Does financial distress risk drive the momentum anomaly?

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Abstract

This paper brings together the evidence on two asset pricing anomalies – continuation of prior returns (momentum) and the market mispricing of distressed firms, using UK data. Our analysis demonstrates both these effects are driven by market underreaction to financial distress risk. In particular, we find momentum is proxying for distress risk, and is largely subsumed by our distress risk factor. We also find, as with US studies, no evidence that size and B/M effects in stock returns are linked to financial distress.

JEL classification: G12, G14, G33

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I. INTRODUCTION

Market pricing of distress risk has attracted a lot of academic interest since the financial distress factor hypothesis of Chan and Chen (1991) and Fama and French (1992) attributed higher returns to small stocks and value stocks to such firms being relatively distressed.[1] If risk of financial distress is pervasive and missed by the standard CAPM, we would observe either a positive or negative risk premium on distressed stocks. A positive risk premium would exist if distress risk is correlated with other factors (such as size and book-to-market (B/M)) but is missed by the market factor or the market overreacts to bankruptcy risk. A negative risk premium would be observed if investors underreact to risk of failure leading to the stock prices of such firms not being discounted sufficiently or due to lower systematic risk. If the market does underreact to bankruptcy risk, distressed firms will have low prior-year returns and such low returns will continue for some time into the future generating a negative financial distress risk premium and continuation of prior returns (momentum). This paper specifically tests whether momentum proxies for distress risk in the UK. Importantly, such a financial distress explanation for the continuation of prior returns anomaly has not been explored in the literature to date.

The existence of medium-term continuation of stock returns (momentum), the most challenging of all anomalies (Fama, 1998), is well established (see e.g., Jegadeesh and Titman, 1993 and 2001; Liu et al., 1999). Jegadeesh and Titman (1993, 2001) and other studies (e.g., Daniel and Titman, 1999; Hong et al., 2000) argue momentum is driven by

[1] Following Fama and French (1993, 1995) we define the term distress factor as representing individual firm financial distress. As such, we use the terms financial distress and bankruptcy risk interchangeably.

market underreaction to information. According to Barberis et al. (1998), investors are slow to update their beliefs in response to new public information leading to underreaction, and this generates positive autocorrelation in stock returns. Beaver (1968) first shows subsequently bankrupt firms underperform the market for up to four years prior to bankruptcy, and particularly during the last year. This suggests that the market is anticipating, but not fully incorporating (i.e. underreacting to), the deteriorating financial health of a firm and distressed firms, therefore, experience lower past realized returns. Hong et al. (2000) and Lesmond et al. (2004) find most of momentum profits come from the returns continuation of poor performers, and Campbell et al. (2006) show that prior year return is a significant predictor of subsequent bankruptcy. This implies momentum is capturing financial distress risk, an important issue not directly addressed in the existing literature. Hence, if the market underreacts to the poor solvency position of firms, we should find that (i) distressed stocks earn lower returns than non-distressed stocks as the market slowly realizes its error and drives down distressed stock prices, and (ii) medium-term continuation of returns is driven by the lower returns earned by distressed stocks.

The only other paper that focuses on the relation between momentum and credit risk is Avramov et al. (2007a) who show that momentum exists only in poorly rated firms, and the underperformance of poor credit risk firms is driven by continuation of low returns for losers. However, Avramov et al.'s sample is restricted to firms that have a credit rating (less than 30% of all firms), and they do not conduct any formal cross-section tests of the relation between credit risk and momentum. Surprisingly, the authors also argue that credit ratings are not the same as default risk, which they suggest is better proxied by leverage.

Linking size and B/M effects to financial distress is consistent with observed high failure rates of small and value stocks since such stocks do earn higher returns (e.g., Fama and French, 1992 and 1993; Strong and Xu, 1997). On this basis, we would expect that (i) distressed stocks earn higher returns than non-distressed stocks, and (ii) there is no size or value effect in stock returns once we control for distress risk.

There is substantial evidence that distressed firms earn lower returns than non-distressed firms. Dichev (1998) finds firms with high probability of bankruptcy on average underperform low risk firms by 1.2% per month over the period 1980-95. He concludes such evidence is hard to reconcile with the pricing of risk in efficient markets and mispricing is a more likely explanation for such anomalous results. Similarly, Lamont et al. (2001), using the Kaplan and Zingales (1997) financial constraints index, find that even though financially constrained firms have characteristics associated with higher returns (high leverage, high B/M, high prior-year returns), they earn lower returns than non-constrained firms. Though their index does not directly measure financial distress, financially constrained firms are more likely to face financial distress than non-constrained firms. Griffin and Lemmon (2002), Ferguson and Shockley (2003) and Campbell et al. (2006) also find distressed firms earn lower returns. In contrast, Vassalou and Xing (2004), adopting a contingent claims approach, find distressed firms earn higher returns. However, Garlappi et al. (2006), using the related EDF measure provided by Moody’s KMV, find no significant difference in returns between distressed and non-distressed firms. Nonetheless, none of these studies explore a potential link between the distress risk and the medium term continuation of prior returns market anomalies, the original contribution of this paper.

We employ a widely-used accounting-ratio based z-score model as a proxy for default risk as with Dichev (1998), Griffin and Lemmon (2002), and Ferguson and Shockley (2003).[2] The main results of our paper are: (i) consistent with a market underreaction story, distress risk appears to have a negative risk premium, (ii) the momentum effect in stock returns is proxying for distress risk and is subsumed by a financial distress factor, and (iii) in contrast to the arguments of Fama and French (1993, 1995), among others, and consistent with Dichev (1998) and Campbell et al. (2006), there is no evidence to suggest size and B/M are capturing bankruptcy risk.

The paper is organized as follows: section 2 provides our hypotheses, data and method, section 3 presents our results using time-series regressions, and section 4 our results using cross-section regressions. Concluding section 5 summarises and discusses our findings.

2. HYPOTHESES, DATA AND METHOD

This section presents our hypotheses, discusses our sample selection and data, and describes how we use the Fama and French (1993) three-factor model and Fama and MacBeth (1973) method to test our hypotheses.

(i) Hypotheses

This paper sets out to establish if three key market anomalies, size, B/M and momentum can be explained by firm financial distress risk. Chan and Chen (1991) and Fama and French (1992), among others, argue that smaller firms and high B/M firms are relatively

[2] Agarwal and Taffler (2007a) show that the z-score measure we use performs at least as well as the contingent claims approach in predicting financial distress.

distressed, and higher returns on such firms are a compensation for this risk (the financial distress factor hypothesis). On this basis, we expect that (i) controlling for size (B/M), distressed stocks will earn a higher return than non-distressed stocks, and (ii) controlling for distress risk, low market capitalization (high B/M) firms will not outperform high market capitalization (low B/M) stocks.

To test the distress factor proposition formally, we establish the following null hypotheses:

$H1_0$: *Distressed stocks do not outperform non-distressed stocks*.

$H2_0$: *Controlling for distress risk, small (high B/M) firms will outperform large (low B/M) stocks*.

If we are able to reject these null hypotheses then we have evidence, consistent with the arguments of Chan and Chen (1991) and Fama and French (1992), that the size and B/M factors are proxying for bankruptcy risk.

On the other hand, if the market underreacts to financial distress risk (the market underreaction hypothesis), as Dichev (1998) and others suggest, then we would expect distressed stocks to underperform non-distressed stocks. In addition, if the medium-term continuation of returns is due to delays in the market assimilating distress risk then we would anticipate momentum only appearing in distressed stocks. To test this market underreaction proposition, we establish two further null hypotheses:

$H3_0$: *Distressed stocks do not underperform non-distressed stocks*.

$H4_0$: *Medium-term continuation of returns is the same for distressed and non-distressed stocks*.

(ii) Sample Selection

This study covers all non-finance industry UK firms listed on the London Stock Exchange (LSE) at any time during the period 1979-2002. [3] If a firm changes industry or exchange of listing, it enters the respective portfolio only after it has been listed on the (main) London Stock Exchange and/or is classified as non-financial for twenty-four months. If the exchange and/or industry change during the holding period, returns after the change are deleted.

To be included in the sample, firms are required to meet three additional conditions:

(1) they should have positive book value because interpretation of negative book-to-market ratios is problematic. The number of negative book value firms till 1990 is small (between 1 and 14 a year); although, during the 1990s the number of such firms increases ranging from 28 to 53 a year. Almost all negative book value firms have bankrupt z-scores.[4]

(2) they should have been listed for at least 24 months before the portfolio formation date due to the data requirement for beta estimation. This constraint also ensures that only post-listing accounting information is used; and

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3 A firm that belongs to any of the following categories in any month is excluded from the population for that month: secondary stocks of existing firms, foreign stocks, or firms traded on the Unlisted Securities Market, Alternative Investment Market (AIM), third market, or over-the-counter. Additionally, a firm that is classified under Financials or Mining Finance by the London Stock Exchange during any month is also excluded for that month.

4 We repeat all our time-series analyses including negative B/M firms and find our results are unchanged. The results are not reported here for brevity but are available from the first author.

(3) they should have been traded in at least 9 of the 12 months subsequent to portfolio formation to circumvent any potential thin trading problem. This rule does not apply to firms that do not survive the holding period.[5]

The last month return for firms that enter into bankruptcy (administration, receivership or creditors' voluntary liquidation etc.) is set to –100% in all but one case.[6] To ensure the required accounting information is available at the time of portfolio formation, a five-month lag between the fiscal year-end date and the reporting date is assumed. So, for the portfolio formed on 30th September,[7] book value of equity and z-score are derived from the latest available financial statements with fiscal year-end on or before April 30th. The final sample consists of 2,459 firms and a total of 22,774 firm years. The yearly number of stocks in the sample ranges from a minimum of 810 in 1992 to a maximum of 1,258 in 1981.

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5 The number of firms excluded is high in the first two years of our sample period and thereafter ranges between 11 and 42 a year. However, the number of financially distressed firms excluded on this criterion is not disproportionately high.

6 The UK bankruptcy regime differs significantly to Chapter 11 in the US (see Franks et al., 1996 for a detailed analysis) and it is very rare indeed for stockholders to receive any terminal distribution (Kaiser, 1996). In fact, there was only one case in our sample period, Railtrack, in which equity holders were promised (by the government) any payout after all creditor claims were met.

7 We choose September 30th rather than June 30th as the portfolio formation date because unlike in the US, in the UK year-ends are more diffuse. While 37% of the firms in our sample have December year-ends, about the same number of firms have year-ends between January and April with approximately 22% of the firms having March year-ends.

(iii) Data

We use z-score as a proxy for distress risk. Following Altman (1968), the z-score of a firm is derived as a weighted sum of a set of pre-defined accounting ratios. Firms with z-scores above a pre-determined cut-off rarely fail while the incidence of failure is high in firms with z-scores below this cut-off. The following UK-based z-score model of Taffler (1983, 1984) and Agarwal and Taffler (2007b) employed in this study is derived in a similar way to Altman (1968) using a discriminant modeling approach:

$$z = 3.20 + 12.18{*}x_1 + 2.50{*}x_2 - 10.68{*}x_3 + 0.029{*}x_4 \qquad (1)$$

where

x_1 = profit before tax (PBT)/current liabilities,

x_2 = current assets/total liabilities,

x_3 = current liabilities/total assets, and

x_4 = no-credit interval computed as (quick assets – current liabilities)/((sales – PBT – depreciation)/365).

Using this bankruptcy model, a firm with a computed $z<0$ has a financial profile more similar to previous bankrupt firms and thus itself is at a risk of bankruptcy, whereas $z>0$ indicates a firm not at such risk. The model was developed in 1977, hence derived z-scores are completely out-of-sample. An average of 24.5% of firms in our sample each year are classified as being at risk of bankruptcy.

The accounting data required for z-score and B/M ratio computations is primarily collected from the Thomson Financial *Company Analysis*, EXSTAT, MicroEXSTAT and DATASTREAM databases in that order. For a small number of remaining cases the data is hand collected from the actual annual reports. This procedure enables us to have complete coverage of all eligible firms and, as such, the study is free of survivorship bias.

Monthly stock returns, exchange of listing and firm stock exchange industrial classifications are collected from the London Business School London Share Price Database (LSPD). The risk free rates (1-month Treasury bill (T-Bill) rates) are collected from DATASTREAM.

The list of firm failures is compiled from LSPD (codes 7, 16 and 20), the *Stock Exchange Official Yearbook,* published by Waterlow Specialist Information Publishing, and *CGT Capital Losses* published by FT Interactive.

(iv) Method

To study the link between size, B/M, momentum and bankruptcy risk we form several different portfolios and use both Fama and French (1993) time-series and Fama and MacBeth (1973) cross-sectional regressions. To simplify our analysis, we treat z-score as a binary measure classifying firms into two categories: those with high risk of bankruptcy ($z<0$) and those with low (negligible) risk ($z>0$).[8]

We use the Fama and French (1993) three-factor model to test whether our various portfolios earn superior returns on a risk-adjusted basis:

$$R_{it} - R_{Ft} = \beta_1 + \beta_2 (R_{Mt} - R_{Ft}) + \beta_3 \, SMB_t + \beta_4 \, HML_t + \varepsilon_{it} \tag{2}$$

where:

R_{it} is the equally-weighted return on portfolio i during month t,

[8] We repeat our time-series tests ranking stocks by z-score in our robustness checks section 3(v) below. Our results are qualitatively the same.

R_{Ft} is the 1-month Treasury bill rate at the beginning of month t,

R_{Mt} is the value-weighted return during month t of all non-financial stocks listed on the London Stock Exchange for at least 24 months prior to month t,

SMB_t is the return on the mimicking portfolio for the size factor during month t,

HML_t is the return on the mimicking portfolio for the B/M factor during month t, and

ε_{it} is a mean-zero stochastic error term.

SMB and HML are formed following exactly the same procedure as Fama and French (1993).

To test whether momentum is capturing bankruptcy risk, we also employ Fama and MacBeth (1973) cross-section methodology. Following Fama and French (1992) and Jegadeesh and Titman (1993), our analysis focuses on a three-factor model augmented by z-score and momentum. The following Fama-MacBeth (1973) cross-section regressions are run each month from October 1979 to September 2003 where the binary variable z(0/1) = 0 if z-score is >0, and = 1 if z-score≤ 0:[9]

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\ln(\text{size}_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}\,\text{Mom}_{it-1} + \gamma_{5t}\,z(0/1)_{it-1} + \gamma_{6t}\,z(0/1)_{it-1} * \text{Mom}_{it-1} + \varepsilon_{it} \quad (3)$$

where:

R_{it} is the equally-weighted return on portfolio i during month t,

R_{Ft} is the 1-month Treasury bill rate at the beginning of month t,

[9] Throughout this paper, subscript 't' represents time of portfolio formation and subscript 't-1' shows that the information is available at the time of portfolio formation.

β_{it-1} is the beta of portfolio i estimated at the portfolio formation date,[10]

$\ln(\text{size}_{it-1})$ is the natural logarithm of average market capitalization of common equity of stocks in portfolio i at the portfolio formation date,

$\ln(B/M_{it-1})$ is the natural logarithm of the average of B/M ratios of stocks in portfolio i at the

portfolio formation date. The B/M ratio of each stock is computed as book value of equity (excluding preference capital) plus deferred taxes less minority interests divided by the market capitalization at the time of portfolio formation. To avoid undue influence of outliers on the regressions, the smallest and largest 1% of observations are set equal to 0.01 and 0.99 fractiles respectively.

Mom_{it-1} is the average monthly raw return over the eleven months from October year t-1 to August year t for all the stocks in portfolio i,

$z(0/1)_{it-1} = 1$ if the latest available z-score is negative, 0 otherwise, and

ε_{it} is a mean-zero stochastic error term.

3. DISTRESS RISK FACTOR PROXIES

In this section, we first show z-score predicts bankruptcy, and then present preliminary evidence on the relation between prior-year returns, z-scores, size, B/M and failure rates. We then explore whether size, B/M and/or momentum are proxying for distress risk and demonstrate that neither size nor B/M is related to bankruptcy risk, whereas continuation of prior-year returns is.

[10] We estimate portfolio beta by regressing monthly excess returns over the previous 24 months (before portfolio formation) on each portfolio against monthly excess returns on an equally-weighted market

(i) Is Z-Score a Valid Measure of Bankruptcy Risk?

In our sample, the mortality rate (delisting for any reason) is much higher in firms with negative z-scores than firms with positive z-scores. Approximately 9.4% of all negative z-score firms are delisted within the next twelve months while the mortality rate for positive z-score firms is almost half at 5.1%. The difference in proportions is highly significant (z = 11.5). Also, out of 205 actual bankruptcies, only 11 firms are misclassified as solvent by their z-scores derived on the basis of last available annual accounts. Our sample comprises of 5,786 firm years with negative z-scores and 17,791 firm years with positive z-scores. The conditional probability of failure given a negative z-score is 3.35%, and is significantly different to the base failure rate of 0.87% (z = 20.4). Similarly, the conditional probability of non-failure given a positive z-score is 99.94%, and differs significantly to the base rate of 99.13% (z = 11.6). As such, our z-score variable constitutes a valid ex-ante measure of corporate bankruptcy risk.

(ii) Size, B/M, Momentum, Z-Scores, and Failure Rates

To unearth the potential relation between size, B/M, momentum and distress factor, we form the following three sets of 10 portfolios using two-way sorts:

(1) We rank firms on z-score and group them into two portfolios – one with negative z-score stocks and the other with positive z-score stocks. Securities are then independently ranked on their market capitalization on September 30th of each year and

index. We use Dimson's (1979) method with one lead and one lag to reduce problems of thin trading.

grouped into five portfolios with approximately equal numbers of securities. Ten portfolios are then formed at the intersections of z-score and market capitalization.

(2) We rank firms on z-score and group them into two portfolios – one with negative z-score stocks, and the other with positive z-score stocks. Securities are then independently ranked on their B/M ratio on September 30th of each year and grouped into five portfolios with approximately equal numbers of securities. Ten portfolios are then formed at the intersections of z-score and B/M.

(3) We rank firms on z-score and group them into two portfolios – one with negative z-score stocks and the other with positive z-score stocks. Securities are then independently ranked on their prior 11-month returns, i.e. from October 1st of year t-1 to August 31st of year t, and grouped into five portfolios with approximately equal numbers of securities. Ten portfolios are then formed at the intersections of z-score and prior-year returns.

Table I presents the portfolio-wise distribution of the 205 firms that failed. Panel A clearly shows that around two-thirds of the failures in our sample are in the smallest size quintile, and the failure rate drops with increasing firm size. Panel B, similarly, shows that approximately half of the failed firms are in the highest B/M quintile. Finally, Panel C shows that half of the failures are in the lowest momentum quintile and there is a monotonic relation between momentum and failure rate.

This table provides some preliminary evidence that smaller firms, high B/M firms and low prior-year return firms are more likely to fail and, therefore, have higher financial distress risk. On this basis, each of the three variables is potentially a proxy for a distress risk factor in stock returns.

Table I here

(iii) Size, B/M, and Distress Risk

Panel A of table II presents summary statistics on our portfolios formed on two-way sorts on size and z-score, while the Fama and French (1993) three-factor model (equation 2) regression results are reported in panel B.

Table II here

Panel A shows that distressed firms (z<0) have similar size and B/M ratios to, and higher betas than, non-distressed firms for each size quintile, and hence do not appear to be less risky than non-distressed firms. Consistent with the market underreaction hypothesis, distressed stocks have lower prior-year returns than non-distressed stocks in smaller size portfolios (quintiles 1 and 2). We are unable to reject null hypothesis $H1_0$ as distressed firms do not earn higher returns than non-distressed firms for any size quintile, a result that is consistent with the evidence of Campbell et al. (2006). There is a strong size effect in both, distressed (0.77% per month, t = 2.27) and non-distressed (0.99% per month, t = 3.74) portfolios. However, contrary to the evidence of Vassalou and Xing (2004), the difference in size effect for distressed and non-distressed stocks is not statistically significant (t = 0.88). We are, therefore, unable to reject null hypothesis $H2_0$, as small firms outperform large firms controlling for distress risk. In addition, the z-score effect does not appear to be driven by very small stocks as the returns on distressed (z<0) and non-distressed (z>0) stocks for the smallest size quintile do not differ significantly (t = 1.30).[11]

Panel B clearly shows the standard Fama and French (1993) model has a problem in pricing distressed stocks with the intercepts of three of the five distressed portfolios (2, 3 and 4) being negative and strongly significant. The small non-distressed portfolio earns anomalously high returns during our sample period (0.79% per month, t = 5.19); it is these stocks that appear to be driving the size effect. Distressed stock risk-adjusted returns are significantly lower than non-distressed stock risk-adjusted returns for all but the largest size quintile, on which basis we are again unable to reject null hypothesis $H1_0$. Further, small firms significantly outperform big firms when they are non-distressed (0.90% per month, t = 5.25) and there is also some similar evidence when they are distressed (0.44% per month, t = 1.72). On this basis we are, again, unable to reject null hypothesis $H2_0$, and thus our evidence does not support the argument that the size effect proxies for distress risk.

Panel A of table III provides summary statistics for our portfolios formed on two-way sorts on B/M and z-score, while the Fama and French (1993) three-factor model regression results are reported in panel B.

Table III here

Panel A shows non-distressed stocks are larger than distressed stocks controlling for B/M. Distressed stocks have higher betas than non-distressed stocks for every B/M quintile, and there is an inverse and monotonic relationship between B/M and prior-year returns for both distressed and non-distressed stocks indicating high B/M stocks are loser stocks.

[11] However, the two size quintiles (2 and 3) with significant z-score effect are still small with average market capitalization of under £50 million ($90 million) and trading costs could be substantial for these firms.

Again, we find no evidence that distressed stocks earn higher returns than non-distressed stocks and are unable to reject null hypothesis $H1_0$ for any B/M quintile. Contrary to the distress factor hypothesis of Chan and Chen (1991) and Fama and French (1992), controlling for distress risk there is a strong B/M effect for non-distressed stocks (1.00% per month, t = 4.55) though it is not significant for distressed stocks (0.41% per month, t = 1.38). On this basis, we are again unable to reject null hypothesis $H2_0$ as well. Contrary to Griffin and Lemmon (2002) and Garlappi et al. (2006), we find our z-score effect is independent of B/M as it is not being driven by any particular B/M quintile.

Panel B of table III similarly shows that, contrary to the distress factor hypothesis, distressed stocks earn significantly lower returns than non-distressed stocks for all B/M quintiles except the lowest B/M quintile, and, as such, we are again unable to reject null hypothesis $H1_0$. The B/M effect is clearly non-existent in distressed stocks (-0.01% per month, t = 0.04) but it is very strong (0.70% per month, t = 4.89) in non-distressed stocks. On this basis we are unable to reject null hypothesis $H2_0$ in respect of book-to-market.

Tables II and III, then, do not provide any evidence that higher returns on small stocks and high B/M stocks are due to such stocks being relatively distressed and hence having higher expected returns. Our findings are consistent with those of Dichev (1998), Ferguson and Shockley (2003), and Campbell et al. (2006), that size and value premia are not related to the distress factor.

(iv) Momentum and Distress Risk

The evidence of sub-section (iii) is inconsistent with the distress factor hypothesis for size and book-to-market effects in stock returns. It also indicates a negative premium for distress risk, consistent with market underreaction to distress risk in stock prices. If there is underreaction to such information, we would expect to find a strong relation between momentum and distress risk, distressed stocks are likely to be loser stocks that continue to earn lower returns as market prices slowly incorporate the true solvency position of the firm.[12] Panel A of table IV presents summary statistics for our portfolios formed on two-way sorts on prior-year returns and z-score, while panel B presents the Fama and French (1993) three-factor model regression results.

Table IV here

Panel A shows that controlling for prior-year returns, distressed stocks are smaller than non-distressed stocks and have higher B/M ratios. Consistent with the evidence of Lesmond et al. (2004) both winner and loser stocks are smaller. Importantly, though, null hypothesis $H3_0$, that distressed stocks earn higher returns than non-distressed stocks, is rejected only for the lowest momentum quintile (-0.66% per month, t = 3.12). This set of distressed firms is also the smallest and has the highest B/M ratio, and thus is likely to be the most difficult to value by the market and consequently prone to market underreaction (Daniel and Titman, 1999; Lee, 2001). Similar to Avramov et al. (2007a) for low credit rating firms, the momentum effect is significant only for distressed stocks (0.65% per month, t = 2.17). On this basis, we are forced to reject null hypothesis $H4_0$, medium-term continuation of returns is driven by distressed stocks. Our empirical findings are consistent with momentum and distress risk being related to each other due to market underreaction to the bankruptcy risk of firms – the market underreaction hypothesis.

[12] Medium-term continuation of returns may, of course, be driven by factors additional to bankruptcy risk. We explore this issue explicitly in the next section.

Panel B shows the failure of the Fama and French (1993) model to explain the returns on low prior-year return distressed portfolios. It also demonstrates that the inability of the model to explain medium-term continuation of returns (as documented by Fama (1998), Jegadeesh and Titman (2001) and Liu et al. (1999) among others) is due to very negative subsequent returns on a risk-adjusted basis for distressed loser firms (-0.85% per month (t = 4.56) for the loser quintile, and –0.55% per month (t = 3.34) for the second lowest quintile). Again, we reject null hypothesis $H3_0$ only for the loser portfolio; distressed firms underperform on a risk-adjusted basis only when their prior-year returns have been low, consistent with an underreaction story.

Table IV provides clear evidence of medium-term continuation of returns proxying for distress risk. This market underreaction leads to an apparent negative risk premium on distressed stocks, and also to loser stocks remaining losers.[13] We again also reject null hypothesis $H4_0$, the momentum effect is significant only for distressed firms (1.04% per month (t = 3.90) against 0.29% per month (t = 1.49) for non-distressed firms) with the difference also statistically significant (t = 2.86).

The factor loadings in equation (2)[14] for the three sets of portfolios in panel B of tables II-IV are all consistent with the respective panel As: distressed portfolios uniformly have higher loadings on the three Fama and French (1993) factors than the equivalent non-

[13] These results that momentum is driven by continuing low returns to losers is consistent with the evidence of Hong et al. (2000) and Lesmond et al. (2004). However, they are in sharp contrast to Avramov et al. (2007a) who find their return continuation is primarily driven by low credit-rated winners remaining winners.

[14] Not reported here to save space.

distressed portfolios, confirming once again that although they are riskier stocks, they still earn lower returns.[15]

(v) Robustness Checks

To explore whether z-score has information on a continuous basis or only on a bifurcated one (positive/negative), as considered in this section, we also form portfolios with finer z-score granularity and repeat all analyses on this basis. Specifically, each year we rank our sample stocks on z-score and divide them into two groups - negative z-score stocks and positive z-score stocks. Within each group, we then form three portfolios of approximately equal numbers of securities based on their z-scores. Finally, we independently sort stocks on size (B/M, prior-year returns) and form three portfolios. Three sets of 18 portfolios result at the intersections of z-score and size (z-score and B/M, z-score and prior-year returns). The results of parallel analyses to tables I to IV using z-score on this quasi-continuous basis demonstrate that the returns earned by the three negative z-score portfolios differ little, neither is there any significant difference in returns across the three positive z-score portfolios. [16] Other results are also qualitatively the same. On this basis, we are justified in working with our simple binary split between distressed (negative z-score) and non-distressed (positive z-score) stocks.

Garlappi et al. (2006) find that the overall underperformance of their distressed firms is driven by firms with low B/M and at high distress risk. They explain this in terms of violation of the absolute priority rule in debt renegotiations. In contrast, we find that our

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[15] Campbell et al. (2006) find the same results in the US.

[16] These results are not reported here to save space but are available from the first author.

lower returns to distressed stocks are not driven by low B/M firms at acute risk of bankruptcy. This is not surprising given that violation of absolute priority in the creditor-friendly UK bankruptcy regime is a very rare event indeed.

4. SIZE, B/M, MOMENTUM, AND Z-SCORES: CROSS-SECTIONAL EVIDENCE

The evidence so far shows there is a link between momentum and bankruptcy risk, although this pattern may be being somewhat obscured by the size and B/M factors. As such, we need to conduct multivariate analysis to disentangle the underlying relations. To explore the relation between size, B/M, prior-year returns and z-score in more detail we form 24 portfolios by four-way sorts as follows: at the end of September of each year we first rank firms on their market capitalization and group them into two portfolios using the median as the break point. The stocks are then independently ranked on B/M and grouped into three portfolios – one with the lowest 30%, one with the middle 40% and one with the highest 30% B/M ratios. Securities are then separately ranked on momentum and grouped into two portfolios using the median as the break point and, finally, the stocks are independently ranked on z-score and grouped into two portfolios – one with negative z-score stocks and the other with positive z-score stocks. Twenty-four size, B/M, momentum and z-score portfolios are then formed at the intersections of the two market capitalization, three B/M portfolios, two momentum and two z-score portfolios.[17]

(i) Summary Statistics

Table V presents the failure rates and distribution of failures for our 24 portfolios formed on size, B/M, momentum, and z-score. Panel A shows that for negative z-score stocks, controlling for size and B/M, small low prior-year return stocks are more likely to fail than small high prior-year return stocks. Also, controlling for size and prior-year return, there is a U-shaped relationship between failure rates and B/M. Interestingly, panel B highlights that 43.5% of the failures are negative z-score, low momentum small stocks with high B/M ratios, while such stocks, in fact, constitute just 5.4% of our sample. The table suggests that all three factors could be related to financial distress in some way and thus formal cross-sectional analysis is required to disentangle the inter-relationships.

Table V here

Table VI presents the characteristics of the 24 portfolios formed by our four-way sorts. Panel A provides evidence of medium-term continuation of returns for all the distressed portfolios (z<0) controlling for size and B/M. There is no evidence of momentum for high B/M non-distressed stocks (z>0). It also shows that, controlling for size and B/M,

[17] Fama (1998) points out that the results of many return predictability studies are sensitive to the trading rules employed. To test the robustness of our results we repeat all our analyses using an alternative portfolio formation method which avoids potential data-snooping bias (Lo and MacKinlay, 1990). Twenty-four size, B/M and z-score portfolios are formed at the intersections of the independently sorted four market capitalization, three B/M and two z-score portfolios. Results are essentially identical to our main findings and thus not reported here to save space.

distressed stocks underperform non-distressed stocks for low prior-year return portfolios (except for small size, low B/M stocks). Panel B demonstrates distressed stocks have higher betas than non-distressed stocks, controlling for size, B/M and prior-year return, showing firms with higher bankruptcy risk tend to have higher sensitivity to market movements. Thus, the first two panels of table VI provide preliminary evidence of the momentum effect being driven by distressed stocks, once the effects of size and B/M on stock returns are controlled for.

Table VI here

Panels C and D of table VI show we are largely successful in controlling for size and B/M effects in our portfolio sorts. Panel E shows higher stock return variability for distressed stocks: such stocks exhibit lower prior-year returns than non-distressed stocks for loser portfolios, and higher prior-year returns for winner portfolios.

(ii) The Relation between Momentum and Distress Risk: Regression Evidence

Table VII presents the results for our Fama and MacBeth (1973) cross-section regressions for the 24 portfolios formed on four-way sorts using equation (3). It shows that negative z-score stocks earn lower returns than positive z-score stocks (models (i), (iii), (v) and (vi)), and the coefficient on the z-score binary measure becomes stronger when size, B/M and prior-year returns are present in the pricing equation. [18]

[18] The respective coefficients on the z-score binary measure are -0.24% per month in model (i), -0.29% per month in model (iii) and -0.28% per month in model (v). This result is also consistent with the findings of Dichev (1998) with respect to size and B/M. Ferguson and Shockley (2003) also find high z-score firms earn higher returns than low z-score firms.

Table VII here

The results (model (v)) show that, conditional on beta, size, B/M and prior-year returns, negative z-score portfolios underperform positive z-score portfolios by 28 basis points per month, a difference that is statistically significant (t = 2.34). As such, we are unable to reject null hypothesis $H1_0$ that distressed firms do not earn higher returns than non-distressed firms. However, we reject companion null hypothesis $H3_0$, that distressed firms do not underperform non-distressed firms. There is little evidence of any size effect (save in model (iv) when z-score is omitted but momentum included), while high B/M stocks outperform low B/M stocks by 37 basis points per month (model (v)), a difference that is highly statistically significant (t = 3.45). The presence of z-score in the pricing equation has no influence on either of the size or B/M coefficients (models (ii) and (iii)) indicating there is no common variation between financial distress risk, size or B/M that is linked to stock returns, leading to rejection of null hypothesis $H2_0$ i.e., controlling for distress risk, small (high B/M) firms outperform large (low B/M) firms[19] The coefficient on momentum is 11 basis points per month (t = 3.12) when z-score is excluded from the pricing equation (model (iv)). Importantly, the coefficient on momentum becomes statistically insignificant (5 basis points; t = 1.23) when z-score is included in the pricing equation (model (v)). This clearly shows that medium-term continuation of returns is proxying for distress risk and makes no material contribution to explaining the cross-

[19] Our results are consistent with Dichev (1998) and Ferguson and Shockley (2003). Vassalou and Xing (2004) find contrary results using an option-based approach for assessing the probability of default although their model is problematic (see Bharath and Shumway (2004)). Also, Da and Gao (2006) find that Vassalou and Xing (2004) results are due to first month returns reversal.

section of stock returns once an explicit proxy for distress risk is incorporated in the pricing equation.

Finally, to test null hypothesis $H4_0$ i.e., whether medium-term continuation of returns is driven by distressed stocks, we introduce an interaction dummy between momentum and z-score (model (vi)). We find that there is no momentum effect for non-distressed stocks (0.01% per month, t = 0.20); however there is a strong effect for distressed firms of 0.08% per month with difference highly significant (t = 2.61), leading to the rejection of null hypothesis $H4_0$. The results of table VII thus strongly confirm our earlier results, medium-term continuation of returns is proxying for distress risk and is being driven by financially distressed firms. Avramov et al. (2007a) argue that momentum profits are not fully explained by credit risk, though no formal tests for this proposition are conducted. However, we find, in contrast, that when a distress factor is added to the asset pricing equation, the momentum factor is no longer significant. Our results are inconsistent with the distress factor hypothesis, but in line with the market underreaction to bankruptcy risk hypothesis.

5. CONCLUDING REMARKS

Consistent with Dichev (1998), and Campbell et al. (2006), we find that, contrary to the distress factor hypothesis, financially distressed stocks earn lower returns than non-distressed stocks, and size and B/M effects are not related to distress risk in the UK. These results are hard to reconcile with rational asset pricing as such financially distressed stocks are riskier on conventional measures (have higher betas, higher B/Ms, and are smaller).

However, the primary contribution of this paper is to provide a potential distress factor explanation for the momentum anomaly. There is a lack of consensus in the existing literature on whether continuation of prior returns is due to risk or market underreaction to new information. Our empirical results argue a market underreaction story, the market is unable to appropriately assimilate bad news (e.g. Barberis et al., 1998). This leads to continuing underperformance of financially distressed firms and drives the medium-term continuation of stock returns. Consistent with this hypothesis, we find that more than half of the bankruptcies in our sample fall in the lowest momentum quintile, the stocks of financially distressed firms (which are also poor past performers) earn lower subsequent returns, and our bankruptcy risk proxy, z-score, drives out momentum in the cross-section. Avramov et al. (2007a) find that low credit-rated stocks drive stock momentum. However, they do not test for whether credit rating fully explains momentum in the cross-section. Further, they argue that leverage is a better proxy for distress risk than credit rating, and as such, distinguish between credit risk and financial distress risk. We disagree with this distinction, in our view credit risk and financial distress risk are synonymous. Our results demonstrate it is the market mispricing of underlying bankruptcy risk that is driving the medium-term continuation of returns. As such, we interpret Avramov et al.'s (2007a) results as consistent with ours.

Taffler et al. (2004) explain significant underperformance of UK firms to first time going-concern audit reports in terms of investor denial of their implications for firm financial distress, and Dichev and Piotroski (2001) use similar arguments to explain underperformance after bond downgradings. Similarly, Avramov et al. (2007b) find that deterioration in financial and operating performance of low grade stocks after ratings downgrades is largely unanticipated by the market leading to subsequent stock price underperformance.

Nonetheless, there is an alternative market microstructure explanation for our findings. Low returns on distressed stocks may not represent an arbitrage opportunity because as Grinblatt and Han (2005) argue, arbitrageurs' actual ability to exploit market mispricing is restricted due to unpredictable fundamental values, short time horizon and limited capital availability. Lesmond et al. (2004), for example, suggest that the momentum anomaly cannot be exploited by investors as it is driven by small illiquid stocks which cannot be easily shorted. Similarly, Taffler et al. (2004) find profitable opportunities to arbitrage underperformance of going-concern stocks are severely limited due to high trading costs, Houge and Loughran (2006) find that small cap growth and value mutual funds earn similar returns even during periods of strong value effect for small firms and argue this is due to lack of liquidity, and Avramov et al. (2007b) demonstrate that their ratings downgrade market underreaction results are driven by their worst-rated stocks comprising just 4% of total market capitalization. Nevertheless, whether we explain our empirical findings with a market underreaction or market microstructure story, our results show that financial distress risk drives out the momentum effect in stock returns.

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Table I: Failure rates in two-way portfolios

Portfolios in panel A are formed as follows: at the end of September of each year from 1979 to 2002, all the stocks in our sample are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are also independently ranked on market capitalization and grouped into five portfolios. Ten portfolios are then formed at the intersections of size and z-score.

Portfolios in panel B are formed as follows: at the end of September of each year from 1979 to 2002, all the stocks in our sample are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are also independently ranked on B/M and grouped into five portfolios. Ten portfolios are then formed at the intersections of B/M and z-score. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available financial statements, divided by the market value of equity on September 30th.

Portfolios in panel C are formed as follows: at the end of September of each year from 1979 to 2002, all the stocks in our sample are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are also independently ranked on momentum and grouped into five portfolios. Ten portfolios are then formed at the intersections of momentum and z-score. Momentum is defined as the 11-month return from October 1st of year t-1 to August 31st of year t.

Portfolios are rebalanced at the end of September each year. Negative B/M stocks are excluded. The list of failures is compiled from LSPD, *The Stock Exchange Official Yearbook* and *CGT Capital Losses*.

	% of firms	Distribution of failures (%)			Failure rate (%)		
	with z<0	z<0	z>0	Total	z<0	z>0	Total
A. Size and z-score portfolios							
Small	38.4	64.4	3.4	67.8	6.5	0.2	2.6
2	28.7	16.6	1.0	17.6	2.6	0.1	0.8
3	21.7	9.3	0.0	9.3	2.0	0.0	0.4
4	17.2	2.9	0.5	3.4	0.8	0.0	0.2
Big	14.8	1.5	0.5	2.0	0.4	0.0	0.1
Total	24.5	94.6	5.4	100.0	3.4	0.1	0.9
B. B/M and z-score portfolios							
Low	25.7	13.7	0.0	13.7	2.3	0.0	0.6
2	19.6	12.7	1.5	14.1	2.8	0.1	0.6
3	19.5	11.2	1.0	12.2	2.5	0.1	0.5
4	24.2	10.7	0.5	11.2	1.9	0.0	0.5
High	33.7	46.3	2.4	48.8	6.0	0.2	2.1
Total	24.5	94.6	5.4	100.0	3.4	0.1	0.9
C. Prior-year returns and z-score portfolios							
Low	35.0	49.8	2.0	51.7	6.2	0.1	2.2
2	21.7	14.1	1.0	15.1	2.8	0.1	0.7
3	19.6	11.2	0.5	11.7	2.5	0.0	0.5
4	19.9	9.8	0.5	10.2	2.1	0.0	0.4
High	26.4	9.8	1.5	11.2	1.6	0.1	0.5
Total	24.5	94.6	5.4	100.0	3.4	0.1	0.9

Table II: Size and distress risk in stock returns

Portfolios are formed as follows: at the end of September of each year from 1979 to 2002, all the stocks in our sample are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are also independently ranked on market capitalization and grouped into five portfolios. Ten portfolios are then formed at the intersections of size and z-score. For each size quintile, an arbitrage portfolio labeled "difference", long on distressed stocks and short on non-distressed stocks, is also formed.

Panel A presents the portfolio summary statistics. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on September 30th. Average monthly excess return is the time series average of the difference between monthly stock returns and one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior and next month's market returns. Average size, average B/M and average momentum are the time-series averages of monthly averages of market capitalizations, B/M and prior 11-month returns (excluding September) respectively for stocks in the portfolio at the end of September of each year.

Panel B presents the intercepts and adjusted R^2 for each of the portfolios from the following Fama and French (1993) three-factor model (equation 2):

$$R_{it} - R_{Ft} = \beta_1 + \beta_2 (R_{Mt} - R_{Ft}) + \beta_3 SMB_t + \beta_4 HML_t + \varepsilon_{it}$$

where R_{it} is the equally-weighted return on portfolio i during month t, R_{Ft} is the 1-month Treasury bill rate at the beginning of month t, and R_{Mt} is the value-weighted return during month t of all non-financial stocks listed on the London Stock Exchange for at least 24 months prior to month t. SMB_t is the return on the mimicking portfolio for the size factor during month t, and HML_t is the return on the mimicking portfolio for the B/M factor during month t. ε_{it} is a mean-zero stochastic error term. SMB and HML are formed following exactly the same procedure as Fama and French (1993).

Negative B/M stocks are excluded. The last monthly return for failed stocks is set equal to –100%. Figures in brackets are the t-statistics.

A. Summary statistics											
Size	**Average market capitalization (£m)**		**Average B/M**		**Average monthly prior-year return (%)**		**Average beta**		**Average excess monthly returns (%)**		
	z<0	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**	**difference**
Small	5.0	5.6	1.67	1.68	0.21	1.25	1.07	0.85	1.17	1.44	-0.27
									(2.94)	(5.11)	(1.30)
2	17.5	17.9	1.23	1.18	1.32	1.53	1.16	0.96	0.15	0.68	-0.54
									(0.39)	(2.38)	(3.11)
3	46.7	48.0	1.05	0.89	1.86	1.70	1.33	1.01	0.22	0.72	-0.49
									(0.55)	(2.43)	(2.66)
4	143.7	145.7	0.79	0.74	2.30	1.98	1.31	1.08	0.21	0.49	-0.28
									(0.55)	(1.62)	(1.62)
Big	2282.4	2341.1	0.77	0.67	1.92	2.01	1.05	1.02	0.41	0.45	-0.05
									(1.19)	(1.42)	(0.33)
Small - Big									0.77	0.99	-0.22
									(2.27)	(3.74)	(0.88)

Table II contd.

B. Fama and French (1993) regression results						
Size	**Intercept (β_1)**			**Adjusted R^2**		
	z<0	**z>0**	**difference**	**z<0**	**z>0**	**difference**
Small	0.23 (1.19)	0.79 (5.90)	-0.56 (-2.99)	0.77	0.78	0.23
2	-0.78 (-5.58)	-0.05 (-0.59)	-0.73 (-4.55)	0.87	0.93	0.17
3	-0.68 (-4.14)	-0.02 (-0.21)	-0.67 (-3.90)	0.84	0.93	0.19
4	-0.64 (-3.75)	-0.19 (-1.98)	-0.45 (-2.75)	0.82	0.90	0.15
Big	-0.21 (-1.43)	-0.11 (-1.24)	-0.10 (-0.68)	0.83	0.93	0.00
Small - Big	0.44 (1.72)	0.90 (5.25)	-0.46 (1.90)	0.46	0.60	0.13

Table III: B/M and distress risk in stock returns

Portfolios are formed as follows: at the end of September of each year from 1979 to 2002, all the stocks in our sample are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are also independently ranked on B/M and grouped into five portfolios. Ten portfolios are then formed at the intersections of B/M and z-score. For each B/M quintile, an arbitrage portfolio labeled "difference", long on distressed stocks and short on non-distressed stocks, is also formed.

Panel A presents the portfolio summary statistics. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on September 30th. Average monthly excess return is the time series average of the difference between monthly stock returns and one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior and next month's market returns. Average size, average B/M and average momentum are the time-series averages of monthly averages of market capitalizations, B/M and prior 11-month returns (excluding September) respectively for stocks in the portfolio at the end of September of each year.

Panel B presents the intercepts and adjusted R^2 for each of the portfolios from the following Fama and French (1993) three-factor model (equation 2):

$$R_{it} - R_{Ft} = \beta_1 + \beta_2 (R_{Mt} - R_{Ft}) + \beta_3 SMB_t + \beta_4 HML_t + \varepsilon_{it}$$

where R_{it} is the equally-weighted return on portfolio i during month t, R_{Ft} is the 1-month Treasury bill rate at the beginning of month t and R_{Mt} is the value-weighted return during month t of all non-financial stocks listed on the London Stock Exchange for at least 24 months prior to month t. SMB_t is the return on the mimicking portfolio for the size factor during month t and HML_t is the return on the mimicking portfolio for the B/M factor during month t. ε_{it} is a mean-zero stochastic error term. SMB and HML are formed following exactly the same procedure as Fama and French (1993).

Negative B/M stocks are excluded. The last monthly return for failed stocks is set equal to –100%. Figures in brackets are the t-statistics.

A. Summary statistics											
B/M	**Average market capitalization (£m)**		**Average B/M**		**Average monthly prior-year return (%)**		**Average beta**		**Average excess monthly returns (%)**		
	z<0	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**	**difference**
Low	549.85	927.47	0.24	0.26	3.68	3.27	1.22	1.09	0.45 (1.09)	0.26 (0.77)	0.20 (0.97)
2	639.92	691.27	0.53	0.54	1.94	2.19	1.14	1.01	0.05 (0.15)	0.44 (1.55)	-0.39 (-1.90)
3	448.52	477.16	0.81	0.81	1.45	1.60	1.08	0.96	0.48 (1.26)	0.72 (2.52)	-0.24 (-1.21)
4	189.39	420.13	1.21	1.20	0.86	1.09	1.13	0.94	0.65 (1.88)	1.06 (3.65)	-0.41 (-2.40)
High	113.92	218.71	2.59	2.45	-0.85	0.27	1.14	0.96	0.86 (2.08)	1.26 (4.40)	-0.40 (-1.88)
High - Low									0.41 (1.38)	1.00 (4.55)	-0.60 (-2.23)

Table III contd.

B. Fama and French (1993) regression results						
B/M	**Intercept (β_1)**			**Adjusted R^2**		
	z<0	**z>0**	**difference**	**z<0**	**z>0**	**difference**
Low	-0.24 (-1.21)	-0.25 (-2.53)	0.02 (0.10)	0.79	0.91	0.19
2	-0.78 (-4.09)	-0.17 (-2.13)	-0.61 (-3.10)	0.75	0.93	0.11
3	-0.40 (-2.25)	0.03 (0.34)	-0.43 (-2.27)	0.79	0.92	0.12
4	-0.22 (-1.41)	0.30 (3.25)	-0.52 (-3.05)	0.80	0.91	0.05
High	-0.24 (-1.38)	0.45 (4.48)	-0.69 (-3.64)	0.82	0.88	0.24
High - Low	-0.01 (-0.04)	0.70 (4.89)	-0.71 (-2.69)	0.29	0.60	0.07

Table IV: Prior-year returns and distress risk in stock returns

Portfolios are formed as follows: at the end of September of each year from 1979 to 2002, all the stocks in our sample are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are also independently ranked on prior-year returns and grouped into five portfolios. Ten portfolios are then formed at the intersections of prior-year returns and z-score. For each prior-year returns quintile, an arbitrage portfolio labeled "difference", long on distressed stocks and short on non-distressed stocks, is also formed.

Panel A presents the portfolio summary statistics. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on September 30th. Average monthly excess return is the time series average of the difference between monthly stock returns and one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior and next month's market returns. Average size, average B/M and average momentum are the time-series averages of monthly averages of market capitalizations, B/M and prior 11-month returns (excluding September) respectively for stocks in the portfolio at the end of September of each year.

Panel B presents the intercepts and adjusted R^2 for each of the portfolios from the following Fama and French (1993) three-factor model (equation 2):

$$R_{it} - R_{Ft} = \beta_1 + \beta_2 (R_{Mt} - R_{Ft}) + \beta_3 SMB_t + \beta_4 HML_t + \varepsilon_{it}$$

where R_{it} is the equally-weighted return on portfolio i during month t, R_{Ft} is the 1-month Treasury bill rate at the beginning of month t, and R_{Mt} is the value-weighted return during month t of all non-financial stocks listed on the London Stock Exchange for at least 24 months prior to month t. SMB_t is the return on the mimicking portfolio for the size factor during month t, and HML_t is the return on the mimicking portfolio for the B/M factor during month t. ε_{it} is a mean-zero stochastic error term. SMB and HML are formed following exactly the same procedure as Fama and French (1993).

Negative B/M stocks are excluded. The last monthly return for failed stocks is set equal to –100%. Figures in brackets are the t-statistics.

A. Summary statistics

Prior-year return	Average market capitalization (£m)		Average B/M		Average monthly prior-year return (%)		Average beta		Average excess monthly returns (%)		
	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	difference
Loser	151.4	360.1	1.74	1.41	-3.79	-2.89	1.04	0.98	0.24 (0.57)	0.90 (2.67)	-0.66 (-3.12)
2	372.9	516.6	1.28	1.11	-0.07	-0.03	1.05	0.91	0.36 (0.99)	0.67 (2.33)	-0.31 (-1.69)
3	558.8	733.2	1.06	0.97	1.51	1.51	1.04	0.93	0.57 (1.63)	0.64 (2.39)	-0.06 (-0.34)
4	568.4	626.5	0.99	0.87	3.06	3.06	1.12	1.01	0.77 (2.32)	0.64 (2.31)	0.13 (0.83)
Winner	368.2	449.1	0.76	0.73	7.40	6.46	1.37	1.18	0.89 (2.18)	0.86 (2.69)	0.02 (0.14)
Winner - Loser									0.65 (2.17)	-0.03 (-0.14)	0.68 (2.67)

Table IV contd.

B. Fama and French (1993) regression results						
Prior-year return	**Intercept (β_1)**			**Adjusted R^2**		
	z<0	**z>0**	**difference**	**z<0**	**z>0**	**difference**
Loser	-0.85 (-4.56)	-0.01 (-0.06)	-0.84 (-4.15)	0.81	0.86	0.10
2	-0.55 (-3.34)	-0.05 (-0.54)	-0.50 (-2.89)	0.81	0.91	0.13
3	-0.23 (-1.42)	0.02 (0.21)	-0.25 (-1.45)	0.79	0.92	0.15
4	0.03 (0.17)	0.04 (0.49)	-0.01 (-0.09)	0.79	0.92	0.07
Winner	0.19 (1.02)	0.29 (2.42)	-0.10 (-0.63)	0.81	0.87	0.18
Winner - Loser	1.04 (3.90)	0.29 (1.49)	0.74 (2.86)	0.24	0.27	0.01

Table V: Failure rates in four-way portfolios

At the end of September of each year from 1979 to 2002, all the stocks in our sample are ranked on market capitalization and grouped into two portfolios, independently ranked on B/M and grouped into three portfolios, independently ranked on prior-year return and grouped into two portfolios and, finally, separately allocated to two groups based on whether their latest available z-score is negative or positive. Twenty-four portfolios are then formed at the intersections of size, B/M, momentum and z-score. Portfolios are rebalanced at the end of September each year. Negative B/M stocks are excluded. The list of failures is compiled from LSPD, *The Stock Exchange Official Yearbook* and *CGT Capital Losses*.

Size	**Prior-year return**	**Low B/M**		**Medium B/M**		**High B/M**	
		z<0	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**
A. Failure rates (%)							
Small	Low	6.7	0.0	4.0	0.0	6.9	0.2
Small	High	3.5	0.1	1.9	0.2	2.6	0.0
Big	Low	1.8	0.2	0.5	0.0	1.3	0.0
Big	High	0.4	0.0	0.8	0.0	1.5	0.0
A. Distribution of failures (%)							
Small	Low	12.0	0.0	12.5	0.0	43.5	2.5
Small	High	8.5	0.5	5.0	1.5	7.0	0.0
Big	Low	2.5	1.0	1.0	0.0	1.5	0.0
Big	High	1.0	0.0	1.5	0.0	1.0	0.0

Table VI: Summary statistics – size, B/M, momentum and z-score portfolios

At the end of September of each year from 1979 to 2002, all the stocks in our sample are ranked on market capitalization and grouped into two portfolios, independently ranked on B/M and grouped into three portfolios and independently ranked on prior-year return and grouped into two portfolios. The stocks are also independently allocated to two groups based on whether their latest available z-score is negative or positive. Twenty-four portfolios are then formed at the intersections of size, B/M, momentum and z-score. Portfolios are rebalanced at the end of September each year. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on September 30th. Average monthly excess return is the time series average of the difference between monthly stock returns and one-month Treasury bill rate observed at the beginning of the month. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior and next month's market returns. Average size, average B/M and average momentum are the time-series averages of monthly averages of market capitalizations, B/M and prior 11-month average monthly returns (October year t-1 to August year t) respectively for stocks in the portfolio at the end of September of each year. Negative B/M stocks are excluded. The last monthly return for failed stocks is set equal to –100%.

Size	Prior-year return	Low B/M		Medium B/M		High B/M	
		z<0	z>0	z<0	z>0	z<0	z>0
A. Average excess monthly returns (%)							
Small	Low	0.56	0.45	0.28	1.04	0.51	1.26
	High	0.68	1.09	0.90	0.92	1.69	1.24
Large	Low	-0.43	-0.04	-0.14	0.39	0.59	1.10
	High	0.32	0.35	0.67	0.71	1.04	1.05
B. Average beta							
Small	Low	0.95	1.03	0.99	0.92	1.06	0.89
	High	1.36	1.05	1.29	1.01	1.11	1.00
Large	Low	0.93	0.90	1.01	0.86	1.18	0.94
	High	1.34	1.01	1.09	0.95	1.49	0.97
C. Average market capitalization (£m)							
Small	Low	14.6	25.3	14.7	20.0	10.5	13.2
	High	18.8	23.9	15.9	19.1	11.4	13.3
Large	Low	1048.1	1135.3	958.4	1048.9	516.5	1137.7
	High	1065.1	931.6	880.8	906.2	922.9	1416.0
D. Average B/M							
Small	Low	0.32	0.37	0.87	0.86	2.44	2.19
	High	0.29	0.35	0.84	0.83	1.94	2.08
Large	Low	0.31	0.35	0.82	0.81	2.00	1.77
	High	0.29	0.32	0.80	0.78	1.61	1.72
E. Average monthly prior-year monthly returns (%)							
Small	Low	-1.61	-0.79	-1.83	-0.85	-2.57	-1.35
	High	6.51	5.44	4.80	4.19	4.02	3.76
Large	Low	-0.47	-0.14	-0.79	-0.38	-1.81	-0.92
	High	5.28	4.28	3.74	3.39	4.16	3.09

Table VII: Cross-section regression results

At the end of September of each year from 1979 to 2002, all the stocks in our sample are ranked on market capitalization and grouped into two portfolios, independently ranked on B/M and grouped into three portfolios and independently ranked on prior-year return and grouped into two portfolios. The stocks are also independently allocated to two groups based on whether their latest available z-score is negative or positive. Twenty-four portfolios are then formed at the intersections of size, B/M, momentum and z-score. Portfolios are rebalanced at the end of September each year.

B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests from the latest available accounts divided by the market value of equity on September 30th. To avoid undue influence of outliers on the regressions, the smallest and largest 1% of the observations on B/M are set equal to 0.01 and 0.99 fractiles respectively. Portfolio betas are the sum of slopes in the regression of the return on a portfolio on the current, prior and following month's market returns.

The estimated Fama-MacBeth (1973) regression equation is:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1}) + \gamma_{4t}\,Mom_{it-1} + \gamma_{5t}\,z(0/1)_{it-1} + \gamma_{6t}\,Mom_{it-1} * z(0/1)_{it-1}$$

Where R_{it} is the equally-weighted return on portfolio i during month t and R_{Ft} is the one-month Treasury bill rate at the beginning of month t. β_{it-1} is the beta of portfolio i estimated at the portfolio formation date. $\ln(size_{it-1})$ and $\ln(B/M_{it-1})$ are the natural logarithms of average of market capitalizations and average of B/M ratios respectively of stocks in portfolio i at the portfolio formation date. Mom_{it-1} is the average monthly return over the 11 months from October year t-1 to August year t prior to the month of portfolio formation of all the stocks in portfolio i. $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth (1973) cross-section regressions for each of the 288 months from October 1979 to September 2003. Figures in brackets are the respective t-statistics. Negative B/M stocks are excluded. The last period return for failed stocks is set equal to –100%.

Model	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6
(i)	0.85	-0.12				-0.24	
	(2.75)	(0.59)				(2.03)	
(ii)	2.28	-0.07	-0.08	0.28			
	(2.44)	(0.39)	(1.59)	(2.88)			
(iii)	2.19	0.01	-0.07	0.31		-0.29	
	(2.33)	(0.05)	(1.41)	(3.19)		(2.50)	
(iv)	2.73	-0.23	-0.11	0.36	0.11		
	(2.88)	(0.82)	(2.12)	(3.43)	(3.12)		
(v)	2.11	-0.01	-0.07	0.37	0.05	-0.28	
	(2.15)	(0.05)	(1.46)	(3.45)	(1.23)	(2.34)	
(vi)	2.17	-0.04	-0.07	0.37	0.01	-0.31	0.07
	(2.22)	(0.11)	(1.49)	(3.48)	(0.20)	(2.25)	(2.61)