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ACADEMIC YEAR 2001-2002

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DOES THE DISTRESS FACTOR HYPOTHESIS EXPLAIN THE SIZE AND VALUE EFFECTS IN EQUITY RETURNS?

SUPERVISOR: RICHARD TAFFLER

AUGUST 2002

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ABSTRACT

The distress factor hypothesis says that value stocks and small stocks are distressed and therefore higher returns on such stocks are merely a compensation for higher risk. I test this hypothesis using z-scores, a cleaner proxy for bankruptcy risk than other proxies used in the literature such as dividend reductions or omissions.

I find that unconditionally, distressed stocks earn significantly lower returns than non-distressed stocks and much underperformance is uninfluenced by size and B/M factors. I also find that z-score, size and B/M effects are stronger in different months suggesting little common variation between the three factors. The results show that size and B/M effects are unrelated to bankruptcy risk on an unconditional basis.

Of crucial importance is a consideration of the time varying behaviour of bankruptcy risk premia and I consider explicitly the impact of changes in GDP growth rate and the impact of stock market movements on the pricing of distressed firms. I find that risk of bankruptcy is a systematic risk with distressed stocks registering strong underperformance during 'bad' states of the world. As with unconditional analysis, the results show there is no link between distress factor and size and B/M effects. Size and B/M effects are stronger in non-distressed stocks.

To ensure that the empirical results are robust across different methodologies, I significantly expand on the work of Dichev (1998) by employing two different portfolio

formation methods and individual securities in my analysis. My main results on z-scores are robust though size and B/M effects are sensitive to alternative trading rules.

I also test the Fama & French (1993) three-factor model for the UK and find that it is unable to explain returns on negative z-score portfolios. A four-factor model that includes a factor mimicking the z-score effect is better specified.

The primary contribution of this study is the direct evidence it provides on the distress factor hypothesis of higher returns on value stocks and small stocks and the four-factor model for stock returns. This research has important implications both for extant asset pricing theories and for practitioners especially in evaluation of portfolio performance and computation of abnormal returns.

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Chapter 1

INTRODUCTION

This thesis is located in empirical finance and tests a key issue dominant in the asset pricing literature. A key empirical finding that has not been satisfactorily explained is the superior performance of high book-to-market (B/M) and small size firms, both in the US and internationally. The dominant explanation is the 'distress factor' hypothesis that says that small stocks and high B/M stocks are distressed stocks and therefore riskier (e.g. Chan & Chen (1991), Fama & French (1992)). Higher returns on such stocks are merely a compensation for higher risk. There is only indirect evidence to support this hypothesis. Though considerable research effort has been put into modeling default risk for valuing corporate debt and derivatives, little attention has been paid to its effect on equity returns. Several studies have used default spread to examine the effect of default risk (e.g. Chen, Roll & Ross (1986), Fama & French (1993)). However, Elton, Gruber, Agrawal & Mann (2001) show that as much as 85% of the spread can be explained as reward for bearing systematic risk unrelated to default. Further, differential taxes seem to have more impact on default spread than the expected loss from default. I explicitly test the distress factor hypothesis using z-score as a proxy for financial distress.

Several studies suggest that size and the B/M effect could be related to a distress factor. Chan & Chen (1991) find that 'marginal firms' seem to drive the small firm effect. Fama & French (1992) conjecture that the B/M effect may be due to a distress factor. Chan, Chen & Hsieh (1985) show that a default factor can explain most of the cross-sectional variation left over after the market factor. Fama & French (1993) and Chen, Roll & Ross (1986) find an aggregate default factor to be significant in explaining stock returns. Most of the work has, however, been done in the US with other markets receiving very little attention.

There is no agreement in the literature about what is meant by the 'distress factor'. While Fama & French (1993, 1995) seem to suggest that the 'distress factor' refers to financially distressed firms (a view taken by Dichev (1998) as well), Cochrane (2001) argues that the term 'distress factor' refers to an aggregate macroeconomic factor and not an individual firm distress factor since the latter is an idiosyncratic risk that can be diversified away and hence, is not priced. Existing evidence on the relation between individual firm distress or bankruptcy risk and the distress factor is contradictory. Lang & Shulz (1992), Denis & Denis (1995) and Vassalou & Xing (2002) show that bankruptcy risk is related to aggregate factors and varies with the business cycle which implies that it should be positively related to systematic risk. Shumway (1996) finds that NYSE and AMEX firms with high risk of exchange delistings earn higher than average returns also consistent with bankruptcy risk being systematic. Opler & Titman (1994) and Asquith, Gertner & Sharfstein (1994) find that bankruptcy risk is idiosyncratic and not systematic. The recent study of Dichev (1998) suggests that distressed firms earn substantially less than average returns over time interpreting this as evidence of mispricing.

In this study, I adopt the interpretation of Fama & French (1993, 1995) and define the term 'distress factor' as representing individual firm distress. As such the terms financial distress and bankruptcy risk are used interchangeably in this study. Whether this factor is idiosyncratic or a priced systematic risk factor is an open question that I test in this study.

Probability of failure is a natural proxy for the distress factor and there is a well-developed literature on failure prediction that provides powerful measures of ex-ante bankruptcy risk. Several proxies for financial distress are used in finance literature, the two most common proxies being dividend cuts or omissions (Chan & Chen (1991)) and losses for a number of years (De Angelo & De Angelo (1990)). The use of dividend cuts/omissions is based on the accepted fact that dividends are 'sticky'. However, the very fact that managers are reluctant to cut dividends means that firms which do so have actually entered the distress phase some time before the cuts/omission making the use of this proxy problematic. Another problem is that a large number of firms do not pay any dividends and no inference can be drawn about their financial health. Further, firms could opt for other ways of distress resolution like mergers, rationalizations, asset sales etc. and not resort to dividend cuts. Finally, De Angelo & De Angelo (1990) find that some firms cut dividends for strategic reasons rather than purely financial reasons though the number of such cases is very small. The other proxy for financial distress – losses for a number of years is problematic as well. Such criteria would exclude new firms that are more likely to be distressed. Moreover, De Angelo & De Angelo (1990) find that in their sample, a typical firm cuts its dividend before the first annual loss. Thus, use of dividend cut would provide a better proxy for firms that pay dividends.

Z-scores, on the other hand, circumvent the above problems. Their use as an indicator of credit worthiness is well established. Positive z-score firms rarely fail while the incidence of failure is high in negative z-score firms. Taffler (1995) finds that while 15% of the companies with negative z-scores at the beginning of 1991 failed in that year, a further 16% suffered other outcomes like capital reconstructions, debt write downs, rescue rights issues, acquisitions and major disposals. A casual inspection of dividend omissions by the UK listed non-financial firms between 1993 and 1998 shows that out of a total of 222 firms that omitted dividends, 165 firms (74%) had negative z-scores in the year of omission while another twenty-three firms re-initiated dividends in the next year. Similarly, of the 406 firms that initiated dividends during the period, only 86 firms (20%) had negative z-scores. Out of these 86 firms, seven omitted and four cut their dividend in the following year while the z-score of a further 26 firms turned positive in the following year. This shows that the z-scores used in this study are a good proxy for financial distress.

The mortality rate (delisting for any reason) is much higher in the firms with negative z-scores than the firms with positive z-scores. Approximately 9.6% 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 4.8%. The difference in proportions is highly significant ($z = 12.39$). In my sample covering 21 years, out of 185 failures (receivership, administration or liquidation), only 6 firms were misclassified as solvent by their z-scores derived on the basis of last available annual accounts. The sample comprises of 4863 company years with negative z-scores and 16215 company years with positive z-scores. The conditional probability of failure given a negative z-score is 3.68% and it is significantly different to the base failure rate of 0.88% ($z = 20.96$).

Similarly, the conditional probability of non-failure given a positive z-score is 99.96% and is significantly different to the base rate of 99.12% (z = 11.48).

The distress factor hypothesis seems to have emerged from two stylized facts in the asset pricing literature. Small size firms and high B/M firms earn superior returns and these stocks are also financially distressed. The two facts are then combined in the literature giving us the distress factor hypothesis – smaller stocks and high B/M stocks have higher bankruptcy risk and therefore, earn higher returns. I start by asking the obvious question – do distressed firms earn higher returns? I use z-score as a proxy for bankruptcy risk and test the distress factor hypothesis for the size and book-to-market effects. The objectives of this study are:

1. To test whether distressed stocks earn a higher return after controlling for market risk. If bankruptcy risk is a systematic risk factor, higher bankruptcy risk should be associated with higher returns.
2. To test whether size and B/M effects are capturing bankruptcy risk. If they are, then they would be correlated with z-score – another factor that is measuring the same risk. Hence, when z-scores, size and B/M are present in the same pricing equation, either z-score will subsume size and/or B/M or vice versa.
3. Dichev (1998) suggests that the relationship between z-scores and stock returns is restricted to stocks with high bankruptcy risk. Also, since size and B/M are hypothesized to be proxies for bankruptcy risk, these effects too would be restricted to high bankruptcy risk stocks. I conduct formal tests of this asymmetric bankruptcy risk hypothesis using z-score interaction terms.

4. To investigate calendar seasonality in equity returns with the limited objective that if z-score, size and B/M effects have common seasonalities, they are likely to be linked to some common underlying risk factor. If however, these effects have different seasonalities, they are unlikely to be proxies for the same risk factor.
5. To provide evidence regarding the nature of bankruptcy risk i.e. whether it is systematic or idiosyncratic. Lakonishok, Shleifer & Vishny (1994) define systematic risk as sensitivity to adverse conditions. So, fundamentally riskier stocks will underperform during 'bad' states of the world because that is when the marginal utility of wealth will be high and riskier stocks will be particularly unattractive to risk averse investors. Using their definition, I investigate the performance of distressed and healthy firms (according to z-score) in the up and down states of stock markets and up and down states of the economy.
6. To test the applicability of the Fama & French (1993) three-factor model for equity returns. The model is currently the dominant asset-pricing model but there are no studies testing its performance in the UK.

I use different methodologies and different trading rules to test my hypotheses because any explanation should be robust to different methodologies. Specifically, I use two different portfolio formation methods along with individual securities and Fama & French (1993) time-series methodology as well as the Fama & MacBeth (1973) cross-sectional approach.

My main findings are:

There is a z-score effect in UK stock returns and unconditionally, distressed stocks underperform non-distressed stocks. There are also size and B/M effects in stock returns and these effects are sensitive to the time period chosen and trading rules adopted. Z-score effect is not influenced by nor does it influence size and B/M effects in stock returns suggesting that size and B/M effects may each be related to something other than bankruptcy risk. The z-score effect seems to be a systematic risk factor since it is time varying, the time variation being linked to the state of the stock market as well as the state of the economy. The B/M effect is more pronounced during the month of April while the size effect is more pronounced during the month of May and z-score effect during May and September suggesting no commonality between size and B/M and z-score and B/M but possibly some relationship between size and z-score. The Fama & French (1993) model provides a better description of equity returns than a single factor model though it is far from perfect. I introduce a four-factor model with a factor designed to capture bankruptcy risk and find that it is much better specified.

The rest of the study is organized as follows: chapter two surveys the existing literature, chapter three develops the hypotheses to be tested, chapter four provides the details of data and methodology employed, chapter five reports tests of Fama & French three factor model, chapter six presents the evidence on bankruptcy risk using two different portfolio formation methods and individual securities, chapter seven tests the ability of the Fama & French three-factor model to explain variation in returns in portfolios of chapter six and introduces a four-factor model, chapter eight analyzes bankruptcy risk in different economic conditions and chapter nine draws conclusions from the work and discusses limitations.

Chapter 2

LITERATURE SURVEY

2.1. Introduction

There are two separate strands in the asset pricing literature – one that explores the size and value effects in equity returns and the other that explores the bankruptcy risk premium in equity returns. This thesis attempts to bring the two strands together. My review of the extant literature on value and size effects and the distress factor is divided into two sections: the value and size effect in stock returns and the bankruptcy risk premium in stock returns.

The chapter is organized as follows: section 2 reviews the literature on size and B/M effects, section 3 reviews the literature on bankruptcy risk and stock returns and section 4 summarizes the literature and identifies the gaps to be exploited in this study.

2.2. Book-to-Market, firm size and stock returns

2.2.1. Introduction

Firm size and the book-to-market ratio (B/M) have emerged as strong contenders for explaining the cross-sectional variation in stock returns. Stattman (1980), Rosenberg, Reid & Lanstein (1985) and Fama & French (1992) find that average returns on US stocks are positively related to B/M. Chan, Hamao & Lakonishok (1991) find similar results for Japan and Strong & Xu (1997) find these effects in the UK. In parallel Capaul, Rowley & Sharpe (1993) and Fama & French (1998) find evidence of the existence of a pervasive value premium internationally. The value and size effects in equity returns contradict the CAPM of Sharpe (1964), Lintner (1965) and Black (1972) or more precisely, the mean variance efficiency of the market proxy[1]. These effects can, however, be consistent with the Intertemporal CAPM of Merton (1973) and Breeden (1979) which allows for the role of other factors in addition to market return to capture the relevant risks.

Four explanations have been proposed for the observed predictive ability of firm size and B/M (and other fundamental variables like earnings-to-price, dividend yield etc.). Lo & MacKinlay (1990), Black (1993), Roll & Ross (1994) and MacKinlay (1995) suggest that the results are an artefact of the data and are period specific. Kothari, Shanken & Sloan (1995) argue that the empirical results of Fama & French (1992) are spurious and induced by data selection biases. Knez & Ready (1997) find that the size effect is driven by a small number of outliers. The coefficient on size is reversed even if only 1% of the influential observations are trimmed. However, they find that the B/M effect is not affected after controlling for size. The second explanation is that these variables capture the risk missed by the market factor and refute the CAPM while being consistent with multi-factor asset pricing models and market efficiency (Fama & French (1993, 1995, 1996, 1998)). Lakonishok, Shleifer & Vishny (1994), Haugen & Baker (1996) and La Porta, Lakonishok, Shleifer & Vishny (1997) offer a third explanation. They argue that these results stem from investors' judgmental biases and institutional problems. Finally, Daniel & Titman (1997) provide a fourth explanation. They argue that the B/M effect is because investors like strong firms (growth firms) and dislike weak firms (value firms) resulting in a value premium not due to risk but driven by firm characteristics.

[1] Berk (1995, 2000b) however argues that these effects should not be considered anomalous.

2.2.2. *Size and B/M as risk factors*

Chan, Chen and Hsieh (1985) use a multi-factor asset pricing model to explore the size effect using firms listed on the NYSE during 1953-77. They form twenty portfolios on size and run generalised least squares regression.[2] The difference in residuals between the top size portfolio and the bottom size portfolio is roughly 1.5% per year which is insignificant both economically and statistically (t = 1.18). The difference in residuals of the top and bottom size quintiles is also an insignificant 0.65% p.a. (t = 1.44). The measure of changing risk premium (defined as the difference between the returns on a low grade bond portfolio and the long term government bond portfolio) explains most of the cross-sectional variation left over after the market index.[3] They conclude that smaller firms are riskier than larger firms and thus higher average returns on them are justified by the additional risks borne in an efficient market. They also conjecture that major movements of marginal firms (which tend to be smaller firms) may not be coincident with major movements of the general market index and the risk of such firms may be better captured by the measure of changing risk premium.

A seminal paper by Fama & French in 1992 provided a catalyst for a move away from a single factor CAPM towards multifactor asset pricing models. Fama & French (1992) document various empirical irregularities of the Capital Asset Pricing Model of Sharpe

[2] The following explanatory variables are used:
EWNY = Equally weighted market index.
IPISA = Seasonally adjusted monthly growth rate of industrial production.
DEI = Change in expected inflation.
UITB = Unexpected inflation.
PREM = Measure of changing risk premium (difference between the returns on low-grade bond portfolio and long term government bond portfolio).
UTS = Measure of change in slope of yield curve (difference in return of long term government bond portfolio and the one month T-Bill).

[3] Of the average difference in return between the top and bottom size portfolio of 0.956% per month, the market index accounts for 0.352% and PREM accounts for 0.453%.

(1964), Lintner (1965) and Black (1972). They use all non-financial firms listed on NYSE, AMEX and NASDAQ for the period 1963-1990 and follow Fama & MacBeth (1973) methodology. They find that after controlling for size, there is no relation between beta and average returns.[4] They also use B/M and a measure of leverage and find that average returns and B/M are strongly positively correlated while size and B/M subsume the effect of leverage. They conclude that size and B/M are sufficient to explain the cross-sectional variation of stock returns. They also find that negative book equity stocks have high average returns like high B/M firms and suggest that this is consistent with the hypothesis that B/M proxies for the relative distress factor of Chan & Chen (1991) who find that marginal firms in distress mainly drive the size effect. These are "fallen angels" with low earnings-to-assets ratio, low fixed expenses coverage ratio, and a substantial proportion of these firms cut their dividends drastically due to bleak future prospects. They postulate those firms that the market judges to have poor prospects (signalled by low price and high B/M) have higher expected stock returns because they are penalised with a higher cost of capital. Fama & French (1992) also find that firms with negative earnings have higher returns similar to high earnings to price stocks and argue that this lends further support to the relative distress hypothesis.

The size and value effects are not restricted to the US. Strong & Xu (1997) replicate Fama & French (1992) using UK data. Similar to Fama & French (1992), they do not find any clear relationship between pre-ranking betas and average returns. The size effect is strong for the period 1960-1992 and market value of equity has a negative correlation with beta though the relationship is weaker than in the US. Unlike Fama &

[4] Roll & Ross (1994) argue that Fama & French (1992) should have added 'for this particular market index proxy'.

French (1992), however, they find beta to be positive and significant when used as the only factor but like Fama & French (1992), they do find that beta becomes negative and insignificant in the presence of size as explanatory variable. The B/M coefficient is positive and significant, both when used as the only factor or when used in multivariate regressions with one or more of other variables (size, assets/market value, assets/book value and earnings/price) for the period 1973-1992.

Fama & French (1998) examine the B/M (and other fundamental variables: cash/price, earnings/price and dividend/price) effect in thirteen countries including the US for the period 1975-1995. Their samples for other countries are based on Morgan Stanley's *Capital International Perspectives* (MSCI). Firms included in MSCI are primarily those in Morgan Stanley's EAFE index or in the MSCI index and aim at covering 80% of market capitalization in these countries. The companies included are therefore larger companies. The difference between the returns of low and high B/M portfolios is statistically insignificant in seven out of thirteen countries including the UK where the difference is 4.62% a year (t = 1.08). For the UK, the difference between returns on value and growth portfolios formed on other criteria is statistically insignificant as well. Since only larger stocks are covered, the finding seems consistent with that of Kothari, Shanken & Sloan (1995) and Loughran (1997) that the B/M effect is driven by small firms and is weak or non-existent for larger firms.

Chen & Zhang (1998) address the question "given the set of economic forces that affect the markets, what are the *differences in structural characteristics* between stocks that would induce the *differences in return responses* to the same economic forces?" (their italics). They study the US and five countries in the Pacific Rim.[5] Similar to other studies, they find that in the US, Japan and Hong Kong, smaller firms tend to have higher B/M ratios. High B/M stocks outperform low B/M stocks in all countries but Thailand and Taiwan. They argue that unlike more mature markets, in fast growing markets value stocks are not much riskier than growth stocks. Across the six countries, small value portfolios have consistently lower return on equity than large growth portfolios. The standard deviation of earnings-to-price, interpreted as the uncertainty of next period's earnings per dollar invested, is higher for small growth firms than large growth firms. More firms in small value portfolios cut dividends by more than 25% as compared to firms in large growth portfolios. Small value firms have higher leverage (total debt to market value equity) than large growth firms do. Thus, small value firms appear to be riskier than large growth firms. B/M is highly correlated to leverage ($r > 0.90$) suggesting that both are proxying for financial risk. The pricing information in size & B/M is mostly reflected in the proportion of firms that cut dividends (distress), leverage (financial risk) and standard deviation of E/P (uncertainty with respect to future earnings).

2.2.3. Size and B/M effects as artefacts of data and/or methodology

However, the evidence for the existence of size and value effects is not entirely clean. There is also a substantial body of literature that casts doubt on the existence of these effects. Amihud, Christensen and Mendelson (1992) replicate the Fama & French (1992) tests employing Generalised Least Squares (GLS) and pooled time-series cross-section analysis. They find the same results as Fama & French using Ordinary Least Squares (OLS) but their results are reversed using either pooled time-series-cross-

[5] The Pacific Rim countries studied are Japan, Hong Kong, Taiwan, Malaysia and Thailand.

section methodology or GLS. This shows that the range of findings in the literature can be affected by the particular econometric technique used. Roll & Ross (1994) argue that GLS produces a positive cross-sectional relation between the true expected returns and true betas regardless of the inefficiency of the market proxy as long as the expected return on the proxy exceeds the expected return of the global minimum variance portfolio. Hence the results from GLS may be more robust than those from OLS. However, if the true variance-covariance matrix is not known, it is uncertain whether GLS corrections are better than OLS in small or moderately size samples (Greene (1999)).

Kim (1995) attributes the Fama & French (1992) results to the errors-in-the-variables (EIV) problem. The standard Fama & MacBeth (1973) methodology involves estimating beta coefficients for each asset through time-series regressions and then using these estimates in cross-sectional regressions. This means that the explanatory variable in the cross-section regressions is itself measured with an error. If the measurement errors and idiosyncratic errors are independent, the OLS estimator is negatively biased (Richardson & Wu (1970)). Hence, the price of beta risk is underestimated. Inclusion of firm specific variables that are measured without error (like size and B/M) leads to beta being even more underestimated. A variable that is negatively correlated to beta (like size) will be negatively biased while a variable that is positively correlated to beta (like B/M) will be positively biased. After correcting for the EIV problem, Kim (1995) finds beta to be significant but also finds size to be significant.

Kothari, Shanken & Sloan (1995) use COMPUSTAT data for 1963-90 and S&P data for 1947-87 to explore the B/M effect. They argue that the B/M effect of Fama & French (1992) is driven by the survivorship bias in their data. Specifically, they find that the return on small firms on COMPUSTAT is 9-10% higher than the small firms not on COMPUSTAT. They also argue that the B/M effect of Fama & French (1992) is time specific. Their low B/M portfolios include relatively large market capitalization winners that experience above average performance prior to ranking on B/M. Their 'winners' outperform the market prior to 1963 but underperform thereafter (the opposite is true for high B/M 'losers'). They use annual betas instead of monthly and employ five different portfolio aggregation methods: on beta alone, on size alone, intersections of independent beta or size groups, first on beta and then on size and first on size and then on beta. Regardless of the portfolio formation method, market risk premia are large and significant for the entire 1927-1990 period. However, they are smaller although still significant for the 1941-90 sub-period and generally dominate size. The size effect though not insignificant is not large either (Shanken (1992) shows that if the true beta is non-zero, t-statistics for size would be upward biased due to measurement errors in beta). Kothari, Shanken & Sloan (1995) replicate Fama & French (1992) for 1963-90 using all AMEX and NYSE firms including financials. Consistent with the survivorship bias theory, they find that the returns on portfolios of firms not on COMPUSTAT are significantly lower than returns on portfolios of firms on COMPUSTAT though the risk characteristics are similar. For S&P data, they form 10 B/M portfolios and find that the average returns are flat as B/M increases for all but the smallest portfolio. For the pre-1963 period, the t-statistic for B/M is around 1.6 and seems to be driven by the lowest B/M portfolio. For the entire period, the t-statistic is slightly above 1. For the largest

500 companies using 10 value weighted B/M portfolios, the t-statistic for B/M is 1.38, while using individual stocks the t-statistic is 1.96 which though significant is substantially lower than the t-statistic for the entire sample. They argue that this provides evidence that the B/M effect is driven by small growth firms.

Kothari, Shanken & Sloan's (1995) conclusions are challenged by other authors. Chan, Jegadeesh & Lakonishok (1995) examine whether sample selection bias explains the B/M effect. They select the largest 20% companies for the period 1968-91 and rank them on B/M. Missing book values on COMPUSTAT are collected manually so that no firm is excluded. The authors find that though missing firms do tend to be concentrated in the highest B/M quintile, they earn higher returns as well and thus there is virtually no difference in average returns between firms that are on COMPUSTAT and all firms. They conclude that the B/M effect is not driven by survivorship bias. Davis (1994) uses data from Moody's manuals for the period 1940-1963 and finds a B/M effect. Davis, Fama & French (2000) extend the analysis back to 1926 and find similar results. They conclude that it is unlikely to be an artefact of the data.

Kothari & Shanken (1997) study the predictive ability of the DJIA B/M over the period 1926-91 and sub-periods 1941-91 and Fama & French sub-period 1963-91. They find that the DJIA B/M explains a much smaller fraction of time-series variation in the value weighted index than in the equally weighted index suggesting that the effect is weaker for larger firms. The effect is weaker for the sub-period 1941-91 and inconclusive for the sub-period 1963-91. They find that the B/M effect is subsumed by dividend yield in multivariate regressions for the entire period and the sub-periods.

Pontiff & Schall (1998) use the Dow Jones Industrial Average (DJIA) B/M ratios and S&P Industrial Index B/M ratios for the period 1926 to 1991 to predict market returns. They argue that the book value of equity proxies for expected cash flows (Ball (1978), Sharathchandra & Thomson (1994) and Berk (1995) argue the same). On this basis, the B/M ratio is the ratio of an expected cash flow proxy and the current price level and captures information about expected future returns. They also use three interest rate variables (3 month T-Bill yield, the difference between average yield of bonds rated Baa and average yield of bonds rated Aaa, and the difference between the average yield of government bonds of more than 10 years maturity and the average yield of three month T-Bills) and dividend yield. The B/M ratio is strongly correlated to default spread (r = 0.50) and to dividend yield (r = 0.67). They find that the B/M ratio is positively correlated to future market returns but the relationship is stronger for an equally weighted index than for a value-weighted index. B/M becomes insignificant when other variables are introduced with the value-weighted index and the only significant variable is the default spread. The effect of the default spread variable is stronger for the equally weighted index than for the value weighted index which would suggest that small firm returns are more sensitive to it. Pontiff & Schall find that this variable has a positive sign i.e. as the spread between returns on Aaa rated bonds and Baa rated bonds increases, so does the return on smaller stocks. They are unable to reject the null hypothesis of no return predictive ability for the DJIA B/M for the period 1961-94. Their results for the S&P B/M are similar. B/M is not significant for the period 1959-94 or for the Fama & French period 1963-91. These findings are contrary to those of Fama & French (1992) who find a strong B/M effect.

Knez & Ready (1997) use least trimmed squares (LTS), an approach that trims a proportion of influential observations and fits the remaining observations using least squares. They emphasize that outliers are not viewed as contaminates to be discarded but LTS is used as a diagnostic technique for evaluating the sensitivity of inference conducted using OLS and for revealing a possible economic role played by these regressors. They find that the size effect reverses (from –12bp to +14bp per month in univariate regressions) even if only 1% of the influential observations are trimmed. The risk premium on B/M is however not affected once they control for size. They investigate reasons as to why a small number of firms drive the size effect and find no evidence that this is due to bias introduced by the bid-ask bounce for low price firms or due to takeover activity. In fact, small firms that are taken over experience large negative returns more often than large positive returns. They do find that a larger number of small young firms experience large positive returns providing some evidence to their "turtle eggs" hypothesis.

Fama & French (1992) table 5 shows that the B/M effect is considerably weaker in the larger size deciles and non-existent in the largest size decile. In the smallest size decile, value stocks outperform the growth stocks by a hefty 1.22% per month while in the largest size decile the difference is much smaller at 0.25% per month. La Porta, Lakonishok, Shleifer & Vishny (1997) find that the difference in annual returns between the lowest B/M decile and the highest B/M decile for all firms during 1971-93 is 12% (t = 4.25) while the annual difference between the two deciles for larger firms (market capitalization greater than median NYSE firm) is much lower at 8% (t = 1.77). The size effect is non-existent in the lowest and highest B/M quintiles. The dispersion of returns decreases monotonically from low B/M to high B/M portfolios except for the highest B/M portfolios and from smaller size portfolios to larger size portfolios suggesting that low B/M portfolios have more total risk than high B/M portfolios as do the smaller size portfolios. However, these observations seem to be specific to the time period studied in Fama & French (1992). Davis, Fama & French (2000) extend the Fama & French (1992) sample to cover 1929 to 1997 and find that over the extended period, the monthly value premium in their large size portfolios (0.45%) is comparable to that in their small size portfolios (0.48%).

2.2.4. Towards a theory for size and B/M effects

There have been many attempts in the literature to derive theories that might explain the size and value effects. Fama & French (1995) use data for the period 1963-92 for firms listed on the NYSE, AMEX and NASDAQ and find that low B/M firms have higher profitability[6] than high B/M firms for four years prior to portfolio formation and five years after. The growth rates of low and high B/M firms start converging after the portfolio formation year (Lakonishok, Shleifer & Vishny (1994) find the same) though low B/M firms remain more profitable than high B/M for five years after portfolio formation. They find a size effect in profitability (Setiono & Strong (1998) find this for UK) though it is conditional on B/M. They argue that this result supports the relative distress hypothesis. They, however, do not find any evidence that the B/M factor in fundamentals[7] is related to the B/M factor in returns which they attribute to noise in measuring shocks to expected earnings. They also find that earnings of firms in different

[6] Their measure of profitability is equity income for the year / opening book value equity.
[7]The fundamentals used are: equity earnings in year t+1 / opening book value of equity, ln(earnings before interest$_{t+1}$) and ln(sales$_{t+1}$).

size and B/M portfolios load on the market, size and B/M factors in earnings in the same way as stock returns load on these factors in returns suggesting a common link.

Barth, Beaver & Landsman (1998) argue that balance sheets provide information about liquidation values while income statements provide information about abnormal earnings opportunities. As liquidation values and probability of default affect equity values, balance sheet importance increases and that of the income statement decreases as financial health deteriorates. To the extent that liquidation value effects dominate, the linkage between book value and market value of equity becomes tighter for financially distressed firms. Using a sample of bankrupt firms, the authors estimate the coefficients[8] in each of the five years before bankruptcy. They find that the coefficient of book value is indeed higher when firms are distressed.

Ball (1978) and Berk (1995) argue that B/M may proxy for risk because of the inverse relation between market value and discount rates. Holding book value constant, the B/M ratio increases as the expected return (and hence the risk) increases. Berk (2000b) argues that market value (and B/M) must be inversely related to stock returns and so, such a relation is not an anomaly. He argues that in a single period economy, if the expected value of every firm's cash flow is the same but variance differs then with risk-averse investors, riskier firms will have lower market value and by definition, higher returns. Berk (1995) shows that the result holds when expected cash flows are not equal as long as expected returns are not positively correlated to expected cash flows. He

[8] The model is:
$MVE_{it} = a_0 + a_1BVE_{it} + a_2NI_{it} + e_{it}$
where: MVE is market value of equity, BVE is book value of equity, NI is net income before extraordinary items, i is the firm and t is the time subscript.

further shows so long as an asset pricing model does not capture all relevant risk factors, γ_S in the following equation is less than zero even if size and expected return are unrelated:

$$E[R_i] = f_i + \gamma_S \, size_i$$

where $E[R_i]$ is the expected return on stock i, f_i is the expected return specified by the asset pricing model and $size_i$ is the market value of stock i

Hence, according to Berk (2000b), the size effect is an anomaly only if asset pricing theory requires a positive correlation between expected returns and expected cash flows. Based on this he argues that any relationship between firm size and stock returns might be due to an endogenous inverse relationship between market value and discount rates rather than evidence of higher exposure to a specific risk factor. Berk also presents a similar argument for B/M. In a single period model, book value of equity measures past investment and is likely to be highly correlated with expected cash flows and is therefore a better measure of expected return than market value. He finds that, as expected, there is no relation between stock returns and other measures of firm size (book value of assets, undepreciated book value of plant, property & equipment (PPE), sales and number of employees).

2.2.5. The Fama & French (1993) three-factor model

Fama & French (1993) use the time-series approach of Black, Jensen and Scholes (1972) on the same data as Fama & French (1992). They form 25 portfolios ranked independently on size and B/M. Their table 2 shows that the relationship between size and returns is erratic for the lowest B/M quintile and there is no size effect for the highest B/M quintile. The table also shows that the difference in returns across B/M portfolios is not constant across size. The difference between lowest B/M portfolio returns and highest B/M portfolio returns is of the order of 0.60% per month for the first four size quintiles but only 0.19% per month for the largest size quintile. The difference in average returns of the lowest and highest B/M portfolios is not statistically significant for any of the five size quintiles. When the returns are regressed on a term structure variable[9] and a default risk variable,[10] the coefficient on the default risk variable is always statistically significant (minimum t = 3.59) and economically large (minimum 0.73% per month). This is consistent with the findings of Chen, Roll & Ross (1986). The coefficient increases monotonically from low to high B/M and monotonically decreases from small to big size portfolios. This latter is consistent with the findings of Chan, Chen & Hsieh (1985) that the effect of this variable is concentrated in smaller size portfolios. Chen, Roll & Ross (1986) argue that under risk neutrality, the mean value of the default risk variable should be zero and higher values provide a direct measure of risk aversion. So the higher coefficient of the default risk variable on higher B/M stocks is consistent with the distress factor hypothesis. They construct factor mimicking portfolios as follows: Each year stocks are sorted into two portfolios on size and, independently, three portfolios on B/M. The factor HML is constructed as the difference in mean monthly returns of the two high B/M portfolios and the two low B/M portfolios. Similarly, the factor HML is constructed as the difference in mean monthly returns of the three small size portfolios and the three large size portfolios. The regression using only HML and SMB (table 5) produces much lower R^2s than the

[9] The term structure variable is defined as difference between long-term government bond return and one month T-Bill rate.

[10] The default risk variable is defined as difference between return on a proxy for the market portfolio of long term corporate bonds and the return on long term government bond.

regression using the market factor alone.[11] This suggests that the market factor captures the bulk of time-series variation while improved R^2s when HML & SMB are included suggests that size and B/M capture some residual variation. Fama & French (1995) find that a typical value firm has had a string of bad news and is now financially distressed. Since distressed stocks survive more often than not, such stocks generate a high return. A similar argument can be put forward for small firms. Hence, SMB and HML can be regarded as state variables that proxy for a distress factor.

The Fama & French (1993) three factor model has generated considerable literature in the US. Lewellen (1999) examines the relationship between expected returns, risk and B/M. He uses industry portfolios (which he argues are less susceptible to data snooping bias) rather than size or B/M sorted portfolios. He uses the Fama & French (1993) three-factor model and also tests a conditional version of the model. His conditional and unconditional regressions yield similar coefficients suggesting that changes in loadings are not correlated with these factors. The B/M ratio captures the time-variation in risk but does not appear to predict expected returns. Lewellen (1999) finds that the coefficient of the interactive term with the intercept in conditional regressions is not significantly different to zero suggesting that B/M does not explain the variation in intercepts – a finding that he argues is inconsistent with the overreaction hypothesis. He finds that HML and SMB are significant in ten of his thirteen industry portfolios while the intercept term is significant in only three. He concludes that HML and SMB are

[11] The market factor when used alone produces R^2 always in excess of 0.65 while size & B/M when used without the market factor produce an R^2 of less than 0.50 in 17 out of 25 cases. This is also consistent with the findings of Chen, Roll & Ross (1986) that the market factor is the most powerful factor in explaining inter-temporal variation in average returns though it has no explanatory power in cross sectional-variation.

proxies for pervasive risk factors and the three-factor model provides a reasonable though not perfect description of average returns.

Liew & Vassalou (2000) further explore the Fama & French (1993) factors as well as momentum in ten countries. They use macroeconomic variables along with the Fama & French variables to predict future GDP growth rate. HML is significant in eight of the ten markets while SMB in only two and momentum in five. For the UK, for the period 1978-1996, the HML return is 6.91% per year (t = 5.14) while the SMB return is 3.17% and not significant. They further find that in the UK, small firms underperform larger firms in bad states of the economy and outperform in good states. Value firms strongly outperform in good states and do better even in bad states while momentum is positive in good states and negative in bad states. They further find that HML and SMB contain information about future economic growth independent of the market factor and retain their predictive ability when other popular business cycle variables are included. Their findings support the risk based explanation of Fama & French in that HML & SMB are state variables that predict future changes in the investment opportunity set in the context of Merton's (1973) Intertemporal CAPM. They do not find such evidence for momentum.

2.2.6. Size and B/M effects due to mispricing

Risk is by no means the only explanation for the size and value effects. Haugen & Baker (1996) use Russell 3000 stocks for the period 1979-1993. They use factors related to risk, liquidity, price-level, growth potential and the technical history of stock returns as explanatory variables. They find that higher returns are associated with lower volatility, lower leverage, higher interest cover, higher rate of earnings growth, higher profitability and larger companies with higher price per share, all of which suggest that firms earning higher returns are actually less risky. The Fama & French (1993) three-factor model produces a statistically and economically significant intercept, the highest return decile has larger firms with lower B/M than the firms in the lowest return decile. Haugen & Baker (1996) also extend their study to four other markets (Japan, Germany, UK and France) and find no evidence from the fundamental firm characteristics that the realised return differences are risk related and conclude that their factor model exploits bias in pricing.

Loughran (1997) uses all firms listed on the NYSE, AMEX and NASDAQ for the period 1963-95. He applies the same restrictions as Fama & French (1992). His Table 1 shows that:

1. The largest size quintile is tilted towards growth – 20% of total market capitalization is in large growth stocks against 11% for large value (Panel A).
2. The variation between growth and value portfolios is not constant across size quintiles. The B/M ratio goes from 0.25 to 1.37 in the largest size quintile as against 0.36 to 2.80 in the smallest size quintile (Panel B).
3. Firms with the highest level of profitability are large growth firms. Both small value and small growth firms in his sample have negative return on assets. Except for the smallest size quintile, growth firms are substantially more profitable than value firms (Panel D).

4. Adjusting for firm size, as one goes from value to growth, the proportion of newly listed firms always increases. Newly listed firms are overwhelmingly growth firms (Panel E).

Loughran's (1997) Table 5 further shows that for equally weighted portfolios, a substantial portion of the B/M effect is driven by newly listed small growth stocks which represent less than 1% of total market capitalization in the US. When the B/M quintiles are value weighted, growth firms have higher annual returns than value firms outside of the 1974-84 sub-period. Size and B/M do not explain cross-sectional variation for the period 1963-95 once January is excluded. The coefficient on B/M is an insignificant 0.02% per month (t = 0.16) for the largest size quintile (representing 73% of total market capitalization). Similarly, for the top dollar volume quintile (representing 69% of total market capitalization), the coefficient on B/M is an insignificant 0.09% per month (t = 0.80). Similarly, Siegel (1995) finds that the 'nifty-fifty' (a group of large growth stocks) outperforms the value-weighted index between January 1972 and May 1995 even though it has low B/M and high P/E ratios. He also shows that the B/M effect is insignificant for the top three quintiles on size outside the month of January. Davis (1994) finds the same results for the period 1940-63 but that small growth firms have the highest level of non-merger delistings (3.93% per year). A bankruptcy risk premium (assuming it is positive) cannot explain higher returns on small value firms.

Lakonishok, Shleifer & Vishny (1994) also find a value effect in stock returns. They argue that value stocks will be fundamentally riskier than growth stocks if they underperform growth stocks in bad states (when the marginal utility of wealth is higher and value stocks would be unattractive to risk averse investors). They find that value stocks did "somewhat better than growth stocks in all states and significantly better in some" implying that they do not expose investors to greater downside risk. They argue that earnings growth rates are predictable only one to two years into the future but the large price-earnings differences between value and glamour stocks seems to reflect an expectation that the past growth differences will persist much longer than is reliably predictable from past data. Value stocks provide superior returns because the market slowly realises that the earnings growth rates for value stocks are higher than it expected (and conversely for glamour stocks).

La Porta, Lakonishok, Shleifer & Vishny (1997) test whether the earnings surprises for value firms are systematically positive over the next five years after portfolio formation and those for glamour firms, systematically negative using NYSE, AMEX and NASDAQ firms for the period 1971-93. They find that this is indeed the case and the difference between event returns for glamour and value stocks is statistically significant.[12] However, the difference is much smaller for larger firms. They argue this smaller difference for larger firms is consistent with the mispricing explanation because larger firms are followed by more analysts and therefore, more efficiently priced.

The evidence in La Porta, Lakonishok, Shleifer & Vishny (1997) should, however, be interpreted cautiously. First, they use annual buy-and-hold returns (BHARs), which are recommended because additive cumulation is systematically positively biased due to bid-ask bounce (Roll (1983), Blume & Stambaugh (1983) and Conrad & Kaul (1993)).

[12] However, the event returns on glamour stocks though negative are not statistically different to the T-Bill rate.

Also, BHARs represent investor experience more accurately than cumulative abnormal returns (CARs). However, Kothari & Warner (1997) show that long horizon BHARs are significantly right skewed and are no better than cumulative abnormal returns. Fama (1998) argues that interpretation of CARs is much simpler than that of BHARs due to the extreme skewness of the latter. Second, Kothari & Warner (1997) find that the standard event study variance estimation methods underestimate the true variance and the test statistics overreject the null of no abnormal returns. Thirdly, they use a portfolio approach for abnormal returns derivation. Barber & Lyon (1997) show that there can be at least two biases in this approach: new listing bias (when the reference portfolio contains firms listed subsequent to the event date) and rebalancing bias (when the portfolios are rebalanced periodically while the sample firm returns are not).

Griffin & Lemmon (2002) use Ohlson's (1980) O-score as a proxy for financial distress. They study the returns around earnings announcement dates and find that consistent with the findings of La Porta, Lakonishok, Shleifer & Vishny (1997), abnormal returns for low B/M portfolios are negative and those for high B/M portfolios are positive. The difference between the returns on low and high B/M stocks is largest for the highest O-score portfolio (highest distress risk) suggesting higher mispricing for such firms. The authors find that high O-score firms have lower analyst coverage and high O-score firms with low B/M have the lowest coverage. They conclude that high O-score firms are more subject to mispricing because they are harder to value due to larger information asymmetries.

Fama & French (1995) find evidence contrary to the errors-in-expectations hypothesis of Lakonishok, Shleifer & Vishny (1994). They show that the ratio of earnings in t+1 to market value at 't' remains stable in the eleven year period (t-5 to t+5) around the portfolio formation date. Also for the errors-in-expectations hypothesis to hold, low returns on growth stocks should be temporary and correct themselves as the market realises that post-formation earnings growth is lower than expected. However, inconsistent with the errors-in-expectations hypothesis, they show that low returns on growth stocks persist for at least five years after portfolio formation.

There is a stalemate between the competing explanations for the size and B/M effects. Empirical findings seem to be consistent with both the risk based and behavioural models. Daniel & Titman (1997) devise one possible method to disentangle the two explanations. They test whether the value and size premia can be attributed to their factor loadings. They find that "once we control for firm characteristics, expected returns do not appear to be positively related to the loadings on the market, HML or SMB factors" (page 4). The average pre-formation returns of the Fama & French (1993) HML portfolios are strongly negative supporting their assertion that value stocks are distressed and growth stocks have performed well in the past. Daniel & Titman (1997), however, find that the common variation in value stocks is present both five-years before and after these firms entered their distress/growth portfolio suggesting that the common variation is not a result of loading on a separate distress factor that is present only when the firms are in a growth/distress phase. They find that within a B/M – size portfolio, the sort on pre-formation factor loadings produces a monotonic ordering of post-formation factor loadings. They form characteristics balanced portfolios within each of their nine B/M-size portfolios and find that the intercepts from time series regressions are positive for eight of the nine portfolios against the zero intercept predicted by the Fama & French (1993) three-factor model. The mean return of the portfolio is negative against positive as predicted by the factor model. Daniel & Titman (1997) conclude that there is no evidence of a separate distress factor. The covariance of value stocks is because stocks with similar factor sensitivities become distressed at the same time. They provide an alternative characteristics-based pricing model where the expected returns are a function of an observable firm attribute that is negatively correlated with the stock returns but not related to the loadings on the distress factor. Hence, there would be some stocks that despite high B/M are not distressed and will earn low returns.

Davis, Fama & French (2000) repeat Daniel & Titman's (1997) analysis using data from 1929-1997 and find evidence consistent with the risk-based explanation for value and size effects. They conclude that the Daniel & Titman (1997) results are period specific.

Guidi & Davies (2000) use UK data for the period 1969-1993 and construct portfolios on characteristics (new listings, marginal stocks and high leverage stocks). They find that consistent with the Fama & French (1993) three-factor model and inconsistent with the Daniel & Titman's (1997) characteristics based model, the intercepts for these portfolios are indistinguishable from zero.

2.2.7. Calendar seasonality in size and B/M effects

There also appears to be calendar seasonality in size and B/M effects. Seasonal variation in stock returns was first reported by Bonin & Moses (1974) for the US and by Officer (1975) for Australia. Rozeff & Kinney (1976) were the first to document the now famous 'January effect' in stock returns in the US. They find that returns on US stocks display significantly higher returns in January than in other eleven months for the period 1904-1974. Gultekin & Gultekin (1983) find seasonality in stock returns in most of the seventeen countries studied by them. Levis (1985) reports a January and April seasonal in UK stock returns. He finds that almost 50% of the size premium in the UK is in the month of May which he attributes to institutional factors. Loughran (1997) and Daniel & Titman (1997) among others report that in the US, size & B/M effects are restricted to January. Blume & Stambaugh (1983) show that after correcting for biases, the size effect in the US is evident only in January. Hawawini & Keim (1995) record international evidence on seasonality in stock returns.

The fact that factors like B/M, firm size and E/P (earnings/price) are all most pronounced during January suggests that they are associated with some common underlying factor. The most popular hypothesis attributes the January effect to year-end tax-loss selling:

> "The hypothesis maintains that tax laws influence investors' portfolio decisions by encouraging the sale of securities that have experienced recent price declines so that the (short term) capital loss can be offset against taxable income. Small stocks are likely candidates for tax-loss selling since these stocks typically have

higher variances of price changes and therefore, larger probabilities of large price declines." (Brown, Keim, Kleidon & Marsh, 1983, p107).

The same argument can also be applied to high B/M stocks – a sharp decline in market value will lead to an increase in B/M. Reinganum (1983) and Roll (1983) find that at least a part of the January effect is related to tax related trading. Schultz (1985) and Jones, Lee & Apenbrink (1991) find that in the US, prior to 1917 when there was no capital gains tax, there is no January effect. Reinganum & Shapiro (1987) find the same for the UK prior to 1965 (before the introduction of capital gains tax).

Another popular explanation for the 'January effect' is institutional window dressing – selling losers at year-end so they do not appear on year-end statements sent to shareholders (Haugen & Lakonishok, 1987).

2.2.8 Summary of the literature on book-to-market, firm size and stock returns

Like PPT

The above literature survey shows that:

1. Size and value effects are pervasive and strong in several markets (Fama & French (1998), Chen & Zhang (1998), Lakonishok, Shleifer & Vishny (1994)) and across several time periods (Davis, Fama & French (2000)). This persistence and pervasiveness means that these effects are unlikely to be artefacts of the data.

2. The book-to-market effect is weaker for larger companies, a finding that is consistent with both the distress factor and mispricing explanations for the superior returns on value stocks. Larger firms are substantially less likely to fail than smaller firms so the

premium for bankruptcy risk (assuming it is positive) would be smaller in the larger size portfolios. Thus the B/M effect is expected to be weaker for larger companies (Davis (1994)). However, as more analysts follow larger firms, pricing mechanisms for these firms should be more efficient. This will lead to a weaker B/M effect if it is due to market mispricing (Lakonishok, Shleifer & Vishny (1994)).

3. Low B/M stocks are more profitable than high B/M stocks (Fama & French (1995)). This is again consistent with both, the distress factor and the mispricing theories. Firms with lower profitability and uncertain prospects are riskier than firms with good profitability and therefore have higher expected returns (Fama & French (1995)). On the other hand, the market may be overly pessimistic about the prospects of poor performers and overly optimistic about the prospects of good performers. The former outperforms the latter as the market realises its mistake (Lakonishok, Shleifer & Vishny (1994)).

4. The evidence on riskiness of value and growth stocks is mixed. On one hand, Chan & Chen (1991), Fama & French (1995) and Chen & Zhang (1998) find that high B/M stocks and smaller size stocks are riskier than low B/M stocks and larger stocks. On the other hand, Haugen & Baker (1997) find that firms that earn high average returns are less risky than firms that earn low average returns.

5. The default risk factor (defined as spread between low-grade corporate bonds and long term government bonds or between average corporate bonds and long term government bonds or between top grade corporate bonds and low-grade corporate bonds) is important in explaining the cross-sectional variation in average stock

returns. This factor provides a measure of risk aversion and is more important for smaller size firms and for higher B/M firms supporting the distress factor theory of higher returns on value stocks (Fama & French (1993)).

6. Most of the empirical evidence is unable to disentangle the risk based and market mispricing explanations for the size and B/M effects.

7. Stock returns are not the same in all months of a year. However, size and value effects are also pronounced in certain months of the year suggesting a common underlying factor driving the returns.

The review of literature on size and value effects shows that there is no direct evidence that size and B/M effects are related to a distress factor. Also, there is no UK-based study that tests the Fama & French (1993) three-factor model using UK data.

2.3. Bankruptcy risk and stock returns

2.3.1. Introduction

The survey in the previous section shows that firm size and the book-to-market ratio can explain cross-sectional variation in stock returns, at least in smaller firms. The dominant explanation for this is that these variables are proxies for a firm distress factor and capture the risk missed by the market factor. This section surveys the literature that has used a different and more powerful proxy for the firm distress factor to study stock returns.

Probability of failure is a natural proxy for the distress factor and the prediction of business failure has been fairly well researched in the US with the studies by Beaver (1966) and Altman (1968) providing a stimulus for a steady stream of academic papers throughout the 1970s and 1980s. The use of financial ratios in credit analysis can be traced back at least to 1908.[13] Z-score models produce powerful ex-ante measures of probability of failure and are well-accepted measures of solvency in credit analysis (Taffler, 1995). Altman & Narayanan (1997) discuss failure prediction models for twenty-two countries. Taffler (1983, 1984) describes a failure prediction model for the UK.

2.3.2. The evidence

Beaver (1968) was one of the first people to study the stock market performance of failing firms. The sample consisted of 34 failed and 42 non-failed firms during 1954-64 matched on industry and total assets. His failed firms under performed their non-failed partners for five years before failure and the dispersion of returns was much higher for the non-failed firms than for the failed firms. He concluded that investors adjust to the new solvency position of the firms continuously over time and the information in their financial ratios is impounded in market prices.

Altman & Brenner (1981) studied the stock market performance of firms with latest z-score below the solvency threshold and the previous year's z-score above the threshold. Their sample consisted of ninety-two firms over 1960-63. They find that the beta of these firms declined after the change in z-score. Cumulative abnormal returns based on post-event beta show a decline of 9.6% over 12 months after the change (t = -3.37).

[13] Rosendale (1908).

However they find the CARs to be sensitive to the choice of market model and are unable to reject the efficient markets hypothesis.

Katz, Lilien & Nelson (1985) study firms that recovered from financial distress to financial health or vice-versa for the period 1968-76 with distress defined through the use of Altman's (1968) z-score model. They find that firms which moved from their healthy to distressed portfolios earn significant abnormal returns from 11 months before the balance sheet date to 12 months after while the opposite is true for the firms which moved from distressed to healthy portfolios.

Healy and Sgromo (1993) examine the returns of portfolios chosen on the basis of balance sheet strength. They use Solvency Analysis Corporation's criteria and find that portfolio returns can be enhanced by decreasing exposure to companies with balance sheet excesses (both very strong balance sheets and very weak balance sheets) and by increasing exposure to companies with improving balance sheets. Firms which improved their ratings next year outperformed firms whose rating deteriorated by 18.8% per year.

Dichev (1998) uses two proxies for bankruptcy risk – Altman's (1968) z-score model and Ohlson's (1980) conditional logit model.[14] He uses all industrial firms listed on NYSE, AMEX & NASDAQ available on CRSP during 1981-95. As hypothesised, he finds a negative correlation between size and bankruptcy risk and a positive correlation between bankruptcy risk and B/M. All the stocks are ranked according to z-score

[14] In Altman's model, the higher the score the lower the probability of failure while in Ohlson's model, the higher the score the higher the probability of failure.

(Altman (1968)) or O-score (Ohlson (1980)) and aggregated into 10 portfolios. He finds that z-score has a positive coefficient for NYSE & AMEX firms that is statistically insignificant in univariate regressions (t = 1.59) and statistically significant in multivariate regressions (t = 3.37). The coefficient though is economically negligible at 0.06% per month for multivariate and 0.03% per month for univariate regressions. The coefficient on size is not significant in either univariate or multivariate regressions while that on B/M is significant in both univariate (t = 3.26) and multivariate (t = 4.59) regressions. For NASDAQ, z-score has a negative and statistically significant coefficient in univariate regressions while the B/M effect is stronger. However, again the coefficient is economically insignificant (2 basis points per month). The z-score coefficient becomes statistically insignificant when size and B/M are introduced in the pricing equation. O-score has a negative coefficient that is significant for both AMEX-NYSE (t = -3.38) and for NASDAQ (t = -4.59) in multivariate regressions. The coefficient on O-score is however a small 0.11% per month.

However, an inspection of his table 3 shows that:

1. The raw returns for his lowest z-score portfolio are extremely low (0.48% per month) and insignificantly different to zero.
2. The relationship between z-score and returns is positive for portfolios 1-4 and negative for portfolios 7-10.
3. The relationship between z-score and returns is flat for portfolios 4-6.

His table 4 shows the same pattern for O-score. To the extent that z-score (O-score) measures financial health of a firm, a very low z-score (high O-score) suggests weak balance sheet and a very high z-score (low O-score) suggests strong balance sheet. The evidence here seems consistent with that of Healy & Sgromo (1985) who find that firms with weak as well as strong balance sheets earn lower returns than firms with average balance sheets.

Dichev hypothesises that the positive association between z-score and returns could mean:

1. Distressed firms have lower systematic risk, or
2. The market does not impound fully the available distress information.

A trading strategy of buying stocks in the top seven deciles and selling stocks in the bottom decile earns positive returns in eleven out of fifteen years. The returns to the strategy are a significant 1.17% per month (t = 3.36). The most distressed firms continue to substantially underperform for four years after portfolio formation. He concludes that this is evidence of the market's inability to properly impound the distress information. He also concludes that the B/M effect is unlikely to proxy for bankruptcy risk since higher bankruptcy risk is associated with lower returns (indeed the B/M effect becomes more pronounced in multivariate regression).

However, Dichev's study is beset by many problems. Firstly, his returns generating models ignore beta completely. This could lead to model misspecification. Secondly, he uses portfolios that are ranked on z-score and then uses average z-score as an explanatory variable. Taffler (1995) points out that z-score is an ordinal measure and cannot be meaningfully averaged. Thirdly, a voluminous literature in asset pricing suggests that results can be sensitive to portfolio formation methods. Dichev provides no alternative trading rules. Fourthly, even though he notes that there appears to be a strong relationship between z-scores and returns for high bankruptcy risk firms, he does not conduct any formal tests for differential risk loadings.

Taffler (1999) studies the effect of the z-score in the UK using all fully listed non-financial firms for the period 1984-94. He also uses macro-economic variables to study the time-varying risk premia. He uses individual stocks in Fama-MacBeth (1973) regressions and finds that for his 11 year period, beta and size are not significant while B/M and momentum are highly significant. When z-score is used as a binary variable (0 if z<0, 1 otherwise), along with beta, size, B/M and momentum, it has a coefficient of 0.96% per quarter (t = 2.14). However, if z-score is treated as a continuous variable, the coefficient is insignificant. Z-score and B/M are uncorrelated in his sample (r = -0.04) and B/M remains highly significant when z-scores are included in the regressions. He concludes that z-score is measuring a different dimension of risk to B/M. He also finds that the z-score risk premium is strongly correlated to macro-economic variables. The negative z-score firms outperformed the positive z-score firms for the period leading up to the 1987 crash, a period of expansion in the UK. Since then the UK economy has experienced severe recession in the early 1990s and has not witnessed strong growth. He conjectures that weaker firms out perform stronger firms during an expansionary phase of the economy but suffer more during recessions or uncertainty.

Vassalou & Xing (2002) use default probabilities of individual firms which they compute using the contingent claims methodology of Merton (1974). They sort securities on the basis of their default probabilities and form ten portfolios. Their high default probability portfolios earn higher returns than low default probability portfolios suggesting default risk is priced. They split each of the ten portfolios into five portfolios on size and find that the size effect is restricted to the high default probability portfolios. When they split each of the original ten portfolios into five B/M portfolios, they find the same result i.e. the B/M effect is present only in the high default probability portfolios. This would suggest that size and B/M effects are linked to a firm distress factor. When they include their default risk measure along with market factor, HML and SMB in the Fama & French (1993) model, all the factors are priced though the effect of the default risk measure is much weaker. They argue that this indicates that though there is some distress related information in HML and SMB, there is a lot more information in these two factors that is not related to default risk though it may be related to risk. The default risk measure also had some ability to predict changes in macro-economic variables.

Griffin & Lemmon (2002) use Ohlson's (1980) O-score as a proxy for bankruptcy risk. For the period 1965-1996, they find results similar to Dichev (1998) i.e. higher bankruptcy risk portfolios earn lower returns. High O-score firms with high B/M ratios exhibit characteristics associated with distress and earn slightly higher returns than other high B/M firms. However, high O-score firms with low B/M ratios earn very low returns (lower than the risk free rate for their sample!). In fact the authors find that low returns for distressed firms in Dichev (1998) are driven by these low B/M firms. Similar to Dichev (1998) and Taffler (1999), they find little correlation between B/M and O-score (r = 0.05) and conclude that O-scores contain different information to B/M.

2.3.3. Summary of the literature on bankruptcy risk and stock returns

The survey of literature on the relationship between bankruptcy risk and stock returns shows that very little work has been done to explore this relationship. The earlier studies

(Beaver (1968) and Altman & Brenner (1981)) indicate that financially weaker firms tend to underperform financially stronger firms.

Three recent studies (Dichev (1998) and Griffin & Lemmon (2002) for the US and Taffler (1999) for the UK) that use a measure of probability of failure as a proxy for the firm distress factor find that distressed firms actually underperform non-distressed firms. This finding is contrary to the hypothesis that distressed firms would outperform non-distressed firms. Moreover, these three studies find no correlation between B/M and z-scores and conclude that B/M and z-scores are capturing different risks. In Dichev's study, the B/M effect becomes stronger in multivariate regressions that indicates that B/M and z-scores are indeed capturing different effects.

The explanations for the findings are different as well. While Altman & Brenner (1981) are unable to reject the efficient markets hypothesis due to sensitivity of results to the returns generation process assumed, Taffler (1999) argues that the returns on distressed firms are consistent with market efficiency. He finds that the bankruptcy risk has a strong time-varying pattern with distressed firms outperforming non-distressed firms during periods of expansion and underperforming during recessions. Dichev (1998), however, argues that underperformance of distressed firms is due to market mispricing since the most distressed firms continue to earn below average returns for four years after portfolio formation indicating a belated and slow adjustment to available information. He argues that to be consistent with a risk based explanation, there has to be a long run shift in the systematic risk of a large sub-population of firms. Griffin & Lemmon (2002) find that their high bankruptcy risk portfolios have lowest analyst coverage and therefore are most likely to be mispriced.

Vassalou & Xing (2002) find results opposite to Dichev (1998), Taffler (1999) and Griffin & Lemmon (2002) i.e. portfolios with higher default risk earn higher returns. They also find that size and value effects are restricted to high default risk portfolios and that HML & SMB contain a lot of information unrelated to default risk along with some information related to default risk.

2.4 Summary

The existing literature on asset pricing was reviewed in two separate strands. The first strand reviews the relationship between stock prices, book-to-market and firm size. It shows that the book-to-market and small firm effects are pervasive across markets and across time periods. The dominant explanation for the superior performance of high book-to-market and small capitalization firms is that such firms are relatively distressed and hence riskier than low book-to-market and large capitalization firms. Value and size premia are thus compensation for risk (missed by the market factor) and consistent with market efficiency and risk based multi-factor asset pricing models. However, the literature on book-to-market and size effects does not provide any direct evidence that high B/M and small size firms are indeed distressed firms. Even though Fama & French (1993) is the dominant multifactor asset pricing model, there are no studies in the UK that test its applicability to the stock returns on the London Stock Exchange. These are two of the key gaps in the literature that this study hopes to address.

The second strand of the literature reviews the performance of distressed firms. It generally finds that distressed firms underperform non-distressed firms (Vassalou & Xing (2002) are an exception), a finding that seems to contradict the distress factor hypothesis. Recent work by Dichev (1998) for the US and Taffler (1999) for the UK, provide the first direct evidence on the performance of distressed firms.

However, several issues have not yet been explored. Dichev (1998) notes that there is a positive relationship between z-scores and stock returns when the bankruptcy risk is high but does not provide any formal evidence. The differential loading on z-score is to be expected because the bankruptcy risk decreases dramatically with increasing z-score. There is little variation in bankruptcy risk once the z-score becomes positive. Taffler (1999) notes the strong correlation between macroeconomic factors and the z-score coefficient but does not conduct a detailed conditional analysis. Such analysis is useful for asset pricing theory because there is evidence of time varying risk premia. It is also useful for market timers. There is also a voluminous literature on stock return seasonality and on the seasonality in size and B/M effects. There is, however, no study that explores seasonality in z-score effects. This is important because if size, B/M and z-scores exhibit similar seasonalities, this would provide evidence that these factors are linked to some common underlying factor in stock returns. Finally, there are no studies that use alternative specifications to Dichev (1998) and Taffler (1999). Such studies are needed to ensure that results are not methodology or period specific.

In the next chapter I build testable hypotheses that address the gaps in the literature identified in this chapter.

Chapter 3

TESTABLE HYPOTHESES

3.1. Introduction

In this chapter I derive testable hypotheses that aim at addressing the gaps in the literature identified in chapter 2. The survey of relevant extant literature in the previous chapter shows that two main explanations have emerged to explain the superior performance of value stocks against growth stocks. The 'distress factor hypothesis' explanation says that small stock and value stocks are riskier than growth stocks and higher returns on the former are expected. The risk factor missed by the market factor is hypothesized to be related to firm distress (Chan & Chen (1991) and Fama & French (1992, 1993)). The other explanation is that the market makes systematic errors by extrapolating past performance too far into the future. The superior performance of value stocks stems from corrections as the market realises its mistake (Lakonishok, Shleifer & Vishny (1994), La Porta, Lakonishok, Shleifer & Vishny (1997)). The main objective of this study is to test the distress factor hypothesis and the nature of bankruptcy risk.

There is no agreement in the literature about what is meant by the 'distress factor'. While Fama & French (1993, 1995) seem to suggest that the 'distress factor' refers to financially distressed firms (a view taken by Dichev (1998) as well), Cochrane (2001) argues that the term 'distress factor' refers to an aggregate macroeconomic factor and not an individual firm distress factor since the latter is an idiosyncratic risk that can be diversified away and hence, is not priced. There is also no agreement in the literature as to whether individual firm distress is an idiosyncratic factor or a systematic risk factor.

For the purpose of this study, I adopt the interpretation of Fama & French (1993, 1995) and define 'distress factor' as individual firm distress. Whether this factor is idiosyncratic or a priced systematic risk factor is an open question that I test in this study. The terms relative financial distress and bankruptcy risk are used interchangeably in this study.

The chapter is organized as follows: section 2 describes the hypotheses to be tested and section 3 summarizes the discussion.

3.2. Hypotheses to be tested

3.2.1. Do distressed firms earn higher returns?

Negative z-score firms have a financial profile similar to firms that have failed in the past. Such firms are more likely to be financially distressed than firms with positive z-scores and, therefore, subject to higher bankruptcy risk. If there is a distress factor with positive risk premium, then, controlling for the market factor, distressed firms will outperform non-distressed firms. I thus establish null hypothesis 1:

$H1_0$: ***There is no difference in the performance between financially distressed and non-distressed firms, controlling for the market factor.***

3.2.2. Do size and B/M capture distress risk?

If the z-score, B/M and firm size are all proxies for the distress factor, we would expect that introduction of size and B/M to the asset pricing equation will subsume, or at least substantially reduce, the z-score effect. Alternatively, size and B/M effects will either be subsumed or at least substantially reduced when z-score is introduced in the asset pricing equation as all three are proxying for the same risk factor. I thus establish null hypothesis 2:

$H2_0$: *The coefficient on z-score is insignificant when size and B/M are included in the asset pricing equation and similarly, size and B/M effects are uninfluenced by inclusion of z-score in the asset pricing equation.*

3.2.3. Is the risk of bankruptcy asymmetric?

Since positive z-score firms rarely fail, the z-score measure will be highly asymmetric. There would be very little difference in bankruptcy risk amongst the positive z-score firms while those with more negative z-scores would be at higher risk than those with less negative z-scores. As such factor loadings for positive z-score firms should not be significant while those for negative z-score firms would be. Therefore, if the distress factor is missed by the market factor we would expect a strong relationship between B/M, size, z-scores and returns for financially distressed firms while the relationship between distress proxies and returns for financially healthy firms would be insignificant. I thus establish null hypothesis 3:

$H3_0$: *There is no association between z-scores and excess returns for both financially distressed and non-distressed firms.*

3.2.4. Do size and B/M reflect asymmetric bankruptcy risk?

If size and B/M are capturing the distress factor, these effects will be strong for financially distressed firms and weak for financially non-distressed firms. I thus establish null hypothesis 4:

H4$_0$: *There is no association between size, B/M and excess returns for both, financially distressed and non-distressed firms.*

3.2.5. Is the distress factor a systematic risk factor?

Most fund managers tend to think of risk as sensitivity to broad movements in the market (Lakonishok, Shleifer & Vishny (1994)). Systematic risk – the only risk that is priced, relates to the covariance of stock returns with the return on the market proxy. Riskier stocks will have higher covariance with the market i.e. they will earn higher returns than less risky stocks when the conditions are good and earn lower returns when market conditions are bad. Lakonishok & Shapiro (1986) find that, as expected, ex post, high beta stocks do better in up-markets and worse in down-markets than do low beta stocks. A similar effect will be observed for z-scores, size and B/M effects if they are proxies for priced risk factors i.e. distressed stocks, small stocks and high B/M stocks will fare worse than non-distressed stocks, large stocks and low B/M stocks during down-markets and fare better during up-markets. Of course, ex ante, investors do not know in which months return on the market will exceed the risk free rate or vice versa. Consistent with the risk explanation, we expect that financially distressed firms will outperform financially non-distressed firms in up-markets and underperform in down-markets. I thus establish null hypothesis 5:

H5$_0$: *There is no difference in the returns of financially distressed and non-distressed firms in up- and down-markets.*

3.2.6. Is there calendar seasonality in size, B/M and z-score effects?

There is a voluminous literature that finds calendar seasonality in stock returns in several countries and across different time periods (Hawawini & Keim (1995) document international evidence). Levis (1985) reports a January and April seasonal in UK stock returns. He finds that almost 50% of the size premium in the UK is in the month of May. Loughran (1997) and Daniel & Titman (1997) among others report that in the US, size & B/M effects are restricted to January. The fact that factors like B/M, firm size and E/P (earnings/price) are all most pronounced during January suggests that they are associated with some common underlying factor. Based on the extensive evidence on calendar seasonality in stock returns, I establish null hypothesis 6:

$H6_0$: *The size, B/M and z-score effects are evenly spread over the year and not concentrated in any particular month(s).*

3.2.7. Bankruptcy risk and the state of the economy

Of crucial importance is how the risk premia vary with time. Lev & Thiagarajan (1993) draw attention to the hazards of drawing inferences from unconditional analysis. Cochrane (2001) also points out that it is possible for a model to hold conditionally period-by-period and still not hold unconditionally. Taffler (1999) points out that it is possible to have a positive risk premium for a factor during one state of the world and a negative risk premium for the same factor during some other state of the world. Bankruptcy risk premium is likely to vary with the state of the economy because poorly performing or distressed firms are likely to be especially sensitive to economic conditions and their returns may be driven by common macro-economic factors such as credit squeeze, liquidity crunch or flight towards quality. Riskier firms are able to prosper better when periods of high economic growth are expected, however, they will be hit harder when economic conditions are bad. The premium on distressed firms will be higher when investors are more risk averse because they will require higher compensation for taking additional risk. Therefore, we would expect that negative z-score firms will underperform in bad states of the economy but will outperform in good states. Hypothesis $H1_0$ to $H4_0$ can be restated to test the differential performance of distressed and non-distressed stocks during different economic conditions as:

$H1'_0$: ***Controlling for the market factor, there is no difference in the performance between financially distressed and non-distressed firms in good and bad states of the economy.***

$H2'_0$: ***The coefficient on z-score is insignificant when size and B/M are included in the asset pricing equation and similarly, size and B/M effects are uninfluenced by inclusion of z-score in the asset pricing equation, in both good and bad states of the economy.***

$H3'_0$: ***There is no association between z-scores and excess returns for both financially distressed and non-distressed firms in good and bad states of the economy.***

$H4'_0$: ***There is no association between size, B/M and excess returns for both, financially distressed and non-distressed firms in either state of the economy.***

3.3. Summary

In this chapter I develop testable hypotheses in an attempt to fill important gaps in the existing asset pricing literature identified in chapter 2. I first derive unconditional hypotheses that test whether there is a separate distress factor that is not captured by the CAPM and then develop associated hypotheses to test whether size and B/M capture this distress factor. I also derive hypotheses that test the nature of this distress factor i.e. whether it is asymmetric and whether it is systematic. Finally, I develop conditional versions of these hypotheses.

In the next chapter I describe the data and methodology that I use in order to formally test the hypotheses described here.

Chapter 4

DATA AND METHODOLOGY

4.1. Introduction

In the last chapter I laid out the hypotheses that are to be tested in this study. In this chapter I describe the data used and the methodology employed in order to test these hypotheses. I use z-scores as a proxy for financial distress and show that there is a strong relationship between z-scores and bankruptcy risk. I also show that, prima facie, there appears to be little correlation between financial distress and the B/M ratio. My study covers a period of 21 years and uses several different data sources. The study is restricted to non-financial stocks listed on the London Stock Exchange between 1979 and 2000.

The chapter is organized as follows: section 2 describes the data used in this study, section 3 describes the sample selection procedure and section 4 describes the methodology employed.

4.2. Data

4.2.1. Z-scores

The first step is the computation of z-scores. The z-score of a firm is derived as a weighted sum of a set of pre-defined accounting ratios. Altman (1968) was the first to develop a z-score model for the US and since then there has been a voluminous literature on failure prediction with models being developed for several countries using several different methodologies (Altman & Narayanan (1997) discuss failure prediction models for twenty-two countries). Scott (1981) succinctly summarises the procedure for development of a failure prediction model as:

> "A number of plausible and traditional financial ratios are calculated from financial statements that were published before failure. Next, the researcher searches for a formula, based either on a single ratio or a combination of ratios that best discriminates between firms that eventually failed and the firms that remained solvent."

Traditional failure prediction models classify firms on the basis of their financial statements into one of the two pre-defined groups. A failing profile indicates that in the past, firms with a similar profile have failed and hence, there is a higher probability of failure of the firm. Such models have been very successful at predicting failure; Taffler (1995) finds that for the UK, his models have "predicted" 170 out of 172 failures. Also during 1991, 15% of firms with negative z-scores failed during the next year and a further 16% experienced some other form of distress. He emphasizes that the model is not prescriptive but a pattern identifier, i.e. a failing profile is not a sufficient condition for failure. Taffler's z-score model is used in this study and is given by:

$$z = 3.20 + 12.18\, x_1 + 2.50\, x_2 - 10.68\, x_3 + 0.0289\, x_4$$

Where:

x_1 = profit before tax / current liabilities

x_2 = current assets / total liabilities

x_3 = current liabilities / total assets

x_4 = No-credit interval in days

This is Taffler's industrial company z-score model (see Taffler (1983, 1984) for a detailed discussion). The model was developed in 1976 and hence derived z-scores are completely out-of-sample.

4.2.2. Ex-post bankruptcy risk and z-scores

In my sample, there is a total of the 185 firms that failed[15] within 12 months of portfolio formation. All but six of these 185 had negative z-score at least for the last available year.

In order to see whether z-scores have the ability to predict failure, I first group all the stocks into two portfolios based on whether the latest available z-score is positive or negative. Each group is then ranked on z-score and split into five portfolios resulting in a total of ten portfolios (the portfolio formation procedure is fully described in section 4.4.2.2).

I also form portfolios by first ranking them on z-score and grouping in two portfolios – one with negative z-score stocks and the other with positive z-score stocks. The stocks are then independently ranked on their market capitalization at 30th September of each year and grouped into four portfolios and finally they are independently ranked on B/M ratios and grouped into three portfolios. Twenty-four size, B/M and z-score portfolios are then formed at the intersections of the two z-score, four market capitalization and three B/M portfolios (the portfolio formation procedure is fully described in section 4.4.2.3).

[15] The list was compiled from London Share Price Database (codes 7, 16 and 20), *Stock Exchange Official Yearbook* and *CGT Capital Losses* published by FT Interactive.

4.2.2.1. Z-score portfolios

Table 4.2.2.1.1 presents the portfolio-wise distribution of failures.

Table 4.2.2.1.1: Distribution of failures according to z-scores
At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios of equal numbers of stocks. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks. Portfolios are rebalanced at the end of September each year. Negative B/M stocks are excluded.

Portfolio	Number of failures	Total number of firm years	Failure rate (%)
1	81	982	8.3
2	44	972	4.5
3	19	963	2.0
4	22	966	2.3
5	13	980	1.3
6-10	6	16215	0.0
Total	185	21078	0.9

Table 4.2.2.1.1 shows that the bottom two z-score portfolios have the highest numbers of failures accounting for over two-thirds of all the failures. The conditional probability of failure given a negative z-score is 3.68% (179/4863) which is significantly different to the base failure rate of 0.88% (z = 20.96). The conditional probability of non-failure given a positive z-score is 99.96% which is significantly different to the base non failure rate of 99.12% (z = 11.48). The table shows a clear relationship between z-scores and financial distress and indicates that the z-score portfolios do capture the variation in bankruptcy risk. The table also shows that the variation in bankruptcy risk is concentrated in negative z-score portfolios with very little bankruptcy risk for positive z-score portfolios.

4.2.2.2. Size, B/M and z-score portfolios

Table 4.2.2.2.1 presents the portfolio-wise distribution of the 185 stocks that failed.

Table 4.2.2.2.1: Failure rate in portfolios formed on size, B/M and z-scores
At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios of equal numbers of stocks and independently ranked on B/M and grouped into three portfolios using 30th and 70th percentile as breakpoints. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score. The portfolios are rebalanced at the end of September each year. Negative B/M stocks are excluded.

	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	7.3	0.3	4.5	0.2	7.1	0.1
2	2.4	0.0	1.7	0.0	3.4	0.1
3	1.5	0.0	0.9	0.0	1.9	0.0
Big	0.7	0.1	0.4	0.0	0.0	0.0
Total	3.3	0.0	2.3	0.0	5.1	0.1
B. Number of failures						
Small	30	1	26	2	76	1
2	8	0	7	0	17	1
3	5	0	3	0	4	0
Big	2	1	1	0	0	0
Total	45	2	37	2	97	2

Panel A of table 4.2.2.2.1 shows that as expected, the failure rate drops with increasing firm size. However, for the smallest 25% of the firms (covering almost three quarters of all failures), the low B/M portfolio has a failure rate comparable to that of the highest B/M portfolio with the medium 40% B/M firms having a lower failure rate. The failure rates for the lowest B/M portfolios remain higher than for medium B/M portfolios for other size quartiles. This indicates that though smaller firms are at a higher risk of failure and less likely to survive 12 months, high B/M firms are not at a higher risk of failure once I control for size and z-score. This provides further evidence against there being a clear link between B/M and financial distress.

Panel B of table 4.2.2.2.1 shows that the failures are concentrated in the smallest size quartile (136 out of 185). It also shows that highest B/M portfolio has twice as many failures as the lowest B/M portfolio though the proportions are similar.

4.2.3. Other variables

Apart from z-scores, variables used in this study are:

1. Market return: the monthly return on FTSE All Share stock index.
2. Risk-free rate: the return on one month Treasury bills measured at the beginning of the month.
3. Stock return: the monthly return on common equity of a firm adjusted for dividends and capital changes.
4. Size: the natural logarithm of market value of common equity of the company at the time of portfolio formation.
5. Book-to-Market: defined as natural logarithm of the book value of equity (excluding preference capital) plus deferred taxes less minority interests divided by the market value of equity. The book value is from the latest available annual accounts at the time of portfolio formation and the market value is at the end of September.[16] To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

[16] The computation of the B/M ratio is problematic. Working with the market value of equity on the balance sheet date may suffer from look ahead bias as the accounting information becomes publicly available at a later date while computing the market value of equity on the reporting date is likely to be biased due to general market movements e.g. if the market has gone up during the year, the ratios computed earlier in the year will be higher than those computed later in the year even if everything else is unchanged (Fama & French (1992)). Another problem is whether to use raw B/M or raw B/M less some aggregate index. Asset pricing theory provides no guidance and I use raw B/M.

6. Beta: is the measure of sensitivity of the stock (or portfolio) return to the movements of the market proxy. For portfolios, it is estimated by time-series regressions (described in section 4.4.3) and for individual securities, it is taken from the *Risk Measurement Service*.

7. GDP growth rate: is the quarter-by-quarter change in the Gross Domestic Product Index at Constant Prices (Seasonally Adjusted).

Monthly returns are collected from LSPD which provides returns as natural logarithms of returns adjusted for capital changes and dividends:

$$\ln(R_t) = \ln\left(\frac{P_t + D_t}{P_{t-1}}\right)$$

The returns are converted to simple arithmetic returns using the following transformation:

$$R_t = \exp(\ln(R_t)) - 1$$

Which is the same as:

$$R_t = \left(\frac{P_t - P_{t-1} + D_t}{P_{t-1}}\right)$$

where:

R_t = return during month t

P_t = price at time t

P_{t-1} = price at time t-1

D_t = dividend going ex-dividend during month t

The last month return for firms that fail (Administration, Receivership or Liquidation) is set to –100%[17]. This may bias the results to the extent that the actual return may be greater than –100% as there may be some terminal distribution to shareholders (Rolls Royce and Railtrack are two rare examples). However, I think such payments are sufficiently small and infrequent if ever, to justify using –100% for the last month returns.

To ensure that 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. This minimizes the look-ahead bias. So, for the portfolio formed on 30th September of year t, book value of equity and z-score are from the latest available financial statements with fiscal year end before 1 May of year t. The market value of equity is as on 30th September of year t. The book-to-market ratio uses the latest available book value and market value on 30th September of year t. I have chosen September 30th rather than June 30th as the portfolio formation date because unlike the US, in the UK year-ends are more diffuse. While 37% of the companies in my sample have December year-ends, about the same number of companies have year-ends between January and April with approximately 22% of the companies having March year-ends. Table 4.2.3.1 gives the month-wise distribution of year-ends of the firms in the sample.

[17] There are no failures in my sample period in which equity holders received any payout after all creditor claims were met.

Table 4.2.3.1: Distribution of accounting year-ends of sample firms

Month	Number of year-ends	% of total
January	1210	5.7
February	539	2.6
March	4641	22.0
April	1436	6.8
May	442	2.1
June	1215	5.8
July	557	2.6
August	392	1.9
September	1861	8.8
October	695	3.3
November	210	1.0
December	7880	37.4
Total	21078	100.0

Stock returns, FTSE All Share index returns and risk free rate data are collected from September 1977. Market capitalizations, stock betas, exchange of listing and industrial classifications are available from 1979 and accounting data is collected from 1978. The study covers twenty-one years from October 1979 to September 2000. Following Fama & French (1992, 1993), negative B/M companies are excluded from the analysis since interpretation of a negative B/M ratio is difficult.

4.2.4. Data Sources

The accounting data required for z-score and B/M ratio computation is primarily collected from Company Analysis and EXSTAT, which between them have almost complete coverage of UK companies listed on London Stock Exchange for the period of this study (1979-2000). For a small number of cases not covered by these two databases, MICROEXSTAT and DATASTREAM are used in that order. For remaining firms, data is hand collected from actual annual reports. This enables me to have complete coverage of all eligible companies and the study is free of survivorship bias.

The stock market data is collected from three sources: DATASTREAM, London Share Price Database (LSPD) and Risk Measurement Service (RMS).

- FTSE All Share index values and risk free rates are collected from DATASTREAM.
- Monthly stock returns and monthly market capitalizations are collected from London LSPD.
- Individual stock betas, exchange of listing and stock exchange industrial classifications are collected from RMS.

The GDP growth rates are downloaded from the Office of National Statistics website (www.statistics.gov.uk).

The list of failures is compiled from London Share Price Database (codes 7, 16 and 20), '*Stock Exchange Official Yearbook*' and '*CGT Capital Losses*' published by FT Interactive.

4.3. Sample Selection

This study covers all non-financial UK companies listed on the London Stock Exchange at any time during the period 1979-2000. The use of RMS enables a more accurate determination of the sample since it provides the industry and exchange of listing history. A security that belongs to any of the following samples in any of the quarters is excluded from the population for that quarter:

- Secondary shares of existing companies,
- Odd foreign mining and banking shares,
- Unlisted Securities Market (USM),
- Third market companies,

- O.T.C. companies, and
- Alternative Investments Market.

Additionally, a company that is classified under 'Financials' or 'Mining Finance' by the London Stock Exchange (LSE) during any quarter is also excluded for that quarter. The USM companies are excluded from the sample because they are much smaller than those listed on the LSE. Figure 4.3.1 plots the year-wise distribution of proportion of firms on LSE and USM that have less than £10 million market capitalization. It shows that for most years, more than half of the USM firms had less than £10 million market capitalization. Figure 4.3.2 plots the median market capitalizations of LSE listed and USM firms for each year from 1982 to 1996. The difference in the size of the firms in the two markets is striking.

Figure 4.3.1: Proportion of firms with market capitalization < £10 million

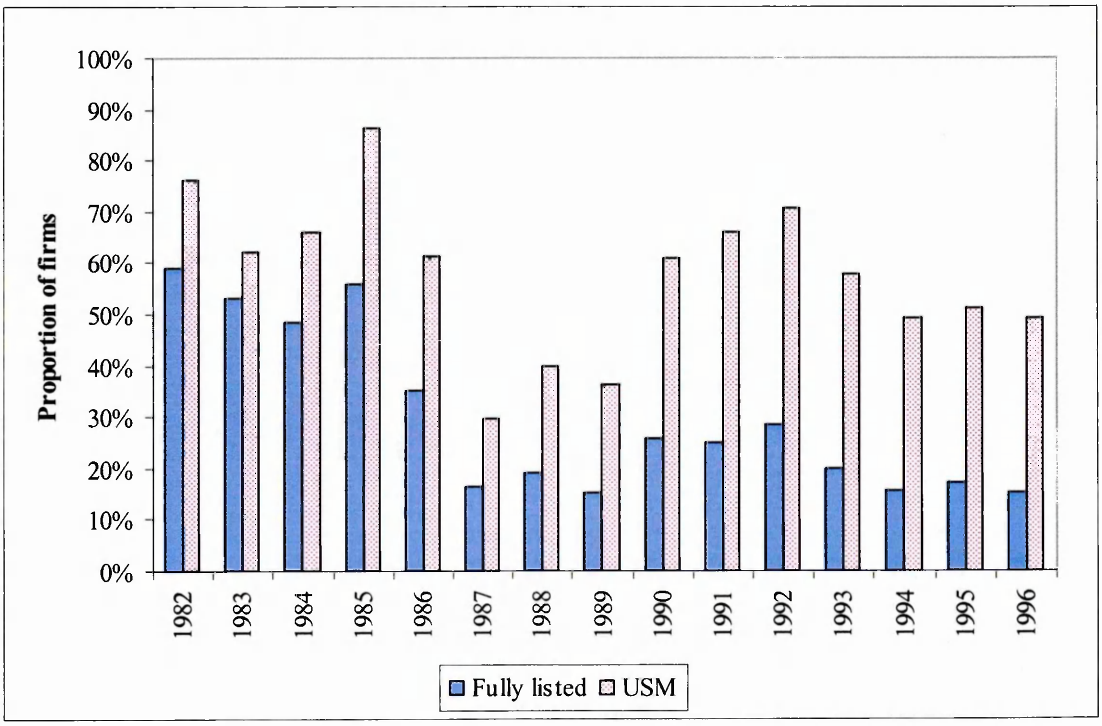
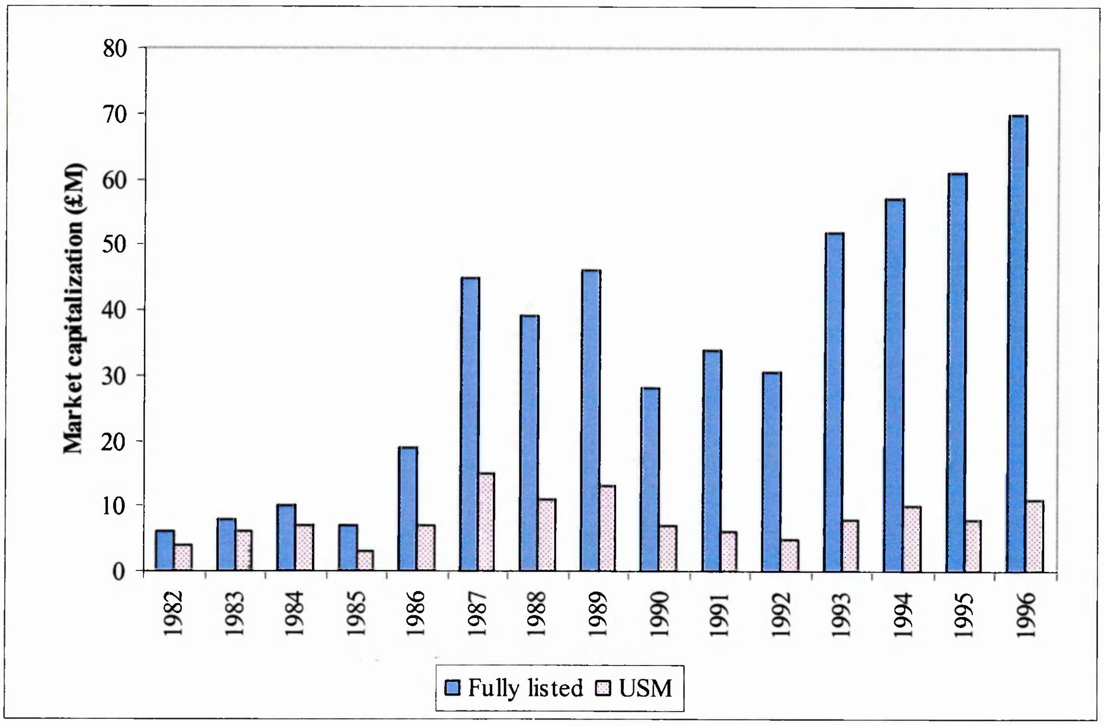


Figure 4.3.2: Median market capitalization of LSE and USM firms



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

(i) Should have positive book value.

(ii) Should have been listed for at least twenty-four months before the portfolio formation date; and

(iii) Should have valid returns for at least nine months over the holding period of twelve months. This rule does not apply to firms that do not survive the holding period.

Firms are required to have positive book values because interpretation of negative book-to-market ratios is problematic. For the same market value, higher book value signifies a lack of growth opportunities but it is not possible to place the same interpretation on the B/M ratio when the book value turns negative. Clearly, there is no reason to believe that a firm with negative book value has more growth opportunities than the firm with small positive book value or that a firm with more negative book value has more growth opportunities than the firm with less negative book value. This does not impose any significant bias till 1990 as the number of negative book value firms is small (between 3 and 14 a year). However, during the 1990s, the number of such firms increased and ranges from 28 to 53 a year. Almost all the negative book value firms have negative z-scores. Table 4.3.1 presents the year-wise distribution of negative B/M stocks excluded from analysis.

Table 4.3.1: Negative B/M stocks excluded from the analysis

Portfolio formed on 30th September	Number of Negative B/M stocks	% of stocks with negative B/M	Number of negative B/M stocks with negative z-score
1979	4	0.3	3
1980	2	0.2	2
1981	1	0.1	1
1982	3	0.3	3
1983	4	0.3	4
1984	5	0.5	5
1985	5	0.5	3
1986	9	0.9	8
1987	8	0.9	8
1988	6	0.7	4
1989	9	1.0	7
1990	14	1.5	11
1991	32	3.6	29
1992	28	3.3	25
1993	35	3.9	33
1994	37	4.1	34
1995	33	3.6	33
1996	39	3.9	34
1997	44	4.2	35
1998	50	4.7	44
1999	53	5.4	42
Total	421	2.0	368

Firms are required to have at least 24 months returns on the portfolio formation date due to data requirement for beta estimation. It also ensures that only post listing accounting information is used.

Firms are also required to have valid returns for at least nine months during the holding period to circumvent the thin trading problem. This means that the stocks should trade at least once a month in nine of the twelve months. Of course, this criterion applies only to firms that survive the entire holding period. The number of firms excluded is high in the first two years and thereafter ranges between 11 and 42. However, negative z-score firms are not disproportionately high in the firms excluded on this criterion. Table 4.3.2 provides the year-wise breakdown of the number of firms excluded due to non trading.

Table 4.3.2: Year-wise distribution of exclusions due to non trading

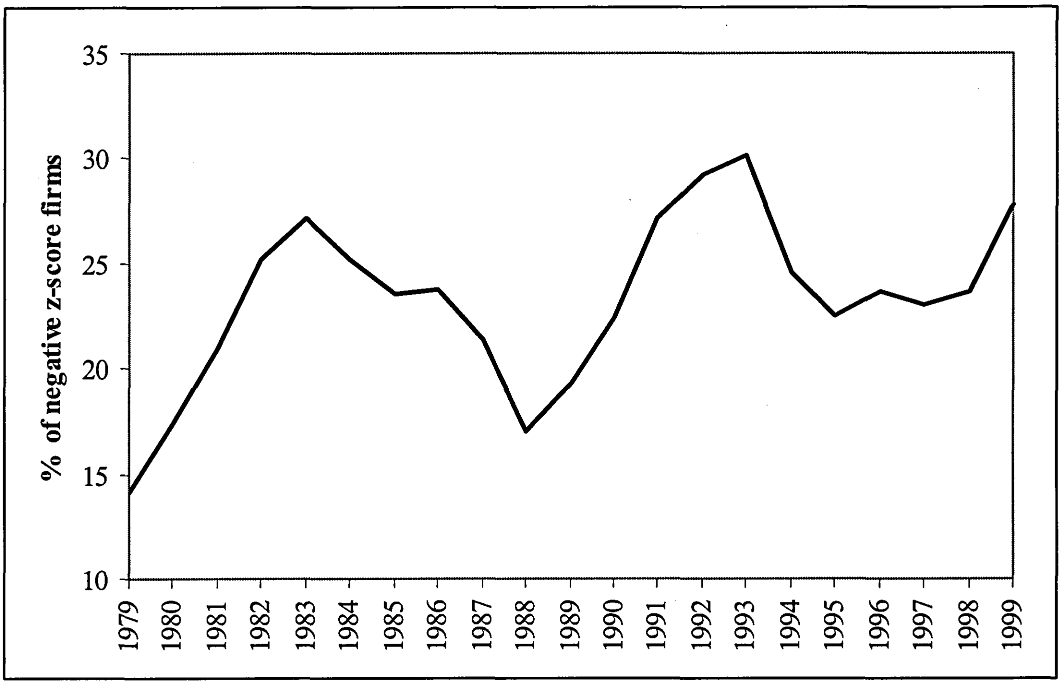
Year	Number of firms excluded due to non trading	Number of firms with negative z-score	% of firms with negative z-score
1979	206	26	12.6
1980	106	15	14.2
1981	35	5	14.3
1982	22	3	13.6
1983	22	5	22.7
1984	26	7	26.9
1985	42	6	14.3
1986	13	2	15.4
1987	11	1	9.1
1988	13	3	23.1
1989	20	2	10.0
1990	21	1	4.8
1991	25	3	12.0
1992	37	6	16.2
1993	41	9	22.0
1994	36	6	16.7
1995	36	11	30.6
1996	27	4	14.8
1997	35	10	28.6
1998	30	5	16.7
1999	25	5	20.0
Total	829	135	16.3

If a company changes industry or exchange of listing, it enters the portfolio only after it has been listed on the main exchange and/or is non-financial for twenty-four months. If the exchange and/or industry changes during the holding period, the returns after the change are deleted. The final sample consists of 2356 companies and a total of 21078 company years. The number of stocks in the sample ranges from a minimum of 810 in 1992 to a maximum of 1258 in 1981. The proportion of negative z-score firms also changes over time from a minimum of 14% in 1979 to a maximum of 30% in 1993. Table 4.3.3 presents the year-wise distribution of sample firms and negative z-score firms and Figure 4.3.3 plots the time-series proportion of negative z-score firms in the sample.

Table 4.3.3 Year-wise proportion of negative z-score firms in the sample

Portfolio formed on 30th September	Total number of stocks	Number of stocks with negative z-score	% of stocks with negative z-score
1979	1179	167	14.2
1980	1242	215	17.3
1981	1258	263	20.9
1982	1205	304	25.2
1983	1169	317	27.1
1984	1103	278	25.2
1985	1033	243	23.5
1986	983	233	23.7
1987	929	198	21.3
1988	919	156	17.0
1989	917	177	19.3
1990	908	203	22.4
1991	868	236	27.2
1992	810	237	29.3
1993	868	262	30.2
1994	864	212	24.5
1995	897	202	22.5
1996	973	230	23.6
1997	1016	234	23.0
1998	1004	237	23.6
1999	933	259	27.8
Total	21078	4863	23.1

Figure 4.3.3: Year-wise proportion of firms with negative z-scores (1979-1999):



4.4. Methodology

Various methodologies have been employed to explore explanatory variables for expected returns. Black, Jensen & Scholes (1972) and Fama & French (1993) use a time-series methodology, Fama & MacBeth (1973) used a cross-sectional methodology while Chan, Chen & Hseih (1985) used generalised least squares (GLS) instead of the more common ordinary least squares (OLS). Chan, Lakonishok & Hamao (1991) employ Seemingly Unrelated Regressions (SUR) while Amihud, Christensen & Mendelsen (1992) introduce pooled time-series-cross-sectional analysis. In this study, I use both the Fama & French (1993) time-series methodology and the Fama & MacBeth (1973) cross-sectional methodology. As a robustness check, I use different portfolio formation methods and repeat the analysis with individual securities. Also, only publicly available information is used.

4.4.1. The asset-pricing framework

The CAPM states that in equilibrium, the ex-ante expected return on an asset i is related to the ex-ante expected return of the market as:

$$E(R_i) = R_F + [E(R_M) - R_F]\beta_i \qquad (1)$$

Where:

$E(R_i)$ = Expected return on security i,

$E(R_M)$ = Expected return on market portfolio,

β_i = Covariance between R_i and R_M, divided by the variance of R_M, and

R_F = Risk free rate.

Jensen (1969) developed the following ex-post version of the above model:

$$R_{it} = R_{Ft} + \beta_i (R_{Mt} - R_{Ft}) + \varepsilon_{it} \qquad (2)$$

where subscript 't' denotes time and ε is the error term with zero expected value and finite variance.

Other factors can be readily incorporated in the model to yield a multi-factor asset-pricing model of the form:

$$R_t - R_{Ft} = \alpha + \beta_j \{F_{jt}\} + \varepsilon_{it} \qquad (3)$$

Where F_{jt} represents the factors used as explanatory variables.

4.4.2. Portfolio formation

I have adopted the portfolio approach to reduce the errors-in-variable (EIV) problem in beta estimates. As portfolios have lower residual variance, portfolio betas are more accurate. Also, whereas individual stock betas move over time as firm characteristics (e.g. leverage, size etc.) change portfolio betas are likely to be more stable and hence easier to measure more accurately. Moreover, use of individual securities rather than portfolios leads to a specification problem since the variance-covariance matrix has a very large number of elements in relation to the available data points (Berk, 2000a). Finally, individual stock returns are so volatile that we cannot reject the hypothesis that all average returns are the same. Grouping into portfolios reduces the variance and makes it possible to observe average returns differences. I use three different procedures to sort stocks in to portfolios.

<u>4.4.2.1. Twenty-five portfolios on size and B/M</u>

In order to test that the Fama & French (1993) three-factor model explains the equity returns in the UK I start by forming twenty-five portfolios on size and B/M as in their study. Securities are ranked on their market capitalization at 30th September of each year and grouped into five portfolios with equal number of securities. They are independently ranked on B/M ratios and grouped into five portfolios again with equal number of securities. Twenty-five size & B/M portfolios are then formed at the intersections of the five market capitalization and five B/M portfolios. The portfolios are rebalanced at the end of September of each year except for delistings. Delisted securities are dropped in the month of delisting and are assumed to earn the portfolio returns if delisted for reasons other than failure. If a security fails, its last period return is set equal to –100%.

4.4.2.2. Ten portfolios on z-score

I also sort securities on their z-scores to analyze the relation between default risk and equity returns i.e. whether portfolios with different default risk characteristics have different returns. Securities are first grouped into two portfolios based on whether the latest available z-score on the portfolio formation date is positive or negative.[18] Each group is then ranked on z-score and split into five portfolios of equal number of stocks. This results in ten portfolios in all.

4.4.2.3. Twenty-four portfolios on size, B/M and z-score

Finally, in order to study size, B/M and z-score effects and as a robustness check, I form portfolios by first ranking them on z-score and grouping in two portfolios – one with negative z-score stocks and the other with positive z-score stocks. The securities are then independently ranked on their market capitalization at 30th September of each year and grouped into four portfolios with equal number of securities. Finally, they are independently ranked on B/M ratios and grouped into three portfolios – one with the lowest 30%, one with the middle 40% and one with the highest 30% B/M ratios. Twenty-four size, B/M and z-score portfolios are then formed at the intersections of the two z-score, four market capitalization and three B/M portfolios.

[18] The annual portfolio rebalancing procedure means that there can be a long lead time between the time a new z-score becomes available and the time it enters the analysis. A more frequent rebalancing would avoid this problem of 'stale' z-scores but would also induce a spurious correlation between size and B/M since book value can change only once a year so any changes in B/M during the year would be solely due to changes in market capitalization.

4.4.3. Beta estimation

RMS provides beta estimates for individual stocks and I use these in my individual securities analysis. However, Blume (1970) shows that portfolio betas can be estimated more accurately than individual securities beta provided the correlation between the errors in beta estimates are less than +1. Therefore, to estimate portfolio betas for year t, I regress monthly excess returns over the previous twenty-four months ending in September of year t on each portfolio against monthly excess returns on the FTSE All Share index employing OLS. To reduce the problem of thin trading I use Dimson's (1979) method with one lead and one lag. So 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. The process is repeated on 30^{th} September of each year. This 'rolling beta' approach allows for non-stationarity of betas. Shanken (1992) argues that assuming stationarity over overlapping periods is similar to assuming stationarity over the entire period. However, he admits the possibility that the rolling beta approach may be more robust to violations of assumptions.

4.4.4. Cross-sectional regressions

The Fama-MacBeth cross-sectional regressions are then carried out each period using beta, size, B/M and z-score as explanatory variables in univariate and multivariate regressions. The basic idea of these regressions is to project the returns on explanatory variables for each cross-section and then aggregate the estimates over the time dimension. The regression model for the t^{th} cross-section of N assets is of the form:

$$R_t - R_{Ft} = \alpha_t + \gamma_t \{F_{t-1}\} + \varepsilon_t \tag{4}$$

Where:

$R_t - R_{Ft}$ = N X 1 vector of excess returns for time t

F = N X 1 vector of the explanatory variable(s)

α = intercept

γ = slope coefficient

ε = error term

t = time subscript

The Fama-MacBeth approach has two steps: first, for T periods, the above regression (equation 4) is estimated for each t using ordinary least squares (OLS) which gives T estimates of α_t and T estimates of γ_t. The estimates γ_t are viewed as the sampled values of the variate F and the test focuses on whether its mean is significantly different from zero. Since the returns are normally distributed and independently and identically distributed (IID), the γs have the same properties enabling analysis of the time series of αs and γs using the normal t-test. The T estimates of γ are averaged:

$$\bar{\gamma} = \frac{1}{T}\sum_{t=1}^{T}\gamma_t$$

The estimated standard error of γ is given by

$$\sigma(\bar{\gamma}) = \left(\frac{1}{(T(T-1)}\sum_t(\gamma_t - \bar{\gamma})^2\right)^{\frac{1}{2}}$$

and tests of significance are carried out using:

$$t = \frac{\bar{\gamma}}{\sigma(\bar{\gamma})}\ .$$

Cochrane (2001) shows that the above procedure is equivalent to pooled time-series and cross-sectional OLS with standard errors corrected for cross-sectional correlation when the right hand side variables do not vary over time. The methodology assumes that there is no autocorrelation.

This approach has two main problems: first, the market betas are not known and have to be estimated. This introduces an Errors-in-Variables (EIV) problem. Kim (1995) argues the EIV problem means that the coefficients of variables that are negatively correlated to beta will be negatively biased and of variables that are positively correlated to beta will be positively biased. Since the z-scores are negatively correlated to beta, any potential bias due to EIV problem will tend to understate the strength of the underlying relationship rather than overstating it. Second, the market portfolio is unobservable. Roll & Ross (1994) show that the cross-sectional relation between expected returns and beta can be extremely sensitive to small deviations of the market proxy from the true market portfolio. Though Kandel & Stambaugh (1995) show that GLS can resolve this extreme sensitivity, implementation of GLS requires knowledge of the true covariance matrix of returns.

When errors are autocorrelated or heteroskedastic, GLS can be more efficient than OLS provided that the variance-coveriance matrix is correctly modeled and the regression is perfectly specified. Violation of these conditions can make GLS estimates worse than OLS estimates.

4.4.4.1. Tests of hypothesis $H1_0$

Suppose z-scores are related to expected stock returns and according to the following generalised linear asset-pricing model relationship:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}z_{it-1} + \varepsilon_{it} \qquad (5)$$

or

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{3t}z(0/1)_{it-1} + \varepsilon_{it} \qquad (6)$$

where: β_i is the covariance between returns on stock (or portfolio) i and the return on market divided by the variance of the return on market, z_i is the latest available z-score for stock (or portfolio) i, $z(0/1)_i$ is the dummy variable that takes the value 1 if the latest available z-score stock (or portfolio) i is negative, 0 otherwise and ε is the error term with zero expected value, finite variance and is independent of other variables.

α, γ_1 and γ_2 are estimated from equation (5) and α, γ_1 and γ_3 are estimated from equation (6) using Fama-MacBeth regressions. The γ coefficients provide evidence on whether the individual factors are priced in the market. If γ_2 (γ_3) is different from zero, then this provides evidence that z-scores are being priced but if γ_2 (γ_3) is not different from zero, it provides evidence that z-scores are not being priced.

4.4.4.2. Tests of hypothesis $H2_0$

To test whether the z-scores have explanatory power incremental to the book-to-market and size factors, I first use the following generalized stochastic linear return generating equation without z-scores:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{4t}\ln(\text{size}_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \qquad (7)$$

I then introduce z-scores in equation (7), first as a continuous variable and then as a binary variable to see if z-scores contain any information additional to that contained in size and B/M:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\,z_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \qquad (8)$$

or

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{3t}\,z(0/1)_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \qquad (9)$$

where: $\ln(size_{it-1})$ is the natural logarithm of the latest available market value and $\ln(B/M_{it-1})$ is the latest available B/M ratio of stock (or portfolio) i. β_i, z_i, $z(0/1)_i$ and ε are as before.

As in the previous sub-section, α and γs are estimated using Fama-MacBeth regressions. If size and B/M were capturing the distress factor, γ_2 in equation (8) and/or γ_3 in equation (9) would not be significantly different to zero or the coefficients γ_4 and γ_5 would be smaller in equations (8) and/or (9) as compared to the coefficients in equation (7) when z-score is omitted from the pricing equation.

4.4.4.3. Tests of hypothesis $H3_0$

To test for asymmetric bankruptcy risk, an interaction term is introduced in the asset pricing equation. If the z-scores are capturing the asymmetric nature of the bankruptcy risk, then we would find a relationship between z-scores and excess returns when z-scores are negative and find no relationship when z-scores are positive. So, the coefficient γ_2 will be equal to zero and the coefficient γ_5 will be different to zero in the following generalized stochastic linear return generating equation:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}z_{it-1} + \gamma_{6t}(z_{it-1} * z(0/1)_{it-1}) + \varepsilon_{it} \quad (10)$$

α and γs are estimated using Fama-MacBeth regressions. γ_2 measures the relationship between stock returns and z-scores when z-scores are positive and γ_6 is the interaction term.

Equation 10 is equivalent to running two separate regressions:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}z_{it-1} + \varepsilon_{it} \quad \text{(when z-score is positive)}$$

and

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + (\gamma_{2t} + \gamma_{6t})\, z_{it-1} + \varepsilon_{it} \quad \text{(when z-score is negative).}$$

Hence, if $H3_0$ holds i.e. negative z-score stocks drive the relationship between z-scores and returns, γ_2 will be zero and γ_6 will be significantly different to zero.

<u>4.4.4.4. Tests of hypothesis $H4_0$</u>

Similarly, if B/M and size are capturing the relative distress factor, we would expect a stronger B/M and size effect for financially weaker firms (negative z-score) than for financially stronger firms (positive z-score). The generalized stochastic linear return generating equation is given by:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \gamma_{7t}(\ln(size_{it-1}) * z(0/1)_{it-1})$$
$$+ \gamma_{8t}(\ln(B/M_{it-1}) * z(0/1)_{it-1}) + \varepsilon_{it} \quad (11)$$

Equation 11 is equivalent to running two separate regressions:

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it}$ (when z-score is positive)

and

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + (\gamma_{4t}+\gamma_{7t})\ln(size_{it-1}) + (\gamma_{5t}+\gamma_{8t})\ln(B/M_{it-1}) + \varepsilon_{it}$ (when z-score is negative).

If γ_{7t} is significantly different to zero, this would provide evidence that size captures the asymmetric nature of bankruptcy risk i.e. it is stronger for distressed firms. A significant γ_{8t} would provide the same evidence for B/M.

4.4.4.5. Tests of hypothesis $H6_0$

To test for calendar seasonality in size effect, first all the stocks are ranked on their market capitalization at 30th September of each year and grouped into ten portfolios with equal number of securities. The portfolios are rebalanced at the end of September of each year except for delistings. The delisted securities are dropped in the month of delisting and are assumed to earn the portfolio returns if delisted for reasons other than failure. If a security fails, its last period return is set equal to –100%. Equally weighted monthly portfolio returns are then computed for each portfolio.

I then group the portfolio returns by month and test each month's return for each portfolio for statistical significance employing the standard t-test:

$$t = \frac{\overline{X}_j}{\sigma_j / \sqrt{n_j}}$$

where: X_j is the mean return during month j, σ_j is the standard deviation of returns during month j and n_j is the number of observations of month j.

I also use the F-test to test whether mean returns over all the months are jointly equal. I repeat the process with ten portfolios formed on B/M and separately on two portfolios formed on z-score; one with positive z-score stocks and the other with negative z-score stocks. Finally, I repeat the tests with the Fama-MacBeth regression coefficients obtained from equation 9 using twenty-four portfolios formed on size, B/M and z-scores in section 4.4.2.3.

4.4.4.6. Is the risk of bankruptcy a systematic risk?

So far the analysis has been unconditional i.e. it assumes that all coefficients are constant over time. Parameter estimates will clearly be misleading if this assumption is violated. Unconditional means and factor loadings can be close to zero but might vary considerably over time. A model can hold conditionally, period by period and yet not hold unconditionally (Cochrane (2001)). Also, risk is commonly understood as the sensitivity to market-wide movements (Lakonishok, Shleifer & Vishny (1994)) and therefore if the factors are capturing risk, they should display sensitivity to broad market movements.

I therefore, bifurcate the analysis into up- and down- market months. An up-market month is when the market return is greater than the risk free rate and a down-market month is where the market return is less than the risk-free rate (Lakonishok & Shapiro (1986)).

I also bifurcate the analysis into quarters where GDP growth rate is below the long run average growth rate and quarters when the GDP growth rate is above the long run average. Following the evidence that stock returns lead the GDP growth rates by a quarter[19], I use the following quarter's GDP to bifurcate the sample.

4.4.5. Time-series regressions

Time series regressions are a natural alternative to cross-sectional regressions and are convenient for studying asset pricing issues because they give direct evidence on whether the variables related to average returns capture shared variation not explained by other factors. They focus on changes in expected returns and not on average returns.

4.4.5.1. The Fama & French (1993) three-factor model

I follow the Fama & French (1993) methodology to test an unconditional version of the three-factor model:

$$R_{Pt} - R_{Ft} = a_{it} + b_t\,(R_M - R_F) + s_t\,SMB_t + h_t\,HML_t + \varepsilon_t \qquad (12)$$

Where:

R_P = the return on portfolio P during the period t

R_F = the risk free rate observed at the beginning of the period t

R_M = the value-weighted return on all stocks in the twenty-five size and B/M portfolios

SMB = the return on the mimicking portfolio for the size factor

HML = the return on the mimicking portfolio for the B/M factor

[19] Fama (1981) documents the presence of a positive and significant relation between market factor and future economic growth in the US and Aylward & Glen (1995) document this internationally

Following Fama & French (1993), R_M is the monthly value-weighted return on all the stocks in the portfolio at the portfolio formation date. HML and SMB are constructed as by Fama & French (1993) i.e., on the 30th of September of each year[20], all the stocks in the portfolio are ranked on size and grouped into two portfolios, using the median size as the breakpoint. The one with lower 50% market capitalizations is designated portfolio S and the other with rest of the stocks is designated portfolio B. Stocks are independently ranked on B/M and grouped into three portfolios, the lowest 30% (portfolio L), middle 40% (portfolio M) and highest 30% B/M (portfolio H). Six portfolios are then formed from the intersections of the two market value and three B/M groups: Small cap – low B/M (S/L), Small cap – medium B/M (S/M), Small cap – high B/M (S/H), Large cap – low B/M (B/L), Large cap – medium B/M (B/M), Large cap – high B/M (B/H). Monthly value-weighted returns are then calculated on each of the portfolios and the portfolios are rebalanced at the end of each September.

Factor SMB is meant to mimic the size related risk factor in returns and constructed as the difference between the simple average of monthly returns on the three small stock portfolios and the simple average of monthly returns on the three large stock portfolios, i.e.:

$$SMB = ((S/L + S/M + S/H) - (B/L + B/M + B/H)) / 3$$

Factor HML is meant to mimic the B/M related risk factor in returns and is constructed as the difference between the simple average of monthly returns on the two high B/M portfolios and the simple average of monthly returns on the two low B/M portfolios, i.e.:

[20] Fama & French (1993) use 30th June as portfolio formation date.

$$HML = ((S/H + B/H) – (S/L + B/L)) / 2$$

If the coefficients on factors SMB & HML are significantly different to zero in the presence of the market factor, it will provide evidence that these two factors are capturing common variation in stock returns missed by the market factor. If the Fama & French (1993) model provides a good description of stock returns, the intercept terms in the regressions should be indistinguishable from zero.

4.4.5.2. The four-factor model

Finally, I test a four-factor model which has a bankruptcy risk factor in addition to the market factor and modified Fama & French factors. The model is:

$$R_{Pt} - R_{Ft} = a_{it} + b_t (R_M - R_F) + s_t\, SMB_t^m + h_t\, HML_t^m + p_t\, PMN_t + \varepsilon_t \qquad (13)$$

Where:

R_P = the return on portfolio P during the period t

R_F = the risk free rate observed at the beginning of the period t

R_M = the value-weighted return on all stocks in the twenty-five size and B/M portfolios

SMB^m = the return on the modified mimicking portfolio for the size factor

HML^m = the return on the modified mimicking portfolio for the B/M factor

PMN = the return on the mimicking portfolio for the z-score factor

Similar to Fama & French (1993), R_M is the monthly value-weighted return on all the stocks in the portfolio at the portfolio formation date. On the 30th of September of each year, all the stocks in the portfolio are ranked on size and grouped into two portfolios, using the median size as the breakpoint. The one with lower 50% market capitalizations is designated portfolio S and the other with rest of the stocks is designated portfolio B.

Stocks are independently ranked on B/M and grouped into three portfolios, the lowest 30% (portfolio L), middle 40% (portfolio M) and highest 30% B/M (portfolio H). Finally the stocks are independently ranked on latest available z-score and grouped into two portfolios, the negative z-score (portfolio N) and the positive z-score (portfolio P). Twelve portfolios are then formed from the intersections of the two market value, three B/M and two z-score groups: Small cap / low B/M / negative z-score (S/L/N), Small cap / low B/M / positive z-score (S/L/P), Small cap / medium B/M / negative z-score (S/M/N), Small cap / medium B/M / positive z-score (S/M/P), Small cap / high B/M / negative z-score (S/H/N), Small cap / high B/M / positive z-score (S/H/P), Large cap / low B/M / negative z-score (B/L/N), Large cap / low B/M / positive z-score (B/L/P), Large cap / medium B/M / negative z-score (B/M/N), Large cap / medium B/M / positive z-score (B/M/P), Large cap / high B/M / negative z-score (B/H/N), Large cap / high B/M / positive z-score (B/H/N). Monthly value-weighted returns are then calculated on each of the portfolios and the portfolios are rebalanced at the end of each September.

Factor SMB^m is meant to mimic the size related risk factor in returns and constructed as the difference between the simple average of monthly returns on the six small stock portfolios and the simple average of monthly returns on the six large stock portfolios, i.e.:

$$SMB^m = ((S/L/N + S/L/P + S/M/N + S/M/P + S/H/N + S/H/P) - (B/L/N + B/L/P + B/M/N + B/M/P + B/H/N + B/H/P)) / 6$$

Factor HML^m is meant to mimic the B/M related risk factor in returns and is constructed as the difference between the simple average of monthly returns on the four high B/M portfolios and the simple average of monthly returns on the four low B/M portfolios, i.e.:

$$HML^{m} = ((S/H/N + S/H/P + B/H/N + B/H/P) - (S/L/N + S/L/P + B/L/N + B/L/P)) / 4$$

Factor PMN is meant to mimic the z-score related risk factor in returns and is constructed as the difference between the simple average of monthly returns on the six positive z-score portfolios and the simple average of monthly returns on the six negative z-score portfolios, i.e.:

$$PMN = ((S/L/P + S/M/P + S/H/P + B/L/P + B/M/P + B/H/P) - (S/L/N + S/M/N + S/H/N + B/L/N + B/M/N + B/H/N)) / 6$$

If the coefficients on factors SMB^{m}, HML^{m} and PMN are significantly different to zero in the presence of the market factor, it will provide evidence that these factors are capturing common variation in stock returns missed by the market factor. If the four-factor model provides a good description of stock returns, the intercept terms in the regressions should be indistinguishable from zero.

In this chapter I have described the data used in this study and the data sources employed. I have also discussed the methodology that I use to test the hypotheses discussed in chapter 3. I show that z-scores are strong predictors of financial distress and are a valid proxy for the distress factor. In the next chapter, I first test whether size and B/M can explain cross-section of stock returns in the UK using Fama-MacBeth (1973) cross-sectional methodology and then test the Fama & French (1993) three-factor model.

Chapter 5

SIZE & B/M PORTFOLIOS AND THE FAMA & FRENCH THREE-FACTOR MODEL

5.1 Introduction

Size and B/M have emerged as strong predictors of cross-sectional stock returns and the Fama & French (1993) three-factor model is currently the dominant asset pricing model. The model has been applied to equity data from several different countries (Fama & French (1998)) and has performed well in explaining most of the anomalies of the CAPM (Fama & French (1996)). Though the model has been applied to UK data, studies are typically conducted in the US and with a limited sub-sample of the population of stocks on the London Stock Exchange (e.g. Liew & Vassalou (2000)). Strong & Xu (1997) replicate Fama & French (1992) for the UK but I am not aware of any UK-based study that tests the Fama & French (1993) three-factor model though several studies use the model implicitly assuming that it explains returns in the UK. In this chapter I replicate the main procedure of Fama & French (1993) for the UK and report the findings.

As described in chapter 4, the stock returns, risk free rate and market capitalizations are collected from September 1979 and accounting data is collected from 1978. The study covers twenty-one years from October 1979 to September 2000. Following Fama & French (1992, 1993), negative B/M companies are excluded from the analysis since interpretation of a negative B/M ratio is difficult.

The chapter is organized as follows: section 2 describes the portfolio formation method, section 3 presents the summary statistics, section 4 presents the results of cross-sectional regressions, section 5 reports the results of time-series regressions first with equally weighted portfolios and then with value weighted portfolios and section 6 summarizes the results.

5.2 Portfolio formation

As described in chapter 4, I construct twenty-five portfolios on size and B/M in the same way as Fama & French (1993). All eligible stocks are ranked on market capitalization on 30th September of year t and sorted into five portfolios with equal numbers of stocks. Stocks are independently ranked on B/M on 30th September of year t and sorted into five portfolios of equal numbers of stocks. Twenty-five size and B/M portfolios are formed at the intersections of the break-points. Equally-weighted monthly returns are computed for each portfolio from October of year t to September of year t+1. The procedure is repeated on 30th September of each year from 1979 to 1999. The last monthly return for failed stocks is set equal to –100%. Other stocks that are delisted during the holding period (for reasons other than failure) are assumed to earn the reference portfolio returns for the remainder of the period.[21]

5.3 Summary statistics

Starting with Chan & Chen (1991), several studied have linked superior performance of small size firms and high B/M firms to a distress factor. In order for size and B/M effects to be manifestations of the distress factor, smaller firms and high B/M firms

[21] This is equivalent to assuming that the terminal payment received (if any) is invested equally in all the other stocks in that portfolio.

should have higher failure rates. The list of failures is compiled from LSPD (codes 7, 16 and 20), *CGT Capital Losses* (published by FT Interactive Data) and the *Stock Exchange Official Yearbooks*. Table 5.3.1 presents the failure rates for the twenty five portfolios.

Table 5.3.1: Failure rates

At the end of September of each year from 1979 to 1999, all the stocks in the population are ranked on market capitalization and grouped into five portfolios. The stocks are also independently sorted on B/M and grouped into five portfolios. Twenty-five portfolios are then formed at the intersections of size and B/M. The portfolios are rebalanced at the end of September each year. Negative B/M stocks are excluded.

	Low B/M	2	3	4	High B/M	Total
Small	3.39%	3.97%	2.12%	1.01%	3.66%	2.84%
2	0.99%	0.60%	0.47%	0.80%	1.12%	0.81%
3	0.70%	0.21%	0.54%	0.24%	1.09%	0.52%
4	0.09%	0.18%	0.22%	0.00%	0.28%	0.14%
Big	0.08%	0.10%	0.10%	0.00%	0.00%	0.07%
Total	0.62%	0.62%	0.57%	0.50%	2.08%	0.88%

The smallest size quintile accounts for two-thirds (120/185) of all failures while the largest size quintile has only three failures. The highest B/M quintile accounts for almost half the failures (88/185) with the rest of the failures almost equally distributed among the other four quintiles. Controlling for size, the failure rates for the lowest B/M quintile are similar to those for the highest B/M quintile. The data here suggests that small growth firms are almost as likely to fail as the small value firms. This could be because young firms tend to be small growth firms while the 'fallen angels' would have high B/M ratios. The data shows a clear relationship between size and failure rate but the relationship between B/M and failure rate is not linear.

Table 5.3.2 shows the characteristics of portfolios formed by independent sorts on size and book-to-market.

Table 5.3.2: Summary statistics of twenty-five portfolios on size and B/M

At the end of September of each year from 1979 to 1999, all the stocks in the population are ranked on market capitalization and grouped into five portfolios. The stocks are also independently sorted on B/M and grouped into five portfolios. B/M is computed as the ratio of book value of equity (excluding preference capital) plus deferred taxes less minority interests taken from the latest available accounts divided by the market value of equity on 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively. Twenty-five portfolios are then formed at the intersections of market capitalization and B/M. The portfolios are rebalanced at the end of September each year. Average 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 and average B/M are the time-series averages of monthly averages of market capitalizations and B/M 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%.

	Low B/M	2	3	4	High B/M
A: Average Monthly Excess Returns (%)					
Small	1.70	1.66	1.68	1.45	1.37
2	0.74	0.30	0.56	0.65	0.69
3	0.50	0.56	0.51	0.60	1.06
4	0.59	0.40	0.44	0.70	0.97
Large	0.46	0.52	0.55	0.85	1.23
B: Average Beta					
Small	1.20	1.06	1.09	0.92	0.99
2	1.27	1.15	1.00	1.06	1.07
3	1.20	1.07	1.01	1.10	1.19
4	1.14	1.07	1.11	1.05	1.10
Large	0.87	0.83	0.89	0.87	0.99
C: Average Size (£M)					
Small	5.4	5.5	5.2	5.4	4.3
2	16.8	16.6	16.0	15.6	15.1
3	43.7	43.1	43.2	41.5	39.9
4	130.4	130.6	127.8	126.9	125.2
Large	1946.1	1869.4	1515.9	1555.6	2541.8
D: Average Book-to-Market					
Small	0.26	0.55	0.82	1.21	2.76
2	0.27	0.55	0.82	1.20	2.32
3	0.28	0.55	0.81	1.19	2.19
4	0.26	0.54	0.81	1.16	2.17
Large	0.26	0.54	0.81	1.17	2.02

Table 5.3.2 panel A shows that the smallest size portfolio earns the highest returns for each B/M quintile but the relationship between size and returns for other quintiles is erratic. The smallest size portfolios outperform largest size portfolios by between 14 and 124 basis points per month. The evidence here suggests prima facie that the size

effect is driven by the smallest 20% of the firms. Except the smallest size quintile and the lowest B/M quintile, average excess returns increase almost monotonically with B/M in every size quintile. The difference between the returns on high B/M portfolios and low B/M portfolios ranges from –33 to 77 basis points per month. Unlike the evidence of Loughran (1997) for US data, the B/M effect here is not driven by small stocks. In fact, the effect is strongest for the largest 20% stocks. Panel B shows that beta decreases with increasing size though the relationship is not monotonic. Similarly, the relationship between beta and B/M is also erratic. Evidence in panels A & B also shows that beta has little ability to explain cross-sectional variation in stock returns. Panel C shows average size is similar across B/M quintiles indicating that the sorting procedure has been successful in controlling for size in each B/M quintile except in the largest size quintile and panel D shows that the sorting procedure has been successful in controlling for B/M in each size quintile.

5.4 Cross-sectional regressions

To test whether size and value effects are present in the stock returns in the UK, I run two hundred and fifty two monthly cross-sectional regressions (12 months X 21 years) employing Fama & MacBeth (1973) methodology on a univariate and multivariate basis for the twenty-five portfolios formed on size and B/M. Table 5.4.1 presents the results of the cross sectional regressions.

Table 5.4.1: Cross-sectional regression results

At the end of September of each year from 1979 to 1999, all the stocks in the population are ranked on market capitalization and grouped into five portfolios. The stocks are also independently sorted on B/M and grouped into five portfolios. 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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively. Twenty-five portfolios are then formed at the intersections of size and B/M. 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 sum of slopes in the regression of the return on portfolio i on the current, prior and next month's market returns estimated at the end of September of year t. $\ln(size_{it-1})$ is the natural logarithm of average of market capitalizations of stocks in portfolio i at the end of September of year t. $\ln(B/M_{it-1})$ is the natural logarithm of average of B/M ratios of stocks in portfolio i at the end of September of year t. α, γ_1, γ_2 and γ_3 are regression parameters from Fama-MacBeth cross-sectional regressions. The portfolios are rebalanced at the end of September each year. 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%.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1})$

α	γ_1	γ_2	γ_3
0.0123	-0.0039		
(3.24)	(-1.52)		
0.0236		-0.0009	
(2.32)		(-1.64)	
0.0092			0.0015
(3.09)			(1.62)
0.0239		-0.0009	0.0014
(2.37)		(-1.57)	(1.42)
0.0289	-0.0036	-0.0009	0.0018
(2.62)	(-1.46)	(-1.60)	(1.77)

Table 5.4.1 shows that the coefficient on beta is negative and not significantly different to zero even when it is the only explanatory variable. Beta remains negative and statistically indistinguishable from zero in multivariate regressions with size and B/M in the pricing equation. Size and B/M coefficients are negative and positive respectively but neither is significantly different to zero in either the univariate or the multivariate regressions. The coefficients of beta, size and B/M are virtually the same in the univariate and multivariate regressions suggesting very little interaction between the three characteristics. A concern with equally-weighted returns is that they give too

much weightage to small stocks. I have repeated the analysis with value-weighted portfolio returns and find qualitatively similar results.

An analysis of the time-series evolution of t-statistics shows that the B/M effect was strong until last year's (2000) data was included (Al-Horani, Pope & Stark (2001) report the same). The collapse of the value effect during the last twelve months of this study is not unique in the UK, the same is also observed in the US (see section 5.5). This collapse is likely to be due to high returns on high technology stocks. Such stocks were characterized by low or negative book values and very high market capitalizations and earned high returns during this period. These stocks would have entered my portfolios during the last twelve months because I have imposed a requirement of at least 24 months of stock returns to be included in the analysis. The size effect was strong during the eighties, briefly reversed itself during the first half of nineties and disappeared thereafter, a finding consistent with other UK studies (e.g. Al Horani, Pope & Stark (2001) and Levis (2000)).

In order to see how the coefficients have evolved over time, I start by accumulating the coefficients for the first thirty months (for statistical validity) and then increase the number of months by one till all 252 months are included. The figures below show that results are sensitive to the time-period chosen for analysis. Figure 5.4.1 plots the time-series evolution of t-statistics of the three variables in the univariate regressions of table 5.4.1 and figure 5.4.2 for the three variable multiple regression.

Figure 5.4.1: Time series evolution of t-statistics from October 1979 to September 2000 – univariate regressions
The time-series is created by accumulating the coefficients for the first 30 months and then increasing the number of months by one till all 252 months are included.

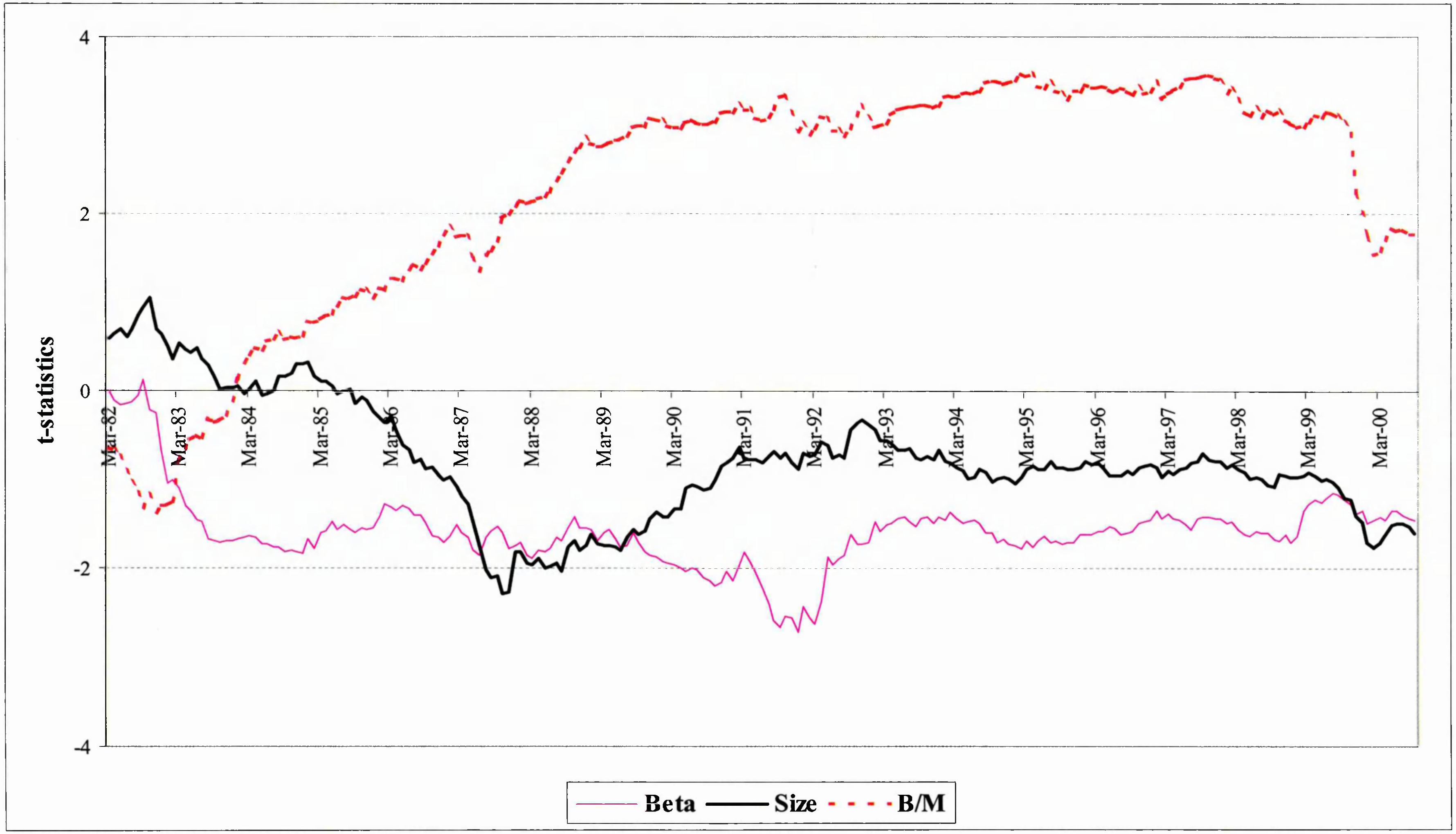
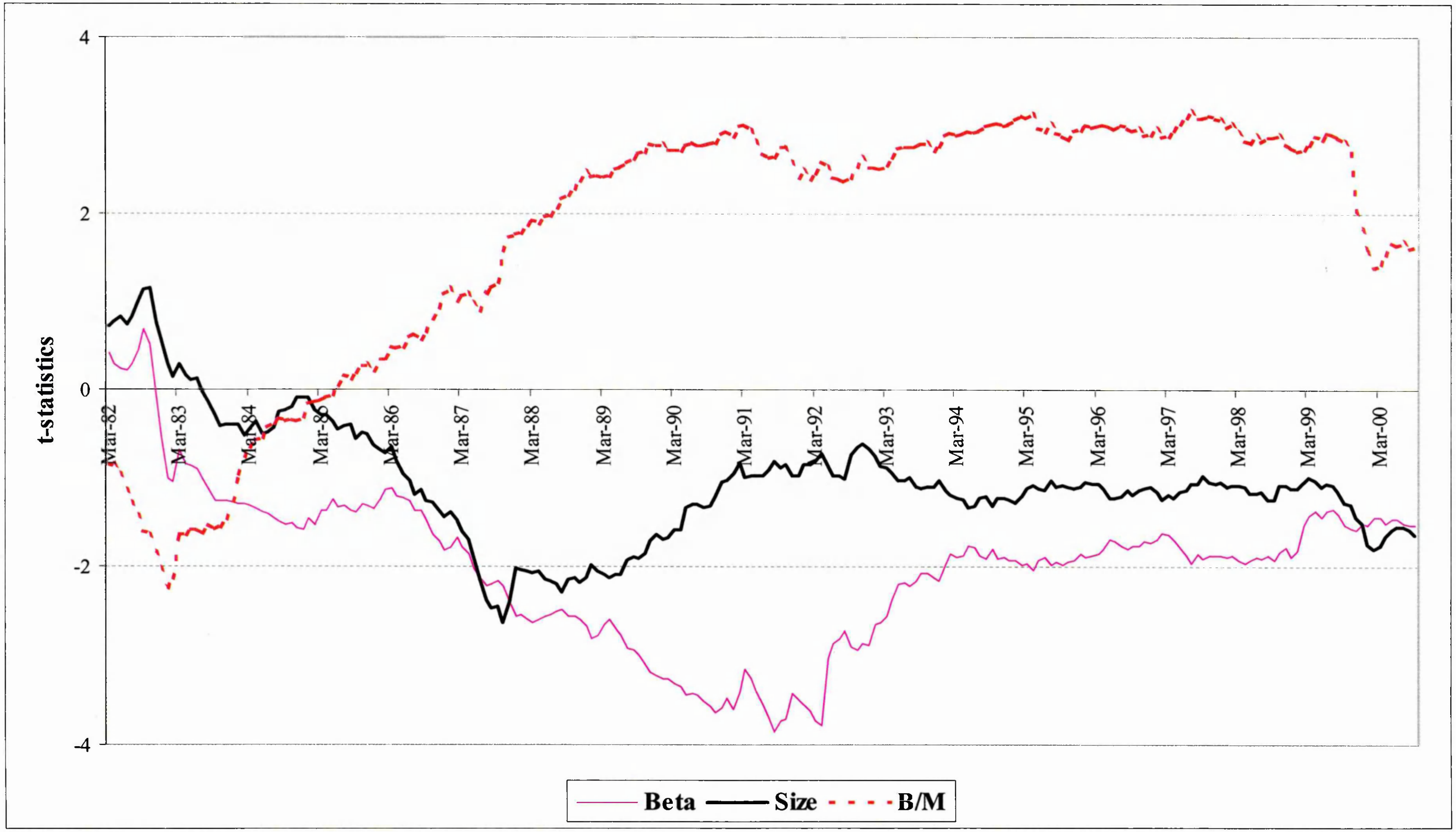


Figure 5.4.2: Time series evolution of t-statistics from October 1979 to September 2000 – three-variable multiple regression
The time-series is created by accumulating the coefficients for the first 30 months and then increasing the number of months by one till all 252 months are included.



The evidence in table 5.4.1 and figures 5.4.1 and 5.4.2 confirms a strong and persistent B/M effect in the UK. Though size and beta are not statistically significant over the entire period, they are time-varying. Beta is positive during the 1990s in both, univariate and multivariate regressions. The size premium seems to have been important during the 1980s but is statistically indistinguishable from zero during the 1990s. The figures graphically present the evidence of table 5.4.1 – the coefficients of beta, size and B/M are uninfluenced by each other suggesting these effects are not related to each other.

5.5 Time-series regressions and the Fama & French (1993) three-factor model

Fama & French (1993) propose the following model for equity returns:

$$R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + s\,SMB_t + h\,HML_t + e_t \qquad (12)$$

Where:

R_P = the return on portfolio P during the period t

R_F = Risk free rate observed at the beginning of the period t

R_M = Value-weighted return on all stocks in the twenty-five size and B/M portfolios

SMB = Return on the mimicking portfolio for the size factor

HML = Return on the mimicking portfolio for the B/M factor

R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1-month Treasury bill rate at the beginning of the month. The factors SMB and HML are constructed in the same way as Fama & French (1993) and described in chapter 4 (section 4.4.5.1).

During the period covered here (October 1979 to September 2000), the average monthly return in the UK on SMB is 0.07% (t = 0.30) and that on HML is 0.25% (t = 1.19). The average monthly return on the market factor is 0.61% (t = 2.08). In comparison, the average SMB for the US during the same period is –0.01% (t = 0.06) and average HML is 0.09% (t = 0.39).[22] Earlier I recorded the disproportionate impact of the last twelve month returns on the B/M coefficient in cross sectional regressions. If I exclude the last twelve months, the average monthly return on SMB is –0.04% (t = 0.17), on HML is 0.36% (t = 2.24) and on the market factor is 0.63% (t = 2.09). As indicated above, the disproportionate impact of the last twelve months is not restricted to the UK. Average SMB for the US for the period October 1979 to September 1999 is –0.05% (t = 0.27) while average HML is 0.21% (t = 1.16). Table 5.5.1 shows the correlations between the three factors in my data.

Table 5.5.1: Correlations between Fama & French factors
RMRF is the excess return on market computed as the difference between monthly value weighted return on all stocks in the portfolios (R_M) and the 1 month Treasury Bill rate at the beginning of the month (R_F). SMB is the return on the mimicking portfolio for the size factor and HML is the return on the mimicking portfolio for the B/M factor in stock returns.

	RMRF	SMB	HML
RMRF	1		
SMB	-0.30	1	
HML	-0.08	-0.29	1

The correlation between SMB and HML is –0.29 (t = 4.82) which is much lower than that in the US for the same period (r = -0.46, t = 8.07). The correlation drops to –0.03 (t = 0.49) if the last twelve months data is removed from the sample. The US data mirrors the pattern, the correlation between SMB and HML in the US for the period

[22] The figures here are based on the data provided on Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/)

October 1979 to September 1999 is –0.25 (t = 4.02). The low correlation between SMB and HML shows that the factor SMB is relatively free of the influence of any B/M effect and the factor HML is relatively free of the size effect. The correlation between RMRF and HML is –0.08 (t = 1.27), much lower than –0.46 in the US. Surprisingly, SMB is also negatively correlated to the market factor in the UK for this period (r = -0.30, t = 4.93) while it has a positive correlation in the US (r = 0.19).

5.5.1 Equally-weighted portfolio returns

In this sub-section, unlike Fama & French (1993), R_P is the monthly equally weighted return on the portfolio P. I have used equally-weighted portfolio returns because most tests of return predictability tend to use equal weights (e.g. Jegadeesh & Titman (1993), Liu, Strong & Xu (1999)) and it will be useful to see the performance of the Fama & French model with equally-weighted portfolios. In the next sub-section I report the results with value-weighted portfolio returns.

Table 5.5.1.1 presents the results of time-series regressions on the twenty-five portfolios with the market factor as the only explanatory variable.

Table 5.5.1.1: Equally-weighted portfolios - regressions with market factor alone

At the end of September of each year from 1979 to 1999, all the stocks in the population are ranked on market capitalization and grouped into five portfolios. The stocks are also independently sorted on B/M and grouped into five portfolios. 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 30th of September. Twenty-five portfolios are then formed at the intersections of size and B/M. The portfolios are rebalanced at the end of September each year. R_P is the monthly equally weighted return on portfolio P, R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1 month Treasury Bill rate at the beginning of the month. Negative B/M stocks are excluded. The last period return for failed stocks is set equal to –100%.

$$R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + e_t$$

	Book-to-Market									
	Low	2	3	4	High	Low	2	3	4	High
			a					t(a)		
Small	0.0126	0.0111	0.0128	0.0106	0.0103	2.32	2.20	3.17	3.45	3.37
2	0.0021	-0.0015	0.0013	0.0018	0.0025	0.61	-0.60	0.54	0.76	0.95
3	-0.0002	0.0010	0.0005	0.0009	0.0052	-0.07	0.44	0.22	0.37	1.78
4	-0.0002	-0.0014	-0.0015	0.0012	0.0039	-0.07	-0.73	-0.76	0.55	1.32
Large	-0.0018	-0.0013	-0.0014	0.0016	0.0050	-1.39	-1.06	-0.99	0.85	1.92
			b					t(b)		
Small	0.7230	0.9010	0.6620	0.6400	0.5560	6.27	8.43	7.77	9.87	8.63
2	0.8640	0.7310	0.6990	0.7590	0.7010	12.07	13.44	13.28	15.23	12.34
3	0.8490	0.7460	0.7460	0.8180	0.8710	14.70	15.87	15.86	15.57	14.01
4	0.9770	0.8730	0.9600	0.9540	0.9500	22.34	21.87	22.39	21.02	15.30
Large	1.0500	1.0540	1.1160	1.1210	1.1790	37.87	41.48	36.74	27.33	21.38
			Adjusted R^2							
Small	0.13	0.22	0.19	0.28	0.23					
2	0.37	0.42	0.41	0.48	0.38					
3	0.46	0.50	0.50	0.49	0.44					
4	0.67	0.66	0.67	0.64	0.48					
Large	0.85	0.87	0.84	0.75	0.65					

Table 5.5.1.1 shows that the market factor captures the bulk of common variation in equity returns for the largest two quintiles where the R^2 is more than 50%. The t-statistics for the market factor are all positive and always highly significant, the lowest being more than six standard errors from zero. The CAPM explains a lot of common variation in stock returns but as in Fama & French (1993) leaves much variation to be explained. Only four of the twenty-five R^2s exceed 70%. The R^2s reported here are much lower than those recorded by Fama & French (1993) for the US but this is to be expected because the portfolio returns here are equally weighted while these are value weighted by Fama & French (1993). The intercept terms show the size and B/M effects

in returns. Within each B/M quintile, the intercepts of the smallest size portfolios exceed the intercepts of the largest size portfolios by 53 to 144 basis points per month and within each size quintile, the intercepts of the highest B/M portfolios exceed the intercepts of the lowest B/M portfolios by 4 to 68 basis points per month except the smallest size quintile where the intercept of the lowest B/M portfolio exceeds that of the highest B/M portfolio by 23 basis points per month. These results mirror the evidence of table 5.4.1 which reports size and B/M effects after controlling for market beta.

Table 5.5.1.2 presents the results for the Fama & French (1993) three-factor model for the twenty-five portfolios.

Table 5.5.1.2: Equally-weighted portfolios – three factor regressions

At the end of September of each year from 1979 to 1999, all the stocks in the population are ranked on market capitalization and grouped into five portfolios. The stocks are also independently sorted on B/M and grouped into five portfolios. 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 30th of September. Twenty-five portfolios are then formed at the intersections of size and B/M. The portfolios are rebalanced at the end of September each year. R_P is the monthly equally weighted return on portfolio P, R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1-month Treasury Bill rate at the beginning of the month. SMB is the return on the mimicking portfolio for the size factor and HML is the return on the mimicking portfolio for the B/M factor in stock returns. Negative B/M stocks are excluded. The last period return for failed stocks is set equal to –100%.

$R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + s\,SMB_t + h\,HML_t + e_t$

	Book-to-Market									
	Low	2	3	4	High	Low	2	3	4	High
	a					t(a)				
Small	0.0084	0.0077	0.0094	0.0066	0.0058	1.96	1.75	3.14	3.47	3.18
2	-0.0006	-0.0046	-0.0017	-0.0017	-0.0019	-0.28	-3.09	-1.29	-1.37	-1.42
3	-0.0020	-0.0014	-0.0027	-0.0029	0.0005	-1.28	-1.27	-2.10	-2.01	0.30
4	-0.0013	-0.0038	-0.0044	-0.0018	0.0000	-1.00	-3.03	-3.05	-1.12	0.02
Large	-0.0015	-0.0020	-0.0026	-0.0006	0.0021	-1.45	-1.72	-2.02	-0.37	0.95
	b					t(b)				
Small	1.1060	1.1970	0.9670	0.9350	0.8600	11.59	12.18	14.45	21.94	20.91
2	1.1290	0.9790	0.9480	1.0080	0.9910	21.55	29.21	32.01	37.05	32.94
3	1.0640	0.9620	0.9710	1.0670	1.1480	30.71	40.21	33.95	32.52	27.70
4	1.1260	1.0480	1.1370	1.1280	1.1550	39.35	37.12	35.19	31.52	22.18
Large	1.0800	1.0970	1.1660	1.2090	1.3060	47.32	42.18	39.85	34.38	26.66
	s					t(s)				
Small	1.4930	1.1330	1.1860	1.0710	1.0660	12.57	9.27	14.25	20.23	20.84
2	1.0500	0.9300	0.9350	0.8930	0.9910	16.12	22.30	25.41	26.42	26.52
3	0.9000	0.8430	0.8040	0.8510	0.9060	20.88	28.35	22.60	20.86	17.57
4	0.6340	0.6240	0.5920	0.5660	0.6300	17.81	17.77	14.73	12.71	9.74
Large	0.1870	0.1400	0.1260	0.2100	0.3310	6.60	4.33	3.47	4.81	5.43
	h					t(h)				
Small	0.2160	0.2360	0.1760	0.4750	0.6360	1.59	1.69	1.84	7.81	10.84
2	0.0644	0.2910	0.2750	0.4470	0.7060	0.86	6.07	6.51	11.52	16.44
3	-0.1310	0.1050	0.4250	0.6250	0.8550	-2.65	3.09	10.39	13.34	14.45
4	-0.1380	0.3250	0.4880	0.5500	0.7910	-3.37	8.06	10.59	10.76	10.64
Large	-0.2750	0.1310	0.3160	0.5890	0.7280	-8.45	3.52	7.55	11.74	10.41
	Adjusted R^2									
Small	0.48	0.42	0.56	0.73	0.72					
2	0.70	0.81	0.84	0.86	0.85					
3	0.83	0.89	0.84	0.83	0.78					
4	0.87	0.85	0.83	0.80	0.68					
Large	0.91	0.88	0.87	0.84	0.75					

Similar to the findings of Fama & French (1993), the market factor, size factor and B/M factor strongly capture the common variation in stock returns. All the coefficients of the market factor are positive and highly significant, the lowest test statistic is more than eleven standard errors from zero. However, the coefficients on the market factor are all close to one (as in Fama & French (1993)) and there is no pattern in the variation of coefficients with size and B/M. The evidence shows that even though the market factor explains the difference of returns between stocks and the 1 month T-Bill rate, it cannot explain the cross-sectional variation in average stock returns.

The t-statistics on the size factor slopes are all in excess of three standard errors from zero and except for the largest size quintile, always in excess of nine standard errors from zero. The size factor (SMB) is clearly capturing common variation in stock returns missed by the market factor and HML. The slopes on SMB decrease monotonically from small to large size firms in each B/M quintile showing that SMB is related to firm size.

Similarly, 21 out of 25 coefficients of HML are highly significant. The B/M factor (HML) is also capturing common variation in stock returns missed by the market factor and SMB. The slopes on HML are related to B/M and the increase from low to high B/M portfolios in each size quintile is almost monotonic.

The Fama & French model is able to capture more common variation in equity returns than the CAPM as is evidenced by much higher adjusted R^2s in table 5.5.1.2 as compared to table 5.5.1.1. The adjusted R^2s are in excess of 70% for almost all the portfolios (except small size – low B/M portfolios). However, the model does not completely capture the size and B/M effects. The difference between the intercepts of the highest and lowest B/M portfolios ranges from –36 to 26 basis points per month and between the intercepts of smallest and largest size portfolios ranges from 37 to 120 basis points per month. In summary, my results show that the three Fama & French factors – Market factor, SMB and HML are able to capture common variation in equity returns. However, what these factors signify continues to be hotly debated in the academic literature.

The intercept terms in table 5.5.1.2 provide evidence as to how well these three factors explain the cross-sectional variation in stock returns. The multi-factor asset pricing models like Merton's (1973) ICAPM imply that the intercepts in the time-series regressions of excess returns on mimicking portfolio returns should be indistinguishable from zero. 9 of the 25 intercept terms with the Fama & French (1993) three-factor model are more than two standard errors from zero showing the inability of the model to fully explain the returns in these portfolios. Also, the model captures less than 70% variation in small size, low B/M portfolios.

The evidence here suggests that the Fama & French three-factor model does a good job in explaining the average returns on the London Stock exchange during the period 1979-2000. It provides a much better description of average returns than the CAPM as the three-factor model R^2s are much higher than the CAPM R^2s during this period. However, the three-factor model is less than perfect as the intercept terms for nine of the twenty-five portfolios are more than two standard errors from zero. The model is also unable to explain a lot of common variation in the small low B/M portfolios where the R^2s are under 60%. As a robustness check, I have repeated the analysis with quarterly returns rather than monthly returns. The results are qualitatively the same though the R^2s are higher. The results of this section also put in perspective other results of return predictability studies that use equally weighted portfolio returns. On an equally-weighted basis, the Fama & French model is not entirely successful in explaining the cross-sectional variation of returns even on the twenty-five size and B/M portfolios. The momentum effect recorded by Liu, Strong & Xu (1999) could be a manifestation of this inability of the Fama & French (1993) model to explain cross-sectional variation in equally-weighted returns rather than a market anomaly.

5.5.2 Value-weighted portfolio returns

In this sub-section, like Fama & French (1993), R_P is the monthly value weighted return on the portfolio P.

Table 5.5.2.1 presents the results of time-series regressions on the twenty-five portfolios with the market factor as the only explanatory variable.

Table 5.5.2.1: Value-weighted portfolios - regressions with market factor alone
At the end of September of each year from 1979 to 1999, all the stocks in the population are ranked on market capitalization and grouped into five portfolios. The stocks are also independently sorted on B/M and grouped into five portfolios. 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 30th of September. Twenty-five portfolios are then formed at the intersections of size and B/M. The portfolios are rebalanced at the end of September each year. R_P is the monthly value weighted return on portfolio P, R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1 month Treasury Bill rate at the beginning of the month. Negative B/M stocks are excluded. The last period return for failed stocks is set equal to –100%.

$R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + e_t$										
	Book-to-Market									
	Low	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
			a					**t(a)**		
Small	0.0113	0.0087	0.0070	0.0067	0.0063	2.10	1.90	1.85	2.22	2.04
2	0.0039	0.0002	0.0016	0.0017	0.0011	1.06	0.07	0.62	0.72	0.43
3	0.0028	0.0012	0.0018	0.0015	0.0055	0.96	0.55	0.84	0.63	1.96
4	0.0008	-0.0006	-0.0007	0.0019	0.0035	0.37	-0.33	-0.34	0.92	1.16
Large	-0.0009	-0.0017	-0.0007	0.0026	0.0056	-0.69	-1.58	-0.50	1.30	2.31
			b					**t(b)**		
Small	0.7600	0.8420	0.6220	0.6260	0.6740	6.70	8.71	7.80	9.80	10.28
2	0.9000	0.7280	0.7060	0.7550	0.7220	11.57	13.48	13.18	15.53	12.82
3	0.8290	0.7530	0.7380	0.8000	0.8370	13.60	15.81	16.42	15.82	14.04
4	0.9820	0.8960	0.9830	0.9450	0.9410	20.54	23.22	23.89	21.92	14.86
Large	1.0380	1.0200	1.0420	1.0380	1.0030	38.19	44.79	34.74	24.64	19.35
			Adjusted R^2							
Small	0.15	0.23	0.19	0.28	0.29					
2	0.35	0.42	0.41	0.49	0.39					
3	0.42	0.50	0.52	0.50	0.44					
4	0.63	0.68	0.69	0.66	0.47					
Large	0.85	0.89	0.83	0.71	0.60					

Table 5.5.2.1 shows that, similar to table 5.5.1.1, the t-statistics for the market factor are all positive and always highly significant, the lowest being more than six standard errors from zero. The CAPM explains a lot of common variation in stock returns but as in table 5.5.1.1 and Fama & French (1993) leaves much variation to be explained. Only four of the twenty-five R^2s exceed 70%. The R^2s reported here are still much lower than those recorded by Fama & French (1993) for the US. The intercept terms still show the size and B/M effects in returns. Within each B/M quintile, the intercepts of the smallest size portfolios exceed the intercepts of the largest size portfolios by 7 to 122 basis points per month (as compared to 53 to 144 basis points per month in table 5.5.1.1) and within each size quintile, the difference between the intercepts of the highest and the lowest B/M portfolios varies from –50 to +65 basis points per month (as against -23 to +68 basis points per month in table 5.5.1.1).

Table 5.5.2.2 presents the results for the Fama & French (1993) three-factor model for the twenty-five portfolios.

Table 5.5.2.2: Value-weighted portfolios – three factor regressions

At the end of September of each year from 1979 to 1999, all the stocks in the population are ranked on market capitalization and grouped into five portfolios. The stocks are also independently sorted on B/M and grouped into five portfolios. 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 30th of September. Twenty-five portfolios are then formed at the intersections of size and B/M. The portfolios are rebalanced at the end of September each year. R_P is the monthly equally weighted return on portfolio P, R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1-month Treasury Bill rate at the beginning of the month. SMB is the return on the mimicking portfolio for the size factor and HML is the return on the mimicking portfolio for the B/M factor in stock returns. Negative B/M stocks are excluded. The last period return for failed stocks is set equal to –100%.

$R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + s\,SMB_t + h\,HML_t + e_t$										
	Book-to-Market									
	Low	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
			a					**t(a)**		
Small	0.0079	0.0064	0.0042	0.0033	0.0019	1.82	1.87	1.56	1.75	1.10
2	0.0020	-0.0024	-0.0010	-0.0015	-0.0030	0.84	-1.62	-0.74	-1.29	-2.28
3	0.0013	-0.0008	-0.0010	-0.0019	0.0013	0.78	-0.74	-0.81	-1.35	0.74
4	0.0001	-0.0027	-0.0031	-0.0006	-0.0001	0.09	-2.10	-2.17	-0.39	-0.04
Large	0.0007	-0.0016	-0.0013	0.0009	0.0038	0.68	-1.44	-1.02	0.55	1.95
			b					**t(b)**		
Small	1.1040	1.1400	0.9100	0.9050	0.9910	11.32	14.95	15.14	21.10	25.57
2	1.1660	0.9660	0.9490	0.9990	1.0040	22.12	29.43	32.46	39.63	33.46
3	1.0460	0.9660	0.9520	1.0380	1.0950	28.57	40.88	35.34	32.71	26.92
4	1.1280	1.0570	1.1440	1.0960	1.1310	36.80	36.93	35.41	30.59	20.76
Large	0.9790	1.0110	1.0390	1.0810	1.0300	45.35	41.59	36.45	29.32	23.76
			s					**t(s)**		
Small	1.3590	1.2330	1.1380	1.0410	1.1240	11.20	13.00	15.23	19.50	23.32
2	1.1140	0.9150	0.9430	0.8890	0.9730	17.00	22.43	25.94	28.37	26.07
3	0.9170	0.8440	0.7780	0.8330	0.8550	20.16	28.73	23.24	21.09	16.89
4	0.6460	0.5810	0.5440	0.4920	0.5820	16.94	16.33	13.54	11.04	8.59
Large	-0.1380	-0.0353	-0.0763	0.0435	-0.0504	-5.13	-1.17	-2.16	0.95	-0.94
			h					**t(h)**		
Small	0.0949	-0.1710	0.0720	0.3510	0.6590	0.68	-1.57	0.84	5.72	11.88
2	-0.2150	0.1670	0.1390	0.3930	0.7100	-2.85	3.57	3.33	10.89	16.54
3	-0.2190	0.0368	0.3510	0.5420	0.8030	-4.18	1.09	9.10	11.93	13.80
4	-0.2690	0.2730	0.4440	0.4980	0.8000	-6.12	6.66	9.60	9.71	10.25
Large	-0.4390	-0.0184	0.2740	0.5660	0.7130	-14.19	-0.53	6.71	10.73	11.49
			Adjusted R^2							
Small	0.45	0.58	0.60	0.71	0.78					
2	0.74	0.81	0.84	0.88	0.85					
3	0.82	0.89	0.85	0.83	0.77					
4	0.87	0.85	0.83	0.79	0.65					
Large	0.92	0.89	0.86	0.80	0.75					

Similar to the findings of Fama & French (1993) and the results in table 5.5.1.2, the market factor, size factor and B/M factor strongly capture the common variation in stock returns. All the coefficients of the market factor are positive and highly significant, the lowest test statistic is more than eleven standard errors from zero. However, the coefficients on the market factor are all close to one (as in Fama & French (1993)) and there is no pattern in the variation of coefficients with size and B/M. As in table 5.5.1.2, the market factor is unable to explain the cross-sectional variation in average stock returns. The results for SMB and HML are similar to those in table 5.5.1.2. The size factor (SMB) is clearly capturing common variation in stock returns missed by the market factor and HML. Similarly, HML is capturing common variation in stock returns missed by the market factor and SMB.

The Fama & French model is able to capture more common variation in equity returns than the CAPM as is evidenced by much higher adjusted R^2s in table 5.5.2.2 as compared to table 5.5.2.1. However, the adjusted R^2s here are similar to those in table 5.5.1.2. There is still residual size and B/M effect and the model is not able to capture these effects completely. The difference between the intercepts of the highest and lowest B/M portfolios ranges from –60 to +31 basis points per month and between the intercepts of smallest and largest size portfolios ranges from -19 to +72 basis points per month.

In sharp contrast to table 5.5.1.2, only 3 of the 25 intercept terms with the Fama & French (1993) three-factor model are more than two standard errors from zero showing that the model is able to better explain cross-sectional variation on a value-weighted basis.

The evidence here suggests that the Fama & French three-factor model does a good job in explaining the average returns on the London Stock Exchange during the period 1979-2000. Though the adjusted R^2s are similar when portfolios are equally-weighted or value-weighted, the model is better specified with value-weighted portfolio returns as evidenced by only 3 intercept terms being significantly different to zero with value weights (as against nine with equal weights).

5.6 Summary

Size and book-to-market ratios have emerged in the literature as variables that are strongly linked to the cross-sectional variation in stock returns. The three-factor asset-pricing model of Fama & French (1993) is widely used and is able to explain many of the anomalies associated with the single factor CAPM. In this chapter, I have tested the ability of beta, size and B/M to explain the cross-sectional variation in UK stock returns for the period 1979-2000 and then implemented the Fama & French (1993) three-factor model for the UK.

I find that beta is negative and statistically insignificant in cross-sectional regressions even when it is the only explanatory variable. There is no significant difference in the returns on smaller size and larger size firms during my sample period. However, I find that size premium is time varying and an unconditional analysis like the one conducted here misses the dynamic nature of returns and risk premia. High B/M firms do better than low B/M firms and the difference is statistically significant till the last year's (2000) returns are included in the sample. The value effect registered a dramatic collapse between October 1999 and September 2000, a collapse that is mirrored in the

US. This is likely to be due to the impact of the boom in 'new economy' stocks hitting my data with a lag because I require stocks to be listed for at least 24 months before they can be included in my sample. The coefficient and t-statistics of beta, size and B/M are virtually the same in univariate and multivariate regressions suggesting that the common variation in the three variables has little relation to excess stock returns. The results are qualitatively the same when I use quarterly returns and also when I use value-weighted rather than equally-weighted portfolio returns (Appendix: tables A1.1).

I also find a clear relation between firm size and failure, smaller firms have substantially higher mortality rates and virtually all failures belong to the smallest 20% stocks. There is also a strong relationship between B/M and failure rate as almost half the failures belong to the highest 20% B/M stocks. However, once I control for firm size, the relationship between failure rates and B/M is U shaped with high failure rates for both low and high B/M firms. Dichev (1998) finds similar results for the US. This is not surprising since it is likely that the book value of distressed firms is wiped out due to continued losses resulting in low B/M ratios. High B/M firms could be those where the market value has declined sharply due to adverse news putting the firms at risk of failure.

I have partially replicated Fama & French (1993) with a view to testing the applicability of the three-factor model in the UK. Though several studies have tested the size and B/M effects in the UK and several studies have used the three-factor model, there is no study that explicitly tests the model for the UK. I hope this chapter addresses this gap. My results here indicate that the three-factor model provides a better description of returns than the single factor CAPM. The single factor model produces adjusted R^2s that are generally below 70% and leaves residual size and B/M effects. The three-factor model produces adjusted R^2s that are generally in excess of 80% and is able to capture size and B/M effects missed by the market factor. The Fama & French (1993) three-factor model, however, does not provide a complete description of returns. It leaves residual size and B/M effects in the cross-section of returns. The model seems misspecified when portfolio returns are equally-weighted with almost a third of the intercepts being statistically significant. However, when I value weight the portfolio returns, the Fama & French model is better specified with only three intercepts being more than two standard errors from zero. The model has particular difficulty in pricing small size – low B/M portfolios where the adjusted R^2s are below 60%. The adjusted R^2s are similar for value-weighted portfolio returns. The results remain qualitatively the same with quarterly returns instead of monthly returns.

In chapter six, I introduce z-score as a proxy for distress factor in the pricing equation. I test the nature of distress factor and also the relationship of size and B/M to this factor.

Chapter 6

BANKRUPTCY RISK, SIZE, B/M

AND THE CROSS-SECTION OF STOCK RETURNS

6.1 Introduction

The distress factor hypothesis for the size and value effects states that small size firms and high book-to-market firms are relatively distressed and, therefore, any observed higher return on such stocks is merely a compensation for higher risk (Chan & Chen (1991) and Fama & French (1993)). In chapter 5 I have documented the presence of size and B/M effects in the UK for the period 1979-2000. I also documented the linkage between size, B/M and failure rates. In chapter 4 I showed that z-scores are strong predictors of bankruptcy and a valid proxy for distress factor. In this chapter I introduce z-scores in the asset pricing equation as a proxy for bankruptcy risk. We would expect z-scores to produce effects similar to size and B/M i.e., negative z-score firms with a higher bankruptcy risk should outperform positive z-score firms, assuming the bankruptcy risk premium is positive. We would expect the z-score effect to either subsume size and B/M effects or be subsumed by them if all three are measuring the same aspect of risk. I find that contrary to the prediction of the distress factor hypothesis, the unconditional return on negative z-score stocks is lower than that on positive z-score stocks. Also, size and B/M effects are unrelated to z-score providing further evidence against the distress factor hypothesis.

I start my analysis of the relation between default risk and equity returns by examining whether portfolios with different default risk characteristics provide significantly different returns. A difference in returns would indicate that default risk might be important for equity pricing. Cochrane (2001) argues that sorting stocks into portfolios based on characteristics related to expected returns is correct because if there is no variation in average returns, then there is nothing for the asset pricing model to test. As a robustness check, I repeat the analysis using a different portfolio formation method and finally keeping in mind data snooping biases (Lo & MacKinlay (1990)), using individual securities.

The chapter is organized as follows: section 2 describes the portfolio formation methods used in this chapter, section 3 presents the summary statistics, section 4 reports the results of hypotheses tests using Fama-MacBeth regressions and section 5 summarizes the results.

6.2 Portfolio formation methods

The results of asset pricing tests can be sensitive to the portfolio formation method used. To ensure that any results are not an artifact of the data, I employ two different portfolio formation methods and then repeat the analyses on an individual securities basis. The two portfolio formation methods are:

Z-score portfolios: This portfolio formation method is motivated by Dichev (1998) who ranks stocks on z-scores and groups them into ten portfolios of equal number of stocks. However, since z-scores are a pattern recognition device that classify firms into one of the two pre-defined groups, the important difference is between the negative and positive z-score stocks rather than the actual z-score itself. Therefore, each 30^{th} of September from 1979 to 1999, I first rank my population of stocks on latest available z-scores and form two groups: one group has stocks with negative z-scores and the other with positive z-scores. Each of the two portfolios is then further divided into quintiles based on z-score yielding ten portfolios in all: five negative z-score portfolios and five positive z-score portfolios. Equally-weighted monthly returns are computed for each portfolio from October of year t to September of year t+1.

Size, B/M and Z-score portfolios: This is the more common sorting procedure employed in the literature and sorts on the characteristics hypothesized to be linked to cross-sectional variation in stock returns. All eligible stocks are ranked on market capitalization on 30th September of year t and sorted into four portfolios with equal numbers of stocks. Stocks are independently ranked on B/M on September 30th of year t and sorted into three portfolios of lowest 30%, middle 40% and highest 30% B/M ratios. Stocks are additionally independently ranked on z-score on September 30th of year t and sorted into two portfolios of negative and positive z-scores. I employ only a binary split because the correct interpretation of z-scores is binary – negative z-score firms have financial profiles similar to those firms that have failed in the past while positive z-score firms have financial profiles similar to those that did not fail. Twenty-four size, B/M and z-score portfolios are formed at the intersections of the break-points (4 X 3 X 2). Equally-weighted monthly returns are computed for each portfolio from October of year t to September of year t+1. The procedure is repeated on 30th September of each year from 1979 to 1999.

6.3 Summary statistics:

6.3.1. Z-score portfolios

Table 6.3.1.1 shows characteristics of portfolios formed on z-score. The portfolio with the highest bankruptcy risk (lowest z-score) earns low returns. It has the highest beta and beta decreases almost monotonically with increasing z-score showing that lower z-score firms have higher systematic risk than higher z-score firms. The negative z-score firms are smaller than positive z-score firms but there does not seem to be any consistent relationship between z-scores and size. The negative z-score portfolios have a higher book-to-market ratio and the B/M ratio declines monotonically with increasing z-scores from portfolio 3. Similar to the findings of Dichev (1998), the three lowest z-score portfolios have the highest B/M ratios. However, the B/M ratios for the first three portfolios are still higher than those for positive z-score portfolios because unlike Dichev (1998), I do not include negative B/M stocks in my analysis because they are difficult to interpret. Table 4.3.1 shows that an overwhelming majority of negative B/M stocks also have negative z-scores and their inclusion would have reduced the average B/M of negative z-score portfolios. Table 6.3.1.1 also shows that there is some relationship between z-scores and returns for distressed portfolios while there does not seem to be any relationship between z-scores and returns for non-distressed portfolios.

Table 6.3.1.1: Summary statistics

At the end of September of each year from 1979 to 1999, all the stocks in the population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks. Portfolios are rebalanced at the end of September each year. 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. 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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively. Average size and average B/M are the time-series averages of monthly averages of market capitalizations and B/M respectively for stocks in the portfolio at the end of September of each year. Negative B/M stocks are excluded. The last month's return for failed firms is set equal to –100%.

Portfolio	Monthly excess returns (%)	Beta	Z-score	Size (£M)	Book-to-Market	Average number of stocks
1	0.51	1.35	-6.14	274.2	1.24	47
2	0.61	1.15	-3.25	275.5	1.26	46
3	0.65	1.24	-1.95	263.7	1.32	46
4	0.49	1.14	-1.05	261.2	1.20	46
5	0.76	1.06	-0.33	365.2	1.15	47
6	0.76	1.05	1.01	464.0	1.11	155
7	0.82	1.03	2.86	443.9	1.07	154
8	0.75	0.99	4.87	490.9	1.01	154
9	0.82	0.98	7.71	446.8	0.93	154
10	0.80	0.86	13.34	336.7	0.86	155

The picture in table 6.3.1.1 looks very different if the last month return for failed firms is not set equal to –100%. Portfolios 1 & 2 earn the highest returns and distressed portfolios earn higher returns than non-distressed portfolios. However, as argued earlier, it is correct to set the last month returns for failure equal to –100% because in the UK, the shareholders never get anything once a firm goes into administration, receivership or liquidation (Rolls Royce and Railtrack are rare exceptions). I therefore, report the results only after setting the last month returns equal to –100%.

6.3.2. Size, B/M and z-score portfolios

Table 6.3.2.1 shows characteristics of portfolios formed on size, B/M and z-score. Panel C shows that the smallest portfolios earn the highest returns for each z-score and B/M portfolio. The relationship between size and returns is erratic for the other four size quartiles. The negative z-score portfolios fare worse than positive z-score portfolios after controlling for size and B/M. High B/M portfolios earn higher returns than low B/M portfolios after controlling for z-score and size though the relationship is not monotonic.

Panel D shows that there is no clear relationship between size and beta or between B/M and beta. However, negative z-score portfolios have higher betas than positive z-score portfolios after controlling for size and B/M. This shows that firms with higher bankruptcy risk have higher sensitivity to market movements. Panel E shows that the sorting procedure has been successful in controlling for size across z-score and B/M while panel F shows that the sorting procedure has been successful in controlling for B/M across z-score and firm size.

Table 6.3.2.1: Summary statistics

At the end of September of each year from 1979 to 1999, all the stocks in my population 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 four portfolios and independently ranked on B/M and grouped into three portfolios. 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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively. Twenty-four portfolios are then formed at the intersections of size, B/M and z-score. The portfolios are rebalanced at the end of September each year. Average 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 and average B/M are the time-series averages of monthly averages of market capitalizations and B/M 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%.

	Low B/M		Medium B/M		High B/M	
	z<0	z>0	z<0	z>0	z<0	z>0
A. Average number of stocks						
Small	20	16	27	50	51	87
2	16	43	20	87	24	61
3	15	80	17	93	10	35
Large	14	96	12	96	5	28
B. Average z-score						
Small	-3.69	5.26	-2.97	6.04	-2.77	5.27
2	-2.75	6.79	-2.20	6.32	-2.22	5.40
3	-2.11	6.77	-2.00	5.93	-1.98	5.29
Large	-1.93	6.64	-2.05	5.36	-2.06	5.03
C. Monthly excess returns						
Small	0.96	1.72	1.12	1.52	1.03	1.44
2	0.21	0.56	-0.08	0.67	0.41	0.85
3	0.16	0.53	0.34	0.50	0.26	0.94
Large	0.39	0.49	0.57	0.62	1.82	1.08
D. Average Beta						
Small	1.25	0.98	1.10	0.96	1.03	0.84
2	1.28	1.02	1.16	0.96	1.12	0.99
3	1.32	1.03	1.25	0.95	1.27	0.98
Large	0.97	0.82	0.84	0.84	1.04	0.87
E. Average Size (£M)						
Small	6.5	7.5	6.0	7.1	5.2	5.6
2	23.7	25.8	22.4	23.6	21.0	22.3
3	88.3	88.1	81.1	84.0	76.3	80.8
Large	1695.1	1532.3	1625.6	1349.5	2260.9	1543.6
F. Average B/M						
Small	0.31	0.37	0.86	0.88	2.38	2.30
2	0.32	0.37	0.87	0.83	1.93	1.91
3	0.31	0.35	0.83	0.80	1.89	1.78
Large	0.33	0.33	0.79	0.80	1.82	1.66

6.4 Tests of hypotheses

In this section I conduct formal unconditional tests of the hypotheses discussed in chapter 3. Fama (1998) points out that results of many of the returns predictability studies are sensitive to the trading rules and this casts doubt as to the validity of their findings. I therefore employ three different trading rules: ten portfolios formed on z-scores, twenty-four portfolios formed on size, B/M and z-scores (4X3X2) and finally individual securities i.e. no portfolio formation. Using individual securities is a guard against data snooping bias (Lo & MacKinlay (1990), Berk (2000)).

$H1_0$: ***There is no difference in the performance between financially distressed and non-distressed firms, controlling for the market factor.***

To test this hypothesis, two hundred and fifty two cross-sectional regressions are carried out for the following two models, one has z-score as a continuous variable and the other has z-score as a dummy variable that takes the value of 1 when z-score is negative and takes a value of 0 if z-score is positive:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\,z_{it-1} \qquad (5)$$

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{3t}\,z(0/1)_{it-1} \qquad (6)$$

If the hypothesis holds, we would expect γ_2 (γ_3) to be indistinguishable from zero.

Table 6.4.1 presents the regression results.

Table 6.4.1: Regression results – two factor model with beta and z-score

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

No portfolios are formed in panel C.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the equally-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. 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%.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}z_{it-1} + \gamma_{3t}z(0/1)_{it-1}$			
α	γ_1	γ_2	γ_3
A. z-score portfolios			
0.0049	0.0025	-0.0001	
(0.76)	(0.49)	(-0.35)	
0.0009	0.0066		-0.0016
(0.19)	(1.48)		(-1.23)
B. Size, B/M and z-score portfolios			
0.0098	-0.0023	0.0002	
(2.61)	(-0.98)	(1.39)	
0.0104	-0.0014		-0.0027
(3.09)	(-0.60)		(-2.36)
C. Individual securities			
0.0155	-0.0003	0.0001	
(5.49)	(-0.10)	(0.70)	
0.0160	-0.0002		-0.0018
(6.84)	(-0.07)		(-1.40)

In panel A of table 6.4.1, beta is positive but indistinguishable from zero, while the coefficient of z-score is negative when used either as a continuous variable or a dummy variable (1 if negative, 0 otherwise). The negative coefficient on continuous z-score shows that lower z-score portfolios outperform higher z-score portfolios. The difference is statistically insignificant (t = 0.35). The negative coefficient on the z-score dummy shows that the negative z-score portfolios underperform positive z-score portfolios by 16 basis points per month, a difference that is indistinguishable from zero (t = 1.23) on a non-conditional basis. The results here show that there is no significant relationship between z-scores and excess returns.

In panel B of table 6.4.1, beta is negative but indistinguishable from zero, while the coefficient of z-score is positive when used as a continuous variable and negative when used as a dummy variable (1 if negative, 0 otherwise). The positive coefficient on continuous z-score shows that lower z-score portfolios underperform higher z-score portfolios. The difference is statistically insignificant (t = 1.39). The negative coefficient on the z-score dummy shows that the negative z-score portfolios underperform positive z-score portfolios by 27 basis points per month, a difference that is more than two standard errors from zero (t = 2.36).

In panel C of table 6.4.1, beta is negative but indistinguishable from zero, while the coefficient of z-score is positive when used as a continuous variable and negative when used as a dummy variable (1 if negative, 0 otherwise). The positive coefficient on continuous z-score is statistically insignificant (t = 0.70). The negative coefficient on the z-score dummy shows that the negative z-score stocks underperform positive z-score stocks by 18 basis points per month, a difference that is statistically insignificant (t = 1.40).

The results in table 6.4.1 highlight how different trading rules can affect the results. While beta remains statistically insignificant and continuous z-score is statistically insignificant in all three trading rules, the z-score dummy is significant in portfolios that control for size and B/M while it is insignificant for z-score portfolios and individual securities. The insignificant coefficient for z-score as a continuous variable is not surprising since there is little variation in bankruptcy risk when z-scores are positive (table 4.2.2.1.1).

The results here do not provide any evidence of the outperformance by lower z-score stocks or negative z-score stocks after taking beta into account for z-score portfolios (panel A) and individual securities (panel C). The null hypothesis $H1_0$ cannot be rejected. However, for size, B/M and z-score portfolios (panel B), negative z-score firms reliably underperform positive z-score firms and $H1_0$ is strongly rejected.

$H2_0$: ***The coefficient on z-score is insignificant when size & B/M are included in the asset pricing equation and size and B/M effects are uninfluenced by inclusion of z-score in the asset pricing equation.***

To test this hypothesis, 252 cross-sectional regressions are carried out as before for the following three models, one without z-score variable, one with z-score as a continuous variable and one with z-score as a dummy variable that takes the value of 1 when z-score is negative and takes a value of 0 if z-score is positive:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \qquad (7)$$

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\,z_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \qquad (8)$$

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{3t}\,z(0/1)_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \qquad (9)$$

If $H2_0$ holds, γ_2 in equation (8) and/or γ_3 in equation (9) would be indistinguishable from zero while the coefficients γ_4 and/or γ_5 will not be affected by introduction of z-score in the regression.

If size and B/M are proxies for the distress factor as conjectured, we would expect weaker effects with the introduction of another variable capturing the same risk. Results are presented in table 6.4.2.

Table 6.4.2: Regression results – Four factor model

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

No portfolios are formed in panel C.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the equally-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. $\ln(size_{it-1})$ 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 end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. 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%.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} z_{it-1} + \gamma_{3t} z(0/1)_{it-1} + \gamma_{4t} \ln(size_{it-1}) + \gamma_{5t} \ln(B/M_{it-1})$					
α	γ_1	γ_2	γ_3	γ_4	γ_5
A. Z-score portfolios					
0.0561	-0.0021			-0.0024	-0.0029
(2.56)	(-0.36)			(-2.26)	(-0.57)
0.0510	-0.0017	0.0000		-0.0021	0.0002
(2.14)	(-0.25)	(0.15)		(-1.84)	(0.02)
0.0669	-0.0011		-0.0035	-0.0030	-0.0010
(2.66)	(-0.18)		(-1.92)	(-2.47)	(-0.17)
B. Size, B/M and Z-score portfolios					
0.0223	-0.0051			-0.0006	0.0017
(2.02)	(-2.16)			(-1.02)	(1.68)
0.0157	-0.0018	0.0004		-0.0004	0.0021
(1.37)	(-0.78)	(2.64)		(-0.76)	(2.10)
0.0169	-0.0012		-0.0036	-0.0004	0.0019
(1.50)	(-0.49)		(-3.28)	(-0.72)	(1.90)
C. Individual securities					
0.0348	0.0047			-0.0013	0.0011
(3.30)	(1.61)			(-2.23)	(1.24)
0.0337	0.0054	0.0002		-0.0014	0.0013
(3.20)	(1.95)	(2.14)		(-2.31)	(1.46)
0.0376	0.0057		-0.0036	-0.0015	0.0011
(3.64)	(2.00)		(-3.57)	(-2.58)	(1.30)

In panel A of table 6.4.2, the cross-sectional regressions indicate beta is negative and insignificant in both the three factor and the two versions of four-factor model. In the three factor model with beta, size and B/M, smaller size portfolios outperform larger size portfolios by 24 basis points per month, a difference that is statistically significant (t = 2.26). Surprisingly, the B/M coefficient is negative though it is statistically insignificant.

In the four-factor model that includes continuous z-score, γ_2 is zero however, its introduction in the pricing equation reduces the size effect to 21 basis points per month and renders it insignificant at the 5% level. The coefficient on B/M is now essentially zero. Introduction of z-score as a dummy variable rather than a continuous variable increases the size effect to 30 basis points per month (t = 2.47) while the B/M coefficient remains statistically insignificant. The negative z-score portfolios underperform by 35 basis points per month and the coefficient is marginally statistically significant (t = 1.92). The coefficient on continuous z-score is similar to that in table 6.4.1 while that on z-score dummy increases showing that there is no common variation between z-score, size and B/M that is related to stock returns. The disappearance of the B/M effect could be an outcome of the sorting procedure. If z-score and B/M are uncorrelated, sorting on z-score will randomize B/M ratios and therefore, no relationship between B/M and returns can be found. The persistence of the size effect seems to support the evidence in chapter 4 – there is some link between size and bankruptcy risk. However, when z-score is used as a binary variable, the two appear independent suggesting that size and z-score may be capturing different aspects of firm distress.

In panel B of table 6.4.2, the cross-sectional regressions indicate that in the three factor model with beta, size and B/M, high beta portfolios underperform low beta portfolios by 51 basis points per month, the difference being statistically significant at the 5% level (t = 2.16). The size effect is insignificant, both, economically (6 basis points per month) and statistically (t = 1.02) while high B/M portfolios outperform low B/M portfolios by 17 basis points per month though the difference is statistically insignificant (t = 1.68). However, a time series investigation of the B/M effect shows results similar to those in chapter 5: the B/M effect is positive and strong (25 basis points per month, t = 2.94) till September 1999.

Introduction of continuous z-score in the pricing equation reduces the underperformance of high beta portfolios to 18 basis points per month which is within two standard errors of zero. γ_2 is 4 basis points per month and statistically significant (t = 2.64). The size effect remains insignificant while the B/M coefficient increases to 21 basis points per month and is now significantly different to zero (t = 2.10). Excluding the last twelve months from the analysis, the B/M coefficient is 30 basis points per month (t = 3.45). Introduction of z-score as a dummy variable rather than a continuous variable has no effect on the size coefficient while the B/M coefficient is 19 basis points per month and marginally statistically significant (t = 1.90). The negative z-score portfolios underperform by 36 basis points per month and the coefficient is statistically significant (t = 3.28). The z-score coefficient in panel B of table 6.4.2 is a third higher than in panel B of table 6.4.1, showing that the z-score effect becomes stronger in the presence of size and B/M. However, size and B/M coefficients are unaffected by the presence of z-score in the pricing equation either as a continuous or as a binary variable. The evidence here shows that there is little common variation between size, B/M and z-score that is linked to stock returns.

In panel C of table 6.4.2, the cross-sectional regressions indicate that in the three factor model with beta, size and B/M, high beta portfolios outperform low beta portfolios by 47 basis points per month though the difference is statistically insignificant at 5% level (t = 1.61). The size effect is 13 basis points per month and statistically significant (t = 2.23) while high B/M stocks outperform low B/M portfolios by 11 basis points per month and the difference is statistically insignificant (t = 1.24). However, the time series investigation of the B/M effect shows results similar to those recorded above; the B/M effect is positive and strong (19 basis points per month, t = 2.67) till September 1999. Also, the size effect is weaker till the last twelve month data is introduced (11 basis points per month, t = 1.91). Introduction of continuous z-score in the pricing equation increases the outperformance of high beta portfolios to 54 basis points per month which is marginally statistically significant (t = 1.95). γ_2 is 2 basis points per month and statistically significant. The size effect remains significant while the B/M coefficient remains positive and insignificant. Excluding the last twelve months from the analysis, the B/M coefficient is 21 basis points per month (t = 3.00). Introduction of z-score as a dummy variable rather than a continuous variable has no effect on the size and B/M coefficients. The negative z-score portfolios underperform by 36 basis points per month and the coefficient is statistically significant (t = 3.57). The z-score coefficient in panel C of tables 6.4.2 is twice as large as in panel C of table 6.4.1, showing that the z-score effect becomes stronger in the presence of size and B/M. However, size and B/M coefficients are unaffected by the presence of z-score in the pricing equation either as a continuous or as a binary variable.

These results indicate that there is no common variation between size, B/M and z-scores that is linked to stock returns. The size and B/M effects are sensitive to the portfolio formation methods while the z-score effect is robust across the alternative trading strategies employed here. The results here do not support the null hypothesis that size and B/M are capturing the distress factor since the size and B/M coefficients are uninfluenced by the presence of z-scores in the pricing equation. Contrary to the null hypothesis, the underperformance of distressed firms is accentuated once I control for beta, size and B/M. The results here provide a strong rejection of $H2_0$.

Analysis of the evolution of t-statistics reveals that till the introduction of the last year's returns (for the year 2000), the B/M coefficient was positive and more than two standard errors from zero. Figure 6.4.1 plots the time series evolution of the t-statistics of the variables in the four-factor model and figure 6.4.2 plots the time-series evolution of the t-statistics of the variables on a rolling thirty month basis.

Figure 6.4.1: Evolution of test statistics (24 size, B/M and z-score portfolios) – Four-factor model
The time-series is created by accumulating the coefficients for the first 30 months and then increasing the number of months by one till all 252 months are included.

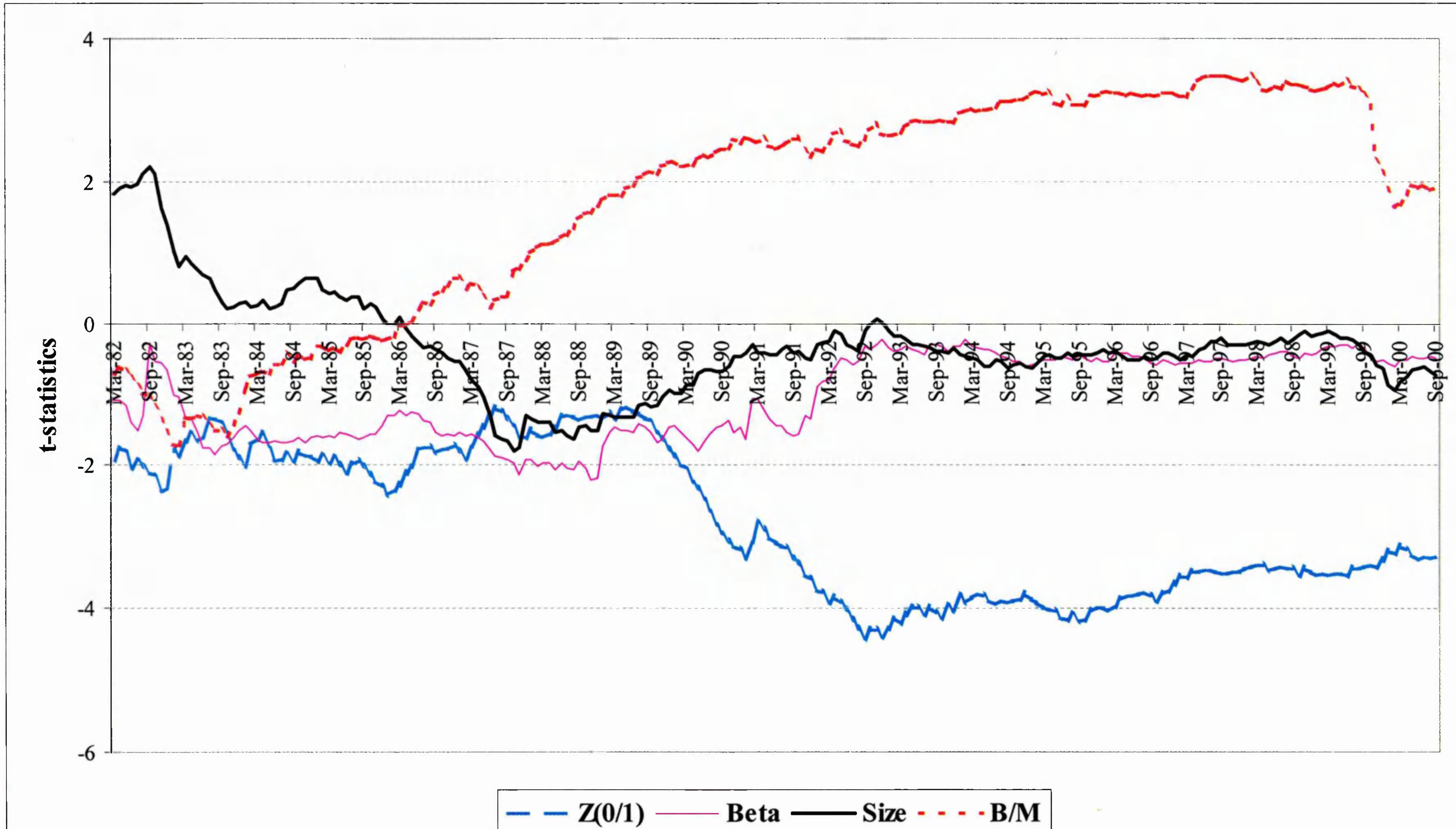
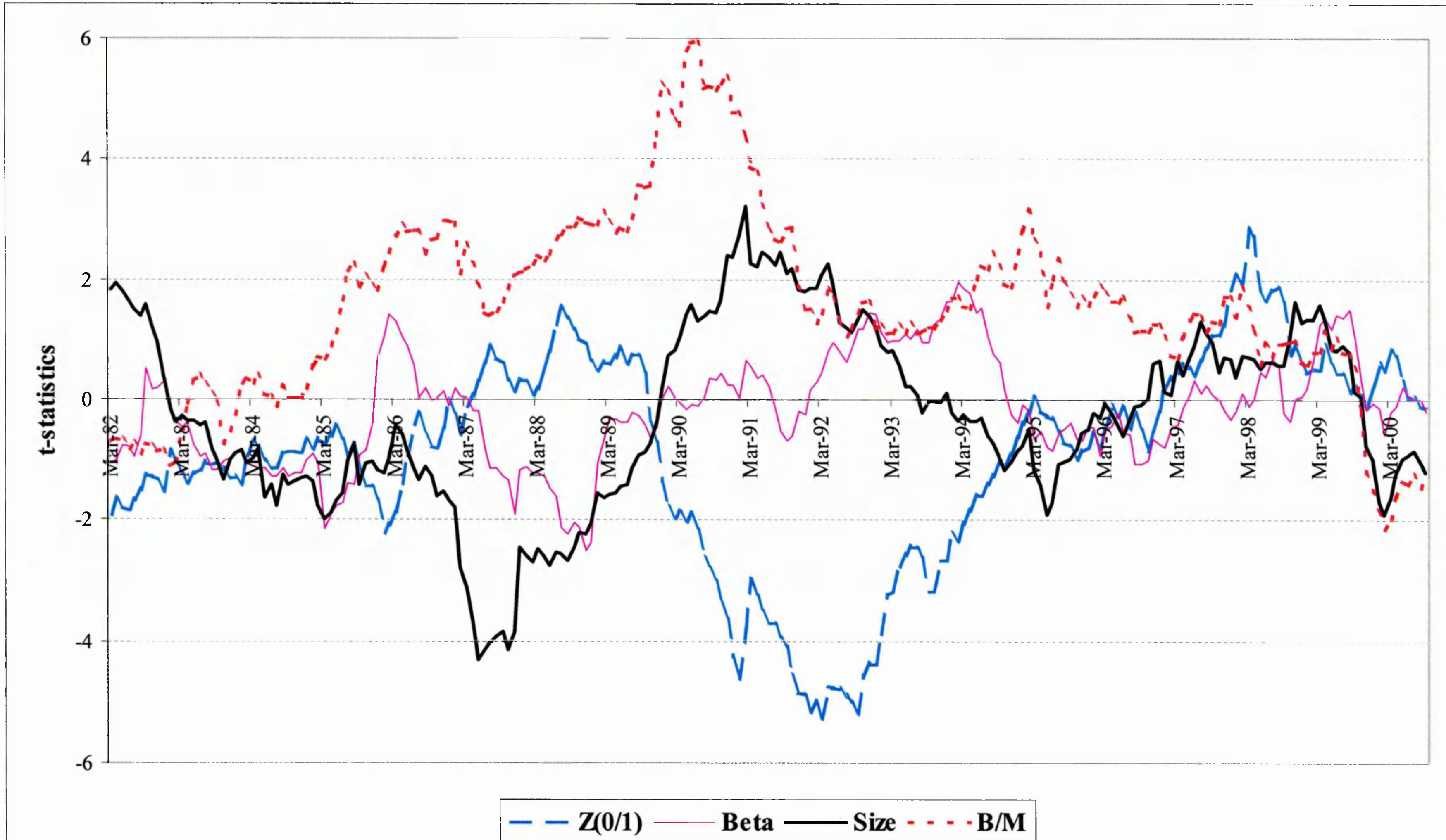


Figure 6.4.2: Rolling thirty-month test statistics (24 size, B/M and z-score portfolios) – Four factor model



Figures 6.4.1 and 6.4.2 show that there is considerable time variation in the coefficients of the variables in the four-factor model. Figure 6.4.2 shows that the negative z-score portfolios underperformed the positive z-score portfolios from the beginning of 1980 till the beginning of 1982 and then from the end of 1989 to the end of 1992. Interestingly, the UK economy was in recession during 1980-81 and then started expanding, the expansionary phase lasting till about 1989 when it again went into recession and emerged out again in 1993. The time-variation in z-score effect seems to coincide with the state of the economy, an observation I will explore in chapter 8.

$H3_0$: ***There is no association between z-scores and excess returns for both financially distressed and non-distressed firms.***

Dichev (1998) notes that there seems to be a positive relationship between z-scores and returns for high bankruptcy risk portfolios though he does not conduct any formal tests. To test this hypothesis and in an attempt to gain further insight into the pricing of bankruptcy risk, cross-sectional regressions similar to the one above are carried out with a z-score interaction term. If bankruptcy risk is asymmetric, the relationship between excess returns and z-score will be strong in the portfolios where bankruptcy risk is higher i.e. the negative z-score portfolios. The relationship will be weak or non-existent for portfolios with little bankruptcy risk. The interaction term is defined to be equal to the z-score when z-score is negative and zero when the z-score is positive. The following pricing equation is used for the regression:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\,z_{it-1} + \gamma_{6t}\,(z_{it-1} {*}\, z(0/1)_{it-1}) + \varepsilon_{it} \qquad (10)$$

The z-score coefficient is γ_2 for positive z-score stocks and $\gamma_2+\gamma_6$ for negative z-score stocks with γ_6 being the difference in z-score coefficient between positive and negative z-score stocks.

If $H3_0$ holds, then we would expect γ_6 not to be significantly different to zero. If, however, bankruptcy risk is asymmetric (i.e. there is little change in the solvency position of a firm with a change in z-score if the z-score is positive while changes in z-score for distressed firms capture a change in solvency position), we would find γ_2 not significantly different to zero and γ_6 negative and significantly different to zero. Table 6.4.3 presents the results.

Table 6.4.3: Regression results – with z-score interaction term

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

No portfolios are formed in panel C.

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 30th of September.

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. Betas in panel C are from RMS.

R_{it} is the equally-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. 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%.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\, z_{it-1} + \gamma_{6t}\,(z_{it-1} * z(0/1)_{it-1}) + \varepsilon_{it}$			
α	γ_1	γ_2	γ_6
A. Z-score portfolios			
0.0010	0.0059	0.0001	0.0002
(0.16)	(1.17)	(0.57)	(0.31)
B. Size, B/M and Z-score portfolios			
0.0041	-0.0027	0.0010	-0.0014
(0.87)	(-1.17)	(1.90)	(-0.67)
C. Individual securities			
0.0158	-0.0001	0.0000	0.0009
(5.87)	(-0.04)	(0.12)	(1.86)

In panel A of table 6.4.3, none of the terms are statistically significant. There is no relationship between z-scores and returns for either distressed or non-distressed portfolios.

In panel B of table 6.4.3, beta is negative but statistically insignificant. For positive z-score portfolios, higher z-score leads to a 10 basis point per month outperformance which is marginally statistically significant (t = 1.90). For negative z-score portfolios, lower z-score leads to a 4 basis point per month (10bp - 14bp) outperformance and the difference between positive and negative z-score portfolios is statistically insignificant. The evidence indicates that unconditionally, there is no difference in the relationship between z-scores and returns for positive and negative z-score firms.

In panel C of table 6.4.3, beta is negative but statistically insignificant. For positive z-score portfolios, there is no relation between z-scores and returns. For negative z-score portfolios, lower z-score leads to a 9 basis point per month underperformance though the difference between positive and negative z-score portfolios is statistically insignificant (t = 1.86).

The results here provide no evidence that there is any difference in the relation between continuous z-score and returns when z-score is positive and when it is negative. The interaction terms are always statistically insignificant. The null hypothesis of symmetric bankruptcy risk cannot be rejected on an unconditional basis.

$H4_0$: There is no association between size, B/M and excess returns for both financially distressed and non-distressed firms.

If both size and B/M factors are capturing bankruptcy risk, they will exhibit the same asymmetry i.e., the size and B/M effects will at least be stronger for the distressed firms than for the non-distressed firms. To test this, I use the following pricing equation:

$$\begin{aligned} R_{it} - R_{Ft} = {} & \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{4t}\ln(Size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) \\ & + \gamma_{7t}\,(\ln(size_{it-1})^{*}\, z(0/1)_{it-1}) + \gamma_{8t}\,(\ln(B/M_{it-1})^{*}\, z(0/1)_{it-1}) + \varepsilon_{it} \end{aligned} \tag{11}$$

The size coefficient is γ_4 for positive z-score stocks and $\gamma_4+\gamma_7$ for negative z-score stocks with γ_7 being the difference in size coefficient between positive and negative z-score stocks. Similarly, the B/M coefficient is γ_5 for positive z-score stocks and $\gamma_5+\gamma_8$ for negative z-score stocks with γ_8 being the difference in B/M coefficient between positive and negative z-score stocks.

If size and B/M reflect the asymmetric bankruptcy risk, the coefficient γ_7 will be negative and γ_8 will be positive. Table 6.4.4 presents the results.

Table 6.4.4: Regression results – interaction terms of size & B/M with the z-score

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

No portfolios are formed in panel C.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the equally-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. $\ln(size_{it-1})$ 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 end of September of year t $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. 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%.

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{4t}\ln(Size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \gamma_{7t}(\ln(size_{it-1})^{*} z(0/1)_{it-1}) + \gamma_{8t}(\ln(B/M_{it-1})^{*} z(0/1)_{it-1}) + \varepsilon_{it}$$

α	γ_1	γ_4	γ_5	γ_7	γ_8
A. Z-score portfolios					
0.0449	0.0093	-0.0022	-0.0008	0.0001	-0.0221
(1.80)	(1.40)	(-1.82)	(-0.15)	(0.17)	(-1.42)
B. Size, B/M and Z-score portfolios					
0.0163	-0.0018	-0.0004	0.0017	-0.0001	0.0000
(1.43)	(-0.73)	(-0.69)	(1.54)	(-1.59)	(0.00)
C. Individual securities					
0.0362	0.0058	-0.0014	0.0016	-0.0002	-0.0015
(3.49)	(2.04)	(-2.44)	(1.80)	(-2.64)	(-1.48)

Panel A of table 6.4.4 shows that beta is positive though statistically insignificant. For the non-distressed portfolios, smaller portfolios outperform larger portfolios by 22 basis points per month though the difference is within two standard errors of zero. The B/M effect in positive z-score portfolios is close to zero. The interaction term of size and z-score is economically and statistically negligible and shows that the size effect is similar in both the distressed and non distressed portfolios. The coefficient of the interaction term of B/M with z-score is negative and economically large (2.21% per month) showing that for the distressed portfolios, high B/M portfolios underperform low B/M portfolios. The coefficient is however, within two standard errors of zero and no reliable conclusions can be drawn. The results provide no evidence that size and B/M effects are any different for distressed and non-distressed firms.

Panel B of table 6.4.4 shows that beta is negative and statistically insignificant. For the non-distressed portfolios, there is no size effect and the B/M effect is statistically insignificant. The insignificant interaction term of size and z-score shows that the size effect in negative z-score portfolios is no different to that in positive z-score portfolios and the insignificant interaction term of B/M with z-score shows the same for the B/M effect. However, the B/M effect was positive and strong (26 basis points per month, t = 2.97) till September 1999.

Panel C of table 6.4.4 shows that high beta firms outperform low beta firms by 58 basis points per month and the coefficient is more than two standard errors from zero. For the non-distressed portfolios, smaller portfolios outperform larger portfolios by 14 basis points per month and the coefficient is statistically significant. The B/M effect in positive z-score portfolios 16 basis points per month though it is within two standard errors of zero. In fact, the coefficient is positive and strong (26 basis points per month, t =3.27) till September 1999. The interaction term of size and z-score shows that the size effect is stronger in negative z-score stocks by a small 2 basis points per month and the difference is statistically significant (t = 2.64). The coefficient of the interaction term of B/M with z-score is negative and within two standard errors of zero.

The evidence here shows that except for individual securities, the size effect is similar for both positive and negative z-score stocks. Even for individual securities, the difference in size premium for negative and positive z-score stocks is an economically negligible 2 basis points per month. Similarly, there is no difference in the value effect for positive and negative z-score stocks. If size and B/M are proxies for relative distress, weaker firms should have driven these effects. I find no evidence that this is the case. I therefore, cannot reject the null hypothesis of no difference in size effect or B/M effect between positive and negative z-score portfolios.

$H5_0$: ***There is no difference in the returns of financially distressed and non-distressed firms in up- and down-markets.***

Systematic risk is commonly viewed as sensitivity to broad movements in the market (Lakonishok, Shleifer & Vishny (1994)). If size, B/M and z-score are systematic risks, their effects on equity prices would be sensitive to market movements. Their coefficients would vary depending on the state of the market. High risk firms would do worse than low risk firms when the market falls and would fare better when the market rises. To test this hypothesis, I run separate cross-sectional regressions for the up- and down-markets using equations (8) and (9). An up-market month is defined as the month when the return on the equally weighted market index is greater than the risk free rate and a down-market is defined as the month when the return on the equally weighted market index is lower than the risk free rate. To be consistent with z-score, size and B/M being systematic risk factors, γ_2 and γ_4 should be positive in down markets and negative in up markets while γ_3 and γ_5 should be negative in down markets and positive in up markets. The results are presented in table 6.4.5.

Table 6.4.5: Regression results – bifurcation into up- and down-markets

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

No portfolios are formed in panel C.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the equally-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. $\ln(size_{it-1})$ 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 end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The months when the return on the market index (FTSE All Share) is lower than the risk-free rate are classified down-market and the months when the return on equally the market index exceeds the risk free rate are classified as up-market. The portfolios are rebalanced at the end of September each year. 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%.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}z_{it-1} + \gamma_{3t}z(0/1)_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1})$					
α	γ_1	γ_2	γ_3	γ_4	γ_5
A. Z-score portfolios					
Return on market < Risk free rate					
-0.0115	-0.0084	0.0012		-0.0014	0.0130
(-0.31)	(-0.91)	(3.55)		(-0.75)	(1.34)
0.0252	-0.0115		-0.0073	-0.0024	-0.0059
(0.68)	(-1.43)		(-3.09)	(-1.31)	(-0.71)
Return on market > Risk free rate					
0.0857	0.0020	-0.0006		-0.0026	-0.0070
(2.82)	(0.21)	(-2.26)		(-1.71)	(-0.80)
0.0900	0.0046		-0.0014	-0.0034	0.0017
(2.72)	(0.54)		(-0.55)	(-2.08)	(0.22)
B. Size, B/M and z-score portfolios					
Return on market < Risk free rate					
-0.0070	-0.0105	0.0013		-0.0014	0.0031
(-0.52)	(-3.39)	(6.01)		(-1.89)	(2.21)
-0.0017	-0.0094		-0.0115	-0.0013	0.0026
(-0.13)	(-2.95)		(-6.41)	(-1.81)	(1.86)
Return on market > Risk free rate					
0.0283	0.0030	-0.0002		0.0001	0.0016
(1.76)	(0.97)	(-1.10)		(0.13)	(1.17)
0.0272	0.0034		0.0007	0.0001	0.0015
(1.71)	(1.09)		(0.57)	(0.11)	(1.12)
C. Individual securities					
Return on market < Risk free rate					
0.0094	-0.0285	0.0010		-0.0010	0.0034
(0.61	(-8.65)	(5.81)		(-1.10)	(2.74)
0.0205	-0.0299		-0.0112	-0.0012	0.0028
(1.32	(-8.81)		(-7.39)	(-1.34)	(2.21)
Return on market > Risk free rate					
0.0473	0.0243	-0.0002		-0.0016	0.0001
(3.40	(7.92)	(-2.33)		(-2.03)	(0.05)
0.0471	0.0255		0.0006	-0.0017	0.0002
(3.48	(8.28)		(0.50)	(-2.19)	(0.15)

Panel A of table 6.4.5 shows that in down-markets, not surprisingly, the coefficient of beta is negative though not significantly different to zero i.e. high beta firms underperform low beta firms. The coefficient of the z-score as a continuous variable is positive and highly significant indicating that low z-score portfolios reliably underperform higher z-score portfolios when the market falls. Smaller firms outperform larger firms by 14 basis points per month though the difference is statistically insignificant (t = 0.75). The high B/M portfolios outperform low B/M portfolios by 1.30% per month though, again, the coefficient is not statistically significant. However, if z-score is introduced as a dummy variable rather than a continuous variable, the negative z-score portfolios underperform positive z-score portfolios by 73 basis points per month, a difference that is statistically significant (t = 3.09). Smaller firms underperform larger firms by 24 basis points per month though the underperformance is statistically insignificant. The B/M coefficient is now negative and remains statistically insignificant. In up-markets, both, the z-score and size coefficients are negative though the size coefficient is not statistically significant while the B/M coefficient is negative but not significant. Using z-score as a dummy variable, negative z-score firms do not reliably underperform while smaller firms underperform by 34 basis points per month, a difference that is statistically significant (t = 2.08).

The results provide clear evidence of differential impact of z-scores in different states of the market. Negative z-score firms have a higher bankruptcy risk and are more sensitive to broad market movements, have a higher covariance with the market and hence, higher systematic risk. They do worse than positive z-score firms when the market falls and do no better when the market rises. Smaller firms do no worse than the larger firms in down-markets but they do significantly better in up-markets. The B/M effect is not significant in up and down markets. These results indicate that while z-scores and size are capturing systematic risk missed by the market factor, it is not clear whether B/M is capturing any systematic risk. The null hypothesis of no difference can be rejected for z-score and size effects but cannot be rejected for the B/M effect.

Panel B of table 6.4.5 not surprisingly again shows that in down-markets, the coefficient of beta is negative but this time it is significantly different to zero i.e. high beta stocks significantly underperform low beta stocks during down markets. The coefficient of the z-score as a continuous variable is positive and highly significant indicating that low z-score portfolios reliably underperform higher z-score portfolios when the market falls. Smaller firms outperform larger firms by 14 basis points per month and the difference is statistically significant at the 10% level (t = 1.89). The coefficient of B/M is positive (31 basis points per month) and statistically significant (t = 2.31) indicating a superior performance of high B/M portfolios relative to low B/M portfolios. However, if the z-score is introduced as a dummy variable rather than continuous variable, the negative z-score portfolios underperform positive z-score portfolios by a massive 1.15% per month, a difference that is statistically significant (t = 6.41). Smaller firms underperform by 13 basis points per month and high B/M firms outperform by 26 basis points per month, however both coefficients are not significant at the 5% level. In up-markets, the z-score coefficient is negative but statistically insignificant. Both the size coefficient and B/M coefficient are positive and neither is statistically significant. Using z-score as a dummy variable, the coefficients on all the variables are positive but statistically insignificant.

These results again show differential loading on z-scores in different states of the market. Lower z-score firms do worse than higher z-score firms during market downturns and do no better during market upturns. Smaller firms outperform larger firms in down-markets but there is no difference in the returns on small and large firms during up-markets. High B/M firms do better than low B/M firms during downmarkets and do no worse during up markets. These results indicate that while z-scores represent a systematic risk, it is not clear whether size and B/M are capturing any systematic risk since smaller stocks and higher B/M stocks do not underperform during down markets. However, the null hypothesis of no difference in returns on financially distressed and non-distressed firms during up- and down- states of the market can be rejected.

Panel C of table 6.4.5 relating to individual securities similarly shows that beta is strongly negative and highly significant in down-markets i.e. high beta firms underperform low beta firms during downturns. The coefficient of size is negative though indistinguishable from zero and that on B/M is positive and more than two standard errors from zero. When z-score is used as a continuous variable, its coefficient is positive and statistically highly significant (t = 5.81) indicating that higher z-score firms do better than lower z-score firms. When the z-score is used as a dummy variable with a value of 1 when negative and a value of 0 when positive, the coefficient is negative and highly significant, both economically (112 basis points per month) and statistically (t = -7.39) indicating that negative z-score firms strongly underperform positive z-score firms during down markets. In up-markets, as expected, beta is strongly positive and highly significant i.e. high beta firms outperform low beta firms when the market rises. The size coefficient is negative and statistically significant and that on B/M is essentially zero. When z-score is used as a continuous variable, its coefficient is negative and statistically significant (t = 2.33) indicating that lower z-score firms do better than higher z-score firms. When z-score is used as a dummy variable, the coefficient is positive (6 basis points per month) and statistically insignificant indicating that negative z-score firms do no better than positive z-score firms during up-markets.

The results confirm differential response of distressed firms to the state of the market and strongly reject the null hypothesis. Negative z-score firms are more sensitive to broad market movements and, hence, have higher systematic risk since they have higher covariance with the market. They do worse than positive z-score firms during down markets as firms with higher systematic risk are expected to do. During up markets, the sign of the coefficient is as expected (negative for continuous z-score and positive for z-score dummy) though statistically insignificant. The evidence on size and B/M effects is less clear. Smaller firms do not do worse than the larger firms in down-markets though riskier firms are expected to underperform during down markets but they do significantly better in up-markets. The results are highly sensitive to trading rules. High B/M firms do better than the low B/M firms in down-markets instead of doing worse as riskier firms are expected to do. These results are again sensitive to time period, high B/M firms reliably outperform during up markets (19 basis points per month, t = 2.20) before the last twelve months enter the analysis. Removing the last twelve months of data renders the size effect insignificant in both states of the market. The results indicate that while bankruptcy risk is systematic, it is less clear whether size and B/M effects are systematic or not since the results for size and B/M effects are sensitive to trading rules and time period.

$H6_0$: *The size, B/M and z-score effects are evenly spread over the year and not concentrated in any particular month(s).*

My focus here is not on causes of seasonality or its implications for market efficiency, but on whether size, B/M and z-score exhibit similar patterns. If they do, this would suggest that these effects are linked to some common underlying factor. I first examine calendar seasonality for size, B/M and z-score effects separately. To examine seasonality in the size effect, on 30th September of each year from 1979 to 1999, I rank all the stocks in my population according to their latest available market capitalization and group them into ten portfolios of equal numbers of stocks. I then compute monthly equally-weighted returns for each portfolio from October 1979 to September 2000. To examine seasonality in the B/M effect, I rank stocks on latest available B/M and form ten portfolios of equal number of securities on 30th September of each year and compute monthly equally weighted returns. To examine seasonality in z-score effect, on the 30th September of each year I rank stocks on latest available z-score and form two portfolios based on whether latest available z-score is positive or negative and compute monthly equally weighted returns.

Table 6.4.6 presents the results for portfolios formed on size, table 6.4.7 presents the results for portfolios formed on B/M and table 6.4.8 presents the results for portfolios formed on z-score.

Table 6.4.6: Seasonality in size effect

At the end of September of each year from 1979 to 1999, all the stocks in my population are ranked on market capitalization and grouped into ten portfolios. The portfolios are rebalanced at the end of September each year. The table presents average returns (in excess of 1 month T-Bill rate) for each portfolio for each of the 12 months. S-B is the difference between the return on smallest portfolio and the return on the biggest portfolio. Figures in brackets are the t-statistics for difference from zero. F-statistics are for the test that the returns in all months are jointly equal.

	Smallest	2	3	4	5	6	7	8	9	Biggest	S-B
January	4.52	4.23	3.58	3.42	4.20	3.84	3.54	4.03	2.71	2.18	2.35
	(2.88)	(3.86)	(3.97)	(3.61)	(4.23)	(4.19)	(3.66)	(3.98)	(2.40)	(1.94)	(1.27)
February	4.56	2.59	2.21	2.43	2.61	2.77	3.02	2.50	2.23	1.52	3.04
	(4.08)	(2.64)	(2.54)	(2.60)	(2.54)	(2.92)	(3.05)	(2.33)	(1.96)	(1.45)	(3.50)
March	1.18	1.51	0.62	1.41	1.01	1.62	1.44	1.96	1.54	1.03	0.15
	(1.10)	(1.29)	(0.64)	(1.18)	(1.01)	(1.57)	(1.52)	(1.86)	(1.80)	(1.18)	(0.16)
April	2.95	3.21	2.32	2.60	2.24	2.38	2.01	2.19	2.59	2.30	0.65
	(2.37)	(3.00)	(2.08)	(2.73)	(2.22)	(2.42)	(2.14)	(2.17)	(2.62)	(2.72)	(0.65)
May	1.95	2.01	1.31	0.52	1.09	0.68	-0.01	-0.50	-0.61	-0.62	2.56
	(1.71)	(1.89)	(1.50)	(0.63)	(1.38)	(0.78)	(-0.01)	(-0.56)	(-0.63)	(-0.57)	(2.11)
June	0.84	0.41	0.46	-0.13	0.03	-0.04	-0.56	-0.48	-0.43	0.00	0.84
	(0.61)	(0.37)	(0.39)	(-0.11)	(0.02)	(-0.04)	(-0.51)	(-0.46)	(-0.38)	(0.00)	(0.74)
July	0.60	0.54	-0.13	-0.30	-1.05	-1.48	-0.62	-0.20	0.47	0.30	0.30
	(0.37)	(0.35)	(-0.11)	(-0.26)	(-0.97)	(-1.50)	(-0.56)	(-0.20)	(0.42)	(0.31)	(0.19)
August	0.92	0.74	0.36	-0.48	0.70	-0.04	0.15	-0.14	0.22	0.33	0.58
	(0.89)	(0.66)	(0.31)	(-0.39)	(0.58)	(-0.03)	(0.12)	(-0.10)	(0.15)	(0.27)	(0.63)
September	-0.56	-0.98	-1.20	-1.95	-1.52	-1.45	-1.44	-2.23	-2.42	-2.09	1.53
	(-0.53)	(-0.84)	(-1.13)	(-1.97)	(-1.35)	(-1.35)	(-1.30)	(-1.70)	(-1.79)	(-1.54)	(1.20)
October	1.29	-0.98	-1.68	-2.06	-1.37	-2.21	-1.58	-1.17	-0.82	-1.18	2.47
	(1.25)	(-0.71)	(-1.34)	(-1.57)	(-1.09)	(-1.67)	(-1.13)	(-0.76)	(-0.47)	(-0.73)	(1.38)
November	1.23	-0.54	-0.62	-0.75	-0.67	-0.65	-1.06	-0.13	0.46	1.13	0.10
	(0.78)	(-0.42)	(-0.45)	(-0.59)	(-0.51)	(-0.57)	(-1.00)	(-0.11)	(0.39)	(1.09)	(0.09)
December	2.38	1.38	1.17	0.60	1.37	1.11	1.35	1.05	1.73	1.78	0.59
	(2.50)	(2.06)	(1.65)	(0.77)	(1.49)	(1.29)	(1.38)	(1.12)	(1.80)	(2.19)	(0.55)
All	1.82	1.18	0.70	0.44	0.72	0.54	0.52	0.57	0.64	0.56	1.26
	(4.97)	(3.45)	(2.20)	(1.38)	(2.23)	(1.73)	(1.63)	(1.70)	(1.83)	(1.73)	(3.46)
F statistic	1.52	2.02	2.01	2.66	2.60	3.21	2.64	2.49	1.73	1.53	0.70
p-value	0.1233	0.0270	0.0278	0.0031	0.0039	0.0004	0.0034	0.0057	0.0678	0.1228	0.7348

Table 6.4.7: Seasonality in B/M effect

At the end of September of each year from 1979 to 1999, all the stocks in my population are ranked on latest available B/M and grouped into ten portfolios. The portfolios are rebalanced at the end of September each year. The table presents average returns (in excess of 1 month T-Bill rate) for each portfolio for each of the 12 months. H-L is the difference between the return on highest B/M portfolio and the return on the lowest B/M portfolio. Figures in brackets are the t-statistics for difference from zero. F-statistics are for the test that the returns in all months are jointly equal.

	Lowest	2	3	4	5	6	7	8	9	Highest	H-L
January	4.08	2.85	3.10	3.19	3.58	3.79	3.89	3.07	4.00	4.65	0.57
	(4.89)	(3.25)	(3.72)	(3.49)	(3.64)	(3.92)	(4.02)	(3.03)	(3.93)	(3.48)	(0.54)
February	3.05	2.95	2.11	2.15	1.81	2.60	2.81	3.14	2.63	3.15	0.09
	(2.65)	(3.04)	(2.23)	(2.15)	(2.25)	(2.34)	(2.81)	(3.06)	(2.26)	(2.96)	(0.09)
March	0.90	0.80	1.03	1.67	1.38	1.41	2.04	1.63	1.29	1.23	0.34
	(0.91)	(0.89)	(1.16)	(1.82)	(1.57)	(1.52)	(2.03)	(1.49)	(1.17)	(1.15)	(0.54)
April	1.11	1.78	1.80	2.32	2.84	2.46	2.85	2.80	3.53	3.41	2.29
	(1.05)	(1.92)	(2.00)	(2.53)	(2.75)	(2.61)	(2.73)	(2.72)	(3.15)	(2.82)	(2.44)
May	-0.32	-0.04	0.45	0.68	0.10	0.95	0.68	1.43	1.28	0.60	0.92
	(-0.32)	(-0.05)	(0.52)	(0.67)	(0.13)	(1.17)	(0.77)	(1.73)	(1.40)	(0.61)	(1.12)
June	-0.53	-0.02	-0.40	0.44	0.34	-0.04	-0.16	0.08	-0.20	0.58	1.12
	(-0.45)	(-0.01)	(-0.39)	(0.43)	(0.28)	(-0.04)	(-0.17)	(0.07)	(-0.19)	(0.48)	(1.25)
July	-0.47	-0.65	-0.52	-0.41	0.11	-0.07	0.43	-0.24	0.07	-0.07	0.40
	(-0.57)	(-0.70)	(-0.52)	(-0.43)	(0.09)	(-0.07)	(0.31)	(-0.21)	(0.06)	(-0.05)	(0.44)
August	0.53	0.27	-0.08	0.06	0.01	0.67	0.12	0.61	0.47	0.02	-0.52
	(0.38)	(0.21)	(-0.07)	(0.05)	(0.01)	(0.55)	(0.10)	(0.55)	(0.39)	(0.01)	(-0.54)
September	-1.86	-1.80	-1.64	-1.93	-1.72	-1.29	-1.31	-1.50	-1.42	-1.50	0.35
	(-1.56)	(-1.49)	(-1.53)	(-1.67)	(-1.58)	(-1.22)	(-1.18)	(-1.45)	(-1.25)	(-1.42)	(0.48)
October	-1.20	-1.18	-1.44	-1.62	-1.44	-1.77	-1.60	-1.20	-1.23	0.94	2.14
	(-0.69)	(-0.75)	(-1.06)	(-1.16)	(-1.08)	(-1.24)	(-1.18)	(-0.96)	(-0.99)	(0.85)	(1.08)
November	0.81	0.20	-0.50	-0.06	-0.28	-0.73	-0.57	-0.17	-0.55	0.25	-0.56
	(0.41)	(0.15)	(-0.44)	(-0.05)	(-0.23)	(-0.68)	(-0.57)	(-0.16)	(-0.48)	(0.21)	(-0.45)
December	1.75	1.78	0.99	1.27	0.62	1.41	1.12	1.23	1.94	1.81	0.06
	(1.89)	(1.97)	(1.31)	(1.64)	(0.82)	(1.69)	(1.21)	(1.69)	(2.42)	(2.14)	(0.09)
All	0.65	0.58	0.41	0.65	0.61	0.78	0.86	0.91	0.98	1.26	0.60
	(1.79)	(1.79)	(1.36)	(2.09)	(1.97)	(2.50)	(2.66)	(2.91)	(3.00)	(3.68)	(2.00)
F statistic	1.91	1.87	2.02	2.22	2.26	2.51	2.58	2.28	2.64	2.26	0.72
p-value	0.0389	0.0440	0.0277	0.0140	0.0124	0.0052	0.0041	0.0116	0.0033	0.0125	0.7033

Table 6.4.8: Seasonality in z-score effect

At the end of September of each year from 1979 to 1999, all the stocks in my population are ranked on latest available z-score and grouped into two portfolios – one with positive z-score stocks and the other with negative z-score stocks. The portfolios are rebalanced at the end of September each year. The table presents average returns (in excess of 1 month T-Bill rate) for each portfolio for each of the 12 months. N-P is the difference between the return on negative z-score portfolio and the return on positive z-score portfolio. Figures in brackets are the t-statistics for difference from zero. F-statistics are for the test that the returns in all months are jointly equal.

	Z<0	Z>0	N-P
January	4.09	3.43	0.66
	(3.53)	(4.02)	(1.15)
February	2.70	2.59	0.11
	(2.38)	(2.91)	(0.28)
March	0.79	1.49	-0.70
	(0.66)	(1.72)	(-1.66)
April	2.82	2.33	0.49
	(2.23)	(2.64)	(0.90)
May	0.56	0.56	0.00
	(0.55)	(0.71)	(-0.01)
June	-0.27	0.09	-0.36
	(-0.21)	(0.09)	(-0.75)
July	-0.45	-0.10	-0.35
	(-0.35)	(-0.10)	(-0.70)
August	-0.09	0.33	-0.42
	(-0.06)	(0.29)	(-1.14)
September	-2.22	-1.41	-0.81
	(-1.98)	(-1.32)	(-1.97)
October	-1.51	-1.09	-0.42
	(-1.02)	(-0.89)	(-1.04)
November	-0.49	-0.08	-0.41
	(-0.36)	(-0.07)	(-0.96)
December	1.42	1.37	0.06
	(1.71)	(1.82)	(0.19)
All	0.61	0.79	-0.18
	(1.68)	(2.74)	(-1.39)
F statistic	2.32	2.31	1.01
p-value	0.0102	0.0103	0.4387

Table 6.4.6 shows that in the UK during 1979-2000, the smallest size decile outperforms the largest size decile by 1.26% per month, a difference that is statistically significant (t = 3.46). The returns in January, February and April are significantly higher than zero for most deciles. However, the size premium (the difference between the returns on smallest and biggest portfolio) is statistically significant only in February and May. The F-statistics show that the null hypothesis of returns being the same across all

months cannot be rejected for the smallest 10% and largest 20% of the stocks. Further, the low F-statistic of the size premium shows that the null hypothesis of evenly distributed size premia cannot be rejected.

Table 6.4.7 shows that the highest B/M decile outperforms the lowest B/M decile by 0.60% per month, a difference that is statistically significant (t = 2.00). Returns in January, February and April are significantly higher than zero for most deciles. However, the value premium (the difference between the returns on the highest and lowest B/M portfolios) is statistically significant only in April. The F-statistics show that the null hypothesis of equal returns across all months can be rejected for most deciles. However, the null hypothesis of the value premium (the difference between the returns on highest and lowest B/M portfolios) being evenly distributed across the year cannot be rejected.

Table 6.4.8 shows that positive z-score stocks outperform negative z-score stocks by 0.18% per month, a difference that is statistically insignificant (t = 1.39). The returns in January, February and April are significantly higher than zero for both the negative and the positive z-score portfolios. However, the z-score premium is marginally statistically significant only in September. The F statistics show that the null hypothesis of same returns across all months can be rejected for both the portfolios. However, the null hypothesis of the z-score effect (the difference between the returns on negative and positive z-score portfolios) being evenly distributed across the year cannot be rejected.

The evidence in tables 6.4.6, 6.4.7 and 6.4.8 shows that in the UK, stock returns are higher in the months of January, February and April for the period October 1979 to September 2000. The results are similar to those reported by Levis (1985) for the period 1958-82. Since the tax year in the UK ends in April, higher April returns can be interpreted as providing support to the tax-loss selling hypothesis. Higher returns in January could be a reflection of the US tax-induced activity. However, the seasonality is uniform across all portfolios (except for the B/M effect) which casts doubt on the validity of this hypothesis. The similar seasonality observed for size, B/M and z-score portfolios would suggest that these are driven by overall market behaviour.

The size effect is strongest in February and May, B/M effect is strongest in April and z-score effect is strongest in September. The strong size effect in May is attributed by Levis (1985) to the old City saying 'sell in May and go away' and could be a manifestation of institutional behaviour. The May seasonal in B/M effect could be a manifestation of the tax-loss selling hypothesis while the September seasonal of z-score effect could be an artefact of the data; portfolios are rebalanced at the end of September each year. Importantly, since the three effects are manifested in different months of the year, it is unlikely that they are proxies for the same underlying risk factor. However, these tables look at each of these effects independent of other effects. In table 6.4.9, I present the results using the coefficients of the Fama-MacBeth (1973) regressions for the four-factor model with beta, size, B/M and z-score dummy for the 24 portfolios formed on size, B/M and z-score.

Table 6.4.9: Seasonality in F-M coefficients

At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score. The portfolios are rebalanced at the end of September each year. The z-score dummy is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by cross-sectional regressions for each of the 252 months from October 1979 to September 2000. Negative B/M stocks are excluded. Figures in brackets are the t-statistics for difference from zero. F-statistics are for the test that the coefficients in all months are jointly equal.

	Beta	Size	B/M	Z (0/1)
January	0.46	-0.18	0.36	-0.06
	(0.36)	(-0.61)	(0.88)	(-0.12)
February	1.06	-0.09	-0.04	-0.02
	(0.98)	(-0.49)	(-0.12)	(-0.05)
March	0.24	0.23	0.38	-0.26
	(0.32)	(1.43)	(1.31)	(-0.57)
April	-0.49	0.07	0.82	0.46
	(-0.79)	(0.39)	(2.42)	(1.28)
May	-0.31	-0.45	0.08	-0.72
	(-0.44)	(-2.24)	(0.27)	(-2.36)
June	-0.99	-0.09	0.16	-0.59
	(-1.54)	(-0.48)	(0.53)	(-1.51)
July	-0.78	0.05	0.28	-0.24
	(-1.76)	(0.22)	(1.21)	(-0.57)
August	0.55	-0.09	0.12	-0.33
	(0.90)	(-0.64)	(0.52)	(-1.14)
September	0.14	-0.09	0.28	-1.08
	(0.13)	(-0.39)	(1.25)	(-3.13)
October	-1.61	0.02	0.16	-0.49
	(-3.02)	(0.16)	(0.36)	(-1.43)
November	-0.50	0.09	-0.19	-0.61
	(-0.52)	(0.39)	(-0.30)	(-1.26)
December	0.82	0.03	-0.10	-0.41
	(1.27)	(0.14)	(-0.34)	(-1.52)
All	-0.12	-0.04	0.19	-0.36
	(-0.49)	(-0.72)	(1.90)	(-3.28)
F statistic	0.95	0.69	0.56	1.06
p-value	0.4909	0.7478	0.8590	0.3956

Table 6.4.9 shows that low beta stocks reliably outperform high beta stocks in the month of October. Similar to the evidence in tables 6.4.6, 6.4.7 and 6.4.8, the size effect is significant only in the month of May, B/M effect is significant only in the month of April while the z-score effect is significant in both May and September. Since the portfolios are rebalanced at the end of September, the October seasonal in beta and

September seasonal in z-score is likely to be an artefact of the data. Again, clearly, there is little in common between B/M effect and size effect or B/M effect and z-score effect. However, the evidence here suggests that size and z-score effects may have some commonality (both the effects are strong in May). The F statistics show that the null hypothesis of no calendar seasonality in the beta, size, B/M and z-score effects cannot be rejected. The evidence supports my earlier conclusion that these effects are unlikely to be linked to a common underlying risk factor.

6.5 Summary

This chapter analyses the relationship between bankruptcy risk and equity returns. I use z-scores as a proxy for bankruptcy risk and test the relationship of z-scores, size and B/M with stock returns. I find that smaller size firms have high bankruptcy risk as do negative z-score firms. Once I control for size and z-score, there is no clear relationship between B/M and bankruptcy risk. I use two different portfolio formation methods and also conduct the analysis on an individual securities basis and find that some results are sensitive to the different trading rules. I test the ability of the Fama & French (1993) three-factor model to explain the returns on portfolios formed on different criteria and finally introduce a four-factor model.

The analysis in section 6.4 shows that beta is generally not significant over the period of this study. The conclusion is robust to different trading rules and different formulations of the asset pricing equation. This is not to say that beta is of no use in equity pricing, a bifurcation of returns into up- and down- markets shows that beta is extremely important in different states of the market. The coefficient on z-score is statistically significant for most of the asset pricing equations and the trading strategies used here.

I find that negative z-score stocks underperform positive z-score stocks over the period of this study and the amount of underperformance is not influenced by the presence or absence of size and B/M as explanatory variables in the asset pricing equation. Similarly, size and B/M coefficients are not influenced by the presence or absence of z-score in the pricing equation. These results suggest that there is little common variation between size, B/M and z-scores that is related to stock returns (Dichev (1998) reaches the same conclusion with his data). While the z-score effect is robust to alternative trading rules employed in this chapter, size and B/M effects are not. When portfolios are formed on z-scores, the B/M effect disappears. This can happen if z-score and B/M are uncorrelated because sorting on z-scores can result in random sorting on B/M and consequently, the B/M effect can vanish. The size effect is strong in z-score portfolios suggesting some link between size and distress. However, even in portfolios formed on z-scores, z-score and size coefficients are virtually independent suggesting that even if both these factors are related to distress, they are capturing different aspects of it. When portfolios are formed on size, B/M and z-scores, the size effect vanishes for the entire period. However, a time-series analysis shows that this result is sensitive to the period chosen. The B/M effect is strong till September 1999 but then there is a collapse during the last twelve months presumably due to high technology stocks entering the sample. This is a collapse that is mirrored in the US.

Dichev (1998) suggests that the relationship between z-scores and returns is different for low and high bankruptcy risk stocks. My formal tests of this asymmetric bankruptcy risk (reported in tables 6.4.3 and 6.4.4) find no evidence of any different relationship between z-score and returns or between size, B/M and returns for positive and negative z-score portfolios.

As to whether bankruptcy risk is a systematic risk or not, I follow the commonly understood definition of systematic risk which measures risk as sensitivity to broad market movements (Lakonishok, Shleifer and Vishny (1994)). I bifurcate the analysis into up and down market months and find that lower z-score and negative z-score stocks reliably underperform higher z-score and positive z-score stocks during down-markets indicating that z-scores are capturing a systematic risk factor missed by beta. During up markets, even when the coefficient is statistically insignificant, its sign shows higher (but economically small) returns for distressed stocks. Conclusions are robust to the trading strategy employed. The evidence regarding size and B/M effects is mixed. Smaller stocks seem to earn higher returns during up-markets but do no worse during down-markets. This is not entirely consistent with the risk argument since riskier firms should do badly under adverse market conditions. The findings are however sensitive to trading strategy and to the time period. Similarly, high B/M stocks seem to outperform during down-markets, a finding that is inconsistent with these stocks being riskier. Again, results are sensitive to trading strategy and to the time period.

Levis (1985) found a January and April seasonal in the stock returns in the UK for the period 1958-82. I find similar results that stock returns are higher during January, February and April during the period 1979-2000. I also find the size premium to be statistically significant during February and May for the period 1979-2000 (Levis (1985) finds it significant only during May). This could be a manifestation of institutional behaviour in the UK. The value premium is significant in April which can be interpreted as evidence in support of tax-loss selling hypothesis. The September seasonal in the z-score premium is likely to be an artefact of the data. The results indicate that the three premia are not due to some common factor since they are manifested in different months of the year. The coefficients on size, B/M and z-score in the Fama-MacBeth regressions also exhibit similar seasonality. The B/M effect is strongest in May while the size effect is strongest in April and z-score effect is strongest in April and September. The results confirm that the B/M effect is not linked to the same underlying risk factor as the size and z-score effects. The results also indicate that there may be some commonality between size and z-score effect.

I have repeated the tests of hypotheses $H1_0$ to $H5_0$ using value weighted portfolio returns for the ten portfolios formed on z-score and for the twenty-four portfolios formed on size, B/M and z-scores. I have also repeated the tests with only the largest 50% of the stocks each year on an individual securities basis. The results are generally weaker but qualitatively the same (Appendix: tables A2.1 to A2.5).

In the next chapter I use the time-series methodology of Fama & French (1993) to further explore bankruptcy risk factor in stock returns. I test the ability of the Fama & French (1993) three-factor model to explain the returns on the portfolios used in this chapter and then introduce a four-factor model that explicitly has a bankruptcy risk factor along with the market, size and B/M factors.

Chapter 7

THE FOUR-FACTOR MODEL

7.1 Introduction

In chapter 6 I presented evidence that bankruptcy risk is a priced risk factor independent of size and B/M effects. I documented that z-score is an important variable in explaining the cross-sectional variation of stock returns in the UK. In this chapter I build on the evidence of chapter 6 and use Fama & French (1993) time-series methodology as an alternative to the Fama-MacBeth (1973) methodology of the previous chapter.

I find that though the Fama & French (1993) three-factor model is reasonably successful at explaining the cross-sectional variation in stock returns for the ten portfolios formed on z-score, it is not very successful with the twenty-four portfolios formed on size, B/M and z-score. I also find that a factor that mimics the return on the z-score factor (constructed in the spirit of Fama & French (1993) factors) captures common variation in stock returns that is missed by the other three factors of the Fama & French (1993) model and is generally better at explaining the cross-sectional variation in stock returns. However, when the portfolio returns are value-weighted, I find that the Fama & French (1993) three-factor model performs as well as the modified four-factor model.

The chapter is organized as follows: section 2 reports time-series tests of the Fama & French (1993) three factor model, section 3 presents time-series tests of the modified four factor model, section 4 presents the tests of the three-factor and the four-factor models with value-weighted portfolio returns and section 5 summarizes the results.

7.2 The Fama & French three-factor model

As described in chapter 4, Fama & French (1993) propose the following model for equity returns:

$$R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + s\,SMB_t + h\,HML_t + e_t \qquad (12)$$

Where:

R_P = the return on portfolio P during the period t

R_F = Risk free rate observed at the beginning of the period t

R_M = Value-weighted return on all stocks in the portfolios

SMB = Return on the mimicking portfolio for the size factor

HML = Return on the mimicking portfolio for the B/M factor

R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1-month Treasury Bill rate at the beginning of the month. The factors R_M-R_F, SMB and HML are the same as described in chapter 4 and used in chapter 5.

7.2.1 Ten z-score portfolios

In this sub section, I report the performance of the Fama & French (1993) three-factor model in explaining the returns on the ten portfolios formed on z-scores. The portfolio formation method is the same as described in section 4.2.2.2 and the same portfolio returns are used as in section 6.4. Table 7.2.1.1 presents the results of time series regressions. Panel A reports the results with the market factor alone and Panel B reports the results with the three-factor model.

Table 7.2.1.1: Time-series regressions

At the end of September of each year from 1979 to 1999, all the stocks in the population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks. The portfolios are rebalanced at the end of September each year. Negative B/M stocks are excluded. The slopes are estimated by time-series regressions for each of the 10 portfolios from October 1979 to September 2000. R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1 month Treasury Bill rate at the beginning of the month. SMB is the return on the mimicking portfolio for the size factor and HML is the return on the mimicking portfolio for the B/M factor in stock returns. Figures in brackets are the respective t-statistics. The last month returns for failed firms is set equal to –100%.

Portfolio	1	2	3	4	5	6	7	8	9	10
A. $R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + e_t$										
a	0.0019	0.0009	0.0015	-0.0003	0.0023	0.0022	0.0029	0.0024	0.0031	0.0038
t(a)	(0.50)	(0.26)	(0.52)	(-0.11)	(0.99)	(1.21)	(1.58)	(1.44)	(1.97)	(2.42)
b	0.9380	0.9200	0.9190	0.9010	0.8840	0.8930	0.8690	0.8390	0.8230	0.6890
t(b)	(11.5)	(13.23)	(15.16)	(18.51)	(18.20)	(22.97)	(22.62)	(23.94)	(24.32)	(20.48)
$\overline{R}^2$	0.34	0.41	0.48	0.58	0.57	0.68	0.67	0.70	0.70	0.63
B. $R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + s\,SMB_t + h\,HML_t + e_t$										
a	-0.0017	-0.0036	-0.0018	-0.0034	-0.0007	-0.0005	0.0002	0.0000	0.0012	0.0020
t(a)	(-0.63)	(-1.91)	(-1.03)	(-2.23)	(-0.53)	(-0.58)	(0.28)	(-0.05)	(1.54)	(2.33)
b	1.2630	1.2530	1.1890	1.1160	1.1110	1.0940	1.0660	1.0170	0.9880	0.8450
t(b)	(21.16)	(29.95)	(29.51)	(33.02)	(36.28)	(58.47)	(56.14)	(56.82)	(55.72)	(43.18)
s	1.2360	1.1960	0.9950	0.7490	0.8170	0.7210	0.7080	0.6380	0.6170	0.5890
t(s)	(16.65)	(22.99)	(19.87)	(17.82)	(21.46)	(30.99)	(29.98)	(28.64)	(27.98)	(24.19)
h	0.2920	0.6120	0.3870	0.5050	0.4100	0.3780	0.3680	0.3470	0.1870	0.1690
t(h)	(3.41)	(10.22)	(6.70)	(10.43)	(9.35)	(14.13)	(13.54)	(13.53)	(7.39)	(6.02)
$\overline{R}^2$	0.69	0.81	0.80	0.82	0.85	0.93	0.93	0.93	0.93	0.89

Panel A of table 7.2.1.1 presents the results for the CAPM with return on market as the only explanatory variable. It shows that the market factor alone is able to capture a bulk of the common variation in stock returns. The adjusted R^2s for the positive z-score portfolios are all in excess of 60% and are over 50% for two of the five negative z-score portfolios. The market factor is highly significant with its coefficient being at least 11 standard errors from zero. The model also does well in explaining the cross section of returns; only one of the ten intercepts is more than two standard errors from zero. However, clearly there is a lot of common variation in average returns that is left unexplained by the market factor.

Panel B of table 7.2.1.1 shows that the three-factor model is able to capture most of the common variation in returns for the ten portfolios. The adjusted R^2 is over 90% for all the positive z-score portfolios except the highest z-score portfolio (adjusted R^2 = 89%) and is over 80% for all the portfolios except the lowest z-score portfolio (adjusted R^2 = 69%). The market factor is highly significant but as in Fama & French (1993), most of the coefficients are close to one showing that though the market factor explains the difference between stock returns and T-Bill returns, it is unable to capture the cross-sectional variation. SMB is always positive and highly significant (at least 16 standard errors from zero) while HML is more than 3 standard errors from zero for all the portfolios. The coefficient on SMB ranges from 1.24 for the lowest z-score portfolio to 0.59 for the highest z-score portfolio. The coefficient decreases monotonically with increasing z-score. The variation in SMB coefficient shows that it is able to capture the cross-sectional variation related to firm size that is missed by the market factor. The coefficient on HML is higher for negative z-score portfolios though the variation is erratic. This lack of pattern could be due to little relation between z-scores and B/M as argued earlier. The intercepts are less than two standard errors from zero for eight of the ten portfolios. The three-factor model actually performs better with these ten portfolios than it did with the twenty-five portfolios in chapter 5. The model provides a satisfactory though not perfect description of the cross-section of average returns.

7.2.2 Size, B/M and z-score portfolios

In this sub section I report the performance of the Fama & French (1993) three-factor model in explaining the returns on the twenty-four portfolios formed on size, B/M and z-scores. The portfolio formation method is again the same as described in section 4.2.2.3 and the same portfolio returns are used as in section 6.4. The factors RMRF, SMB and HML are as estimated in chapter 5. Table 7.2.2.1 presents the results of time series regressions. Panel A reports the results of regressions using the market factor as the only explanatory variable and Panel B reports the results with the Fama & French (1993) three-factor model.

Table 7.2.2.1: Time-series regressions

At the end of September of each year from 1979 to 1999, all the stocks in the population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and are independently sorted on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score. The z-score dummy is equal to 1 if the latest available z-score is negative, 0 otherwise. The portfolios are rebalanced at the end of September each year. Negative B/M stocks are excluded. The slopes are estimated by time-series regressions for each of the 24 portfolios from October 1979 to September 2000. R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1 month Treasury Bill rate at the beginning of the month. SMB is the return on the mimicking portfolio for the size factor and HML is the return on the mimicking portfolio for the B/M factor in stock returns. The last month returns for failed firms is set equal to –100%.

	Book-to-Market											
	Low		2		High		Low		2		High	
	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0
A. $R_{Pt} - R_{Ft} = a + b\ RMRF_t + e_t$												
	a						t(a)					
Small	0.0054	0.0121	0.0061	0.0113	0.0052	0.0112	1.10	2.61	1.44	3.81	1.42	4.36
2	-0.0036	0.0008	-0.0061	0.0024	-0.0012	0.0042	-0.96	0.30	-1.98	1.13	-0.35	1.86
3	-0.0049	0.0000	-0.0030	0.0000	-0.0041	0.0045	-1.40	0.02	-0.97	-0.02	-1.09	2.10
Large	-0.0026	-0.0015	-0.0010	-0.0004	0.0119	0.0037	-1.32	-1.31	-0.40	-0.30	3.09	1.78
	b						t(b)					
Small	0.6840	0.8280	0.8260	0.6420	0.8250	0.5180	6.55	8.39	9.15	10.21	10.59	9.48
2	0.9300	0.7800	0.8710	0.6970	0.8650	0.7060	11.75	13.97	13.36	15.30	11.89	14.69
3	1.0640	0.8500	1.0470	0.8270	1.0810	0.8090	14.36	20.43	16.00	20.64	13.74	17.95
Large	1.0630	1.0360	1.0880	1.0790	1.0270	1.1570	25.36	42.91	21.01	37.73	12.58	26.03
	Adjusted R^2											
Small	0.14	0.22	0.25	0.29	0.31	0.26						
2	0.35	0.44	0.41	0.48	0.36	0.46						
3	0.45	0.62	0.50	0.63	0.43	0.56						
Large	0.72	0.88	0.64	0.85	0.39	0.73						

Table 7.2.2.1: cont'd

	Book-to-Market											
	Low		2		High		Low		2		High	
	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0
B. $R_{Pt} - R_{Ft} = a + b\ RMRF_t + s\ SMB_t + h\ HML_t + e_t$												
	a						t(a)					
Small	0.0009	0.0097	0.0020	0.0084	0.0005	0.0076	0.23	2.70	0.68	4.38	0.21	5.28
2	-0.0055	-0.0009	-0.0097	-0.0006	-0.0060	0.0005	-2.30	-0.70	-4.42	-0.68	-2.66	0.51
3	-0.0074	-0.0018	-0.0062	-0.0027	-0.0082	0.0015	-2.69	-1.51	-2.48	-2.53	-2.65	1.02
Large	-0.0028	-0.0016	-0.0029	-0.0018	0.0095	0.0012	-1.54	-1.71	-1.26	-1.52	2.58	0.71
	b						t(b)					
Small	1.0410	1.1280	1.1910	0.9030	1.1800	0.7830	11.67	14.05	18.20	20.96	22.91	24.33
2	1.1990	1.0010	1.1380	0.9350	1.1810	0.9530	22.24	34.37	23.15	45.91	23.26	40.04
3	1.3070	1.0260	1.2720	1.0190	1.3260	0.9970	21.24	38.62	22.56	42.06	19.13	30.36
Large	1.1220	1.0810	1.1760	1.1480	1.1300	1.2750	27.24	53.10	23.15	43.74	13.65	34.52
	s						t(s)					
Small	1.3110	1.2300	1.3820	0.9990	1.2730	0.9390	11.82	12.31	16.98	18.65	19.87	23.48
2	1.1270	0.9180	0.9580	0.8660	1.0790	0.8490	16.82	25.33	15.67	34.17	17.08	28.70
3	0.9500	0.6830	0.7850	0.6760	0.8010	0.6290	12.41	20.68	11.20	22.45	9.29	15.40
Large	0.2680	0.2180	0.2420	0.2060	0.2730	0.3270	5.23	8.62	3.83	6.30	2.66	7.11
	h						t(h)					
Small	0.5480	-0.1200	0.3650	0.2190	0.6650	0.5490	4.29	-1.05	3.89	3.56	9.02	11.92
2	-0.2220	-0.1340	0.5120	0.3870	0.8530	0.6230	-2.87	-3.21	7.28	13.29	11.73	18.28
3	0.1110	0.0989	0.5200	0.4170	0.8220	0.5530	1.26	2.60	6.45	12.03	8.28	11.76
Large	-0.1360	-0.1570	0.4820	0.3270	0.6170	0.6530	-2.31	-5.39	6.64	8.69	5.21	12.36
	Adjusted R^2											
Small	0.45	0.54	0.65	0.71	0.73	0.77						
2	0.74	0.87	0.71	0.91	0.72	0.88						
3	0.67	0.87	0.68	0.88	0.61	0.80						
Large	0.76	0.93	0.69	0.89	0.44	0.84						

Panel A of table 7.2.2.1 shows that the market factor alone is unable to capture the bulk of the common variation in returns for the smaller two size quintiles where the adjusted R^2s are under 50%. The adjusted R^2 never exceeds 70% except for the largest size quintile. The coefficient on the market factor itself is always positive and highly significant being at least 6 standard errors from zero. However, the market factor alone seems to do a reasonably good job of explaining the cross section of returns, only five out of twenty four intercepts are more than two standard errors from zero.

Panel B of table 7.2.2.1 shows that the three-factor model performs better than the CAPM. Only two out of twenty four R^2s are under 50% and a majority are over 70%. The market factor remains highly significant for each of the portfolios (at least 11 standard errors from zero). However, as in Fama & French (1993) and table 7.2.1.1, the coefficients are close to one. The variation of coefficients with size and B/M is erratic showing that the market factor is not able to capture cross-sectional variation linked to size and B/M. The market factor coefficient is always higher for negative z-score portfolios as compared to positive z-score portfolios within the same size and B/M portfolio suggesting at least some ability of the market factor to capture cross-sectional variation related to z-score. SMB is always positive and highly significant (at least 2 standard errors from zero). Its coefficient varies from 1.31 for the smallest size portfolios to 0.21 for the largest size portfolios. The coefficient declines monotonically with increasing size for all B/M and z-score portfolios showing that SMB is capturing cross-sectional variation related to size that is missed by the market factor and HML. The SMB coefficient is always higher for negative z-score portfolios than for positive z-score portfolios of the same size and B/M suggesting that it is capturing at least part of the distress factor. HML is more than 2 standard errors from zero for all but two of the portfolios. The coefficient increases monotonically with increasing B/M for all size and z-score portfolios showing that HML is capturing cross-sectional variation related to B/M that is missed by the market factor and SMB. The HML coefficient is always higher for negative z-score portfolios than positive z-score portfolios of the same size and B/M again suggesting that it is capturing at least part of the distress factor. However, the model is not very successful at explaining the cross-section of stock returns; eleven of the intercepts are more than two standard errors from zero. The model has particular difficulty in explaining the returns on negative z-score portfolios, seven of the significant intercepts are for the negative z-score portfolios. The Fama & French (1993) three factor model once again provides a far from perfect description of average returns.

7.3 Modification of the Fama & French three-factor model

In this section, I draw upon the evidence of section 6.4 where I showed that a fourth factor namely z-score is also important in explaining the cross section of stock returns in addition to beta, size and B/M. I develop a four factor model which has the market factor, modified versions of SMB and HML and a fourth factor PMN (for positive minus negative) that is designed to mimic the return on the z-score factor. The construction of the factors is described in chapter 4. To distinguish between the original Fama & French factors and the modified factors, I add the superscript 'm' to the modified factors. The four-factor model is of the form:

$$R_{Pt} - R_{Ft} = a + b(R_{Mt} - R_{Ft}) + s\ SMB^{m}{}_{t} + h\ HML^{m}{}_{t} + p\ PMN_{t} + e_{t} \qquad (13)$$

Where:

R_P = the return on portfolio P during the period t

R_F = the risk free rate observed at the beginning of the period t

R_M = the value-weighted return on all stocks in the portfolios

SMB^m = the return on the modified mimicking portfolio for the size factor

HML^m = the return on the modified mimicking portfolio for the B/M factor

PMN = the return on the mimicking portfolio for the z-score factor

The average monthly return on the market factor is 0.61% (t = 2.08), on SMB^m it is –0.14% (t = 0.55), on HML^m it is 0.37% (t = 1.68) and on PMN it is –0.03% (t = 0.28). Again, excluding the last twelve months changes the average monthly returns on the market factor to 0.63% (t = 2.09), on SMB^m to –0.26% (t = 1.14) and on HML^m to 0.50% (t = 2.86). The average monthly return on PMN is unchanged. Panel A of table 7.3.1 shows the correlations between the four factors for the full period and panel B shows the correlations between the four factors after removing the last twelve months.

Table 7.3.1: Correlations between the four factors

	RMRF	SMB^m	HML^m	PMN
A. October 1979 to September 2000				
RMRF	1			
SMB^m	-0.24	1		
HML^m	-0.06	-0.29	1	
PMN	-0.12	-0.07	-0.08	1
B. October 1979 to September 1999				
RMRF	1			
SMB^m	-0.26	1		
HML^m	-0.04	-0.04	1	
PMN	-0.11	-0.08	-0.12	1

Low correlations between PMN and SMB^m and between PMN and HML^m show that PMN is largely free of size and B/M effects. It also shows that SMB^m and HML^m are largely free of z-score effects in equity returns.

Table 7.3.2 presents the results of time series regressions on the same ten z-score portfolios as in section 7.2.1.

Table 7.3.2: Time series regressions

At the end of September of each year from 1979 to 1999, all the stocks in the population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks. The portfolios are rebalanced at the end of September each year. Negative B/M stocks are excluded. The slopes are estimated by time-series regressions for each of the 10 portfolios from October 1979 to September 2000. R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1 month Treasury Bill rate at the beginning of the month. SMB^m is the return on the modified mimicking portfolio for the size factor, HML^m is the return on the modified mimicking portfolio for the B/M factor in stock returns and PMN is the return on the mimicking portfolio for the z-score factor in the stock returns. Figures in brackets are the respective t-statistics. The last month returns for failed firms is set equal to –100%.

Portfolio	1	2	3	4	5	6	7	8	9	10
A. $R_{Pt} - R_{Ft} = a + b\ RMRF_t + p\ PMN_t + e_t$										
a	0.0019	0.0008	0.0014	-0.0003	0.0022	0.0022	0.0028	0.0024	0.0031	0.0038
t(a)	(0.53)	(0.26)	(0.54)	(-0.13)	(1.04)	(1.25)	(1.62)	(1.45)	(1.98)	(2.45)
b	0.8750	0.8720	0.8800	0.8710	0.8530	0.8700	0.8500	0.8260	0.8130	0.6770
t(b)	(11.71)	(13.42)	(15.37)	(18.80)	(18.56)	(23.39)	(22.75)	(23.86)	(24.13)	(20.33)
p	-1.3950	-1.0670	-0.8710	-0.6580	-0.6850	-0.5020	-0.4170	-0.2930	-0.2250	-0.2640
t(p)	(-7.28)	(-6.40)	(-5.93)	(-5.54)	(-5.81)	(-5.26)	(-4.35)	(-3.30)	(-2.61)	(-3.10)
$\overline{R}^2$	0.46	0.49	0.54	0.62	0.62	0.71	0.69	0.71	0.71	0.64
B. $R_{Pt} - R_{Ft} = a + b\ RMRF_t + s\ SMB^m_t + h\ HML^m_t + e_t$										
a	0.0009	-0.0013	0.0002	-0.0019	0.0010	0.0010	0.0016	0.0012	0.0026	0.0033
t(a)	(0.33)	(-0.65)	(0.11)	(-1.15)	(0.66)	(0.96)	(1.60)	(1.30)	(2.90)	(3.47)
b	1.1850	1.1750	1.1250	1.0590	1.0500	1.0380	1.0140	0.9710	0.9460	0.8080
t(b)	(19.25)	(27.23)	(27.27)	(29.74)	(31.43)	(44.91)	(45.24)	(47.48)	(48.11)	(38.78)
s	1.1310	1.1100	0.9240	0.6750	0.7300	0.6360	0.6330	0.5750	0.5640	0.5430
t(s)	(15.04)	(21.07)	(18.34)	(15.53)	(17.89)	(22.52)	(23.10)	(23.01)	(23.47)	(21.35)
h	0.2870	0.5760	0.3510	0.4280	0.3460	0.3220	0.3310	0.3130	0.1520	0.1540
t(h)	(3.40)	(9.72)	(6.20)	(8.76)	(7.55)	(10.14)	(10.75)	(11.13)	(5.62)	(5.40)
$\overline{R}^2$	0.66	0.79	0.78	0.79	0.81	0.90	0.90	0.90	0.91	0.87
C. $R_{Pt} - R_{Ft} = a + b\ RMRF_t + s\ SMB^m_t + h\ HML^m_t + p\ PMN_t + e_t$										
a	0.0012	-0.0011	0.0004	-0.0018	0.0011	0.0011	0.0017	0.0012	0.0026	0.0033
t(a)	(0.47)	(-0.63)	(0.20)	(-1.14)	(0.77)	(1.09)	(1.70)	(1.33)	(2.93)	(3.52)
b	1.1150	1.1280	1.0870	1.0310	1.0200	1.0190	1.0000	0.9640	0.9420	0.8000
t(b)	(20.12)	(28.62)	(28.07)	(30.11)	(32.27)	(46.24)	(45.48)	(46.94)	(47.41)	(38.28)
s	1.0540	1.0590	0.8820	0.6450	0.6970	0.6140	0.6170	0.5670	0.5590	0.5350
t(s)	(15.60)	(22.04)	(18.68)	(15.44)	(18.09)	(22.87)	(23.02)	(22.65)	(23.08)	(21.00)
h	0.2090	0.5250	0.3080	0.3970	0.3130	0.3000	0.3150	0.3050	0.1470	0.1460
t(h)	(2.76)	(9.73)	(5.82)	(8.48)	(7.25)	(9.97)	(10.49)	(10.85)	(5.40)	(5.11)
p	-1.1210	-0.7410	-0.6210	-0.4470	-0.4750	-0.3140	-0.2260	-0.1140	-0.0747	-0.1190
t(p)	(-8.14)	(-7.56)	(-6.45)	(-5.26)	(-6.05)	(-5.73)	(-4.13)	(-2.24)	(-1.51)	(-2.29)
$\overline{R}^2$	0.73	0.83	0.81	0.81	0.84	0.91	0.90	0.91	0.91	0.87

Panel A of table 7.3.2 shows that the two factor model with the market factor and PMN produces higher adjusted R^2s than with the market factor alone. As expected, the model performs better at capturing the common variation in the negative z-score portfolios. The coefficients on the market factor remain highly significant (at least 11 standard errors from zero). There is little variation in the coefficients showing the inability of the market factor to capture cross-sectional variation. The coefficients on the PMN are all negative and significant (at least two standard errors from zero). The coefficients vary from 1.40 for the lowest z-score portfolio to 0.26 for the highest z-score portfolio and the decrease is monotonic. The variation shows the ability of PMN to capture cross-sectional variation linked to z-score that is missed by the market factor. Only one of ten intercept terms is statistically significant. However, the adjusted R^2s are still quite low and clearly there is a lot of common variation left to be explained.

Panel B shows that the Fama & French three factor model with modified factors is able to explain more common variation than the two-factor model with all but the adjusted R^2 for lowest z-score portfolio being over 75%. Once again, coefficients on the market factor are all close to one showing its inability to capture cross-sectional variation. The coefficient on SMB ranges from 1.13 to 0.54 and decreases monotonically with increasing z-score while the coefficients of HML are erratic though statistically significant. That the modified model performs almost as well as the original model is clear by the comparison of panel B here to the panel B of table 7.2.1.1. The modified model produces two intercepts more than two standard errors from zero which is the same as the original three-factor model. SMB and HML coefficients remain positive and highly significant.

Panel C shows the results for the four-factor model. Factor PMN remains negative and highly significant for nine out of ten portfolios in the presence of the market factor and SMB^m and HML^m. Its coefficient ranges from 1.12 to 0.07 and decreases (in absolute terms) monotonically with increasing z-score showing that it is capturing cross-sectional variation missed by the other three factors. There is still some variation in the SMB coefficient suggesting that it is capturing some cross-sectional variation. Variation in HML is erratic showing that it has little ability to explain the cross-sectional variation of z-score portfolios. The adjusted R^2s for the negative z-score portfolios are slightly higher than for the three-factor model with modified factors (panel B) and also than the three-factor model with original factors. The model produces two intercepts more than two standard errors from zero.

The evidence here clearly shows that the four-factor model with modified Fama & French factors does a better job of capturing the common variation in returns of negative z-score portfolios. The model is reasonably successful at explaining the cross-section of returns as only two out of ten intercepts are more than two standard errors from zero.

Table 7.3.3 presents the results of time series regressions on the twenty four size, B/M and z-score portfolios as in section 7.2.1. Panel A presents the results for the two factor model, panel B for the three factor model with modified factors and panel C for the four factor model.

Table 7.3.3: Time series regressions

At the end of September of each year from 1979 to 1999, all the stocks in the population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and are independently sorted on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score. The z-score dummy is equal to 1 if the latest available z-score is negative, 0 otherwise. The portfolios are rebalanced at the end of September each year. Negative B/M stocks are excluded. The slopes are estimated by time-series regressions for each of the 24 portfolios from October 1979 to September 2000. R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1 month Treasury Bill rate at the beginning of the month. SMB is the return on the mimicking portfolio for the size factor and HML is the return on the mimicking portfolio for the B/M factor in stock returns. The last month returns for failed firms is set equal to –100%.

	Book-to-Market											
	Low		2		High		Low		2		High	
	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0
A. $R_{Pt} - R_{Ft} = a + b\,RMRF_t + p\,PMN_t + e_t$												
	a						t(a)					
Small	0.0053	0.0121	0.0061	0.0113	0.0052	0.0112	1.14	2.63	1.48	3.94	1.48	4.52
2	-0.0036	0.0008	-0.0061	0.0024	-0.0013	0.0042	-1.03	0.30	-2.12	1.14	-0.39	1.89
3	-0.0049	0.0000	-0.0030	-0.0001	-0.0041	0.0044	-1.45	0.01	-1.01	-0.03	-1.19	2.14
Big	-0.0026	-0.0015	-0.0010	-0.0004	0.0118	0.0037	-1.38	-1.33	-0.44	-0.30	3.31	1.78
	b						t(b)					
Small	0.6210	0.7970	0.7820	0.6100	0.7810	0.4890	6.24	8.12	8.91	10.00	10.45	9.25
2	0.8800	0.7610	0.8300	0.6810	0.8180	0.6860	11.72	13.75	13.41	15.10	11.91	14.53
3	1.0340	0.8340	1.0200	0.8110	1.0290	0.7900	14.18	20.29	15.86	20.55	13.88	17.85
Big	1.0420	1.0330	1.0540	1.0770	0.9700	1.1460	25.59	42.50	21.62	37.36	12.74	25.78
	p						t(p)					
Small	-1.3880	-0.6950	-0.9690	-0.6900	-0.9930	-0.6220	-5.44	-2.76	-4.30	-4.41	-5.18	-4.58
2	-1.0900	-0.4120	-0.8950	-0.3540	-1.0320	-0.4480	-5.66	-2.90	-5.64	-3.06	-5.86	-3.70
3	-0.6500	-0.3350	-0.5910	-0.3500	-1.1310	-0.4230	-3.47	-3.18	-3.58	-3.45	-5.94	-3.73
Big	-0.4600	-0.0569	-0.7580	-0.0313	-1.2660	-0.2250	-4.41	-0.91	-6.06	-0.42	-6.49	-1.98
	Adjusted R^2											
Small	0.23	0.24	0.30	0.34	0.37	0.32						
2	0.43	0.45	0.48	0.50	0.43	0.49						
3	0.47	0.64	0.53	0.64	0.50	0.58						
Big	0.74	0.88	0.68	0.85	0.47	0.73						

Table 7.3.3: cont'd

	Book-to-Market											
	Low		2		High		Low		2		High	
	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0
B. $R_{Pt} - R_{Ft} = a + b\ RMRF_t + s\ SMB^m_t + h\ HML^m_t + e_t$												
	a						**t(a)**					
Small	0.0039	0.0125	0.0050	0.0106	0.0029	0.0095	0.96	3.44	1.69	5.14	1.24	5.83
2	-0.0023	0.0013	-0.0079	0.0012	-0.0045	0.0022	-0.95	0.86	-3.60	1.06	-2.00	1.69
3	-0.0054	-0.0002	-0.0046	-0.0015	-0.0071	0.0026	-1.95	-0.18	-1.76	-1.21	-2.25	1.64
Big	-0.0018	-0.0010	-0.0025	-0.0014	0.0085	0.0017	-0.95	-1.06	-1.06	-1.14	2.48	0.94
	b						**t(b)**					
Small	0.9520	1.0680	1.1090	0.8370	1.0980	0.7120	10.69	13.36	16.96	18.45	21.01	20.06
2	1.1340	0.9520	1.0810	0.8730	1.1120	0.8860	21.65	29.40	22.54	35.33	22.73	31.41
3	1.2580	0.9840	1.2110	0.9690	1.2510	0.9420	20.74	35.77	21.24	36.83	18.02	27.02
Big	1.0870	1.0740	1.1220	1.1240	1.0870	1.2320	26.58	52.23	21.97	41.77	14.57	31.63
	s						**t(s)**					
Small	1.2090	1.1730	1.3000	0.9050	1.1870	0.8420	11.11	12.02	16.28	16.33	18.60	19.39
2	1.0550	0.8550	0.9180	0.7800	1.0140	0.7570	16.48	21.62	15.67	25.84	16.97	21.96
3	0.9100	0.6340	0.7060	0.6070	0.6560	0.5420	12.28	18.85	10.13	18.89	7.73	12.71
Big	0.1630	0.2120	0.0847	0.1660	0.1050	0.2520	3.26	8.42	1.36	5.06	1.15	5.30
	h						**t(h)**					
Small	0.4220	-0.0695	0.3160	0.1940	0.6150	0.4790	3.45	-0.63	3.52	3.12	8.58	9.82
2	-0.3040	-0.0972	0.4780	0.3370	0.8570	0.5410	-4.22	-2.19	7.26	9.92	12.76	13.96
3	0.1470	0.0832	0.4240	0.3780	0.7990	0.4870	1.76	2.20	5.41	10.48	8.38	10.17
Big	-0.2130	-0.1230	0.3850	0.2570	0.8770	0.5330	-3.80	-4.37	5.49	6.96	8.56	9.96
	Adjusted R^2											
Small	0.42	0.53	0.64	0.66	0.71	0.71						
2	0.74	0.83	0.71	0.86	0.73	0.83						
3	0.66	0.85	0.65	0.85	0.59	0.76						
Big	0.75	0.92	0.67	0.88	0.53	0.81						

Table 7.3.3: cont'd

	Book-to-Market											
	Low		2		High		Low		2		High	
	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0
C. $R_{Pt} - R_{Ft} = a + b\ RMRF_t + s\ SMB^m_t + h\ HML^m_t + p\ PMN_t + e_t$												
	a						t(a)					
Small	0.0041	0.0126	0.0052	0.0107	0.0031	0.0095	1.06	3.49	1.79	5.36	1.36	6.07
2	-0.0021	0.0013	-0.0077	0.0012	-0.0043	0.0022	-0.97	0.91	-3.74	1.09	-2.06	1.74
3	-0.0053	-0.0002	-0.0045	-0.0014	-0.0069	0.0027	-1.94	-0.15	-1.75	-1.20	-2.31	1.69
Big	-0.0017	-0.0010	-0.0023	-0.0014	0.0087	0.0017	-0.93	-1.06	-1.06	-1.14	2.76	0.95
	b						t(b)					
Small	0.8850	1.0390	1.0690	0.8080	1.0580	0.6900	10.29	12.96	16.64	18.18	21.00	19.82
2	1.0770	0.9370	1.0420	0.8660	1.0690	0.8740	22.63	29.05	22.69	34.81	23.02	31.01
3	1.2310	0.9730	1.1880	0.9590	1.1960	0.9280	20.34	35.36	20.83	36.36	17.93	26.60
Big	1.0570	1.0720	1.0790	1.1270	1.0170	1.2260	26.65	51.44	22.18	41.34	14.54	31.10
	s						t(s)					
Small	1.1350	1.1420	1.2560	0.8730	1.1430	0.8170	10.82	11.68	16.04	16.11	18.61	19.24
2	0.9910	0.8390	0.8750	0.7720	0.9670	0.7430	17.09	21.33	15.63	25.46	17.08	21.64
3	0.8800	0.6210	0.6800	0.5960	0.5950	0.5260	11.93	18.52	9.78	18.54	7.32	12.36
Big	0.1300	0.2090	0.0368	0.1700	0.0271	0.2460	2.69	8.25	0.62	5.11	0.32	5.12
	h						t(h)					
Small	0.3480	-0.1010	0.2710	0.1620	0.5710	0.4540	2.96	-0.92	3.09	2.67	8.29	9.54
2	-0.3680	-0.1140	0.4350	0.3280	0.8100	0.5270	-5.65	-2.58	6.93	9.65	12.76	13.69
3	0.1170	0.0706	0.3980	0.3680	0.7380	0.4720	1.41	1.88	5.10	10.20	8.09	9.88
Big	-0.2460	-0.1250	0.3370	0.2610	0.7990	0.5270	-4.53	-4.40	5.06	6.99	8.36	9.77
	p						t(p)					
Small	-1.0740	-0.4520	-0.6390	-0.4650	-0.6400	-0.3620	-5.02	-2.27	-4.01	-4.21	-5.12	-4.19
2	-0.9240	-0.2400	-0.6250	-0.1250	-0.6810	-0.1930	-7.82	-3.00	-5.48	-2.02	-5.90	-2.76
3	-0.4310	-0.1820	-0.3720	-0.1540	-0.8750	-0.2270	-2.86	-2.67	-2.63	-2.36	-5.28	-2.61
Big	-0.4700	-0.0297	-0.6950	0.0496	-1.1300	-0.0839	-4.77	-0.57	-5.75	0.73	-6.51	-0.86
	Adjusted R^2											
Small	0.48	0.53	0.66	0.68	0.74	0.73						
2	0.79	0.83	0.74	0.86	0.76	0.83						
3	0.67	0.85	0.66	0.86	0.63	0.76						
Big	0.77	0.92	0.71	0.88	0.59	0.81						

Panel A of table 7.3.3 shows that addition of PMN to the market factor improves the explanatory power of the model especially for the negative z-score portfolios. The coefficient of PMN is always negative and more than two standard errors from zero for 21 of the 24 portfolios. The results show that PMN is able to capture common variation in returns over and above the market factor.

Panel B shows that the modified three factor model is able to capture the bulk of the common variation in returns, only one of twenty four adjusted R^2 is under 50% and a majority are over 70%. SMB^m is positive and more than 2 standard errors from zero for all but two portfolios while HML^m is more than 2 standard errors from zero for all but two of the portfolios. However, the model is not very successful at explaining the cross sectional variation in returns as 7 out of 24 intercepts are more than two standard errors from zero. A comparison of the results here with those in panel B of table 7.2.2.1 shows that the model with modified factors produces slightly lower adjusted R^2s but is better specified as it does a better job of explaining the cross sectional variation in returns.

Panel C shows that the modified four-factor model is able to capture more common variation in returns than the modified three-factor model, the improvement being most noticeable in the negative z-score portfolios. SMB^m is positive and more than 2 standard errors from zero for all but two portfolios while HML^m is more than 2 standard errors from zero for all but three of the portfolios. PMN is also statistically significant for 21 of the 24 portfolios. The results show that the z-score factor has the ability to explain the average returns independent of the market, size and B/M factors. However, the model is no more successful at explaining the cross sectional variation in returns than the modified three-factor model and produces the same number (7) of statistically significant intercepts. A comparison of the results here with those in panel B of table 7.2.2.1 shows that the four-factor model produces slightly lower adjusted R^2s for positive z-score portfolios and slightly higher adjusted R^2s for the negative z-score portfolios. The four factor model is better specified as it produces 7 significant intercepts against 11 produced by the Fama & French three-factor model and does a better job of explaining the cross sectional variation in returns.

7.4 Value-weighted returns

The analysis so far uses equally-weighted portfolio returns. In chapter 5 I documented that the Fama & French (1993) model was not very successful at capturing the cross-sectional variation in stock returns when the portfolios were equally-weighted (9 out of 25 intercepts were more than two standard errors from zero). The model performed much better with value-weighted portfolio returns (only 3 out of 25 intercepts were more than two standard errors from zero). In this section I report the results for the twenty-four portfolios formed on size, B/M and z-scores with value-weighted returns[23]. In panel A of table 7.4.1, I report the results for the original Fama & French (1993) three-factor model and in panel B, the results for the modified four-factor model.

[23] Since both the three-factor and the four-factor models did a good job at explaining the returns on the ten z-score portfolios even with equally-weighted returns, I do not report the results of value-weighted returns for these portfolios explicitly.

Table 7.4.1: Time series regressions

At the end of September of each year from 1979 to 1999, all the stocks in the population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and are independently sorted on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score. The z-score dummy is equal to 1 if the latest available z-score is negative, 0 otherwise. The portfolios are rebalanced at the end of September each year. Negative B/M stocks are excluded. The slopes are estimated by time-series regressions for each of the 24 portfolios from October 1979 to September 2000. R_M is the monthly value weighted return on all stocks in the portfolios and R_F is the 1 month Treasury Bill rate at the beginning of the month. SMB is the return on the mimicking portfolio for the size factor and HML is the return on the mimicking portfolio for the B/M factor in stock returns. The last month returns for failed firms is set equal to –100%.

	Book-to-Market											
	Low		2		High		Low		2		High	
	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0
A. $R_{Pt} - R_{Ft} = a + b\ RMRF_t + s\ SMB_t + h\ HML_t + e_t$												
	a						**t(a)**					
Small	0.0027	0.0076	-0.0002	0.0049	-0.0021	0.0026	0.75	2.29	-0.10	2.69	-0.97	1.91
2	-0.0015	0.0007	-0.0080	0.0018	-0.0053	0.0003	-0.63	0.52	-4.02	1.98	-2.42	0.32
3	-0.0036	-0.0007	-0.0047	-0.0021	-0.0067	0.0018	-1.49	-0.60	-1.91	-1.89	-2.17	1.14
Big	0.0008	-0.0001	-0.0005	-0.0005	0.0142	-0.0003	0.34	-0.13	-0.17	-0.48	3.52	-0.20
	b						**t(b)**					
Small	1.0150	1.1170	1.1330	0.8880	1.1830	0.9170	12.46	15.00	20.22	21.96	24.66	29.92
2	1.2150	1.0030	1.1410	0.9140	1.1700	0.9660	22.30	31.11	25.43	44.54	23.99	43.32
3	1.2560	1.0510	1.2540	1.0280	1.2350	0.9690	23.09	38.75	23.02	40.92	17.82	27.51
Big	0.9200	0.9830	1.0930	1.0640	1.0130	1.0480	17.25	56.05	15.62	47.26	11.20	31.92
	s						**t(s)**					
Small	1.1110	1.1850	1.3500	0.9840	1.2870	0.9560	10.96	12.80	19.37	19.57	21.58	25.06
2	1.1750	0.9400	0.9450	0.8870	1.0260	0.8380	17.34	23.45	16.95	34.77	16.92	30.21
3	0.8690	0.6750	0.7490	0.6450	0.7790	0.5180	12.85	20.02	11.05	20.66	9.03	11.84
Big	-0.0027	-0.1200	0.0236	-0.0278	0.1440	0.0001	-0.04	-5.50	0.27	-0.99	1.28	0.00
	h						**t(h)**					
Small	0.2980	-0.2060	0.1450	0.1070	0.6740	0.5120	2.55	-1.94	1.81	1.84	9.82	11.67
2	-0.4940	-0.3480	0.3970	0.2790	0.7820	0.6400	-6.34	-7.53	6.19	9.49	11.20	20.05
3	-0.0916	0.0199	0.4740	0.3840	0.8030	0.5110	-1.18	0.51	6.08	10.68	8.09	10.14
Big	-0.2520	-0.3620	0.3110	0.2480	0.6220	0.6780	-3.30	-14.41	3.10	7.69	4.81	14.44
	Adjusted R^2											
Small	0.45	0.58	0.71	0.73	0.76	0.82						
2	0.76	0.86	0.74	0.91	0.73	0.90						
3	0.71	0.87	0.68	0.87	0.58	0.76						
Big	0.59	0.94	0.52	0.91	0.36	0.84						

Table 7.4.1: cont'd

	Book-to-Market											
	Low		2		High		Low		2		High	
	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0	z<0	z>0
B. $R_{Pt} - R_{Ft} = a + b\ RMRF_t + s\ SMB^m_t + h\ HML^m_t + p\ PMN_t + e_t$												
	a						t(a)					
Small	0.0057	0.0106	0.0030	0.0073	0.0005	0.0046	1.63	3.13	1.23	3.79	0.22	2.99
2	0.0021	0.0032	-0.0061	0.0038	-0.0036	0.0020	1.00	1.94	-3.26	3.32	-1.82	1.60
3	-0.0016	0.0009	-0.0030	-0.0008	-0.0055	0.0028	-0.66	0.72	-1.20	-0.69	-1.82	1.66
Big	0.0021	-0.0004	-0.0001	-0.0007	0.0128	-0.0005	1.06	-0.48	-0.05	-0.63	4.25	-0.28
	b						t(b)					
Small	0.8820	1.0360	1.0190	0.7950	1.0470	0.8240	11.39	13.87	19.04	18.74	22.36	23.90
2	1.0970	0.9440	1.0550	0.8420	1.0750	0.8880	23.16	25.92	25.66	32.88	24.21	32.89
3	1.2030	1.0030	1.1690	0.9720	1.1180	0.9070	22.27	36.22	21.15	35.92	16.54	24.68
Big	0.8150	1.0120	0.9480	1.0720	0.8620	1.0660	18.67	49.99	16.02	46.76	12.90	29.41
	s						t(s)					
Small	0.9690	1.1050	1.2450	0.8550	1.1210	0.8240	10.27	12.14	19.08	16.53	19.64	19.60
2	1.0500	0.8640	0.8830	0.7860	0.9490	0.7320	18.18	19.45	17.62	25.16	17.53	22.25
3	0.8300	0.6240	0.6340	0.5700	0.5960	0.4240	12.61	18.50	9.40	17.29	7.24	9.46
Big	-0.2720	-0.0654	-0.3190	-0.0090	-0.1970	0.0537	-5.12	-2.65	-4.42	-0.32	-2.43	1.22
	h						t(h)					
Small	0.1150	-0.1830	0.0931	0.0550	0.5990	0.4210	1.09	-1.80	1.27	0.95	9.36	8.93
2	-0.5910	-0.3040	0.3410	0.2160	0.7560	0.5430	-9.12	-6.10	6.06	6.17	12.44	14.71
3	-0.0607	0.0067	0.3580	0.3360	0.7310	0.4270	-0.82	0.18	4.74	9.08	7.90	8.50
Big	-0.5300	-0.2460	0.1050	0.2030	0.8500	0.5290	-8.89	-8.89	1.30	6.48	9.30	10.68
	p						t(p)					
Small	-0.9840	-0.3640	-0.6700	-0.4570	-0.7800	-0.3340	-5.12	-1.96	-5.04	-4.34	-6.70	-3.90
2	-0.9760	-0.2010	-0.5600	-0.1400	-0.5420	-0.1910	-8.29	-2.22	-5.48	-2.20	-4.91	-2.84
3	-0.2290	-0.1630	-0.3850	-0.1360	-0.7230	-0.2160	-1.71	-2.38	-2.80	-2.02	-4.30	-2.36
Big	-0.8940	0.0880	-1.3360	0.1820	-1.6890	0.4930	-8.24	1.75	-9.09	3.19	-10.17	5.48
	Adjusted R^2											
Small	0.49	0.57	0.73	0.70	0.77	0.77						
2	0.82	0.81	0.78	0.85	0.77	0.85						
3	0.71	0.86	0.67	0.85	0.59	0.73						
Big	0.72	0.92	0.65	0.91	0.64	0.80						

Panel A of table 7.4.1 shows that the three-factor model captures the bulk of the common variation in stock returns. The adjusted R^2s are similar to those in panel B of table 7.2.2.1. Only two out of twenty four R^2s are under 50% and a majority are over 70%. The market factor is highly significant for each of the portfolios (at least 12 standard errors from zero) but the coefficients are close to one showing its inability to capture cross-sectional variation in stock returns. SMB is positive and highly significant except for the largest 25% of the stocks. As in panel B of table 7.2.2.1, the coefficient declines monotonically with increasing size for all B/M and z-score portfolios showing that SMB is capturing cross-sectional variation related to size that is missed by the market factor and HML. The SMB coefficient is always higher for negative z-score portfolios than positive z-score portfolios of the same size and B/M suggesting that it is capturing at least part of the distress factor. HML is more than 2 standard errors from zero for 19 of the 24 portfolios (as against 22 in table 7.2.2.1). As in table 7.2.2.1, the coefficient increases monotonically with increasing B/M for all size and z-score portfolios showing that HML is capturing cross-sectional variation related to B/M that is missed by the market factor and SMB. The HML coefficient is almost always higher for negative z-score portfolios than positive z-score portfolios of the same size and B/M again suggesting that it is capturing at least part of the distress factor.

As in chapter 5 with 25 size and B/M portfolios, the model is better at explaining the cross-section of stock returns with only six of the intercepts being more than two standard errors from zero as against eleven in table 7.2.2.1.

Panel B of table 7.4.1 shows that the modified four-factor model produces results similar to those of panel A. SMB^m is positive and more than 2 standard errors from zero for all but the largest 25% of the firms while HML^m is more than 2 standard errors from zero for 17 out of 24 portfolios. Similar to panel C of table 7.3.3, PMN is statistically significant for 21 of the 24 portfolios. The results show that the z-score factor has the ability to explain the average returns independent of the market, size and B/M factors and whether the returns are equally-weighted or value-weighted. However, the model is no more successful at explaining the cross sectional variation in returns than the three-factor model and produces the same number (6) of statistically significant intercepts. A comparison of the results here with those in panel A of table 7.4.1 shows that the four-factor model generally produces lower adjusted R^2s for positive z-score portfolios and higher adjusted R^2s for the negative z-score portfolios.

The evidence here suggests that the Fama & French (1993) three-factor model is better able to explain cross-sectional variation of stock returns when portfolio returns are value-weighted. The four factor model on the other hand performs equally well with equally and value weighted returns.

7.5 Summary

In this chapter I test the ability of the Fama & French (1993) three-factor model to explain cross-sectional variation in stock returns first on ten portfolios formed on z-scores and then on twenty-four portfolios formed on size, B/M and z-scores. I then introduce a four-factor model that includes the z-score factor and test its ability to explain the returns on the same portfolios.

I find that the Fama & French (1993) three factor model does much better than the single factor model in explaining the returns on the ten z-score portfolios and the twenty-four size, B/M and z-score portfolios. The market factor is unable to capture cross-sectional variation in stock returns. SMB and HML capture the cross-sectional variation missed by the market factor. However, the three-factor model does less than a perfect job, 2 out of 10 intercepts for the z-score portfolios and 11 out of 24 intercepts for the size, B/M and z-score portfolios are more than two standard errors from zero. A four-factor model with modified SMB and HML along with market factor and a factor that mimics the z-score factor in stock returns (PMN) is better specified. PMN proves able to capture cross-sectional variation missed by the other three factors. Also, similar to the findings of section 6.3, SMB seems to be able to capture some cross-sectional variation related to bankruptcy risk while HML seems unable to do so.

Similar to the findings in chapter 5, I find that the Fama & French (1993) model is better specified when portfolio returns are value-weighted rather than equally-weighted. The modified four-factor model, however, seems equally well specified regardless of the weighting scheme employed.

In chapter 6 I documented time-variation in the bankruptcy risk premium that seemed to be linked to the state of the economy. I also documented that bankruptcy risk premium varies with the state of the stock market in a manner consistent with its being a priced risk factor. In the next chapter I explore the bankruptcy risk premium under different economic conditions using GDP growth rates to measure good and bad states of the economy.

Chapter 8

SIZE, B/M, Z-SCORES AND THE STATE OF THE ECONOMY

8.1 Introduction

In this chapter I revisit the results of previous chapters and investigate the distress factor under different economic conditions. Lev & Thiagarajan (1993) draw attention to the hazards of drawing inferences from unconditional analysis. Cochrane (2001) also points out that it is possible for a model to hold conditionally period-by-period and still not hold unconditionally. It is possible that exposure to some factors may be rewarded in certain states and penalized in other states of the world (Taffler (1999)). Bankruptcy risk premium is likely to vary with the state of the economy because poorly performing or distressed firms are likely to be especially sensitive to economics conditions and their returns may be driven by common macro-economic factors such as credit squeeze, liquidity crunch or flight towards quality. Riskier firms may be able to prosper better when periods of high economic growth are expected, however, they are hit harder when the economic conditions are bad.

I use the next quarter GDP growth rate as an indicator of state of the economy based on evidence that the stock market seems to lead GDP growth rate by at least a quarter (Fama (1981) and Aylward & Glen (1995)). I compute the quarterly long run average GDP growth rate from 1955 to 2001 and bifurcate the quarters into those with better than average growth and those with worse than average growth.

The chapter is organized as follows: section 2 presents preliminary evidence on the relation between returns and GDP growth rates, section 3 presents the tests of hypotheses under different economic conditions using the three trading rules of chapter 6 namely z-score portfolios, size, B/M and z-score portfolios and individual securities, section 4 explores the size and B/M effects under different economic conditions using the size and B/M portfolios of chapter 5 and section 5 summarizes the results.

8.2 Excess portfolio returns

If the z-score is proxying for bankruptcy risk, then firms with high risk of failure (negative z-score) will underperform during downturns and outperform during upturns of the economy. This is because during downturns, the marginal utility of wealth will be higher and distressed firms are more likely to fail. There will therefore be a "flight towards quality" as investors will move towards safer securities. This will drive prices of non-distressed securities up and drive the prices of distressed securities down.

Table 8.2.1 presents the average monthly returns for the ten z-score portfolios during downturns and upturns of the economy.

Table 8.2.1: Average monthly excess returns under different economic conditions
At the end of September of each year from 1979 to 1999, all the stocks in the population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five consist of positive z-score stocks. The portfolios are rebalanced at the end of September each year. 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. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. The last month returns for failed firms are set equal to –100%. t-statistics are for the difference in means.

Portfolio	Average monthly excess returns (%)			
	GDP growth rate < Average	GDP growth rate > Average	Difference	t
1	-1.24	2.11	3.35	3.58
2	-0.92	2.01	2.93	3.51
3	-0.67	1.85	2.52	3.27
4	-0.55	1.42	1.97	2.85
5	-0.08	1.53	1.61	2.35
6	-0.15	1.59	1.74	2.75
7	0.04	1.53	1.49	2.40
8	0.00	1.44	1.43	2.43
9	0.29	1.30	1.01	1.74
10	0.28	1.28	1.01	1.96

Table 8.2.1 shows a clear pattern in returns during up-turns and downturns of the economy. Each of the ten portfolios earns higher returns when next quarter GDP growth rate is higher than the average. The difference in returns ranges from 1.01% per month for the highest z-score portfolio to 3.35% per month for the lowest z-score portfolio. The difference in returns between the two states of the economy is statistically significant for eight of the ten portfolios. During downturns, the distressed firms (negative z-score) earn lower returns than non-distressed firms and there is an almost monotonic relationship between z-scores and average returns. Portfolio 1 underperforms portfolio 5 by 1.16% per month and underperforms portfolio 10 by 1.52% per month. Portfolio 6 also underperforms portfolio 10, though by a smaller 0.43% per month. During up-turns, the relationship between z-scores and average returns is again monotonic but the pattern is now reversed with the distressed firms earning higher returns than non-distressed firms. Now, portfolio 1 outperforms portfolio 5 by 0.58% per month and outperforms portfolio 10 by 0.83% per month. Portfolio 6 also outperforms portfolio 10 by a smaller 0.31% per month. The differences though

statistically insignificant are economically large. The results provide prima facie evidence of strong time variation in stock returns and this time variation is linked to the state of the economy.

Table 8.2.2 presents the difference in average monthly excess returns during upturns and downturns of the economy for the twenty four portfolios formed on size, B/M and z-score.

Table 8.2.2: Average monthly excess returns under different economic conditions
At the end of September of each year from 1979 to 1999, all the stocks in my population 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 four portfolios and independently ranked on B/M and grouped into three portfolios. 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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively. Twenty-four portfolios are then formed at the intersections of size, B/M and z-score. Average excess returns is the time series average of the difference between monthly stock returns and one-month T- bill rate observed at the beginning of the month. The difference in excess returns is the difference in portfolio returns between up- and down-states of the economy. The portfolios are rebalanced at the end of September each year. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. The last month returns for failed firms are set equal to –100%.

	Low B/M		**Mid B/M**		**High B/M**		**Low B/M**		**Mid B/M**		**High B/M**	
	z<0	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**	**z<0**	**z>0**
	Difference in monthly excess returns(%)						*t*					
Small	3.08	2.47	3.76	2.27	3.45	2.11	2.94	2.38	4.01	3.34	4.07	3.62
2	1.09	0.92	2.11	1.76	2.31	1.91	1.18	1.32	2.67	3.02	2.74	3.17
3	1.86	0.68	0.84	1.21	2.87	1.29	1.98	1.08	0.96	1.98	2.97	2.03
Big	0.96	0.44	1.43	0.98	0.75	1.67	1.29	0.67	1.77	1.42	0.77	2.09

Table 8.2.2 shows that all the twenty four portfolios earn higher returns when economic conditions are expected to be good. The table also shows that the return differences are most pronounced for the smallest size quartile. The return differences are also more pronounced for negative z-score stocks as compared to positive z-score stocks of same

size and B/M. These are precisely the securities that are likely to be riskier and therefore more sensitive to broad market movements. The evidence here supports that in table 8.2.1 regarding time variation in equity returns that is linked to the state of the economy.

Table 8.2.3 provides further evidence regarding time variation of stock returns and, in particular, the time variation in risk premia that is related to the state of the economy. Since GDP growth rates are available only quarterly, I have used quarterly stock returns to estimate the coefficients of beta, size, B/M and z-score for different trading rules and alternative asset pricing equations.

Table 8.2.3: Correlations between risk premia and next quarter GDP growth rates:

The table presents the coefficients of correlation between the F-M regression slopes and next quarter GDP growth rates.

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and 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 accounts divided by the market value of equity on 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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.

R_{it} is the equally-weighted return on portfolio i during quarter t and R_{Ft} is the three-month Treasury bill rate at the beginning of quarter t. β_{it-1} is the beta of portfolio i estimated at the end of September of year t. $\ln(size_{it-1})$ 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 end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 84 quarters from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. The quarterly GDP growth rates refer to the growth in output at constant prices.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} z_{it-1} + \gamma_{3t} z(0/1)_{it-1} + \gamma_{4t} \ln(size_{it-1}) + \gamma_{5t} \ln(B/M_{it-1})$				
γ_1	γ_2	γ_3	γ_4	γ_5
A. Z-score portfolios				
0.13		0.31^{**}		
0.01			-0.21^{*}	0.08
0.04		0.02	-0.17	0.10
-0.01	-0.27^{**}		-0.20	-0.03
B. Size, B/M and Z-score portfolios				
0.07		0.33^{**}		
0.09			-0.44^{**}	0.03
-0.05		0.34^{**}	-0.44^{**}	0.03
-0.06	-0.40^{**}		-0.44^{**}	0.01

* denotes significance at 5% level
** denotes significance at 1% level

The correlations between coefficients on beta and GDP growth rates are low showing that a fundamental aspect of risk linked to macro-economic movements is being captured here that is not merely due to movements in the stock market.

In panel A of table 8.2.3, the correlation between the coefficient on z-score dummy and next quarter GDP growth rate is 0.31 when beta and z-score are the only two explanatory variables. The high correlation shows that the risk premium on negative z-score stocks varies in line with expectations regarding the state of the economy. If the economy is expected to do badly, riskier firms are badly hit and there is a flight towards quality. The evidence here suggests that z-score is a 'state variable' in the context of Merton's (1973) ICAPM. On the other hand, the B/M coefficient has a low correlation with GDP growth rates with or without z-scores in the pricing equation casting doubt as to whether it is a state variable. Thus the evidence here for the B/M effect seems consistent with that in chapter 6 where it did not appear to covary much with state of the market. Size effect is negatively correlated to the GDP growth rate i.e. size premium is lower when the economy is expected to do badly and higher when the economy is expected to do well. This is consistent with size being a 'state variable' since we would expect smaller firms to be hit harder by economic downturns and, therefore, a lower size premium during such periods. The evidence here supports the view that smaller firms are fundamentally riskier than larger firms. Interestingly, in the four-factor model, there is no correlation between coefficient on z-score dummy and GDP growth rate once size and B/M are added to the asset pricing equation. This would suggest that the z-score effect is a manifestation of some common underlying risk factor that is also picked up by size and/or B/M. However, the correlation between the coefficient of z-score as a continuous variable and GDP growth rates remains strong and negative suggesting that during periods of economic downturns, higher z-score stocks do better than lower z-score stocks as expected.

In panel B of table 8.2.3, the correlation between the coefficient on z-score dummy and next quarter GDP growth rate is 0.33 when beta and z-score are the only two explanatory variables showing that the correlation between z-score premium and GDP growth rates is robust to alternative trading rules. As in panel A, the B/M coefficient has little correlation with GDP growth rates with or without z-scores in the pricing equation. Size effect is now very strongly negatively correlated to the GDP growth rate ($r = -0.44$) i.e. size premium is lower when the economy is expected to do badly and higher when the economy is expected to do well. The correlation coefficient is not influenced by the presence of z-score in the pricing equation showing that the size premium is independent of any z-score effect. Unlike panel A, the correlation between the coefficients on z-score dummy and GDP growth rate is uninfluenced by the presence of size and B/M in the asset pricing equation. This would suggest that size and z-score effects are capturing separate underlying risk factors. The correlation between the coefficient of z-score as a continuous variable and GDP growth rates remains strong and negative (r = -0.40) suggesting, again, that during periods of economic downturns, higher z-score stocks do better than lower z-score stocks as expected.

The evidence in table 8.2.3 suggests that the z-score premium is time varying and inversely related to expected economic conditions. The evidence is consistent with z-scores proxying for a fundamental priced risk factor. The evidence on size premium is similar. There is a strong correlation between size premium and GDP growth rates and the direction of the relationship is as expected, i.e. the size premium is smaller during downturns and bigger during upturns. There is no evidence that B/M premium is related to the state of the economy; there is no significant correlation between the coefficients on B/M and GDP growth rates.

8.3. Tests of hypotheses

In this section I bifurcate the months according to the state of the economy (i.e. whether the next quarter GDP growth rate is above or below the long run average growth rate) and conduct formal tests of the hypotheses discussed in chapter 3 (section 3.2.7). I use the same three trading rules as in chapter 6: ten portfolios formed on z-scores, twenty-four portfolios formed on size, B/M and z-scores (4X3X2) and finally individual securities i.e. no portfolio formation. The results with quarterly buy-and-hold returns are similar to the results with monthly returns reported here.

Do the returns on distressed stocks vary with the state of the economy?

If the bankruptcy risk is a systematic risk factor, the distressed firms will underperform during bad states of the economy and outperform during good states of the economy. Thus, hypothesis $H1_0$ can be restated as:

$H1'_0$: *Controlling for the market factor, there is no difference in the performance between financially distressed and non-distressed firms in good and bad states of the economy.*

The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. To test this hypothesis, separate cross-sectional regressions are carried out for the following two models, one with z-score as a continuous variable and the other with z-score as a dummy variable (takes the value of 1 when z-score is negative and takes a value of 0 if z-score is positive) for good and bad states of the economy:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\,z_{it-1} \tag{5}$$

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{3t}\,z(0/1)_{it-1} \tag{6}$$

If the hypothesis holds, we would expect γ_2 (γ_3) to be indistinguishable from zero for both states of the economy. Table 8.3.1 presents the results of bifurcating the quarters into up and down states of the economy using next quarter GDP growth rates and then running separate regressions for the two states of the economy with beta and continuous z-score as explanatory variables in one regression and beta and z-score dummy as explanatory variables in the other.

Table 8.3.1: Regression results with beta and z-score

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

No portfolios are formed in panel C.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the equally-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. Figures in brackets are the respective t-statistics.

$R_{it} - R_{Ft} = \alpha_t + \gamma_{1t}$ **Beta**$_{it-1} + \gamma_{2t}\, z_{it-1} + \gamma_{3t}\, \mathbf{z(0/1)}_{it-1} + \varepsilon_t$			
α	γ_1	γ_2	γ_3
A. Z-score portfolios			
GDP growth rate < Average growth rate			
-0.0133	0.0092	0.0005	
(-1.43)	(1.16)	(2.19)	
-0.0054	0.0048		-0.0049
(-0.75)	(0.68)		(-2.71)
GDP growth rate > Average growth rate			
0.0216	-0.0035	-0.0006	
(2.41)	(-0.51)	(-2.63)	
0.0067	0.0082		0.0014
(1.04)	(1.46)		(0.81)
B. Size, B/M and z-score portfolios			
GDP growth rate < Average growth rate			
-0.0020	-0.0018	0.0007	
(-0.36)	(-0.45)	(3.21)	
0.0011	-0.0008		-0.0062
(0.21)	(-0.18)		(-3.33)
GDP growth rate > Average growth rate			
0.0205	-0.0027	-0.0003	
(4.27)	(-1.03)	(-1.67)	
0.0189	-0.0021		0.0005
(4.37)	(-0.78)		(0.38)
C. Individual securities			
GDP growth rate < Average growth rate			
0.0025	0.0042	0.0006	
(0.68)	(0.84)	(3.87)	
0.0070	0.0035		-0.0077
(2.17)	(0.70)		(-4.37)
GDP growth rate > Average growth rate			
0.0272	-0.0044	-0.0004	
(6.92)	(-1.10)	(-2.29)	
0.0243	-0.0036		0.0036
(7.52)	(-0.88)		(2.08)

Panel A of table 8.3.1 confirms the evidence of table 8.2.1. There is no significant difference in the performance of high and low beta stocks in the two states of the economy showing that the time variation being captured here is not merely due to stock market movements but linked to fundamental macro-economic variables. During periods of expected economic downturn, high z-score stocks outperform low z-score stocks and during periods of economic upturns, high z-score stocks underperform low z-score stocks, the coefficients in both the states are more than two standard errors from zero. When z-score is used as a binary variable, the distressed portfolios underperform non-distressed portfolios by 49 basis points per month during expected downturns and the coefficient is more than two standard errors from zero. During expected upturns, the distressed firms outperform non-distressed firms by a small 14 basis points per month; the coefficient is indistinguishable from zero but the direction of the relationship is as hypothesized. The results are also confirmed by a non-parametric test for population proportions. During downturns, the coefficient of z-score as a binary variable is negative in 78 out of 120 months, this difference in proportions is statistically significant at 5% (test statistic is 3.29). The evidence here provides a strong rejection of the null hypothesis of time invariance.

Panel B of table 8.3.1 confirms the evidence of table 8.2.2. Again, the performance of high and low beta firms in the two states of the economy is similar. During periods of expected downturn, higher z-score firms outperform lower z-score firms by 7 basis points per month and the coefficient is more than two standard errors from zero. The difference in performance is statistically insignificant during periods of expected economic downturn. When z-score is used as a binary variable, the distressed portfolios underperform non-distressed portfolios by 62 basis points per month during expected downturns and the coefficient is more than two standard errors from zero. During expected upturns, the distressed firms outperform non-distressed firms by a small 5 basis points per month, the coefficient is indistinguishable from zero. The results are again confirmed by a non-parametric test for population proportions. During downturns, the coefficient of z-score as a binary variable is negative in 77 out of 120 months, the difference in proportions is statistically significant at 5% (test statistic is 3.10). The evidence here again strongly rejects the null hypothesis.

Panel C of table 8.3.1 shows that there is little difference in the performance of high and low beta firms in the two states of the economy. During periods of expected downturn, higher z-score firms outperform lower z-score firms by 6 basis points per month and during periods of expected upturn, higher z-score firms underperform lower z-score firms by 4 basis points per month and the coefficients are more than two standard errors from zero. When z-score is used as a binary variable, the distressed stocks underperform non-distressed portfolios by 77 basis points per month during expected downturns and the coefficient is more than two standard errors from zero. During expected upturns, the distressed firms outperform non-distressed firms by 36 basis points per month and the coefficient is statistically significant. The results are again confirmed by a non-parametric test for population proportions. During downturns, the coefficient of z-score as a binary variable is negative in 80 out of 120 months, the difference in proportions is statistically significant at 5% (test statistic is 3.65). The evidence here once again strongly rejects the null hypothesis.

The evidence of table 8.2.3 is confirmed in table 8.3.1. The low correlations between beta coefficient and GDP growth rates and no difference in the returns on high and low beta stocks in the two states of the economy show that the dimension of risk being captured here is different to that related to stock market movements. The results in table 8.3.1 show that distressed firms underperform non-distressed firms during periods of expected economic downturns. These results are robust to alternative trading rules and are not driven by outliers as shown by non-parametric tests of sample proportions. The evidence also shows that the underperformance of distressed firms is not due to movements in the stock market but is linked to the macroeconomic variables suggesting that z-score is a 'state variable'. Even though distressed stocks do not register significant outperformance during upturns for all trading rules, the sign of the coefficient is always consistent with bankruptcy risk being systematic. The evidence here strongly rejects the null hypothesis of no difference in performance in up and down states of the economy.

Are size and B/M effects related to distress risk?

If size and B/M are capturing systematic risk, then smaller firms and high B/M firms will underperform during bad states and outperform during good states of the economy. If z-score is proxying for the same risk factor as size and B/M and it is introduced in the regressions then either the z-score will subsume the size and B/M effects or will be subsumed by them. Hypothesis $H2_0$ can be restated as:

$H2'_0$: *The coefficient on z-score is insignificant when size & B/M are included in the asset pricing equation and size and B/M effects are uninfluenced by inclusion of z-score in the asset pricing equation, in both, good and bad states of the economy.*

To test this hypothesis, separate cross-sectional regressions are carried out for each state of the economy for the following three models, one without the z-score variable, one with z-score as a continuous variable and one with z-score as a dummy variable that takes the value of 1 when z-score is negative and takes a value of 0 if z-score is positive:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \tag{7}$$

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\,z_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \tag{8}$$

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{3t}\,z(0/1)_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \tag{9}$$

If hypothesis $H2'_0$ holds, γ_2 (γ_3) would be indistinguishable from zero in this regression while the coefficients γ_4 and γ_5 will not be affected by introduction of z-score in the regression. Also, to be consistent with the risk based explanation, γ_4 will be positive and γ_5 negative in downturns while γ_4 will be negative and γ_5 positive during upturns.

Table 8.3.2 presents the results of bifurcating the months into up and down states of the economy using next quarter growth rates and then running separate regressions for the two states of the economy.

Table 8.3.2: Regression results with beta, size, B/M and z-score

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

No portfolios are formed in panel C.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the equally-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. $\ln(size_{it-1})$ 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 end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. Figures in brackets are the respective t-statistics.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\,z_{it-1} + \gamma_{3t}\,z(0/1)_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1})$					
α	γ_1	γ_2	γ_3	γ_4	γ_5
A. Z-score portfolios					
GDP growth rate < Average growth rate					
0.0261	0.0070			-0.0017	-0.0131
(0.75)	(0.74)			(-1.02)	(-1.57)
0.0115	0.0080	0.0006		-0.0013	-0.0027
(0.29)	(0.79)	(1.51)		(-0.69)	(-0.23)
0.0340	0.0032		-0.0029	-0.0020	-0.0104
(0.86)	(0.32)		(-1.12)	(-1.03)	(-1.05)
GDP growth rate > Average growth rate					
0.0834	-0.0104			-0.0030	0.0063
(3.07)	(-1.45)			(-2.30)	(1.05)
0.0869	-0.0106	-0.0005		-0.0029	0.0028
(3.05)	(-1.11)	(-1.88)		(-2.12)	(0.42)
0.0968	-0.0051		-0.0040	-0.0039	0.0075
(3.05)	(-0.64)		(-1.58)	(-2.56)	(1.16)
B. Size, B/M and z-score portfolios					
GDP growth rate < Average growth rate					
-0.0108	-0.0072			0.0009	0.0001
(-0.72)	(-1.71)			(1.12)	(0.05)
-0.0232	-0.0006	0.0009		0.0012	0.0007
(-1.48)	(-0.15)	(3.90)		(1.42)	(0.45)
-0.0206	0.0004		-0.0074	0.0012	0.0004
(-1.33)	(0.09)		(-4.12)	(1.51)	(0.26)
GDP growth rate > Average growth rate					
0.0523	-0.0032			-0.0020	0.0032
(3.36)	(-1.35)			(-2.43)	(2.44)
0.0511	-0.0028	-0.0001		-0.0019	0.0035
(3.20)	(-1.26)	(-0.60)		(-2.35)	(2.63)
0.0510	-0.0026		-0.0002	-0.0019	0.0033
(3.24)	(-1.14)		(-0.16)	(-2.37)	(2.52)
C. Individual securities					
GDP growth rate < Average growth rate					
0.0026	0.0023			0.0002	-0.0009
(0.19)	(0.48)			(0.29)	(-0.70)
0.0013	0.0048	0.0006		0.0000	-0.0004
(0.09)	(1.04)	(4.33)		(0.06)	(-0.33)
0.0089	0.0045		-0.0079	-0.0002	-0.0008
(0.65)	(0.96)		(-5.28)	(-0.19)	(-0.63)
GDP growth rate > Average growth rate					
0.0641	0.0069			-0.0028	0.0029
(4.19)	(1.98)			(-3.19)	(2.39)
0.0632	0.0060	-0.0001		-0.0026	0.0028
(4.15)	(1.81)	(-0.84)		(-3.09)	(2.37)
0.0637	0.0068		0.0002	-0.0027	0.0028
(4.26)	(2.00)		(0.19)	(-3.23)	(2.43)

Table 8.3.2 panel A shows that smaller firms outperform larger firms during economic upturns and do no worse during economic downturns. The results remain the same whether z-score is present in the pricing equation or not. The B/M effect does not exist in either state of the economy and, again, the results are not affected by the presence of z-score in the model. The z-score effect also becomes statistically insignificant in the presence of size and B/M in the pricing equation. The results suggest that size and B/M are capturing part of the distress factor since the z-score effect is smaller in their presence.

Table 8.3.2 panel B shows that smaller firms outperform larger firms during economic upturns and do no worse during economic downturns. The results are consistent with size being a priced risk factor with smaller firms being riskier and more sensitive to changes in the economy. Similarly, high B/M firms outperform low B/M firms during periods of expected economic upturns and do no worse during the periods of expected economic downturns. The results remain the same whether z-score is present in the pricing equation or not. Higher z-score firms do better during economic downturns and do no worse during expected upturns. Distressed firms underperform non-distressed firms by 74 basis points per month during downturns while there is no difference in performance during economic upturns. The non-parametric test of proportions shows that the coefficient of z-score dummy is negative in 79 of the 120 down months, a difference that is significant at the 5% level (z = 3.47). A comparison of the results here with those is table 8.3.1 panel B shows that the z-score coefficient is almost uninfluenced by size and B/M. The results suggest that the z-score effect is independent of size and B/M effects and is manifested in a different state of the economy than the other two effects.

Table 8.3.2 panel C shows that smaller firms outperform larger firms during economic upturns and do no worse during economic downturns. Similarly, high B/M firms outperform low B/M firms during periods of expected economic upturns and do no worse during the periods of expected economic downturns. The results are uninfluenced by the z-score. Higher z-score firms do better during economic downturns and do no worse during expected upturns. Distressed firms underperform non-distressed firms by 79 basis points per month during downturns while there is no difference in performance during economic upturns. The non-parametric test of proportions shows that the coefficient of the z-score dummy is negative in 86 of the 120 down months, a difference that is significant at the 5% level ($z = 4.75$). A comparison of the results here with those is table 8.3.1 panel C show that the z-score coefficient is almost uninfluenced by size and B/M. The results again suggest that the z-score effect is independent of the size and B/M effects and is manifested in a different state of the economy than the other two effects.

These results indicate that low z-score firms and negative z-score firms underperform during bad states of the economy. These are the periods when the marginal utility of wealth of investors is higher and the results are consistent with z-score being a priced risk factor. During upturns distressed stocks do not register significant outperformance but the sign of the coefficient is generally consistent with z-scores representing a systematic risk factor. Small size firms and high B/M firms do not fare worse than larger firms and low B/M firms during periods of expected downturns while they do better during expected upturns of the economy. The z-score effect is independent of size and B/M effects and size and B/M effects are independent of the z-score effect. The evidence here is consistent with z-scores being related to some fundamental risk factor. The evidence for size and B/M is not clear. However, even if size and B/M are systematic risk factors, they are unlikely to be related to the same risk factor as z-scores. The results here provide a strong rejection of the null hypothesis $H2'_0$.

Is the risk of bankruptcy asymmetric?

If z-scores are capturing asymmetry in bankruptcy risk, there would be a strong association between excess returns and z-score when z-score is negative and there would be little or no association between z-score and excess returns when z-score is positive. Also, more negative z-score firms will underperform less negative z-score firms during downturns and outperform during upturns. The variation in the excess returns of positive z-score firms will be much less with the state of the economy. Thus, hypothesis $H3_0$ can be restated as:

$H3'_0$: *There is no association between z-scores and excess returns for both financially distressed and non-distressed firms in good and bad state of the economy.*

To test this hypothesis, cross-sectional regressions similar to the one above are carried out with a z-score interaction term. The interaction term is defined to be equal to the z-score when z-score is negative and zero when the z-score is positive. The following pricing equation is used for the regression:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\, z_{it-1} + \gamma_{6t}\,(z_{it-1} * z(0/1)_{it-1}) + \varepsilon_{it} \qquad (10)$$

For positive z-score stocks, z-score coefficient is γ_2 while for negative z-score stocks, z-score coefficient is $\gamma_2 + \gamma_6$.

If the hypothesis holds, then we would expect γ_6 not to be significantly different to zero. If, however, the bankruptcy risk is asymmetric (i.e. there is little change in the solvency position of a firm with a change in z-score if the z-score is positive while changes in z-score for distressed firms capture a change in solvency position), we would find γ_2 not significantly different to zero and γ_6 positive and significant in downturns and negative and significant in upturns of the economy.

Table 8.3.3 presents the results of bifurcating the months into up and down states of the economy using next quarter growth rates and then running separate regressions for the two states of the economy. The independent variables are z-score and the z-score interaction term.

Table 8.3.3: Regression results with z-score interaction term

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

No portfolios are formed in panel C.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.
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. Betas in panel C are from RMS.
R_{it} is the equally-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.
The portfolios are rebalanced at the end of September each year. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. Figures in brackets are the respective t-statistics.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} z_{it-1} + \gamma_{6t}(z_{it-1} * z(0/1)_{it-1}) + \varepsilon_{it}$			
α	γ_1	γ_2	γ_6
A. Z-score portfolios			
GDP growth rate < Average growth rate			
-0.0202	0.0171	0.0006	0.0021
(-2.34)	(2.48)	(2.57)	(2.22)
GDP growth rate > Average growth rate			
0.0203	-0.0043	-0.0003	-0.0016
(2.26)	(-0.61)	(-1.63)	(-2.24)
B. Size, B/M and z-score portfolios			
GDP growth rate < Average growth rate			
-0.0008	-0.0022	0.0005	0.0033
(-0.11)	(-0.54)	(0.70)	(1.09)
GDP growth rate > Average growth rate			
0.0086	-0.0032	0.0014	-0.0057
(1.39)	(-1.29)	(1.96)	(-2.03)
C. Individual securities			
GDP growth rate < Average growth rate			
0.0042	0.0045	0.0003	0.0024
(1.14)	(0.89)	(2.15)	(3.12)
GDP growth rate > Average growth rate			
0.0263	-0.0043	-0.0002	-0.0004
(7.13)	(-1.09)	(-1.60)	(-0.72)

Table 8.3.3 panel A shows that during downturns, for non-distressed portfolios, the z-score coefficient is +6 basis points and statistically significant. For the distressed portfolios, the z-score coefficient is a much larger +27 basis points (0.0006 + 0.0021) and the difference between the two is statistically significant (t = 2.22). The higher the z-score, the better the performance during downturn and the interaction term shows that

the effect is much stronger for distressed firms i.e. during downturns, the underperformance of more negative z-score firms relative to less negative z-score firms is worse than the underperformance of less positive z-score firms relative to more positive z-score firms. During upturns, for non-distressed portfolios, the z-score coefficient is –3 basis points and statistically insignificant. For the distressed portfolios, the z-score coefficient is –19 basis points (-0.0003 - 0.0016) and the difference between the two is significant (t = 2.24). The results show that during economic upturns the lower the z-score, the better the returns though the returns difference is not significant for non-distressed portfolios. The interaction term shows that the effect is strong for distressed firms and more distressed firms reliably outperform less distressed firms. The results show a clear asymmetry in response of distressed and non-distressed stock returns to expected good or bad economic conditions. The evidence here is consistent with bankruptcy risk being a systematic risk factor with distressed firms being more sensitive to expected changes in economic conditions and leads to rejection of the null hypothesis.

Table 8.3.3 panel B shows that during downturns, for non-distressed portfolios, the z-score coefficient is +5 basis points and statistically insignificant. For the distressed portfolios, the z-score coefficient is +38 basis points (0.0005 + 0.0033) though the difference between the two is statistically insignificant (t = 1.09). The higher the z-score, the better the performance during downturn and the interaction term shows that the effect is much stronger for distressed firms i.e. during downturns, the underperformance of more negative z-score firms relative to less negative z-score firms is worse than the underperformance of less positive z-score firms relative to more positive z-score firms. However, no conclusions can be drawn since the coefficients are statistically insignificant. During upturns, for non-distressed portfolios, the z-score coefficient is 14 basis points and marginally statistically significant ($t = 1.96$). For the distressed portfolios, the z-score coefficient is –43 basis points (0.0014 - 0.0057) and the difference between the two is statistically significant ($t = 2.03$). The results show that during economic upturns, for non-distressed portfolios, the higher the z-score, the better the returns but for distressed firms, a more negative z-score leads to superior performance. The results clearly show asymmetric response of distressed and non-distressed stock returns to expected good or bad economic conditions. There is no significant difference in returns during expected economic downturns. However, during the periods of expected economic upturn, firms at higher bankruptcy risk do better than firms with lower bankruptcy risk. The evidence here is consistent with bankruptcy risk being a systematic risk factor with distressed firms being more sensitive to expected changes in economic conditions and again rejects the null hypothesis.

Table 8.3.3 panel C shows that during downturns, for non-distressed portfolios, higher z-score firms outperform lower z-score firms by 3 basis points per month and the coefficient is more than two standard errors from zero. The interaction term shows that for negative z-score firms, higher z-score leads to a 27 basis points per month underperformance (0.0003 + 0.0024), the difference being statistically significant. During upturns, there is no relationship between z-scores and returns for neither distressed nor non-distressed firms. The results again show the asymmetric response of distressed and non-distressed stock returns to expected good or bad economic conditions. There is no significant difference in returns during expected economic upturns. However, during periods of expected economic downturns, firms at higher bankruptcy risk do worse than firms with lower bankruptcy risk. The evidence here once again rejects the null hypothesis.

Evidence in table 8.3.3 shows that there is a clear asymmetry in response of distressed and non distressed firms to future expected economic conditions. The results indicate that there is little relationship between z-scores and returns when z-scores are positive and there is a strong relationship between z-scores and returns when z-scores are negative. Consistent with bankruptcy risk being systematic, the relationship is different in different states of the economy. The results are robust to three different trading rules employed here and provide a clear rejection of the null hypothesis in each case. The evidence is consistent with z-scores capturing bankruptcy risk and that bankruptcy risk is systematic.

Do size and B/M reflect asymmetric bankruptcy risk?

The previous analysis shows that the bankruptcy premium is greater in negative z-score portfolios. If size and B/M are proxies for bankruptcy risk, they would be stronger in negative z-score portfolios. So, in bad states of the economy, the size coefficient will be positive and B/M coefficient negative for the negative z-score portfolios. To test this hypothesis $H4_0$ can be restated as:

$H4'_0$: ***There is no association between size, B/M and excess returns for both, financially distressed and non-distressed firms in either state of the economy.***

To see the interaction of size and B/M with z-score, I conduct regressions with interaction terms of z-score(0/1) with size and B/M. If the size and B/M factors are capturing bankruptcy risk, they will exhibit the same asymmetry i.e., the size and B/M effects will be at least stronger for the distressed firms than for the non-distressed firms. To test this, I use the following pricing equation:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{4t}\ln(Size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \gamma_{7t}\,(\ln(size_{it-1}) * z(0/1)_{it-1}) + \gamma_{8t}\,(\ln(B/M_{it-1}) * z(0/1)_{it-1}) + \varepsilon_{it} \qquad (11)$$

If size and B/M reflect asymmetric bankruptcy risk, the coefficient γ_7 will be negative and γ_8 will be positive during upturns and the coefficient γ_7 will be positive and γ_8 will be negative during downturns. γ_4 and γ_5 will be weak. Table 8.3.4 presents the results of bifurcating the quarters into up and down states of the economy using next quarter growth rates and then running separate regressions for the two states of the economy.

Table 8.3.4: Regression results – interaction terms of size & B/M with the z-score

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

No portfolios are formed in panel C.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the equally-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. $\ln(size_{it-1})$ 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 end of September of year t. $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. Figures in brackets are the respective t-statistics.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{4t}\ln(Size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \gamma_{7t}(\ln(size_{it-1})^{*} z(0/1)_{it-1}) + \gamma_{8t}(\ln(B/M_{it-1})^{*} z(0/1)_{it-1}) + \varepsilon_{it}$					
α	γ_1	γ_4	γ_5	γ_7	γ_8
A. Z-score portfolios					
GDP growth rate < Average growth rate					
0.0190	0.0110	-0.0014	-0.0091	-0.0008	-0.0142
(0.49)	(1.00)	(-0.73)	(-1.06)	(-0.70)	(-0.53)
GDP growth rate > Average growth rate					
0.0685	0.0078	-0.0030	0.0067	0.0010	-0.0293
(2.14)	(0.98)	(-1.91)	(0.95)	(1.25)	(-1.71)
B. Size, B/M and z-score portfolios					
GDP growth rate < Average growth rate					
-0.0226	-0.0008	0.0013	0.0000	-0.0003	0.0000
(-1.46)	(-0.17)	(1.65)	(0.00)	(-2.66)	(-0.01)
GDP growth rate > Average growth rate					
0.0517	-0.0027	-0.0020	0.0032	0.0000	0.0000
(3.23)	(-1.19)	(-2.41)	(2.19)	(0.45)	(0.01)
C. Individual securities					
GDP growth rate < Average					
0.0061	0.0045	0.0000	-0.0001	-0.0004	-0.0023
(0.45)	(0.95)	(0.01)	(-0.11)	(-4.07)	(-1.52)
GDP growth rate > Average					
0.0635	0.0070	-0.0027	0.0031	0.0000	-0.0008
(4.22)	(2.07)	(-3.22)	(2.59)	(0.30)	(-0.56)

Table 8.3.4 panel A shows that during downturns there is no size effect nor is there a B/M effect. This is true for both positive and negative z-score portfolios. During upturns, the size effect is 30 basis points per month for positive z-score portfolios. For negative z-score portfolios, smaller firms register 20 basis points per month (-0.0030 + 0.0010) outperformance. The t-statistics for the interaction term of size and z-score shows that the difference of size effect between negative and positive z-score firms is statistically insignificant (t = 1.25) and economically small (10 basis points). The B/M effect is not statistically significant in both positive and negative z-score portfolios. The risk based explanation for size effect would suggest that smaller distressed firms being riskier, would do better than larger distressed firms during periods of economic upturns

but the results do not support this. It would also suggest the opposite during downturns, i.e. small distressed firms will do worse than large distressed firms, an implication not supported by the evidence here. Also, there is no evidence of differential B/M effect either in distressed and non-distressed portfolios, nor in up and down states of the economy. The evidence here cannot reject the null for size effect or for B/M effect.

Table 8.3.4 panel B shows that during downturns there is no size effect for positive z-score portfolios while smaller distressed firms do better than larger distressed firms. The evidence is contrary to the distress factor hypothesis. However, the difference is economically insignificant (3 basis points per month). There is no B/M effect for distressed or non-distressed firms. During upturns, the size effect is 20 basis points per month for both the positive and the negative z-score portfolios. The B/M effect is 32 basis points per month and, again, it is the same for both distressed and non-distressed firms. Table 8.3.4 panel C shows similar results for individual securities. The evidence here cannot reject the null hypothesis and supports evidence in chapter 6 that there is little if any relationship between bankruptcy risk and size and B/M effects.

8.4 Size and B/M effects in the twenty-five size and B/M portfolios

In this sub-section, I investigate the size and B/M effects in the twenty-five portfolios formed on size and B/M, again bifurcating the analysis into upturns and downturns. If size and B/M are capturing a systematic risk factor missed by the market factor and small stocks and high B/M stocks are fundamentally riskier, then they will underperform during expected downturns, as investors will move towards safer stocks. Table 8.4.1 presents the results.

Table 8.4.1: Regression results with beta, size and B/M

At the end of September of each year from 1979 to 1999, all the stocks in the population are ranked on market capitalization and grouped into five portfolios. The stocks are also independently sorted on B/M and grouped into five portfolios. 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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively. Twenty-five portfolios are then formed at the intersections of size and B/M. 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 sum of slopes in the regression of the return on portfolio i on the current, prior and next month's market returns estimated at the end of September of year t. $\ln(size_{it-1})$ is the natural logarithm of average of market capitalizations of stocks in portfolio i at the end of September of year t. $\ln(B/M_{it-1})$ is the natural logarithm of average of B/M ratios of stocks in portfolio i at the end of September of year t. α, γ_1, γ_2 and γ_3 are regression parameters from Fama-MacBeth cross-sectional regressions. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. Figures in brackets are the respective t-statistics. The last month returns for failed firms are set equal to –100%.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{3t}\ln(size_{it-1}) + \gamma_{4t}\ln(B/M_{it-1})$			
α	γ_1	γ_3	γ_4
A. GDP growth rate < Average growth rate			
-0.0066	-0.0040	0.0006	-0.0005
(-0.45)	(-0.94)	(0.77)	(-0.33)
B. GDP growth rate > Average growth rate			
0.0612	-0.0033	-0.0023	0.0038
(3.86)	(-1.19)	(-2.83)	(2.84)

Table 8.4.1 panel A shows that beta is negative but not statistically significant in either state of the economy. During downturns there is no difference in the returns of smaller and larger stocks, nor is there any difference between the returns on low and high B/M

stocks. Panel B shows that during upturns, small firms outperform larger firms by 23 basis points per month and the coefficient is more than two standard errors from zero. The high B/M firms outperform low B/M firms by 38 basis points per month and the coefficient is again more than two standard errors from zero. The risk based explanation for size and B/M effects implies that smaller firms and high B/M firms being riskier would underperform when economic conditions are expected to be bad and outperform when economic conditions are expected to be good. The evidence here is partly consistent with the risk based explanation, it records outperformance under good economic conditions but no significant underperformance during bad states of the economy, though the sign of the coefficients during downturns is in the right direction.

8.5 Summary

This chapter follows on from the unconditional analysis in chapter 6 and analyses the relation of size, B/M and z-scores with excess returns under different economic conditions and different trading rules. I show that there is strong time variation in UK stock returns for the period 1979 to 2000 and this time variation is associated with the state of the economy. Distressed stocks (negative z-score) earn significantly different returns during downturns and upturns in the economy (measured by growth in GDP at constant prices). If the risk of bankruptcy is a systematic risk and z-scores are proxying for this 'state variable', the z-score risk premium will be sensitive to the state of the economy. Analysis in this chapter shows that this is indeed the case. In the four-factor model with beta, size and B/M, the correlation between z-score coefficient and next quarter GDP growth rate is 0.34 when z-score is used as a dummy variable and portfolios are formed on size, B/M and z-score. This correlation coefficient is highly significant (t = 3.23). Even when z-score is used as a continuous variable, the correlation coefficient with GDP growth rate is –0.40 and highly significant (t = 3.93). The risk based explanation for z-score effect predicts that lower z-score firms, being subject to higher bankruptcy risk will be hit harder during economic downturns and earn lower returns. The correlation coefficients show that there is an inverse relationship between GDP growth rate and returns on distressed stocks. The low correlation between beta and GDP growth rates confirm that the time variation recorded here is not due to stock market movements but is linked to a fundamental risk factor.

In chapter 6, I recorded that there is very little ex-post bankruptcy risk for positive z-score stocks (only 6 out of 185 failures had positive z-scores). Consistent with the findings of Dichev (1998), there is little variation in bankruptcy risk that is related to z-scores when z-scores are positive. I hypothesised that the relationship between z-scores and returns will also be asymmetric, i.e. there will be a relationship when z-scores are negative but little relationship when z-scores are positive. Consistent with the asymmetric bankruptcy risk hypothesis, the z–score effect is much stronger in the negative z-score stocks as compared to positive z-score stocks. Also, consistent with bankruptcy risk being systematic, the z-score effect is stronger for negative z-score stocks during economic downturns, i.e. distressed stocks are hit harder during downturns while the relationship between z-scores and returns is almost flat for non-distressed stocks. These conclusions are robust to alternative trading strategies employed in this study.

The correlation coefficient between size and GDP growth rate is negative and significant for portfolios formed on size, B/M and z-scores. The correlation is still negative (though marginally statistically significant) for z-score portfolios. A negative coefficient implies that the size effect is weaker during upturns and stronger during downturns. Results are as expected; smaller firms, being riskier, will be hit harder by economic downturns and should therefore underperform during these periods while these firms will prosper during upturns and outperform during these periods. Further analysis in table 8.3.2 finds that though smaller firms do not underperform during downturns, they do outperform during upturns. The coefficient on size is also unaffected by the presence of z-score suggesting that the two are capturing different risks. There is very low correlation between B/M coefficient and GDP growth rates suggesting no relationship between the value effect and fundamental risk factors. However, further analysis shows that while there is no relationship between B/M and returns during economic downturns, high B/M stocks outperform low B/M stocks during economic upturns. The evidence is consistent with size and B/M being related to some fundamental risk factor different to z-scores.

If size is capturing the firm distress factor in returns, its effect should be weaker in distressed firms during economic downturns and stronger during economic upturns. I find that, contrary to this hypothesis, the size effect is stronger in distressed firms during downturns. However, the difference in the returns on small distressed stocks and large distressed stocks is economically very negligible. Also, during upturns, there is no size effect in the distressed stocks. The size effect is driven by non-distressed stocks during economic upturns. The evidence here confirms that elsewhere – there is little relation between the size effect and bankruptcy risk. I find the same results for the B/M effect – the effect is driven by non-distressed firms during economic upturns and there is little relation between B/M effect and bankruptcy risk.

I have repeated the tests of hypotheses $H1'_0$ to $H4'_0$ using value weighted portfolio returns for the ten portfolios formed on z-score and for the twenty-four portfolios formed on size, B/M and z-scores. I have also repeated the tests with only the largest 50% of the stocks each year on an individual securities basis. The results are qualitatively the same (Appendix: tables A3.1 to A3.4).

The analysis in this chapter shows that bankruptcy risk is systematic with distressed stocks underperforming during periods of economic downturns and the returns are related to z-score for distressed stocks only. The evidence also shows little relation between size, B/M and bankruptcy risk though size and B/M appear to be systematic risk factors. In the final chapter I summarize the findings of this study, discuss its limitations and bring out its principal contributions to the academic literature and investment practice.

Chapter 9

CONCLUSIONS AND LIMITATIONS

Size and book-to-market ratios are powerful predictors of stock returns. The extant literature hypothesizes small size firms and high B/M firms are relatively distressed and that these factors capture the distress risk that is missed by the market factor. There has been very little work done on pricing of bankruptcy risk in equity returns to date and this thesis is an attempt to fill this gap in the literature. In this study I use z-score - an accounting based measure that is known to be a powerful predictor of firm failure as a proxy for bankruptcy risk. I explore the nature of bankruptcy risk using different portfolio methods and under different market conditions. The results seem to be sensitive to the portfolio formation method, the B/M effect vanishes when the portfolios are formed on z-score and the size effect disappears when portfolios are formed on size, B/M and z-scores. I also test the three-factor model of Fama & French (1993), which is now the dominant asset-pricing model. Fama & French (1996) argue that their three-factor model is able to explain most of the anomalies associated with the single factor CAPM. There is, however, no UK-based study that tests the ability of the model to explain stock returns in the UK. In chapter 5, I test the ability of beta, size and B/M to explain the cross-sectional variation in UK stock returns for the period 1979-2000 first by using Fama MacBeth (1973) cross-sectional regressions and then implementing the Fama & French (1993) three-factor model for the UK. I have also modified the three-factor model and added a fourth (distress) factor and then tested this four-factor model.

I find that there is a clear relation between firm size and failure, smaller firms have substantially higher mortality rates and virtually all the failures in my population of stocks belong to the smallest 20% stocks. There is also a strong relationship between B/M and failure rate as almost half the failures belonged to the highest 20% B/M stocks. However, once I control for firm size, the relationship between failure rates and B/M becomes U shaped with high failure rates for both, low and high B/M firms. This is not surprising since it is likely that the book value of distressed firms is wiped out due to continued losses resulting in low B/M ratios. High B/M firms could be those where market value has declined sharply due to adverse news putting the firms at risk of failure.

The tests on 25 portfolios formed on size and B/M show that beta is negative and statistically insignificant in cross-sectional regressions even when it is the only explanatory variable. There is no significant difference in the returns on smaller size and larger size firms during my 21 year sample period. However, I find that size premium is time varying and in chapter 7 I find that this time variation is related to the state of the economy. High B/M firms do better than low B/M firms and the difference is statistically significant until the last year's (2000) returns are included in the sample. High B/M firms registered a dramatic collapse between October 1999 and September 2000, a collapse that is mirrored in the US. This is the period when the high technology stocks boom would have hit my data (there is a lag because I require at least 24 months returns before a stock can enter my portfolios). High technology stocks during this boom were characterized by low or negative book values, very high market capitalizations and earned very high stock returns. I also find that the coefficients and t-statistics of beta, size and B/M are virtually the same in univariate and multivariate regressions suggesting that the common variation in the three variables has little relation to excess stock returns.

Though several studies have tested the size and B/M effects in the UK and several studies have used the three-factor model, there is no study that explicitly tests the model for the UK. I hope chapter 5 addresses this gap. The tests on 25 portfolios formed on size and B/M indicate that the three-factor model provides a better description of returns than the single factor CAPM. The single factor model produces adjusted R^2s that are generally below 70% and leaves residual size and B/M effects. The three factor model produces adjusted R^2s that are generally in excess of 80% and is able to capture the size and B/M effects missed by the market factor. The Fama & French (1993) three factor model, however, does not provide a complete description of returns. It leaves residual size and B/M effects in the cross-section of returns and almost a third of the intercepts are statistically significant. The model has particular difficulty in pricing small size – low B/M portfolios where the adjusted R^2s are below 60%. The results remain qualitatively the same with quarterly returns. The model fares much better when the portfolios returns are value-weighted. The adjusted R^2s are similar to those with equally-weighted portfolio returns but only 3 out of 25 intercept terms are more than two standard errors from zero.

I further test the three-factor model on ten portfolios formed on z-scores and on 24 portfolios formed on size, B/M and z-scores. The results are similar; the Fama & French (1993) three factor model does much better than the single factor model in explaining average returns. The market factor captures a lot of common variation but is unable to capture the cross-sectional variation. SMB and HML capture the cross-sectional variation missed by the market factor. However, the three-factor model does less than a perfect job, 2 out of 10 intercepts for the z-score portfolios and 11 out of 24 intercepts for the size, B/M and z-score portfolios are more than two standard errors from zero. The four-factor model with modified size factor (SMB^m) and modified B/M factor (HML^m) along with market factor and a factor mimicking the z-score (distress factor) effect (PMN) is better specified. PMN is able to capture cross-sectional variation missed by the other three factors. Also, SMB^m seems to be able to capture some cross-sectional variation related to bankruptcy risk while HML^m seems unable to do so. The three-factor model is better specified when portfolio returns are value-weighted and then performs as well as the four-factor model.

Chapter 6 analyses the relationship between bankruptcy risk and equity returns using z-scores as a proxy for bankruptcy risk. In chapter 4 I show that z-scores are powerful predictors of bankruptcy risk. In my population of stocks the z-score model used incorrectly classified only 6 out of 185 failures over twenty-one years. I show that the conditional probability of failure given a negative z-score is significantly different to the base failure rate and the conditional probability of non-failure given positive z-score is significantly different to the base rate of non-failure in the population. I find that smaller size firms have high bankruptcy risk as do negative z-score firms. However, once I control for size and z-score, there is no clear relationship between B/M and bankruptcy risk. I use two different portfolio formation methods and also conduct the analysis on an individual securities basis and find that some results are sensitive to the trading rules.

I find that beta is generally not significant over the period of this study. This conclusion is robust to different trading rules and different formulations of the asset pricing equation. This is not to say that beta is of no use in equity pricing, a bifurcation of returns into up- and down- markets shows that beta is extremely important in some states of the market. The coefficient on z-score, whether used as a continuous or a binary variable, is statistically significant for most of the asset pricing equations and the trading strategies used here.

I find that negative z-score stocks underperform positive z-score stocks over the period of this study and the amount of underperformance is not influenced by the presence or absence of size and B/M as explanatory variables in the asset pricing equation. Similarly, size and B/M coefficients are not influenced by the presence and absence of z-score in the pricing equation. These results suggest that there is little common variation between size, B/M and z-scores that is related to stock returns (Dichev (1998) reaches the same conclusion with his data) and contrary to the distress factor hypothesis, distressed stocks earn lower returns than non-distressed stocks. Fama & French (1995) argue that only a small proportion of distressed stocks actually go bankrupt, a vast majority survive and therefore, a strategy that invests in distressed stocks earns higher returns. I, however, find empirically that the proportion of distressed stocks that go bankrupt is sufficient to drive down the realised returns on the strategy of investing in distressed stocks. While the z-score effect is robust to alternative trading rules employed in this study, size and B/M effects are not. When portfolios are formed on z-scores, the B/M effect disappears. This can happen if z-score and B/M are uncorrelated because, then, sorting on z-scores can result in random sorting on B/M and consequently, the

B/M effect can vanish. The size effect is strong in z-score portfolios suggesting some link between size and distress. However, even in portfolios formed on z-scores, z-score and size coefficients are virtually independent suggesting that even if both these factors are related to distress, they are capturing different aspects of it. When portfolios are formed on size, B/M and z-scores, the size effect vanishes for the entire period. However, a time-series analysis shows that this result is sensitive to the period chosen. The B/M effect is strong until September 1999 but there is a collapse during the last twelve months of the period covered here (due to the internet bubble), a collapse that is mirrored in the US.

I find that there is strong time variation in UK stock returns for the period 1979 to 2000 and this time variation is associated with the state of the economy. Lakonishok, Shleifer and Vishny (1994) argue that riskier stocks should underperform less risky stocks during some states of the world and on average, these states should be bad states in which marginal utility of wealth is high making riskier stocks unattractive to risk averse investors. I follow this definition to assess whether z-score, size and B/M effects are systematic risks.

Bifurcating the analysis into good and bad states of the economy I find that distressed stocks (negative z-score) earn significantly different returns during downturns and upturns in the economy (measured by growth in GDP at constant prices). If the risk of bankruptcy is a systematic risk and z-scores are proxying for a 'state variable', the z-score risk premium will be sensitive to the state of the economy. In the four-factor model with beta, size and B/M, the correlation between z-score coefficient and next quarter GDP growth rate is 0.34 when z-score is used as a dummy variable and portfolios are formed on size, B/M and z-score. The correlation coefficient is highly significant (t = 3.23). Even when z-score is used as a continuous variable, the correlation coefficient with GDP growth rate is –0.40 and highly significant (t = 3.93). The risk based explanation for z-score effect predicts that lower z-score firms, being subject to higher bankruptcy risk, will be hit harder during economic downturns and earn lower returns. The correlation coefficients show that there is an inverse relationship between GDP growth rate and returns on distressed stocks. The low correlation between beta and GDP growth rates confirms that the time variation recorded here is not due to stock market movements but is linked to a fundamental risk factor.

The correlation coefficient between size and GDP growth rate is negative and significant for portfolios formed on size, B/M and z-scores. The correlation is still negative (though marginally statistically significant) for z-score portfolios. A negative coefficient implies that the size effect is stronger during upturns and weaker during downturns. The results are as expected; smaller firms, being riskier, will be hit harder by economic downturns and should therefore underperform during these periods while these firms will prosper during upturns and outperform during these periods. Further analysis in chapter 8 finds that though smaller firms do not underperform during downturns, they do outperform during upturns. The size coefficient is also unaffected by presence of z-score suggesting that the two are capturing different risks. There is very low correlation between B/M coefficient and GDP growth rates suggesting no relationship between the value effect and fundamental risk factors. However, further analysis shows that while there is no relationship between B/M and returns during economic downturns, high B/M stocks outperform low B/M stocks during economic upturns. The evidence is consistent with size and B/M being related to some fundamental risk factor though it is unlikely that they are related to the same distress risk factor as z-scores.

Dichev (1998) suggests that the relationship between z-scores and returns is different for low and high bankruptcy risk stocks. In chapter 4, I record that there is very little ex-post bankruptcy risk for positive z-score stocks (only 6 out of 185 failures had positive z-scores). Consistent with the suggestion of Dichev (1998), there is little variation in bankruptcy risk that is related to z-scores when the z-scores are positive. I hypothesize that the relationship between z-scores and returns will also be asymmetric, i.e. there will be a relationship when z-scores are negative but little relationship when z-scores are positive. My formal tests of this asymmetric bankruptcy risk find no evidence of a different relationship between z-score and returns for positive and negative z-score stocks. However, bifurcating the analysis into good and bad states of the economy alters the conclusions. Consistent with the asymmetric bankruptcy risk hypothesis, the z–score effect is much stronger in negative z-score stocks as compared to positive z-score stocks. Also, consistent with bankruptcy risk being systematic, the z-score effect is stronger for negative z-score stocks during economic downturns, i.e. distressed stocks are hit harder during downturns, while the relationship between z-scores and returns is almost flat for non-distressed stocks. These conclusions are robust to the alternative trading strategies employed in this study and provide evidence that z-scores are related to bankruptcy risk which is a fundamental risk factor.

I also hypothesize that if size and B/M are capturing the firm distress factor in returns, they should be stronger in negative z-score portfolios because that is where most of the bankruptcy risk is concentrated. Again, unconditional analysis provides no evidence that size and B/M effects are any stronger for distressed stocks. Bifurcating the analysis into good and bad states of the economy, we would expect that during bad states of the economy small distressed firms will do a lot worse than large distressed firms and high B/M distressed firms will do worse than low B/M distressed firms. In other words, during economic downturns, the regression coefficient on size will be positive for negative z-score firms and that on B/M will be negative. I find that contrary to this hypothesis, the size effect is stronger in distressed firms during downturns. However, the difference in the returns on small distressed stocks and large distressed stocks is economically negligible. Also, during upturns, there is no size effect in the distressed stocks. The results indicate that the size effect is driven by non-distressed stocks during economic upturns. The results here confirm the evidence elsewhere – there is little relation between size effect and bankruptcy risk. I find the same results for the B/M effect – the effect is driven by non-distressed firms during economic upturns and there is little relation between B/M effect and bankruptcy risk.

As to whether the bankruptcy risk is a systematic risk or not, I follow the definition of Lakonishok, Shleifer and Vishny (1994) i.e. it is the sensitivity to broad market movements. Following their argument, negative z-score stocks, small size stocks and high B/M stocks should all underperform when the market falls. I bifurcate my analysis into up and down market months and find that negative z-score stocks reliably underperform positive z-score stocks during down-markets indicating that z-scores are capturing a systematic risk factor missed by beta. These conclusions are robust to the trading strategy employed. The evidence regarding size and B/M effects is mixed. Smaller stocks seem to earn higher returns during up-markets but do no worse during down-markets. This is not entirely consistent with the risk argument since riskier firms should do badly under adverse market conditions. The findings are, however, sensitive to trading strategy and to time period. Similarly, high B/M stocks seem to outperform during down-markets, a finding that is inconsistent with these stocks being riskier. Again, the results are sensitive to trading strategy and to the time period.

Levis (1985) found January and April seasonals in UK stock returns for the period 1958-82. I conduct a seasonality study of size, B/M and z-score effects with the sole purpose of unearthing common links between the three effects and not speculating about the implications for market efficiency. I find that stock returns are higher during January, February and April during my sample period 1979-2000. I also find the size premium to be statistically significant in February and May for the period 1979-2000 (Levis (1985) finds it significant only during May). The value premium is significant in April while the z-score premium is significant in the month of September. The results indicate that the three premia are not due to some common factor since they are manifested in different months of the year. The coefficients of size, B/M and z-score in Fama-MacBeth regressions also exhibit some seasonality. B/M effect is strongest in April while the size effect is strongest in May and the z-score effect is strongest in May and September. The results indicate that the B/M effect is not linked to the same underlying risk factor as size and z-score effects. The results also indicate that while there is some commonality between size and z-score effect, z-score is also linked to some other risk factor that is independent of firm size.

To summarize, my results show that:

1. Unconditionally, distressed stocks do not earn a higher return than non-distressed firms. In fact, the returns on distressed stocks are lower than that on non-distressed stocks.

2. Distressed stocks fare better than non-distressed stocks when the stock market rises and do worse when the stock market falls suggesting that the bankruptcy risk premium covaries with the market and bankruptcy risk is systematic.

3. Size effect does not seem to be related to z-score effect and is equally strong for distressed and non-distressed securities. Though size effect seems to be related to a fundamental risk factor in stock returns, the results are sensitive to trading rules and provide little evidence that it is related to bankruptcy risk.

4. B/M effect is also unrelated to bankruptcy risk. The disappearance of any B/M effect in z-score sorted portfolios indicates no common variation between B/M and z-scores. The coefficient on B/M is uninfluenced by presence of z-score in the pricing equation. The B/M effect is equally strong in distressed and non-distressed stocks again suggesting it is unrelated to bankruptcy risk. High B/M stocks outperform during down markets casting doubts as to whether B/M is capturing systematic risk.

5. Distressed firms fare worse than non-distressed firms when the economic outlook is bad. This is consistent with the bankruptcy risk being systematic. Distressed firms are more likely to fail when economic conditions are bad and the marginal utility of wealth is higher. Investors would therefore move towards safer securities when bad states are expected.

6. Stock returns are higher during January, February and April. The B/M effect is strongest in the month of April while size effect is strongest in the month of May. Z-score effect is strongest in May and September suggesting little common variation between the three variables.

7. The Fama & French (1993) three factor model does a better job of explaining equity returns in the UK than the single factor model. However, it does not provide a complete description and several of the intercepts are more than two standard errors from zero. A four factor model with modified Fama & French (1993) factors seems better specified though unable to capture all cross-sectional variation in stock returns.

Limitations:

1. In line with all other studies, this study uses realized returns based on the assumption that over the long run, expected returns equal realised returns. Elton (1999) however, raises serious questions about this assumption.

2. The study assumes a five-month lag period between the financial year-end and the date of publication of annual report. However, it is not possible to collect the actual publication dates given the coverage of this study.

3. The study employs annual rebalancing of portfolios. This combined with the assumed lag of five months between financial year-end and the publication date means that there could be a significant gap between the availability of new accounting information and its incorporation in the study. A more frequent rebalancing would mitigate this problem but would induce spurious correlation between book-to-market and firm size because the book value changes only once a year and any more frequent changes in B/M would be purely due to change in market value of equity. My results are conservative due to less frequent portfolio rebalancing.

4. The Fama-MacBeth procedure assumes no autocorrelation and any violation can bias the t-statistics. They should hence be interpreted with this caveat in mind.

5. This study principally employs equally weighted portfolios. Such equal weighting leads to unduly high weightage to small stocks. I thus repeat my main tests with value-weighted portfolios (and with largest 50% of the stocks each

year on an individual securities basis). The results are weaker, as expected, but the z-score effect remains statistically significant in both Fama-MacBeth cross-sectional regressions and Fama & French (1993) time-series regressions.

Contribution to the theory and practice

This thesis explicitly tests the dominant explanation for a key empirical finding in the finance literature, the superior performance of high book-to-market and small size firms, viz. the distress factor hypothesis. I use a cleaner proxy for bankruptcy risk – z-score and find that contrary to the prediction of the distress factor hypothesis, distressed stocks underperform non-distressed stocks on an unconditional basis. As a further blow to the distress factor hypothesis, I also find that size and B/M effects are not related to bankruptcy risk.

There is no agreement in the literature regarding the nature of bankruptcy risk i.e. whether it is systematic or idiosyncratic. I find that stocks with higher bankruptcy risk are more sensitive to broad market movements. Consistent with bankruptcy risk being systematic risk, distressed firms underperform during bad states of the stock market as well as bad states of the economy. As a further blow to the hypothesis that size and B/M are proxies for bankruptcy risk, I find that smaller stocks and higher B/M stocks do not underperform during bad states of the market or bad states of the economy.

The thesis also adds to the literature on seasonality in stock returns. I find that stock returns in the UK are higher during the months of January, February and April. More importantly, I find that B/M effect and z-score effect are more pronounced in different months suggesting no common underlying risk factor and providing further evidence against the distress factor hypothesis. Booth & Keim (2000) point out that knowledge of seasonality is important for investors who have prior commitments to trade in certain types of stocks but have some flexibility regarding the timing of these trades. If an investor is committed to buying small stocks, she can improve returns by buying in January or April. On the other hand, if she is committed to selling small stocks, she can benefit by selling in February or May.

I also formulate a four-factor model that includes a financial distress factor in addition to other Fama & French (1993) factors and find that the four-factor model is better specified. This model can be used in applications that require estimates of expected stock returns such as evaluating portfolio performance and measuring abnormal returns in event studies. The intercept term of the time-series regressions of excess returns against the four factors of the model gives the average abnormal return.

My results also indicate that z-scores can be used as an additional factor in quantitative fund management models. Given the time varying risk premia linked to the state of the economy and the state of the market, the results are also of direct relevance to market timers.

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APPENDIX: VALUE-WEIGHTED PORTFOLIO RETURNS

Equally-weighted returns give too much weightage to small stocks. Fama (1998) notes that most of the anomalies in the asset pricing literature either disappear or are substantially reduced when portfolio returns are value-weighted. Here I repeat the main analyses of the study using value-weighted returns for the portfolios and using the largest 50% of the stocks each year on the individual securities basis.

A1. Twenty-five portfolios formed on size and B/M

In chapter 5 I formed twenty-five portfolios on size and B/M (section 5.2). In this section I repeat the analysis of table 5.4.1 using value-weighted portfolio returns. Table A1.1 presents the results.

A1.1 Cross-sectional regression results: Value-weighted portfolio returns

At the end of September of each year from 1979 to 1999, all the stocks in the population are ranked on market capitalization and grouped into five portfolios. The stocks are also independently sorted on B/M and grouped into five portfolios. 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 30th of September. R_{it} is the value-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 sum of slopes in the regression of the return on portfolio i on the current, prior and next month's market returns estimated at the end of September of year t. $\ln(size_{it-1})$ is the natural logarithm of average of market capitalizations of stocks in portfolio i at the end of September of year t. $\ln(B/M_{it-1})$ is the natural logarithm of average of B/M ratios of stocks in portfolio i at the end of September of year t-1. α, γ_1, γ_2 and γ_3 are regression parameters from Fama-MacBeth cross-sectional regressions. The portfolios are rebalanced at the end of September each year. 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%.

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}\ln(size_{it-1}) + \gamma_{3t}\ln(B/M_{it-1})$$

α	γ_1	γ_2	γ_3
0.0105	-0.0024		
(2.93)	(-0.92)		
0.0161		-0.0005	
(1.49)		(-0.87)	
0.0086			0.0005
(3.03)			(0.53)
0.0164		-0.0005	0.0004
(1.53)		(-0.83)	(0.39)
0.0210	-0.0019	-0.0006	0.0005
(1.91)	(-0.77)	(-1.08)	(0.50)

The results are in table A1.1 are similar to those in table 5.4.1. Coefficients on beta and size are negative and statistically insignificant while that on B/M is positive and significant in both univariate and multivariate regressions. Consistent with the evidence elsewhere in the literature, coefficients with value-weighted portfolios are smaller than those with equally-weighted portfolios.

A2. Bankruptcy risk, size and B/M

In chapter 6 I formed ten portfolios on z-score and another twenty-four portfolios on size, B/M and z-score (section 6.2). In this section I repeat the analyses of chapter 6 testing the relationship between bankruptcy risk, size and B/M and also the nature of bankruptcy risk.

<u>A2.1. Do distressed firms earn higher returns?</u>

This section presents the results of the test of null hypothesis $H1_0$:

$H1_0$: ***There is no difference in the performance between financially distressed and non-distressed firms, controlling for the market factor.***

To test this hypothesis, two hundred and fifty two cross-sectional regressions are carried out for the following two models:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\,z_{it-1} \quad (5)$$

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{3t}\,z(0/1)_{it-1} \quad (6)$$

Table A2.1 presents the results.

Table A2.1: Regression results – two factor model with beta and z-score

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

Largest 50% of the stocks are used in panel C without any portfolio formation.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the value-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. 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%.

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t}z_{it-1} + \gamma_{3t}z(0/1)_{it-1}$$

α	γ_1	γ_2	γ_3
A. z-score portfolios			
0.0093	-0.0030	-0.0003	
(1.00)	(-0.36)	(-1.12)	
0.0063	-0.0016		0.0016
(0.97)	(-0.26)		(0.93)
B. Size, B/M and z-score portfolios			
0.0095	-0.0025	0.0000	
(2.84)	(-1.01)	(0.27)	
0.0093	-0.0019		-0.0010
(3.07)	(-0.75)		(-0.96)
C. Individual securities			
0.0112	0.0024	0.0001	
(4.18)	(0.73)	(0.84)	
0.0117	0.0025		-0.0019
(4.66)	(0.77)		(-1.64)

The results in table A2.1 are similar to those in table 6.4.1. The coefficients on z-score (both as a continuous variable and as a binary variable) are statistically insignificant at the 5% level. The coefficients are also generally smaller than in table 6.4.1.

A2.2. Do size and B/M capture distress risk?

This section presents the results of the test of null hypothesis $H2_0$:

$H2_0$: ***The coefficient on z-score is insignificant when size & B/M are included in the asset pricing equation and size and B/M effects are uninfluenced by inclusion of z-score in the asset pricing equation.***

To test this hypothesis, 252 cross-sectional regressions are carried out for the following three models:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{4t}\ln(\mathrm{size}_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \qquad (7)$$

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\,z_{it-1} + \gamma_{4t}\ln(\mathrm{size}_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \qquad (8)$$

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{3t}\,z(0/1)_{it-1} + \gamma_{4t}\ln(\mathrm{size}_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \qquad (9)$$

Table A2.2 presents the results.

Table A2.2: Regression results – Four factor model

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

Largest 50% of the stocks are used in panel C without any portfolio formation.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the value-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. $\ln(\mathrm{size}_{it-1})$ 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 end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. 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%.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} z_{it-1} + \gamma_{3t} z(0/1)_{it-1} + \gamma_{4t} \ln(size_{it-1}) + \gamma_{5t} \ln(B/M_{it-1})$					
α	γ_1	γ_2	γ_3	γ_4	γ_5
A. Z-score portfolios					
0.0049	0.0051			-0.0005	-0.0090
(0.14)	(0.75)			(-0.3)	(-1.33)
0.0158	0.0057	0.0003		-0.0013	0.0021
(0.45)	(0.69)	(0.71)		(-0.73)	(0.23)
-0.0024	0.0042		0.0003	0.0000	-0.0041
(-0.06)	(0.59)		(0.15)	(-0.03)	(-0.59)
B. Size, B/M and Z-score portfolios					
0.0131	-0.0029			-0.0003	0.0006
(1.17)	(-1.25)			(-0.42)	(0.53)
0.0081	-0.0002	0.0002		-0.0001	0.0009
(0.70)	(-0.08)	(1.62)		(-0.23)	(0.87)
0.0087	0.0002		-0.0021	-0.0001	0.0007
(0.76)	(0.10)		(-2.09)	(-0.21)	(0.69)
C. Individual securities					
0.0075	0.0029			0.0002	0.0014
(0.66)	(0.91)			(0.37)	(1.45)
0.0061	0.0031	0.0001		0.0003	0.0016
(0.53)	(1.00)	(1.24)		(0.46)	(1.69)
0.0088	0.0033		-0.0019	0.0002	0.0015
(0.77)	(1.07)		(-1.65)	(0.26)	(1.61)

Results in table A2.2 show that the size coefficient is not significant for any of the three trading rules and for any of the three pricing equations. This indicates that the size effect in panels A and B of table 6.4.2 is driven by small stocks. The B/M effect is highly sensitive to the trading rule employed. In panel A, the coefficient on B/M is negative and larger (in absolute value) than that in panel A of table 6.4.2 though it remains statistically insignificant. In panel B, the B/M coefficient is positive and statistically insignificant suggesting that the B/M effect in panel B of table 6.4.2 is driven by smaller stocks. However, the B/M coefficient for the largest 50% of the stocks in panel C is similar to that in panel C of table 6.4.2. The coefficient on continuous z-score is lower than in table 6.4.2 and statistically insignificant. The coefficient on z-score dummy is also greatly reduced in panel B and panel C though it remains statistically significant in panel B of table A2.2. As in table 6.4.1, introduction of z-score does not influence the size and B/M coefficients and z-score effect does not become weaker in the presence of size and B/M in the pricing equation. The evidence here provides a rejection of hypothesis $H2_0$.

The reduced z-score and size effects in table A2.2 are not really surprising. Larger firms have a much lower bankruptcy risk than smaller firms and therefore, if size and z-score are linked to bankruptcy risk, the relationship between these variables and stock returns will be weaker for larger stocks.

A2.3. Is the risk of bankruptcy asymmetric?

This section presents the results of the test of null hypothesis $H3_0$:

$H3_0$: *There is no association between z-scores and excess returns for both financially distressed and non-distressed firms.*

I use the following pricing equation:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\, z_{it-1} + \gamma_{6t}\,(z_{it-1} * z(0/1)_{it-1}) + \varepsilon_{it} \qquad (10)$$

Table A2.3 presents the results.

Table A2.3: Regression results – with z-score interaction term

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

Largest 50% of the stocks are used in panel C without any portfolio formation.

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 30th of September.

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. Betas in panel C are from RMS.

R_{it} is the value-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. 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%.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} z_{it-1} + \gamma_{6t}(z_{it-1} * z(0/1)_{it-1}) + \varepsilon_{it}$			
α	γ_1	γ_2	γ_6
A. Z-score portfolios			
0.0050	-0.0002	0.0000	-0.0005
(0.53)	(-0.02)	(-0.17)	(-0.62)
B. Size, B/M and Z-score portfolios			
0.0058	-0.0023	0.0005	0.0000
(1.20)	(-0.89)	(0.85)	(-0.01)
C. Individual securities			
0.0113	0.0026	0.0000	0.0007
(4.19)	(0.81)	(0.23)	(1.24)

The results in table A2.3 show that unconditionally, there is no relationship between z-scores and stock returns whether the z-score is positive or negative. The results are similar to those in table 6.4.3 and the evidence cannot reject the null hypothesis $H3_0$.

A2.4. Do size and B/M reflect asymmetric bankruptcy risk?

This section presents the results of the test of null hypothesis $H4_0$:

$H4_0$: There is no association between size, B/M and excess returns for both financially distressed and non-distressed firms.

I use the following pricing equation:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{4t}\ln(Size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \gamma_{7t}\,(\ln(size_{it-1})^{*}\, z(0/1)_{it-1}) + \gamma_{8t}\,(\ln(B/M_{it-1})^{*}\, z(0/1)_{it-1}) + \varepsilon_{it} \qquad (11)$$

Table A2.4 presents the results.

Table A2.4: Regression results – interaction terms of size & B/M with the z-score

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

Largest 50% of the stocks are used in panel C without any portfolio formation.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the value-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. $\ln(size_{it-1})$ 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 end of September of year t $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. 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%.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{4t}\ln(Size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \gamma_{7t}(\ln(size_{it-1})^{*} z(0/1)_{it-1}) + \gamma_{8t}(\ln(B/M_{it-1})^{*} z(0/1)_{it-1}) + \varepsilon_{it}$					
α	γ_1	γ_4	γ_5	γ_7	γ_8
A. Z-score portfolios					
-0.0108	0.0125	0.0010	0.0206	-0.0002	-0.0426
(-0.28)	(1.69)	(0.52)	(1.28)	(-0.16)	(-1.39)
B. Size, B/M and Z-score portfolios					
0.0089	-0.0003	-0.0001	0.0003	0.0000	0.0005
(0.78)	(-0.12)	(-0.25)	(0.25)	(-0.67)	(0.40)
C. Individual securities					
0.0079	0.0033	0.0002	0.0014	0.0000	-0.0003
(0.69)	(1.05)	(0.32)	(1.47)	(-0.53)	(-0.25)

The results in table A2.4 are similar to those in table 6.4.4 with the exception of those in panel C. Panel A and B of table A2.4 show that unconditionally, there is no asymmetry in the size and B/M effects i.e., the size and B/M effects are same for positive and for negative z-score stocks. Consistent with the evidence in table A2.2, panel C of table A2.4 does not show any size effect even for the positive z-score stocks. The evidence here cannot reject the null hypothesis $H4_0$.

A2.5. Is the distress factor a systematic risk factor?

This section presents the test of hypothesis $H5_0$:

$H5_0$: *There is no difference in the returns of financially distressed and non-distressed firms in up- and down-markets.*

I use the following pricing equation to test this hypothesis:

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{2t}\,z_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \quad (8)$$

$$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\,\beta_{it-1} + \gamma_{3t}\,z(0/1)_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \varepsilon_{it} \quad (9)$$

Table A2.5 presents the results.

Table A2.5: Regression results – bifurcation into up- and down-markets

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

Largest 50% of the stocks are used in panel C without any portfolio formation.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the value-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. $\ln(size_{it-1})$ 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 end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The months when the return on the market index (FTSE All Share) is lower than the risk-free rate are classified down-market and the months when the return on equally the market index exceeds the risk free rate are classified as up-market. The portfolios are rebalanced at the end of September each year. 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%.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} z_{it-1} + \gamma_{3t} z(0/1)_{it-1} + \gamma_{4t}\ln(size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1})$					
α	γ_1	γ_2	γ_3	γ_4	γ_5
A. Z-score portfolios					
Return on market < Risk free rate					
-0.1082	0.0029	0.0011		0.0042	0.0429
(-1.86)	(0.22)	(1.49)		(1.40)	(2.67)
-0.1813	0.0016		0.0047	0.0092	0.0247
(-2.82)	(0.15)		(1.10)	(2.94)	(2.20)
Return on market > Risk free rate					
0.0846	0.0072	-0.0002		-0.0044	-0.0205
(1.94)	(0.70)	(-0.36)		(-1.99)	(-1.85)
0.0969	0.0057		-0.0021	-0.0052	-0.0200
(2.04)	(0.59)		(-0.78)	(-2.26)	(-2.35)
B. Size, B/M and z-score portfolios					
Return on market < Risk free rate					
-0.0473	-0.0082	0.0010		0.0008	0.0023
(-3.22)	(-2.62)	(5.17)		(1.03)	(1.53)
-0.0435	-0.0073		-0.0091	0.0009	0.0018
(-3.01)	(-2.28)		(-5.75)	(1.13)	(1.23)
Return on market > Risk free rate					
0.0389	0.0042	-0.0002		-0.0007	0.0002
(2.51)	(1.37)	(-1.56)		(-0.82)	(0.13)
0.0378	0.0044		0.0017	-0.0007	0.0001
(2.45)	(1.41)		(1.41)	(-0.85)	(0.10)
C. Individual securities					
Return on market < Risk free rate					
-0.0565	-0.0303	0.0006		0.0025	0.0018
(-3.12)	(-7.80)	(4.45)		(2.81)	(1.43)
-0.0480	-0.0309		-0.0085	0.0023	0.0014
(-2.69)	(-7.86)		(-4.72)	(2.60)	(1.08)
Return on market > Risk free rate					
0.0409	0.0216	-0.0002		-0.0010	0.0014
(2.86)	(6.14)	(-2.14)		(-1.33)	(1.14)
0.0403	0.0223		0.0018	-0.0011	0.0016
(2.87)	(6.36)		(1.34)	(-1.43)	(1.24)

The results for z-score in table A2.5 are similar to those in table 6.4.5. The z-score coefficient is sensitive to the state of the market and except for panel A, lower z-score and negative z-score stocks underperform during bad states of the market. During good states of the market, even though the z-score coefficients are not statistically significant, they are in the direction consistent with the z-score being a systematic risk factor.

However, the results for size and B/M effects are different from those in table 6.4.5 suggesting that the results in table 6.4.5 are driven by small stocks. In table A2.5 the coefficient of size is positive in bad states of the economy (i.e. smaller stocks do worse than larger stocks) and is negative in good states of the economy (i.e. smaller stocks do better than larger stocks). This is consistent with size being a systematic risk factor.

However, except in panel A, the B/M coefficient shows little sensitivity to market movements and even in panel A, the sign of the coefficients is not in the direction consistent with its being a systematic risk factor.

Thus, the evidence in table A2.5 rejects the null hypothesis $H5_0$ for z-score and size effects but is unable to do so for the B/M effect.

A3. Bankruptcy risk, size, B/M and the state of the economy

In this section I repeat the analyses of chapter 8 testing the relationship between bankruptcy risk, size and B/M under different states of the economy.

<u>A3.1. Do the returns on distressed stocks vary with the state of the economy?</u>

In this section I present the results of test of hypothesis $H1'_0$:

$H1'_0$: *Controlling for the market factor, there is no difference in the performance between financially distressed and non-distressed firms in good and bad states of the economy.*

Table A3.1 presents the results.

Table A3.1: Regression results with beta and z-score

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

Largest 50% of the stocks are used in panel C without any portfolio formation.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the value-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. Figures in brackets are the respective t-statistics.

$R_{it} - R_{Ft} = \alpha_t + \gamma_{1t}$ **Beta**$_{it-1} + \gamma_{2t} z_{it-1} + \gamma_{3t} z(0/1)_{it-1} + \varepsilon_t$			
α	γ_1	γ_2	γ_3
A. Z-score portfolios			
GDP growth rate < Average growth rate			
0.0076	-0.0035	-0.0001	
(0.55)	(-0.27)	(-0.29)	
0.0032	0.0011		-0.0023
(0.31)	(0.11)		(-0.81)
GDP growth rate > Average growth rate			
0.0108	-0.0025	-0.0004	
(0.87)	(-0.24)	(-1.38)	
0.0092	-0.0041		0.0052
(1.09)	(-0.53)		(2.50)
B. Size, B/M and z-score portfolios			
GDP growth rate < Average growth rate			
0.0015	-0.0036	0.0004	
(0.30)	(-0.90)	(2.17)	
0.0032	-0.0030		-0.0036
(0.70)	(-0.72)		(-2.25)
GDP growth rate > Average growth rate			
0.0167	-0.0014	-0.0003	
(3.85)	(-0.49)	(-1.85)	
0.0148	-0.0009		0.0013
(3.76)	(-0.30)		(1.00)
C. Individual securities			
GDP growth rate < Average growth rate			
0.0053	0.0031	0.0004	
(1.42)	(0.6)	(2.84)	
0.0079	0.0027		-0.0045
(2.24)	(0.52)		(-2.32)
GDP growth rate > Average growth rate			
0.0166	0.0017	-0.0002	
(4.36)	(0.42)	(-1.76)	
0.0151	0.0023		0.0004
(4.28)	(0.56)		(0.27)

Consistent with the evidence in table 8.3.1, results in table A3.1 show that low z-score stocks and negative z-score stocks underperform during bad states of the economy (except in panel A here). Even in panel A, the sign of the z-score dummy coefficient is in the correct direction. The evidence here is consistent with z-score being a priced risk factor.

A3.2. Are size and B/M effects related to distress risk?

In this section I present the results of test of hypothesis $H2'_0$:

$H2'_0$: *The coefficient on z-score is insignificant when size & B/M are included in the asset pricing equation and size and B/M effects are uninfluenced by inclusion of z-score in the asset pricing equation, in both, good and bad states of the economy.*

Table A3.2 presents the results.

Table A3.2: Regression results with beta, size, B/M and z-score

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.
Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.
Largest 50% of the stocks are used in panel C without any portfolio formation.
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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.
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. Betas in panel C are from RMS.
R_{it} is the value-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. $\ln(size_{it-1})$ 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 end of September of year t. z_{it-1} is the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.
The portfolios are rebalanced at the end of September each year. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. Figures in brackets are the respective t-statistics.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} z_{it-1} + \gamma_{3t} z(0/1)_{it-1} + \gamma_{4t} \ln(size_{it-1}) + \gamma_{5t} \ln(B/M_{it-1})$					
α	γ_1	γ_2	γ_3	γ_4	γ_5
A. Z-score portfolios					
GDP growth rate < Average growth rate					
-0.0413	0.0148			0.0012	-0.0290
(-0.75)	(1.43)			(0.46)	(-2.81)
-0.0236	0.0164	0.0006		-0.0003	-0.0102
(-0.40)	(1.27)	(0.84)		(-0.10)	(-0.69)
-0.0582	0.0199		0.0002	0.0019	-0.0255
(-0.94)	(2.03)		(0.06)	(0.63)	(-2.96)
GDP growth rate > Average growth rate					
0.0468	-0.0038			-0.0020	0.0092
(1.11)	(-0.43)			(-1.01)	(1.09)
0.0516	-0.0041	0.0000		-0.0022	0.0133
(1.26)	(-0.40)	(0.07)		(-1.10)	(1.15)
0.0483	-0.0101		0.0005	-0.0018	0.0154
(0.99)	(-0.98)		(0.15)	(-0.79)	(1.49)
B. Size, B/M and z-score portfolios					
GDP growth rate < Average growth rate					
-0.0185	-0.0053			0.0013	-0.0018
(-1.21)	(-1.34)			(1.55)	(-1.14)
-0.0284	-0.0001	0.0006		0.0015	-0.0013
(-1.81)	(-0.01)	(3.08)		(1.81)	(-0.81)
-0.0263	0.0006		-0.0051	0.0015	-0.0015
(-1.69)	(0.15)		(-3.31)	(1.84)	(-0.98)
GDP growth rate > Average growth rate					
0.0418	-0.0007			-0.0016	0.0027
(2.63)	(-0.26)			(-1.95)	(1.88)
0.0413	-0.0003	-0.0001		-0.0016	0.0030
(2.54)	(-0.12)	(-0.80)		(-1.91)	(2.03)
0.0406	-0.0001		0.0005	-0.0016	0.0028
(2.51)	(-0.04)		(0.36)	(-1.92)	(1.94)
C. Individual securities					
GDP growth rate < Average growth rate					
-0.0082	0.0017			0.0008	-0.0010
(-0.49)	(0.34)			(0.99)	(-0.68)
-0.0113	0.0028	0.0003		0.0009	-0.0005
(-0.67)	(0.57)	(2.89)		(1.04)	(-0.37)
-0.0059	0.0026		-0.0041	0.0007	-0.0008
(-0.36)	(0.52)		(-2.23)	(0.86)	(-0.53)
GDP growth rate > Average growth rate					
0.0218	0.0039			-0.0003	0.0035
(1.39)	(1.02)			(-0.43)	(2.87)
0.0219	0.0033	-0.0001		-0.0003	0.0035
(1.38)	(0.87)	(-1.22)		(-0.35)	(2.88)
0.0221	0.0040		0.0002	-0.0004	0.0036
(1.41)	(1.04)		(0.14)	(-0.45)	(2.93)

Similar to the evidence in table 8.3.2, the low z-score and negative z-score stocks fare worse than high z-score and positive z-score stocks except in panel A. Unlike in table 8.3.2, in table A3.2, the size effect is insignificant (except in panel B where it is marginally significant during economic upturns). In panel A, the B/M effect is significant during downturns and in the direction consistent with its being a priced factor. In panel B and C, B/M effect is positive and significant during upturns and even though it is statistically insignificant during downturns, the sign on the coefficient is always in the direction consistent with its being a priced risk factor.

The evidence here suggests that z-scores are a priced risk factor and independent of size and B/M effects.

A3.4. Is the risk of bankruptcy asymmetric?

In this section I test hypothesis $H3'_0$:

$H3'_0$: *There is no association between z-scores and excess returns for both financially distressed and non-distressed firms in good and bad state of the economy.*

Table A3.3 presents the results.

Table A3.3: Regression results with the z-score interaction term

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

Largest 50% of the stocks are used in panel C without any portfolio formation.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the value-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. z_{it-1} is

the latest available z-score and $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.
The portfolios are rebalanced at the end of September each year. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. Figures in brackets are the respective t-statistics.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{2t} z_{it-1} + \gamma_{6t} (z_{it-1} * z(0/1)_{it-1}) + \varepsilon_{it}$			
α	γ_1	γ_2	γ_6
A. Z-score portfolios			
GDP growth rate < Average growth rate			
0.0042	-0.0020	0.0001	-0.0012
(0.27)	(-0.13)	(0.28)	(-1.10)
GDP growth rate > Average growth rate			
0.0058	0.0014	-0.0002	0.0002
(0.51)	(0.13)	(-0.68)	(0.14)
B. Size, B/M and z-score portfolios			
GDP growth rate < Average growth rate			
0.0020	-0.0026	0.0001	0.0041
(0.29)	(-0.62)	(0.16)	(1.22)
GDP growth rate > Average growth rate			
0.0092	-0.0020	0.0008	-0.0037
(1.37)	(-0.64)	(1.01)	(-1.27)
C. Individual securities			
GDP growth rate < Average growth rate			
0.0048	0.0035	0.0004	0.0001
(1.25)	(0.69)	(2.52)	(0.16)
GDP growth rate > Average growth rate			
0.0172	0.0018	-0.0003	0.0011
(4.61)	(0.44)	(-2.45)	(1.79)

Unlike in table 8.3.3, the results in table A3.3 provide no evidence that the relationship between z-scores and stock returns is asymmetric. The results of table 8.3.3 seem to be driven by smaller stocks.

A3.4. Do size and B/M reflect asymmetric bankruptcy risk?

In this section I present the tests of hypothesis $H4'_0$:

$H4'_0$: *There is no association between size, B/M and excess returns for both, financially distressed and non-distressed firms in either state of the economy.*

Table A3.4 presents the results.

Table A3.4: Regression results – interaction terms of size & B/M with the z-score

Panel A portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks in each group are ranked on z-score and each group is divided into five portfolios. The first five portfolios consist of negative z-score stocks and the next five portfolios consist of positive z-score stocks.

Panel B portfolios are formed as follows: At the end of September of each year from 1979 to 1999, all the stocks in my population are allocated to two groups based on whether their latest available z-score is negative or positive. The stocks are independently ranked on market capitalization and grouped into four portfolios and independently ranked on B/M and grouped into three portfolios. Twenty-four portfolios are then formed at the intersections of size and B/M and z-score.

Largest 50% of the stocks are used in panel C without any portfolio formation.

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 30th of September. To avoid undue influence of outliers on the regressions, the smallest and largest 0.5% of the observations on B/M are set equal to 0.005 and 0.995 fractiles respectively.

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. Betas in panel C are from RMS.

R_{it} is the value-weighted return on portfolio (or stock) 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 (or stock) i estimated at the end of September of year t. $\ln(size_{it-1})$ 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 end of September of year t. $z(0/1)_{it-1}$ is equal to 1 if the latest available z-score is negative, 0 otherwise. The slopes are estimated by Fama-MacBeth cross-sectional regressions for each of the 252 months from October 1979 to September 2000.

The portfolios are rebalanced at the end of September each year. The quarters when the GDP growth rate is lower than the long run average are classified as downturns and the quarters when the GDP growth rate exceeds long run average are classified as upturns. Negative B/M stocks are excluded. Figures in brackets are the respective t-statistics.

$R_{it} - R_{Ft} = \alpha_{it} + \gamma_{1t}\beta_{it-1} + \gamma_{4t}\ln(Size_{it-1}) + \gamma_{5t}\ln(B/M_{it-1}) + \gamma_{7t}(\ln(size_{it-1})^* z(0/1)_{it-1}) + \gamma_{8t}(\ln(B/M_{it-1})^* z(0/1)_{it-1}) + \varepsilon_{it}$					
α	γ_1	γ_4	γ_5	γ_7	γ_8
A. Z-score portfolios					
GDP growth rate < Average growth rate					
-0.0470	0.0233	0.0025	0.0295	-0.0023	-0.0512
(-0.76)	(2.12)	(0.81)	(1.21)	(-1.77)	(-1.42)
GDP growth rate > Average growth rate					
0.0220	0.0028	-0.0004	0.0125	0.0017	-0.0348
(0.45)	(0.28)	(-0.17)	(0.59)	(0.68)	(-0.71)
B. Size, B/M and z-score portfolios					
GDP growth rate < Average growth rate					
-0.0275	-0.0004	0.0016	-0.0013	-0.0002	-0.0011
(-1.78)	(-0.09)	(1.98)	(-0.77)	(-2.14)	(-0.64)
GDP growth rate > Average growth rate					
0.0420	-0.0002	-0.0018	0.0017	0.0001	0.0020
(2.59)	(-0.08)	(-2.04)	(1.08)	(1)	(1.14)
C. Individual securities					
GDP growth rate < Average					
-0.0074	0.0025	0.0008	-0.0010	-0.0001	0.0001
(-0.45)	(0.5)	(0.92)	(-0.71)	(-1.24)	(0.04)
GDP growth rate > Average					
0.0218	0.0040	-0.0004	0.0036	0.0001	-0.0007
(1.38)	(1.03)	(-0.44)	(2.91)	(0.60)	(-0.42)

Table A3.4 shows that the results are sensitive to the trading rules employed. In panel A, there is no asymmetry in the size and B/M effects in either state of the economy. The asymmetry in size effect in panel A of table 8.3.4 seems to be driven by small stocks. The results in panel B are consistent with those of panel B of table 8.3.4 i.e. there is some asymmetry in the size effect but it is economically negligible and there is no asymmetry in the B/M effect. The results in panel C provide no evidence that relationship between size and returns or B/M and returns is different for distressed and non-distressed stocks.