firms (mean 0.89 and t = 17.09).

To summarise, Table 3 shows that failed firms are less profitable than non-failed firms in terms of net income but the operating cash flows do not differ significantly. However, failed firms have lower cash balances and both higher short-term debt and total debt. Also, their BM ratios are higher than for non-failed firms. The size measures show that failed firms are significantly smaller than non-failed firms. Failed firms underperform non-failed firms in the portfolio year prior to failure and their stock returns are more volatile.

**Table 3 Hybrid Models: Summary Statistics Independent Variables**

The table reports summary statistics of potential bankruptcy prediction variables of UK non-financial firms listed in the Main market segment of the London Stock Exchange. Variables are taken at the end of September each year from 1985 to 2009 (portfolio formation). Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. NITA is net income available to common shareholders (NI) over book value of total assets (TA). NIMTA is NI over the book value of total liabilities plus market value of common equity (MTA). CFMTA is operating cash flow over MTA. CASHMTA is cash and cash equivalents over MTA. NCASHMTA is CASH less short-term debt over MTA. TLTA (TLMTA) is book value of total assets excluding total common shareholders' equity over book value of total assets (MTA). BM is book value of shareholders' equity less preference shares and minorities over market value of common equity (MV). RSIZE is log of MV over the market value of the FTSE All Share Index. PRICE is share price. EXRET is log excess return over the FTSE All Share Index over the 12 months prior to portfolio formation. SIGMA is the annualised standard deviation of daily returns for the three months prior to portfolio formation. Mean, Median, Min, and Max are time-series averages. All variables are winsorised at the 5.0% level. Panel A contains all sample firms with 22,217 firm years and 2,428 firms. Panel B contains non-failed firms (22,015 observations). Panel C reports the statistics of failed firms (202 observations) and the differences to the non-failed group (Δ Mean NF-F).

| | **NITA** | **NIMTA** | **CFMTA** | **CASHMTA** | **NCASHMTA** | **TLTA** | **TLMTA** | **BM** | **RSIZE** | **PRICE** | **EXRET** | **SIGMA** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Panel A. All Firms** | | | | | | |
| Mean | 3.83 | 2.28 | 4.26 | 6.33 | 0.56 | 55.22 | 42.19 | 0.75 | -9.23 | 2.27 | -5.98 | 0.46 |
| Median | 4.96 | 3.47 | 4.76 | 4.04 | 0.84 | 55.60 | 41.17 | 0.58 | -9.32 | 1.67 | -2.38 | 0.38 |
| Min | -16.37 | -13.21 | -22.21 | 0.03 | -25.46 | 22.49 | 11.01 | 0.08 | -12.31 | 0.13 | -85.13 | 0.13 |
| Max | 15.17 | 10.43 | 27.51 | 23.25 | 20.73 | 88.17 | 82.58 | 2.82 | -5.79 | 6.87 | 56.54 | 1.25 |
| Std Dev | 7.67 | 5.46 | 11.84 | 6.57 | 10.57 | 18.09 | 20.21 | 0.64 | 1.84 | 1.96 | 36.67 | 0.30 |
| Obs | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 |
| | | | | | | **Panel B. Non-Failed Firms** | | | | | | |
| Mean | 3.92 | 2.35 | 4.25 | 6.34 | 0.65 | 55.08 | 41.98 | 0.74 | -9.21 | 2.29 | -5.54 | 0.46 |
| Median | 5.00 | 3.49 | 4.76 | 4.06 | 0.88 | 55.46 | 40.99 | 0.58 | -9.30 | 1.69 | -2.04 | 0.38 |
| Obs | 22,015 | 22,015 | 22,015 | 22,015 | 22,015 | 22,015 | 22,015 | 22,015 | 22,015 | 22,015 | 22,015 | 22,015 |
| | | | | | | **Panel C. Failed Firms** | | | | | | |
| Mean | -5.51 | -4.67 | 4.29 | 5.39 | -9.00 | 71.49 | 66.03 | 1.18 | -10.96 | 0.52 | -46.11 | 0.89 |
| Median | -6.44 | -5.96 | 3.92 | 3.57 | -9.61 | 73.40 | 71.02 | 1.11 | -11.24 | 0.38 | -56.18 | 0.96 |
| Obs | 202 | 202 | 202 | 202 | 202 | 202 | 202 | 202 | 202 | 2.02 | 202 | 202 |
| Δ Mean | 0.09 | 0.07 | 0.00 | 0.01 | 0.10 | 0.16 | 0.24 | 0.43 | 1.73 | 1.75 | 0.40 | 0.42 |
| NF-F | (13.91) | (12.58) | (0.03) | (1.93) | (9.70) | (13.07) | (16.05) | (5.87) | (18.30) | (30.08) | (14.66) | (17.09) |

### 5.4.2 Hybrid Model Specifications

The variables introduced above are included in different hybrid model specifications. Table 4 presents key statistics for the models in Shumway (2001), Campbell et al. (2008), Christidis and Gregory (2010).

Columns one and two in Table 4 present the analysis with the model in Shumway (2001). The model includes profitability (NITA), leverage (TLTA), prior-returns in excess of the market (EXRET), total volatility of stock returns (SIGMA) and the relative firm size measure (RSIZE). As expected, NITA, EXRET, and RSIZE are negatively associated with bankruptcy risk (the coefficients are -4.65, -1.52 and -0.37 respectively). Also, TLTA and SIGMA have a positive association with bankruptcy risk (the coefficients are 2.66 and 1.13 respectively). Importantly, all the coefficients are statistically significant (lowest t-statistic is 5.38). The evidence shows that firms with higher profitability, higher prior-year stock return, larger size, lower leverage and lower volatility of stock returns are less likely to fail.

Columns three and four in Table 4 present the analysis with the model in Campbell et al. (2008). Similar to Shumway (2001), the model includes profitability (NIMTA), leverage (TLMTA), prior-returns in excess of the market (EXRET), total volatility of stock returns (SIGMA) and the relative firm size measure (RSIZE). In addition to that, it includes a cash ratio (CASHMTA), book equity over market equity (BM) and share price (PRICE). NIMTA, EXRET, RSIZE, CASHMTA, and PRICE are negatively associated with bankruptcy risk (the coefficients are -5.77, -1.20, -0.22, -2.30 and -0.36 respectively). TLMTA and SIGMA have a positive association with bankruptcy risk (the coefficients are 2.60, 1.11 respectively). Except for BM ($t = 0.05$), all coefficients are statistically significant (lowest t-statistics is 2.17). As such, the evidence shows that firms with higher leverage and higher total volatility are more likely to fail while the opposite is true for firms with high profitability, higher past returns, bigger size, higher cash holdings and higher share price.

Columns five and six in Table 4 document the analysis with the accounting, market and economic model (2) in Christidis and Gregory (2010). As with the other two specifications, the model includes profitability (NIMTA), leverage (TLMTA), prior-returns in excess of the market (EXRET), total volatility of stock returns (SIGMA) and the relative firms size measure (RSIZE). In addition to that, Christidis and Gregory (2010) include PRICE and the cash flow (CFMTA). They also include macroeconomic variables: the Treasury Bill rate (DEFLTBR), the term structure premium (LONGSHT), and the change in the UK industrial production index (INDPROD). NIMTA, EXRET, RSIZE, PRICE, LONGSHT, and INDPROD are negatively associated with bankruptcy risk (the coefficients are -6.94, -0.94, -0.21, -0.38, -0.20, and -3.58 respectively). TLMTA, SIGMA, and CFMTA have a positive association with bankruptcy risk (the coefficients are 2.96, 1.10, and 0.83 respectively). Except for DEFLTBR ($t = 0.81$), all the coefficients are statistically significant (lowest t-statistics is 2.09).

The model statistics presented on the bottom of Table 4 are very similar for the models. The pseudo $R^2$s for the three models are tightly ranged from 24.8% for the Shumway (2001) model to 26.6% for the Christidis and Gregory (2010) model. Similarly, the $\chi^2$ is bound between 768.4 and 823.5. Although, the models are very similar, the summary statistics of the model in Christidis and Gregory (2010) show a slightly better model fit.

**Table 4 Hybrid Models: Coefficients and Summary Statistics**

The table reports results from binary logit regressions using UK non-financial firms listed in the Main market segment of the London Stock Exchange. The predictor variables are taken at the end of each September from 1979 to 2009 (portfolio formation). Dependent variable: failure indicator and 1 (0) if the firm failed (not failed) in the twelve months following portfolio formation. Predictors: NITA is net income available to common shareholders (NI) over book value of total assets (TA). NIMTA is NI over the book value of total liabilities plus market value of common equity (MTA). TLTA (TLMTA) is book value of total assets excluding total common shareholders' equity over book value of total assets (MTA). EXRET is log excess return over the FTSE All Share Index over the 12 months prior to portfolio formation. SIGMA is the annualised standard deviation of daily returns for the three months prior to portfolio formation. RSIZE is log of market value of common equity (MV) over the market value of the FTSE All Share Index. CASHMTA is cash and cash equivalents over MTA. BM is book value of shareholders' equity less preference shares and minorities over MV. PRICE is share price. CFMTA is operating cash flow over MTA. DEFLTBR is the deflated Treasury Bill rate. LONGSHT is the term structure premium. INDPROD is the change in the UK industrial production index. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. Variables (not macroeconomic) are winsorised at the 5.0% level. I present the models in Shumway (2001), Campbell et al. (2008), Christidis and Gregory (2010). I report coefficients, t-statistics in parentheses as well as summary regression statistics.

| **Shumway (2001)** | | **Campbell et al. (2008)** | | **Christidis and Gregory (2010)** | |
|---|---|---|---|---|---|
| NITA | -4.65 | NIMTA | -5.77 | NIMTA | -6.94 |
| | (6.12) | | (6.31) | | (7.33) |
| TLTA | 2.66 | TLMTA | 2.60 | TLMTA | 2.96 |
| | (7.35) | | (5.73) | | (7.19) |
| EXRET | -1.52 | EXRET | -1.20 | EXRET | -0.94 |
| | (8.44) | | (6.40) | | (4.97) |
| SIGMA | 1.13 | SIGMA | 1.11 | SIGMA | 1.10 |
| | (5.38) | | (5.27) | | (5.05) |
| RSIZE | -0.37 | RSIZE | -0.22 | RSIZE | -0.21 |
| | (6.56) | | (3.58) | | (3.52) |
| | | CASHMTA | -2.30 | PRICE | -0.38 |
| | | | (2.17) | | (2.84) |
| | | BM | 0.00 | CFMTA | 0.83 |
| | | | (0.05) | | (2.09) |
| | | PRICE | -0.36 | DEFLTBR | -30.48 |
| | | | (2.74) | | (0.81) |
| | | | | LONGSHT | -0.20 |
| | | | | | (4.28) |
| | | | | INDPROD | -3.58 |
| | | | | | (2.39) |
| Constant | -11.28 | Constant | -9.05 | Constant | -8.78 |
| | (18.04) | | (12.33) | | (11.69) |
| Obs | 28,804 | Obs | 28,804 | Obs | 28,804 |
| Firms | 2,748 | Firms | 2,748 | Firms | 2,748 |
| Failures | 274 | Failures | 274 | Failures | 274 |
| $\chi^2$ | 768.4 | $\chi^2$ | 796.6 | $\chi^2$ | 823.5 |
| Pseudo $R^2$ | 24.8 | Pseudo $R^2$ | 25.7 | Pseudo $R^2$ | 26.6 |

## 5.5 Evaluating Distress Risk Models

The previous sub-chapter introduces the summary statistics of the hybrid models. In this sub-chapter, I continue to use the three hybrid models and add the accounting-based z-score model (Taffler, 1983) and the market-based model of Bharath and Shumway (2008) as well.

In the previous sub-chapter I use the full sample period covering the months from October 1979 to September 2010. That is, the coefficients presented in Table 4 are obtained using the total observation period (i.e., in-sample). In the remaining analysis (including the subsequent chapters) I use a sample period from October 1985 to September 2010. This is necessary because using the coefficients from the total sample period to predict bankruptcy risk in (say) 1985 would involve a look-ahead bias as these coefficients are not known before October 2010. In order to avoid this, I use annually extending regression windows with a fixed start date in 1979. However, since the logit regressions of the hybrid models require a certain amount of observations, especially failures, I leave a calibration period of six years and start with the first bankruptcy risk assessment at the end of September 1985. Specifically, I assess the bankruptcy risk assessment at the end of September of 1985 (at the end of September 1986) with coefficients obtained from a regression using data from October 1979 to September 1985 (October 1979 to September 1986) and so on. As such, all tests are out-of-sample.

### 5.5.1 Default Probabilities

Table 5 presents the default probabilities from the hybrid models in Shumway (2001) (Shum), Campbell, Hilscher and Szilagyi (2008) (CHS) and Christidis and Gregory (2010) (CG) and as well for the accounting-based z-score (Taffler, 1983) and the market-based model in Bharath and Shumway (2008) (BS). Figures in column All represent the default probabilities of the total sample while non-failed and failed firms contain the respective firms only.

The hybrid models return an average default probability of around 1.00% (ranging from 0.90% to 1.10%) while the average default probabilities of z-score and BS are clearly higher (26.30% and 10.88% respectively). Recalling from Table 1 in Chapter 4 that the actual failure rate for the final sample is 0.91%, the hybrid models seem to be able to replicate this average default probability. In this context, z-score and BS are mis-calibrated since they overstate the actual failure probability.

However, for bankruptcy prediction it is more important to focus on the relative performance of each model than on absolute failure probability. As such, it is of greater importance that the expected failure probability is greater for failed firms than for non-failed firms. Figures in column Non-Failed report the failure probability of non-failed firms. They are very similar to the failure probability of the total sample for Shum, CHS, CG, z-score and BS (the default probabilities are 1.03%, 0.83%, 0.91%, 25.86%, and 10.46% respectively). In contrast, the column Failed containing only failed firms shows increased default probabilities (7.81%, 6.87%, 7.02%, 73.83%, and 51.12% respectively). The difference between the non-failures and failures is highly significant for all the models (t = statistics are 10.20, 10.71, 10.02, 17.78, and 16.44 respectively).

Table 5 therefore clearly shows that all models are able to differentiate significantly between non-failures and failures by allocating lower (higher) default probabilities to non-failed (failed) firms.

**Table 5 Distress Risk Models: Default Probabilities**

The table reports time-series averages of default probabilities using all UK non-financial firms listed in the Main market segment of the London Stock Exchange. Default probabilities are calculated at the end of each September from 1985 to 2009 for the model in Shumway (2001), Campbell et al. (2008), Christidis and Gregory (2010), z-score (Taffler, 1983) and the market-based model in Bharath and Shumway (2008). I transform the z-score into probability: $p = e^{z\text{-score}} / (1+ e^{z\text{-score}})$. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at the end of each September. I display failure rates (in per cent) for all firms, for the non-failed firms and for failed firms. The t-statistic indicates the significance of the difference between the non-failed and failed group (ΔF-NF).

| | **All** | **Non-Failed** | **Failed** | **ΔF-NF** | **t-stat** |
|---|---|---|---|---|---|
| Shumway (2001) | 1.10 | 1.03 | 7.81 | 6.78 | 10.20 |
| Campbell et al. (2008) | 0.90 | 0.83 | 6.87 | 6.04 | 10.71 |
| Christidis and Gregory (2010) | 0.98 | 0.91 | 7.02 | 6.11 | 10.02 |
| Z-score (Taffler, 1983) | 26.30 | 25.86 | 73.83 | 47.97 | 17.78 |
| Bharath and Shumway (2008) | 10.88 | 10.46 | 51.12 | 40.65 | 16.44 |

### 5.5.2 Test of Predictive Ability (ROC)

Having illustrated that all models are able to differentiate between non-failures and failures I now test the predictive ability of the models using receiver operating characteristics (ROC) curves.

Table 6 presents the area under ROC curve (AUC) for all bankruptcy prediction models. In addition, I test for the predictive ability of common risk factors used in the Carhart (1997) model. The table shows that the hybrid models have similar AUCs with all being close to 0.90. The accounting-based z-score model has lower prediction accuracy with an AUC of 0.81. The predictive ability of the market-based BS model is between that of the hybrid and that of the accounting-based model (AUC = 0.87). The AUC of the common risk factors BETA, SIZE, BM, and PYR vary strongly and are 0.59, 0.80, 0.61, and 0.78 respectively.

The third column indicates the standard error (SE) of the AUC while the fourth column presents the significance of the AUC (i.e. difference in model performance relative to that of a random model). The AUC of each bankruptcy prediction model is significantly higher than that of a random model. The hybrid models have a z-statistic slightly above 26.00 while z-score ($z = 16.95$) and the BS model ($z = 22.49$) have lower z-statistics. Also, the common risk factors BETA, SIZE, BM, and PYR forecast bankruptcies better than a random model ($z = 4.15$, 16.19, 5.19, and 14.32 respectively).

Table 6 provides evidence that all bankruptcy prediction models as well as the common risk factors have better forecasting accuracy than a random model. However, the hybrid models (more specifically, the model in Shumway (2001)) have the best forecasting accuracy.

**Table 6 Distress Risk Models: Area under ROC Curve**

The table reports receiver operating characteristics (ROC) curve analysis using all UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I calculate the default probabilities from the model in Shumway (2001), Campbell et al. (2008), Christidis and Gregory (2010), z-score (Taffler, 1983) and the market-based model in Bharath and Shumway (2008). I transform the z-score into probability: $p = e^{z\text{-score}} / (1+ e^{z\text{-score}})$. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables are winsorised at the 5.0% level, default probabilities at 0.00000001 and 0.99999999. AUC is the area under the ROC curve estimated as the Wilcoxon statistic. SE is the standard error of the estimated area and z is the Hanley and McNeil (1983) test-statistic for the null-hypothesis that the area under the ROC curve is equal to 0.5.

| **Model** | **AUC** | **SE** | **z** |
|---|---:|---:|---:|
| Shumway (2001) | 0.896 | 0.0148 | 26.83 |
| Campbell et al. (2008) | 0.894 | 0.0149 | 26.57 |
| Christidis and Gregory (2010) | 0.892 | 0.0150 | 26.25 |
| Z-score (Taffler, 1983) | 0.812 | 0.0184 | 16.95 |
| Bharath and Shumway (2008) | 0.866 | 0.0163 | 22.49 |
| BETA | 0.587 | 0.0211 | 4.15 |
| SIZE | 0.802 | 0.0187 | 16.19 |
| BM | 0.610 | 0.0212 | 5.19 |
| PYR | 0.777 | 0.0194 | 14.32 |

Figure 4 illustrates the results of Table 6 graphically. However, as the hybrid models have very similar forecasting accuracy, Figure 4 only contains the model in Shumway (2001) in addition to the z-score and market-based BS. The graph clearly shows the superior performance of Shum (i.e. hybrid models) over the z-score and market-based BS model. It also shows that the outperformance of the hybrid models over the BS approach becomes apparent from integer $\lambda = 15$ onwards. For reasons of completeness, I report the graph including all three hybrid models in Figure 5A in the appendix to this chapter.

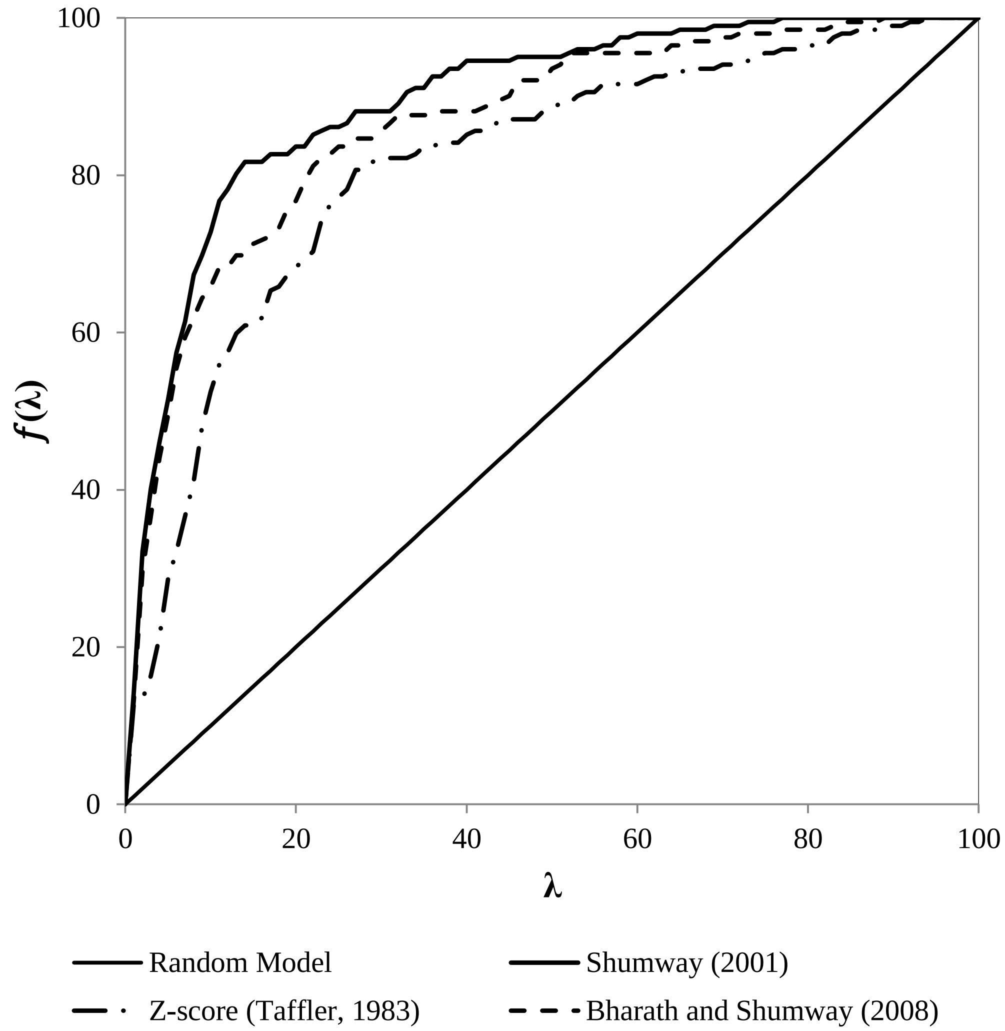


**Figure 4 Distress Risk Models: Area under ROC Curve**

The figure illustrates the receiver operating characteristics curves using all UK non-financial firms listed in the Main market segment of the London Stock Exchange. λ is an integer between 0 and 100 and describes the λ% of the highest bankruptcy risk firms. ***f***(λ) is a function of λ that divides the number of failures in the highest λ% of default risk by the total number of failures. Bankruptcy risk is determined at the end of September each year from 1985 to 2009 using the model in Shumway (2001), z-score (Taffler, 1983) and the market-based model in Bharath and Shumway (2008). I transform the z-score into probability: $p = e^{z\text{-score}} / (1+ e^{z\text{-score}})$. Random Model represents the results of random bankruptcy prediction model. All variables are winsorised at the 5.0% level, default probabilities at 0.00000001 and 0.99999999.

Table 7 reports the z-statistics for difference between the AUCs to test the relative performance of the bankruptcy prediction models and the common risk factors. The table confirms evidence in Table 6 that the hybrid models have very similar forecasting accuracy. The difference between their AUCs is insignificant (maximum z = 0.42). On the other hand, hybrid models significantly outperform both the z-score (minimum z = 5.96) and market-based BS (minimum z = 3.10) as well as the common risk factors (minimum z = 7.66).

The BS model has a significantly better forecasting accuracy than the z-score (z = 3.83). While BS is better than any of the common risk factors (minimum z = 5.40), z-score has a better forecasting accuracy than BETA, BM, and PYR (minimum z = 2.36) but not better than SIZE (z = 0.70).

The results in Table 7 are in contrast to those in Agarwal and Taffler (2008a) as they find z-score to have similar forecasting accuracy as the market-based bankruptcy prediction models using as well UK Main-listed firms. However, my sample period is longer and covers more recent years than the sample period in Agarwal and Taffler (2008a). To have a better understanding of the difference, Table 8 reports the differences in AUCs for the sub-period of portfolio years 1985 to 2000. The sub-period moderates the results from the entire sample period since the outperformance of the BS over z-score is now insignificant (z = 1.79). While the other results remain unchanged, z-score is, in contrast to the previous results, outperforming all common risk factors (minimum z = 2.43). This confirms the proposition in Agarwal and Taffler (2007) that the performance of the accounting-based z-score model has deteriorated since the late 1990s. The results with respect to the hybrid models remain unchanged.

### Table 7 Distress Risk Models: Difference Area under ROC Curve

The table reports the significance of difference in area under receiver operating characteristics curves using all UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I calculate the default probabilities from the model in Shumway (2001) (Shum), Campbell, Hilscher and Szilagyi (2008) (CHS), Christidis and Gregory (2010) (CG), z-score (Taffler, 1983) and the market-based model in Bharath and Shumway (2008) (BS). I transform the z-score into probability: $p = e^{z\text{-score}} / (1 + e^{z\text{-score}})$. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables are winsorised at the 5.0% level, default probabilities at 0.00000001 and 0.99999999. The figures in the table present test-statistics of Hanley and McNeil (1983) to compare the area under the curve (AUC) for two different variables/models. AUC is estimated as the Wilcoxon statistic.

| | **Shum** | **CHS** | **CG** | **Z-score** | **BS** | **BETA** | **SIZE** | **BM** |
|---|---|---|---|---|---|---|---|---|
| CHS | 0.19 | | | | | | | |
| CG | 0.42 | 0.23 | | | | | | |
| Z-score | 5.96 | 6.74 | 6.58 | | | | | |
| BS | 3.51 | 3.33 | 3.10 | 3.83 | | | | |
| BETA | 19.39 | 19.29 | 19.16 | 14.69 | 17.37 | | | |
| SIZE | 7.66 | 7.84 | 7.68 | 0.70 | 5.40 | 13.16 | | |
| BM | 19.44 | 18.80 | 18.68 | 12.79 | 18.31 | 1.43 | 12.99 | |
| PYR | 9.41 | 9.65 | 9.50 | 2.36 | 7.03 | 11.14 | 2.42 | 10.78 |

**Table 8 Distress Risk Models: Difference Area under ROC Curve 1985 to 2000**

The table reports the significance of difference in area under receiver operating characteristics curves using all UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2000 (portfolio formation), I calculate the default probabilities from the model in Shumway (2001) (Shum), Campbell, Hilscher and Szilagyi (2008) (CHS), Christidis and Gregory (2010) (CG), z-score (Taffler, 1983) and the market-based model in Bharath and Shumway (2008) (BS). I transform the z-score into probability. $p = e^{z\text{-score}} / (1+ e^{z\text{-score}})$. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables are winsorised at the 5.0% level, default probabilities at 0.00000001 and 0.99999999. The figures in the table present test-statistics of Hanley and McNeil (1983) to compare the area under the curve (AUC) for two different variables/models. AUC is estimated as the Wilcoxon statistic.

| | **Shum** | **CHS** | **CG** | **Z-score** | **BS** | **BETA** | **SIZE** | **BM** |
|---|---|---|---|---|---|---|---|---|
| CHS | 0.12 | | | | | | | |
| CG | 0.41 | 0.29 | | | | | | |
| Z-score | 3.15 | 3.34 | 3.16 | | | | | |
| BS | 2.52 | 2.40 | 2.20 | 1.79 | | | | |
| BETA | 14.54 | 14.76 | 14.61 | 12.43 | 13.85 | | | |
| SIZE | 5.97 | 6.09 | 5.90 | 2.43 | 4.73 | 10.00 | | |
| BM | 15.59 | 15.52 | 15.36 | 12.72 | 14.79 | 0.59 | 11.11 | |
| PYR | 7.63 | 7.31 | 7.25 | 3.96 | 5.88 | 8.27 | 1.86 | 9.00 |

The previous tables report the differences between the models and the common risk factors. As a further robustness test, I test whether the bankruptcy prediction models have greater forecasting accuracy than their individual variables. Table 9 presents the z-statistics for differences in AUC between the bankruptcy prediction model and its respective variables (please see Table 2A on page 91 for a definition of the key variables).

Shumway (2001) including NITA, TLTA, EXRET, SIGMA, and RSIZE clearly outperforms its individual components (minimum z = 5.95). The same is true for Campbell et al. (2008) which includes NIMTA, TLMTA, EXRET, SIGMA, RSIZE, CASHMTA, BM, and PRICE (minimum z = 4.48). Also, the composite measure of Christidis and Gregory (2010) outperforms its individual variables (minimum z = 4.48).[26] The forecasting ability of z-score against its individual variables is better for CATL, CLTA, and NCI (minimum z = 6.57). However, the difference between the AUC of z-score and PBTCL is insignificant (z = 0.98) showing that PBTCL has similar bankruptcy forecasting power as z-score. As such, profitability has the same forecasting accuracy as the composite z-score measure. Agarwal and Taffler (2007) discuss the importance of profits although their tests show that z-score significantly outperforms profit before tax. The BS market-based model clearly outperforms its individual components (minimum z = 3.00).[27]

The results in this sub-chapter provide clear evidence in support of research proposition P1, that the bankruptcy prediction measures have different predictive ability. While the hybrid models outperform both the z-score and the BS model, the forecasting accuracy of z-score is mixed and depends on the time period used.

In the next sub-chapter I test for bankruptcy related information carried by the distress risk measures.

[26] In this test, the macroeconomic variables are excluded because they are the same for all firms and thus, lead to a random sort.

[27] Similar results are obtained using the sub-period for portfolio years 1985 to 2000.

**Table 9 Variables Distress Risk Models: Difference Area under ROC Curve**

The table reports the significance of difference in area under receiver operating characteristics curves using all UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I calculate the default probabilities from the model in Shumway (2001), Campbell et al. (2008), Christidis and Gregory (2010), z-score (Taffler, 1983) and the market-based model in Bharath and Shumway (2008). I transform the z-score into probability: $p = e^{z\text{-score}} / (1+ e^{z\text{-score}})$. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. NITA is net income available to common shareholders (NI) over book value of total assets (TA). NIMTA is NI over the book value of total liabilities plus market value of common equity (MTA). TLTA (TLMTA) is book value of total assets excluding total common shareholders' equity over book value of total assets (MTA). EXRET is log excess return over the FTSE All Share Index over the 12 months prior to portfolio formation. SIGMA is the annualised standard deviation of daily returns for the three months prior to portfolio formation. RSIZE is log of market value of common equity (MV) over the market value of the FTSE All Share Index. CASHMTA is cash and cash equivalents over MTA. BM is book value of shareholders' equity less preference shares and minorities over MV. PRICE is share price. CFMTA is operating cash flow over MTA. PBTCL is profit before tax over current liabilities. CATL is current assets over total liabilities. CLTA is current liabilities over total assets. NCI is the no-credit interval calculated as (quick assets – current liabilities) / ((sales – profit before tax – depreciation) / 365). ER1y is the prior-year return. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables are winsorised at the 5.0% level, default probabilities at 0.00000001 and 0.99999999. The figures in the table present test-statistics of Hanley and McNeil (1983) to compare the area under the curve (AUC) for two different variables/models. AUC is estimated as the Wilcoxon statistic. I present the t-statistic for difference in AUC between Shumway (2001), Campbell et al. (2008), Christidis and Gregory (2010), z-score (Taffler, 1983) and the market-based model in Bharath and Shumway (2008) and its respective individual variables. The macro-economic variables of Christidis and Gregory (2010) are not contained as they are the same for all sample firms.

| **Shumway (2001)** | | **Campbell et al. (2008)** | | **Christidis and Gregory (2010)** | | **Z-score (Taffler, 1983)** | | **Bharath and Shumway (2008)** | |
|---|---|---|---|---|---|---|---|---|---|
| NITA | 8.36 | NIMTA | 9.51 | NIMTA | 9.51 | PBTCL | 0.98 | ER1y | 7.25 |
| TLTA | 11.19 | TLMTA | 8.19 | TLMTA | 8.19 | CATL | 8.04 | TLMTA | 6.15 |
| EXRET | 8.67 | EXRET | 8.36 | EXRET | 8.36 | CLTA | 6.57 | SIGMA | 3.00 |
| SIGMA | 5.95 | SIGMA | 5.92 | SIGMA | 5.92 | NCI | 7.36 | | |
| RSIZE | 7.46 | RSIZE | 7.59 | RSIZE | 7.59 | | | | |
| | | CASHMTA | 15.28 | CFMTA | 21.57 | | | | |
| | | BM | 19.22 | PRICE | 4.48 | | | | |
| | | PRICE | 4.48 | | | | | | |

### 5.5.3 Test of Information Content

The information content tests are based on Hillegeist et al. (2004) and estimated by logistic regressions with the test-statistic adjusted for multiple observations per firm. I use different specifications to test for information content. These include the hybrid models, the accounting-based z-score model and the market-based BS model. I also include the common risk factors BETA, SIZE, BM and PYR and the base rate of default risk measured by the trailing sample failure rate following Hillegeist et al. (2004).

With the information content tests I examine to what extent the bankruptcy prediction models carry bankruptcy related information incremental to each other. Before running the logistic regressions, I test for multicollinearity using correlations. Table 10 presents a matrix of the Spearman/Pearson correlation coefficients for the variables used in the information content tests. With respect to the hybrid models, Table 10 provides further evidence for their similarity (correlation coefficients are $\geq 0.90$). Also, hybrid models seem to have more in common with the market-based BS model (correlation coefficients range between 0.77 and 0.81) than with z-score (correlation coefficients range between 0.46 and 0.52).[28] Due to their different informational background, z-score and BS are moderately correlated (correlation coefficients: Spearman 0.37, Pearson 0.33). Looking at the correlation coefficients with the common risk factors, it can be observed that the hybrid models (all including RSIZE) and SIZE have elevated correlation coefficients (Pearson correlation coefficients range between -0.68 and -0.73)

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[28] As mentioned earlier and following Hillegeist et al. (2004), I change the sign of z-score to conform to the hybrid and market-based models. As such, distress risk is higher for higher scores from Shum, z-score, and BS. The same applies to logit regressions and cross-sectional tests in other parts of the study. Clearly, the sign-change has no impact on the significance of the coefficients.

and thus, regressions using the scores of the hybrid models and SIZE suffer from multicollinearity. However, for testing the different models, it follows that information content tests (i) including two or more hybrid models suffer from multicollinearity, (ii) including hybrid models and BS have to be interpreted with care, and (iii) combining hybrid models or BS with z-score has no problem of multicollinearity.

**Table 10 Distress Risk Models: Correlation Common Risk Factors**

This table presents time-series averages of correlation coefficients for variables of UK non-financial firms listed in the Main market segment of the London Stock Exchange. The lower-left side of the matrix presents Spearman rank correlation coefficients. The upper-right side of the matrix presents Pearson correlation coefficients. Correlation coefficients are calculated at the end of each September from 1985 to 2009 (portfolio formation). Variables are: Shum is the score from the model in Shumway (2001), CHS from Campbell, Hilscher and Szilagyi (2008), CG from Christidis and Gregory (2010), z-score (Taffler, 1983) and BS from Bharath and Shumway (2008). In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at the end of each September. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables are winsorised at the 5.0% level, scores are winsorised at ±18.4207.

| | **Shum** | **CHS** | **CG** | **Z-score** | **BS** | **BETA** | **SIZE** | **BM** | **PYR** |
|---|---|---|---|---|---|---|---|---|---|
| **Shum** | 1 | 0.91 | 0.90 | 0.51 | 0.77 | 0.05 | -0.73 | 0.24 | -0.50 |
| **CHS** | 0.90 | 1 | 0.99 | 0.48 | 0.81 | 0.07 | -0.68 | 0.41 | -0.48 |
| **CG** | 0.90 | 0.99 | 1 | 0.47 | 0.80 | 0.07 | -0.70 | 0.43 | -0.44 |
| **Z-score** | 0.52 | 0.47 | 0.46 | 1 | 0.33 | 0.06 | -0.17 | -0.04 | -0.12 |
| **BS** | 0.80 | 0.78 | 0.77 | 0.37 | 1 | 0.08 | -0.51 | 0.38 | -0.59 |
| **BETA** | 0.07 | 0.08 | 0.08 | 0.07 | 0.07 | 1 | -0.01 | -0.04 | 0.00 |
| **SIZE** | -0.49 | -0.47 | -0.49 | -0.08 | -0.30 | 0.08 | 1 | -0.21 | 0.10 |
| **BM** | 0.28 | 0.43 | 0.45 | 0.00 | 0.39 | -0.06 | -0.36 | 1 | -0.29 |
| **PYR** | -0.50 | -0.48 | -0.44 | -0.11 | -0.56 | -0.01 | 0.22 | -0.28 | 1 |

Table 11 summarises the key results from the information content tests while Table 13A in the appendix to this chapter contains all relevant specifications.

Models 1 to 3 of Table 11 show that all the hybrid models carry significant information about failure in the next twelve months. The coefficients (1.02 for Shum, 0.95 for CHS, and 0.96 for CG) show that the scores of the hybrid models are positively related with actual failures. Importantly, the t-statistics range from 5.21 (CHS) to 5.39 (Shum). None of the risk factors (maximum t-statistic 1.70) or Rate (maximum t-statistic 0.63) is significant. Model 4 shows a positive and highly significant ($t = 3.83$) coefficient for z-score, i.e. higher default risk measured by z-score is positively associated with actual failures. However, PYR is also significant ($t = 2.44$) showing that it carries bankruptcy related information incremental to z-score. Model 5 demonstrates that the market-based BS model also carries significant bankruptcy related information ($t = 2.88$) while the common risk factors and RATE are insignificant.

Model 6 combines the z-score and the BS in one equation. It shows that both carry significant bankruptcy related information incremental to each other ($t = 2.95$ and 2.26 respectively). This is consistent with the evidence in Hillegeist et al. (2004) and Agarwal and Taffler (2008a) who argue that the two models capture distinct aspects of bankruptcy risk.

Models 7, 8, and 9 combine Shum with z-score, BS or both. They demonstrate that the coefficients on both z-score and market-based model estimates become statistically insignificant (t-statistic are between 0.67 and 0.90) while Shum continues to be significant (minimum $t = 3.16$) although Shum and BS are moderately correlated. Overall, this shows (i) that Shum carries significant bankruptcy related information incremental to z-score (see Charalambakis et al. (2009) for similar results) and BS and (ii) that once the bankruptcy related information of Shum is included, the information carried by z-score and BS is irrelevant.

The results in this sub-chapter demonstrate clear support for research proposition P2 as the distress risk measures carry bankruptcy related information incremental to each other. While z-score and BS have distinct bankruptcy related information, the hybrid models subsume the information of both z-score and BS.

Overall, the results show a clear outperformance of the hybrid models using ROC curve analysis and information content tests. While the outperformance of hybrids as a group is distinct, both tests are unable to distinguish between them. In the next sub-chapter, I therefore analyse the three hybrid models testing the economic impact of differential misclassification costs using the three hybrid models only.

**Table 11 Distress Risk Models: Information Content Tests**

The table reports different specifications of logit regressions to test for information content. At the end of each September from 1985 to 2009 (portfolio formation), I take the independent variables of UK non-financial firms listed in the Main market segment of the London Stock Exchange. Dependent binary variable: failure (1) or non-failed (0). Independent variables: Shum is the score from the model in Shumway (2001), CHS from Campbell, Hilscher and Szilagyi (2008), CG from Christidis and Gregory (2010), z-score (Taffler, 1983) and BS from Bharath and Shumway (2008). In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. RATE is the sample failure rate over the previous twelve months. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables (except RATE) are winsorised at the 5.0% level, scores are winsorised at ±18.4207.

| **Model** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
|---|---|---|---|---|---|---|---|---|---|
| Shum | 1.02 | | | | | | 0.91 | 0.94 | 0.82 |
| | (5.39) | | | | | | (4.00) | (4.17) | (3.16) |
| CHS | | 0.95 | | | | | | | |
| | | (5.21) | | | | | | | |
| CG | | | 0.96 | | | | | | |
| | | | (5.34) | | | | | | |
| Z-score | | | | 0.09 | | 0.08 | 0.03 | | 0.03 |
| | | | | (3.83) | | (2.95) | (0.88) | | (0.90) |
| BS | | | | | 0.30 | 0.22 | | 0.06 | 0.06 |
| | | | | | (2.88) | (2.26) | | (0.67) | (0.69) |
| BETA | 0.14 | 0.15 | 0.12 | 0.18 | 0.19 | 0.16 | 0.14 | 0.14 | 0.14 |
| | (0.83) | (0.89) | (0.71) | (0.98) | (1.03) | (0.94) | (0.81) | (0.83) | (0.81) |
| SIZE | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.08) | (0.07) | (0.02) | (1.20) | (0.97) | (0.85) | (0.01) | (0.14) | (0.04) |
| BM | 0.41 | 0.05 | -0.08 | 0.41 | 0.09 | 0.25 | 0.45 | 0.36 | 0.40 |
| | (1.70) | (0.22) | (0.31) | (1.61) | (0.35) | (1.00) | (1.84) | (1.46) | (1.59) |
| PYR | 0.21 | -0.01 | -0.05 | -1.77 | 0.00 | -0.16 | 0.10 | 0.46 | 0.36 |
| | (0.29) | (0.01) | (0.07) | (2.44) | (0.00) | (0.19) | (0.14) | (0.58) | (0.45) |
| RATE | -0.16 | -0.24 | -0.08 | -0.04 | -0.09 | -0.13 | -0.15 | -0.16 | -0.16 |
| | (0.41) | (0.63) | (0.22) | (0.10) | (0.23) | (0.34) | (0.40) | (0.43) | (0.43) |
| Constant | -0.62 | -0.17 | -0.20 | -5.08 | -3.61 | -4.05 | -1.15 | -0.70 | -1.25 |
| | (0.73) | (0.19) | (0.22) | (9.52) | (5.90) | (6.55) | (1.10) | (0.83) | (1.20) |
| Obs | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 |
| $\chi^2$ | 614.3 | 613.7 | 631.9 | 461.2 | 452.8 | 530.2 | 621.2 | 618.8 | 626.0 |
| Pseudo $R^2$ | 26.7 | 26.7 | 27.5 | 20.0 | 19.7 | 23.0 | 27.0 | 26.9 | 27.2 |

### 5.5.4 Test of Economic Value

The results in the two previous sub-sections present strong evidence for superiority of the hybrid models over the z-score and market-based BS model. Hence, in this sub-chapter I restrict the analysis to the three hybrid models that my previous performance tests are unable to distinguish between.

Agarwal and Taffler (2008a) note that the credit spread as defined in Eq. (21) is a function of the probability of non-failure and failure, and is therefore influenced by both the power as well as the calibration of the model. In order to have clean measures of the economic impact of model power uncontaminated by possible differences in calibration (see Table 5), I use bankruptcy probability percentiles as in Agarwal and Taffler (2008a). Further, I smooth the ROC curve using the method of Burgt (2007). Similar to Agarwal and Taffler (2008a), I assume that the three banks follow the Basel III Foundation Internal Ratings-Based approach, all loans are unsecured senior debt (i.e., LGD is 45.0%), and the risk premium for the highest quality customer to be 0.30% (k).

Table 12 presents the revenue, profitability, and other statistics for the three banks under the mixed-regime competitive loan market. The first row presents the loans granted to the sample firms. Please note that the credits, market share and defaults does not sum up to the total observations (22,217) or 100.0% because banks reject all firms with default probabilities that fall in the bottom 5.0% based on their respective model (this affects 843 firms of which 92 failed). The market share figures show that Bank 1 (Shumway, 2001) has the largest market share of 54.7% as compared to 19.9% and 21.7% respectively for the other two banks that use Campbell et al. (2008) and Christidis and Gregory (2010). The quality of loans granted by Bank 1 is also better as only 0.40% of its customers default compared to 0.61% and 0.73% for the other two banks. The better credit quality of Bank 1 loans is also reflected in the lower average spread it earns (50 bps against 52 bps for Bank 2 and 63 bps for Bank 3). However, the higher market share and the better credit quality of Bank 1 translate into much higher profits (£177.7m vs. £49.2m for Bank 2 and £65.6m for Bank 3). While the ROA of the three banks is tightly ranging between 0.25% (Bank 2) and 0.33% (Bank 1), the RORWA, which measures profitability as a function of risk, of Bank 1 (1.21%) clearly outperforms the other two banks (0.81% Bank 2 and 0.80% Bank 3). On this basis, considering the differential misclassification costs, the Shumway (2001) model clearly outclasses the other two hybrid models in economic terms.[29]

The clear outperformance of Shum might appear surprising since the estimates of the three hybrid models are highly correlated (minimum Spearman/Pearson correlation coefficient 0.90). However, as the results in Agarwal and Taffler (2008a) demonstrate, small differences in the predictive ability can lead to sharp differences in the economic value of the models once the differential misclassification costs are considered. A detailed inspection of the pricing characteristics of the models shows that the market share of Shum is almost linearly increasing with credit quality. For instance, for the highest risk firms Shum has a market share of 43 % while it goes up to 78 % for the safest firms. At the same time, for the high risk portfolios the fails per loans granted is lower than for CHS and about the same as for CG. Therefore, the outperformance of Shum is due to its high volume, especially in the high quality loan portfolios, while its

[29] The finding (based on LGD 45.00% and k 0.30%) is robust to alternative model assumptions. For instance, changing LGD to 50.00% and k to 0.40% leads to a RORWA of 1.44% for Shum, 1.01% for CHS, and 0.96% for CG.

default rate in the low quality loan portfolios is better or about the same as for the other hybrid models.

Taken together the results in Table 12, the differential misclassification costs matter even for the hybrid models that have very close performance when tested using ROC curve analysis and information content tests. The most parsimonious hybrid model Shum performs best in an illustrative loan market. Hence the results provide strong support for research proposition P3, that there is a difference in performance once differential misclassification costs are taken into account.

**Table 12 Hybrid Models: Test of Economic Value**

The table is an illustrative example of a competitive credit market. I hypothesise three banks using default probabilities from the models in Shumway (2001) (Shum), Campbell, Hilscher and Szilagyi (2008) (CHS), Christidis and Gregory (2010) (CG) using UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I calculate default probabilities. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. The banks reject all firms with probabilities that fall in the bottom 5.0% based on their respective models while offering credit to all others at a credit spread derived using the centred default probability of Burgt (2007) and as defined in Eq. (21). The bank with the lowest credit spread is assumed to grant the loan. Market share is the total number of loans granted as a percentage of total number of firm years, defaults is the number of firms to whom a loan is granted that went bankrupt. Revenue = market size*market share*average credit spread. Loss = market size*prior probability of failure*share of defaulters*loss given default. Profit = Revenue - Loss. Return on assets is profit divided by market size * market share. The market size is £ 100.0 billion, loans are of equal size, loss given default is 45.0%, and credit spread for the highest quality customers is 0.30%. The prior probability of failure is taken to be the same as the ex-post failure rate of 0.91% during the sample period.

| Model | Bank 1<br>Shum | Bank 2<br>CHS | Bank 3<br>CG |
|---|---:|---:|---:|
| Credits | 12,144 | 4,418 | 4,812 |
| Market Share (%) | 54.7 | 19.9 | 21.7 |
| Defaults | 48 | 27 | 35 |
| Defaults/Credits (%) | 0.40 | 0.61 | 0.73 |
| Avg. Credit Spread (%) | 0.50 | 0.52 | 0.63 |
| Revenue (£m) | 275.0 | 103.9 | 136.6 |
| Loss (£m) | 97.3 | 54.7 | 71.0 |
| Profit (£m) | 177.7 | 49.2 | 65.6 |
| Return on asset (%) | 0.33 | 0.25 | 0.30 |
| Return on RWA (%) | 1.21 | 0.81 | 0.80 |

## 5.6 Conclusion and Discussion of Findings

This chapter provides the first comprehensive test of hybrid, accounting-based and market-based bankruptcy prediction models. For hybrid models, I apply the seminal model of Shumway (2001), the model of Campbell et al. (2008) as well as the model of Christidis and Gregory (2010). Further, I include Taffler's (1983) accounting-based z-score model as well as the market-based model of Bharath and Shumway (2008). To test the models' performance, I use receiver operating characteristics (ROC) curves, information content tests, and the economic impact of differential misclassification costs to test the models.

The tests using ROC curve analysis demonstrate that (i) all bankruptcy prediction models have a greater forecasting accuracy than a random model and that the composite models perform better than their individual variables (except for z-score and PBTCL). (ii) Hybrid models have a significantly higher forecasting accuracy than both z-score and BS. (iii) There is no difference in forecasting accuracy between the hybrid models. (iv) The outperformance of BS over z-score is not present in the earlier half of the sample period (see Hillegeist et al., 2004; Agarwal and Taffler, 2008a).

Information content tests provide evidence that (i) all models carry significant bankruptcy related information when tested individually. (ii) Z-score and BS carry distinct and bankruptcy related information complementary to each other (Agarwal and Taffler, 2008a). (iii) Hybrid models subsume the bankruptcy related information carried by z-score and BS.

The first two tests show a sharp outperformance of the hybrid models over z-score and BS but they are unable to distinguish between the three hybrid models. Therefore, the last test examines the economic value with differential misclassification costs for credit pricings using the models in Shumway (2001), Campbell et al. (2008) and Christidis and Gregory (2010). In this illustrative loan market, the model in Shumway (2001) leads to greater market share, higher credit quality and higher profits.

The results in this chapter clearly show that the hybrid models outperform the two alternatives, the z-score and BS model using ROC curve analysis and information content tests. There are several potential explanations for this outperformance. First, the z-score model was derived using a sample of firms failing between 1968 and 1976 (Taffler, 1983). As argued in Agarwal and Taffler (2007), the component ratios need to reflect the current key dimensions of firm financial profiles, and these are quite likely to have changed over the almost 35 years since the model was developed. Indeed, Agarwal and Taffler (2007) note that the firms at risk (and thus the Type II error rate) have dramatically increased from 1997 onwards. Also, my results show that an earlier sub-sample period leads to improved results. The BS model, while being theoretically sound, requires the estimation of several unobservable variables and thus introduces potential measurement error although existing studies suggest that the different estimators (e.g. asset volatility or asset returns) might have little impact on performance (e.g. Bharath and Shumway, 2008; Agarwal and Taffler, 2008a). Most importantly, the BS and the z-score do not account for time-varying effects on firm bankruptcy risk. In contrast, hybrid models assess firm bankruptcy risk with an annual re-estimation of the coefficients.[30] Thus, hybrid models are by definition more contemporaneous as the alternative models tested here. Consistent with Hillegeist et al. (2004) and Agarwal and Taffler (2008a), the information content tests show that accounting-based and market-based models carry bankruptcy related information incremental to each other. This also explains why hybrid models that draw upon both information sources are superior in assessing firm bankruptcy risk.

For the following analysis, I use the three approaches to predict bankruptcy, i.e. hybrid, accounting-based and market-based, but, due to its outperformance when considering differential misclassification costs, I continue with the model in Shumway (2001) to represent the hybrid models.

In the following chapter, I review the evidence on distress risk pricing using the alternative three approaches to proxy for distress risk.

[30] However, this is unlikely to be the main reason for their outperformance as Begley et al. (1996) show that simply re-estimating the coefficients of existing z-score models does not improve the performance significantly.

## 5.7 Appendix

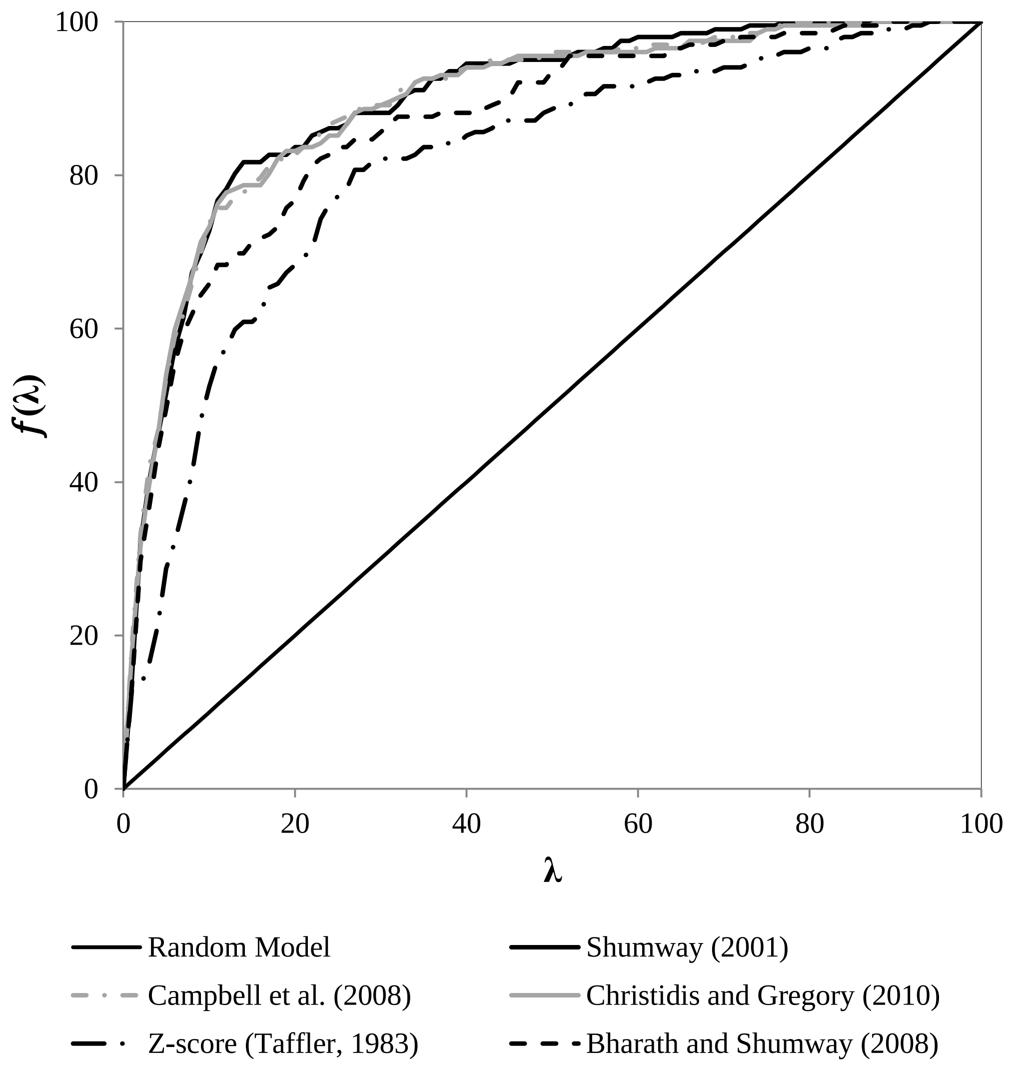


**Figure 5A Distress Risk Models: Area under ROC Curves (Hybrids)**
The figure illustrates the receiver operating characteristics curves using all UK non-financial firms listed in the Main market segment of the London Stock Exchange. λ is an integer between 0 and 100 and describes the λ% of the highest bankruptcy risk firms. $\boldsymbol{f}(\lambda)$ is a function of λ that divides the number of failures in the highest λ% of default risk by the total number of failures. Bankruptcy risk is determined at the end of September each year from 1985 to 2009 using the model in Shumway (2001), Campbell et al. (2008), Christidis and Gregory (2010), z-score (Taffler, 1983) and the market-based model in Bharath and Shumway (2008). I transform the z-score into probability: $p = e^{\text{z-score}} / (1+ e^{\text{z-score}})$. Random Model represents the results of random bankruptcy prediction model. All variables are winsorised at the 5.0% level, default probabilities at 0.00000001 and 0.99999999.

**Table 13A Distress Risk Models: Information Content Tests (Hybrids)**

The table reports different specifications of logit regressions to test for information content. At the end of each September from 1985 to 2009 (portfolio formation), I take the independent variables of UK non-financial firms listed in the Main market segment of the London Stock Exchange. Dependent binary variable: failure (1) or non-failed (0). Independent variables: Shum is the score from the model in Shumway (2001), CHS from Campbell, Hilscher and Szilagyi (2008), CG from Christidis and Gregory (2010), z-score (Taffler, 1983) and BS from Bharath and Shumway (2008). In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. RATE is the sample failure rate over the previous twelve months. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables (except RATE) are winsorised at the 5.0% level, scores are winsorised at ±18.4207.

| **Model** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
|---|---|---|---|---|---|---|---|---|---|
| Shum | 0.91 | 0.94 | 0.82 | | | | | | |
| | (4.00) | (4.17) | (3.16) | | | | | | |
| CHS | | | | 0.83 | 0.91 | 0.79 | | | |
| | | | | (3.89) | (4.06) | (3.08) | | | |
| CG | | | | | | | 0.85 | 0.91 | 0.80 |
| | | | | | | | (4.13) | (4.28) | (3.40) |
| Z-score | 0.03 | | 0.03 | 0.03 | | 0.03 | 0.03 | | 0.03 |
| | (0.88) | | (0.90) | (1.00) | | (1.02) | (1.06) | | (1.06) |
| BS | | 0.06 | 0.06 | | 0.03 | 0.03 | | 0.03 | 0.03 |
| | | (0.67) | (0.69) | | (0.27) | (0.32) | | (0.36) | (0.36) |
| BETA | 0.14 | 0.14 | 0.14 | 0.15 | 0.15 | 0.15 | 0.12 | 0.13 | 0.12 |
| | (0.81) | (0.83) | (0.81) | (0.86) | (0.89) | (0.86) | (0.70) | (0.72) | (0.71) |
| SIZE | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.01) | (0.14) | (0.04) | (0.15) | (0.05) | (0.13) | (0.09) | (0.01) | (0.06) |
| BM | 0.45 | 0.36 | 0.40 | 0.14 | 0.05 | 0.13 | 0.02 | -0.08 | 0.02 |
| | (1.84) | (1.46) | (1.59) | (0.55) | (0.20) | (0.52) | (0.09) | (0.32) | (0.08) |
| PYR | 0.10 | 0.46 | 0.36 | -0.10 | 0.11 | 0.03 | -0.12 | 0.11 | 0.04 |
| | (0.14) | (0.58) | (0.45) | (0.14) | (0.13) | (0.04) | (0.16) | (0.14) | (0.05) |
| RATE | -0.15 | -0.16 | -0.16 | -0.23 | -0.24 | -0.23 | -0.11 | -0.10 | -0.12 |
| | (0.40) | (0.43) | (0.43) | (0.60) | (0.63) | (0.60) | (0.28) | (0.25) | (0.31) |
| Constant | -1.15 | -0.70 | -1.25 | -0.82 | -0.24 | -0.91 | -0.80 | -0.26 | -0.86 |
| | (1.10) | (0.83) | (1.20) | (0.73) | (0.25) | (0.79) | (0.75) | (0.29) | (0.80) |
| Obs | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 | 22,217 |
| $\chi^2$ | 621.2 | 618.8 | 626.0 | 622.7 | 614.4 | 623.6 | 642.0 | 633.2 | 643.2 |
| Pseudo $R^2$ | 27.0 | 26.9 | 27.2 | 27.1 | 26.7 | 27.1 | 27.9 | 27.5 | 28.0 |

# CHAPTER 6: NEGATIVE DISTRESS RISK PREMIUM

## 6.1 Introduction

A key assertion of theoretical finance literature is that higher systematic risk is rewarded with higher returns. Chan and Chen (1991) and Fama and French (1992) hypothesise that high returns on small size and high BM firms are due to higher financial distress risk of such firms. If financial distress risk is systematic, then investors expect a positive premium for bearing this risk. Campbell et al. (2008) and Chava and Purnanandam (2010) note that the standard implementation of the capital asset pricing model (CAPM) might fail to completely capture the distress risk premium if corporate failures are correlated with deteriorating investment opportunities (Merton, 1973) or unmeasured components of wealth such as human capital (Fama and French, 1996) and debt securities (Ferguson and Shockley, 2003). Following this argument, distress risk would result in the return patterns related to size and value as argued by Fama and French (1996).

Chava and Purnanandam (2010) find expected returns to be higher for distressed firms. Vassalou and Xing (2004) observe a positive distress risk premium using realised returns. However, in the majority of the literature a negative relation between distress risk and realised stock returns is found (e.g. Dichev, 1998; Griffin and Lemmon, 2002; Agarwal and Taffler, 2008b). This is in sharp contrast with the risk-reward relation of theoretical finance, and moreover, it rejects the distress hypothesis proposed by Chan and Chen (1991) and Fama and French (1992).

Although the majority of studies document a negative distress risk premium, the reasons for this anomalous finding are still not clear. Also, studies with the same bankruptcy prediction measure document conflicting results (e.g. Vassalou and Xing, 2004 and Da and Gao, 2010). Moreover, the existing studies do not examine the pricing impact comprehensively by using all three available approaches to measure distress risk. This chapter fills this gap by providing evidence on the pricing of distress risk by first testing whether the documented negative distress risk premium in the literatures is sensitive to the distress risk proxy. Also, while Agarwal and Taffler (2008b) provide evidence of negative distress risk premium using z-score, there is no study that provides similar evidence using market-based or hybrid models in the UK. The analysis in this chapter fills this gap as well.

Importantly, the evidence in Chapter 5 clearly demonstrates that the hybrid model of Shumway (2001) is a better predictor of bankruptcy than other models and that it subsumes the bankruptcy related information of both, the z-score and market-based model. If the observed lower returns on distressed firms are due to their higher risk of failure, I expect the Shumway (2001) model-based proxy for distress risk will subsume the information related to future stock returns contained in the other two measures. Therefore and in contrast to other studies, this chapter is essentially able to test whether there is a *distress risk* premium: the best bankruptcy prediction model is expected to be the most significant in distress risk pricing. This dimension has so far been disregarded in literature.

The remainder of this chapter is organised as follows: in sub-chapter 2 I present the research question and research propositions. In sub-chapter 3 I briefly describe the data and method used. Sub-chapter 4 tests the distress risk premium using time-series regressions. Sub-chapter 5 tests the distress risk premium using cross-sectional regressions. Sub-chapter 6 concludes.

## 6.2 Research Question

While the majority of previous studies focus on using one or two distress risk proxies and explore its impact on stock prices (e.g. Dichev, 1998; Griffin and Lemmon, 2002; Agarwal and Taffler, 2008b), I review the relation between distress risk and subsequent stock returns using the three available approaches to proxy for distress risk. The research question and propositions tested in this chapter are as follows:

**Is there a distress risk premium and does it depend on the distress risk measure?**

*P4: There is a distress risk premium in stock returns.*

*P5: The distress risk premium depends on the proxy for distress risk.*

## 6.3 Data and Methodology

My sample consists of UK non-financial firms listed in the Main market segment of the London Stock Exchange anytime between October 1985 and September 2010. It includes 22,217 observations with 2,428 unique firms of which 202 failed.

The test of economic value with differential misclassification costs in Chapter 5 shows that the hybrid model of Shumway (2001) (Shum) outperforms the two alternative hybrid models. Therefore, in all subsequent parts in this thesis, I use Shum to represent the hybrid models. In addition to Shum, I apply the accounting-based z-score (Taffler, 1983) and the market-based model of Bharath and Shumway (2008) (BS) to proxy for distress risk.

In this chapter, I use two testing procedures. First, I use time-series regressions on average portfolio excess returns using the Fama and French (1993) model (Fama and

French model) as well as the Carhart (1997) model (Carhart model) as defined in Eq. (25). Second, I use cross-sectional regressions following the method of Fama and MacBeth (1973) as defined in Eq. (24).

## 6.4 Time-Series Regressions

To test the time-series characteristics of distress risk, I use decile portfolios sorts on each distress risk measure. Specifically, at the end of September of each year from 1985 to 2009, I sort all stocks on their failure probability and group them into ten portfolios with equal number of stocks.

### 6.4.1 Portfolios on Shumway (2001)

Table 14 summarises the portfolio characteristics of decile portfolios sorted on Shum. Using value-weighted average excess portfolio returns, the high distress risk portfolio clearly stands out with a negative return of -28 bps per month. Likewise, the low distress risk portfolio earns 61 bps per month (t = 2.21), the highest return of all portfolios. The H-L portfolio, that is a portfolio long on distressed and short on non-distressed stocks, earns a significant negative premium of -89 bps per month (t = 2.23). Using equally-weighted returns, the highest distress risk portfolio underperforms all other portfolios (21 bps per month) while the low distress risk portfolio earns the second highest returns (63 bps). The return on the H-L portfolio is -42 bps per month though statistically not significant (t = 1.09). The returns between the two extreme portfolios do not follow any pattern. BETA increases (monotonically) with distress risk. The low distress risk portfolio has an average equity beta of 1.04 while the high distress risk portfolio has an average equity beta of 1.25. SIZE is negatively related with distress risk. The average market capitalisation of the low distress risk portfolio is £ 1,104m. In sharp contrast to that, the high distress risk portfolio has the lowest average market capitalisation of only £ 23m. Also, BM increases monotonically in distress risk from 0.49 for the low distress risk portfolio to 1.05 for the high distress risk portfolio. PYR provides another monotonic relation with Shum as the prior-year returns decrease from 38 bps for the low risk portfolio to -23 bps to the high risk portfolio. However, interpreting the results one has to keep in mind that Shum contains a SIZE-related variable (RSIZE) as well as a PYR-related variable (EXRET). As such, it is not surprising that the two variables are related with Shum, though this does not change the fact that they are good proxies for distress risk. Def Prob presents the average default probabilities of the portfolios. Recalling from Chapter 5, the average sample default probability using Shum is 1.10%. As such, P1 to P8 have substantially lower than average failure probabilities while for the high risk portfolio the average failure probability is 7.43%. Demonstrating the ability of Shum to predict failures, Fail Rate shows that the failure rate of the high risk portfolio is 6.46% compared to an average failure rate of 0.91% (see Chapter 4). This equals to 144 out of 202 failures in the high default risk portfolio.

**Table 14 Shumway (2001) Decile Portfolios: Summary Statistics**

The table presents summary statistics of decile portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability obtained from the model in Shumway (2001) and sort into equally populated decile portfolios. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. ER vw (ER ew) reports the value-weighted (equally-weighted) average monthly portfolio excess return for the 12 months following portfolio formation. Time-series portfolio averages are reported for: BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Def Prob is the average default probability measured by Shumway (2001). Act Fails is the number of actuals failures within the respective portfolio. Fail Rate is Act Fails over the total number of firms in the portfolio. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. The return of the month of failure is set to -100.0%. All variables are winsorised at the 5.0% level, default probabilities at 0.00000001 and 0.99999999.

| | **Low** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High** | **H-L** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ER vw | 0.61 | 0.47 | 0.45 | 0.48 | 0.24 | 0.37 | 0.23 | 0.47 | 0.44 | -0.28 | -0.89 |
| | (2.21) | (1.65) | (1.52) | (1.49) | (0.67) | (1.06) | (0.59) | (1.12) | (0.83) | (0.56) | (2.23) |
| ER ew | 0.63 | 0.54 | 0.57 | 0.64 | 0.37 | 0.61 | 0.39 | 0.56 | 0.55 | 0.21 | -0.42 |
| | (2.24) | (1.94) | (1.98) | (2.13) | (1.19) | (1.95) | (1.16) | (1.59) | (1.29) | (0.44) | (1.09) |
| BETA | 1.04 | 1.02 | 1.05 | 1.09 | 1.07 | 1.06 | 1.12 | 1.14 | 1.15 | 1.25 | 0.20 |
| SIZE | 1,104 | 718 | 539 | 389 | 292 | 207 | 139 | 82 | 56 | 23 | -1,082 |
| BM | 0.49 | 0.55 | 0.57 | 0.61 | 0.67 | 0.76 | 0.82 | 0.93 | 1.02 | 1.05 | 0.56 |
| PYR | 0.38 | 0.29 | 0.27 | 0.24 | 0.20 | 0.16 | 0.12 | 0.05 | -0.03 | -0.23 | -0.61 |
| Def Prob | 0.04 | 0.07 | 0.11 | 0.15 | 0.22 | 0.30 | 0.46 | 0.77 | 1.54 | 7.34 | 7.30 |
| Act Fails | 0 | 0 | 2 | 2 | 6 | 2 | 12 | 10 | 24 | 144 | 144 |
| Fail Rate | 0.00 | 0.00 | 0.09 | 0.09 | 0.27 | 0.09 | 0.54 | 0.45 | 1.08 | 6.46 | 6.46 |

Table 15 presents the risk-adjusted returns and adjusted $R^2$s using the Fama and French model and Carhart model for decile portfolios sorted on Shum. Panel A in Table 15 reports the results for value-weighted portfolio average excess returns. The results show a sharp underperformance of distressed stocks. The H-L portfolio earns a significant premium of -131 bps per month ($t = 5.14$) using the Fama and French model. The negative premium is driven by both the high distress risk portfolio (-96 bps, $t = 4.10$) and the low distress risk portfolio (35 bps, $t = 3.59$). Like the intercept, the adjusted $R^2$s are generally lower for high distress risk portfolios (overall ranging from 88% to 67%).

The inclusion of the momentum factor (Carhart model) reduces the premium on the H-L portfolio to -104 bps but it is still statistically highly significant (t = 4.15). Again, the distress risk premium is driven by the two extreme portfolios (-81 bps, t = 3.44 and 22 bps, t = 2.37 respectively). The adjusted $R^2$s increase only little with the inclusion of the momentum factor (ranging from 71% to 89%).

Panel B presents the portfolio statistics using equally-weighted returns. Again, there is a negative distress risk premium with a substantial underperformance of the H-L portfolio of -77 bps per month (t = 3.12) using the Fama and French model. The distress risk premium is driven by both distressed stocks (-44 bps, t = 1.97) and the non-distressed stocks (32 bps, t = 3.23). Interestingly, the adjusted $R^2$s are higher using equal weights (ranging from 78% to 91%). Using the Carhart (1997) risk-adjustment, the negative H-L remains (-62 bps, t = 2.49). However, the risk-adjusted return of the highly distressed firms are insignificant (-40 bps, t = 1.73) and thus, the negative distress risk premium is mainly driven by outperforming non-distressed stocks contributing with 22 bps (t = 2.24). As with value-weighted returns, the adjusted $R^2$s do not increase significantly with the inclusion of the momentum factor (ranging from 78% to 91%).

The results in Table 15 clearly show that when distress risk is proxied by Shumway (2001) model, the distressed stocks significantly underperform non-distressed stocks on a risk-adjusted basis. Thus, I find evidence in favour of proposition P4, as there is a distress risk premium in stock returns, albeit negative.

**Table 15 Shumway (2001) Decile Portfolios: Time-Series Regression**

The table presents summary statistics of time-series regressions on decile portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability obtained from the model in Shumway (2001) and sort into equally populated decile portfolios. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. I report the intercepts $\beta_1$, the corresponding t-statistics in brackets, and the adjusted R² for the asset pricing model of Fama and French (1993) (excl. $WML_{t+m}$) and Carhart (1997) as defined in Eq. (25):

$R_{i,t+m} - R_{f,t+m} = \beta_1 + \beta_{MKT}RmRf_{t+m} + \beta_{SMB}SMB_{t+m} + \beta_{HML}HML_{t+m} + \beta_{WML}WML_{t+m} + \varepsilon_{i,t+m}$,

where $R_{i,t+m}$ is the return on portfolio i during month m (integer 1 to 12) in portfolio year t, $R_{f,t+m}$ the one-month UK Treasury Bill rate at the beginning of month t+m, $RmRf_{t+m}$ the return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate during month t+m, $SMB_{t+m}$ the return on the mimicking portfolio for the size factor during month t+m, $HML_{t+m}$ the return on the mimicking portfolio for the BM factor during month t+m and $WML_{t+m}$ the return on the mimicking portfolio for the return momentum factor during month t+m. The results in Panel A are based on value-weighted monthly portfolio average excess returns. The results in Panel B are based on equally-weighted monthly portfolio average excess returns. The return of the month of failure is set to -100.0%.

| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A. Value-Weighted Returns** | | | | | | | | | | | |
| **Fama and French Model** | | | | | | | | | | | |
| $\beta_1$ | 0.35 | 0.10 | 0.01 | 0.05 | -0.31 | -0.16 | -0.35 | -0.19 | -0.34 | -0.96 | -1.31 |
| | (3.59) | (0.98) | (0.05) | (0.37) | (2.07) | (1.00) | (1.55) | (0.80) | (1.17) | (4.10) | (5.14) |
| Adj. R² | 0.88 | 0.88 | 0.85 | 0.82 | 0.83 | 0.80 | 0.67 | 0.69 | 0.71 | 0.77 | 0.60 |
| **Carhart Model** | | | | | | | | | | | |
| $\beta_1$ | 0.22 | 0.12 | 0.09 | 0.20 | -0.17 | 0.02 | -0.21 | 0.03 | -0.10 | -0.81 | -1.04 |
| | (2.37) | (1.21) | (0.77) | (1.43) | (1.18) | (0.11) | (0.91) | (0.12) | (0.37) | (3.44) | (4.15) |
| Adj. R² | 0.89 | 0.88 | 0.86 | 0.83 | 0.84 | 0.81 | 0.68 | 0.71 | 0.73 | 0.78 | 0.63 |
| **Panel B. Equally-Weighted Returns** | | | | | | | | | | | |
| **Fama and French Model** | | | | | | | | | | | |
| $\beta_1$ | 0.32 | 0.16 | 0.14 | 0.20 | -0.12 | 0.12 | -0.16 | 0.00 | -0.14 | -0.44 | -0.77 |
| | (3.23) | (1.53) | (1.34) | (1.87) | (1.20) | (1.27) | (1.45) | (0.03) | (0.91) | (1.97) | (3.12) |
| Adj. R² | 0.88 | 0.87 | 0.87 | 0.88 | 0.89 | 0.91 | 0.89 | 0.89 | 0.88 | 0.78 | 0.61 |
| **Carhart Model** | | | | | | | | | | | |
| $\beta_1$ | 0.22 | 0.13 | 0.14 | 0.23 | -0.11 | 0.18 | -0.13 | 0.05 | -0.06 | -0.40 | -0.62 |
| | (2.24) | (1.20) | (1.30) | (2.14) | (1.02) | (1.86) | (1.19) | (0.40) | (0.41) | (1.73) | (2.49) |
| Adj. R² | 0.89 | 0.87 | 0.87 | 0.88 | 0.89 | 0.91 | 0.89 | 0.89 | 0.88 | 0.78 | 0.62 |

### 6.4.2 Portfolios on z-score (Taffler, 1983)

Table 16 summarises the portfolio characteristics of the ten portfolios sorted on z-score. Similar to the sort on Shum, excess returns using equal weights are generally lower for firms with higher distress risk. The highest distress risk portfolio earns a return of only

8 bps per month (t = 0.23). In contrast, the low distress portfolio has an average return of 54 bps. As such, the return of the H-L portfolio is -46 bps per month though insignificant (t = 1.68). Using equal weights, the negative distress risk-return relation is more apparent. The high distress risk portfolio again has the lowest returns (-2 bps, t = 0.05) while the low distress risk portfolio earns high positive returns (64 bps, t = 2.27). The negative premium of -66 bps per month on the H-L portfolio is highly significant (t = 2.62). BETA increases monotonically with distress risk from 0.99 for the low distress risk portfolio to 1.25 for the high distress risk portfolio. SIZE is not as pronounced as in the Shum sort and in fact, it shows a hump-shaped relation with z-score (£ 282m for the low distress risk portfolio, £ 460m for P5, and £ 167m for the high distress risk portfolio). The relation between BM and z-score shows a distinct U-shape with similar BM ratios for the low and high distress risk portfolios (0.84 for the low distress risk portfolio, 0.80 for the high distress risk portfolio, and a drop to 0.68 in P3). PYR is fairly constant (between 15 bps and 18 bps) for portfolios 1 to 8 and declines sharply for the two high distress risk portfolios (12 bps and 1 bps respectively). The average failure probability predicted by z-score increases to nearly 100% for the high distress risk portfolio showing again the mis-calibration of the model (see Chapter 5). However, in relative terms, z-score is able to predict failures as the failure rate and the distribution of failures show. The high default risk portfolio has an average failure rate of 4.71% (about four times higher than average) and contains more than half of all failures (105 out of 202).

**Table 16 Z-score (Taffler, 1983) Decile Portfolios: Summary Statistics**

The table presents summary statistics of decile portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability obtained from z-score (Taffler, 1983) and sort into equally populated decile portfolios. I transform the z-score into probability: $p = e^{z\text{-score}} / (1 + e^{z\text{-score}})$. In order to avoid look-ahead bias, I take the predictor variables that are known at portfolio formation. ER vw (ER ew) reports the value-weighted (equally-weighted) average monthly portfolio excess return for the 12 months following portfolio formation. Time-series portfolio averages are reported for: BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September Def Prob is the average default probability measured by z-score (Taffler, 1983). Act Fails is the number of actuals failures within the respective portfolio. Fail Rate is Act Fails over the total number of firms in the portfolio. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. The return of the month of failure is set to -100.0%. All variables are winsorised at the 5.0% level, default probabilities at 0.00000001 and 0.99999999.

| | **Low** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High** | **H-L** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ER vw | 0.54 | 0.61 | 0.54 | 0.55 | 0.51 | 0.44 | 0.48 | 0.22 | 0.42 | 0.08 | -0.46 |
| | (1.60) | (2.06) | (1.78) | (1.91) | (1.73) | (1.48) | (1.62) | (0.70) | (1.25) | (0.23) | (1.68) |
| ER ew | 0.64 | 0.71 | 0.61 | 0.65 | 0.54 | 0.48 | 0.56 | 0.43 | 0.45 | -0.02 | -0.66 |
| | (2.27) | (2.46) | (2.10) | (2.08) | (1.68) | (1.59) | (1.71) | (1.29) | (1.24) | (0.05) | (2.62) |
| BETA | 0.99 | 1.03 | 1.09 | 1.09 | 1.10 | 1.08 | 1.11 | 1.10 | 1.16 | 1.25 | 0.26 |
| SIZE | 282 | 392 | 452 | 459 | 460 | 394 | 349 | 321 | 280 | 167 | -115 |
| BM | 0.84 | 0.72 | 0.68 | 0.69 | 0.70 | 0.74 | 0.75 | 0.76 | 0.80 | 0.80 | -0.04 |
| PYR | 0.17 | 0.17 | 0.18 | 0.17 | 0.17 | 0.15 | 0.15 | 0.15 | 0.12 | 0.01 | -0.16 |
| Def Prob | 0.00 | 0.00 | 0.04 | 0.33 | 1.60 | 6.41 | 20.94 | 50.04 | 84.31 | 98.98 | 98.98 |
| Act Fails | 2 | 5 | 5 | 5 | 6 | 8 | 5 | 30 | 31 | 105 | 103 |
| Fail Rate | 0.09 | 0.22 | 0.22 | 0.23 | 0.27 | 0.36 | 0.23 | 1.35 | 1.39 | 4.71 | 4.62 |

Table 17 reports the summary results for time-series regressions on decile portfolios sorted on z-score. The pricing analysis using z-score is of great interest since, as opposed to the other two bankruptcy prediction models, the accounting-based z-score is completely independent of the risk factors. However, like the sort on Shum, Panel A in Table 17 reveals a highly significant distress risk premium of -57 bps (t = 2.12) using the Fama and French model. The distress risk premium is driven by both the low distressed firms (20 bps, t = 1.09) and the high distress portfolio (-37 bps, t = 1.91). The adjusted $R^2$s show that the Fama and French model has problems in pricing these two portfolios especially (72% and 71% respectively) while for the other portfolios it is 75% to 87%. The risk-adjusted returns of the Carhart model show a weaker but still significant negative distress risk premium. The H-L portfolio earns a negative distress risk premium of -57 bps per month (t = 2.07). While the mispricing of the high distress risk portfolio has increased with the inclusion of the momentum factor (-40 bps, t = 1.99), it slightly decreased for the low distress risk portfolio (17 bps, t = 0.94). There is no difference in adjusted $R^2$s between the pricing models.

Panel B presents equally-weighted risk-adjusted portfolios returns. Using the Fama and French model, there is a substantial distress risk premium of -89 bps per month (t = 4.50) that is mostly due to the high distress risk portfolio (-66 bps, t = 3.44) and partly driven by low distress risk portfolio (23 bps, t = 2.21). As with the sort on Shum, using equal weights increases the adjusted $R^2$s to about 87% but there is still a low fit for the high distress risk portfolio (82%). The momentum factor (Carhart model) is again unable to capture the distress risk premium. The H-L portfolio still earns a premium of -93 bps per month (t = 4.59). The returns of the low and high distress risk portfolio remain significant as well (26 bps, t = 2.42 and -67 bps, t = 3.42 respectively). Adjusted $R^2$s are still at around 88% except for the high distress risk portfolio (82%).

Table 17 clearly shows that when z-scores are used to proxy for distress risk, on a risk-adjusted basis, the distressed stocks underperform the non-distressed stocks on value-weighted and equally-weighted basis. Thus, I again find supporting evidence of proposition P4, there is a negative distress risk premium in stock returns.

**Table 17 Z-score (Taffler, 1983) Decile Portfolios: Time-Series Regression**

The table presents summary statistics of time-series regressions on decile portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability obtained from the z-score (Taffler, 1983) and sort into equally populated decile portfolios. I transform the z-score into probability: p = $e^{z\text{-score}}$ / (1+ $e^{z\text{-score}}$). In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. I report the intercepts $\beta_1$, the corresponding t-statistics in brackets, and the adjusted R² for the asset pricing model of Fama and French (1993) (excl. $WML_{t+m}$) and Carhart (1997) as defined in Eq. (25):

$R_{i,t+m} - R_{f,t+m} = \beta_1 + \beta_{MKT}RmRf_{t+m} + \beta_{SMB}SMB_{t+m} + \beta_{HML}HML_{t+m} + \beta_{WML}WML_{t+m} + \varepsilon_{i,t+m}$,

where $R_{i,t+m}$ is the return on portfolio i during month m (integer 1 to 12) in portfolio year t, $R_{f,t+m}$ the one-month UK Treasury Bill rate at the beginning of month t+m, $RmRf_{t+m}$ the return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate during month t+m, $SMB_{t+m}$ the return on the mimicking portfolio for the size factor during month t+m, $HML_{t+m}$ the return on the mimicking portfolio for the BM factor during month t+m, and $WML_{t+m}$ the return on the mimicking portfolio for the return momentum factor during month t+m. The results in Panel A are based on value-weighted monthly portfolio average excess returns. The results in Panel B are based on equally-weighted monthly portfolio average excess returns. The return of the month of failure is set to -100.0%.

| | **Low** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High** | **H-L** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A. Value-Weighted Returns** | | | | | | | | | | | |
| **Fama and French Model** | | | | | | | | | | | |
| $\beta_1$ | 0.20 | 0.21 | 0.15 | 0.16 | 0.12 | 0.02 | 0.05 | -0.22 | 0.02 | -0.37 | -0.57 |
| | (1.09) | (1.76) | (1.36) | (1.37) | (1.06) | (0.19) | (0.38) | (1.53) | (0.12) | (1.91) | (2.12) |
| Adj. R² | 0.72 | 0.84 | 0.87 | 0.84 | 0.87 | 0.84 | 0.84 | 0.79 | 0.75 | 0.71 | 0.04 |
| **Carhart Model** | | | | | | | | | | | |
| $\beta_1$ | 0.17 | 0.25 | 0.17 | 0.18 | 0.15 | 0.07 | 0.07 | -0.11 | 0.03 | -0.40 | -0.57 |
| | (0.94) | (2.03) | (1.45) | (1.53) | (1.29) | (0.56) | (0.55) | (0.76) | (0.18) | (1.99) | (2.07) |
| Adj. R² | 0.72 | 0.84 | 0.87 | 0.84 | 0.87 | 0.85 | 0.84 | 0.80 | 0.75 | 0.71 | 0.04 |
| **Panel B. Equally-Weighted Returns** | | | | | | | | | | | |
| **Fama and French Model** | | | | | | | | | | | |
| $\beta_1$ | 0.23 | 0.26 | 0.16 | 0.15 | 0.03 | 0.01 | 0.04 | -0.07 | -0.07 | -0.66 | -0.89 |
| | (2.21) | (2.52) | (1.60) | (1.38) | (0.28) | (0.12) | (0.35) | (0.65) | (0.52) | (3.44) | (4.50) |
| Adj. R² | 0.87 | 0.87 | 0.89 | 0.88 | 0.87 | 0.88 | 0.88 | 0.89 | 0.87 | 0.82 | 0.40 |
| **Carhart Model** | | | | | | | | | | | |
| $\beta_1$ | 0.26 | 0.29 | 0.16 | 0.20 | 0.10 | 0.03 | 0.05 | -0.08 | -0.09 | -0.67 | -0.93 |
| | (2.42) | (2.74) | (1.63) | (1.74) | (0.83) | (0.24) | (0.44) | (0.68) | (0.67) | (3.42) | (4.59) |
| Adj. R² | 0.87 | 0.87 | 0.89 | 0.88 | 0.88 | 0.88 | 0.88 | 0.89 | 0.87 | 0.82 | 0.40 |

### 6.4.3 **Portfolios on Bharath and Shumway** (2008)

Table 18 presents the summary characteristics for the sort on the market-based Bharath and Shumway (2008) model. The value-weighted average excess returns show a negative premium on the H-L portfolios of -31 bps (t = 0.76). However, the distress risk-return relation is less clear than for the previous two sorts. The high distress risk portfolio earns a fairly low return (23 bps, t = 0.45) while the lowest return is earned by P8 (2 bps, t = 0.05). However, the returns for low distress risk firms are higher and more stable, ranging from 53 bps to 64 bps for portfolios 1 to 3 (minimum t = 1.92). Using equal weights gives a less clear picture. Although there is a negative distress risk premium (-40 bps, t = 1.12), P9 earns the highest returns (70 bps, t = 1.73). The low distress risk portfolio has an average return of 53 bps (t = 2.01). BETA generally increases with distress risk from 0.94 to 1.22 with a small drop in P8. SIZE decreases with distress risk to £ 51m for the high distress risk portfolio (peaking in P3 with £ 598m). BM increases monotonically in distress risk from 0.39 to 1.30. Not surprisingly, PYR, which is similar to the BS component ER1y, decreases monotonically with distress risk from 42 bps to -30 bps. Similar to z-score, the BS is mis-calibrated as the average default probabilities are too high for the high risk portfolios (up to 60%). But again, the ability of BS in predicting bankruptcy is shown by the high failure rates (5.87%) and concentration of failures in the high distress risk portfolio (131 out of 202 failures).

**Table 18 Bharath and Shumway (2008) Decile Portfolios: Summary Statistics**

The table presents summary statistics of decile portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability obtained from the model in Bharath and Shumway (2001) and sort into equally populated decile portfolios. In order to avoid look-ahead bias, I take the predictor variables that are known at portfolio formation. ER vw (ER ew) reports the value-weighted (equally-weighted) average monthly portfolio excess return for the 12 months following portfolio formation. Time-series portfolio averages are reported for: BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Def Prob is the average default probability measured by Bharath and Shumway (2008). Act Fails is the number of actuals failures within the respective portfolio. Fail Rate is Act Fails over the total number of firms in the portfolio. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. The return of the month of failure is set to -100.0%. All variables are winsorised at the 5.0% level, default probabilities at 0.00000001 and 0.99999999.

| | **Low** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High** | **H-L** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ER vw | 0.53 | 0.64 | 0.59 | 0.43 | 0.34 | 0.44 | 0.18 | 0.02 | 0.41 | 0.23 | -0.31 |
| | (1.92) | (2.27) | (2.09) | (1.45) | (1.06) | (1.29) | (0.49) | (0.05) | (0.88) | (0.45) | (0.76) |
| ER ew | 0.53 | 0.53 | 0.70 | 0.52 | 0.46 | 0.51 | 0.49 | 0.54 | 0.70 | 0.13 | -0.40 |
| | (2.01) | (1.94) | (2.45) | (1.76) | (1.45) | (1.64) | (1.49) | (1.53) | (1.73) | (0.27) | (1.12) |
| BETA | 0.94 | 0.99 | 1.06 | 1.07 | 1.10 | 1.13 | 1.14 | 1.10 | 1.25 | 1.22 | 0.28 |
| SIZE | 451 | 568 | 598 | 557 | 452 | 340 | 256 | 169 | 115 | 51 | -400 |
| BM | 0.39 | 0.48 | 0.53 | 0.61 | 0.66 | 0.73 | 0.81 | 0.93 | 1.04 | 1.30 | 0.91 |
| PYR | 0.42 | 0.36 | 0.30 | 0.27 | 0.20 | 0.17 | 0.09 | 0.03 | -0.09 | -0.30 | -0.71 |
| Def Prob | 0.00 | 0.00 | 0.03 | 0.20 | 0.92 | 2.75 | 6.56 | 13.03 | 25.50 | 59.62 | 59.62 |
| Act Fails | 0 | 3 | 2 | 4 | 4 | 11 | 7 | 17 | 23 | 131 | 131 |
| Fail Rate | 0.00 | 0.13 | 0.09 | 0.18 | 0.18 | 0.50 | 0.32 | 0.77 | 1.03 | 5.87 | 5.87 |

Table 19 presents summary statistics for time-series regressions on decile portfolios sorted on BS. Panel A reports value-weighted returns and again shows a substantial distress risk premium of -92 bps (t = 3.08) using the Fama and French model. The low distress risk portfolio contributes about a third (30 bps, t = 2.70) while the high distress risk portfolio contributes two thirds (-61 bps, t = 2.26) to the premium. The highest and lowest risk-adjusted returns are earned by P2 (43 bps, t = 3.91) and P8 (-68 bps, t = 3.06) respectively. The adjusted $R^2$s are low for the high distressed portfolios, for P9 especially (68%). The inclusion of the momentum factor (Carhart model) returns a weak distress risk premium of -54 bps (t =1.88) while the two extreme portfolios do not earn abnormal returns (low distress risk 18 bps, t = 1.67 and high distress risk -35 bps, t = 1.31). As such, the Carhart model is able to account for the low and high distress risk portfolio especially while P2 and P8 still earn abnormal returns (t = 2.91 and 1.93). The increased model fit is also illustrated by higher adjusted $R^2$s ranging from 72% to 89%.

Panel B shows the results using equal-weights. Here, the outperformance is more apparent since the H-L premium using the Fama and French model is -89 bps and highly significant (t = 3.78). The high risk portfolio contributes about two thirds to the premium (-66 bps, t = 3.21) while the low distress risk portfolio still earns an abnormal return (23 bps, t = 2.16). Again, the adjusted $R^2$s are higher for equally-weighted returns as they range between 83% and 90%. The momentum (Carhart model) is unable to capture the distress risk premium. It is still -74 bps per month (t = 3.14) and driven mostly by the high distress risk portfolio (-58 bps, t = 2.76). The adjusted $R^2$s hardly change with the inclusion of the momentum factor.

Similar to Tables 15 and 17, the results in Table 19 support proposition P4 as they show a negative distress risk premium.

The evidence in this chapter demonstrates that the underperformance of distressed firms relative to non-distressed firms is robust to different proxies for distress risk. While the portfolio excess returns generally show lower returns for high distress risk firms, the underperformance worsens with risk-adjustment, i.e. the stock underperform although they load high on the common risk factors. As this is independent of the distress risk proxy applied, I find strong evidence not just in support of proposition P4, that there is a negative distress risk premium, but I also do not find evidence for proposition P5, the negative distress risk premium exists regardless of which proxy is used. These findings are robust as 11 out of 12 H-L portfolios (using three distress risk measures, two risk-adjustments, and two weighting-schemes) document significant negative risk premia.

In the next sub-chapter, I test the same propositions using cross-sectional regressions.

**Table 19 Bharath and Shumway (2008) Decile Portfolios: Time-Series Regression**

The table presents summary statistics of time-series regressions on decile portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability obtained from the model in Bharath and Shumway (2008) and sort into equally populated decile portfolios. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. I report the intercepts $\beta_1$, the corresponding t-statistics in brackets, and the adjusted R² for the asset pricing model of Fama and French (1993) (excl. $\mathrm{WML}_{t+m}$) and Carhart (1997) as defined in Eq. (25):

$$R_{i,t+m} - R_{f,t+m} = \beta_1 + \beta_{MKT} RmRf_{t+m} + \beta_{SMB} SMB_{t+m} + \beta_{HML} HML_{t+m} + \beta_{WML} WML_{t+m} + \varepsilon_{i,t+m},$$

where $R_{i,t+m}$ is the return on portfolio i during month m (integer 1 to 12) in portfolio year t, $R_{f,t+m}$ the one-month UK Treasury Bill rate at the beginning of month t+m, $RmRf_{t+m}$ the return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate during month t+m, $SMB_{t+m}$ the return on the mimicking portfolio for the size factor during month t+m, $HML_{t+m}$ the return on the mimicking portfolio for the BM factor during month t+m, and $WML_{t+m}$ the return on the mimicking portfolio for the return momentum factor during month t+m. The results in Panel A are based on value-weighted monthly portfolio average excess returns. The results in Panel B are based on equally-weighted monthly portfolio average excess returns. The return of the month of failure is set to -100.0%.

| | **Low** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High** | **H-L** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A. Value-Weighted Returns** | | | | | | | | | | | |
| **Fama and French Model** | | | | | | | | | | | |
| $\beta_1$ | 0.30 | 0.43 | 0.30 | 0.00 | -0.12 | -0.09 | -0.45 | -0.68 | -0.33 | -0.61 | -0.92 |
| | (2.70) | (3.91) | (2.92) | (0.01) | (0.91) | (0.59) | (2.63) | (3.06) | (1.25) | (2.26) | (3.08) |
| Adj. $R^2$ | 0.84 | 0.85 | 0.87 | 0.89 | 0.84 | 0.79 | 0.77 | 0.72 | 0.68 | 0.71 | 0.48 |
| **Carhart Model** | | | | | | | | | | | |
| $\beta_1$ | 0.18 | 0.32 | 0.24 | 0.04 | -0.04 | 0.10 | -0.20 | -0.41 | 0.00 | -0.35 | -0.54 |
| | (1.67) | (2.91) | (2.32) | (0.37) | (0.30) | (0.63) | (1.23) | (1.93) | (0.00) | (1.31) | (1.88) |
| Adj. $R^2$ | 0.86 | 0.86 | 0.88 | 0.89 | 0.85 | 0.81 | 0.81 | 0.75 | 0.72 | 0.73 | 0.54 |
| **Panel B. Equally-Weighted Returns** | | | | | | | | | | | |
| **Fama and French Model** | | | | | | | | | | | |
| $\beta_1$ | 0.23 | 0.20 | 0.32 | 0.09 | -0.04 | 0.01 | -0.07 | -0.02 | 0.05 | -0.66 | -0.89 |
| | (2.16) | (1.98) | (3.13) | (0.98) | (0.34) | (0.07) | (0.64) | (0.18) | (0.31) | (3.21) | (3.78) |
| Adj. $R^2$ | 0.84 | 0.86 | 0.88 | 0.90 | 0.89 | 0.90 | 0.88 | 0.90 | 0.86 | 0.83 | 0.57 |
| **Carhart Model** | | | | | | | | | | | |
| $\beta_1$ | 0.16 | 0.12 | 0.28 | 0.07 | 0.01 | 0.06 | -0.05 | 0.04 | 0.16 | -0.58 | -0.74 |
| | (1.55) | (1.18) | (2.73) | (0.78) | (0.06) | (0.56) | (0.42) | (0.31) | (1.05) | (2.76) | (3.14) |
| Adj. $R^2$ | 0.85 | 0.87 | 0.88 | 0.90 | 0.89 | 0.90 | 0.88 | 0.90 | 0.87 | 0.83 | 0.58 |

## 6.5 Cross-Sectional Regressions

In addition to the previously reported time-series regressions I test as well for the distress risk-return relation using cross-sectional regressions. Before introducing the results, I test for multicollinearity.

The cross-sectional tests apply the common risk factors as well as the three distress risk measures Shum, z-score and BS. Table 20 reports the matrix of Spearman rank and Pearson correlation coefficients. Three relations are of importance to the cross-sectional tests: correlation within the risk factors, correlation within the default measures and correlation between risk factors and default measures. As Table 20 shows, there is only a moderate correlation between the risk factors BETA, SIZE, BM and PYR (maximum coefficient is 0.36). Within the distress risk measures, there are fairly high correlation coefficients between Shum and BS (Spearman 0.80 and Pearson 0.77). The correlations between z-score and the other two bankruptcy prediction models BS and Shum are relatively low (maximum coefficients: Spearman 0.52, Pearson 0.51). There is moderate correlation between PYR and BS (Spearman coefficient -0.59 and Pearson coefficient -0.56) since BS includes ER1y. This logic applies to Shum with SIZE (RSIZE is variable) and PYR (EXRET is variable) as well.

**Table 20 Distress Risk Models: Correlation Common Risk Factors**

This table presents time-series averages of correlation coefficients for variables of UK non-financial firms listed in the Main market segment of the London Stock Exchange. The lower-left side of the matrix presents Spearman rank correlation coefficients. The upper-right side of the matrix presents Pearson correlation coefficients. Correlation coefficients are calculated at the end of each September from 1985 to 2009 (portfolio formation). Variables are: BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. I use as well Shum, the score from the model in Shumway (2001), z-score (Taffler, 1983) and BS, the score from the market-based model in Bharath and Shumway (2008). In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. All variables are winsorised at the 5.0% level, scores are winsorised at ±18.4207.

| | **BETA** | **SIZE** | **BM** | **PYR** | **Shum** | **Z-score** | **BS** |
|---|---|---|---|---|---|---|---|
| **BETA** | 1 | -0.01 | -0.04 | 0.00 | 0.07 | 0.07 | 0.07 |
| **SIZE** | 0.08 | 1 | -0.21 | 0.10 | -0.49 | -0.08 | -0.30 |
| **BM** | -0.06 | -0.36 | 1 | -0.29 | 0.28 | 0.00 | 0.39 |
| **PYR** | -0.01 | 0.22 | -0.28 | 1 | -0.50 | -0.11 | -0.56 |
| **Shum** | 0.05 | -0.73 | 0.24 | -0.50 | 1 | 0.51 | 0.77 |
| **Z-score** | 0.06 | -0.17 | -0.04 | -0.12 | 0.52 | 1 | 0.33 |
| **BS** | 0.08 | -0.51 | 0.38 | -0.59 | 0.80 | 0.37 | 1 |

Table 21 presents the results from the cross-sectional regressions. Following the risk argument of Fama and French (1993), Models 1 to 4 include the risk factors BETA, SIZE, and BM combined with the individual distress risk measures Shum, z-score and BS. Following the risk argument of Carhart (1997), Models 5 to 8 repeat the regressions including PYR. Model 9 to 11 add combinations of the distress risk measures.

Model 1 in Table 21 shows that contrary to its risk prediction neither BETA (t = 1.35) nor SIZE (t = 0.15) is associated with stock returns. BM is significant (t = 2.31) and carries a positive premium. Model 2 adds the score from Shum and shows a negative and significant distress risk premium (t = 2.62): the higher (lower) the bankruptcy risk, the lower (higher) the subsequent stock returns. BETA is still insignificant (t = 1.32) while SIZE becomes significant (t = 2.06) with the inclusion of Shum (Pearson correlation coefficient -0.49). BM is insignificant (t = 1.72) when Shum is included. Model 3 adds the accounting-based z-score (t = 3.17) to the basic model and confirms the negative distress risk premium observed in Model 2. BETA and SIZE (t = 1.23 and 0.48 respectively) are similar to the basic Model 1 whereas BM has now a t-statistic of 1.95, i.e. the BM effect is lowered by the inclusion of z-score (Fama and French, 1992). Model 4 adds the BS score to the basic model and shows, against the results of Vassalou and Xing (2004), a negative distress risk premium (t = 2.47). Overall, the results provide no evidence for the distress hypothesis of Chan and Chen (1991) and Fama and French (1992) because (i) the risk factors, especially SIZE, are found to be insignificant, (ii) SIZE and BM are not related to distress risk, and (iii) coefficients on distress risk proxies are negative and highly significant demonstrating a negative relation between distress risk and subsequent stock returns.

Model 5 reports the coefficients and t-statistics for BETA, SIZE, BM, and PYR. BETA and SIZE are still found to be insignificant (t = 1.69 and 0.54 respectively) whereas BM (t = 2.76) and PYR (t = 2.38) have a positive and significant relation with returns. Model 6 shows a negative and significant distress risk premium for Shum (t = 2.07). The PYR coefficient is now insignificant (t = 1.28) but this is not surprising as Shum already includes EXRET. Model 7 presents a negative and significant distress risk premium for z-score (t = 3.08). BM and PYR are independent from z-score and significant (t = 2.33 and 2.07 respectively). Model 8 shows a negative but insignificant distress risk premium for BS (t = 1.91). PYR (t = 1.74) and BM (t = 3.03) are positive and highly significant. The results further confirm (i) BM and SIZE are independent of distress risk, (ii) PYR is partially lowered with the inclusion of distress risk (Agarwal and Taffler, 2008b), and (iii) there is a significant and negative distress risk premium for all distress risk proxies, albeit hardly significant when distress is proxied by BS and controlled for the common risk factors.

Model 9 includes scores from both Shum and z-score. It follows that Shum (t = 1.25) is insignificant once z-score (t = 2.25) is included. Also, z-score is the most significant risk factor followed by BM (t = 1.90) and PYR (t = 1.68). Model 10 includes the z-score and BS score. The significance of BS (t = 1.23) is heavily reduced once z-score (t = 2.91) is included. BM is also the only significant variable (t = 2.58) of the common risk factors. Having showed that z-score absorbs the distress related information carried by Shum and BS, Model 11 includes all three scores and confirms the superior role of z-score (t = 2.43) in explaining the cross-section of subsequent stock returns.

Chapter 5 shows that Shum is the best bankruptcy prediction model and is therefore expected to be most relevant in pricing of distress risk. However, results in Table 21 clearly show that once z-score is included in the regressions (Model 9 to 11), the Shum and BS measures do not carry any incremental information about stock returns. In other words, the best bankruptcy prediction model is not the most relevant in explaining subsequent stock returns. This is a remarkable new finding as it suggests that while the distress risk measures are priced, *distress risk* may not be driving the observed 'negative distress risk premium'. This raises the possibility that it may not be the composite distress risk measure but one or more elements of the distress risk measures that drive the observed relation between distress risk and stock returns. In Chapter 8 of this study I deconstruct each distress risk measure to explore the pricing impact of the individual components of each of the three distress risk proxies.

Apart from the pricing impact of each individual bankruptcy measure in Table 21, the evidence in this sub-chapter is consistent with that in the existing literature as well as that of my time-series regressions: firms with higher distress risk earn lower subsequent stock returns and the conclusions are robust to different proxies for bankruptcy risk. The evidence provides strong support for proposition P4 and once again, I do not find any evidence to support proposition P5.

**Table 21 Distress Risk Models: Cross-Sectional Regression**

This table presents results from cross-sectional regressions on individual stock returns of UK non-financial firms listed in the Main market segment of the London Stock Exchange. I employ the method of Fama and MacBeth (1973) as defined in Eq. (24) and add default scores to the basic model:
$R_{i,t+m} - R_{f,t+m} = \alpha_{i,t+m} + \gamma_{1,t+m}BETA_t + \gamma_{2,t+m}LN(SIZE)_t + \gamma_{3,t+m}LN(BM)_t + \gamma_{4,t+m}PYR_t,$
where subscript t denotes the portfolio year starting at the beginning of October each year from 1985 to 2009 and t+m for integer m = 1 to 12 denotes the month-ends of the portfolio year. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the natural log of the market value of common equity (MV). BM is the natural log of book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. I add to the regression the failure indicators Shum, the score from the model in Shumway (2001), z-score (Taffler, 1983) and BS, the score from the market-based model in Bharath and Shumway (2008). In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at the end of each September (portfolio formation). All variables are winsorised at the 5.0% level, scores are winsorised at ±18.4207. The return of the month of failure is set to -100.0%.

| | **γ1** | **γ2** | **γ3** | **γ4** | **γ5** | **γ6** | **γ7** |
|---|---|---|---|---|---|---|---|
| **Model** | **BETA** | **SIZE** | **BM** | **PYR** | **Shum** | **Z-score** | **BS** |
| **1** | -0.10 | -0.01 | 0.20 | | | | |
| | (1.35) | (0.15) | (2.31) | | | | |
| **2** | -0.09 | -0.13 | 0.15 | | -0.22 | | |
| | (1.32) | (2.06) | (1.67) | | (2.62) | | |
| **3** | -0.09 | -0.03 | 0.17 | | | -0.02 | |
| | (1.23) | (0.48) | (1.95) | | | (3.17) | |
| **4** | -0.10 | -0.07 | 0.25 | | | | -0.03 |
| | (1.43) | (1.32) | (2.89) | | | | (2.47) |
| **5** | -0.12 | -0.03 | 0.22 | 0.40 | | | |
| | (1.69) | (0.54) | (2.76) | (2.38) | | | |
| **6** | -0.09 | -0.12 | 0.15 | 0.17 | -0.18 | | |
| | (1.32) | (1.84) | (1.87) | (1.28) | (2.07) | | |
| **7** | -0.11 | -0.04 | 0.19 | 0.33 | | -0.02 | |
| | (1.58) | (0.78) | (2.33) | (2.07) | | (3.08) | |
| **8** | -0.10 | -0.06 | 0.24 | 0.26 | | | -0.02 |
| | (1.52) | (1.16) | (3.03) | (1.74) | | | (1.91) |
| **9** | -0.09 | -0.09 | 0.16 | 0.23 | -0.12 | -0.01 | |
| | (1.49) | (1.37) | (1.90) | (1.68) | (1.25) | (2.25) | |
| **10** | -0.10 | -0.06 | 0.21 | 0.25 | | -0.02 | -0.01 |
| | (1.53) | (1.12) | (2.58) | (1.70) | | (2.91) | (1.23) |
| **11** | -0.09 | -0.07 | 0.17 | 0.23 | -0.06 | -0.01 | -0.01 |
| | (1.48) | (1.07) | (2.04) | (1.67) | (0.62) | (2.43) | (0.79) |

## 6.6 Conclusion

The analysis presented in this chapter tests for the relation between distress risk and subsequent stock returns using three bankruptcy prediction models: the hybrid model of Shumway (2001), the accounting-based z-score (Taffler, 1983) and the market-based model of Bharath and Shumway (2008).

The characteristics on decile distress risk portfolios confirm prior findings that distressed stocks generally score high on the conventional risk measures BETA, SIZE, BM, and PYR while the risk-adjustments actually worsen the underperformance. This finding is robust and generally independent of the distress risk measure applied.

Time-series regressions show that although the conventional risk measures are associated with higher returns, consistent with existing literature (e.g. Dichev, 1998; Griffin and Lemmon, 2002; Agarwal and Taffler, 2008b), I find that distressed stocks underperform. The negative distress risk premium is robust to (i) the distress risk proxy I use (i.e. Shum, z-score, and BS), (ii) value-weighted and equally-weighted average portfolio returns, and (iii) risk-adjustments using the Fama and French model (1996) and the Carhart (1997) model.

The cross-sectional results corroborate these findings. Consistent with the majority of prior studies, I find no evidence for the distress hypothesis of Chan and Chen (1991) and Fama and French (1992) that SIZE and BM are proxies for distress risk. Although BS is insignificant using the Carhart (1997) risk-adjustment, it is still far away from being positive and significant as claimed by Vassalou and Xing (2004).

Overall, the evidence provides strong support for proposition P4 that there is a negative premium on the distress risk measure. I do not find any evidence to support research proposition P5, as the distress risk premium is independent of the distress risk proxy.

However, the more interesting finding is the role of z-score. Fama and French (1992) argue that ratios scaling market prices extract the information in prices about risk and expected returns. Following their argument, the premia earned on z-score - as an accounting data-only model without any market price information - can be interpreted as being particularly robust. Importantly, the cross-sectional regressions show that z-score is able to subsume the information about future returns carried by Shum and BS. Since z-score is a weaker bankruptcy predictor than Shum and BS, this finding suggests that it might not be distress risk *per se* but an element of the distress risk measures that drives the premia.

In the next Chapter 7, I test whether the proposed explanations for the negative distress risk premium are able to explain it. In Chapter 8, I further explore whether it is distress risk that drives the premia earned by the distress risk measures.

# CHAPTER 7: EXPLAINING THE NEGATIVE DISTRESS RISK PREMIUM

## 7.1 Introduction

Theory suggests that distressed firms should earn higher returns than non-distressed firms. However, Chapter 5 of this study provides evidence for a puzzling underperformance of distressed firms and, in addition, shows that it is robust to alternative distress risk proxies. Moreover, existing literature is almost unanimous in finding an underperformance of distressed firms (e.g. Dichev, 1998; Griffin and Lemmon, 2002; Agarwal and Taffler, 2008b).[31] The focus of current literature is on solving this puzzle (Campbell et al., 2008).

There are several potential explanations for the underperformance of distressed firms. Garlappi and Yan (2011) provide a risk-based explanation arguing that due to the ability of shareholders to strategically default at the cost of debt holders, equity risk decreases with high levels of distress risk. Thus, the stocks of highly distressed firms are expected to earn low returns. Alternatively, Shleifer and Vishny (1997) argue that limits of arbitrage hinder institutional investors' ability to trade on mispriced stocks. The characteristics that are associated with limits of arbitrage are also shared by distressed firms (Taffler et al., 2004; Campbell et al., 2008). Related to that, Han and Kumar (2011) argue that the priority of retail investor is not on profit maximisation but on gambling. Since distressed stocks have lottery-type characteristics, they attract retail investors that could drive the overpricing in the first place (Coelho et al., 2010).

The shareholder advantage effect has been empirically tested by Zhang (2012) who finds that the strategic default effect is limited to firms with private debt. However, he

[31] The only exceptions are the findings in Vassalou and Xing (2004) and Chava and Purnanandam (2010).

focuses primarily on shareholders' bargaining power, not on testing the hump-shaped characteristics in distress risk. Moreover, the pricing impact of the shareholder advantage effect has yet not been tested in the UK market. The more creditor friendly insolvency regime in the UK (Franks and Nyborg, 1996) does not necessarily imply there is no shareholder advantage. Indeed, Garlappi and Yan (2011) argue that shareholder recovery is not restricted to 'violations of absolute priority rule'. They rather describe it as the resolution of financial distress which, undeniably, is generally independent of the bankruptcy regime. To what extent is the shareholder advantage theory applicable to the significantly different insolvency regime of the UK is ultimately an empirical question.

The limits of arbitrage is explored on several anomalies (e.g. Wurgler and Zhuravskaya, 2002; Mendenhall, 2004), while Taffler et al. (2004) and Kausar et al. (2009) provide a link to distress as they find limits of arbitrage to hinder trading on the going-concern anomaly. Similarly, Avramov et al. (2010) use credit ratings to establish a link between distress risk and short-selling constraints. The potential of gambling to explain the overpricing of distress risk is underpinned by Coelho et al. (2010) who show that Chapter 11 firms are primarily traded by retail investors while being unattractive to arbitrageurs.

Besides this first evidence, none of the studies explores the potential of the three explanations in detail using different bankruptcy prediction models. In this chapter, I introduce various tests to provide evidence on the potential explanatory power of shareholder advantage, limits of arbitrage and lottery stocks using the bankruptcy prediction models of Shumway (2001) (Shum), z-score (Taffler, 1983) and the model of Bharath and Shumway (2008) (BS).

The remainder of this chapter is organised as follows: in sub-chapter 2 I present the research question and research propositions. In sub-chapter 3 I briefly describe the data and method. Sub-chapter 4 empirically evaluates the explanatory power of the potential explanation proposed by Garlappi and Yan (2011). Sub-chapter 5 presents the results on characteristics that are associated with both limits of arbitrage and gambling stocks. Sub-chapter 6 concludes and discusses the results.

## 7.2 Research Question

The majority of the literature on distress risk pricing finds a negative distress risk premium. There are several potential explanations for this underperformance. In this chapter, I test the potential of shareholder advantage, limits of arbitrage, and gambling retail investors to explain the pricing of distress risk. The prevailing research question therefore is:

**Can shareholder advantage, gambling retail investors or limits of arbitrage explain the negative distress risk premium?**

The main predictions of the Garlappi and Yan (2011) shareholder advantage theory are that beta (and thus returns) and book-to-equity ratio (BM) are hump-shaped in distress risk. I therefore test the following proposition.

*P6: There is a hump-shaped relation between BETA and distress risk as well as between the value premium and distress risk.*

Shleifer and Vishny (1997) argue that for mispricings to persist in the presence of sophisticated investors there must be some limits of arbitrage. Distressed firms have characteristics that are usually associated with limits of arbitrage (Taffler et al., 2004; Kausar et al., 2009). Thus, my research proposition is:

*P7: Limits of arbitrage hinder sophisticated investors' ability to correct the overpricing of distressed firms.*

Kumar (2009) argues that the priority of retail investors is on gambling, not on profit maximisation. As such, the demand for lottery-type stocks could lead to an overpricing of those stocks. Since, Coelho et al. (2010) find that Chapter 11 firms have lottery-type characteristics, I test the following proposition:

*P8: Gambling retail investors drive the overpricing of distressed firms.*

## 7.3 Data and Method

My sample consists of UK non-financial firms listed in the Main market segment of the London Stock Exchange anytime between October 1985 and September 2010. It includes 22,217 observations with 2,428 unique firms of which 202 failed.

Following Han and Kumar (2011) I form a lottery-index that consists of PRICE, idiosyncratic volatility (IVOL) and idiosyncratic skewness (ISKEW). At the end of each September from 1985 to 2009, I rank the sample firms on each variable and sort into virgintile portfolios. For each firm, I calculate an index by taking the sum of the stock's virgintile portfolio assignment divided by 60.

In this chapter I apply two testing procedures: first, I use time-series regressions on average portfolio excess returns using the Fama and French (1993) model as well as the Carhart (1997) model as defined in Eq. (25). Second, I use cross-sectional regressions following the method of Fama and MacBeth (1973) as defined in Eq. (24).

## 7.4 Shareholder Advantage

In this sub-chapter I test for the predictions of Garlappi and Yan (2011) that equity beta and thus, stock returns, as well as the value premium have a hump-shaped relation with distress risk.

Panel A in Table 22 presents the decile portfolio beta for sorts on Shum, z-score and BS.[32] BETA on the Shum sort increases monotonically with distress risk (except for a small drop in P2 to 1.02). The low distress risk portfolio has an average equity beta of 1.04 while the high distress risk portfolio has an average equity beta of 1.25. In contrast to the predictions of Garlappi and Yan (2011), the relation between equity risk and distress risk measured by Shum is strictly linear rather than hump-shaped. The sort on z-score shows that, besides a small drop in P6, BETA increases monotonically with z-score from 0.99 for the low distress risk portfolio to 1.25 for the high distress risk portfolio. It follows, that BETA is also not hump-shaped in distress risk using z-score. The last row summarises the BETA of decile portfolios sorted on BS. Similar to the sort on Shum, BETA increases monotonically with distress risk from 0.94 to 1.22 with a small drop in P8. It again rejects the propositions of Garlappi and Yan (2011) as BETA

[32] The analysis repeats parts of the analysis presented in Chapter 6. However, while the focus of Chapter 6 is to explore the impact of distress risk on stock returns, the focus of this chapter is to test the predictions of Garlappi et al. (2008) and Garlappi and Yan (2011).

is linearly related with distress risk measured by BS (the only exception is BS where the highest risk portfolio has slightly lower BETA than the second highest risk portfolios but is still considerably higher than all other portfolios).

Panel B and Panel C in Table 22 report the equally-weighted and value-weighted portfolio average excess returns for the decile sorts on Shum, z-score and BS. As described in detail in Chapter 6, there is a general negative return association with distress risk independent of the distress risk measure or the weighting-scheme applied. Although returns decrease for the high distress risk portfolios, they are not increasing with distress risk at lower levels and thus, in sharp contrast to the predictions of Garlappi and Yan (2011), there is no hump-shaped relation between excess returns and distress risk. In addition to that, the risk-adjusted returns of CAPM as well as the risk-adjusted returns of the Fama and French (1993) and Carhart (1997) model would imply a negative distress risk-return relation that is not hump-shaped independent of the distress risk proxy (not tabulated).

Thus, the evidence in Table 22 clearly shows that proposition P6 of a hump-shaped relation between BETA or returns and distress risk does not hold. Regardless of the proxy used for distress risk, the relation between beta and distress risk increases linear-like, especially in higher risk portfolios rather than being hump-shaped.

**Table 22 Shareholder Advantage: BETA and Returns**

The table presents decile portfolio betas based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability obtained from Shum, the model in Shumway (2001), z-score (Taffler, 1983), and on BS, the model in Bharath and Shumway (2008) and sort into equally populated decile portfolios. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). I report time-series averages. BETA is winsorised at the 5.0% level. ER vw (ER ew) reports the value-weighted (equally-weighted) average monthly portfolio excess return for the 12 months following portfolio formation.

| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A. BETA** | | | | | | | | | | | |
| Shum | 1.04 | 1.02 | 1.05 | 1.09 | 1.07 | 1.06 | 1.12 | 1.14 | 1.15 | 1.25 | 0.20 |
| Z-score | 0.99 | 1.03 | 1.09 | 1.09 | 1.10 | 1.08 | 1.11 | 1.10 | 1.16 | 1.25 | 0.26 |
| BS | 0.94 | 0.99 | 1.06 | 1.07 | 1.10 | 1.13 | 1.14 | 1.10 | 1.25 | 1.22 | 0.28 |
| **Panel B. Equally-Weighted Return** | | | | | | | | | | | |
| Shum | 0.61 | 0.47 | 0.45 | 0.48 | 0.24 | 0.37 | 0.23 | 0.47 | 0.44 | -0.28 | -0.89 |
| Z-score | 0.54 | 0.61 | 0.54 | 0.55 | 0.51 | 0.44 | 0.48 | 0.22 | 0.42 | 0.08 | -0.46 |
| BS | 0.53 | 0.64 | 0.59 | 0.43 | 0.34 | 0.44 | 0.18 | 0.02 | 0.41 | 0.23 | -0.31 |
| **Panel C. Value-Weighted Return** | | | | | | | | | | | |
| Shum | 0.63 | 0.54 | 0.57 | 0.64 | 0.37 | 0.61 | 0.39 | 0.56 | 0.55 | 0.21 | -0.42 |
| Z-score | 0.64 | 0.71 | 0.61 | 0.65 | 0.54 | 0.48 | 0.56 | 0.43 | 0.45 | -0.02 | -0.66 |
| BS | 0.53 | 0.53 | 0.70 | 0.52 | 0.46 | 0.51 | 0.49 | 0.54 | 0.70 | 0.13 | -0.40 |

In the following, I present evidence on the relation of distress risk and the value premium using independent sorts on distress risk portfolios and BM. For each year, I sort into decile distress risk portfolios using Shum, z-score and BS. Independently, I split the sample into low and high BM using median. I form 20 portfolios at the intersections of the two sorts. I calculate the value premium, i.e. the return on a portfolio that is long on the high BM stocks and short on low BM stocks, for each distress portfolio after risk-adjustment using the Carhart (1997) model. Garlappi and Yan (2011) predict the value premium to be hump-shaped in distress risk.

Figure 6 shows the value premium for the 10x2 sort on distress risk and BM using value-weighted returns (the equivalent information of Figures 6 and 7 is presented in

Table 28A in the appendix to this chapter). The sort on Shum shows that the value premium is close to zero at both ends i.e. the low and the high distress risk portfolio. However, between these two portfolios the relation is far from being hump-shaped. In fact, the value premium peaks in P5 and P8 with a sharp drop in P7. The value premium using the 10x2 z-score sort shows a similar chart. The value premium oscillates between the low distress risk and high distress risk portfolios with peaks in P5 and P9. The chart using the BS sort is slightly different. There is a hump-shaped relation of the value premium with BS. However, it is limited to P4 to P9 and, more importantly, the value premium increases sharply for the high distress risk portfolio.

Figure 7 illustrates the value premium for the 10x2 sort on distress risk and BM using equally-weighted returns. The value premium on Shum is very volatile as it is oscillating increasingly with higher distress risk with a sharp peak in P8. The value premium using z-score again alternates between the low and the high distress risk portfolio with peaks in P5 and 9 while the lowest value premium is earned in P3 and P8. While all charts so far provide clear evidence that the relation between value premium and distress risk is not hump-shaped, the chart on BS using equally-weighted returns is most similar to being hump-shaped but, again, this is limited for the portfolios P4 to P10.

Overall, the results from Figure 6 and 7 provide clear evidence that the relation between the value premium and distress risk is not hump-shaped, except for the limited hump-shape using BS and equal-weighted returns. Thus, similar to the results on BETA and distress risk, I again find no support for my proposition P6, that there is a hump-shaped relation of the value premium in distress risk.

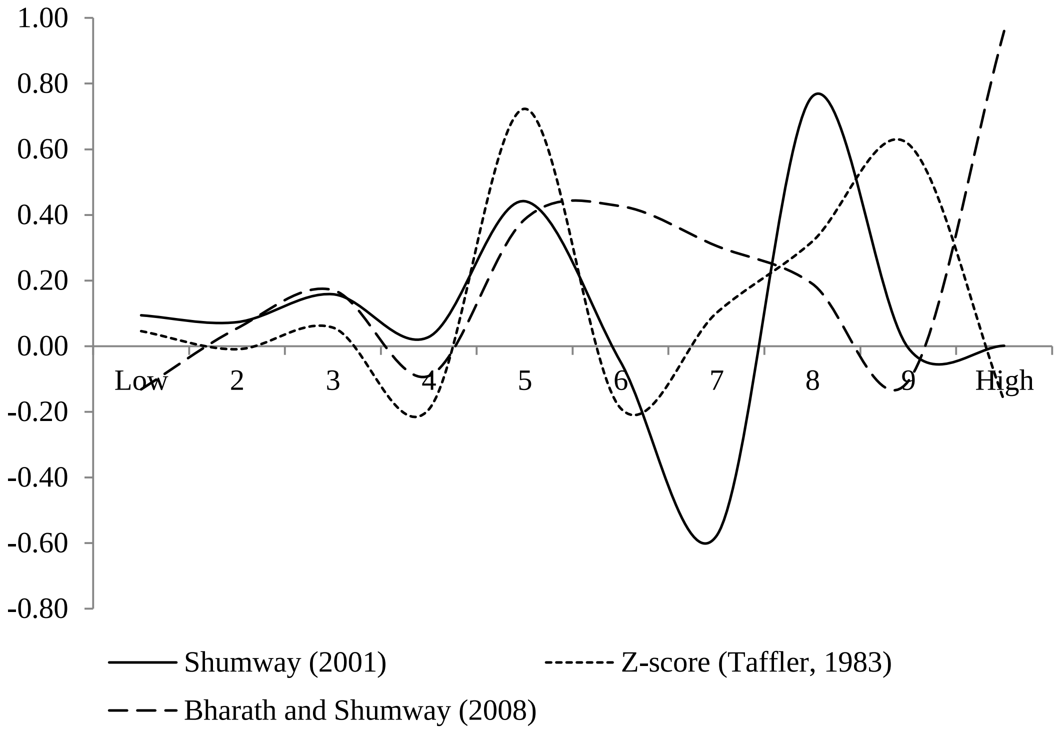


**Figure 6 Shareholder Advantage: Value Premium (value-weighted)**
The figure plots the risk-adjusted value premium of decile distress risk portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability and sort into equally populated decile portfolios (low to high distress risk). Independently, I rank the sample firms on BM (book value of shareholders' equity less preference shares and minorities over market value of common equity) and form two equally populated portfolios (high and low BM). I form 20 portfolios at the intersections of the two sorts as well as the value premium portfolio with the value-weighted return that is long on high BM and short on low BM stocks. Per value premium portfolio, I run the time-series regressions using the model in Carhart (1997). I repeat this for each default probability obtained from the model in Shumway (2001), z-score (Taffler, 1983), and the model in Bharath and Shumway (2008). The returns of the month of failure are set to -100.0%. The figure plots the intercepts from the regressions on the value-premium.

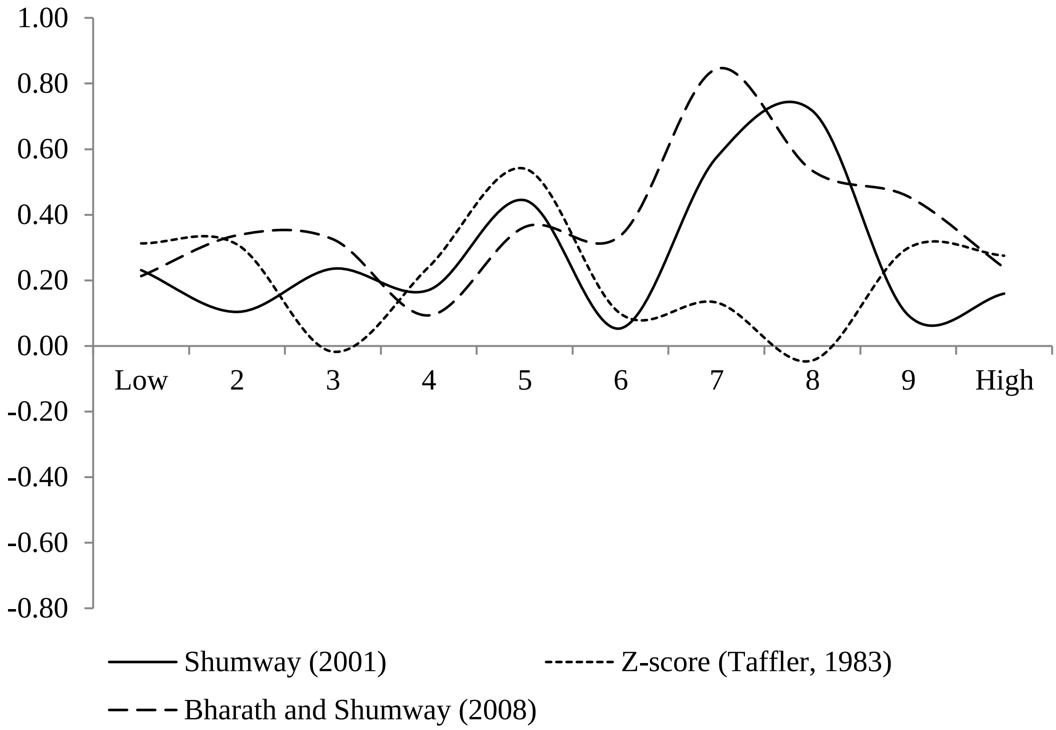


**Figure 7 Shareholder Advantage: Value Premium (equally-weighted)**
The figure plots the risk-adjusted value premium of decile distress risk portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability and sort into equally populated decile portfolios (low to high distress risk). Independently, I rank the sample firms on BM (book value of shareholders' equity less preference shares and minorities over market value of common equity) and form two equally populated portfolios (high and low BM). I form 20 portfolios at the intersections of the two sorts as well as the value premium portfolio with the equally-weighted return that is long on high BM and short on low BM stocks. Per value premium portfolio, I run the time-series regressions using the model in Carhart (1997). I repeat this for each default probability obtained from the model in Shumway (2001), z-score (Taffler, 1983), and the model in Bharath and Shumway (2008). The returns of the month of failure are set to -100.0%. The figure plots the intercepts from the regressions on the value-premium.

## 7.5 Limits of Arbitrage and Gambling

In this sub-chapter I present the tests of whether the distress risk premium is caused by limits of arbitrage and/or stock gambling.

Han and Kumar (2011) form a lottery-index that consists of PRICE, idiosyncratic volatility (IVOL) and idiosyncratic skewness (ISKEW). I construct a lottery index (LOTT) following their methodology and as defined in Eq. (26).

The literature on limits of arbitrage associates generally high arbitrage costs with firms that have high transaction costs, low level of investor sophistication and small firm size (Ali et al., 2003). Common proxies are PRICE, idiosyncratic volatility, idiosyncratic skewness, bid-ask spread, institutional ownership, and low analyst coverage (e.g. Shleifer and Vishny, 1997; Wurgler and Zhuravskaya, 2002; Mashruwala et al., 2006). As such, the proxies for limits of arbitrage are very similar to the ones of lottery-type stocks. Han and Kumar (2011) provide direct evidence for the connection between the two as they note that lottery stocks are not only dominated by retail investors, they also face high limits of arbitrage as they tend to have very low market cap, low price, high idiosyncratic volatility, low institutional ownership and low analyst coverage. Similarly, Coelho et al. (2010) conclude that the post-Chapter 11 filing drift is caused by both gambling retail investors and limits of arbitrage. As such, the symptoms are the same while the cause is different. Following the literature, I argue that the lottery index is able to capture both the limits of arbitrage and the impact of gambling retail investors on distressed stocks. And thus, I test for the impact of the lottery index on stock returns whether it is proxying for limits of arbitrage or gambling retail investors.

Table 23 presents the summary statistics of the lottery index (LOTT). The mean of LOTT for the total sample is at 0.52 (non-failed firms 0.52). Failed firms have an average LOTT of 0.74 that is significantly different from the non-failed firms ($t = 18.68$). Since the median is close to the mean (0.52 vs. 0.52 for all firms, 0.52 vs. 0.51 for non-failed firms, 0.74 vs. 0.75 for failed-firms), the spread of LOTT within each of the sub-samples is low. While the minimum LOTT for the total sample is 0.07, the minimum for the failed firms is 0.53. Although the average in means is significantly different, the failed firms sub-sample does not contain the stocks with the highest LOTT (maximum failed firms 0.91 vs. maximum of all firms 0.99) showing that the LOTT of failed firms is more homogeneous. Moreover, the ROC curve analysis also demonstrates the forecasting ability of LOTT. The AUC of LOTT is 0.80 which is significantly better than that of a random model ($z = 15.93$). Recalling from Chapter 5, the AUC of Shum, z-score and BS are 0.90, 0.81, and 0.87 respectively. As such, there is evidence that LOTT is not only able to differentiate between non-failed and failed firms but can also forecast bankruptcies. This underlines its potential for explaining the distress risk premium.

**Table 23 Lottery Stocks: Non-Failed and Failed Firms**

The table presents summary statistics of lottery characteristics of UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I construct a lottery index (LOTT) following Han and Kumar (2011) and as defined in Eq. (26). That is, I rank the sample firms on share price (PRICE) and form virgintile portfolios. I repeat that for IVOL and ISKEW. LOTT is the sum of the virgintile assignments for the sort on PRICE, IVOL and ISKEW divided by 60. At portfolio formation, I run the regression using the Carhart (1997) model over the previous 24 months and collect the residual terms per firm. IVOL is the variance and ISKEW the skewness of the residual terms. The figures on Mean, Median, Min and Max are based on time-series averages. AUC is the area under the receiver operating characteristic (ROC) curve for LOTT and estimated as the Wilcoxon statistic. Z-statistic is the Hanley and McNeil (1983) test-statistic for the null hypothesis that the area under the ROC curve is equal to 0.5 (random model). Column All presents the statistics for all sample firms which split into Non-Failed firms (Column 3) and Failed Firms (Column 4). Δ NF-F is the difference between the two sub-samples.

| | **All** | **Non-Failed** | **Failed** | **Δ NF-F** |
|---|---|---|---|---|
| Mean | 0.52 | 0.52 | 0.74 | 0.22 |
| | | | | (18.68) |
| Median | 0.52 | 0.51 | 0.75 | 0.24 |
| Min | 0.07 | 0.07 | 0.53 | 0.46 |
| Max | 0.99 | 0.99 | 0.91 | -0.09 |
| Std Dev | 0.21 | 0.21 | 0.16 | -0.04 |
| Obs | 22,217 | 22,015 | 202 | |
| **Receiver Operating Characteristics** | | | | |
| AUC | 0.800 | | | |
| z-statistic | 15.93 | | | |

In Table 24 I present characteristics of decile portfolios sorted on LOTT. The market share of each decile shows that the stocks in the highest LOTT portfolio only make up 1.2% of the total market while the stocks in the lowest LOTT portfolio make up more than a quarter of the total market value (27.7%). BETA increases monotonically with LOTT. The lowest decile has an average equity beta of 0.87 rising to 1.35 in the highest decile portfolio. SIZE declines sharply with LOTT. The average market capitalisation for the low LOTT firms is £ 922m while high LOTT stocks have an average market capitalisation of only £ 46m. The average BM increases from 0.56 for non-lottery stocks to 0.86 in P7 and remains at this level for portfolios 8 to 10. There seems to be no pattern in PYR as it is fairly stable across the LOTT deciles ranging from 10% (P10) to

18% (P2) but generally lower at high levels of LOTT. The default probability of Shum increases monotonically with LOTT from 0.2% for the low LOTT stocks to 3.5% for the high LOTT stocks. This is not surprising as there are similar components in both LOTT and Shum (i.e. IVOL and SIGMA, PRICE and RSIZE). However, the results are further confirmed by z-score showing that the default probability is nearly linearly increasing with LOTT from 15.0% (low LOTT) to 52.7% (high LOTT). Also, the default probability using BS is monotonically related with LOTT (1.6% low LOTT to 24.4% high LOTT). The overview of the failures provides further evidence of the relation between LOTT and distress risk. 79 out of 202 failures are in the high LOTT portfolio while in the lowest 50% of LOTT stocks only 21 firms failed. The value-weighted excess returns do not show any pattern: while the high LOTT stocks earn the lowest returns (29 bps, t = 0.57) the neighbouring P9 and P7 have the highest excess returns (63 bps, t = 1.31 and 68 bps, t = 1.75 respectively). The H-L premium is negative (-22 bps) and insignificant (t = 0.56). Similar results are obtained using equal-weights. The high LOTT portfolio earns the lowest returns (34 bps, t = 0.74), and the H-L premium is insignificant (-26 bps, t = 0.80).

The table presents preliminary evidence that while stocks with high LOTT score are riskier (higher BETA, smaller SIZE, higher BM, and higher default probability), they earn the lowest excess returns of the ten portfolios though the H-L return premium is statistically insignificant.

**Table 24 Lottery Stocks Decile Portfolios: Summary Statistics**

The table presents summary statistics of decile portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I construct a lottery index (LOTT) following Han and Kumar (2011) and defined in Eq. (26). That is, I rank the sample firms on share price (PRICE) and form virgintile portfolios. I repeat that for IVOL and ISKEW. LOTT is the sum of the virgintile assignments for the sort on PRICE, IVOL and ISKEW divided by 60. At portfolio formation, I run the regression using the Carhart (1997) model over the previous 24 months and collect the residual terms per firm. IVOL is the variance and ISKEW the skewness of the residual terms. I then rank all sample firms on LOTT and form decile portfolios. The table reports time-series averages. Frac Mkt is the total portfolio market value over the total market value. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. Default probabilities are estimated using the model in Shumway (2001) (Shum), z-score (Taffler, 1983) and the market-based model in Bharath and Shumway (2008) (BS). In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. All variables are winsorised at the 5.0% level. ER vw reports the value-weighted average monthly portfolio excess return. ER ew reports the equally-weighted average monthly portfolio excess return. The return of the month of failure is set to -100.0%. T-statistics are reported in brackets below.

| | **Low** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High** | **H-L** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Frac Mkt | 27.66 | 19.96 | 15.84 | 10.83 | 8.34 | 6.07 | 4.53 | 3.28 | 2.31 | 1.19 | -26.46 |
| BETA | 0.87 | 0.97 | 0.97 | 1.03 | 1.09 | 1.13 | 1.15 | 1.21 | 1.23 | 1.35 | 0.48 |
| SIZE | 922 | 701 | 563 | 398 | 309 | 228 | 174 | 123 | 88 | 46 | -875 |
| BM | 0.56 | 0.60 | 0.64 | 0.67 | 0.73 | 0.75 | 0.86 | 0.88 | 0.90 | 0.88 | 0.32 |
| PYR | 0.17 | 0.18 | 0.17 | 0.17 | 0.16 | 0.14 | 0.11 | 0.11 | 0.12 | 0.10 | -0.07 |
| Shum | 0.2 | 0.2 | 0.3 | 0.3 | 0.5 | 0.6 | 1.3 | 2.0 | 2.1 | 3.5 | 3.4 |
| Z-score | 15.0 | 14.4 | 17.0 | 17.4 | 21.6 | 20.6 | 28.4 | 36.1 | 39.7 | 52.7 | 37.7 |
| BS | 1.6 | 2.5 | 4.6 | 5.5 | 8.0 | 9.7 | 15.1 | 18.4 | 19.1 | 24.4 | 22.9 |
| Fails | 1 | 4 | 3 | 8 | 5 | 9 | 25 | 32 | 45 | 79 | 78 |
| ER vw | 0.51 | 0.50 | 0.40 | 0.39 | 0.59 | 0.35 | 0.68 | 0.39 | 0.63 | 0.29 | -0.22 |
| | (1.90) | (1.82) | (1.34) | (1.25) | (1.80) | (0.99) | (1.75) | (0.96) | (1.31) | (0.57) | (0.56) |
| ER ew | 0.59 | 0.51 | 0.51 | 0.41 | 0.65 | 0.52 | 0.49 | 0.46 | 0.61 | 0.34 | -0.26 |
| | (2.33) | (1.89) | (1.75) | (1.41) | (2.10) | (1.58) | (1.41) | (1.26) | (1.55) | (0.74) | (0.80) |

The results in Table 24 show that LOTT shares common characteristics with distress risk although the return premium on LOTT is insignificant. In order to further explore the potential of LOTT to explain the distress risk premium, I conduct time-series analysis using the decile portfolios. Table 25 reports the risk-adjusted returns using the Fama and French (1993) and the Carhart (1997) model risk-adjustment.

Panel A reports the portfolio intercepts using value-weighted portfolio average returns. Similar to the excess returns, there is no return pattern in LOTT. None of the decile portfolios earns abnormal returns using either the Fama and French (1993) or Carhart (1997) risk-adjustment. While the return of the portfolio long on high LOTT stocks and short on low LOTT stocks is negative (-53 bps and -45 bps respectively), it is insignificant (t = 1.68 and 1.41 respectively) independent of the risk-adjustment.

Panel B repeats the analysis using equally-weighted returns. The results show higher significance since the low LOTT portfolio earns an abnormal return of 21 bps (t = 2.27) using the Fama and French risk-adjustment and 20 bps (t = 2.14) using the Carhart risk-adjustment. Although returns do not show a specific pattern in distress risk, the high lottery stocks underperform all other portfolios (-27 bps, t = 1.40 and -29 bps, t = 1.48 respectively). As such, the H-L premium using equal-weights is negative and significant (-48 bps, t = 2.26 and -49 bps, t = 2.28 respectively).

The results in Panel B (equally-weighted return) show a significant return premium for LOTT stocks while the results in Panel A (value-weighted returns) do not find a return association with LOTT. This suggests that the premium observed in Panel B is driven by stocks with low market capitalisation. This is consistent with the evidence in Angelidis and Tessaromatis (2005; 2008) who show that idiosyncratic risk (as part of LOTT) is only related to the returns of stocks with small market capitalisation. Fama and French (2008) argue that both weighting schemes might lead to unrepresentative results: value-weighted returns might overvalue large market capitalisation stocks and equally-weighted returns might overvalue small market capitalisation stocks. Only when a return pattern is independent of the weighting scheme (as e.g. throughout sub-chapter 6.4), can the results be considered to be robust.

**Table 25 Lottery Stocks Decile Portfolios: Time-Series Regression**

The table presents summary statistics of time-series regressions on decile portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I construct a lottery-index (LOTT) following Han and Kumar (2011) and as defined in Eq. (26). That is, I rank the sample firms on share price (PRICE) and form virgintile portfolios. I repeat that for IVOL and ISKEW. LOTT is the sum of the virgintile assignments for the sort on PRICE, IVOL and ISKEW divided by 60. At portfolio formation, I rank stocks on LOTT and form decile portfolios. I run regressions using the Carhart (1997) model in Eq. (25) over the previous 24 months and collect the residual terms per firm. IVOL is the variance and ISKEW the skewness of the residual terms. I then rank all sample firms on LOTT and form decile portfolios. I report the intercepts $\beta_1$ and the corresponding t-statistics in brackets for the asset pricing model of FF, the Fama and French (1993) model (excl. $\mathrm{WML_{t+m}}$) and Car, the Carhart (1997) model as defined in Eq. (25): $\mathrm{R_{i,t+m} - R_{f,t+m} = \beta_1 + \beta_{MKT}RmRf_{t+m} + \beta_{SMB}SMB_{t+m} + \beta_{HML}HML_{t+m} + \beta_{WML}WML_{t+m} + \varepsilon_{i,t+m}}$, where $\mathrm{R_{i,t+m}}$ is the return on portfolio i during month m (integer 1 to 12) in portfolio year t, $\mathrm{R_{f,t+m}}$ the one-month UK Treasury Bill rate at the beginning of month t+m, $\mathrm{RmRf_{t+m}}$ the return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate during month t+m, $\mathrm{SMB_{t+m}}$ the return on the mimicking portfolio for the size factor during month t+m, $\mathrm{HML_{t+m}}$ the return on the mimicking portfolio for the BM factor during month t+m and $\mathrm{WML_{t+m}}$ the return on the mimicking portfolio for the return momentum factor during month t+m. The results in Panel A are based on value-weighted monthly portfolio average excess returns. The results in Panel B are based on equally-weighted monthly portfolio average excess returns. The return of the month of failure is set to -100.0%.

| LOTT | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Panel A. Value-Weighted Returns** | | | | | | |
| FF | 0.16 | 0.14 | -0.01 | -0.04 | 0.15 | -0.16 | 0.22 | -0.01 | 0.09 | -0.37 | -0.53 |
| | (1.86) | (1.42) | (0.08) | (0.32) | (1.02) | (0.97) | (1.18) | (0.05) | (0.31) | (1.23) | (1.68) |
| Car | 0.15 | 0.14 | 0.01 | -0.01 | 0.18 | -0.09 | 0.31 | 0.09 | 0.24 | -0.30 | -0.45 |
| | (1.70) | (1.42) | (0.12) | (0.05) | (1.22) | (0.54) | (1.69) | (0.39) | (0.84) | (0.99) | (1.41) |
| | | | | | **Panel B. Equally-Weighted Returns** | | | | | | |
| FF | 0.21 | 0.10 | 0.07 | -0.04 | 0.16 | 0.00 | -0.02 | -0.06 | 0.04 | -0.27 | -0.48 |
| | (2.27) | (0.96) | (0.63) | (0.41) | (1.54) | (0.02) | (0.20) | (0.41) | (0.27) | (1.40) | (2.26) |
| Car | 0.20 | 0.08 | 0.07 | -0.02 | 0.17 | 0.02 | 0.00 | -0.04 | 0.04 | -0.29 | -0.49 |
| | (2.14) | (0.75) | (0.62) | (0.18) | (1.63) | (0.17) | (0.04) | (0.26) | (0.29) | (1.48) | (2.28) |

Given the positive premium for LOTT reported in Han and Kumar (2011), the results from the time-series regressions on decile LOTT portfolios in Table 25 might appear surprising. However, LOTT is an equally-weighted index consisting of price, idiosyncratic skewness and idiosyncratic volatility and their individual return impact has to be considered: Price is related to firm size and its effect is thus likely to be captured by SMB factor of the four factor model in time-series regression and SIZE factor in cross-sectional regression. Also, the evidence on pricing of the idiosyncratic risk components in the literature is mixed. For instance, Goyal and Santa-Clara (2003) find a positive relation between idiosyncratic volatility and stock returns while Wei and Zhang (2005) show that the positive relation is sample specific and Bali, Cakici, Yan and Zhang (2008) find no confirmation for the return pattern after controlling for small stock and liquidity premium. Similarly, Bali and Cakici (2005) argue that the premium is sensitive to the method applied. In contrast, Ang et al. (2006, 2009) report a negative return premium for high idiosyncratic risk firms. As such, to further understand the stock return association of LOTT I decompose LOTT into its component parts and test their pricing impact using cross-sectional regressions.

Before conducting the cross-sectional regressions, I report the Spearman and Pearson correlation coefficients of LOTT and its individual components as well as the common risk factors and the distress risk proxies Table 26. It shows that LOTT is moderately correlated with SIZE (Spearman: -0.58, Pearson: -0.45) and Shum (Spearman: 0.59, Pearson: 0.58). Due to SIGMA (component of Shum and similar to IVOL), there is moderate correlation between IVOL and Shum (Spearman: 0.53, Pearson: 0.49). ISKEW is only marginally correlated with the risk factors and distress risk measures. As expected, PRICE is correlated with SIZE (Spearman: 0.64, Pearson: 0.50) and, due to RSIZE, with Shum (Spearman: -0.69, Pearson: -0.59). Since the correlation coefficients are not particularly high between the variables, no adjustment is required for the following cross-sectional regressions.

**Table 26 Lottery Stocks: Correlation**

This table presents time-series averages of correlation coefficients for variables of UK non-financial firms listed in the Main market segment of the London Stock Exchange. Spear is the Spearman and Pear the Pearson correlation coefficient. Correlation coefficients are calculated at the end of each September from 1985 to 2009 (portfolio formation). Variables are: BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. I use Shum, the score from the model in Shumway (2001), z-score (Taffler, 1983) and BS, the score from the market-based model in Bharath and Shumway (2008). I transform the z-score into probability: $p = e^{z\text{-score}} / (1+ e^{z\text{-score}})$. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. LOTT is the lottery-index following Han and Kumar (2011) and as defined in Eq. (26). That is, I rank the sample firms on share price (PRICE) and form virgintile portfolios. I repeat that for IVOL and ISKEW. LOTT is the sum of the virgintile assignments for the sort on PRICE, IVOL and ISKEW divided by 60. At portfolio formation, I rank stocks on LOTT and form decile portfolios. I run regressions using the Carhart (1997) model over the previous 24 months and collect the residual terms per firm. IVOL is the variance and ISKEW the skewness of the residual terms. I then rank all sample firms on LOTT and form decile portfolios. All variables (except LOTT) are winsorised at the 5.0% level, default probabilities at 0.00000001 and 0.99999999.

| | LOTT | | IVOL | | ISKEW | | PRICE | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Spear** | **Pear** | **Spear** | **Pear** | **Spear** | **Pear** | **Spear** | **Pear** |
| BETA | 0.13 | 0.14 | 0.20 | 0.18 | -0.01 | 0.00 | -0.09 | -0.10 |
| SIZE | -0.58 | -0.45 | -0.44 | -0.27 | -0.16 | -0.11 | 0.64 | 0.50 |
| BM | 0.15 | 0.18 | 0.02 | 0.04 | -0.01 | -0.02 | -0.28 | -0.27 |
| PYR | -0.13 | -0.09 | -0.10 | -0.02 | 0.16 | 0.17 | 0.32 | 0.27 |
| Shum | 0.59 | 0.58 | 0.53 | 0.49 | 0.05 | 0.03 | -0.69 | -0.59 |
| Z-score | 0.28 | 0.27 | 0.28 | 0.30 | 0.01 | 0.02 | -0.31 | -0.25 |
| BS | 0.48 | 0.47 | 0.45 | 0.35 | -0.02 | -0.02 | -0.61 | -0.52 |

Using cross-sectional analysis in Table 27, I formally test whether (i) there is a premium on LOTT, and (ii) if LOTT is able to account for the premium earned by Shum, z-score and BS. Model 1 repeats the basic regression using the Carhart (1997) risk factors BETA, SIZE, BM, and PYR (t = 1.69, 0.54, 2.76 and 2.38 respectively). Model 2 includes IVOL as additional explanatory variable. IVOL (t = 0.67) is not able to add any pricing relevant information in addition to the risk factors. The significance of the risk factors remains unchanged. Model 2 includes ISKEW (t = 0.61) and provides similar results. Model 3 adds PRICE which is again insignificant (t = 0.94) and does not change the significant levels of the risk factors. As such, none of the individual variables of LOTT carries significant pricing information in addition to the risk factors. It is therefore not surprising that the composite of the variables, LOTT, is also insignificant (t = 0.61). As such, LOTT has no significance in explaining the cross-section of subsequent stock returns. I report the results of Model 6 to 8 that include the default scores from Shum, z-score and BS which are all negative and significant (t = 2.32, 3.28, and 2.16 respectively) while LOTT remains insignificant (maximum t = 0.26).

Due to its ability to forecast bankruptcies (AUC of 0.80), LOTT might have been expected to earn a 'distress risk measure' premium. Though, while two of the components of LOTT have some similarity with Shum and BS, there is no commonality with z-score, the distress risk proxy with the strongest association with future stock returns. [33] Thus, the results in Table 27 do not only confirm the time-series regressions on decile portfolio sorts on LOTT (Table 25) but they further corroborate the first indication in Table 21 that it might not be distress risk that is priced.

The results in Table 27 show clear evidence against research propositions P7 and P8. Neither the composite LOTT measure nor any of the individual components is significant in the cross-sectional analysis. LOTT has no impact on the negative distress risk premium. Thus, I conclude that limits of arbitrage or gambling retail investors do not account for the overpricing of distressed firms.

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[33] Most similar to PRICE is RSIZE in Shum. Most similar to IVOL (volatility of error terms from Carhart (1997) model) is SIGMA (the volatility of stock returns) in Shum and BS. The Pearson correlation coefficient between LOTT and Shum, BS, and z-score is 0.59, 0.48, and 0.28 respectively.

**Table 27 Lottery Stocks: Cross-Sectional Regression**

This table presents results from cross-sectional regressions on individual stock returns of UK non-financial firms listed in the Main market segment of the London Stock Exchange. I employ the method of Fama and MacBeth (1973) as defined in Eq. (24) and add various variables to the basic model:

$\mathrm{R_{i,t+m}} - \mathrm{R_{f,t+m}} = \alpha_{\mathrm{i,t+m}} + \gamma_{1,\mathrm{t+m}}\mathrm{BETA_t} + \gamma_{2,\mathrm{t+m}}\mathrm{LN(SIZE)_t} + \gamma_{3,\mathrm{t+m}}\mathrm{LN(BM)_t} + \gamma_{4,\mathrm{t+m}}\mathrm{PYR_t}$,

where subscript t denotes the portfolio year starting at the beginning of October each year from 1985 to 2009 and t+m for integer m = 1 to 12 denotes the month-ends of the portfolio year. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the natural log of the market value of common equity (MV). BM is the natural log of book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. I add IVOL, ISKEW, PRICE, LOTT, the failure indicators Shum, the score from the model in Shumway (2001), z-score (Taffler, 1983) and BS, the score from the market-based model in Bharath and Shumway (2008). I take the coefficients from failure indicators and predictor variables known at the end of each September from 1985 to 2009 (portfolio formation). LOTT is the lottery-index following Han and Kumar (2011): I run regressions using the Carhart (1997) model over the previous 24 months and collect the residual terms. IVOL is the variance and ISKEW the skewness of the residual terms. I rank the sample firms on share price (PRICE) and form virgintile portfolios. I repeat that for IVOL and ISKEW. LOTT (Eq. (26)) is the sum of the virgintile portfolio assignments divided by 60. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables (not LOTT) are winsorised at the 5.0% level, scores are winsorised at ±18.4207. The return of the failure month is set to -100.0%.

| Model | γ1 BETA | γ2 SIZE | γ3 BM | γ4 PYR | γ5 IVOL | γ6 ISKEW | γ7 PRICE | γ8 LOTT | γ9 Shum | γ10 Z-score | γ11 BS |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | -0.12 | -0.03 | 0.22 | 0.40 | | | | | | | |
| | (1.69) | (0.54) | (2.76) | (2.38) | | | | | | | |
| **2** | -0.10 | -0.04 | 0.21 | 0.44 | -1.08 | | | | | | |
| | (1.45) | (0.80) | (2.78) | (2.64) | (0.67) | | | | | | |
| **3** | -0.12 | -0.03 | 0.22 | 0.41 | | 0.03 | | | | | |
| | (1.72) | (0.49) | (2.76) | (2.37) | | (0.61) | | | | | |
| **4** | -0.10 | -0.06 | 0.22 | 0.42 | | | 0.00 | | | | |
| | (1.52) | (0.93) | (2.77) | (2.68) | | | (0.94) | | | | |
| **5** | -0.10 | -0.05 | 0.21 | 0.42 | | | | -0.21 | | | |
| | (1.51) | (0.80) | (2.70) | (2.51) | | | | (0.61) | | | |
| **6** | -0.07 | -0.12 | 0.15 | 0.16 | | | | -0.01 | -0.19 | | |
| | (1.19) | (1.83) | (1.84) | (1.21) | | | | (0.05) | (2.32) | | |
| **7** | -0.10 | -0.05 | 0.18 | 0.35 | | | | -0.09 | | -0.02 | |
| | (1.46) | (0.88) | (2.29) | (2.19) | | | | (0.26) | | (3.28) | |
| **8** | -0.09 | -0.06 | 0.24 | 0.27 | | | | -0.06 | | | -0.02 |
| | (1.42) | (1.13) | (3.02) | (1.72) | | | | (0.18) | | | (2.16) |

## 7.6 Conclusion and Discussion of Findings

The results in this chapter provide no evidence for the predictions of Garlappi and Yan (2011). In contrast to their predictions but in line with other studies, I find that equity beta as well as BM increases with distress risk (e.g. Dichev, 1998; Avramov, Chordia, Jostova and Philipov, 2009). More importantly, while Garlappi and Yan (2011) apply only a market-based measure, I reject their proposition using a hybrid, accounting-based and market-based measure to proxy for distress risk.

Garlappi and Yan (2011) argue that their valuation model originally introduced to the US market is broader than a simple violation of the absolute priority rule. However, its applicability to the UK market is an empirical question because Franks and Nyborg (1996) highlight significant differences between the US and the UK bankruptcy regime, in particular, the UK bankruptcy regime is more creditor-friendly. Kaiser (1996) finds that UK stockholders are passed over in terminal payments and similarly, Agarwal and Taffler (2008b) find that over their sample period of 24 years in only one instance did the shareholders of a failed firm receive any pay-out. I find no evidence in support of the shareholder advantage theory of Garlappi and Yan (2011). Hence, the negative distress risk premium in the UK is unlikely to be driven by the shareholder advantage effect.

However, my findings could also be different to the results of Garlappi and Yan (2011) because of sample and method. Dichev (1998) finds a hump-shaped distress risk-return relation only to be true for NASDAQ stocks using z-score. As such, the findings of Garlappi and Yan (2011) could be driven by a class of small stocks listed at NASDAQ. The fact that I exclude AIM, i.e. the equivalent to NASDAQ, might explain why my results do not support the findings in Garlappi and Yan (2011). Alternatively, the shareholder advantage might be a myopic view of reality. Zhang (2012) argues that the model of Garlappi and Yan (2011) assumes that there are no renegotiation frictions. However, Zhang (2012) shows that such frictions exist and have a negative effect on the shareholder advantage.

The second part of this chapter demonstrates that firms with lottery-type characteristics or limits of arbitrage share similar characteristics with distressed firms. However, the pricing impact of these characteristics is marginal. Decile sorts on LOTT show no return association with value-weighted portfolio returns though the association with equally-weighted portfolio returns suggests that the return premium is due to stocks with low market capitalisation. The results from cross-sectional regressions are even weaker as they demonstrate that the characteristics are not relevant in subsequent stock returns and that the distress risk premium is not affected. This might appear surprising because (i) LOTT was found significant in previous studies (e.g. Han and Kumar, 2011), and (ii) LOTT is associated with distress risk and thus might earn a 'distress risk measure' premium. However, the impact of the individual components of LOTT is likely to be controlled for by the risk-adjustment applied. The size factor covers the share price component of LOTT and the remaining idiosyncratic risk components (Angelidis and Tessaromatis, 2005; 2008). Moreover, the fact that LOTT is not priced although being a fairly good failure predictor (AUC of 0.80) further corroborates the first indication from Chapter 6 that it might not be distress risk that is priced but an element of the distress measures not shared by LOTT.

Overall, the results in this chapter present no evidence to support the research propositions P6 to P8. I therefore conclude that there is no shareholder advantage effect in the UK as described by Garlappi and Yan (2011) and the negative distress risk measure premium is not driven by gambling retail investors or limits of arbitrage.

In the next chapter, I explore the drivers of the distress risk measures as I break each of them down into its individual variables and test for their price impact in subsequent stock returns.

## 7.7 Appendix

### Table 28A Shareholder Advantage: Value Premium

The table presents value premia from time-series regressions on decile portfolios based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability and sort into equally populated decile portfolios (low to high distress risk). Independently, I rank the sample firms on BM (book value of shareholders' equity less preference shares and minorities over market value of common equity) and form two equally populated portfolios (high and low BM). I form 20 portfolios at the intersections of the two sorts. Per decile distress risk portfolio, I calculate the risk-adjusted value premium using the Carhart (1997) model as defined in Eq. (25), i.e. the risk-adjusted return on a portfolio that is long on high BM and short on low BM stocks. The portfolio returns are value-weighted (vw) or equally-weighted (ew). I repeat this for each default probability obtained from the model in Shumway (2001), z-score (Taffler, 1983), and the model in Bharath and Shumway (2008).

| | **Low** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High** | **H-L** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Panel A. Shumway (2001)** | | | | | | |
| vw | 0.09 | 0.07 | 0.16 | 0.03 | 0.44 | -0.05 | -0.58 | 0.76 | -0.01 | 0.00 | -0.09 |
| | (0.56) | (0.37) | (0.86) | (0.13) | (1.96) | (0.17) | (1.66) | (2.16) | (0.01) | (0.00) | (0.19) |
| ew | 0.23 | 0.10 | 0.24 | 0.17 | 0.44 | 0.05 | 0.57 | 0.72 | 0.09 | 0.16 | -0.07 |
| | (1.46) | (0.66) | (1.53) | (1.12) | (2.77) | (0.30) | (3.01) | (3.21) | (0.34) | (0.43) | (0.17) |
| | | | | | **Panel B. Z-score (Taffler, 1983)** | | | | | | |
| vw | 0.05 | -0.01 | 0.06 | -0.19 | 0.72 | -0.19 | 0.10 | 0.32 | 0.62 | -0.17 | -0.21 |
| | (0.14) | (0.04) | (0.27) | (1.08) | (3.69) | (0.83) | (0.46) | (1.12) | (1.90) | (0.47) | (0.48) |
| ew | 0.31 | 0.31 | -0.02 | 0.24 | 0.54 | 0.10 | 0.13 | -0.04 | 0.30 | 0.28 | -0.04 |
| | (1.46) | (1.61) | (0.10) | (1.31) | (3.31) | (0.58) | (0.70) | (0.21) | (1.30) | (0.81) | (0.10) |
| | | | | | **Panel C. Bharath and Shumway (2008)** | | | | | | |
| vw | -0.13 | 0.05 | 0.17 | -0.09 | 0.39 | 0.43 | 0.31 | 0.19 | -0.11 | 0.96 | 1.09 |
| | (0.58) | (0.27) | (0.93) | (0.48) | (1.85) | (1.79) | (1.12) | (0.53) | (0.27) | (1.55) | (1.66) |
| ew | 0.21 | 0.34 | 0.33 | 0.09 | 0.36 | 0.34 | 0.84 | 0.53 | 0.46 | 0.24 | 0.03 |
| | (1.16) | (2.02) | (2.15) | (0.56) | (2.16) | (1.91) | (4.29) | (2.49) | (1.53) | (0.48) | (0.05) |

# CHAPTER 8: UNRAVELLING THE NEGATIVE DISTRESS RISK PREMIUM

## 8.1 Introduction

Chapter 6 presents clear evidence that distressed stocks underperform while scoring high on conventional risk measures. Since this is hard to reconcile with the traditional risk-return paradigm, literature proposes alternative explanations for the anomalous distress risk return pattern. However, the tests in Chapter 7 do not find any evidence in support of the shareholder advantage theory of Garlappi and Yan (2011) in the UK. The results in Chapter 7 also show that distressed firms have characteristics that are associated with high limits of arbitrage (Shleifer and Vishny, 1997) and that attract gambling retail investors (Han and Kumar, 2011) but, there is no evidence that these characteristics drive the overpricing of distressed firms.

Literature hitherto assumes that the lower returns on distressed stocks provide evidence that distress risk is priced, albeit counterintuitively (e.g. Campbell et al., 2008). The results in the previous chapters raise fundamental doubts on this assumption. First, if it is distress risk that is priced, the best distress risk measure is expected to be the most strongly related to future stock returns. In sharp contrast to this, I find that z-score, the weakest bankruptcy prediction model (Chapter 5), subsumes the pricing information of the stronger bankruptcy predictors (Chapter 6). A second doubt is raised by the results on LOTT (Chapter 7). I find that while LOTT is a fairly good bankruptcy predictor (AUC = 0.80), it has no association with subsequent stock returns. These empirical findings suggest that it is not distress risk but one or more elements of the distress risk measures that drive the observed premium. As z-score is the dominant distress risk measure in the returns analysis, it suggests that the pricing element is most pronounced within z-score.

These conflicting findings make it a requisite to explore the underlying drivers of the distress risk premium. The existing literature only works with the composite measures and this chapter fills this gap in the literature by testing whether it is distress risk (i.e. the composite) or some individual components that drive the observed negative distress risk premium.

The remainder of this chapter is organised as follows: in sub-chapter 2 I present the research question and research proposition. In sub-chapter 3 I briefly describe the data and method used. Sub-chapter 4 uses cross-sectional regressions to tests for the pricing relevance of the individual variables of each distress risk measure. Sub-chapter 5 provides robustness tests using time-series regressions. Sub-chapter 6 concludes and discusses the results.

## 8.2 Research Question and Propositions

In this chapter I explore the relation between distress risk and returns more thoroughly than current studies by testing the drivers of the distress risk proxies using their individual components. As such, I examine the following research question:

**Does one of the components of the distress risk measures drive the returns or is it the composite?**

The corresponding research proposition is therefore:

*P9: One or more of the components of the distress risk measures drive the observed distress risk premium.*

## 8.3 Data and Method

My sample consists of UK non-financial firms listed in the Main market segment of the London Stock Exchange anytime between October 1985 and September 2010. It includes 22,217 observations with 2,428 unique firms of which 202 failed.

In this chapter I apply two testing procedures: First, I use cross-sectional regressions following the method of Fama and MacBeth (1973) as defined in Eq. (24) to test for pricing significance of each distress risk measures' individual variables (I use Shum, z-score and BS). Second, based on the results of the cross-sectional regressions, I use sorts on distress risk and profitability. I test for abnormal returns using time-series regressions with the Fama and French (1993) model as well as the Carhart (1997) model as defined in Eq. (25). Following Novy-Marx (2010), I add a risk factor to represent profitability as defined in Eq. (28).

## 8.4 Cross-Sectional Regressions

### 8.4.1 Distress Risk Measures: Individual Variables

In this sub-chapter I conduct cross-sectional tests to identify the drivers of the distress risk premium. In doing so, I analyse the cross-sectional impact of the individual variables of each distress risk measure on subsequent stock returns controlling for the common risk factors.

Before conducting the cross-sectional analysis, I test for the correlation between the distress risk measure components and the common risk factors. Since the distress risk measures of Shumway (2001) and Bharath and Shumway (2008) contain variables similar to the risk factors, I expect high correlations. Table 29 presents the Spearman and Pearson correlation coefficients for the common risk factors BETA, SIZE, BM and PYR with the distress risk measures Shum, z-score and BS. I break down each distress risk measure into the individual component parts i.e. Shum into NITA, TLTA, EXRET, SIGMA and RSIZE; z-score into PBTCL, CATL, CLTA and NCI; and BS into ER1y, TLMTA, and SIGMA (please see Table 2A on page 91 for a definition of the key variables).

First, I examine the correlations of Shum's components and the risk factors. BETA shows no relation with the individual components (maximum: Spearman 0.13, Pearson 0.12). SIZE shows a high correlation with Shum (Spearman -0.73, Pearson -0.49) while, as expected, it is highly correlated with RSIZE (Spearman 1.00, Pearson 0.79). BM has a low correlation with all the Shum variables (maximum Spearman -0.37, Pearson -0.38). Unsurprisingly, PYR is highly correlated with EXRET (Spearman 0.95, Pearson 0.93). Within the Shum variables there are no high correlations (see Appendix). As such, when I run the cross-sectional regressions with the individual variables, I either exclude SIZE or RSIZE and PYR or EXRET.

Next, I look at the correlation coefficients of the z-score components and the risk factors. Z-score is a purely accounting-based distress risk measure. Since the risk factors are all market-based variables, the correlation between the individual z-score variables and the risk factors is low. The maximum Spearman rank correlation coefficient is 0.35 and between PBTCL and SIZE, while the maximum Pearson correlation coefficient is -0.28 and between CLTA and BM. Within the individual variables of z-score there is no significant correlation (see Appendix). It follows that no adjustment is required for running cross-sectional tests using the z-score components and risk factors.

Third, I examine the correlation coefficients of the individual BS components and the risk factors. BETA has no correlation with the BS components (maximum Spearman 0.13, Pearson 0.12). SIZE has as well moderate correlation with the individual BS variables (maximum Spearman -0.54, Pearson -0.31). BM has a moderate correlation with TLMTA (Spearman 0.46, Pearson 0.48). Unsurprisingly, PYR is a substitute for ER1y (Spearman 0.95, Pearson 0.96). The three individual components of BS are not highly correlated (see Appendix). As such, I use either PYR or ER1y in the cross-sectional tests.

**Table 29 Variables Distress Risk Models: Correlation Common Risk Factors**

This table presents time-series averages of correlation coefficients for variables of UK non-financial firms listed in the Main market segment of the London Stock Exchange. Spear is the Spearman and Pear the Pearson correlation coefficient. Correlation coefficients are calculated at the end of each September from 1985 to 2009 (portfolio formation). Variables are: Shum, the score from the model in Shumway (2001), z-score (Taffler, 1983) and BS, the score from the market-based model in Bharath and Shumway (2008). NITA is net income available to common shareholders over book value of total assets. TLTA (TLMTA) is book value of total assets excluding total common shareholders' equity over book value of total assets (over book value of total liabilities plus market value of common equity). EXRET is log excess return over the FTSE All Share Index over the 12 months prior to portfolio formation. SIGMA is the annualised standard deviation of daily returns for the three months prior to portfolio formation. RSIZE is log of market value of common equity (MV) over the market value of the FTSE All Share Index. PBTCL is profit before tax over current liabilities. CATL is current assets over total liabilities. CLTA is current liabilities over total assets. NCI is the no-credit interval calculated as (quick assets – current liabilities) / ((sales – profit before tax – depreciation) / 365). ER1y is the prior-year return. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables are winsorised at the 5.0% level, scores are winsorised at ±18.4207.

| | **BETA** | | **SIZE** | | **BM** | | **PYR** | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Spear** | **Pear** | **Spear** | **Pear** | **Spear** | **Pear** | **Spear** | **Pear** |
| Shum | 0.05 | 0.07 | -0.73 | -0.49 | 0.24 | 0.28 | -0.50 | -0.50 |
| NITA | -0.05 | -0.08 | 0.32 | 0.19 | -0.33 | -0.23 | 0.18 | 0.18 |
| TLTA | 0.07 | 0.08 | 0.09 | 0.10 | -0.36 | -0.29 | -0.03 | -0.03 |
| EXRET | -0.03 | -0.05 | 0.21 | 0.14 | -0.29 | -0.31 | 0.95 | 0.93 |
| SIGMA | 0.13 | 0.12 | -0.54 | -0.31 | 0.17 | 0.24 | -0.26 | -0.25 |
| RSIZE | 0.08 | 0.06 | 1.00 | 0.79 | -0.37 | -0.38 | 0.22 | 0.19 |
| Z-score | 0.06 | 0.07 | -0.17 | -0.08 | -0.04 | 0.00 | -0.12 | -0.11 |
| PBTCL | -0.08 | -0.09 | 0.35 | 0.20 | -0.15 | -0.16 | 0.17 | 0.15 |
| CATL | 0.01 | 0.00 | -0.25 | -0.23 | 0.05 | 0.06 | 0.02 | 0.03 |
| CLTA | 0.05 | 0.06 | -0.13 | -0.12 | -0.34 | -0.28 | -0.02 | -0.01 |
| NCI | 0.01 | 0.01 | -0.04 | -0.06 | -0.01 | 0.00 | 0.05 | 0.04 |
| BS | 0.08 | 0.07 | -0.51 | -0.30 | 0.38 | 0.39 | -0.59 | -0.56 |
| ER1y | -0.03 | -0.03 | 0.22 | 0.10 | -0.29 | -0.30 | 0.95 | 0.96 |
| TLMTA | 0.02 | 0.02 | -0.27 | -0.12 | 0.46 | 0.48 | -0.28 | -0.30 |
| SIGMA | 0.13 | 0.12 | -0.54 | -0.31 | 0.17 | 0.24 | -0.26 | -0.25 |

Table 30 reports the cross-sectional regressions using the individual distress risk measure variables. Model 1 is the basic regression using the common risk factors and the starting point of the analysis. As such, I test for significance of the individual variables after controlling for BETA, SIZE, BM and PYR.

Model 2 contains the variables of Shum. As discussed above, I exclude either SIZE and PYR or RSIZE and EXRET. Being a substitute of PYR, EXRET shows high significance (t = 2.27) in explaining the cross-section of subsequent stock returns. Similar to SIZE, RSIZE is insignificant (t = 1.60). Looking at the other two risk factors, BETA remains insignificant (t = 1.62) while the coefficient of BM is lowered to an insignificant level (t = 1.82). This might be due to the fact that BM has a moderate correlation with the Shum components and thus, the BM effect might be covered collectively by them. Apart from that, Model 2 highlights the relevance of profitability. NITA is positively related with subsequent stock returns (t = 2.27). TLTA and SIGMA are both insignificant (t = 0.80 and 1.36).[34] Model 3 is similar to Model 2 but it uses SIZE instead of RSIZE and PYR instead of EXRET. BETA, SIZE, and BM are again insignificant (t = 1.17, 1.64, and 1.87 respectively). Similar to EXRET in Model 2, PYR is significant in explaining the cross-section of subsequent stock returns (t = 2.43). Further confirming the results of Model 2, NITA (t = 2.24) is again the only Shum component that is significant in addition to the risk factors. As such, TLTA (t = 0.83) and SIGMA (t = 1.37) are insignificant. The results clearly show that the premium on Shum is mainly driven by NITA.

Model 4 examines the effects of the individual components of z-score. Similar to the basic Model 1, BETA and SIZE are insignificant (t = 1.55 and 0.61) while BM and PYR are significant (t = 2.72 and 1.95). The z-score components show that, again, profitability measured by PBTCL, is highly significant (t = 2.69). Besides that, the firm-

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[34] This confirms results in Chapter 7 where IVOL (idiosyncratic volatility), that is similar to SIGMA (total volatility), is also found to be insignificant.

liquidity ratio NCI is also significant (t = 2.52) in explaining subsequent stock returns. The remaining two z-score variables CATL and CLTA are insignificant (t = 0.19 and 1.48 respectively). As such, confirming the results on Shum, the z-score effect is driven by profitability and NCI.

Model 5 presents the results on the components of BS. Similar to Model 1, BETA and SIZE have no impact on subsequent stock returns (t = 1.46 and 1.53 respectively) while BM is highly significant (t = 2.81). As a substitute of PYR, ER1y is highly significant (t = 2.75) too. Similar to Model 2 and 3, SIGMA has no statistical relevance (t = 1.62) and the coefficient on TLMTA is also statistically insignificant (t = 0.59). Model 6 repeats the results using PYR instead of ER1y and the results remain unchanged. BETA, SIZE, SIGMA, and TLMTA are insignificant (t = 1.22, 1.43, 1.68, and 0.75 respectively) while BM and PYR are the only significant variables in explaining the cross-section of subsequent stock returns (t = 2.80 and 2.56 respectively). As such, none of the BS variables is significant in addition to the common risk factors. However, this is not surprising because, recalling from Model 8 in Table 21, BS itself is only marginally significant (t = 1.91).

The results in Table 30 can be summarised as follows: (i) the coefficients of the common risk factors generally do not differ when the individual variables of the distress risk measures are included instead of the composite measure itself. As such, Table 30 confirms the results from Table 21 in Chapter 6 in terms of the risk factors, and (ii) I find profitability and firm-liquidity to be relevant in explaining cross-sectional variation of stock returns in addition to the common risk factors. For Shum, NITA is positive and significant and for z-score, PBTCL is positive and significant. In addition, for z-score, NCI is also positive and significant. The other variables of Shum and z-score are insignificant.

As such, I find supporting evidence for research proposition P9, that profitability and firm-liquidity drives the distress scores of Shum and z-score. In the following, I further explore this finding employing orthogonalised distress risk proxies in cross-sectional regressions.

**Table 30 Variables Distress Risk Models: Cross-Sectional Regression**

This table presents results from cross-sectional regressions on individual stock returns of UK non-financial firms listed in the Main market segment of the London Stock Exchange. I employ the method of Fama and MacBeth (1973) as defined in Eq. (24) and add various variables to the basic model:
$R_{i,t+m} - R_{f,t+m} = \alpha_{i,t+m} + \gamma_{1,t+m}BETA_t + \gamma_{2,t+m}LN(SIZE)_t + \gamma_{3,t+m}LN(BM)_t + \gamma_{4,t+m}PYR_t,$
where subscript t denotes the portfolio year starting at the beginning of October each year from 1985 to 2009 and t+m for integer m = 1 to 12 denotes the month-ends of the portfolio year. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the natural log of the market value of common equity (MV). BM is the natural log of book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. NITA is net income available to common shareholders over book value of total assets. TLTA (TLMTA) is book value of total assets excluding total common shareholders' equity over book value of total assets (over book value of total liabilities plus market value of common equity). EXRET is log excess return over the FTSE All Share Index over the 12 months prior to portfolio formation. SIGMA is the annualised standard deviation of daily returns for the three months prior to portfolio formation. RSIZE is log of market value of common equity (MV) over the market value of the FTSE All Share Index. PBTCL is profit before tax over current liabilities. CATL is current assets over total liabilities. CLTA is current liabilities over total assets. NCI is the no-credit interval calculated as (quick assets – current liabilities) / ((sales – profit before tax – depreciation) / 365). ER1y is the prior-year return. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation (end of September from 1985 to 2009), market data is taken at portfolio formation. All variables are winsorised at the 5.0% level, scores are winsorised at ±18.4207. The return of the month of failure is set to -100.0%.

| Model | γ1 BETA | γ2 SIZE | γ3 BM | γ4 PYR | γ5 NITA | γ6 TLTA | γ7 EXRET | γ8 SIGMA | γ9 RSIZE | γ10 PBTCL | γ11 CATL | γ12 CLTA | γ13 NCI | γ14 ER1y | γ15 TLMTA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | -0.12 | -0.03 | 0.22 | 0.40 | | | | | | | | | | | |
| | (1.69) | (0.54) | (2.76) | (2.38) | | | | | | | | | | | |
| **2** | -0.10 | | 0.17 | | 1.60 | -0.25 | 0.48 | -0.35 | -0.08 | | | | | | |
| | (1.62) | | (1.82) | | (2.13) | (0.80) | (2.27) | (1.36) | (1.60) | | | | | | |
| **3** | -0.07 | -0.09 | 0.17 | 0.34 | 1.69 | -0.26 | | -0.39 | | | | | | | |
| | (1.17) | (1.64) | (1.87) | (2.43) | (2.24) | (0.83) | | (1.37) | | | | | | | |
| **4** | -0.11 | -0.03 | 0.24 | 0.31 | | | | | | 0.57 | -0.02 | 0.44 | 0.00 | | |
| | (1.55) | (0.61) | (2.72) | (1.95) | | | | | | (2.69) | (0.19) | (1.48) | (2.52) | | |
| **5** | -0.09 | -0.08 | 0.22 | | | | | -0.48 | | | | | | 0.50 | -0.18 |
| | (1.46) | (1.53) | (2.81) | | | | | (1.62) | | | | | | (2.75) | (0.59) |
| **6** | -0.08 | -0.08 | 0.21 | 0.36 | | | | -0.50 | | | | | | | -0.23 |
| | (1.22) | (1.43) | (2.80) | (2.56) | | | | (1.68) | | | | | | | (0.75) |

### 8.4.2 Distress Risk and Profitability

Chapter 6 demonstrates that there is a negative distress risk premium in stock returns. The results in Table 30 show that profitability and firm-liquidity are the drivers of the negative distress risk premium. To further test these findings, I separate the information carried by profitability and firm-liquidity from the distress risk measure and test for significance of the remaining information of the distress risk measure. As such, I orthogonalise Shum by NITA and, likewise, I orthogonalise z-score by PBTCL and NCI using Eq. (27).

Table 31 presents the results for the orthogonalised Shum measure. Model 1 repeats the basic regression with the Shum score (not orthogonalised) showing the negative distress risk premium ($t = 2.07$). Model 2 includes the Shum measure orthogonalised by NITA i.e. the distress information unrelated to profitability and shows that the remaining distress related information is not significant ($t = 0.91$) in explaining the cross-section of subsequent stock returns. At the same time, BETA, BM and PYR become significant ($t = 1.98$, 2.21, and 2.66 respectively) while SIZE remains insignificant ($t = 0.88$) when the profitability related information in the distress risk measure is excluded. This suggests that collectively BETA, BM, and PYR account for the information carried by NITA (the maximum correlation coefficient between NITA and the other variables I -0.33). Model 3 includes NITA and shows that profitability is significant ($t = 2.08$) while Shum remains insignificant ($t = 1.54$). Also, the risk factors BETA, SIZE, BM, and PYR have significance levels similar to Model 1 ($t = 1.54$, 1.68, 1.87, and 1.66 respectively).

**Table 31 Profitability and Shumway (2001)**

This table presents results from cross-sectional regressions on individual stock returns of UK non-financial firms listed in the Main market segment of the London Stock Exchange. I employ the method of Fama and MacBeth (1973) as defined in Eq. (24) and add various variables to the basic model:
$R_{i,t+m} - R_{f,t+m} = \alpha_{i,t+m} + \gamma_{1,t+m}BETA_t + \gamma_{2,t+m}LN(SIZE)_t + \gamma_{3,t+m}LN(BM)_t + \gamma_{4,t+m}PYR_t$,
where subscript t denotes the portfolio year starting at the beginning of October each year from 1985 to 2009 and t+m for integer m = 1 to 12 denotes the month-ends of the portfolio year. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the natural log of the market value of common equity (MV). BM is the natural log of book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Shum is the score from the model in Shumway (2001). NITA in column Orthogonalised reports when Shum is orthogonalised by NITA. NITA is net income available to common shareholders over book value of total assets. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation (end of September from 1985 to 2009), market data is taken at portfolio formation. All variables are winsorised at the 5.0% level, scores are winsorised at ±18.4207. The return of the month of failure is set to -100.0%.

| | | **γ1** | **γ2** | **γ3** | **γ4** | **γ5** | **γ6** |
|---|---|---|---|---|---|---|---|
| **Model** | **Orthogonalised** | **BETA** | **SIZE** | **BM** | **PYR** | **Shum** | **NITA** |
| **1** | **-** | -0.09 | -0.12 | 0.15 | 0.17 | -0.18 | |
| | | (1.32) | (1.84) | (1.87) | (1.28) | (2.07) | |
| **2** | NITA | -0.14 | -0.06 | 0.20 | 0.38 | -0.07 | |
| | | (1.98) | (0.88) | (2.21) | (2.66) | (0.91) | |
| **3** | NITA | -0.10 | -0.11 | 0.17 | 0.23 | -0.17 | 2.30 |
| | | (1.54) | (1.68) | (1.87) | (1.66) | (1.54) | (2.08) |

Table 32 documents the comprehensive analysis on z-score. Model 1 repeats the basic cross-sectional regression in Table 21 Chapter 6 (Model 7) showing a significant z-score (t = 3.08). Model 2 includes the z-score orthogonalised by PBTCL i.e. the distress information unrelated to profitability. Similar to the orthogonalised Shum measure, Model 2 shows that the remaining distress related information is not significant (t = 1.21) in explaining the cross-section of stock returns. The common risk factors BETA, SIZE, BM, and PYR (t = 1.68, 0.55, 2.73, and 2.37) show similar significance levels as Model 1 and, also, similar to the results in Model 2 in Table 31.[35] When PBTCL is added in Model 3, significance levels hardly change but PBTCL is positive and significant (t = 2.72). Model 4 further adds NCI with a significant coefficient (t = 1.97) while PBTCL remains highly significant (t = 2.41) as well.

In Model 5 to 7 I repeat the analysis for the z-score measure orthogonalised by NCI. Likewise, in Model 5 the orthogonalised (by NCI) z-score measure is insignificant (t = 0.45). While the risk factors BETA and SIZE are insignificant (t = 1.66 and 0.54 respectively), BM and PYR remain significant (t = 2.74 and 2.37 respectively). Adding NCI to the pricing equation in Model 6 returns a significant (t = 2.14) and positive coefficient while the significance of the coefficients of the risk factors as well as the orthogonalised z-score (by NCI) remain unchanged. Model 7 combines the orthogonalised z-score, PBTCL and NCI and shows that both z-score and NCI are insignificant (t = 0.04 and 1.90 respectively) while PBTCL is highly significant (t = 2.39).

In Model 8 to 10 I present the results for the z-score measure that is orthogonalised by both PBTCL and NCI and generally corroborate prior findings. Model 10 shows that the orthogonalised measure is insignificant (t = 0.18) while profitability is highly significant (t = 2.37) and NCI returns a marginally significant coefficient (t = 1.98).

[35] The models are similar as both contain only the distress related information that is unrelated to profitability. Thus, I expect similar significance for the common risk factors and the orthogonalised models.

**Table 32 Profitability and z-score (Taffler, 1983)**

This table presents results from cross-sectional regressions on individual stock returns of UK non-financial firms listed in the Main market segment of the London Stock Exchange. I employ the method of Fama and MacBeth (1973) as defined in Eq. (24) and add various variables to the basic model:

$R_{i,t+m} - R_{f,t+m} = \alpha_{i,t+m} + \gamma_{1,t+m}BETA_t + \gamma_{2,t+m}LN(SIZE)_t + \gamma_{3,t+m}LN(BM)_t + \gamma_{4,t+m}PYR_t$,

where subscript t denotes the portfolio year starting at the beginning of October each year from 1985 to 2009 and t+m for integer m = 1 to 12 denotes the month-ends of the portfolio year. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the natural log of the market value of common equity (MV). BM is the natural log of book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. Z-score is from Taffler (1983). PBTCL (NCI) in column Orthogonalised reports when z-score is orthogonalised by PBTCL (NCI). PBTCL is profit before tax over current liabilities. NCI is the no-credit interval calculated as (quick assets – current liabilities) / ((sales – profit before tax – depreciation) / 365). Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation (end of September from 1985 to 2009), market data is taken at portfolio formation. All variables are winsorised at the 5.0% level, scores are winsorised at ±18.4207. The return of the month of failure is set to -100.0%.

| **Model** | **Orthogonalised** | **γ1 BETA** | **γ2 SIZE** | **γ3 BM** | **γ4 PYR** | **γ5 Z-score** | **γ6 PBTCL** | **γ7 NCI** |
|---|---|---|---|---|---|---|---|---|
| **1** | **-** | -0.11 | -0.04 | 0.19 | 0.33 | -0.02 | | |
| | | (1.58) | (0.78) | (2.33) | (2.07) | (3.08) | | |
| **2** | PBTCL | -0.12 | -0.03 | 0.22 | 0.40 | 0.01 | | |
| | | (1.68) | (0.55) | (2.73) | (2.37) | (1.21) | | |
| **3** | PBTCL | -0.10 | -0.05 | 0.21 | 0.34 | 0.01 | 0.51 | |
| | | (1.49) | (0.99) | (2.63) | (2.13) | (1.23) | (2.72) | |
| **4** | PBTCL | -0.11 | -0.04 | 0.21 | 0.32 | 0.01 | 0.47 | 0.00 |
| | | (1.59) | (0.82) | (2.63) | (1.96) | (1.27) | (2.41) | (1.97) |
| **5** | NCI | -0.12 | -0.03 | 0.22 | 0.40 | 0.00 | | |
| | | (1.66) | (0.54) | (2.74) | (2.37) | (0.45) | | |
| **6** | NCI | -0.12 | -0.02 | 0.22 | 0.37 | 0.00 | | 0.00 |
| | | (1.72) | (0.40) | (2.73) | (2.16) | (0.45) | | (2.14) |
| **7** | NCI | -0.11 | -0.04 | 0.21 | 0.32 | 0.00 | 0.46 | 0.00 |
| | | (1.56) | (0.82) | (2.64) | (1.97) | (0.04) | (2.39) | (1.90) |
| **8** | PBTCL+NCI | -0.12 | -0.03 | 0.22 | 0.40 | 0.00 | | |
| | | (1.73) | (0.51) | (2.59) | (2.43) | (0.11) | | |
| **9** | PBTCL+NCI | -0.11 | -0.05 | 0.21 | 0.34 | 0.00 | 0.50 | |
| | | (1.54) | (0.94) | (2.50) | (2.18) | (0.19) | (2.67) | |
| **10** | PBTCL+NCI | -0.11 | -0.04 | 0.21 | 0.32 | 0.00 | 0.46 | 0.00 |
| | | (1.63) | (0.78) | (2.51) | (2.02) | (0.18) | (2.37) | (1.98) |

Table 33 presents the results for the market-based BS measure (not orthogonalised) when profitability (PBTCL and NITA) and firm-liquidity (NCI) are included in the regression models. BS itself is weakly significant with a t-statistic of 1.91 (Model 1). However, Model 2 and 4 include the profitability factor PBTCL which half the coefficient of BS. In contrast, PBTCL is highly significant (t = 2.63 and 2.37 respectively). NCI is irrelevant in explaining the cross-section of subsequent stock returns (t = 1.64, Model 3). Model 5 presents the coefficients and significance when NITA (t = 1.90), the profitability factor from Shum, is included and corroborates the findings.

**Table 33 Profitability and Bharath and Shumway (2008)**

This table presents results from cross-sectional regressions on individual stock returns of UK non-financial firms listed in the Main market segment of the London Stock Exchange. I employ the method of Fama and MacBeth (1973) as defined in Eq. (24) and add various variables to the basic model:
$R_{i,t+m} - R_{f,t+m} = \alpha_{i,t+m} + \gamma_{1,t+m}BETA_t + \gamma_{2,t+m}LN(SIZE)_t + \gamma_{3,t+m}LN(BM)_t + \gamma_{4,t+m}PYR_t$,
where subscript t denotes the portfolio year starting at the beginning of October each year from 1985 to 2009 and t+m for integer m = 1 to 12 denotes the month-ends of the portfolio year. BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the natural log of the market value of common equity (MV). BM is the natural log of book value of shareholders' equity less preference shares and minorities over MV. PYR is the prior 11-months return excluding September. BS is the score from the market-based model in Bharath and Shumway (2008). PBTCL is profit before tax over current liabilities. NCI is the no-credit interval calculated as (quick assets – current liabilities) / ((sales – profit before tax – depreciation) / 365). Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation (end of September from 1985 to 2009), market data is taken at portfolio formation. NITA is net income available to common shareholders over book value of total assets. All variables are winsorised at the 5.0% level, scores are winsorised at ±18.4207. The return of the month of failure is set to -100.0%.

| Model | γ1 BETA | γ2 SIZE | γ3 BM | γ4 PYR | γ5 BS | γ6 PBTCL | γ7 NCI | γ8 NITA |
|---|---|---|---|---|---|---|---|---|
| **1** | -0.10 | -0.06 | 0.24 | 0.26 | -0.02 | | | |
| | (1.52) | (1.16) | (3.03) | (1.74) | (1.91) | | | |
| **2** | -0.10 | -0.07 | 0.23 | 0.26 | -0.01 | 0.46 | | |
| | (1.45) | (1.30) | (2.85) | (1.70) | (1.30) | (2.63) | | |
| **3** | -0.10 | -0.06 | 0.22 | 0.26 | -0.01 | 0.43 | 0.00 | |
| | (1.58) | (1.12) | (2.81) | (1.69) | (1.03) | (2.37) | (1.64) | |
| **4** | -0.10 | -0.08 | 0.24 | 0.24 | -0.02 | | | 1.53 |
| | (1.41) | (1.40) | (2.96) | (1.63) | (1.68) | | | (1.90) |

The results from the cross-sectional regressions with a focus on profitability can be summarised as follows: (i) NITA drives the premium earned by Shum, (ii) PBTCL and NCI drive the premium earned by z-score, however, PBTCL is more robust than NCI, and (iii) the marginal distress effect of BS is captured by PBTCL.

As such, I further corroborate the findings in the previous sub-chapter as I find supporting evidence for proposition P9, that profitability drives the negative distress risk premium.

## 8.5 Time-Series Regressions

The previous sub-chapter provides a detailed cross-sectional analysis of the distress risk premium. The major conclusion from these tests is that profitability drives the distress risk premium. In the following, I complement the cross-sectional tests with time-series regression analysis.

To be consistent with previous analysis, I estimate the risk-adjusted returns using the Fama and French (1993) model as well as the Carhart (1997) model. Similar to the cross-sectional tests, my objective is to test whether profitability drives the distress risk premium. For this purpose, I amend the Carhart (1997) model by a fifth factor that accounts for profitability see Eq. (28). See Chapter 4 for details on the formation of the profitability factor PMU.

### 8.5.1 Five Factor Profitability Model

The introduction of the profitability factor PMU and the five factor model is solely for providing robustness tests of the results documented in the previous sub-chapter. My intention is not on providing a new asset pricing model (including the theoretical reasons behind it) but on testing the role of profitability in asset pricing.

Table 34 reports the Spearman and Pearson correlation coefficients of the common risk factors and PMU. The table demonstrates that HML and WML are moderately correlated (Spearman -0.45, Pearson -0.61). Importantly, PMU is only moderately correlated with the Carhart factors: the highest correlation of PMU is with SMB (Spearman -0.41, Pearson -0.46). As such, PMU has less in common with the common risk factors using correlation analysis.

**Table 34 Profitability Factor: Correlation Common Risk Factors**

This table presents correlation coefficients factors formed by using UK non-financial firms listed in the Main market segment of the London Stock Exchange. The lower-left side of the matrix presents Spearman rank correlation coefficients. The upper-right side of the matrix presents Pearson correlation coefficients. RmRf is the monthly return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate. SMB is the return on the mimicking portfolio for the size factor, HML the return on the mimicking portfolio for the value premium, WML is the return on the mimicking portfolio for return momentum, and PMU is the return on the mimicking portfolio for profitability effect. Factors are formed following the procedure in Fama and French (1996).

| **Variable** | **RmRF** | **SMB** | **HML** | **WML** | **PMU** |
|---|---:|---:|---:|---:|---:|
| RmRF | 1 | -0.11 | -0.05 | -0.12 | -0.35 |
| SMB | -0.15 | 1 | -0.22 | -0.04 | -0.46 |
| HML | 0.01 | -0.11 | 1 | -0.61 | 0.14 |
| WML | -0.09 | -0.06 | -0.45 | 1 | 0.12 |
| PMU | -0.33 | -0.41 | 0.07 | 0.13 | 1 |

In order to test the information carried by PMU and whether it is already captured by the common risk factors, I conduct time-series regressions using PMU as dependent variable and the common risk factors as independent variables. Model 1 in Table 35 provides the coefficients of time-series regressions that use PMU as dependent variable and the common risk factors as independent variables. Model 1 represents the standard CAPM. While RmRf is significant, the significant intercept (t = 3.22) reveals that

CAPM is unable to fully explain PMU. Also, the negative loading on RmRF shows that more profitable firms have lower exposure to the market factor than less profitable firms. Model 2 employs the factors of the Fama and French (1993) model. While RmRf (t = 8.59) and SMB (t = 10.38) significantly contribute to explaining PMU returns, the intercept is again statistically highly significant (t = 3.88). Both RmRf and SMB are negatively related with PMU, while HML is positively but insignificantly related with PMU. The returns show that while more profitable firms have lower betas and higher market capitalisation, they still earn higher returns. In Model 3 I add the momentum factor WML and find it to be insignificant (t = 1.49). While the other common risk factors remain unchanged (t = 8.04, 9.68, and 1.13 respectively), PMU earns still a risk-adjusted return of 46 bps per month (t = 3.50) that is unexplained by the common risk factors. As such, PMU has potential in explaining the significant negative distress risk premium found in the decile portfolios in Chapter 6.

**Table 35 Profitability Factor: Time-Series Regression Common Risk Factors**

The table presents summary statistics of time-series regressions of factors based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. I use monthly time-series regression from October 1985 to September 2010 as defined in Eq. (29):

$$\mathrm{PMU}_{t+m} = \beta_1 + \beta_{\mathrm{MKT}}\mathrm{RmRf}_{t+m} + \beta_{\mathrm{SMB}}\mathrm{SMB}_{t+m} + \beta_{\mathrm{HML}}\mathrm{HML}_{t+m} + \beta_{\mathrm{WML}}\mathrm{WML}_{t+m} + \varepsilon_{i,t+m},$$

where $\mathrm{PMU}_{i,t+m}$ is the return on the mimicking portfolio for the profitability effect during month m of portfolio year t, $\mathrm{RmRf}_{t+m}$ is the return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate, $\mathrm{SMB}_{t+m}$ the return on the mimicking portfolio for the size factor, $\mathrm{HML}_{t+m}$ the return on the mimicking portfolio for the value premium, $\mathrm{WML}_{t+m}$ the return on the mimicking portfolio for return momentum, and $\varepsilon_{i,t+m}$ is the error term. The factors are formed following Fama and French (1996). I report the intercept and the coefficients of the factors as well as the respective t-statistics.

| Model | Ind Var | $\beta_1$ | $\beta_{MKT}$ | $\beta_{SMB}$ | $\beta_{HML}$ | $\beta_{WML}$ |
|---|---|---|---|---|---|---|
| 1 | PMU | 0.48 | -0.20 | | | |
| | | (3.22) | (6.40) | | | |
| 2 | PMU | 0.49 | -0.23 | -0.34 | 0.01 | |
| | | (3.88) | (8.59) | (10.38) | (0.21) | |
| 3 | PMU | 0.46 | -0.22 | -0.32 | 0.06 | 0.06 |
| | | (3.50) | (8.04) | (9.68) | (1.13) | (1.49) |

### 8.5.2 Decile Portfolios on Distress Risk

In this sub-chapter I again use the decile portfolios obtained from sorts on Shum, z-score and BS respectively. Table 36 reports only the H-L premia for a portfolio long on the high distress risk decile and short on the low distress risk decile after the risk-adjustment using the Fama and French (1993) model and the Carhart (1997) model (see Chapter 6) as well as the five factor model including PMU. The risk-adjusted returns using Fama and French (1993) model show a strong negative distress risk premium regardless of the distress risk proxy and weighting-scheme: for Shum, the premia are -131 bps (t = 5.14) and -77 bps (t = 3.12) using value- and equal-weights respectively, for z-score they are -57 bps (t = 2.12) and -89 bps (t = 4.50), and for BS -92 bps (t = 3.08) and -89 bps (t = 3.78). Using the Carhart risk-adjustments, the H-L premia is still highly negative using Shum (-104 bps, -62 bps on value- and equal-weights respectively), z-score (-57 bps, -93 bps), or BS (-54 bps, -74 bps). Importantly, except for the value-weighted BS premium, the premia are highly significant (Shum: t = 4.15 and 2.49; z-score: t = 2.07 and 4.59; BS: t = 1.88 and 3.14). Including the PMU factor in the Carhart model reduces the H-L premia heavily for all distress risk proxies, i.e. Shum is reduced to -73 bps and -40 bps, z-score to -21 bps, and -70 bps, and BS to -36 bps and -66 bps respectively. More importantly, the premia is insignificant for equally-weighted returns on Shum (t = 1.62) and value-weighted returns on z-score (t = 0.80) and BS (t = 1.25). The other distress risk premia remain highly significant, i.e. value-weighted returns on Shum (t = 3.05) and using equally-weighted returns on z-score (t = 3.59) and BS (t = 2.74). Novy-Marx (2010) reports similar results using time-series regressions on value-weighted portfolio returns (decile portfolios using o-score and CHS) in time-series regressions including PMU. My analysis clearly shows that including PMU leaves half of the coefficients significant but reduces the negative distress risk premium substantially and thus, profitability accounts for a large part of the negative distress risk premium in time-series regressions.

**Table 36 Profitability Factor: Decile Portfolios Distress Risk Premium**

The table presents summary statistics of time-series regressions based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on default probability and sort into equally populated decile portfolios. Default probability obtained from the model in Shumway (2001) (Shum), the z-score (Taffler, 1983), the market-based model in Bharath and Shumway (2008) (BS). In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. I only report the intercepts $\beta_1$ and the corresponding t-statistics in brackets for the H-L portfolio long on the high decile distress risk portfolio and short on the low distress decile portfolio. I employ the model of Fama and French (1993) (excl. $WML_{t+m}$ and $PMU_{t+m}$), Carhart (1997) (excl. $PMU_{t+m}$), and the five factor model including the profitability factor PMU as defined in Eq. (28):
$R_{i,t+m}$-$R_{f,t+m}$=$\beta_1+\beta_{MKT}RmRf_{t+m}+\beta_{SMB}SMB_{t+m}+\beta_{HML}HML_{t+m}+\beta_{WML}WML_{t+m}+\beta_{PMU}PMU_{t+m}+\varepsilon_{i,t+m}$ , where $R_{i,t+m}$ is the return on portfolio i during month m (integer 1 to 12) in portfolio year t, $R_{f,t+m}$ the one-month UK Treasury Bill rate at the beginning of month t+m, $RmRf_{t+m}$ the return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate during month t+m, $SMB_{t+m}$ the return on the mimicking portfolio for the size factor during month t+m, $HML_{t+m}$ the return on the mimicking portfolio for the BM factor during month t+m and $WML_{t+m}$ the return on the mimicking portfolio for the return momentum factor during month t+m, and $PMU_{i,t+m}$ the return on the mimicking portfolio for the profitability effect during month t+m. VW indicates value-weighted returns while EW indicates equally-weighted returns. The return of the month of failure is set to -100.0%.

| | **Shum** | | **Z-score** | | **BS** | |
|---|---|---|---|---|---|---|
| **Model** | **VW** | **EW** | **VW** | **EW** | **VW** | **EW** |
| Fama and French | -1.31 | -0.77 | -0.57 | -0.89 | -0.92 | -0.89 |
| | (5.14) | (3.12) | (2.12) | (4.50) | (3.08) | (3.78) |
| Carhart | -1.04 | -0.62 | -0.57 | -0.93 | -0.54 | -0.74 |
| | (4.15) | (2.49) | (2.07) | (4.59) | (1.88) | (3.14) |
| Five Factor PMU | -0.73 | -0.40 | -0.21 | -0.70 | -0.36 | -0.66 |
| | (3.05) | (1.62) | (0.80) | (3.59) | (1.25) | (2.74) |

### 8.5.3 3x3 Portfolios on Distress Risk and Profitability

The previous results confirm the importance of profitability in explaining subsequent stock returns. To further analyse the relation of profitability, distress risk, and stock returns, I use a 3x3 independent sort on distress risk and profitability. That is, at the beginning of each portfolio year I rank the stocks on either of the distress risk measures

(Shum, z-score and BS) and split them equally into terciles. Independently, I rank the stocks on PBTCL and split them equally into terciles. I form a nine-portfolio-matrix at the intersections of the tercile portfolios. The following tables present for each sort (i) the characteristics of the nine-portfolio-matrix, (ii) the returns of the tercile portfolios and (iii) the return matrix of the nine-portfolios-matrix. Each sort is displayed from low (L) to high (H). Characteristics are time-series averages while returns are value-weighted and risk-adjusted using the models of Fama and French (1993), Carhart (1997), and the five factor model including PMU introduced above (see Eq. (28)).

#### 8.5.3.1 Portfolios on Shumway (2001) and Profitability

Table 37 presents the summary statistics of portfolios formed on independent sorts on Shum and PBTCL. Unsurprisingly, Panel A shows that the diagonal portfolios are the most populated (202, 135, 186).[36] Further, the high distress risk portfolios have the highest failure rates, albeit there is a clear reduction in distress risk with profitability (3.13% for low profitability to 0.85% for high profitability). All other portfolios have a substantially lower than average failure rate (recall that the sample failure rate is 0.91%). Controlling for distress risk, BETA decreases monotonically with profitability but controlling for profitability, the relation between distress risk and BETA is mixed. The SIZE matrix shows that profitable firms as well as high distress risk firms tend to be smaller. Remarkably, the average market capitalisation of the high distress risk portfolios is only £ 58m. The BM ratio increases monotonically with increasing distress risk while there is a U-shape relation between profitability and BM once I control for

[36] The Pearson correlation coefficient between Shum and PBTCL is -0.63 (see Table 43A in the appendix to this chapter).

distress risk.[37] The pattern on prior-year returns clearly shows that controlling for PBTCL, distressed firms are past losers while controlling for distress risk, more profitable firms underperform less profitable firms in the year prior to portfolio formation.

As such, controlling for profitability, distressed firms have higher betas, smaller size, higher BM ratios, and lower prior-year returns. Controlling for distress risk, profitable firms have lower failure rates, lower beta, smaller market capitalisation, and they have lower prior-year returns.

[37] An inspection of the average BM ratios of decile PBTCL portfolios does not confirm this. As such, the U-shaped relation is due to the coarse ranking and the distress risk sort.

**Table 37 Profitability Factor: 3x3 Shum-PBTCL Characteristics**

The table presents summary statistics of UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on the Shumway (2001) model and sort into equally populated tercile portfolios. Independently, I rank the sample firms on profitability (PBTCL) and sort into equally populated tercile portfolios. I form nine portfolios at the intersections of the tercile portfolios. L indicates low, M medium and H high default probability (profitability). H-L is the difference between the high portfolio and the low portfolio in the respective row or column. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. I report summary statistics including Fail Rate (in per cent), the number of portfolio failures divided by the number of portfolio observations (Obs). BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR (in per cent) is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables are winsorised at the 5.0% level.

| | PBTCL | | | | PBTCL | | | | PBTCL | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Shum** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** |
| | **Avg Obs** | | | | **Fail Rate** | | | | **BETA** | | | |
| **L** | 21 | 90 | 186 | 164 | 0.19 | 0.04 | 0.02 | -0.17 | 1.23 | 1.09 | 1.01 | -0.22 |
| **M** | 74 | 135 | 87 | 13 | 0.33 | 0.24 | 0.09 | -0.23 | 1.22 | 1.07 | 0.97 | -0.25 |
| **H** | 202 | 71 | 24 | -178 | 3.13 | 1.13 | 0.85 | -2.28 | 1.19 | 1.14 | 1.13 | -0.06 |
| **H-L** | 181 | -19 | -162 | | 2.94 | 1.09 | 0.83 | | -0.04 | 0.05 | 0.12 | |
| | **SIZE** | | | | **BM** | | | | **PYR** | | | |
| **L** | 889 | 860 | 686 | -203 | 0.67 | 0.53 | 0.53 | -0.13 | 41.15 | 33.43 | 28.00 | -13.16 |
| **M** | 314 | 254 | 196 | -118 | 0.77 | 0.67 | 0.73 | -0.04 | 29.71 | 18.34 | 8.10 | -21.62 |
| **H** | 59 | 68 | 48 | -11 | 1.01 | 0.90 | 0.99 | -0.02 | -4.17 | -6.87 | -14.59 | -10.42 |
| **H-L** | -831 | -792 | -639 | | 0.34 | 0.37 | 0.46 | | -45.33 | -40.30 | -42.59 | |

Table 38 presents the intercepts and t-statistics for portfolio regressions using the models in Fama and French (1993), Carhart (1997) and the five factor model including PMU. As I use a tercile sort on each variable, I report the results of the tercile portfolios and the matrix formed at the intersections of the tercile portfolios below. Similar to the decile portfolios, the results using the Fama and French (1993) model show a negative distress risk premium of -50 bps (t = 2.57). There is also a profitability effect as more profitable firms outperform less profitable firms by 47 bps per month (t = 3.13). The matrix below combines the two sorts and confirms that both effects are driven by the low distress risk-high profitability portfolio which earns a risk-adjusted return of 28 bps per month (t = 3.05). Controlling for profitability, the distress risk premium is negative but insignificant (t-statistic ranging from 1.38 to 1.80) and controlling for distress risk, the profitability effect is positive but insignificant (t-statistic ranging from 0.26 to 1.49). As such, the two effects are closely related to each other because controlling for distress (profitability) diminishes the return impact of profitability (distress). Using the Carhart (1997) model, the distress effect (Shum) is still negative (-25 bps per month) but insignificant (t = 1.34). Recalling from Table 15 in Chapter 6 that the returns on the H-L portfolio using decile portfolios is significant (-104 bps, t = 4.15), the distress risk premium diminishes most probably because the tercile sorting is too coarse. While the profitability effect is reduced to 41 bps per month with the inclusion of the momentum factor, it is still highly significant (t = 2.69). Again, it is the low distress risk-high profitability portfolio that drives the relative distress effect and profitability effect (24 bps per month, t = 2.65) while none of the other portfolios earn abnormal returns. Interestingly, the inclusion of WML leads to a profitability effect in the medium distress risk portfolio (54 bps, t = 2.14). Using the five factor model including PMU, the distress effect completely vanish (0 bps, t = 0.01) and the profitability effect becomes insignificant as well (-4 bps, t = 0.41). Looking at the matrix, the profitability factor PMU is able to account for the high returns earned by the low distress risk-high profitability portfolio (12 bps, t = 1.40) while all other portfolios, including H-L, are insignificant as well.

Table 38 therefore shows that the profitability factor PMU is able to reduce the distress risk premium and to account for the profitability premium driven mostly by the low distress risk-high profitability portfolio.

**Table 38 Profitability Factor: 3x3 Shum-PBTCL Returns**

The table presents summary statistics of time-series regressions based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on the Shumway (2001) model and sort into equally populated tercile portfolios. Independently, I rank the sample firms on profitability (PBTCL) and sort into equally populated tercile portfolios. I form nine portfolios at the intersections of the tercile portfolios. L indicates low, M medium and H high default probability (profitability). H-L is the difference between the high portfolio and the low portfolio in the respective row or column. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. I report portfolio intercepts $\beta_1$ and the corresponding t-statistics in brackets for the asset pricing model of Fama and French (1993) (excl. $WML_{t+m}$ and $PMU_{t+m}$), Carhart (1997) (excl. $PMU_{t+m}$) as well as the five factor model containing the profitability factor PMU as defined in Eq. (28):
$R_{i,t+m} - R_{f,t+m} = \beta_1 + \beta_{MKT} RmRf_{t+m} + \beta_{SMB} SMB_{t+m} + \beta_{HML} HML_{t+m} + \beta_{WML} WML_{t+m} + \beta_{PMU} PMU_{t+m} + \varepsilon_{i,t+m}$ ,
where $R_{i,t+m}$ is the return on portfolio i during month m (integer 1 to 12) in portfolio year t, $R_{f,t+m}$ the one-month UK Treasury Bill rate at the beginning of month t+m, $RmRf_{t+m}$ the return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate, $SMB_{t+m}$ the return on the mimicking portfolio for the size factor, $HML_{t+m}$ the return on the mimicking portfolio for the BM factor, $WML_{t+m}$ the return on the mimicking portfolio for the return momentum factor, and $PMU_{i,t+m}$ the return on the mimicking portfolio for the profitability effect (all during month t+m). Returns are value-weighted. The return of the month of failure is set to -100.0%.

| | **Fama and French (1993)** | | | | **Carhart (1997)** | | | | **Five Factor Model PMU** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **All** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** |
| **Shum** | 0.19 | -0.14 | -0.32 | -0.50 | 0.16 | 0.00 | -0.09 | -0.25 | 0.11 | 0.11 | 0.11 | 0.00 |
| | (2.51) | (1.17) | (1.70) | (2.57) | (2.11) | (0.03) | (0.50) | (1.34) | (1.42) | (0.95) | (0.63) | (0.01) |
| **PBTCL** | -0.23 | 0.01 | 0.23 | 0.47 | -0.17 | 0.05 | 0.24 | 0.41 | 0.16 | 0.05 | 0.12 | -0.04 |
| | (1.69) | (0.05) | (2.74) | (3.13) | (1.22) | (0.56) | (2.71) | (2.69) | (1.50) | (0.50) | (1.48) | (0.41) |
| | **PBTCL** | | | | **PBTCL** | | | | **PBTCL** | | | |
| **Shum** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** |
| **Low** | 0.02 | 0.07 | 0.28 | 0.26 | -0.01 | 0.07 | 0.24 | 0.26 | 0.25 | 0.06 | 0.12 | -0.12 |
| | (0.09) | (0.70) | (3.05) | (1.49) | (0.08) | (0.67) | (2.65) | (1.44) | (1.57) | (0.56) | (1.40) | (0.85) |
| **Med** | -0.32 | -0.11 | 0.08 | 0.40 | -0.25 | 0.06 | 0.28 | 0.54 | 0.10 | 0.05 | 0.23 | 0.13 |
| | (1.60) | (0.74) | (0.45) | (1.60) | (1.26) | (0.42) | (1.67) | (2.14) | (0.58) | (0.32) | (1.35) | (0.56) |
| **High** | -0.37 | -0.24 | -0.28 | 0.09 | -0.17 | 0.05 | -0.11 | 0.06 | 0.15 | 0.04 | -0.20 | -0.35 |
| | (1.59) | (1.13) | (0.93) | (0.27) | (0.74) | (0.25) | (0.36) | (0.18) | (0.68) | (0.20) | (0.66) | (1.03) |
| **H-L** | -0.39 | -0.31 | -0.56 | | -0.16 | -0.02 | -0.35 | | -0.10 | -0.02 | -0.33 | |
| | (1.38) | (1.38) | (1.80) | | (0.57) | (0.08) | (1.14) | | (0.34) | (0.07) | (1.03) | |

#### 8.5.3.2 Portfolios on Z-score and Profitability

Table 39 presents summary statistics of the tercile sorts on z-score and PBTCL. There is a high concentration of stocks in the high distress risk-low profitability portfolio (215) and low distress risk-high profitability portfolio (224). As expected, failure incidence is higher in the high distress risk-low profitability portfolio (2.95%). The low failure rate of the high distress risk-high profitability portfolio (0.0%) is most likely due to the low population of the portfolio (on average only 13 firms per year). Controlling for profitability, BETA is stable across distress risk portfolios but controlling for distress risk, it decreases with profitability (-0.29, -0.10, and -0.20 respectively). SIZE is more influenced by profitability because controlling for profitability, the size difference does not vary much with distress risk. Usually, size and distress risk are found to have a strong negative relation. Controlling for distress risk (profitability), BM decreases with profitability (distress risk) except for the high profitability portfolio. Again, this is unusual since one would expect BM to increase with distress risk.[38] In contrast to the Shum sort, controlling for profitability, prior-year returns are stable across distress risk portfolios (except for low profitability) while controlling for distress risk, they increase with profitability (9.11%, 6.50%, and 13.09% respectively).

As such, the patterns on z-score are less distinct as there is no difference in BETA, little increase in SIZE and stable PYR once controlled for profitability. However, profitability is positively related with the common risk factors: profitable firms have lower BETA, they are bigger, they have lower BM ratios, and higher prior-year returns.

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[38] In Table 16 in Chapter 6, I show that SIZE is hump-shaped in decile z-score portfolios while BM is U-shaped in decile z-score portfolios.

**Table 39 Profitability Factor: 3x3 Z-score-PBTCL Characteristics**

The table presents summary statistics of UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on the z-score (Taffler, 1983) and sort into equally populated tercile portfolios. Independently, I rank the sample firms on profitability (PBTCL) and sort into equally populated tercile portfolios. I form nine portfolios at the intersections of the tercile portfolios. L indicates low, M medium and H high default probability (profitability). H-L is the difference between the high portfolio and the low portfolio in the respective row or column. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. I report summary statistics including Fail Rate (in per cent), the number of portfolio failures divided by the number of portfolio observations (Obs). BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR (in per cent) is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables are winsorised at the 5.0% level.

| | **PBTCL** | | | | **PBTCL** | | | | **PBTCL** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Z-score** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** |
| | **Avg Obs** | | | | **Fail Rate** | | | | **BETA** | | | |
| **L** | 23 | 50 | 224 | 201 | 0.52 | 0.40 | 0.09 | -0.44 | 1.30 | 1.06 | 1.01 | -0.29 |
| **M** | 58 | 179 | 59 | 0 | 0.21 | 0.38 | 0.20 | 0.00 | 1.12 | 1.10 | 1.02 | -0.10 |
| **H** | 215 | 68 | 13 | -202 | 2.95 | 0.41 | 0.00 | -2.95 | 1.21 | 1.09 | 1.01 | -0.20 |
| **H-L** | 192 | 18 | -211 | | 2.43 | 0.01 | -0.09 | | -0.09 | 0.03 | 0.00 | |
| | **SIZE** | | | | **BM** | | | | **PYR** | | | |
| **L** | 148 | 251 | 440 | 292 | 1.13 | 0.96 | 0.65 | -0.48 | 9.55 | 16.13 | 18.66 | 9.11 |
| **M** | 194 | 407 | 686 | 492 | 1.06 | 0.68 | 0.49 | -0.56 | 11.50 | 16.63 | 17.99 | 6.50 |
| **H** | 194 | 440 | 419 | 225 | 0.87 | 0.52 | 0.81 | -0.06 | 6.51 | 18.01 | 19.60 | 13.09 |
| **H-L** | 46 | 189 | -21 | | -0.26 | -0.44 | 0.16 | | -3.04 | 1.88 | 0.94 | |

Table 40 presents the regression of the sorts on z-score and PBTCL using the Fama and French (1993) model, the Carhart (1997) model and the five factor model including PMU. The portfolio long on distressed and short on non-distressed firms earns a negative monthly return of -33 bps (t = 2.69) while this return is primarily driven by the low distress risk portfolio (20 bps, t = 2.16). Note that the profitability premium (47 bps, t = 3.13) and terciles are, as expected, the same as in Table 38 Panel B.[39] Again, the low distress risk-high profitability portfolio drives both return effects. While this portfolio earns a monthly return premium of 25 bps (t = 2.57), the other portfolios are all insignificant (except the profitability premium for the low distress risk portfolio (80 bps, t = 2.09)). The inclusion of the momentum factor by Carhart (1997) does not change the overall picture: the distress risk premium of -29 bps per month hardly changes and is still highly significant (t = 2.32) and, as noted earlier, the profitability effect is present (41 bps, t = 2.69). The return of the low distress risk-high profitability portfolio is still 26 bps per month (t = 2.57) while the H-L profitability premium of the low distress risk firms is 83 bps (t = 2.12). The inclusion of PMU as a fifth factor is able to account for both the distress effect (-6 bps, t = 0.51) and the profitability effect (-4 bps, t = 0.41). Again, the returns earned by the low distress risk-high profitability portfolio are only 13 bps per month and insignificant (t = 1.35).

[39] As I use independent sorts, the profitability effect remains constant while the returns on the distress sort change due to the different distress risk measure applied.

The results in Table 40 clearly show that, in contrast to the Fama and French (1993) and Carhart (1997) model, the five factor model including PMU is able to account for the high returns of the low distress risk-high profitability portfolio and thus, for both the distress and the profitability effect using tercile portfolios.

**Table 40 Profitability Factor: 3x3 Z-score-PBTCL Returns**

The table presents summary statistics of time-series regressions based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on the z-score (Taffler, 1983) and sort into equally populated tercile portfolios. Independently, I rank the sample firms on profitability (PBTCL) and sort into equally populated tercile portfolios. I form nine portfolios at the intersections of the tercile portfolios. L indicates low, M medium and H high default probability (profitability). H-L is the difference between the high portfolio and the low portfolio in the respective row or column. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. I report portfolio intercepts $\beta_1$ and the corresponding t-statistics in brackets for the asset pricing model of Fama and French (1993) (excl. $\mathrm{WML}_{t+m}$ and $\mathrm{PMU}_{t+m}$), Carhart (1997) (excl. $\mathrm{PMU}_{t+m}$) as well as the five factor model containing the profitability factor PMU as defined in Eq. (28):

$$R_{i,t+m} - R_{f,t+m} = \beta_1 + \beta_{MKT}\mathrm{RmRf}_{t+m} + \beta_{SMB}\mathrm{SMB}_{t+m} + \beta_{HML}\mathrm{HML}_{t+m} + \beta_{WML}\mathrm{WML}_{t+m} + \beta_{PMU}\mathrm{PMU}_{t+m} + \varepsilon_{i,t+m} ,$$

where $R_{i,t+m}$ is the return on portfolio i during month m (integer 1 to 12) in portfolio year t, $R_{f,t+m}$ the one-month UK Treasury Bill rate at the beginning of month t+m, $\mathrm{RmRf}_{t+m}$ the return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate, $\mathrm{SMB}_{t+m}$ the return on the mimicking portfolio for the size factor, $\mathrm{HML}_{t+m}$ the return on the mimicking portfolio for the BM factor, $\mathrm{WML}_{t+m}$ the return on the mimicking portfolio for the return momentum factor, and $\mathrm{PMU}_{i,t+m}$ the return on the mimicking portfolio for the profitability effect (all during month t+m). Returns are value-weighted. The return of the month of failure is set to -100.0%.

| | **Fama and French (1993)** | | | | **Carhart (1997)** | | | | **Five Factor Model PMU** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **All** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** |
| **Z-score** | 0.20 | 0.08 | -0.13 | -0.33 | 0.21 | 0.10 | -0.08 | -0.29 | 0.12 | 0.09 | 0.06 | -0.06 |
| | (2.16) | (0.86) | (1.25) | (2.69) | (2.21) | (1.15) | (0.78) | (2.32) | (1.24) | (0.99) | (0.57) | (0.51) |
| **PBTCL** | -0.23 | 0.01 | 0.23 | 0.47 | -0.17 | 0.05 | 0.24 | 0.41 | 0.16 | 0.05 | 0.12 | -0.04 |
| | (1.69) | (0.05) | (2.74) | (3.13) | (1.22) | (0.56) | (2.71) | (2.69) | (1.50) | (0.50) | (1.48) | (0.41) |
| | **PBTCL** | | | | **PBTCL** | | | | **PBTCL** | | | |
| **Z-score** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** |
| **Low** | -0.55 | 0.10 | 0.25 | 0.80 | -0.58 | 0.18 | 0.26 | 0.83 | -0.32 | 0.31 | 0.13 | 0.45 |
| | (1.43) | (0.58) | (2.57) | (2.09) | (1.46) | (1.02) | (2.57) | (2.12) | (0.81) | (1.82) | (1.35) | (1.16) |
| **Med** | -0.12 | 0.03 | 0.15 | 0.28 | -0.03 | 0.08 | 0.17 | 0.20 | 0.27 | 0.07 | 0.08 | -0.19 |
| | (0.58) | (0.30) | (1.35) | (1.15) | (0.13) | (0.69) | (1.46) | (0.81) | (1.33) | (0.62) | (0.70) | (0.84) |
| **High** | -0.19 | -0.12 | 0.02 | 0.21 | -0.13 | -0.05 | -0.04 | 0.09 | 0.22 | -0.09 | -0.03 | -0.26 |
| | (1.24) | (0.90) | (0.06) | (0.77) | (0.81) | (0.38) | (0.15) | (0.33) | (1.76) | (0.68) | (0.14) | (0.97) |
| **H-L** | 0.36 | -0.21 | -0.24 | | 0.45 | -0.23 | -0.29 | | 0.54 | -0.40 | -0.16 | |
| | (0.87) | (1.13) | (0.89) | | (1.07) | (1.16) | (1.08) | | (1.26) | (2.09) | (0.59) | |

#### 8.5.3.3 Portfolios on Bharath and Shumway (2008) and Profitability

Table 41 provides summary statistics of the tercile sorts on BS and PBTCL. There is again high dependency between distress risk and profitability as the diagonal portfolios are the most populated (174, 118, 162). The failure rate of the high distress risk-low profitability portfolio clearly stands out (3.39%) and is reducing with lower distress risk and higher profitability. Controlling for profitability, BETA increases moderately with distress risk (0.01, 0.19, and 0.16 respectively). However, controlling for distress risk, profitability leads to a greater equity risk reduction (-0.23, -0.16, and -0.08 respectively). SIZE is negatively related with distress risk (similar to Shum) and positively with profitability (similar to z-score). Controlling for profitability, BM is doubling (0.61, 0.52, and 0.55 respectively) in distress risk across the profitability sorts while it is hardly changing in profitability when controlled for distress risk. Similar to Shum, prior-year returns reduce with distress risk (-57.44%, -46.82%, and -41.96% respectively) and decrease with profitability.

Table 41 therefore shows that distressed firms score high on the conventional risk measures, i.e. high beta, small size, high BM, and low prior-year returns, while the opposite is true for profitable firms (except for PYR).

**Table 41 Profitability Factor: 3x3 BS-PBTCL Characteristics**

The table presents summary statistics of UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on the Bharath and Shumway (2008) model and sort into equally populated tercile portfolios. Independently, I rank the sample firms on profitability (PBTCL) and sort into equally populated tercile portfolios. I form nine portfolios at the intersections of the tercile portfolios. L indicates low, M medium and H high default probability (profitability). H-L is the difference between the high portfolio and the low portfolio in the respective row or column. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. I report summary statistics including Fail Rate (in per cent), the number of portfolio failures divided by the number of portfolio observations (Obs). BETA is the beta factor calculated for each firm according to Dimson (1979) over the previous 24 months (± 1 month lag). SIZE is the market value of common equity (MV). BM is book value of shareholders' equity less preference shares and minorities over MV. PYR (in per cent) is the prior 11-months return excluding September. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables are winsorised at the 5.0% level.

| | **PBTCL** | | | | **PBTCL** | | | | **PBTCL** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **BS** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** |
| | **Avg Obs** | | | | **Fail Rate** | | | | **BETA** | | | |
| **L** | 39 | 95 | 162 | 123 | 0.31 | 0.08 | 0.02 | -0.28 | 1.19 | 1.00 | 0.95 | -0.23 |
| **M** | 83 | 118 | 95 | 11 | 0.67 | 0.17 | 0.00 | -0.67 | 1.20 | 1.09 | 1.04 | -0.16 |
| **H** | 174 | 82 | 39 | -135 | 3.39 | 1.07 | 0.71 | -2.68 | 1.20 | 1.19 | 1.12 | -0.08 |
| **H-L** | 135 | -13 | -123 | | 3.09 | 0.99 | 0.68 | | 0.01 | 0.19 | 0.16 | |
| | **SIZE** | | | | **BM** | | | | **PYR** | | | |
| **L** | 413 | 558 | 561 | 149 | 0.51 | 0.45 | 0.49 | -0.02 | 46.89 | 38.27 | 30.32 | -16.57 |
| **M** | 282 | 419 | 482 | 200 | 0.74 | 0.67 | 0.71 | -0.03 | 27.06 | 17.52 | 11.55 | -15.51 |
| **H** | 83 | 160 | 197 | 114 | 1.11 | 0.97 | 1.04 | -0.08 | -10.55 | -8.55 | -11.65 | -1.10 |
| **H-L** | -330 | -398 | -364 | | 0.61 | 0.52 | 0.55 | | -57.44 | -46.82 | -41.96 | |

Table 42 presents the results for the sorts on BS and PBTCL. For the Fama and French (1993) risk-adjustment, the H-L portfolio on the tercile BS sort provides a substantial negative premium of -81 bps per month (t = 4.14). As illustrated on the other two sorts, the profitability effect is 47 bps per month (t = 3.13). The low distress risk-high profitability portfolio again earns a positive return of 40 bps (t = 3.97) driving the distress anomaly for profitable firms (-87 bps, t = 3.12). The pendant portfolio of high distress risk-low profitability earns a substantial return of -72 bps per month (t = 3.08) driving the distress anomaly for unprofitable firms (-98 bps, t = 3.38). The Carhart (1997) model reduces the distress risk premium to -43 bps (t = 2.57, profitability effect is 41 bps, t = 2.69). The premium earned by low distress risk-high profitability firms is reduced but still 30 bps per month (t = 3.08). The high distress risk-low profitability portfolio is also heavily reduced to -48 bps but it remains significant (t = 2.10) and the distress effect is only present in the low profitability portfolio (-62 bps, t = 2.23). Similar, to the Fama and French (1993) risk-adjustment, the distress and the profitability effect are driven mostly by the high returns of low distress risk-high profitability firms and by the low returns of the high distress risk-low profitability firms. The PMU factor is, again, able to account for the distress risk premium as it is reduced to -27 bps per month (t = 1.64, profitability effect: -4 bps, t = 0.41). In contrast to Tables 38 and 40, PMU is unable to reduce the returns of the low distress risk-high profitability to an insignificant level (21 bps, t = 2.13). However, its pendant portfolio is insignificant (-9 bps, t = 0.43) with the inclusion of PMU and thus, the overall distress and profitability effect is insignificant.

Overall, characteristics show that high distress risk (low profitability) stocks score high on common risk factors while there is a puzzling mispricing for low distress risk-high profitability firms. The PMU factor is once again able to account for the distress (BS) and profitability effect using a tercile sort. In addition to the sorts on Shum and z-score, the results in Table 42 provide evidence that PMU is able to reduce the effects on both ends, i.e. low distress risk-high profitability and *vice versa*.

**Table 42 Profitability Factor: 3x3 BS-PBTCL Returns**

The table presents summary statistics of time-series regressions based on UK non-financial firms listed in the Main market segment of the London Stock Exchange. At the end of each September from 1985 to 2009 (portfolio formation), I rank the sample firms on the Bharath and Shumway (2008) model and sort into equally populated tercile portfolios. Independently, I rank the sample firms on profitability (PBTCL) and sort into equally populated tercile portfolios. I form nine portfolios at the intersections of the tercile portfolios. L indicates low, M medium and H high default probability (profitability). H-L is the difference between the high portfolio and the low tercile portfolio in the respective row or column. In order to avoid look-ahead bias, I take the coefficients from failure indicators and predictor variables that are known at portfolio formation. I report portfolio intercepts $\beta_1$ and the corresponding t-statistics in brackets for the asset pricing model of Fama and French (1993) (excl. $WML_{t+m}$ and $PMU_{t+m}$), Carhart (1997) (excl. $PMU_{t+m}$) as well as the five factor model containing the profitability factor PMU as defined in Eq. (28):
$R_{i,t+m} - R_{f,t+m} = \beta_1 + \beta_{MKT} RmRf_{t+m} + \beta_{SMB} SMB_{t+m} + \beta_{HML} HML_{t+m} + \beta_{WML} WML_{t+m} + \beta_{PMU} PMU_{t+m} + \varepsilon_{i,t+m}$ ,
where $R_{i,t+m}$ is the return on portfolio i during month m (integer 1 to 12) in portfolio year t, $R_{f,t+m}$ the one-month UK Treasury Bill rate at the beginning of month t+m, $RmRf_{t+m}$ the return difference of the FTSE All Share Index and the one-month UK Treasury Bill rate, $SMB_{t+m}$ the return on the mimicking portfolio for the size factor, $HML_{t+m}$ the return on the mimicking portfolio for the BM factor, $WML_{t+m}$ the return on the mimicking portfolio for the return momentum factor, and $PMU_{i,t+m}$ the return on the mimicking portfolio for the profitability effect (all during month t+m). Returns are value-weighted. The return of the month of failure is set to -100.0%.

| | **Fama and French (1993)** | | | | **Carhart (1997)** | | | | **Five Factor Model PMU** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **All** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** |
| **BS** | 0.31 | -0.13 | -0.49 | -0.81 | 0.23 | -0.01 | -0.21 | -0.43 | 0.19 | -0.01 | -0.08 | -0.27 |
| | (3.63) | (1.29) | (2.84) | (4.14) | (2.68) | (0.12) | (1.31) | (2.57) | (2.21) | (0.12) | (0.52) | (1.64) |
| **PBTCL** | -0.23 | 0.01 | 0.23 | 0.47 | -0.17 | 0.05 | 0.24 | 0.41 | 0.16 | 0.05 | 0.12 | -0.04 |
| | (1.69) | (0.05) | (2.74) | (3.13) | (1.22) | (0.56) | (2.71) | (2.69) | (1.50) | (0.50) | (1.48) | (0.41) |
| | **PBTCL** | | | | **PBTCL** | | | | **PBTCL** | | | |
| **BS** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** | **L** | **M** | **H** | **H-L** |
| **Low** | 0.26 | 0.18 | 0.40 | 0.14 | 0.14 | 0.13 | 0.30 | 0.17 | 0.34 | 0.11 | 0.21 | -0.14 |
| | (1.43) | (1.77) | (3.97) | (0.77) | (0.76) | (1.31) | (3.08) | (0.91) | (1.95) | (1.09) | (2.13) | (0.84) |
| **Med** | -0.35 | -0.10 | -0.02 | 0.32 | -0.27 | 0.01 | 0.12 | 0.39 | -0.01 | 0.01 | 0.00 | 0.02 |
| | (2.06) | (0.79) | (0.18) | (1.70) | (1.60) | (0.09) | (0.95) | (2.03) | (0.09) | (0.08) | (0.00) | (0.09) |
| **High** | -0.72 | -0.25 | -0.47 | 0.25 | -0.48 | 0.04 | -0.14 | 0.35 | -0.09 | 0.01 | -0.21 | -0.12 |
| | (3.08) | (1.17) | (1.78) | (0.84) | (2.10) | (0.19) | (0.53) | (1.13) | (0.43) | (0.06) | (0.81) | (0.43) |
| **H-L** | -0.98 | -0.42 | -0.87 | | -0.62 | -0.10 | -0.44 | | -0.43 | -0.10 | -0.41 | |
| | (3.38) | (1.87) | (3.12) | | (2.23) | (0.46) | (1.70) | | (1.55) | (0.47) | (1.57) | |

## 8.6 Summary and Discussion of Findings

### 8.6.1 Summary of Findings

This chapter provides new evidence on the drivers of distress risk pricing. The cross-sectional regressions of the individual component parts of the distress risk measure unravel the negative distress risk premium by showing that it is driven by profitability and firm-liquidity. For the measure of Shumway (2001), the profitability factor NITA is highly significant, for z-score (Taffler, 1983) PBTCL as well as NCI are highly significant in explaining the cross-section of subsequent stock returns.

These findings are further corroborated using orthogonalised distress risk measures. I orthogonalise the distress risk measures Shum by NITA and z-score by PBTCL and NCI respectively. The results show that the distress information unrelated to profitability is not significant in explaining the cross-section of subsequent stock returns. As such, Shum orthogonalised by NITA and z-score orthogonalised by PBTCL and NCI are insignificant. At the same time, profitability (NITA and PBTCL) retains its explanatory power while NCI is less significant. As a robustness test, I show that profitability reduces the coefficient of the measure of Bharath and Shumway (2008). Overall, the findings argue that profitability drives the distress risk premium.

The results using time-series regressions confirm these findings by introducing a profitability factor PMU, the return on the mimicking portfolio for the profitability effect. The tests show that the factors of the common asset pricing models, i.e. CAPM, Fama and French (1993) and Carhart (1997), are unable to account for the pricing related information carried by PMU. Using decile sorts on the distress risk proxies, I find that there is a significant distress risk premium after risk-adjustments following

Fama and French (1993) and Carhart (1997) and independent of the weighting-scheme. The inclusion of PMU is able to reduce the premia substantially albeit it remains significant for some proxies.

In addition to the decile sorts I test the five factor model including PMU using independent 3x3 sorts on PBTCL and distress risk measure. The results show both a profitability and a distress risk premium on tercile portfolios using the Fama and French (1996) and the Carhart (1997) model. Both effects are intimately related to each other and driven by the positive abnormal returns of stocks with low distress risk and high profitability. This finding is robust to how distress risk is measured (i.e. Shum, z-score and BS). The five factor model including PMU is able to account for both the distress anomaly and the profitability effect. However, unlike the cross-sectional tests, the time-series results are unable to distinguish between distress and profitability because the two are very closely related to each other.

Anginer and Yildizhan (2010) report similar results using time-series regressions and argue that the distress risk premium (measured by Campbell et al., 2008) is insignificant once it is controlled for profitability. However, there are a number of problems with their results: First, profitability and distress are highly correlated. As such, their results are likely to suffer from a similar problem as my 3x3 sorts using time-series regressions (e.g. illustrated by the concentration of firms in the diagonal portfolios from high distress risk-low profitability to low distress risk-high profitability). Second, Anginer and Yildizhan (2010) use sequential sorts which are unable to control for the profitability effect (see as well the discussion of Vassalou and Xing (2004) in Chapter 2). Novy-Marx (2010) provides a five factor model similar to the one I apply.

In line with my results, he finds that the distress risk premium (decile portfolios) proxied by o-score and the measure of Campbell et al. (2008) is insignificant when a fifth profitability factor is included. Again, since distress and profitability are highly correlated, Novy-Marx (2010) does not disentangle the two. Both, Anginer and Yildizhan (2010) and Novy-Marx (2010) fail to provide cross-sectional evidence to differentiate whether it is distress risk driving profitability or *vice versa*. As such, my results contribute to literature as, in contrast to previous studies, my cross-sectional results show successfully that profitability drives the distress risk premium in subsequent stock returns.

### 8.6.2 Discussion of Findings

Existing literature attributes the negative return premium associated with bankruptcy risk proxies to distress risk (e.g. Campbell et al., 2008). However, I find that while Shum subsumes all failure related information in z-score, z-score subsumes all returns related information in Shum, raising the possibility that the observed distress risk premium may be driven by something other than distress risk itself. I unravel the distress risk measure premium by breaking down the hybrid model (Shumway, 2001) (Shum), the accounting-based z-score (Taffler, 1983), and the market-based model in Bharath and Shumway (2008) (BS) into their individual component parts to test each for their impact on subsequent stock returns. I show that the distress risk anomaly is caused by the profitability element of the distress risk measures and once I control for profitability, the distress anomaly is non-existent. Thus, the negative return premium associated with higher bankruptcy risk is not due to distress risk but due to profitability.

There are preliminary findings on the association between distress risk and profitability. Anginer and Yildizhan (2010) use time-series regressions and argue that controlling for profitability, the distress risk premium diminishes. However, distress risk is highly related with profitability and hence, the sequential sorts applied in their study are unable control for the two effects (see Table 3 in Anginer and Yildizhan (2010)). Similar to my findings in Chapter 8.5, Novy-Marx (2010) shows that the distress risk premium is captured by a five factor model including a profitability factor. However, this only shows that there is an association between distress risk and profitability. My study extends existing literature on the relation between distress risk and profitability by showing that it is profitability that drives the distress risk anomaly.

The implication of my finding is that distressed firms earn lower returns because they are relatively unprofitable. More profitable (unprofitable) firms earn higher (lower) subsequent stock returns after controlling for well-accepted risk measures (i.e. beta, size, BM and momentum). This is surprising since Fama and French (1992; 2008) show that the pricing related information of profitability is less robust once controlled for size and BM.

Fama and French (2006), Novy-Marx (2010) and Chen, Novy-Marx and Zhang (2011) discuss the implications of profitability within the valuation framework which defines current market prices as the discounted value of future pay-offs.[40] Controlling for current prices, more profitable (unprofitable) firms have higher (lower) discount rates

[40] Wu, Zhang and Zhang (2010) make a similar argument using q-theory.

i.e. higher (lower) expected returns.[41] However, the valuation framework assumes that current market prices are unbiased and it suffers from not considering the uncertainty attached to future payoffs. Clearly, the valuation framework is unable to determine the risk association with profitable firms. And indeed, Fama and French (2006) refer to Campbell and Shiller (1988) who argue that the valuation framework is a tautology that defines the internal rate of return and that tests of the valuation framework are unable to tell whether the prices are determined on rational or biased judgements. Essentially, the question that the valuation framework is unable to answer is why are profitable firms more risky?

Indeed, the results in Chapter 6 provide no evidence for a risk-based explanation for the underperformance of unprofitable (i.e. distressed firms) because such firms have higher betas, lower market capitalisation and higher BM, all characteristics associated with higher risk. My results therefore seem to be counterintuitive from a risk-based perspective.

However, my findings fit well into existing research on the implications of earnings variables on stock returns. Haugen and Baker (1996) argue for the predictability of future returns based on variables that are able to describe historic returns. They find that, among others, the earnings to price and cash flow to price ratios are positively related to future stock returns. They do not find evidence for a risk-based explanation of the return differences, and argue that the predictability of stock returns is due to biases

[41] Agarwal, Bellotti, Nash and Taffler (2010) and Agarwal, Taffler and Brown (2011) also find that more profitable firms also tend to have lower cost of equity but they do not test for the relation of profit and subsequent stock returns. Also, in terms of sample the two papers are different to my study. For instance, Agarwal et al. (2010) use a three year sample of US data (years 2000 to 2002) and Agarwal et al. (2011) select the ten largest companies from around 25 industry sectors.

in market pricing. Although Hanna and Ready (2005) show that the return difference found in Haugen and Baker (1996) diminishes once controlled for transaction costs and momentum, they also note that irrational pricing might still take place within the transaction cost boundaries.

Similarly, Sloan (1996) claims that stock prices act as if investors fixate on earnings. He argues that the persistence of earnings is only provided for earnings with a low accruals (high cash flow) component. Looking at the market price reaction to earnings, he demonstrates that firms whose earnings have low accruals component earn as well high stock returns. This suggests that the positive profitability-return relation is due to the negative accruals-return relation (positive cash flow-return relation). Following its initial discovery in Sloan (1996), the accruals anomaly became well established in the literature (e.g. Teoh, Welch and Wong, 1998; Fama and French, 2008; Hirschleifer, Teoh and Yu, 2011). In explaining this empirical pattern, the literature generally argues that investors are unable to fully reflect the information contained in the earnings components accruals and cash flow. Bradshaw, Richardson and Sloan (2001) reach a similar conclusion for sell-side analysts and auditors.

However, the misjudgement of the investors on the firms' earnings is to some extent intentional since there is prevailing evidence that firms hamper a fair judgement as they 'window-dress' their accounts. For instance, Rosner (2003) and Charitou, Lambertides and Trigeorgis (2007) argue that failed firms significantly used accruals to manage their earnings upwards in the years preceding bankruptcy. Specifially for the UK, Lara, Osma and Neophytou (2009) demonstrate that up to five years prior to the bankruptcy event, firms are likely to fully exhaust possibilities of accruals management before they aggressively manipulate real operations to make earnings look higher as they actually are. Therefore, it is likely that distressed firms in particular are affected by the low returns associated with the accruals anomaly.

Beside the predictability of abnormal stock returns related to earnings variables (more precisely, the earnings components accruals and cash flows), literature documents as well a return predictability following earnings announcements dates. This literature strand goes back to Ball and Brown (1968), however, in more recent years the finding that firms announcing positive (negative) unexpected earnings drift upwards (downwards) for an extended period after the announcement date has been frequently confirmed (among others Bernard and Thomas, 1990; Ball and Bartov, 1996; Chordia and Shivakumar, 2006).[42] Liu, Strong and Xu (2003) use UK data and, in line with the findings in the US, they document a robust disproportionately post-earnings announcement drift. Similar to others, they further argue that the post-earnings announcement drift is due to investors' failure of fully realising the implications of current earnings for future earnings and that their prior incorrect beliefs are updated. This argument is corroborated by Sloan (1996) who shows that the accruals component of earnings is faster mean-reverting than the cash flow component, suggesting that firms with high accruals are stronger affected by the post-earnings announcement drift.

[42] Chordia and Shivakumar (2006) use the commonly applied standardised unexpected earnings (SUE) measure. Similar to Chan, Jegadeesh and Lakonishok (1996), they classify their research under earnings momentum. Myers, Myers and Skinner (2007) define earnings momentum as the long strings of consecutive increases in earnings per share and report a positive relation with subsequent stock returns. Independent of the various definitions, the referenced studies share the common theme of underreaction to earnings related information.

To some extent, the underreaction to earnings news, or to bad news in general, has been researched in the distress risk literature as well. For instance, Taffler et al. (2004) for the UK and Kausar et al. (2009) for the US observe an underreaction to first time going-concern modified (GCM) audit reports issue as those firms experience a significant downward price drift in the twelve months subsequent to the GCM audit report. They further show that the GCM audit report drift is among others robust to, the post-earnings announcement drift. A similar underreaction to distress-related news is documented by Dichev and Piotroski (2001). They find a significant underreaction to rating downgrades for small and low rated firms in the year subsequent to the rating downgrade. They argue that a large part of the abnormal return is earned subsequent to deteriorating earnings announcements. In contrast to that, Griffin and Lemmon (2002) using o-score and Campbell et al. (2008) using their hazard model observe a positive return premium following earnings announcements. Campbell et al. (2008: p. 2930) argue that "possibly because the ability to announce earnings is itself good news for companies that are in severe financial difficulty". On the other hand, Ang (2012) shows that the positive returns of earnings surprises and post-earnings announcements dates is driven by firms that are subsequently delisted. Moreover, Ang (2012) argues for a "negative pre-delisting drift" that even accounts for the anomalous return premium earned by alternative distress measures. However, the findings of Ang (2012) (i) are essentially what would be expected when failure-related delistings are excluded as (parts of) the most severely distressed firms are eliminated and (ii) are derived with substantial look-ahead bias. More clean evidence that the distress anomaly is driven by the underreaction to earnings news is provided by Balakrishnan, Bartov and Faurel (2010). They demonstrate that the negative post-earnings announcement drift of firms reporting extremely deteriorating earnings is robust to the negative returns earned by distressed firms (measured by z-score).

In summary, this chapter suggests that there is rather a profitability effect than a distress anomaly: the low returns of distressed firms are due to the low profitability. The common risk measures beta, size, BM and prior-year returns fail to provide first evidence for a risk-based explanation. However, existing research on earnings and earnings announcement shows that investors fail to fully account for the information provided in current earnings. The prevailing argument is that this underreaction causes the observed negative return drift of unprofitable firms. Several studies show that there is as well an underreaction to GCM audit reports (Taffler et al., 2004; Kausar et al. 2009) or rating downgrades (Dichev and Piotroski, 2001). While Griffin and Lemmon (2002) and Campbell et al. (2008) find no evidence for the post-earnings announcement drift to explain the return premium earned by the distress measure, Balakrishnan et al. (2010) argue that the earnings announcement drift is found to be robust to the distress anomaly. As such, the main finding presented in this chapter, that the distress anomaly is driven by profitability, cannot be explained from a risk-based perspective. Although existing literature is yet discordant in linking the two return patterns, my results conjecture that the distress anomaly is a manifestation of the underreaction to current earnings news.

## 8.7 Appendix

**Table 43A Variables Distress Risk Models: Correlation**

This table presents time-series averages of correlation coefficients for variables of UK non-financial firms listed in the Main market segment of the London Stock Exchange. The lower-left (upper right) side of the matrix presents Spearman rank (Pearson) time-series average correlation coefficients calculated at the end of each September from 1985 to 2009 (portfolio formation). Shum is the score from the model in Shumway (2001) which includes NITA net income available to common shareholders over book value of total assets, TLTA (TLMTA) book value of total assets excluding total common shareholders' equity over book value of total assets (book value of total liabilities plus market value of common equity), EXRET log excess return over the FTSE All Share Index over the 12 months prior to September, SIGMA annualised standard deviation of daily returns for the three months prior to September, RSIZE log of firm MV over FTSE All Share Index MV. Z score (Taffler, 1983) contains PBTCL profit before tax over current liabilities, CATL current assets over total liabilities, CLTA current liabilities over total assets, NCI no-credit interval calculated as (quick assets – current liabilities) / ((sales – profit before tax – depreciation) / 365). BS score (Bharath and Shumway, 2008) includes ER1y prior-year return, TLMTA and SIMGA. Latest accounting data is taken with a minimum lag of five months between financial year-end and portfolio formation, market data is taken at portfolio formation. All variables are winsorised at the 5.0% level, scores are winsorised at ±18.4207.

| | Shum | NITA | TLTA | EXRET | SIGMA | RSIZE | Z | PBTCL | CATL | CLTA | NCI | BS | ER1y | TLMTA | SIGMA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Shum** | 1 | -0.64 | 0.42 | -0.58 | 0.69 | -0.71 | 0.51 | -0.63 | -0.10 | 0.37 | -0.14 | 0.77 | -0.51 | 0.61 | 0.69 |
| **NITA** | -0.58 | 1 | -0.18 | 0.22 | -0.40 | 0.32 | -0.55 | 0.79 | 0.10 | -0.07 | 0.06 | -0.40 | 0.18 | -0.38 | -0.40 |
| **TLTA** | 0.39 | -0.19 | 1 | -0.06 | 0.09 | 0.09 | 0.51 | -0.34 | -0.54 | 0.64 | -0.36 | 0.25 | -0.04 | 0.57 | 0.09 |
| **EXRET** | -0.51 | 0.18 | -0.04 | 1 | -0.33 | 0.21 | -0.15 | 0.20 | 0.02 | -0.04 | 0.04 | -0.60 | 0.96 | -0.33 | -0.33 |
| **SIGMA** | 0.64 | -0.34 | 0.07 | -0.26 | 1 | -0.54 | 0.26 | -0.38 | 0.07 | 0.16 | -0.01 | 0.69 | -0.24 | 0.28 | 1.00 |
| **RSIZE** | -0.73 | 0.32 | 0.09 | 0.23 | -0.52 | 1 | -0.15 | 0.31 | -0.25 | -0.13 | -0.04 | -0.48 | 0.19 | -0.27 | -0.52 |
| **Z-score** | 0.52 | -0.53 | 0.56 | -0.12 | 0.25 | -0.17 | 1 | -0.71 | -0.39 | 0.48 | -0.62 | 0.33 | -0.12 | 0.43 | 0.25 |
| **PBTCL** | -0.65 | 0.79 | -0.37 | 0.17 | -0.39 | 0.34 | -0.74 | 1 | 0.10 | -0.35 | 0.16 | -0.42 | 0.15 | -0.43 | -0.39 |
| **CATL** | -0.05 | 0.19 | -0.45 | 0.02 | 0.10 | -0.25 | -0.35 | 0.07 | 1 | -0.08 | 0.47 | -0.09 | 0.03 | -0.40 | 0.10 |
| **CLTA** | 0.34 | -0.02 | 0.63 | -0.03 | 0.15 | -0.13 | 0.55 | -0.39 | 0.06 | 1 | -0.34 | 0.20 | -0.02 | 0.28 | 0.15 |
| **NCI** | -0.13 | 0.12 | -0.35 | 0.05 | 0.00 | 0 | -0.63 | 0.19 | 0.47 | -0.32 | 1.00 | -0.12 | 0.04 | -0.30 | 0.00 |
| **BS** | 0.80 | -0.43 | 0.26 | -0.61 | 0.74 | -0.51 | 0.37 | -0.47 | -0.08 | 0.20 | -0.14 | 1 | -0.57 | 0.60 | 0.74 |
| **ER1y** | -0.51 | 0.18 | -0.04 | 1.00 | -0.26 | 0.22 | -0.12 | 0.17 | 0.02 | -0.03 | 0.05 | -0.61 | 1 | -0.30 | -0.26 |
| **TLMTA** | 0.58 | -0.47 | 0.55 | -0.30 | 0.24 | -0.27 | 0.48 | -0.48 | -0.36 | 0.26 | -0.31 | 0.61 | -0.31 | 1 | 0.24 |
| **SIGMA** | 0.64 | -0.34 | 0.07 | -0.26 | 1.00 | -1 | 0.26 | -0.38 | 0.07 | 0.16 | -0.01 | 0.69 | -0.24 | 0.28 | 1.00 |

# CHAPTER 9: SUMMARY AND CONCLUSION

## 9.1 Introduction

In sharp contrast to the basic risk-return relation hypothesised in theoretical finance, distressed firms underperform non-distressed firms (e.g. Dichev, 1998; Griffin and Lemmon, 2002; Agarwal and Taffler, 2008b). Since literature agrees on this empirical evidence, more recent studies propose explanations to solve this puzzle (e.g. Shleifer and Vishny, 1997; Han and Kumar, 2011; Garlappi and Yan, 2011). There has been very little work on whether these explanations are actually able to capture the negative distress risk premium. In addition to that, existing studies do not explore the drivers of the distress risk premium. The analysis in this thesis aims to fill this gap by (i) testing whether the distress risk premium is sensitive to the distress risk measure, (ii) testing for the validity of the proposed explanations, and (iii) testing for the drivers of the negative distress risk premium.

Researching the pricing of distress risk requires potent distress risk proxies. The basic approaches forecast bankruptcies using accounting data, market data or both. The performance of those models is tested by assessing their forecasting accuracy, the bankruptcy related information they carry, and their economic value when differential misclassification costs are incurred. However, existing studies fail to comprehensively incorporate all three available approaches in a unified test using the three different available performance measures. The analysis in this thesis aims to fill this gap in literature by (i) combining hybrid, accounting-based, and market-based bankruptcy prediction approaches in a unified test and (ii) by assessing the performance using the three major testing procedures examining forecasting accuracy, bankruptcy related information, and differential misclassification costs of the three approaches.

The tests are based on UK non-financial firms listed in the Main market segment of the London Stock Exchange anytime between 1985 and 2010. It includes 22,217 observations with 2,428 unique firms of which 202 failed.

## 9.2 Summary and Discussion of Findings

**Bankruptcy Prediction**

The analysis on bankruptcy prediction models uses the hybrid models in Shumway (2001) (Shum), Campbell et al. (2008) and Christidis and Gregory (2010). In addition, I include the accounting-based z-score model of Taffler (1983) as well as the market-based model of Bharath and Shumway (2008) (BS).

The test of forecasting accuracy using receiver operating characteristic curves demonstrates a clear outperformance of the hybrid models. Hybrid models have a significantly higher forecasting accuracy than both z-score and BS. However, between the hybrid models there is little to differentiate. As such, it is the general approach of using both accounting and market data that leads to a superior forecasting accuracy. There is also a significant outperformance of the market-based BS model over the accounting-based z-score, though, the outperformance is limited to the more recent years in the sample period.

The information content tests document that all bankruptcy prediction models carry significant bankruptcy related information individually. Testing the incremental information of the models, the hybrid models clearly outperform the accounting-based and market-based approaches. Combining one of the hybrids with either z-score or BS, the results unanimously show that all three hybrids tested here subsume the information carried by both the z-score and BS. Similar to the forecasting accuracy, z-score and BS come second. Testing them together in the logit regression, both have significant bankruptcy related information. As Agarwal and Taffler (2008a) note, z-score and BS carry complementary information about future bankruptcy.

While the outperformance of the hybrid approach is clear in general, it is hard to distinguish between the three hybrid models. In the last test I assess the economic value of the three hybrids in an illustrative credit loan market with differential misclassification costs. The results show that the bank using the Shum model offers the lowest credit spreads, the biggest market share as well as the highest credit quality portfolio. This results in the highest return on risk-weighted assets for the Shum model. It follows that: while the forecasting accuracy tests were unable to distinguish between the hybrids, the economic value under differential misclassification costs provides clear evidence for the superiority of Shum. Interestingly, Shum is the first and the most parsimonious hybrid model of the three models tested.

Overall, my results show that the hybrid models, and in particular the model in Shumway (2001), are the best approach in predicting bankruptcies.

**Distress Risk Premium**

The bankruptcy prediction tests mark the clear outperformance of the Shum model over all other approaches. Therefore, I include Shum in the pricing tests as a hybrid-based distress risk proxy. To test for any difference between the different bankruptcy prediction approaches, I continue as well with z-score and BS in the pricing analysis.

The characteristics on decile distress risk portfolios demonstrate that, in general, distressed stocks score high on the conventional risk measures BETA, SIZE, BM, and PYR. Although the conventional risk measures are associated with higher returns, the time-series regressions show that distressed stocks earn lower returns than non-distressed stocks. For robustness, I use both the Fama and French (1993) and the Carhart (1997) risk-adjustment as well as value- and equally-weighted returns. The H-L premium, i.e. the return long on distressed and short on non-distressed firms, is significantly negative and independent of the distress risk proxy I employ.

The cross-sectional results on individual securities corroborate these findings. Consistent with the majority of prior studies, I find no evidence for the distress hypothesis of Chan and Chen (1991) and Fama and French (1992) that SIZE and BM are proxies for distress risk. Using the common risk factors, the premium on Shum and z-score is highly significant while the premium on BS is significant at the 10% level.

Due to the low correlation between z-score and the other bankruptcy prediction models and risk factors, I combine z-score with each of the other measures. Based on its forecasting accuracy, Shum is expected to be the most relevant in pricing of distress risk. In contrast to that, z-score – the weakest bankruptcy predictor - subsumes the pricing related information of Shum and BS. This is a remarkable new finding as it suggests that while the distress risk measures are priced, distress risk may not be driving the observed 'negative distress risk premium'. This raises the possibility that it may not be the composite distress risk measure but one or more elements of the distress risk measures that drive the relation between distress risk and stock returns.

Overall, my results confirm existing evidence by showing that there is a negative distress risk premium. Moreover, I present evidence that the distress risk premium is robust to the distress risk proxy applied but, against expectations, the best bankruptcy proxy does not have the most distinct premium raising doubts on whether it is really distress risk that drives the premium.

**Potential Explanations**

The analysis explores the potential of shareholder advantage, limits of arbitrage and gambling retail investors to explain the negative distress risk premium.

The main predictions of the shareholder advantage valuation model of Garlappi et al. (2008) and Garlappi and Yan (2011) are that both equity beta and the value premium are hump-shaped with increasing distress risk. My results reject these predictions: equity beta increases linearly with distress risk measured by Shum, z-score and BS. While Garlappi and Yan (2011) report a clear hump-shape for the value-premium and distress risk, my results provide no evidence for such a relation. I sort into decile distress portfolios and independently into equally populated BM portfolios. The resulting value premium for each distress decile has no relation with distress risk. The graphs I present in Chapter 7 show a value premium that oscillates between the low and high distress risk premium. The predictions of Garlappi and Yan (2011) in respect to beta and value premium are rejected independently of the distress risk proxy and the weighting-scheme I apply.[43]

[43] The only weak indication of hump-shaped relation comes from using BS as a bankruptcy risk proxy and equally-weighted portfolio returns.

Franks and Nyborg (1996) argue that the UK bankruptcy regime is more creditor-friendly. Kaiser (1996) and Agarwal and Taffler (2008b) find that UK stockholders are generally passed over in terminal payments These bankruptcy regime factors further corroborate my empirical findings that the negative distress risk premium in the UK is unlikely to be driven by the shareholder advantage effect.

The difference in results could also be due to sample and method. Dichev (1998) finds a hump-shaped distress risk-return relation only to be true for NASDAQ stocks using z-score. As such, the findings of Garlappi and Yan (2011) could be driven by a class of small stocks listed at NASDAQ. Since I exclude AIM, i.e. the equivalent to NASDAQ, this might explain why my results do not support the findings in Garlappi and Yan (2011). Alternatively, the shareholder advantage might be a myopic view on reality. Zhang (2012) argues that the model of Garlappi and Yan (2011) assumes that there are no renegotiation frictions. However, Zhang (2012) shows that such frictions exist and have an effect on the shareholder advantage.

Limits of arbitrage are, *inter alia*, proxied by a low share price, high idiosyncratic volatility, high idiosyncratic skewness, high bid-ask spread, low institutional ownership, and low analyst coverage. Han and Kumar (2011) construct their lottery-index with the variables share price, idiosyncratic volatility, and idiosyncratic skewness. As such, the characteristics of stocks with high limits of arbitrage and stocks with high lottery features are congruent. Han and Kumar (2011) provide direct evidence for the connection as they note that lottery stocks are not only dominated by retail investors, they also face high limits of arbitrage. Similarly, Coelho et al. (2010) conclude that the post-Chapter 11 filing drift is caused by both gambling retail investors and limits of arbitrage. As such, there is one symptom for two potential causes while, clearly, there has to be a mispricing (e.g. due to gambling motivated investors) in first place before limits of arbitrage hinder sophisticated investors to correct the mispricing.

I construct a lottery-index (LOTT) following Han and Kumar (2011). Ranking on decile portfolios, I show that lottery-type stocks share common characteristics with distressed firms: I find them to be small, having high BM ratios and low prior-year returns. Moreover, default probability increases monotonically in LOTT. I conduct ROC curve analysis using LOTT as well and find that the AUC is 0.80 showing a high accuracy in bankruptcy forecasting. For comparison, the AUC of Shum is 0.90, for z-score it is 0.81, and for BS it is 0.87.

Although there is a high commonality between LOTT and distress risk, the H-L premium in time-series regressions (decile portfolios) is insignificant for value-weighted returns. The cross-sectional regressions confirm that neither the individual components nor the composite measure LOTT is significant in subsequent stock returns. Combining LOTT with each of the distress risk measures returns insignificant coefficients for LOTT while the negative distress risk premium remains robust. As such, the tests provide no evidence that limits of arbitrage or gambling retail investors drive the overpricing of distressed firms. Moreover, while LOTT is a fairly good bankruptcy predictor, its irrelevance in subsequent stock returns further corroborates the indication that it might not be distress risk that is priced.

Overall, my results show that in the UK there is no shareholder advantage effect as proposed by Garlappi and Yan (2011). Moreover, there is no evidence that limits of arbitrage hinder sophisticated investors to correct the overpricing of distressed stocks or that gambling retail investors drive the overpricing of distressed firms in the first place.

**Drivers of Negative Distress Risk Premium**

The potential explanations fail to account for the negative distress risk premium. Moreover, the analysis in Chapters 5 and 6 provide first indication that the relation between distress risk and stock returns might not be as hitherto assumed in literature: I find that while Shum subsumes all failure related information in z-score, z-score subsumes all returns related information in Shum. Also, LOTT is a fairly good failure predictor but not relevant in the pricing of stock returns.

In this thesis, I explore the drivers of the distress risk premium by breaking the distress risk measures down into its individual variables to unravel the premium by testing their influence on stock prices using cross-sectional regressions. For Shum, the profitability ratio NITA is highly significant, while for z-score, the profitability ratio PBTCL and the firm-liquidity ratio NCI are highly significant in addition to the common risk factors. Further, the coefficient of the Shum measure orthogonalised by NITA is insignificant while NITA remains highly significant. Similarly, z-score orthogonalised by PBTL is insignificant while PBTCL is highly significant. For NCI, the results are less strong. As a robustness test, I show that profitability reduces the coefficient of the measure of BS. These findings argue that profitability drives the distress risk premium.

I employ a five factor model including a profitability factor (PMU) formed following Fama and French (1993). An analysis of the risk factor shows that PMU is unrelated to the common risk factors and the returns on PMU are not fully explained by BETA, SMB, HML, and WML. The results using time-series regressions confirm the important role of profitability. I find that independent of how I measure distress, PMU is able to reduce the distress risk premia (decile sorts on Shum, z-score, and BS, value- and equally-weighted returns), although the H-L premia remain significant in half of the cases.

In addition to the decile sorts, I test the five factor model using independent 3x3 sorts on PBTCL and distress risk proxies. The results provide both a profitability and a distress risk premium on the tercile portfolios using the Fama and French (1993) and the Carhart (1997) model. For all distress risk proxies I use, both the profitability and the distress effect are intimately related to each other and driven by the positive abnormal returns earned by stocks with low distress risk and high profitability. The five factor model including PMU is able to account for both the distress anomaly and the profitability effect. However, unlike the cross-sectional tests, the time-series results are unable to distinguish between distress and profitability because the two are very closely related to each other.

Overall, my results show that the high stock returns of profitable firms relative to unprofitable firms drive the negative distress risk premium. This is counterintuitive as profitable firms score high on the conventional risk measures. Subsequently, this suggests that current risk-based explanations might fail in explaining the findings in this study.

Similar to my findings, existing literature finds profitability to be positively related with stock returns (e.g. Haugen and Baker, 1996). There is as well an extant literature on earnings and, in particular, earnings news suggesting that investors are unable to account for the information in current earnings for future earnings (e.g. Sloan, 1996).

The prevailing argument is that this underreaction causes the observed post-earnings announcement drift (e.g. Liu et al, 2003).

The underreaction has been, to some extent, observed in the context of distress risk. However, existing literature provides mixed results. On the one hand, Taffler et al. (2004) and Kausar et al. (2009) show that the post-GCM audit report drift is robust to the post-earnings announcement drift and similarly, Griffin and Lemmon (2002) as well as Campbell et al. (2008) show that the distress anomaly is robust to the post-earnings announcement drift. On the other hand, Dichev and Piotroski (2001) demonstrate that the negative returns of rating downgrades are concentrated around earnings announcements while Balakrishnan et al. (2010) show that the earnings announcement drift is robust to the distress anomaly.

These findings show that literature is ambiguous in bringing together the underreaction to distress news and profitability related news. However, my findings provide a way forward for future research as they unambiguously show that there is an association between distress risk and profitability.

## 9.3 Limitations of Research

Like other empirical studies in finance, the results presented in this thesis contain some limitations.

I use a portfolio formation date at the end of September. This date is the information cut-off date for e.g. industry or market segment affiliation.[44] The use of annual portfolio formation dates implicitly assumes that firms do not change their industry or market segment affiliation between the portfolio formation dates. Monthly or quarterly cut-off dates (firms listed in the Main market segment publish accounting data on a quarterly basis) could improve results.

Importantly, I assume that accounting data is available five months after the end of the financial year. Thus, I incorporate the firm in the September portfolio formation if the financial year-end was at the end of April latest. Obviously, this omits taking into account the actual publication dates of accounting information.

Similar to other studies, the pricing analysis assumes that realised returns equal expected returns. Elton (1999) provides arguments that raise doubts about the validity of this assumption.

This study uses independent sorts on profitability and distress risk (3x3 matrix in Chapter 8). The general reason of using sorts is to control for one variable while observing the effects of the other variable. Since profitability and distress are highly correlated, the effects will always be overlapping.

I use share price, idiosyncratic volatility and idiosyncratic skewness as proxies for both limits of arbitrage and lottery features. There are additional variables such as institutional shareholders or liquidity measures. Employing these would lead to more

[44] Industry affiliation is important because I exclude financial firms. Market segmentation is important as discussed in Chapter 4 (I restrict my sample to the Main market segment).

robust findings. However, the availability of this data for the UK market limits this robustness test.

## 9.4 Contributions to Knowledge and Practice

The thesis has two original contributions. First, the analysis of bankruptcy prediction models contributes in two ways as it compares all available approaches as well as using the available testing procedures. As such, the results of this study contribute to the literature of bankruptcy prediction. In a more narrow sense, my analysis contributes to the UK-specific literature on hybrid models as I show that the most parsimonious and original hybrid model of Shumway (2001) outperforms the hybrid model of Christidis and Gregory (2010).

In the context of bankruptcy prediction the thesis also has practical relevance. With the introduction of the Basel II Accord, the Basel Committee on Banking Supervision allows banks to develop their own credit rating models in the Internal Ratings Based framework. This study provides evidence on the performance of models to assess the counterparty risk, especially when testing the economic value with differential misclassification costs, a problem area of particular importance for financial institutions and regulators.

Second, until now, the return drivers of the negative distress risk premium were not fully understood. Therefore, the second original contribution of my thesis is within the pricing of distress risk. First, I test various potential explanations for the underperformance of distressed firms. Second, I break the distress risk proxy down into its component parts and identify the drivers of the negative distress risk premium. In doing so, I provide a direct link between distress risk and profitability. This is an important contribution to existing literature as it moderates previous findings on the distress risk pricing.

As my findings identify the drivers of the negative distress risk premium, its increasing the understanding of the returns that were until now associated with distress risk. Moreover, I show that a model employing an additional profitability factor leads to less pricing deviation than the standard model of Carhart (1997). These findings are of practical relevance for stock market investors such as fund managers.

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