Distress Risk and Stock Returns:

The neglected Profitability Effect?

Julian Bauer
BW PARTNER

Vineet Agarwal
Cranfield School of Management

*Corresponding author:
Vineet Agarwal
Cranfield School of Management
Bedford MK43 0AL
United Kingdom
Vineet.agarwal@cranfield.ac.uk
Tel: + 44 (0) 1234 751122

Distress Risk and Stock Returns:

The neglected Profitability Effect

Abstract

We measure distress risk using Shumway's hazard model (2001), Z-score (Agarwal and Taffler, 2007) and Bharat and Shumway's market model (2008). All measures show a negative premium while Z-score even subsumes the pricing information of the other two. We examine whether it is actually distress risk that earns the negative premium and find profitability to be significant and positively related to returns. Distress risk without profitability related information is not relevant in pricing. A new five factor model that extends the Carhart model (1997) by a profitability factor eliminates the distress anomaly.

JEL classification: G12; G14; G33

Keywords: market anomalies, distress risk, hazard models, Z-score, option pricing

1 Introduction

Theoretical finance literature is based on the assumption that higher risk is rewarded with higher returns. Chan and Chen (1991) and Fama and French (1996) firstly state this risk-return relationship in the context of financial distress. If distress risk is systematic, then investors expect a positive premium for bearing the distress risk. As Campbell et al. (2008) (CHS) and Chava and Purnanandam (2010) note, 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). [1] As such, distress risk would advocate the return patterns related to size and value found by Fama and French (1996).

However, in empirical finance literature the majority of studies find a negative relation between distress risk and stock returns (Campbell et al., 2008; e.g. Dichev, 1998; Da and Gao, 2010). Only a small number of studies find the projected positive relation between distress risk and return (Vassalou and Xing, 2004; Chava and Purnanandam, 2010). The studies differ in terms of how distress risk is actually measured. While accounting models have been the seminal models in early years (Altman, 1968; Ohlson, 1980), bankruptcy prediction using reduced form hazard models became the established approach more recently. In addition, a theoretical sound approach stems from the contingent claims approach of Black and Scholes (1973) and Merton (1974).

There are some questions that are unanswered in empirical literature. The first issue is that the majority of studies find a negative return premium for distress while there are other studies

[1] Throughout the paper we use the terms bankruptcy and failure interchangeably. Likewise, firms with a higher risk to fail are in (financial) distress.

that find a positive relation. We are left with a level of uncertainty. What returns are actually earned by distressed firms? Since the studies differ in terms of the distress measure applied: is the distress risk return relation depending on how we measure distress?

The second issue is of even greater importance. The different measures have been tested in terms of their predictive ability. CHS (2008) argue that in recent years bankruptcy prediction became more reliable using reduced form hazard models than accounting or market models. Agarwal and Taffler (2008a) find that the accounting and market approach carry different bankruptcy related information. In other words, the distress measures differ in terms of their predictive power and distress related information. Does this have implications on the pricing of distress risk? More importantly: does the best performing distress measure also result in the most significant distress premium?

The research questions addressed in this paper put these issues together: First, does the distress anomaly exist? And does it matter how distress is measured? Second, is it distress or any element of the distress measure that drives the returns? We address the research questions in four steps.

First, we start our analysis by introducing the three different distress measures while examining stock returns. (i) we use the reduced form hazard model of Shumway (2001) (Shum). Alternatives are provided in Chava and Jarrow (2004) or Charalambakis et al. (2009). CHS (2008) examine stock returns using an alternative hazard model and find a negative premium for distressed stocks. (ii) we also apply Taffler's UK-version of the Z-score model (Taffler, 1983; Agarwal and Taffler 2007). The Z-score has been widely applied in empirical literature. Dichev (1998), Griffin and Lemmon (2002) and Ferguson and Shockley (2003) use Z-score to assess stock returns. The studies confirm the anomalous relation between distress risk and returns. (iii) we also use a market approach that is based on the Black and Scholes (1973) and Merton (1974) measuring the distance-to-default. However, we follow Bharat and

Shumway (2008) and apply their naïve distance-to-default measure (Naïve DD). There are several studies that apply the market approach (e.g. Hillegeist et al., 2004; Reisz and Perlich, 2007). Vassalou and Xing (2004) using Moody's KMV argue for a positive distress risk premium. Although, Da and Gao (2010) critique their results as the positive premium is only present in the first month after risk measurement and turns negative afterwards. It follows that one major contribution of this paper is that it provides a comprehensive pricing analysis of the major models for the first time in literature. We briefly summarise the first part and answer the first research questions as follows: (i) distress risk earns a negative return premium (Campbell et al., 2008; e.g. Dichev, 1998; Da and Gao, 2010). (ii) in contrast to Vassalou and Xing (2004), we find the negative premium to be independent on how we measure distress risk. (iii) Size and BM do not cover distress risk (Chan and Chen, 1991; Fama and French, 1996; Vassalou and Xing, 2004). (iv) distress risk is related to the price momentum effect {{3864 Avramov, Doron 2007; 3730 Agarwal,Vineet 2008}}. (v) whatever pricing information is carried by the Shum and the Naïve DD, Z-score subsumes it.

Second, while analysing the pricing of the three different measures we can directly compare it to their predictive ability. In this sense, we are able to differentiate whether the model with the best bankruptcy prediction characteristics is also the one that returns the most significant premium in pricing. We therefore test the information content of our models and interpret it in context of our results from the first part. Previous studies, such as CHS (2008) focus on the information content of the individual variables by including a distance-to-default measure in the reduced-form econometric model. A comparison with Z-score or the alternative O-score model is not presented in their study. Agarwal and Taffler (2008a) provide information content tests using Z-score and the market approach of Hillegeist et al. (2004) and the Naïve DD of Bharat and Shumway (2008) and find no significant outperformance of one of them. The relevant results for the second part of our study can briefly be summarised: (i) all models are able to predict defaults. (ii) Shum absorbs the predictive information carried by Z-score and Naïve DD. (iii) taken together, Shum subsumes the information of the other models and remains significant. In connection with the finding that Z-score subsumes the pricing related information, we answer the second research question: the best default prediction model is not the most relevant in pricing, in fact, the reverse is true.

Third, from previous studies we know that distress risk is significant in pricing (Campbell et al., 2008; e.g. Dichev, 1998; Da and Gao, 2010). Agarwal and Taffler (2008b) as well as Agarwal and Poshakwale (2010) report the same instance for the UK market. Current studies actually go one step further and put greater focus on finding explanations for the low returns (e.g. CHS, 2008; Avramov et al., 2009). Potential explanations could be found in behavioural arguments (Hong et al., 2000; Kausar et al., 2009), short-selling constraints (Nagel, 2005) or a violation of the absolute priority rule (Garlappi and Yan, 2011).[2] Exploring these potential explanations is vital in understanding stock returns. However, as we show above there are important questions in relation to distress that have to be understood first. We analyse the drivers of the distress premium. As such, we provide an original contribution by examining what elements of the distress measure are actually relevant in pricing stocks. This will actually complement the results from the first two steps since it will enable us to disentangle the relevant pricing information. We briefly summarise the third part and answer the second research questions as follows: (i) profitability (and to some extent liquidity) is positive and significant in pricing distressed stocks. (ii) we disentangle profitability (and liquidity) from the distress measure and find the remaining information not to be relevant for pricing while profitability itself remains significant. As such, it is not distress but profitability that causes the return premium of distressed stocks.

---

[2] For the UK the violation of the absolute priority rule is virtually non-existent. Agarwal and Taffler (2008b) show that between 1979 and 2002 there was only one case where shareholders were promised any payments after default.

Fourth, we further test the return drivers of distress risk by suggesting a five factor model. This complements the Carhart model (1997) by a profitability factor. In the mood of Fama and French (1996) and Carhart (1997) we construct a return factor that is long on profitable and short on unprofitable firms. We briefly summarise the fourth part and answer the second research questions as follows: (i) a profitability factor adds additional information to the established risk factors. (ii) it is able to reduce the mispricing of the established models significantly. (iii) distressed stocks tend to be unprofitable, small, have higher BM ratios and low prior year returns. Likewise, profitable firms are less likely to fail, big, have low BM ratios and high prior year returns. (iv) the distress anomaly and profitability effect is mainly driven by the low distress risk-high profitable firms. (v) both mispricings are significantly reduced by the profitability factor. We therefore argue that profitability drives the distress effect.

We are aware of the potential impact our findings have on existing literature. However, since we know that distressed stocks earn a negative return premium and tend to be unprofitable, it is not surprising that low (high) profitability is to some extent related with negative (high) returns. Both characteristics do not fit into the usual risk-return-structure. Though what is surprising and the original contribution of this study is that the loadings on profitability subsume the remaining distress pricing element. Due to the characteristics associated with profitability, the proposed explanations for the underperformance of distressed stocks apply as well to profitability.

The paper proceeds as follows: In the next section we describe the methodological background of the distress measures and asset pricing tests. We then describe our sample and the data sources used. We also introduce the variables required to implement the distress measures and asset pricing tests. In the following section we present our results: First, we examine the pricing of distress risk using the three measures. Second, we briefly summarise the relative predictive ability of the measures. Third, we analyse the pricing of the individual variables of the measures. Fourth, we introduce a new five factor model and test for its ability to price distressed stock portfolios. We then conclude and give an outlook for further research.

2 Data and Method

2.1 Data and Data Sources

Our sample contains UK non-financial industrial firms listed at the Main-market at London Stock Exchange (LSE). The analysis and tests presented in this paper cover a time period from Oct 1985 to Sept 2010. We use the subsequently named data sources and selection process.

Our primary data source is the London Share Price Database (LSPD). We exclude secondary and non-equity listings, non-UK/GBP companies, financial industry firms (e.g. banks, insurance companies, trusts and investment companies). We match our sample with Datastream, the source of all our market and macro-economic data. Accounting Data is sourced from Datastream, Exstat and Company Analysis (in that order). For some failed firms we add hand collected data from Fame (Bureau van Dijk) and the London Business School Library.

We follow Agarwal and Taffler (2008b) and chose the portfolio formation date to be at the end of September each year. A portfolio year is defined as the twelve month period starting with October each year. To be included, companies must have market data available one year before portfolio formation. All market data is taken at portfolio formation date. We use current accounting data with a lag of five months i.e. at the end of September in year t, the company must show accounting data with a fiscal year ending between May t-1 and April t.

We relax this restriction in the portfolio year of failure and use the most recent accounting data with fiscal years ending between May t-2 and April t.[3]

Failure is not a strictly defined term. Studies of this nature are interested in economic failures. We identify an economic failure by equating it with one of the following terminologies: liquidation, administration/receivership or valueless company. First, we use LSPD and classify failures by the death codes 7, 16, 20 and 21. In contrast to Christidis and Gregory (2010) we exclude all other cases of cancellations or suspensions. Second, we complement our 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, we use Factiva (primary source is Regulatory News Service) to complement and cross-check our list of failures (receivership or administration announcements). The failure date is given by the last trading day of the failed company found in the regulatory news, LSPD or Datastream (in that order).[4] The monthly return is set to -100.0% in the month of failure.[5]

Table 1 Observations in Sample

Our final sample consists of 22,217 firm years between 1985 and 2009. This equals to 2,748 firms of which 211 failed. Our sample has an average annual failure rate of 0.9% and 9.15 observations (i.e. years) per firm. Table 1 presents the distribution over the portfolio years 1985 to 2009. In the following we introduce the individual variables required.

---

[3] This procedure allows using accounting data for failed firms twice in the sample. This approach is used since failed companies are unlikely to report their results timely or even fail to report their latest accounts (Keasey and Watson, 1988). This actually corroborates our research design as we assess the bankruptcy risk with all information that is actually available. Obviously, if a firm fails to update its financial data, we can only judge on latest available data.

[4] Failures and failure dates are primarily sourced from LSPD but most data could be matched to the other sources.

[5] Franks et al. (1996) argue that the UK bankruptcy regime is more creditors friendly and Kaiser (1996) shows that stockholders are passed over in terminal payments. In a similar empirical study, Agarwal and Taffler (2008b) find only one case where equity holders received a terminal payment. Thus, it is a very valid generalisation to allocate a maximum loss to equity holders.

2.2 Default Prediction Models

The first default prediction model we use is Shumway's (2001) discrete hazard model to estimate bankruptcy risk (Shum). Discrete hazard models use time varying variables to estimate a firm's bankruptcy risk at each point in time. The probability of default at time t is conditional on survival until t-1. The dependent variable is of binary form i.e. survival or failure in t. We use annual data to assess each year the risk that a firm will go bankrupt in the next twelve months. Following Chava and Jarrow (2004) and CHS (2008) we specify the discrete probability of failure at time t-1 as

$$P_{i,t}(Y_{i,t+1}=1|Y_{i,t+1}=0)=\frac{1}{1+e^{-\alpha_t-\beta \mathbf{X}_{i,t}}}$$

Where $Y_{i,t+1}$ is coded 1 if the company failed in t+1 (0 if not) and $\mathbf{X}_{i,t}$ is the vector of the time varying covariates known at time t and with its coefficients given by $\boldsymbol{\beta}$. Shumway (2001) defines $\mathbf{X}_{i,t}$ as a vector consisting of NITA, TLTA, EXRET, SIGMA and RSIZE for company i known at time t. NITA is a profitability ratio and derived by taking net income - after minorities and preference share - over book value of total assets (TA). TLTA measures leverage from a shareholder perspective and is total liabilities over total assets. TL is defined as the difference between book value of total assets and BV, the book value of shareholders' equity. TA is total assets. EXRET is log excess return over the FTSE All Share within the twelve months prior to the portfolio formation date. SIGMA is the annualised standard deviation of daily return data over the three months prior to portfolio formation. We follow CHS (2008) and use the cross-sectional average for companies that have less than five non-zero observations in the three-month window.[6] RSIZE is a relative size measure. It is the log

[6] 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 our study. This refers to the portfolio years 1979 to 1985 i.e. it includes the calibration period of the first six years.

of the firm's MV over the aggregate market value of the FTSE All Share index. MV is the market value of common equity at portfolio formation date.

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

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

Where x_1 measures profitability by taking profit before tax over current liabilities. x_2 is a working capital ratio and defined as current assets over total liabilities. x_3 represents financial risk and is current liabilities over total assets. x_4 measures the degree of liquidity and calculated as (quick assets – current liabilities) / ((sales – profit before tax – depreciation) / 365).[7] Variables are defined as above or directly taken from the balance sheets.

The third default prediction model is a marked-based approach. Traditional market models apply the contingent claims framework of Black and Scholes (1973) and Merton (1974) (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 discount bond maturing at time T. The equity value is defined in the BSM option pricing formula. We apply the naïve version of the market model of Bharat and Shumway (2008) who argue that the value of BSM lies in its functional form rather than in solving the BSM-model (Bharat and Shumway, 2008, p. 1356). As such,

7 Agarwal and Taffler (2008a) note that the model was constructed in 1977 and thus, it is completely out-of-sample.

Bharat and Shumway's (2008) naïve version (Naïve DD) retains the functional form of BSM but bypasses the simultaneous calculation of unobservable parameters. According to Bharat and Shumway (2008), debt volatility $\delta_{\mathrm{D,naïve}}$ can be simplified as

$$\delta_{\mathrm{D,naïve}}=0.05+0.25\delta_{\mathrm{E}}.$$

Where δ_E is equity volatility (SIGMA). The naïve firm volatility $\delta_{A,na\text{ïve}}$ is then defined as the weighted average of the equity and debt volatility:

$$\delta_{\mathrm{A,naïve}}=\frac{\mathrm{MV}}{\mathrm{BV+TL}}\delta_{\mathrm{E}}+\frac{\mathrm{TL}}{\mathrm{BV+TL}}\delta_{\mathrm{D}}$$

Bharat and Shumway (2008) derive their naïve distance-to-default measure and probability of default as

$$\mathrm{P_{naïve}}=\mathrm{N(\text{-}DD_{naïve})}=\mathrm{N}\left(\text{-}\frac{\ln\left(\frac{\mathrm{MV+TL}}{\mathrm{TL}}\right)+\left(\mathrm{r_{i,t\text{-}1}}\text{-}0.5\delta^2_{\mathrm{A,naïve}}\right)\mathrm{T}}{\delta_{\mathrm{A,naïve}}\sqrt{\mathrm{T}}}\right).$$

Where $\mathrm{P_{naïve}}$ is the probability of default for the naïve DD model, $\mathrm{N}(\cdot)$ describes the cumulative standard normal distribution, $r_{i,t-1}$ is the return over the previous year. The strike price is TL that is assumed to be a single discount bond maturing at T. In line with the hybrid models, we set T to one year and thus use a one year forecasting period.

In order to determine the probability of default from a naïve contingent claims model we estimate the current value of total debt as strike price, the current market value of equity, a measure of equity volatility and the equity over the past twelve months.

In our analysis we use default probabilities and scores derived from the default prediction models. Where necessary we use the following logit transformation:

$$\mathrm{p}=\frac{\mathrm{e^{score}}}{1+\mathrm{e^{score}}}$$

We winsorise probabilities (scores) at 0.00001 and 0.99999 (±18.4207). Variables included in the models are winsorised at the 5^{th} and 95^{th} percentile across all observations.

2.3 Cross-Sectional Regressions

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

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

Where subscript t denotes the portfolio year starting in October each year between 1985 to 2009, t-1 is the end of September before each portfolio year and t+m for m = 0 to 11 denotes the month of the portfolio year. $R_{i,t+m}$ is the exccess return of firm i in month t+m, $R_{f,t+m}$ the 1-month UK Treasury Bill rate of month t+m. $Beta_{i,t-1}$ is the beta factor calculated for each firm according to Dimson (1979) over the previous twelve months with a one month time-lag. SIZE and PYR are defined as above. BM is the book-to-market ratio and defined as shareholders' equity (BV) over market value of common equity (MV). We also run specifications of this model while including the score of one of the distress measures (Shum, Z-score and Naïve DD) at t-1, the individual variables of the default measures (e.g. NITA or PBT/CL) taken at t-1 or distress measures orthogonalised by NITA (Shum) and by PBT/CL and NCI (Z-score) taken at t-1.

For individual assets, we run a Fama and MacBeth (1973) regressions. We use the following basic regression formula that we shorten and extent for different tests:

$$(R_{i,t}-R_{f,t})= \alpha_{i,t}+\gamma_{1,t}Beta_{i,t-1}+\gamma_{2,t}SIZE_{i,t-1}+\gamma_{3,t}BM_{i,t-1}+\gamma_{4,t}PYR_{i,t-1}$$

Where $Beta_{i,t-1}$ is the beta factor calculated for each firm according to Dimson (1979) over the previous twelve months with a two months-time lag for firm i at time t-1, $SIZE_{i,t-1}$ is market capitalisation for firm i at time t-1, $BM_{i,t-1}$ is the book to market equity for firm i at time t-1and $PYR_{i,t-1}$ is prior-year-return for firm i at time t-1.

2.4 Time-Series Regressions

We use time-series regressions to test the explanatory power of various pricing factors over time by using three established asset pricing models: CAPM (Sharpe, 1964; Lintner, 1965), Fama and French (1996) and Carhart (1997). Throughout the analysis we focus on risk-adjusted returns i.e. the intercepts resulting from regressions. Since the CAPM (RmRf) and the Fama and French (RmRf, SMB and HML) are reduced versions of Carhart (RmRf, SMB, HML and WML) we only introduce the Carhart model (1997) here:

$$\left(R_{i,t}\text{-}R_{f,t}\right)= \beta_1+\beta_{MKT}RmRf_t+\beta_{SMB}SMB_t+\beta_{HML}HML_t+\beta_{WML}WML_t+\varepsilon_{i,t}$$

Where $R_{i,t}$ is the value-weighted return on portfolio i during month t, $R_{f,t}$ the three-month UK Treasury Bill rate at the beginning of month t, $RmRf_t$ the return difference of the FTSE All Share Index and the three-month UK Treasury Bill during month t, SMB_t the return on the mimicking portfolio for the size factor during month t, HML_t the return on the mimicking portfolio for the BM factor during month t and WML_t the return on the mimicking portfolio for the price momentum factor during month t.

In this paper we find distress risk to be negatively priced. This premium is robustly driven by profitability. To take account of that, we propose to extent the Carhart model:

$$\left(R_{i,t}\text{-}R_{f,t}\right)= \beta_1+\beta_{MKT}RmRf_t+\beta_{SMB}SMB_t+\beta_{HML}HML_t+\beta_{WML}WML_t+\beta_{PMU}PMU_t+\varepsilon_{i,t}$$

Where PMU_t is the return on the mimicking portfolio for profitability factor during month t. We follow previous terminologies and label the factor PMU ('Profitable Minus Unprofitable').

We form PMU and the factors following Fama and French (1996): (a) at the end of each September from 1985 to 2009 we rank all stocks on market capitalization and sort them into two equally populated portfolios using median. (b1) for SMB and HML, we independently rank the stocks on B/M and sort them into three portfolios using the 30th and 70th percentile.

Six portfolios are then formed at the intersections of the break-points i.e. small-low BM, small medium-BM,…, large-high BM. We calculate value-weighted monthly portfolio excess returns for the subsequent twelve months (October year t to September year t+1). 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). (b2) for WML (PMU), we independently rank the stocks on PYR (PBT/CL) and sort them into three portfolios using the 30th and 70th percentile. Six portfolios are then formed at the intersections of the break-points i.e. small-low PYR, small-medium PYR,…, large-high PYR (small-low PBT/CL, small-medium PBT/CL,…, large-high PBT/CL). We calculate value-weighted monthly portfolio excess returns for the subsequent twelve months (October year t to September year t+1). WML is the difference between average returns of the two high and the two low PYR portfolios (equally weighted). PMU is the difference between average returns of the two high and the two low PBT/CL portfolios (equally weighted).

Test assets are monthly value-weighted excess returns of portfolios formed in two ways at the end of each September from 1985 to 2009: First, we rank all stocks on one of the distress measures i.e. Shum, Z-score and Naïve DD and sort into decile portfolios. Second, we use nine portfolios formed independently at the intersections of one of the distress measures and PBT/CL. That is at the end of each September from 1985 to 2009 we rank all stocks on e.g. Shum and sort into tertials. We do the same for PBT/CL. We then independently form nine portfolios at the intersections consisting of stocks with low distress risk-low PBT/CL, medium distress risk-low PBT/CL,…, high distress risk-high PBT/CL. This results in a 3x3-matrix. We also calculate the (value-weighted) averages of the three low distress (profitability), medium distress (profitability) and high distress (profitability) labelled All. Leverage portfolios long on High and short on Low are labelled H-L.

Since our time-series regressions are on portfolios, we use the Gibbons, Ross and Shanken (1989) (GRS) *F*-statistic to test whether the regression intercepts are jointly zero. GRS (1989) show that the following statistic is *F*-distributed:

$$\left[\frac{(T/N)\times(T\text{-}N\text{-}L)}{T\text{-}N\text{-}1}\right]\times\left[1+\left(\bar{\mathbf{r}}_{\mathbf{p}}'\hat{\boldsymbol{\Omega}}^{-1}\bar{\mathbf{r}}_{\mathbf{p}}\right)\right]^{-1}\times\left(\hat{\boldsymbol{\delta}}_{0}'\hat{\boldsymbol{\Sigma}}^{-1}\hat{\boldsymbol{\delta}}_{0}\right)$$

With degrees of freedom with N numerator and T-N-L denominator and where T is the number of months, N the number of portfolios, L the number of factors, $\bar{\mathbf{r}}_{\mathbf{p}}'$ the column vector (Lx1) of sample means for each of the factors, $\hat{\boldsymbol{\Omega}}$ the covariance matrix (LxL) of the factors, $\hat{\boldsymbol{\delta}}_{0}$ the column vector (Nx1) of regression intercepts and $\hat{\boldsymbol{\Sigma}}$ the covariance matrix (NxN) of residuals of N regressions.

3 Results

3.1 Distress risk and stock returns

In this sub-section, we test the relation between distress risk and returns using Fama and MacBeth (1973) cross-sectional regressions. Table 3 model 1 shows a negative but insignificant premium associated with beta and firm size while the book-to-market effect is a statistically highly significant 22 basis points per month (t = 2.8). It also shows a strong momentum effect of 41 basis points per month (t = 2.4).

Models 2 to 4 introduce the scores from Shumway (2001), Taffler (1983) and Bharath and Shumway (2008) models respectively in the pricing equation. They show that stocks with lower scores (i.e., higher distress risk) reliably underperform those with higher scores regardless of the model used (t = 2.2, 3.2, and 1.9 respectively). Further, similar to the evidence in Dichev (1998) and Agarwal and Taffler (2008), the value premium remains highly significant in models 3 and 4 (t = 2.3 and 3.0 respectively) though it is weaker in model 2 (t = 1.9). Also, consistent with the evidence in Agarwal and Taffler (2008), we find that inclusion of direct proxies for distress risk weakens the momentum effect though it remains statistically significant in model 3 (t = 2.1).

Models 5 and 6 in table 3 show that z-score subsumes the returns related information in the Shumway (2001) and Bharath and Shumway (2008) measures of distress risk respectively.

The evidence in table 3 shows that higher distress risk is associated with lower subsequent stock returns regardless of the proxy for bankruptcy risk. It also shows that while the book-to-market effect remains statistically significant, the distress risk measures subsume the momentum effect.

3.2. Distress risk premium and shareholder advantage

Garlappi and Yan (2011) theoretically model equity values when the shareholders get a positive return in the event of bankruptcy. They show that for low levels of distress risk, equity beta would be positively related to distress risk. Shareholders' option of strategic bankruptcy becomes more valuable for high levels of distress risk, hence transferring risk from equity holders to debt holders and consequently reducing equity risk. Thus, equity beta and book-to-market ratio are hypothesised to have a hump-shaped relation with distress risk while the momentum effect will be driven primarily by high distress risk stocks. In this sub-section, we test the predictions of their theoretical model.

Table 4 panel A shows that in contrast to the prediction of Garlappi and Yan (2011), both equity betas and book-to-market are monotonically increasing in distress risk as measured by Shumway (2001). Panel B shows that when distress risk is measured by z-score, the equity betas are increasing in risk while the boo-to-market ratios show a distinct U-shaped pattern as in Agarwal and Taffler (2008). Finally, panel C where Moody's KMV type model proxies for distress risk, also does not show the predicted humped relation with equity betas (the lowest risk portfolio has a beta of 0.94 vs 1.15 for the highest risk portfolio). The book-to-market ratio is again monotonically increasing in distress risk. In summary, irrespective of the distress risk proxy used, we do not find any evidence in support of the predictions of Garlappi and Yan (2011).

Table 4 here

3.3. Distress risk premium and lottery characteristics

Han and Kumar (2011) argue that the primary objective of retail investors with a strong propensity to gamble is entertainment rather than profit maximisation. Hence they prefer lottery type stocks characterised by high idiosyncratic volatility, idiosyncratic skewness, low price and poor liquidity. The literature on short selling constraints finds similar characteristics for stocks with high limits to arbitrage [references]. Coelho et al. (2011) find that the majority of trades in bankrupt firms or those close to bankruptcy are by individual investors. They also demonstrate that firms announcing bankruptcy have lottery type characteristics, and that the underperformance of the firms in Chapter 11 is not arbitraged away by sophisticated investors because of high transaction costs.

In this sub-section we analyse whether the lottery type characteristics of distressed firms are able to explain their underperformance since investors in distressed firms have other than profit maximising objectives. Since the characteristics of lottery type stocks and stocks with high arbitrage costs are identical, it also provides evidence on the potential explanatory power of limits to arbitrage in explaining the overpricing of distressed firms.

Table 4 presents characteristics of decile portfolios ranked on the lottery index constructed on idiosyncratic volatility, idiosyncratic skewness and price following Han and Kumar (2011). It shows that the high lottery stocks make up only 1.25% of total market. Similar to Han and Kumar (2011), beta and book-to-market increase with lottery features while size is monotonically decreasing. [PYR]. Importantly, as in Coelho et al. (2010), we find that irrespective of the distress measure, default probability is monotonically increasing in lottery index and the highest lottery type stocks have highest default probabilities. This suggests that the negative distress risk premium could result from mispricing of distressed stocks either due to activities of retail investors or due to limits to arbitrage.

Table 4 here

Table 5 presents the correlations between the lottery index, conventional risk factors and our three distress risk proxies using individual stocks. It shows the lottery index has a Pearson correlation of -0.55 with market capitalisation, 0.56 with Shumway (2001), -0.28 with z-score and 0.44 with market based bankruptcy prediction model estimates.[8]

Table 5 here

We formally test whether the negative distress risk premium is due to lottery stock/difficult to arbitrage characteristics of distressed stocks through Fama and MacBeth (1973) regressions using equation (). Table 6 models 1 to 3 show that none of the three components of the lottery index are able to explain stock returns, and model 4 shows that lottery characteristics are not related to subsequent stock returns. Models 5 to 7 show that controlling for the lottery characteristics has no impact on underperformance of distressed stocks.

Table 6 here

The evidence in table 6 clearly demonstrates that in our sample, the characteristics typically identified with lottery stocks or with stocks that are difficult to arbitrage have no role in subsequent stock returns. Further, it also shows that the negative distress risk premium is not

---

[8] The Spearman correlations are.... respectively

a result of mispricing due to limits to arbitrage or activities of individual investors who trade for entertainment rather than investment value.

3.4. The source of negative distress risk premium

The evidence presented so far shows that the negative distress risk premium does not depend on how we measure probability of failure, and that it is not driven by lottery characteristics or problems of arbitraging. In this sub-section, we explore another possible source of the distress risk anomaly.

Table 2 shows that z-score measure is able to subsume all pricing related information in both, Shumway (2001) as well as KMV Moody's type proxy for bankruptcy risk. However, Bauer and Agarwal (2011) show that of the three proxies, z-score is the weakest in terms of predicting corporate failure with Shumway (2001) model subsuming all bankruptcy related information in z-scores. This provides prima facie evidence that the observed distress risk premium may be driven by something other than probability of failure itself. In order to identify the source of the distress risk premium, we investigate the relation of subsequent stock returns with the individual components of the distress risk measures.

Table 6 presents the correlations between the conventional risk measures and the components of our distress risk proxies. It shows that size and RSIZE as well as PYR and EXRET are highly correlated and hence their inclusion in the same regression will be problematic. None of the other correlations are high enough to raise concerns about multicollinearity.

Table 6 here

Table 7 presents the results of the Fama and MacBeth (1973) regressions using individual components of our bankruptcy risk proxies. Model 1 is the base model that shows superior returns for value stocks and past winners. Model 2 shows that of the five components of the Shumway (2001) model, only the profitability component (NITA) is associated with reliably positive relation with subsequent stock returns.[9] Model 3 shows that two components of z-score model, profitability (PBTCL) and liquidity (NCI) are associated with superior stock returns. Finally, model 4, with Moody's KMV type proxy, which has the weakest relation with subsequent stock returns (see table (), model()), only total volatility (SIGMA) is weakly significant (t = 1.9).

Table 7 here

The evidence in table 7 shows that for Shumway (2001) and z-score model, profitability is the driver for the relation with stock returns. We explore this further by orthogolanising Shumway (2001) estimates with respect to NITA and z-score with respect to PBTCL, NCI and both.

Table 8 model 1 shows that once the Shumway (2001) estimate is orthogonalised with respect to NITA, there is no significant distress risk premium (t = 1.5) as all the information related to subsequent stock returns is contained in NITA that is highly significant (t = 2.2). Model 2 shows that when the z-score is orthogonalised with respect to PBTCL, the premium is associated with PBTCL (0.48% per month, t = 2.5) and weakly with NCI (t = 1.9). Similarly, models 3 and 4 show that the higher stock returns are strongly associated with PBTCL and weakly with NCI when z-score is orthogonalised with respect to NCI and both, PBTCL and NCI respectively. Finally, models 5 and 6 show that the Moody's KMV type distress risk proxy's ability to explain stock returns is subsumed by PBTCL and NITA respectively.

Table 8

The evidence in table 8 clearly shows that the observed distress risk anomaly is not due to mispricing of distress risk at all. Subsequent stock returns are positively related to

[9] While EXRET also has a significantly positive coefficient, it is simply the momentum effect.

profitability. The negative relation between distress risk and stock returns is driven by the negative relation between profitability and distress risk.

4 Conclusions and Outlook

We use the reduced form hazard model of Shumway (2001), the Z-score model of Agarwal and Taffler (2007) and the naïve distance-to-default measure of Bharat and Shumway (2008). We corroborate the results of the majority of studies by finding a negative return premium for distress risk (Campbell et al., 2008; e.g. Dichev, 1998; Da and Gao, 2010). In addition to that, we find the negative premium on distress risk to be independent on how we measure distress risk (Vassalou and Xing, 2004). Size and BM cannot cover the distress effect (Chan and Chen, 1991; Fama and French, 1996) while momentum is related to distress (Agarwal and Taffler, 2008b). Importantly, Z-score is most significant in pricing and subsumes the pricing information carried by Shumway (2001) and the Naïve measure of (Bharat and Shumway, 2008). On the other hand, Shumway (2001) is most significant in pricing and subsumes the default prediction information carried by Z-score and the Naïve measure of (Bharat and Shumway, 2008)

We therefore test whether it is actually distress risk or an element of the distress measure that carries the pricing related information. We provide new insights since we find that profitability is driving the negative distress risk premium: once we disentangle profitability from the distress measure we find the remaining information to be irrelevant for pricing while profitability remains significant. We therefore argue that profitability drives the distress effect.

We suggest a new five factor asset pricing model. In addition to the Carhart factor we include a profitability factor that is long on profitable stocks and short on unprofitable stocks. The factor is found to carry additional information to the established pricing factors. Time-series regressions on distress risk sorted portfolios show that the profitability factor erases the distress anomaly. Independent sorts on distress risk and profitability show that the profitability factor is able to account for both the profitability effect and the distress anomaly.

Due to the distress anomaly and the similar characteristics of distressed and unprofitable stocks, we argue it is not surprising that profitability is related to stock returns. Though, what is surprising is that profitability drives the distress anomaly. We are aware of the implications our findings have on existing literature. However, the possible explanations that are proposed for the distress anomaly do also apply to the profitability effect.

For the future, we argue that the three potential explanations have to be further researched in the light of our findings. Literature suggests that such research could be nested in behavioural arguments (Hong et al., 2000; Kausar et al., 2009), short-selling constraints (Nagel, 2005) or a violation of the absolute priority rule (Garlappi and Yan, 2011). We explicitly stress that the violation of the absolute priority rule does not apply to the UK as it is non-existent. Any explanation in this context would therefore be market specific. Since the distress anomaly and the characteristics of the stocks are found to be market independent, we argue that this explanation is unlikely to be valid.[10]

We put more emphasis on researching the characteristics that are associated with distress and profitability. Distressed stocks tend to be unprofitable, small, have higher BM ratios and low prior year returns. Likewise, profitable firms are less likely to fail, big, have low BM ratios and high prior year returns. Also, indicative analysis shows that these stocks are also low priced and have high idiosyncratic volatility. Since these characteristics match with the

[10] An indicative replication of the core analysis of Garlappi and Yan (2011) support our argument. We do not find the described Beta-BM relation.

explanations based on behavioural arguments or short-selling constraints, we see enough potential to link the topics.

5 Bibliography

Agarwal, V. and Poshakwale, S. (2010), "Size and book-to-market anomalies and omitted leverage risk", *European journal of finance,* vol. 16, no. 3, pp. 263-279.

Agarwal, V. and Taffler, R. (2008a), "Comparing the performance of market-based and accounting-based bankruptcy prediction models", *Journal of Banking & Finance,* vol. 32, no. 8, pp. 1541-1551.

Agarwal, V. and Taffler, R. (2008b), "Does Financial Distress Risk Drive the Momentum Anomaly?", *Financial Management (Blackwell Publishing Limited),* vol. 37, no. 3, pp. 461-484.

Agarwal, V. and Taffler, R. J. (2007), "Twenty-five years of the Taffler z-score model: does it really have predictive ability?", *Accounting & Business Research,* vol. 37, no. 4, pp. 285-300.

Altman, E. I. (1968), "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy", *Journal of Finance,* vol. 23, no. 4, pp. 589-609.

Avramov, D., Chordia, T., Jostova, G. and Philipov, A. (2007), "Momentum and Credit Rating", *Journal of Finance,* vol. 62, no. 5, pp. 2503-2520.

Avramov, D., Chorida, T., Jostova, G. and Philipov, A. (2009), "Credit Ratings and The Cross-Section of Stock Returns", *Working Paper,* .

Avramov, D., Chordia, T., Jostova, G. and Philipov, A. (2010), "Anomalies and Financial Distress", *Working Paper,* .

Bharath, S. T. and Shumway, T. (2008), "Forecasting Default with the Merton Distance to Default Model", *Review of Financial Studies,* vol. 21, no. 3, pp. 1339-1369.

Black, F. and Scholes, M. (1973), "The Pricing of Options and Corporate Liabilities", *Journal of Political Economy,* vol. 81, no. 3, pp. 637.

Breeden, D. T., Gibbons, M. R. and Litzenberger, R. H. (1989), "Empirical tests of the consumption-oriented CAPM", *Journal of Finance,* vol. 44, no. 2, pp. 231-262.

Campbell, J. Y., Hilscher, J. and Szilagyi, J. (2008), "In Search of Distress Risk", *Journal of Finance*, vol. 63, no. 6, pp. 2899-2939.

Carhart, M. M. (1997), "On Persistence in Mutual Fund Performance", *Journal of Finance*, vol. 52, no. 1, pp. 57-82.

Chan, K. C. and Nai-Fu Chen (1991), "Structural and Return Characteristics of Small and Large Firms", *Journal of Finance*, vol. 46, no. 4, pp. 1467-1484.

Charalambakis, E. C., Espenlauby, S. K. and Garrett, I. (2009), "Assessing the probability of financial distress of UK firms", *Working Paper*, .

Chava, S. and Jarrow, R. A. (2004), "Bankruptcy Prediction with Industry Effects", *Review of Finance*, vol. 8, no. 4, pp. 537-569.

Chava, S. and Purnanandam, A. (2010), "Is Default Risk Negatively Related to Stock Returns?", *Review of Financial Studies*, vol. 23, no. 6, pp. 2523-2559.

Christidis, A. C. and Gregory, A. (2010), "Some New Models for Financial Distress Prediction in the UK", *Working Paper*, .

Coyle, B. (ed.) (2000), *Corporate Credit Analysis* Global Professional Publishi.

Da, Z. and Gao, P. (2010), "Clientele Change, Liquidity Shock, and the Return on Financially Distressed Stocks", *Journal of Financial & Quantitative Analysis*, vol. 45, no. 1, pp. 27-48.

Dichev, I. D. (1998), "Is the Risk of Bankruptcy a Systematic Risk?", *Journal of Finance*, vol. 53, no. 3, pp. 1131-1147.

Dimson, E. (1979), "Risk Measurement when Shares are Subject to Infrequent Trading", *Journal of Financial Economics*, vol. 7, no. 2, pp. 197-226.

Fama, E. F. and French, K. R. (1992), "The Cross-Section of Expected Stock Returns", *Journal of Finance*, vol. 47, no. 2, pp. 427-465.

Fama, E. F. and French, K. R. (1996), "Multifactor Explanations of Asset Pricing Anomalies", *Journal of Finance*, vol. 51, no. 1, pp. 55-84.

Fama, E. F. and French, K. R. (2006), "The value premium and the CAPM", *Journal of Finance,* vol. 61, no. 5, pp. 2163-2186.

Fama, E. F. and MacBeth, J. D. (1973), "Risk, Return, and Equilibrium: Empirical Tests", *Journal of Political Economy,* vol. 81, no. 3, pp. 607-607.

Ferguson, M. F. and Shockley, R. L. (2003), "Equilibrium “Anomalies”", *Journal of Finance,* vol. 58, no. 6, pp. 2549-2580.

Franks, J. R. and Nyborg, K. G. (1996), "A Comparison of US, UK, and German Insolvency Codes. (cover story)", *FM: The Journal of the Financial Management Association,* vol. 25, no. 3, pp. 86-101.

Garlappi, L. and Yan, H. (2011), "Financial Distress and the Cross-section of Equity Returns ", *Journal of Finance,* vol. 66, no. 3, pp. 789-822.

Griffin, J. M. and Lemmon, M. L. (2002), "Book–to–Market Equity, Distress Risk, and Stock Returns", *Journal of Finance,* vol. 57, no. 5, pp. 2317-2336.

Hillegeist, S. A., Keating, E. K., Cram, D. P. and Lundstedt, K. G. (2004), "Assessing the Probability of Bankruptcy", *Review of Accounting Studies,* vol. 9, no. 1, pp. 5-34.

Hong, H., Lim, T. and Stein, J. C. (2000), "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies", *Journal of Finance,* vol. 55, no. 1, pp. 265-295.

Kaiser, K. M. J. (1996), "European Bankruptcy Laws: Implications for Corporations Facing Financial Distress. (cover story)", *FM: The Journal of the Financial Management Association,* vol. 25, no. 3, pp. 67-85.

Kausar, A., Taffler, R. J. and Tan, C. (2009), "The Going-Concern Market Anomaly", *Journal of Accounting Research,* vol. 47, no. 1, pp. 213-239.

Keasey, K. and Watson, R. (1988), "The Non-submission of Accounts and Small Company Financial Failure Prediction", *Accounting & Business Research,* vol. 19, no. 73, pp. 47-54.

Lamont, O., Polk, C. and Saá-Requejo, J. (2001), "Financial constraints and stock returns", *Review of Financial Studies,* vol. 14, no. 2.

Lintner, J. (1965), "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets", *Review of Economics and Statistics,* vol. 47, pp. 13-47.

Merton, R. C. (1974), "On the Pricing of Corporate Debt: the Risk Structure of Interest Rates", *Journal of Finance,* vol. 29, no. 2, pp. 449-470.

Merton, R. C. (1973), "An Intertemporal Capital Asset Pricing Model", *Econometrica,* vol. 41, no. 5, pp. 867-887.

Nagel, S. (2005), "Short sales, institutional investors and the cross-section of stock returns", *Journal of Financial Economics,* vol. 78, no. 2, pp. 277-309.

Ohlson, J. A. (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", *Journal of Accounting Research,* vol. 18, no. 1, pp. 109-131.

Reisz, A. S. and Perlich, C. (2007), "A market-based framework for bankruptcy prediction", *Journal of Financial Stability,* vol. 3, no. 2, pp. 85-131.

Sharpe, W. F. (1964), "Capital Asset Prices: a Theory of Market Equilibrium Under Conditions of Risk", *Journal of Finance,* vol. 19, no. 3, pp. 425-442.

Shumway, T. (2001), "Forecasting Bankruptcy More Accurately: A Simple Hazard Model", *Journal of Business,* vol. 74, no. 1, pp. 101.

Taffler, R. J. (1983), "The Assessment of Company Solvency and Performance Using a Statistical Model", *Accounting & Business Research,* vol. 13, no. 52, pp. 295-307.

Vassalou, M. and Xing, Y. (2004), "Default Risk in Equity Returns", *Journal of Finance,* vol. 59, no. 2, pp. 831-868.

6 Tables

Table 1 Observations in Sample

This table gives an overview of our sample population. It contains UK non-financial industrial firms listed at the Main-market at London Stock Exchange. We form portfolios at the end of each September between 1985 and 2009. To be included, the firms must be listed for at least one year at portfolio formation. Portfolio Year is defined as the twelve months period starting in October year t and ending with September in year t+1. Observations is the number of sample firms for a portfolio year. Failures is the number of firms that went into liquidation, administration/receivership or were declared valueless during the portfolio year (LSPD: death codes 7, 16, 20 and 21; Capital Gains Tax Book: companies in receivership and/or liquidation or companies with negligible value; Regulatory News from Factiva: receivership or administration announcements). Failure Rate is failures over observations. Firms is the total number of firms that are included in our sample.

Portfolio Year	No. Observations	No. Failures	Failure Rate
1985	1,018	3.0	0.3
1986	954	0.0	0.0
1987	907	2.0	0.2
1988	866	1.0	0.1
1989	841	9.0	1.1
1990	811	19.0	2.3
1991	824	18.0	2.2
1992	1,011	9.0	0.9
1993	1,015	4.0	0.4
1994	1,064	6.0	0.6
1995	1,213	8.0	0.7
1996	1,265	10.0	0.8
1997	1,280	14.0	1.1
1998	1,235	13.0	1.1
1999	1,111	10.0	0.9
2000	987	9.0	0.9
2001	916	20.0	2.2
2002	843	12.0	1.4
2003	747	7.0	0.9
2004	669	8.0	1.2
2005	606	2.0	0.3
2006	559	3.0	0.5
2007	510	10.0	2.0
2008	493	8.0	1.6
2009	472	6.0	1.3
Total	**22,217**	**211**	**0.9**
Firms	**2,428**		
Obs per Firm	**9.15**		

Table 2 Correlations: Distress measures

This table presents correlation coefficients of the independent variables for cross-section regressions. The lower-left side of the matrix presents Spearman rank correlation coefficients. The upper-right side of the matrix presents Pearson correlation coefficients. At the end of each September from 1985 to 2010 we take the independent variable of each firm. Beta is beta factor calculated for each firm according to Dimson (1979) over the previous twelve months with a two months-time lag. SIZE is the log of market capitalisation. BM is the log of book-equity over market value of common equity. PYR is the prior-year-return. Variables are winsorised at the 5th and 95th percentile across all observations. Shum is the score obtained from the model in Shumway (2001). Z-score is the Z-score obtained from the model in Agarwal and Taffler (2007). Naïve DD is the score obtained from the model in Bharat and Shumway (2008). Scores are winsorised at ±18.4207.

Spearman/Pearson Correlation Matrix							
	BETA	**SIZE**	**BM**	**PYR**	**Shum**	**Z-Score**	**Naïve DD**
BETA	1	0.01	-0.02	0.04	0.08	-0.08	0.07
SIZE	0.11	1	-0.21	0.03	-0.44	0.07	-0.26
BM	-0.06	-0.36	1	-0.27	0.31	-0.02	0.43
PYR	-0.02	0.18	-0.29	1	-0.35	0.04	-0.45
Shum	0.02	-0.66	0.25	-0.49	1	-0.52	0.75
Z-Score	-0.05	0.17	0.03	0.10	-0.52	1	-0.32
Naïve DD	0.06	-0.45	0.40	-0.65	0.78	-0.35	1

Table 3 Pricing Analysis: Distress Measures

This table presents cross-sectional regressions on individual stock returns. The models are specifications of the Fama and MacBeth method (1973). At the end of each September from 1985 to 2010 we take the independent variable of each firm and regress it against the firm's subsequent twelve month returns. Independent variables are: Beta is beta factor calculated for each firm according to Dimson (1979) over the previous twelve months with a two months-time lag. SIZE is the log of market capitalisation. BM is the log of book-equity over market value of common equity. PYR is the prior-year-return. Variables are winsorised at the 5^{th} and 95^{th} percentile across all observations. Shum is the score obtained from the model in Shumway (2001). Z-score is the Z-score obtained from the model in Agarwal and Taffler (2007). Naïve DD is the score obtained from the model in Bharat and Shumway (2008). Scores are winsorised at ±18.4207. The last month return for failed firms is -100%. Per model we run 300 monthly regressions. We report average coefficients and the t-statistics in brackets below.

Model	**γ1 Beta**	**γ2 SIZE**	**γ3 BM**	**γ4 PYR**	**γ5 Shum**	**γ6 Z-Score**	**γ7 Naïve DD**
Model 1	-0.11	-0.01	0.21				
	(1.42)	(0.11)	(2.31)				
Model 2	-0.09	-0.13	0.15		-0.23		
	(1.40)	(2.16)	(1.72)		(2.73)		
Model 3	-0.10	-0.03	0.17			0.02	
	(1.30)	(0.46)	(1.94)			(3.26)	
Model 4	-0.10	-0.07	0.25				-0.03
	(1.51)	(1.29)	(2.89)				(2.47)
Model 5	-0.13	-0.03	0.22	0.41			
	(1.75)	(0.51)	(2.78)	(2.44)			
Model 6	-0.09	-0.12	0.16	0.17	-0.19		
	(1.39)	(1.95)	(1.95)	(1.29)	(2.20)		
Model 7	-0.12	-0.04	0.19	0.33		0.02	
	(1.65)	(0.76)	(2.33)	(2.09)		(3.18)	
Model 8	-0.11	-0.06	0.25	0.27			-0.02
	(1.60)	(1.12)	(3.04)	(1.83)			(1.88)
Model 9	-0.10	-0.09	0.16	0.23	-0.12	0.01	
	(1.56)	(1.46)	(1.96)	(1.73)	(1.33)	(2.32)	
Model 10	-0.11	-0.06	0.21	0.26		0.02	-0.01
	(1.62)	(1.09)	(2.56)	(1.77)		(3.03)	(1.16)

Table 4 Correlations: Variables Distress Measures

This table presents correlation coefficients of the independent variables for cross-section regressions. The lower-left side of the matrix presents Spearman rank correlation coefficients. The upper-right side of the matrix presents Pearson correlation coefficients. At the end of each September from 1985 to 2010 we take the independent variable of each firm. Beta is beta factor calculated for each firm according to Dimson (1979) over the previous twelve months with a two months-time lag. SIZE is the log of market capitalisation. BM is the log of book-equity over market value of common equity. PYR is the prior-year-return. We also include Shumway (2001) variables: NITA is net income over total assets, TLTA is total liabilities over total assets, RSIZE is the firm's market value over the aggregate market value of the FTSE All Share index, EXRET is log excess return of asset i over FTSE All Share Index, SIGMA is the annualised standard deviation of daily return data over the three months prior to portfolio formation. We also include the Z-score variables (Agarwal and Taffler, 2007): PBT/CL is profit before tax over current liabilities. CA/TL is current assets over total liabilities. CL/TA is current liabilities over total assets. NCI is the no-credit interval calculated as (quick assets – current liabilities) / ((sales – profit before tax – depreciation) / 365). MV/MVTL is the part of the Naïve DD in Bharat and Shumway (2008). Variables are winsorised at the 5th and 95th percentile across all observations.

Spearman/Pearson Correlation Matrix														
	BETA	**SIZE**	**BM**	**PYR**	**NITA**	**TLTA**	**RSIZE**	**EXRET**	**SIGMA**	**PBT/CL**	**CA/TL**	**CL/TA**	**NCI**	**MV/MVTL**
BETA	1	0.01	-0.02	0.04	-0.11	0.06	0.06	-0.07	0.14	-0.12	0.01	0.03	0.03	-0.02
SIZE	0.11	1	-0.21	0.03	0.16	0.10	0.76	0.13	-0.28	0.17	-0.25	-0.15	-0.05	0.12
BM	-0.06	-0.36	1	-0.27	-0.25	-0.27	-0.38	-0.32	0.29	-0.18	0.04	-0.27	0.00	-0.53
PYR	-0.02	0.18	-0.29	1	0.06	-0.01	0.11	0.71	-0.15	0.05	0.04	0.03	0.01	0.27
NITA	-0.04	0.28	-0.33	0.13	1	-0.17	0.31	0.19	-0.41	0.81	0.11	-0.03	0.04	0.38
TLTA	0.07	0.07	-0.34	-0.03	-0.18	1	0.07	-0.06	0.11	-0.33	-0.53	0.64	-0.35	-0.54
RSIZE	0.11	0.95	-0.36	0.21	0.31	0.07	1	0.23	-0.52	0.31	-0.23	-0.14	-0.03	0.29
EXRET	-0.03	0.20	-0.27	0.87	0.14	-0.04	0.22	1	-0.34	0.18	0.02	-0.05	0.03	0.34
SIGMA	0.10	-0.47	0.19	-0.29	-0.34	0.09	-0.54	-0.25	1	-0.39	0.04	0.15	-0.01	-0.33
PBT/CL	-0.07	0.32	-0.15	0.13	0.79	-0.38	0.34	0.14	-0.39	1	0.09	-0.31	0.13	0.42
CA/TL	0.00	-0.27	0.04	0.04	0.21	-0.45	-0.22	0.02	0.04	0.09	1	-0.05	0.45	0.39
CL/TA	0.04	-0.17	-0.33	-0.01	0.02	0.62	-0.13	-0.03	0.13	-0.36	0.08	1	-0.33	-0.25
NCI	0.01	-0.01	-0.02	0.04	0.12	-0.33	-0.02	0.04	-0.02	0.19	0.45	-0.30	1	0.29
MV/MVTL	-0.01	0.28	-0.50	0.30	0.48	-0.53	0.28	0.30	-0.27	0.48	0.36	-0.24	0.31	1

Table 5 Pricing Analysis: Variables Distress Measures

This table presents cross-sectional regressions on individual stock returns. The models are specifications of the Fama and MacBeth method (1973). At the end of each September from 1985 to 2010 we take the independent variable of each firm and regress it against the firm's subsequent twelve month returns. Independent variables are: Beta is beta factor calculated for each firm according to Dimson (1979) over the previous twelve months with a two months-time lag. SIZE is the log of market capitalisation. BM is the log of book-equity over market value of common equity. PYR is the prior-year-return. We also include Shumway (2001) variables: NITA is net income over total assets, TLTA is total liabilities over total assets, EXRET is log excess return of asset i over FTSE All Share Index, SIGMA is the annualised standard deviation of daily return data over the three months prior to portfolio formation, RSIZE is the firm's market value over the aggregate market value of the FTSE All Share index. We also include the Z-score variables (Agarwal and Taffler, 2007): PBT/CL is profit before tax over current liabilities. CA/TL is current assets over total liabilities. CL/TA is current liabilities over total assets. NCI is the no-credit interval calculated as (quick assets – current liabilities) / ((sales – profit before tax – depreciation) / 365). MV/MVTL is the part of the Naïve DD in Bharat and Shumway (2008). The last month return for failed firms is 100%. Per model we run 300 monthly regressions. We report average coefficients and the t-statistics in brackets below.

Model	γ1	γ2	γ3	γ4	γ5	γ6	γ7	γ8	γ9	γ10	γ11	γ12	γ13	γ14
	Beta	**SIZE**	**BM**	**PYR**	**NITA**	**TLTA**	**EXRET**	**SIGMA**	**RSIZE**	**PBT/CL**	**CA/TL**	**CL/TA**	**NCI**	**MV/MVTL**
Model 1	-0.13	-0.03	0.22	0.41										
	(1.75)	(0.51)	(2.78)	(2.44)										
Model 2	-0.11		0.17		1.68	-0.24	0.47	-0.38	-0.09					
	(1.70)		(1.82)		(2.23)	(0.77)	(2.21)	(1.48)	(1.62)					
Model 3	-0.08	-0.09	0.18	0.34	1.77	-0.25		-0.42						
	(1.22)	(1.67)	(1.89)	(2.45)	(2.34)	(0.79)		(1.47)						
Model 4	-0.11	-0.03	0.25	0.32						0.58	-0.02	0.47	0.00	
	(1.63)	(0.59)	(2.77)	(1.99)						(2.76)	(0.25)	(1.59)	(2.58)	
Model 5	-0.10	-0.08	0.20				0.53	-0.52						0.13
	(1.61)	(1.50)	(2.58)				(2.50)	(1.90)						(0.43)

Table 6 Pricing Analysis: Distress and Profitability

This table presents cross-sectional regressions on individual stock returns. The models are specifications of the Fama and MacBeth method (1973). At the end of each September from 1985 to 2010 we take the independent variable of each firm and regress it against the firm's subsequent twelve month returns. Independent variables are: Beta is beta factor calculated for each firm according to Dimson (1979) over the previous twelve months with a two months-time lag. SIZE is the log of market capitalisation. BM is the log of book-equity over market value of common equity. PYR is the prior-year-return. O_Z-score is the Z-score obtained from Agarwal and Taffler (2007) orthogonalised by PBT/CL and NCI. O_Shum is the score obtained from Shumway (2001) orthogonalised by NITA. Naïve DD is the score obtained from the model in Bharat and Shumway (2008). Scores are winsorised at ±18.4207. PBT/CL 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). NITA is net income over total assets. Variables are winsorised at the 5th and 95th percentile across all observations. The last month return for failed firms is -100%. Per model we run 300 monthly regressions. We report average coefficients and the t-statistics in brackets below.

Model	**γ1 Beta**	**γ2 Size**	**γ3 BM**	**γ4 PYR**	**γ5 O_Z-score**	**γ6 O_Shum**	**γ7 Naïve DD**	**γ8 PBT/CL**	**γ8 NCI**	**γ8 NITA**
Model 1	-0.13	-0.03	0.22	0.41						
	(1.75)	(0.51)	(2.78)	(2.44)						
Model 2	-0.13	-0.03	0.22	0.41	0.00					
	(1.80)	(0.48)	(2.61)	(2.49)	(0.13)					
Model 3	-0.11	-0.05	0.21	0.35	0.00			0.51		
	(1.61)	(0.92)	(2.51)	(2.22)	(0.21)			(2.72)		
Model 4	-0.12	-0.04	0.21	0.33	0.00			0.47	0.00	
	(1.69)	(0.76)	(2.52)	(2.05)	(0.20)			(2.42)	(1.97)	
Model 5	-0.13	-0.03	0.22	0.40		-0.04				
	(1.76)	(0.53)	(2.75)	(2.37)		(1.34)				
Model 6	-0.11	-0.05	0.22	0.35		-0.04				1.90
	(1.55)	(1.00)	(2.72)	(2.15)		(1.46)				(2.23)
Model 7	-0.11	-0.05	0.21	0.34		-0.04		0.52		
	(1.57)	(0.98)	(2.64)	(2.11)		(1.48)		(2.75)		
Model 8	-0.11	-0.04	0.21	0.32		-0.04		0.48	0.00	
	(1.66)	(0.82)	(2.65)	(1.95)		(1.57)		(2.46)	(1.89)	
Model 9	-0.10	-0.07	0.23	0.27			-0.01	0.48		
	(1.53)	(1.28)	(2.85)	(1.79)			(1.25)	(2.69)		
Model 10	-0.11	-0.06	0.22	0.26			-0.01	0.45	0.00	
	(1.66)	(1.10)	(2.82)	(1.76)			(0.98)	(2.44)	(1.63)	
Model 11	-0.10	-0.08	0.24	0.25			-0.02			1.63
	(1.49)	(1.38)	(2.97)	(1.70)			(1.62)			(2.01)

Table 7 Correlations: Pricing Factors

This table presents correlation coefficients of the monthly pricing factors for time-series regressions from October 1985 to September 2010. The lower-left side of the matrix presents Spearman rank correlation coefficients. The upper-right side of the matrix presents Pearson correlation coefficients. At the end of each September from 1985 to 2009, we form the pricing portfolios PMU, SMB, HML and WML following Fama and French (1996) and Carhart (1997). At the end of each September from 1985 to 2009 we rank all stocks on SIZE (market capitalization) and sort them into two equally populated portfolios. RmRf is the monthly return difference of the FTSE All Share index and the three-month UK Treasury Bill. We independently rank the stocks on BM (PYR, PBT/CL) and sort them into three portfolios using the 30th and 70th percentile. Six portfolios are then formed at the intersections of the Size-BM (PYR, PBT/CL) break-points. We calculate value-weighted monthly portfolio excess returns for the subsequent twelve months (October year t to September year t+1). SMB is the difference between average returns of the three small and the three large portfolios on the SIZE-BM-sort (equally weighted). HML (WML, PMU) is the difference between average returns of the two high and the two low BM (PYR, PBT/CL) portfolios (equally weighted). BM is book- over market-value of common equity. PYR is the prior-year-return. PBT/CL is profit before tax over current liabilities. HML (WML, PMU) is high BM (PYR, PB/CL) minus low BM (PYR, PB/CL). The last month return for failed firms is -100%.

Spearman/Pearson Correlation Matrix					
	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
UMD	-0.09	-0.06	-0.45	1	0.12
PMU	-0.33	-0.41	0.07	0.13	1

Table 8 Information of Additional Profitability Factor

This table presents results from time-series regressions on portfolio returns. At the end of each September from 1985 to 2009, we form the pricing portfolios PMU, SMB, HML and WML following Fama and French (1996) and Carhart (1997). At the end of each September from 1985 to 2009 we rank all stocks on SIZE (market capitalization) and sort them into two equally populated portfolios. RmRf is the monthly return difference of the FTSE All Share index and the three-month UK Treasury Bill. We independently rank the stocks on BM (PYR, PBT/CL) and sort them into three portfolios using the 30th and 70th percentile. Six portfolios are then formed at the intersections of the Size-BM (PYR, PBT/CL) break-points. We calculate value-weighted monthly portfolio excess returns for the subsequent twelve months (October year t to September year t+1). SMB is the difference between average returns of the three small and the three large portfolios on the SIZE-BM-sort (equally weighted). HML (WML, PMU) is the difference between average returns of the two high and the two low BM (PYR, PBT/CL) portfolios (equally weighted). BM is book- over market-value of common equity. PYR is the prior-year-return. PBT/CL is profit before tax over current liabilities. HML (WML, PMU) is high BM (PYR, PB/CL) minus low BM (PYR, PB/CL). The last month return for failed firms is -100%.

Model	**Dep. Var**	**Alpha**	**RmRf**	**SMB**	**HML**	**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)

Table 9 Pricing Analysis: New Five Factor Model on Distress Portfolios

This table presents results from time-series regressions on portfolio returns. At the end of each September from 1985 to 2009, all stocks in our sample are ranked on the default probability and sorted into decile portfolios from Low to High. Shum is the probability obtained from the model in Shumway (2001), Z-score is the probability obtained from the model in Agarwal and Taffler (2007), Naïve DD is the probability obtained from the model in Bharat and Shumway (2008). All represents all stocks in our sample and H-L is the return difference of the High and Low portfolio. Returns are monthly value-weighted average portfolio excess returns. We report intercepts and t-statistics as well as adjusted R^2 for Carhart Model (1997) i.e. RmRf, SMB, HML and WML and the Carhart model complemented by PMU that is a factor mimicking the profitability effect. RmRf is the monthly return difference of the FTSE All Share index and the three-month UK Treasury Bill. We independently rank the stocks on BM (PYR, PBT/CL) and sort them into three portfolios using the 30th and 70th percentile. Six portfolios are then formed at the intersections of the Size-BM (PYR, PBT/CL) break-points. We calculate value-weighted monthly portfolio excess returns for the subsequent twelve months (October year t to September year t+1). SMB is the difference between average returns of the three small and the three large portfolios on the SIZE-BM-sort (equally weighted). HML (WML, PMU) is the difference between average returns of the two high and the two low BM (PYR, PBT/CL) portfolios (equally weighted). BM is book- over market-value of common equity. PYR is the prior-year-return. PBT/CL is profit before tax over current liabilities. HML (WML, PMU) is high BM (PYR, PB/CL) minus low BM (PYR, PB/CL). The last month return for failed firms is -100%.

Var	Low	2	3	4	5	6	7	8	9	High	All	H-L
Panel A. Shum												
Carhart Model												
a	0.22	0.13	0.10	0.12	-0.06	-0.03	-0.24	-0.01	-0.24	-0.49	0.09	-0.71%
t-Stat a	2.25	1.28	0.89	0.83	-0.42	-0.20	-1.03	-0.05	-1.02	-1.61	1.23	-2.26
Adj R2	0.88	0.88	0.86	0.82	0.85	0.81	0.66	0.74	0.79	0.69	0.94	0.52
Five Factor Model												
a	0.15	0.09	0.08	0.15	0.02	0.05	-0.05	0.16	-0.07	-0.20	0.08	-0.35%
t-Stat a	1.49	0.89	0.68	1.03	0.12	0.32	-0.20	0.76	-0.31	-0.67	1.13	-1.14
Adj R2	0.89	0.89	0.86	0.82	0.85	0.82	0.68	0.76	0.79	0.71	0.94	0.57
Panel B. Z-score												
Carhart Model												
a	0.17	0.24	0.17	0.18	0.15	0.07	0.07	-0.11	0.03	-0.40	0.09	-0.57%
t-Stat a	0.92	1.95	1.45	1.53	1.29	0.56	0.55	-0.76	0.18	-2.02	1.23	-2.08
Adj R2	0.72	0.84	0.87	0.84	0.87	0.85	0.84	0.80	0.75	0.71	0.94	0.04
Five Factor Model												
a	0.07	0.13	0.10	0.14	0.10	0.05	0.12	-0.03	0.24	-0.13	0.08	-0.20%
t-Stat a	0.37	1.05	0.83	1.16	0.86	0.41	0.96	-0.23	1.49	-0.71	1.13	-0.78
Adj R2	0.72	0.85	0.87	0.85	0.87	0.84	0.84	0.81	0.78	0.75	0.94	0.18
Panel C. Naïve DD												
Carhart Model												
a	0.18	0.31	0.24	0.04	-0.04	0.10	-0.20	-0.41	0.00	-0.35	0.09	-0.53%
t-Stat a	1.61	2.91	2.32	0.37	-0.30	0.63	-1.28	-1.93	0.00	-1.31	1.23	-1.86
Adj R2	0.85	0.86	0.88	0.89	0.85	0.81	0.81	0.75	0.72	0.73	0.94	0.54
Five Factor Model												
a	0.15	0.27	0.21	-0.03	-0.03	0.13	-0.21	-0.32	0.24	-0.20	0.08	-0.35%
t-Stat a	1.34	2.48	2.03	-0.29	-0.20	0.86	-1.31	-1.47	0.93	-0.74	1.13	-1.22
Adj R2	0.85	0.86	0.88	0.89	0.85	0.81	0.81	0.75	0.74	0.74	0.94	0.56

Table 10 Pricing Analysis: New Five Factor Model on Distress-Profitability Portfolios

This table presents results from time-series regressions on portfolio returns. Portfolios are formed: At the end of each September from 1985 to 2009, all stocks in our sample are ranked on the default probability and sorted into tertial portfolios Low, Medium and High. We repeat this for PBT/CL that is profit before tax over current liabilities. We form nine portfolios at the intersections of the two sorts. All represents all stocks in our sample and H-L is the return difference of the High and Low portfolio in each column/row. Min is minimum. In Panel A. we report portfolio characteristics for sorts on Z-score and PBT/CL: Returns shows monthly value-weighted portfolio excess returns of the subsequent twelve months. Distribution gives the average number of firms per portfolio and Min returns the minimum number of firms during the sample period. Measure at the end of September each year is Size that is market capitalisation, BM that is book- over market-value of equity and PYR that is prior-year-return. Size and BM are winsorised at the 5^{th} and 95^{th} percentile across all observations. In Panel B. we report regression results for sorts on Shum, Z-score, Naïve DD and PBT/CL. We report intercepts and t-statistics in brackets below for regressions with the Carhart model (1997) and our new factor model (i.e. Carhart amended by a profitability factor PMU). GRS is the *F*-statistic from Gibbons, Ross and Shanken (1989). PBT/CL that is profit before tax over current liabilities. Shum is the probability obtained from the model in Shumway (2001), Z-score is the probability obtained from the model in Agarwal and Taffler (2007), Naïve DD is the probability obtained from the model in Bharat and Shumway (2008). The last month return for failed firms is -100%.

Panel A. Portfolio Characteristics

Failures	**PBT/CL**				
Z-score	**Low**	**Med**	**High**	**All**	**H-L**
Low	0.5	0.4	0.1	0.2	-0.4
Med	0.2	0.4	0.2	0.3	0.0
High	3.1	0.4	0.0	2.3	-3.1
All	2.3	0.4	0.1	**0.9**	-2.2
H-L	2.5	0.0	-0.1	2.1	-2.7

Distribution	**PBT/CL**				
Z-score	**Low**	**Med**	**High**	**Min**	
Low	23	50	224	13	
Med	58	179	59	29	
High	215	68	13	4	
Min	13	21	4	**4**	
Total					22,217

Beta	**PBT/CL**				
Z-score	**Low**	**Med**	**High**	**All**	**H-L**
Low	1.4	1.0	1.0	1.0	-0.4
Med	1.2	1.1	1.0	1.1	-0.2
High	1.3	1.1	0.9	1.2	-0.3
All	1.3	1.1	1.0	**1.1**	-0.2
H-L	-0.2	0.1	-0.1	0.2	0.1

Size	**PBT/CL**				
Z-score	**Low**	**Med**	**High**	**All**	**H-L**
Low	148	223	406	355	258
Med	183	370	626	384	443
High	165	408	406	232	240
All	167	354	449	**324**	282
H-L	18	186	0	-124	-18

BM	**PBT/CL**				
Z-score	**Low**	**Med**	**High**	**All**	**H-L**
Low	1.14	0.96	0.65	0.74	-0.49
Med	1.06	0.67	0.49	0.71	-0.57
High	0.86	0.52	0.83	0.78	-0.03
All	0.92	0.69	0.63	**0.75**	-0.30
H-L	-0.28	-0.44	0.18	0.04	0.46

PYR	**PBT/CL**				
Z-score	**Low**	**Med**	**High**	**All**	**H-L**
Low	0.06	0.15	0.18	0.17	0.13
Med	0.11	0.16	0.17	0.15	0.05
High	0.06	0.17	0.20	0.09	0.14
All	0.07	0.16	0.18	**0.14**	0.11
H-L	0.00	0.02	0.02	-0.08	0.01

Table 10 Pricing Analysis: New Five Factor Model on Distress-Profitability Portfolios contd.

Panel B. Portfolio Regressions

Carhart	PBT/CL				
Shum	**Low**	**Med**	**High**	**All**	**H-L**
Low	-0.05	0.08	0.27	0.19	0.32
	(0.26)	(0.86)	(3.02)	(2.52)	(1.79)
Med	-0.34	-0.166	0.08	-0.17	0.42
	(1.89)	(1.14)	(0.48)	(1.44)	(1.86)
High	-0.38	-0.185	-0.35	-0.33	0.03
	(1.62)	(0.83)	(1.19)	(1.73)	(0.09)
All	-0.23	0.0051	0.23	**0.07**	0.47
	(1.71)	(0.05)	(2.71)	**(0.90)**	(3.12)
H-L	-0.33	-0.269	-0.62	-0.52	-0.28
	(1.17)	(1.15)	(2.05)	(2.64)	(0.75)
GRS	2.17	***p***	0.024		

Carhart	PBT/CL				
Z-score	**Low**	**Med**	**High**	**All**	**H-L**
Low	-0.55	0.10	0.25	0.20	0.80
	(1.43)	(0.58)	(2.53)	(2.13)	(2.08)
Med	-0.12	0.032	0.15	0.08	0.28
	(0.58)	(0.30)	(1.35)	(0.86)	(1.15)
High	-0.20	-0.117	0.02	-0.14	0.21
	(1.27)	(0.90)	(0.06)	(1.28)	(0.78)
All	-0.23	0.0051	0.23	**0.07**	0.47
	(1.71)	(0.05)	(2.71)	**(0.90)**	(3.12)
H-L	0.36	-0.214	-0.23	-0.33	-0.59
	(0.86)	(1.13)	(0.87)	(2.68)	(1.21)
GRS	1.83	***p***	0.063		

Carhart	PBT/CL				
Naive DD	**Low**	**Med**	**High**	**All**	**H-L**
Low	0.26	0.18	0.39	0.31	0.13
	(1.43)	(1.77)	(3.95)	(3.62)	(0.75)
Med	-0.35	-0.1	-0.03	-0.13	0.32
	(2.07)	(0.79)	(0.19)	(1.30)	(1.69)
High	-0.73	-0.245	-0.47	-0.50	0.26
	(3.12)	(1.17)	(1.78)	(2.86)	(0.86)
All	-0.23	0.0051	0.23	**0.07**	0.47
	(1.71)	(0.05)	(2.71)	**(0.90)**	(3.12)
H-L	-0.99	-0.424	-0.87	-0.81	0.12
	(3.41)	(1.87)	(3.11)	(4.15)	(0.36)
GRS	3.14	***p***	0.001		

Carhart	PBT/CL				
Shum	**Low**	**Med**	**High**	**All**	**H-L**
Low	-0.11	0.07	0.23	0.15	0.34
	(0.62)	(0.75)	(2.55)	(2.01)	(1.89)
Med	-0.26	0.01	0.29	-0.01	0.54
	(1.42)	(0.10)	(1.74)	(0.12)	(2.40)
High	-0.20	0.11	-0.15	-0.11	0.05
	(0.85)	(0.49)	(0.51)	(0.59)	(0.14)
All	-0.17	0.05	0.23	**0.09**	0.41
	(1.23)	(0.56)	(2.68)	**(1.23)**	(2.67)
H-L	-0.09	0.03	-0.38	-0.26	-0.29
	(0.31)	(0.14)	(1.26)	(1.40)	(0.75)
GRS	1.51	***p***	0.143		

Carhart	PBT/CL				
Z-score	**Low**	**Med**	**High**	**All**	**H-L**
Low	-0.58	0.18	0.25	0.21	0.83
	(1.46)	(1.02)	(2.52)	(2.17)	(2.11)
Med	-0.03	0.08	0.17	0.10	0.20
	(0.13)	(0.69)	(1.46)	(1.15)	(0.81)
High	-0.13	-0.05	-0.04	-0.09	0.09
	(0.82)	(0.38)	(0.15)	(0.79)	(0.34)
All	-0.17	0.05	0.23	**0.09**	0.41
	(1.23)	(0.56)	(2.68)	**(1.23)**	(2.67)
H-L	0.45	-0.23	-0.29	-0.29	-0.74
	(1.06)	(1.16)	(1.07)	(2.29)	(1.49)
GRS	1.62	***p***	0.109		

Carhart	PBT/CL				
Naive DD	**Low**	**Med**	**High**	**All**	**H-L**
Low	0.14	0.13	0.30	0.23	0.16
	(0.76)	(1.31)	(3.05)	(2.66)	(0.90)
Med	-0.27	0.01	0.12	-0.01	0.39
	(1.60)	(0.09)	(0.94)	(0.13)	(2.02)
High	-0.49	0.04	-0.14	-0.21	0.35
	(2.12)	(0.19)	(0.53)	(1.32)	(1.14)
All	-0.17	0.05	0.23	**0.09**	0.41
	(1.23)	(0.56)	(2.68)	**(1.23)**	(2.67)
H-L	-0.62	-0.10	-0.44	-0.43	0.19
	(2.24)	(0.45)	(1.69)	(2.57)	(0.53)
GRS	1.92	***p***	0.049		

Carhart+PMU	PBT/CL				
Shum	**Low**	**Med**	**High**	**All**	**H-L**
Low	0.12	0.07	0.12	0.10	-0.01
	(0.74)	(0.70)	(1.33)	(1.34)	(0.05)
Med	0.06	-0.02	0.20	0.06	0.15
	(0.36)	(0.15)	(1.22)	(0.48)	(0.73)
High	0.18	0.11	-0.25	0.14	-0.44
	(0.87)	(0.51)	(0.85)	(0.79)	(1.28)
All	0.16	0.05	0.12	**0.08**	-0.04
	(1.52)	(0.50)	(1.44)	**(1.13)**	(0.47)
H-L	0.06	0.04	-0.37	0.03	-0.43
	(0.21)	(0.18)	(1.20)	(0.20)	(1.09)
GRS	0.63	***p***	0.773		

Carhart+PMU	PBT/CL				
Z-score	**Low**	**Med**	**High**	**All**	**H-L**
Low	-0.32	0.31	0.12	0.11	0.44
	(0.81)	(1.82)	(1.30)	(1.20)	(1.15)
Med	0.27	0.07	0.08	0.09	-0.19
	(1.33)	(0.62)	(0.70)	(0.99)	(0.84)
High	0.22	-0.09	-0.03	0.06	-0.26
	(1.79)	(0.68)	(0.14)	(0.58)	(0.98)
All	0.16	0.05	0.12	**0.08**	-0.04
	(1.52)	(0.50)	(1.44)	**(1.13)**	(0.47)
H-L	0.54	-0.40	-0.16	-0.05	-0.70
	(1.27)	(2.09)	(0.58)	(0.47)	(1.39)
GRS	1.17	***p***	0.317		

Carhart+PMU	PBT/CL				
Naive DD	**Low**	**Med**	**High**	**All**	**H-L**
Low	0.34	0.11	0.20	0.19	-0.14
	(1.95)	(1.09)	(2.09)	(2.19)	(0.86)
Med	-0.01	0.01	0.00	-0.01	0.01
	(0.09)	(0.08)	(0.01)	(0.13)	(0.08)
High	-0.08	0.01	-0.21	-0.08	-0.12
	(0.42)	(0.06)	(0.81)	(0.51)	(0.44)
All	0.16	0.05	0.12	**0.08**	-0.04
	(1.52)	(0.50)	(1.44)	**(1.13)**	(0.47)
H-L	-0.43	-0.10	-0.41	-0.27	0.02
	(1.54)	(0.47)	(1.56)	(1.62)	(0.05)
GRS	0.93	***p***	0.502		

7 Appendix A

Failure Prediction: Information Content Measures

This table presents information content tests using a logit regression function. At the end of each September from 1985 to 2010 we take the independent variable of each firm and regress it against the firm's status (binary code; 1 the firm failed in the subsequent twelve month returns, 0 if not). Independent variables are: Rate is the sample failure rate over the previous twelve months. Beta is beta factor calculated for each firm according to Dimson (1979) over the previous twelve months with a two months-time lag. SIZE is the log of market capitalisation. BM is the log of book-equity over market value of common equity. PYR is the prior-year-return. Variables are winsorised at the 5^{th} and 95^{th} percentile across all observations. Shum is the score obtained from the model in Shumway (2001). Z-score is the Z-score obtained from the model in Agarwal and Taffler (2007). Naïve DD is the score obtained from the model in Bharat and Shumway (2008). Scores are winsorised at ±18.4207. We report coefficients and Wald statistic in brackets below. The Wald statistic is adjusted for multiple observations per firm by dividing by 9.15, the average number of observations per firm.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.73	-0.65	-1.15	-0.80	-0.41	-0.98
	(0.87)	(0.88)	(1.24)	(0.80)	(0.46)	(0.94)
Rate	0.09	0.01	0.04	-0.08	-0.10	-0.09
	(0.26)	(0.04)	(0.11)	(0.22)	(0.28)	(0.24)
Beta				0.13	0.13	0.13
				(0.92)	(0.95)	(0.93)
SIZE				0.03	0.05	0.02
				(0.13)	(0.25)	(0.09)
BM				0.29	0.22	0.26
				(1.42)	(1.04)	(1.22)
PYR				-0.11	0.03	-0.04
				(0.20)	(0.07)	(0.07)
Shum	0.88	0.83	0.71	0.86	0.93	0.78
	(5.28)	(4.21)	(3.06)	(3.32)	(3.48)	(2.60)
Z-score	-0.02		-0.03	-0.03		-0.04
	(0.72)		(0.89)	(1.08)		(1.11)
Naïve DD		0.06	0.07		0.03	0.04
		(0.86)	(0.99)		(0.43)	(0.49)
Observations	22,217	22,217	22,217	22,217	22,217	22,217
Log-likelihood	-910.2	-908.8	-905.2	-894.9	-899.3	-893.8
Pseudo R^2	23.68	23.80	24.10	24.96	24.59	25.05