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THE EFFECTS OF BETA, SIZE AND BOOK-TO-MARKET ON UK STOCK RETURNS:

Risk Adjustment, Characteristic factors and the Cross-Section of Expected Stock Returns

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ABSTRACT

This research examines the cross-section of expected returns in the UK stock market for the period January 1969-December 2001, with particular reference to the role of risk adjustments and the pricing of characteristic factors.

This study has three empirical parts. This first part of the empirical study is concerned with the testing for cross-sectional relationships between expected returns and firm size, book-to-market equity ratio and beta. A methodology similar to that of Fama and French (1992) is employed for this purpose. Most of the research relating the behavior of stock returns to variables such as beta, size and book-to-market equity ratio has been done for the US markets, but there has been limited research relating to the UK markets. In order to further fill the gap, this study provides new evidence by using a more up to date dataset for the UK stock market. In addition, this study further tests the relationship by employing methods not previously employed for the UK market. The cross sectional relationships are tested using robust regressions. Because of seasonal patterns and small-firm effects detected in prior cross-sectional studies, this study also explores cross-section relations for different months of the year and different size cohorts.

In the second part, this study analyses models that explain the time series of stock returns using portfolios that mimic the characteristics found to be priced in the first stage cross-section analysis. It was ascertained whether these characteristics proxy for sensitivity to risk factors in returns or whether the characteristics themselves explain the cross section of expected stock returns. This study also discriminates between these two explanations by testing whether it is the time variation in expected risk premiums as measured by the characteristic factors or time variation in the risk loadings as measured by the risk factors arising from characteristic factors.

In the third part, it was determined whether the characteristic factors found to priced in the first and second stage have any explanatory power relative to the loadings on the factors through the different asset pricing risk models. Throughout the study, other issues in both the cross-section and time-series analysis, such as data-snooping biases and residual analysis are also addressed.

From all three parts, there is strong evidence that the book-to-market equity ratio is a very important determinant of the cross-sectional variation in average stock returns while there is hardly any role for beta or size effects in explaining returns. However, the book-to-market effect is only visible for portfolios of small firms and for the month of April. This study further finds some evidence supporting a rational asset-pricing risk model as a possible explanation of book-to-market and size premiums and some evidence supporting book-to-market and size characteristics as a possible explanation. But the analysis of risk-adjusted returns through different factor models suggests that, the priced firm characteristics like book-to-market equity and size are not proxying for loadings on omitted factors that are priced.

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CHAPTER 1

THE AIMS AND OBJECTIVES OF THE STUDY

1.1. BACKGROUND, AIMS AND OBJECTIVES

There is a well known statement in economics that there is no such thing as a free lunch. When this idea is applied to the stock market, it implies that the only way an investor can get a higher expected return on his investment is by taking higher non-diversifiable risk. This idea is formalized in the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965) Mossin (1966) and Treynor (1961). The CAPM is a model with a single risk factor, and the single factor is called the market factor. The CAPM implies a positive linear relationship between expected security returns and market betas. The CAPM also implies that market beta is sufficient to describe cross-sectional expected returns. This parsimonious approach enables the equilibrium asset pricing relationship to be presented in a simple and intuitively appealing way, which has helped the CAPM to become one of the dominant paradigms in modern finance.

The first major challenge to the CAPM emerged in 1981 when Banz (1981) found that firm size explained variation in average returns not explained by beta, he found that small firms have higher returns than large firms even after adjusting for risk using the CAPM. In 1992, however in the article entitled 'Beta is dead', Hulbert (1992) mentioned that Eugene Fama and Kenneth French had discovered that beta was worthless as an explanation of stocks' relative performance over time. Fama and French (1992) found that the size effect

was significant in explaining average returns with or without beta in the model. They found that for a large range of stocks beta has no ability to explain the cross-sectional variation in average returns whereas size has substantial power. Fama and French also considered the ratio of Book-to-Market Equity, (BE/ME), as an additional variable to size, and they found it to be more powerful than size. More recently Strong and Xu (1997), for the UK stock market, found that the BE/ME has the strongest relation to return.

In theory, the role of size and BE/ME has not been explained in an equilibrium model, or could not possibly be accounted for by their statistical properties as proxies for expected returns. Hence the role of firm size and BE/ME has become a puzzle in finance literature. The existence of such variables has therefore questioned the empirical validity of asset-pricing models such as the CAPM. These findings have given rise to many questions: Is beta really dead, whereby no relationship exists between beta and rate of returns? Why and how do the BE/ME and size variables help predict expected rates of return? Are the variables like BE/ME and size representing risk or characteristics of the firm? These questions will be central issues in this study.

In contrast to the large body of research in the US relating the cross-sectional behaviour of stock returns to variables such as beta, firm size and BE/ME, there has been only very limited research relating to the UK market. One of the main objectives of this study is therefore to analyse the ability of beta and other factors, such as BE/ME and size, to explain the cross-sectional variation in average stock returns on the UK stock market, over the period 1969-2001. After Strong and Xu (1997) and Chan and Chui (1996), this is the third study of its kind in the finance literature covering the UK stock market. Moreover, in contrast to the

earlier studies on UK stock market, this study incorporates more recent data. The examination of new and non-US evidence may enlighten the debate on the variables to be included in cross-sectional asset pricing models. However, when placed alongside the evidence accumulated from studies of US data and other UK evidence, this study may also be useful in evaluating empirical models of the determinants of stock returns.

The empirical findings of Fama and French (1992) and Strong and Xu (1997) have caused a great deal of controversy. Some studies (Kothari, Shanken and Sloan (1995)) defend the usefulness of market beta by reporting a positive relationship between returns and beta and questions the existence and/or the economic significance of the premium obtained by the BE/ME variable. Some have argued that the testing methodology used by Fama and French (1992) may be inappropriate. According to Roll (1977), a correct and unambiguous test of the CAPM has not appeared in the literature. Roll (1977) argues that the CAPM is not testable unless the exact composition of the true market is known and used in tests. This study therefore seeks to contribute to the tests of the CAPM by using techniques; and to do so in variety of situations. Specifically, this study investigates the robustness of the estimated risk premia for beta, size and BE/ME by applying robust techniques.

After the 'failure' of the CAPM, subsequent empirical work has uncovered stock market regularities in the form of small firm returns and seasonal effects, which also appear to be puzzling. Seasonal patterns and small-firm effects have always been of interest to financial scholars and practitioners. These effects or anomalies have been regarded as constituting strong evidence against the efficient market hypothesis by financial economist. Not only are small firm returns predictable, but a large proportion of the predictability (in the US and UK)

has been associated with two months of the year, January and April (e.g. Chelley-Steeley (1996) for the UK stock market). This study determines whether the CAPM is a seasonal or a small-firm phenomenon and whether the BE/ME factor is the outcome of any month-of-the year effects or firm size effect. In other words, this study will seek to establish whether firm size contributes to the magnitude of the monthly risk premiums associated with beta and BE/ME and whether monthly seasonalities can be linked to the pricing of beta and BE/ME for both large and small firms. Overall, this study is valuable for several reasons. First, the monthly and small-firm effects are investigated using cross-sectional data and time-series data. Second, none of the existing studies of the UK stock market have determined, whether the relationship between BE/ME and returns is influenced at all by the calendar month or small-firm effects. Finally, the use of recent data will provide insights into monthly effects in the UK stock market.

This study indicates that BE/ME has the strongest relation to UK returns. One has reached the conclusion that at least the BE/ME effects are real, since they have been observed in the UK stock market and over several decades in the US, and in other countries as well. The next empirical problem, investigated in this study is why size or BE/ME are able to produce cross-sectional dispersion in average returns, which has dominated empirical research on the characteristics of cross-sectional and time series variation in expected stock returns. There are two sides of this debate. One side favours a risk-based explanation and contends that these factors reflect systematic risk that the static CAPM has failed to capture. Based on the evidence of Fama and French (1992), Fama and French (1993) test the existence of risk factors associated with size and BE/ME. Fama and French (1993) suggest that if stocks are priced rationally, then systematic differences in average returns should be due to differences

in risk. They show that the prices of high BE/ME and low size stock tend to move together in a way similar to a risk factor. They found that risk factors based on value-weighted market portfolios, size and BE/ME can explain the differences between average returns on stocks and bonds. Thus, given rational pricing, the market, size and BE/ME exposures must proxy for sensitivity to pervasive risk factors in returns. Fama and French (1993) proposed a three-factor model to explain the premium over the risk-free rate as a more satisfactory explanation of returns than the CAPM. Their three-factor model approach has become more popular since further empirical evidence by Fama and French (1996b) shows that the three-factor model can explain the variation of stock returns much better than the CAPM. Guidi and Davies (1997) and Toms and Hussain (2002) for the UK stock market also supported the Fama-French three-factor model. Recently, Gregory, Harris and Michou (2001) for the UK stock market found that the Fama and French factors behave in a manner consistent with the rational pricing model but they also found some evidence in favour of non-risk explanations. In Chapter 5, the burgeoning research literature contradicting, confirming, criticising, and extending the Fama-French model is reviewed. In addition to all this, a four-factor model, which includes the market, SMB, HML and a 'momentum factor' is also tested. 'Momentum factor' is formed by taking an effective long position in high performance past return portfolios and a short position in low performance past return portfolios. This study also examines the continuation of short-term returns (momentum) itself through the three-factor model.

The other side of the debate favours a non-risk explanation for the empirical success of the Fama and French Factors. Several authors have criticised the multi-factor model developed by Fama and French (1993, 1996b). Daniel and Titman (1997) provide evidence

that the return premia on small-firm stocks and high BE/ME do not arise from the comovements of these stocks with pervasive risk factors; rather, the characteristics themselves explain the cross section of expected returns. They conclude that portfolios of firms that have similar characteristics (size and BE/ME), but different loadings on the Fama-French factors, have similar returns, so that it is the security characteristics and not their loadings on the Fama-French factors that determine expected returns. One single study on such an issue for the UK stock market was conducted by Strong, Liu and Lee (2001) who found convincing evidence that stock returns have a stronger relationship with characteristics than with loadings on the factors suggested by Fama and French (1993, 1996b). Hence these results are in contrast to the notion that the Fama and French results provide a risk-based explanation of expected returns.

This study also empirically examines the Fama-French three-factor model and the characteristics-based model of Daniel and Titman (1997) for the UK stock market. This study analyses whether the market, size and BE/ME factors are pervasive in the cross-section of UK stock returns and also investigates whether the risk or non-risk explanations better explain the size and BE/ME premia. This analysis is important for several reasons. The Daniel and Titman (1997) results are clearly controversial; they reject a model that captures the central intuition of traditional asset pricing models in favour of a model that is almost completely ad hoc. Moreover, it is still largely unknown whether the Fama-French model or a characteristics-based model has any specific economic interpretation. These conflicting findings suggest that additional examinations of the relation between Fama-French factors and stock returns are warranted. It is also argued in Davis, Fama and French (2000) that it is very important to test the robustness of Daniel and Titman results on different samples.

Hence, new evidence from the UK should help researchers to determine whether the evidence provided by Daniel and Titman is just specific to their rather short time period. Given that, this study is only the fifth[1] of its kind in the finance literature, the results from this study should provide a valuable alternative source of evidence on the viability of the asset pricing models in the finance literature.

However this study goes further than this by using the methodology of Lewellen (1999). This study basically shows whether factors like BE/ME and size are associated with changes in risk, as measured by Fama-French or with changes in the expected premium as measured by Daniel and Titman (1997), when additionally the factor loadings and expected returns are allowed to vary with factors and with time. This is an innovative way of testing the Fama-French and characteristics based models, and have only been applied so far to US data. One reason for applying this methodology to the UK stock market is to counter criticisms that some of the explanations of BE/ME for the US are due to data-snooping and data-mining biases (see e.g. Berk (2000), Black (1993a, 1993b), Mackinlay (1995) and White (2000)). Hence, this method is particularly valuable, given the data snooping criticism, in that it provides non-US sample test. This is also useful because any rational asset-pricing model must be tested to work under a variety of conditions, not just from the same set of condition used in the literature.

In this line of inquiry, this study provides new evidence on the extent to which expected returns can be explained by risk factors rather than by non-risk characteristics like BE/ME and size. Specifically, this study shows whether the cross-sectional behaviour of size and

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[1] Daniel and Titman (1997) for US, Davis Fama and French (2000) for US, Daniel, Titman and Wei (2001) for Japan and Strong, Liu and Lee (2001) for UK.

BE/ME, in relation to returns, is consistent with risk, once the returns are fully adjusted for risk. This study is the first one to address this issue for the UK stock market. Different specifications of the factor models are used to adjust for risk: the CAPM, the Fama-French three-factor model and a Principal Component Analysis (PCA) approach, see e.g. Connor and Korajczyk (1988). First, PCA is used to obtain risk factors for a statistically based, or an APT influenced, model. Second, this study determines whether characteristics such as BE/ME and size have any explanatory power relative to the factor specifications of the statistical model (PCA factors), the Fama and French model or the CAPM. Under the rational-asset-pricing framework, the risk-adjusted returns obtained by the risk-models should be independent of other (non-risk) security characteristics.

As will be evident from the chapters of this study, a substantial amount of research relating to beta, size and BE/ME has been conducted on data relating to companies listed on the US stock markets. In contrast, relatively few studies have conducted research on beta, size and BE/ME for firms listed on the UK stock market. The main aim of this thesis is therefore to provide a comprehensive study of "beta", "size" and "BE/ME" in the UK stock market using the most recent data and extending the cross-sectional studies, which have been used so far in this field. The study is also interesting because most of the anomalies (for e.g. BE/ME effect in returns) in the literature do not hold up in different sample periods. After the anomalies are documented and analysed in the academic literature, anomalies often seem to disappear, reverse, or attenuate. Practitioners usually follow the investment vehicle which implements the strategies implied by academic papers. Hence, the findings of this study will help practitioners to gain some new insights on the working of the various asset-pricing models in the literature.

1.2. STRUCTURE OF THE STUDY

The thesis begins by reviewing[2] the empirical work on the determinants of the cross-section of expected returns. The study begins by presenting the Capital Asset Pricing Model (CAPM). Chapter 2 develops a version of the CAPM and describes how it measures the risk and expected return relation of investing in particular assets. There is a section on the derivation of the CAPM in its empirical form, on the testable hypotheses and the assumptions pertaining to the tests. The chapter then reviews the studies, which support the cross-sectional relationships between the CAPM beta and stock returns. In the 1970s and 1980s, some anomalies in the stock market were discovered. In particular, stock return characteristics seemed to contradict the CAPM principle that beta risk is solely able to explain the cross-section of expected returns. The chapter then reviews the studies related to these anomalies in detail. The chapter then presents the influential studies, in which the size, BE/ME and other financial variables and not the CAPM beta seem to explain the cross-sectional variation in stock returns. One study specific to the US stock market (Fama and French (1992)) and two studies specific to the UK stock market (Strong and Xu (1997) and Chan and Chui (1996)) are discussed in detail. As stated earlier, the results of these tests question the validity of the CAPM. Arguments that implicitly or explicitly challenge the studies of Fama and French (1992) and Strong and Xu (1997) are then discussed in detail. These include Lo and Mackinlay (1990), Kothari, Shanken and Sloan (1995), Clare, Priestly and Thomas (1998) and Berk (2000).

[2] This study brings extensive literatures means that in addition to a chapter on the literature survey, this study also includes the surveys within some chapters at a location designed to indicate, how this work progresses from the current state of knowledge, and why it is useful to do so.

In Chapter 3, the first part of the empirical work is presented. This study presents new evidence by examining the role of beta, size, and BE/ME in explaining the cross-section of expected returns on UK stocks for the period January 1969-December 2001. Fama and French (1992) approach is used to explain the cross-section of UK expected stock returns. This analysis is necessary to provide assistance in establishing the contribution made by the empirical work presented in later chapters of this thesis.

Chapter 3 is divided in six parts. First, data is described which will be used throughout the study. Second, the empirical methodology adopted for this study is explained. Third, evidence on the cross-sectional relationships for our sample of UK equities is presented. Fourth, robustness tests in such studies have been centred around the issues of: types of returns to be used, the length of the return-interval for beta estimation, and the choices of indexes to be used in estimation. This chapter explores these issues in detail. Fifth, the study also tests the cross-sectional relationships between beta, size, BE/ME and returns using different sub-periods. In addition to this, the study also test the robustness of results by eliminating extreme returns, using up and down market conditions and a different set of sample firms. The economic reasons behind the use of such techniques are also provided in the chapter.

Chapter 4 reviews the empirical work and presents the evidence on beta, size and BE/ME across different firm sizes and calendar seasonalities for the UK stock market during the sample period: 1969-2001. The focus of this chapter will be on extending the work of Chelley-Steeley (1996), who found that the high January and April returns in the UK appeared to be associated with the pricing of risk, and only for the large firms. Analysis of

the UK stock market from the most recent data, and different statistical methods, may offer insights into controversies relating to calendar and small firm effects surrounding the US and UK markets. Surprisingly, the role that BE/ME in relation to different firm sizes and different months of the year has not been previously investigated for the UK stock market.

Surprisingly, very few studies have been concerned with identifying the reasons for the existence of size and BE/ME premiums in returns. Chapter 5 responds to this by providing a substantial amount of information on such issues. Fama and French found that the size and BE/ME might be a proxy for some unexplained risk factor, while Daniel and Titman (1997) found that size and BE/ME might just be characteristics that explain the cross-section in expected stock returns. The empirical work on these issues is reviewed, the empirical methodology adopted relating to the risk-based explanations is explained, and then the evidence relating to the three-factor model is presented, followed by the evidence relating to the study of Daniel and Titman (1997) for the UK stock market. In this chapter, one also discriminates between these two explanations by testing whether it is the time variation in expected premiums, as measured by characteristics, or time variation in the risk loadings, as measured by the risk factors arising from characteristics, as suggested by Lewellen (1998). Finally, this chapter also examines the momentum effect via the Fama-French three-factor model. Although Strong, Liu and Xu (1999) find some evidence of a momentum effect for the UK stock market, no one has tested the momentum effect in the UK stock market by adding it as a fourth factor in the Fama-French three-factor model.

In Chapter 6, the thesis provides new evidence on the risk factors using UK stock returns. While the effects of size and BE/ME have been analysed in earlier studies, this is the first

attempt to provide a joint analysis of the marginal effects of the BE/ME and size characteristics on expected returns, after adjusting the returns using different sets of risk factors. The different sets of risk factors are Principal Component Analysis (PCA), Fama and French factors or CAPM factor. In other words, this chapter complements the earlier analysis by investigating further the ability of size and BE/ME to explain the cross-section of returns after accounting for the effects of factors using PCA, Fama-French based model and the CAPM. This analysis will suggest whether the effects of BE/ME and size are subsumed by the risk factors (statistical, Fama and French or CAPM) or not. Surprisingly, this has not been done on the UK stock market before. Throughout this study, the portfolio grouping procedure is used to avoid an Errors-In-Variable problem. But, according to Lo and Mackinlay (1990), if researchers form portfolios on the basis of characteristics which prior research has shown to be relevant to expected returns, they will be inclined to reject the null hypothesis too often due to a "data-snooping-bias". To avoid data-snooping biases, the study complements the work in earlier chapters by using individual securities in this chapter. In this chapter, the standard Fama and French (1992) approach is modified by applying individual securities rather than portfolio groupings. This is, again, something new for studies of the UK stock market. In addition to BE/ME and size characteristics, the lagged returns (momentum factor) are also used as one of the characteristics in explaining the stock returns.

Chapter 7 provides a summary, and conclusions, and draws attention to the limitations of the study. It also contains some implications of the study and suggestions for further work.

CHAPTER 2

EXPECTED RETURN AND BETA: A LITERATURE REVIEW

2.1. INTRODUCTION

There is one basic principle followed by investors in the stock market: higher expected return on investment can only be obtained by taking higher systematic risk. This principle is formalized in Capital Asset Pricing Model (CAPM) (Sharpe (1964), Lintner (1965), Mossin (1966), Treynor (1961)). The CAPM states that the expected return on a stock is determined by the risk free rate and a risk premium, which is a function of the stock's measure of responsiveness to the overall movements in the market, that is its beta coefficient. Early empirical tests of the model generally supported the CAPM's main prediction of beta being the only explanatory factor in explaining the cross sectional variation across stock portfolios. But some of the recent empirical findings suggest that the betas of common stocks do not adequately explain cross-sectional differences in stock returns. Instead, a number of other variables (such as firm size, the ratio of book-to-market values, earning yields, leverage, past returns, volume trading, and macroeconomics factors) that have no basis in existing theoretical models seem to have significant predictive ability.

The question is not, whether the CAPM is misleading, but the main issue is whether the systematic deviations from CAPM are economically important enough to be considered in the literature. In other words, are the variables of the existing model simply correlated with,

or perhaps acting as a proxy for, other "true" explanatory variables, that is, those variables for which there is economic justification?

In this chapter, the evidence on the cross-sectional behaviour of common stock returns in the US and UK stock markets are reviewed. This study intends to evaluate the arguments in favour of CAPM against the alternative models presented, which either implicitly or explicitly challenges the CAPM. This study will, in turn, assess whether the relationship between risk and return can be captured adequately by beta in CAPM or, whether risk is better proxied by other factors. This is a good starting point for this study since the main objective of this study is to test the cross-sectional relationships between the common stock returns and other factors in the UK stock market.

The review in this chapter has several stages. Between 1950 to 1970 (first-stage), the CAPM and a few of its competing models were developed in the literature. In order to gain a strong theoretical understanding of this study, a review of these developments is very important. Several cross-sectional tests were done using the CAPM, however during the 1970s (second-stage), methodological flaws were discovered in the testing procedures of the CAPM which were adopted earlier. Thus new findings brought refinements to the earlier developments. In this chapter, these flaws are surveyed and findings of both stages are compared. During the 1980s (third-stage), several other additional factors, in addition to market beta were found to be important in the cross-sectional studies of the CAPM. These findings are reviewed in this chapter. But the most wide ranging criticism of CAPM came in 1990s (fourth-stage), which could be seen as a turning point in the finance literature, although during the same stage, several other authors attacked these great findings, there was

an equally good response to these criticisms. The empirical analysis in this study starts from this point.

In the next section, there is an overview of the financial theory that underlies the behaviour of stock returns. Section 2.3 presents the econometric model used to test the theory. Section 2.4 to Section 2.7 discusses the vast empirical studies that have been published during the past quarter-century. Section 2.8 concludes this chapter.

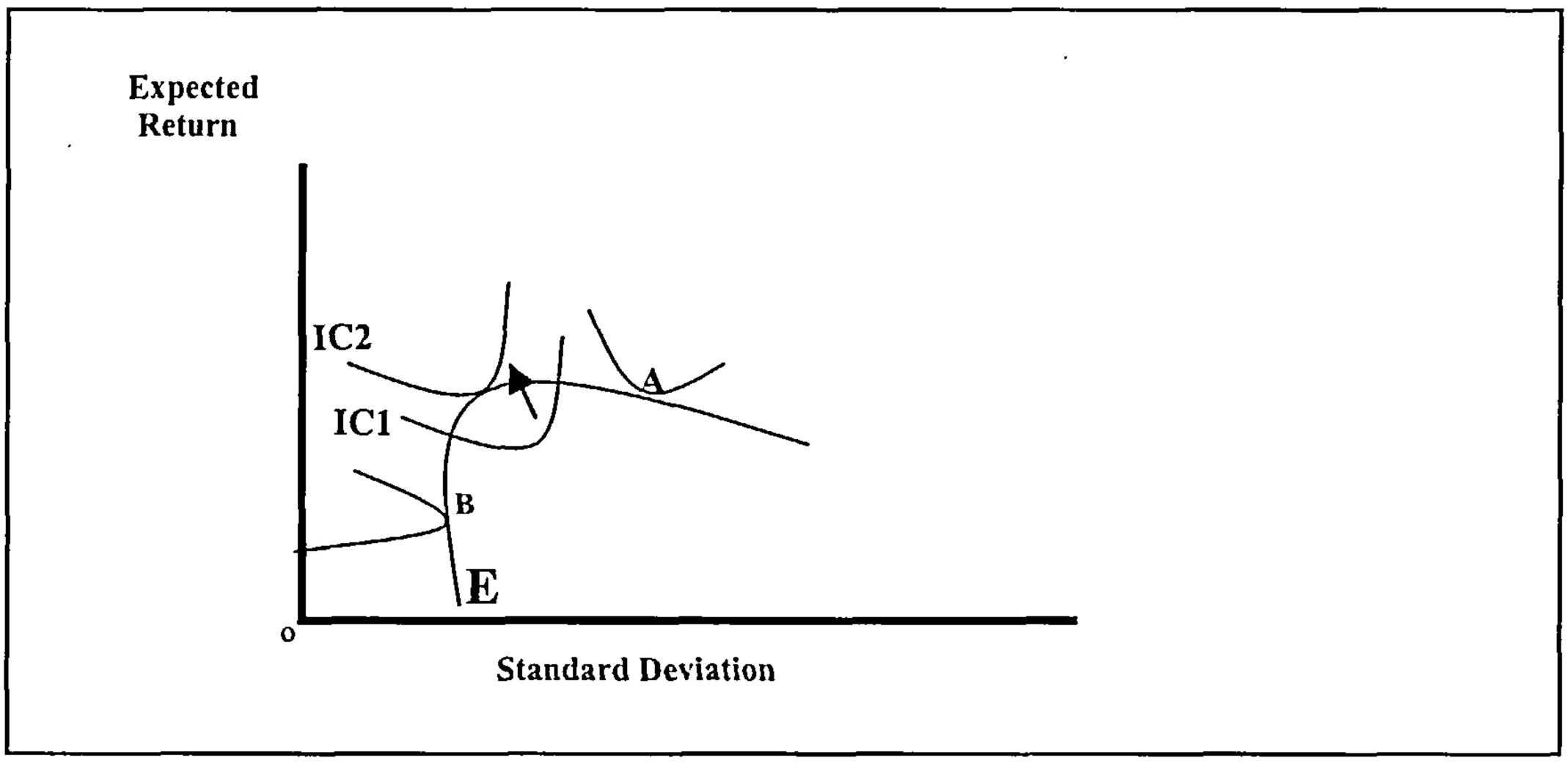
2.2. THEORETICAL BACKGROUND

2.2.1. THEORY

While the roots of asset pricing models can be traced to Bernoulli (1738), it was not until the twentieth century that general theories of portfolio selection and asset pricing were formulated. The 1950s[1] saw the formation of the ideas that shaped asset pricing. The theory of portfolio optimisation (Markowitz (1959)) showed how risk and return must be related in optimal portfolio construction. In the Markowtiz model (1959), the investor's objective is to maximize the portfolio's expected return, subject to an acceptable level of risk (or minimize risk, subject to an acceptable expected return). The assumption of a single time period, coupled with assumption about the investors attitude toward risk, allows risk to be measured by the variance (or standard deviation) of the portfolios return. This is shown in Figure 2.1 (dotted line can be ignored for time being).

[1] The 1950s saw the formation of ideas that shaped asset pricing. First, Arrow and Debreu (1954) developed their general equilibrium theory, which gave the insight that consumption in different future states could simply be viewed as different consumption goods. Second, Modgliani and Miller (1958) showed that the value of a firm was independent of the capital structure. This was the first occurrence of arguments based on the assumption of no arbitrage.

FIGURE 2.1 MARKOWITZ PORTFOLIO SELECTION



Markowitz asserts that investors should base their portfolio decisions solely on expected returns and standard deviations and then choose the "best portfolio" based on the relative magnitudes of these two parameters. According to Markowitz's investment approach, the method that should be used in selecting the most desirable portfolio involves the use of indifference curves $(IC)^2$. These curves represent an investor's preference for risk and return. As indicated by the arrow in Figure 2.1, an investor will find any portfolio that is lying on an indifference curve that is "as far northwest as possible" to be more desirable than any portfolio lying on an indifference curve that is "not as far northwest".

As the securities are added to a portfolio, the expected return and standard deviation change in very specific ways, based on the way in which the added securities co-vary with

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[2] It is assumed that the reader is familiar with the derivation and meaning of this term-it is explained in most basic economic textbooks. In rough terms, indifference curves are curves of constant utility or welfare, and when mapped on to graph of consumption 'now' and consumption 'next year', an individual indifference curve indicates all possible combinations of consumption at the two points in time which give the same level of utility. The curve are convex to the origin, indicating that there is diminishing marginal utility attached to consumption at any single point of time, and each indifference curve, moving from left to right, gives the individual a higher overall level of utility.

the other securities in the portfolio. In Markowitz investment approach, investor looks at only a subset of the available portfolios that lies in the efficient set theorem. According to this theorem, an investor will choose his or her optimal portfolio from the set of portfolios that offer: (a) maximum expected return for varying level of risk, and (b) offer minimum risk for varying levels of expected return. The set of portfolios meeting these two conditions is known as efficient frontier (E). An investor's optimal portfolio is indentified as the tangency point between the investor's indifference curves and the efficient set.

According to the Markowitz model, investors select portfolios, along this curve, according to the tolerance for risk. An investor who can live with lot of risk might choose portfolio A, while a more risk-averse investor would be more likely to choose portfolio B. One of the major insights of the Markowitz model is that it is security's expected return, coupled with how it co-varies with other securities, that determines how it is added to investor portfolios.

Markowitz showed how to create an efficient frontier. Tobin (1958) took Markowitz's analysis one step further by showing how to identify which efficient portfolio an individual investor should hold. According to Tobin, if one hold risk securities and are able to borrow-buying stocks on margin-or lend-buying risk-free assets- and if one do this at the same rate, then the efficient frontier is a single portfolio of risky securities plus borrowing and lending. Tobin's separation or two-fund theorem states that we can separate the problem into first, finding that optimal combination of risk securities; then, deciding whether to lend or borrow, depending on individual's attitude toward risk. He then showed that if there's only one portfolio plus borrowing and lending, that is a market. However, there was one significant drawback with this approach. Although, Tobin's separation theorem clarified the task of

portfolio selection, but even with Tobin's contribution it was still necessary to use Markowitz's model. The data and computational requirements of this approach were massive, particularly for applications that embraced individual securities. There are well over 2,000 securities traded in the London Stock Exchange and, even more in the US. To use the Markowitz model with 2,000 securities required estimates of over two million risks and return characteristics.

Soon after this, Treynor (1961) began working on the portfolio-selection problem. He showed that the risk premium per share for one of the investment is proportional to the covariance of the investment with the total of all the investment in the market. Shortly, after Treynor began his work on asset-pricing, Sharpe (1963) also set out to determine the relationship between the prices of assets and their risk attributes. The paper published by Sharpe (1964) notes that through diversification, some of the risk inherent in an asset can be avoided so that its total risk is obviously not the relevant influence on its price; unfortunately little has been said concerning the particular risk component which is relevant. Sharpe's (1964) paper was supplemented by contributions from Lintner (1965) and Mossin (1966).

The work of Tobin (1958), Treynor (1961), Sharpe (1963), Lintner (1965) and Mossin (1966) not only increased financial economists understanding of portfolio selection, but also reduced the complexity of portfolio choice problem. This research yielded insights into how and which risks should be managed. In turn, this raised the issue of how risk should be measured in the portfolios. It was only small leap from the portfolio choice problem to a model of asset pricing. Treynor (1961) and Sharpe (1964) argued that since investors would expect all investors to make this trade off between risk and return, then in equilibrium high

risk assets must compensate investors by offering higher expected returns. This gave rise to the CAPM, which has been the cornerstone of asset pricing. The CAPM tells us that only systematic risk, as measured by beta, is rewarded, and that the relationship between expected return and beta is linear. Black (1972) extended the CAPM to a world in which one cannot borrow at the riskless rate of interest. Sometimes, a model without a risk-free rate is called two–parameter model. In the next section, derivation of CAPM is presented.

2.2.2. ASSUMPTIONS AND DERIVATION OF THE CAPM

Sharpe (1964) and Treynor (1961) can be attributed as one of the first to derive the CAPM[3]. It is based on a number of assumptions. First, investors have a utility function that is defined over terminal wealth whose value is uncertain. The investor prefers more wealth and is risk averse. For a terminal wealth x, the utility function U(x) satisfies: $U'(x)>0$ and $U''(x)<0$. Second, given a choice between two uncertain terminal wealth levels, the investor will prefer the one that provides the highest expected utility E (U).

With the above assumptions of non-satiation and risk aversion, the choice of assets available for the investor can be identified through the mean and variance of return of the asset. This is however made possible if either the investor has a quadratic utility function or that the probability density function follows a normal distribution. It is further assumed that the capital markets are perfect, in the sense that investors are price takers and there are neither transaction costs nor information costs. On the basis of these assumptions, investors can expand their choices to portfolio of assets. Markowitz (1952) formulated a procedure towards this purpose, where:

The return, expected return, and variance of return on a portfolio p are,

$$Rp = \sum_{i=1}^{n} x_{ip} Ri \tag{2.1}$$

$$E(Rp) = \sum_{i=1}^{n} x_{ip} E(Ri) \tag{2.2}$$

$$\sigma^2(Rp) = \sum_{i=1}^{n} \sum_{j=1}^{n} x_{ip} x_{jp} \sigma_{ij} \tag{2.3}$$

where n is the number of securities available for inclusion in portfolios, x_{ip} is the proportion of portfolio funds invested in security i in portfolio p, *E(Ri)* is the expected return on security i, and $\sigma_{ij} = \text{cov}(Ri, Rj)$ is the covariance between the returns on securities i and j.

Rewriting (2.3) as,

$$\sigma 2(Rp) = \sum_{i=1}^{n} x_{ip} \left(\sum_{j=1}^{n} x_{jp} \sigma_{ij} \right) \tag{2.4}$$

it can be seen that, the contribution of security i to portfolio variance is: x_{ip}, the proportion of portfolio funds invested in i, multiplied by $\left(\sum_{j=1}^{n} x_{jp} \sigma_{ij} \right)$, the weighted average of the

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[3] The derivation in this chapter comes from Fama (1976, Chapter 8, pg.259-269)

pairwise covariances between the return on security i and the returns on each of the securities in p, where the weight applied to σ_{ij} is x_{jp}, the proportion of portfolio funds invested in security j to obtain p.

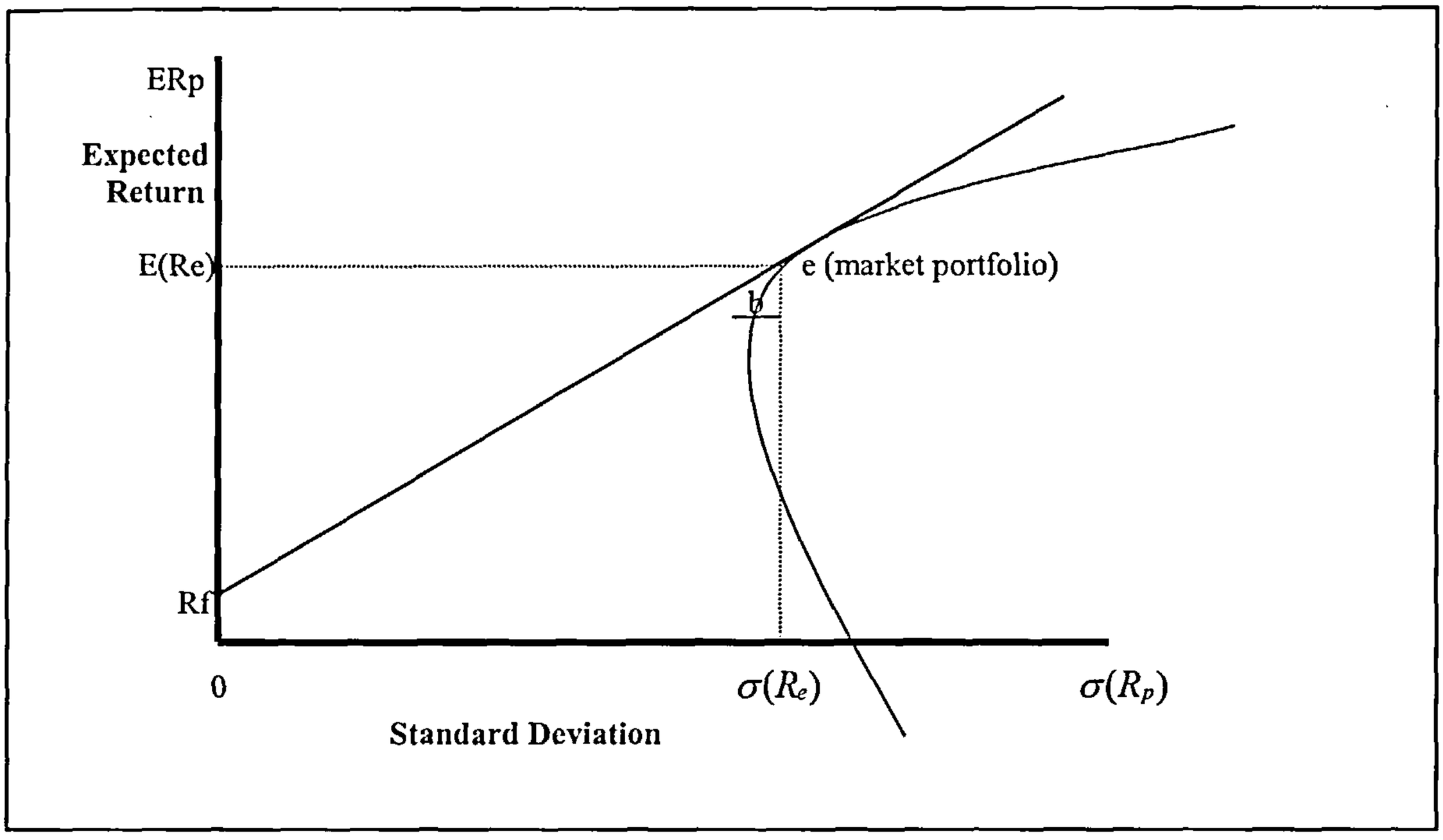
The RHS of equation: (2.4) could be interpreted as the risk of security i in portfolio p. But, it is more convenient to call it the weighted average of covariances, which can be shown to be (also see, Fama (1976, p.259))

$$\sum_{j=1}^{n} x_{jp}\sigma_{ij} = \text{cov}(Ri,Rp) \tag{2.5}$$

the risk of security i in p. If one interprets (2.5) as the risk of security i in portfolio p, then from (2.4) the risk of portfolio is the weighted average of the risks of individual securities.

This study now wants to determine what the model says about the relationships between expected return and risk. For any efficient portfolio, there is an equation relating the expected return on any security in that portfolio to the risk of the security in the portfolio. More specifically, the mathematical conditions suggest that a portfolio must satisfy to be efficient. This efficient portfolio defines the relationship between expected return and risk for individual securities in that portfolio. To be efficient, a portfolio must have a property that no other portfolio with the same or higher expected return has lower standard deviation of return. Efficient portfolio was also discussed in Section 2.2.1. This is also shown in the following figure:

FIGURE 2.2 EFFICIENT PORTFOLIOS



Note that in Figure 2.2 efficient portfolios are minimum variance portfolios, but not all minimum variance portfolios are efficient. An efficient portfolio should satisfy the conditions mentioned in Section 2.2.1. Thus, the efficient portfolios in Figure 2.2 are those along the left boundary above the point b, but points below b along the boundary are minimum variance portfolios.

The mathematical details for the conditions in Section 2.2.1 are now presented. Any portfolio that satisfies condition (a) is called a minimum variance portfolio. Any such minimum variance portfolio can be viewed as the solution to a problem of the form:

$$Minimize\ x_{ip}\ \ \sigma^2(Rp)\ ,\ i=1,\ldots\ldots\ldots n \tag{2.6}$$

subject to the constraints:

$$\sum_{i=1}^{n} x_{ip} E(Ri) = E(Re), \tag{2.7}$$

and

$$\sum_{i=1}^{n} x_{ip} = 1.0 \tag{2.8}$$

Here *E (Re)* is some given level of expected return. The problem stated in equations (2.6) to (2.8) is to choose proportions x_{ip}, $i=1,....n$, invested in individual securities that minimize the variance of portfolio return subject to the constraints that expected portfolio return is equal to *E(Re)* and that the sum of the proportions invested in individual securities is *1.0*.

To solve the problem stated in equation (2.6) to (2.8), first form the LaGrangian expression,

$$L = \sigma^2(Rp) + 2\lambda_e[E(Re) - \sum_{i=1}^{n} x_{ip}\ E(Ri)] + 2\varphi_e[1 - \sum_{i=1}^{n} x_{ip}] \tag{2.9}$$

where $2\lambda_e$ and $2\phi_e$ are the LaGrange multipliers for the constraints of (2.7) and (2.8). Minimizing the variance of portfolio subject to the constraints of (2.7) and (2.8) involves differentiating (2.9) with respect to $2\lambda_e$ and $2\phi_e$ and $x_{ip}, i = 1,....n,$ and setting these partial derivatives equal to 0.0, and then solving the n and 2 first order conditions. For $2\lambda_e$ and

$2\phi_e$, this procedure simply tells us that the proportions invested in individual securities must satisfy (2.7) and (2.8). For the $x_{ip}, i = 1,....n,$ however, the procedure yields n new first order conditions:

$$\sum_{j=1}^{n} x_{je}\sigma_{ij} - \lambda_e E(Ri) - \phi_e = 0.0, \quad i=1,..n \tag{2.10}$$

where $x_{je}, j=1....n$ are the specific proportions invested in individual securities that define the minimum variance portfolio with expected return E(Re).

The equation set (2.10) are conditions on the proportions invested in individual securities that must be met by the minimum variance portfolio. It can now be shown that the equation: (2.10) delivers the relationship between the expected return on a security and its risk in the minimum variance portfolio e.

Since (2.10) holds for every security, it holds for security k

$$\sum_{j=1}^{n} x_{je}\sigma_{kj} - \lambda_e E(Rk) - \phi_e = 0.0 \tag{2.11}$$

and (2.10) and (2.11) together

$$\sum_{j=1}^{n} x_{je}\sigma_{kj} - \lambda_e E(Rk) = \sum_{j=1}^{n} x_{je}\sigma_{ij} - \lambda_e E(Ri) \tag{2.12}$$

Multiplying both sides of (2.12) by x_{ke} to get

$$x_{ke}\sum_{j=1}^{n} x_{je}\sigma_{kj} - \lambda_e x_{ke}E(Rk) = x_{ke}(\sum_{j=1}^{n} x_{je}\sigma_{ij} - \lambda_e E(Ri)) \tag{2.13}$$

applying equations (2.2) and (2.4) to portfolio e, with a change in subscripts and since none of the terms within the parentheses on the RHS of (2.13) involve security k, and since $\sum_{k=1}^{n} x_{ke} = 1$, summing (2.13) over k yields:

$$\sigma^2(Re) - \lambda_e E(Re) = \sum_{j=1}^{n} x_{je}\sigma_{ij} - \lambda_e E(Ri) \tag{2.14}$$

When (2.14) is rearranged, its results in:

$$E(Ri) - E(Re) = 1/\lambda_e(\sum_{j=1}^{n} x_{je}\sigma_{ij} - \sigma^2(Re)), i = 1,\ldots n \tag{2.15}$$

Since equation (2.15) is the direct implication of equation (2.9), equation (2.15) can be interpreted as a condition on the weight $x_{je,j=1,2....n,}$ that must be met if these weights describe the minimum variance portfolio that has expected return *E (Re)*. In determining the weights $x_{je,j=1,2....n,}$ that cause (2.15) to be satisfied for every security i, the risk of portfolio e, $\sum_{j=1}^{n} x_{je}\sigma_{ij,}, i = 1,\ldots n$ are determined. Once the weights are known, however equation (2.15)

can be interpreted as the relationship between the expected return on any security i and the risk of the security in the minimum variance portfolio e. The equation says that the difference between the expected return on any security i and the expected return on e is proportional to the difference between the risk of i in e and the risk of e, and where the proportionality factor is $1/\lambda_e$.

To complete the interpretation of the relationship between expected return and risk in the minimum variance portfolio e, quantity $1/\lambda_e$ must be interpreted. The LaGrange multiplier $2\lambda_e$ in (2.9) is the rate of change of the minimum value of $\sigma^2(Rp)$ in (2.6) with respect to a small change in the target value of the expected portfolio return: $2\lambda_e = (d\sigma^2(Re))/(dE(Re))$. This derivative is related to the slope of the boundary of the opportunity set at the point e. If Se denotes the slope, then: $Se = dE(Re)/d\sigma(Re)$; that is, the slope of the boundary at the point e is the rate of change of expected return with respect to a change in the minimum value of portfolio standard deviation. To show the relationship between λ_e and Se, the chain rule of differentiation is used to determine that

$$
\begin{aligned}
&1/Se = d\sigma(Re)/dE(Re) = \\
&(d\sigma(Re)/d\sigma^2(Re)) * (d\sigma^2(Re)/dE(Re)) = \\
&(1/2\sigma(Re)) * (d\sigma^2(Re)/dE(Re)) \\
&= \lambda_e/\sigma(Re)
\end{aligned}
$$

After rearranging:

$$1/\lambda_e = Se/\sigma(Re) \tag{2.16}$$

Substituting (2.16) and (2.5) into (2.15) and rearranging yields,

$$E(Ri)=[E(Re)-Se\sigma(Re)]+(Se/\sigma(Re))cov(Ri,Re) \tag{2.17}$$

The square bracket are to indicate that the quantity,

$$E(Re)\text{-}Se\,\sigma(\mathrm{Re}) = Rf \tag{2.18}$$

has a special interpretation. This interpretation is based on an assumption. If it is assumed that there exists a riskless asset where borrowing and lending can be done in an unlimited basis, then the efficient portfolio for the investors can be a combination of that riskless asset (Rf) and the risky asset. This is also shown in Figure 2.2. In Figure 2.2, the slope of the left boundary of the investment opportunity set at the point corresponding to the portfolio e is:

$$Se= (E(Re)\text{-}Rf)/\sigma(Re) \tag{2.19}$$

With (2.18) and (2.19), the expected risk-return relationship of (2.17) becomes

$$E(Ri)=Rf+[E(Re)\text{-}Rf]\ \beta_{ie} \tag{2.20}$$

where

$$\beta_{ie} = [cov(Ri, Re)]/[\sigma^2(Re)]$$

is the (beta coefficient) risk of security i in the portfolio e measured relative to the risk of the portfolio.

In equation (2.20), the expected return of security i is described by a risk-return relationship known as Capital Asset Pricing Model (CAPM). It states that the expected return is linearly related only to risk that is associated with the market.

2.2.3. THEORETICAL INTERPRETATION OF THE CAPM

CAPM assumes that investors use the logic of Markowitz in forming portfolios. It further assumes that there is an asset (risk-free asset) that has a certain return. With a risk-free asset, the efficient frontier in Figure 2.1 is no longer the best investor can do. The straight line in Figure 2.2, which has the risk-free rate as its intercept and is tangent to the efficient frontier, is now the northwest boundary of the investment opportunity set. Efficient portfolios plot along this line starting at Rf and going through e and consist of alternative combinations of risk and return obtainable by combining market portfolio[4] with riskfree borrowing or lending. This linear efficient set of the CAPM is known as the Capital Market line (CML). All portfolios other than those employing the market portfolio and risk free borrowing or lending would lie below the CML, although some plot very close to it.

[4] The market portfolio is a portfolio consisting of all securities where the proportion invested in each security corresponds to its relative market value. The relative market value of a security is simply equal to the aggregate market value of the security divided by the sum of aggregate market values of all securities. The reason the market portfolio plays a central role in the CAPM is that the efficient portfolio consists of an investment in the market portfolio, coupled with a desired amount of either riskfree borrowing or lending. Thus it is common practice to refer to the tangency portfolio as the market portfolio.

In order for markets to be in equilibrium, the portfolio e must be the market portfolio of all risky assets. So, in equilibrium, all the investors combine the market portfolio and the risk-free asset, and the only risk that investors are paid for bearing is the risk associated with the market portfolio. The important point to remember here is that the risk taken on arises purely from the portfolios holding in the market portfolio. As the riskiness of the market portfolio is all non-diversifiable (by definition- it is the ultimately diversified portfolio), the risk premium given by the market is only for non-diversifiable risk. This non-diversifiable risk has been redefined for a fully diversified investor as "beta". The relationship between risk as measured by beta and expected return of a security is shown by the security market line. This relationship thus described is usually known as the CAPM. Thus the exact form of the equilibrium relationship between risk and return or CAPM equation can be written as:

$$E(Ri)=Rf+[E(Re)-Rf]\,\beta_{ie} \tag{2.20}$$

where *E (Ri)* and *E(Re)* are the expected returns to asset *i* and the market portfolio, respectively, *Rf* is the risk free rate, and beta (β_{ie}) is the beta coefficient for asset *i*.

The term [E(Re)-Rf] β_{ie} in (2.20) can be interpreted as the risk premium in the relationship between the expected return on security i and its risk in the portfolio e or the difference between the expected return on the market portfolio and the riskless asset, multiplied by beta coefficient (β_{ie}) (systematic risk) the risk of the security i measured relative to the risk of e. In other words, if the portfolio e is efficient, then equation (2.20) aims to explain average excess asset returns over the riskless asset, by formalising the positive and linear relationship between risk (beta) and return. The beta represents the part of the asset's risk that cannot be diversified away, and this is the risk that investors are

compensated for bearing. In theory if the CAPM is an accurate description of the way assets are priced, the positive linear relation should be observed when the average portfolio returns are compared to portfolio betas. Further, when the beta is included as an explanatory variable, no other variable should be able to explain cross-sectional differences in average returns. Beta should be all that matters in a CAPM.

2.2.4. BLACK'S (1972) CAPM VERSION

Black (1972) provides an extension of the CAPM by considering the absence of risk-free asset. The model of Black (1972) requires unlimited short selling and can be derived by forming a portfolio between a risky asset Z, which is on the efficient frontier and the market M. The asset Z has a minimum variance and is uncorrlelated with the market. In Black's (1972) model, Rf in equation (2.20), changes with E(Rz), where E(Rz) is the expected return on any security whose return is uncorrelated and thus has a zero covariance with the return on the portfolio e. Using a similar argument from expression (2.18) and (2.19), the return of an asset i can be expressed as:-

$$E(Ri)=E(Rz)+[E(Re)-E(Rz)]\ \beta_{ie} \qquad (2.21)$$

and is normally known as the zero-beta CAPM.

2.2.5. DEVELOPMENTS AFTER CAPM

While the CAPM is a simple model that is based on sound assumptions, some of the assumptions that underline the model are unrealistic[5]. Roll (1977) was the first one to raise an issue against the CAPM. He argues that the theory is not testable unless the exact composition of the true market is known and used in tests. This implies that the theory is not testable unless all individual assets are included in the sample and that the tests of the CAPM can be extremely sensitive to the choice of market proxy. He had shown that an empirical test not incorporating the true market portfolio could reject the hypothesis of a linear relationship between returns and systematic risk or beta simply because the proxy market portfolio being employed is not ex post efficient[6]. Stambaugh (1982) argues that the relationship between risk and return does not appear to be sensitive to the proxy for the market portfolio which is used, because the relationship between risk and return does not appear to be any different even when four different market portfolios are utilised in tests of CAPM. Shanken (1987) suggests refining statistical techniques, which are used when choosing a market portfolio: he terms this "Living with the Roll critique". His work develops an empirical framework in which prior beliefs about the correlation between a proxy and the true market portfolio can be explicitly incorporated. Overall, the Roll's critique does not imply that the CAPM is an invalid theory. But, it does means that the tests of the CAPM must be interpreted with great caution.

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[5] For example, all investors are assumed to have the same information and this information is costless to gather and process. In addition, there are no taxes, transaction costs, or other "frictions". It is also assumed that investors can readily borrow funds at the risk free rate of interest.

[6] According to Roll (1977), it is always possible to choose an efficient portfolio as an index, then find the minimum variance portfolio, which is uncorrelated with the selected efficient index. Once this has been done, the CAPM equation can be derived. In Roll (1977), the CAPM equation is given as:

$$E(R_i) = E(R_{Z,I}) + [E(R_I) - E(R_{Z,I})]\beta_{i,I} \qquad (1)$$

Instead of simply extending an existing theory, Ross (1976a, 1976b) addresses the CAPM problem by developing a completely different model: Arbitrage Pricing Theory (APT). Unlike the CAPM, which is a model of financial market equilibrium, the APT starts with the premise that arbitrage opportunities should not be present in efficient financial markets. The assumption is much less restrictive than those required to derive the CAPM.

The APT starts by assuming that there are n factors, which cause asset returns to systematically deviate from their expected values. The theory does not specify how large the number n is, nor does it identify the factors. It simply assumes that these n factors cause returns to vary together. There may be other firm specific reasons for returns to differ from their expected values, but these firm-specific deviations are not related across stocks. Since the firm-specific deviations are not related to one another, all returns variation not related to the n common factors can be diversified away. Based on these assumptions, Ross shows that, in order to prevent arbitrage, an asset's expected return must be linear function of its sensitivity to the n common factors:

$$ER_i = Rf + \sum_{j=1}^{n} \lambda_j \beta_{ij} \tag{2.22}$$

where *ERi* is the return on the individual security i; *Rf* is risk-free rate; each beta coefficient (β_{ij}) represents the sensitivity of asset *i* to risk factor *j*; lambda represents the risk premium for factor *j* and *n* is the number of factors. As with the CAPM, there is an expression for

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Note that the market portfolio Rm has been replaced by efficient index R_I and the beta is measured relative to the selected efficient index, $\beta_{i,I}$. Because the expected return on any asset can be written as a linear function of its beta measured relative to any efficiency index, then it is not

expected return that is a linear function of the asset's sensitivity to systematic risk. Under the assumptions of APT, there are n sources of systematic risk, where there is only one in a CAPM world.

But APT was not without criticism too. Both the CAPM and the APT are static, or single-period models. As such, they ignore the multi-period nature of participation in the capital markets. Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM) was developed to capture this multi-period aspect of financial market equilibrium. Merton (1973) relaxed the assumption of constant investment opportunity set and therefore the risk-free rate was nonstochastic. With these changes, the investors' decision will be based on a 'three-fund theorem'. These funds are the risk-free asset, the market portfolio and a portfolio n, whose returns are negatively correlated with the risk-free rate. There is one important difference, which differentiates the ICAPM from APT. APT gives little guidance as to the number and nature of factors. The numbers of factors appearing in the ICAPM are also not fixed, but the ICAPM atleast gives us some guidance on the nature and number of factors[7].

Breeden (1979) came up with another competing model. In the Consumption-based Capital Asset Pricing Model (CCAPM), expected returns of assets are related to one source of uncertainty, that is changes in aggregate consumption.

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necessary to know the market index. One only needs to know the composition of any efficient index in order to write (1).

[7] The number of assumptions that appear in the ICAPM equation are those that satisfy the following conditions:

a) They describe the evolution of the investment opportunity set over time.

b) Investors care enough about them to hedge their effects.

For example, there might be a priced factor for unexpected changes in the real interest rate. Such a change would certainly shift the investment opportunity set, and the effect would be pervasive enough that investors would want to protect themselves from the negative consequences.

Overall, out of all the models discussed above, the CAPM has been extensively used in the empirical analysis. One of the objectives of this study is to analyse the CAPM, so now, the next section turns to the testing procedure of the CAPM.

2.3. ECONOMETRIC MODEL OF THE CAPM

The basic CAPM can be written as

$$E(r_i)=r_f+[E(r_m)-r_f]\,\beta_{im} \tag{2.23}$$

where r_i, r_f, and r_m are the return of asset i, risk free rate of return and market rate of return respectively.

The first problem in empirically testing the CAPM is that the model as in equation (2.23) above is expressed in terms of expectations of returns[8]. Since tests could be carried out only on observed data, the CAPM has to be expressed in an ex-post form. This problem raises the logical question of how one justifies testing an expectational model in terms of realizations.

The problem is solved by assuming that security returns are linearly related to the return on market portfolio. In theory, CAPM is a single-period model and does not have a time dimension. For econometric analysis of the model, one needs to add an assumption concerning the time series properties of returns over times. It is assumed that the returns are Independently and Identically Distributed (IID) and are jointly multivariate normal.

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[8] CAPM can only be tested if the expected returns and betas were known. If these estimates are available, then all one has to do to examine the empirical support for the CAPM is by plotting the return and beta data against each other. Unfortunately, neither of these is known.

Defining excess returns $\tilde{r}$ and rewriting the expression (2.23) as:

$$E(\tilde{r}_i) = E(\tilde{r}_m)\,\beta_{im} \tag{2.24}$$

$$\tilde{r}_i = r_i - r_f \text{ and } \tilde{r}_m = r_m - r_f \tag{2.25}$$

Imposing the restriction that R_{it} and R_{mt} are multivariate normal, it follows that

$$E(\tilde{r}_{it} \setminus \tilde{r}_{mt}) = \alpha + \beta \tilde{r}_{mt} \tag{2.26}$$

$$\beta_{im} = \mathrm{cov}(\tilde{r}_{it}\tilde{r}_{mt}) / \mathrm{var}(\tilde{r}_{mt}) \tag{2.27}$$

and

$$\alpha_i = E(\tilde{r}_{it}) - \beta_{im} E(\tilde{r}_{mt}) \tag{2.28}$$

therefore

$$\tilde{r}_{it} = \alpha_i + \beta_{im}\tilde{r}_{mt} + \varepsilon_{it} \tag{2.29}$$

The CAPM mentioned above assumes that the joint distribution of security returns is multivariate normal[9]. This implies that the joint distribution of the return on any security and

[9] If the returns are IID, then following assumptions are made concerning the right-hand side variables and disturbances of equation (2.29) in the text:

the return on the market portfolio is bivariate normal. Bivariate normality implies 'a market model' relationship between R_i & R_m of the form: equation (2.29)[10]. Traditionally the market model has been estimated by Ordinary Least Square (OLS) using equation (2.29). To test the CAPM, is equivalent to testing the restriction that the intercept α_i is zero.

A few assumptions are needed if equation (2.29) is to be used as a basis to test CAPM. First, as empirical tests are conducted using a series of stock returns, the CAPM (equation (2.23)) is assumed to be stable across time. Hence, the beta should be stable over time. Second, the CAPM states that the market includes all assets, however there are assets, which are not measurable. Therefore, the next assumption is the ability to use proxies for the market portfolio. The details relating to the proxies for the market portfolio are discussed later in this chapter.

2.3.1. IMPORTANCE OF BETA VARIABLE IN CAPM

Since in the market model (equation 2.29), ε_i and R_m are independent, then

$$\sigma^2(R_i)=\beta_{im}^2\sigma^2(R_m)+\sigma^2(\varepsilon_{im}) \qquad (2.30)$$

(where σ^2 is the variance of the terms)

OR

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zero mean: $E(\varepsilon_t)=0$ where t=1,....n ; constant variance: $Var(\varepsilon_t)=\sigma^2$ (constant) ; zero covariance: $Cov(\varepsilon_t, \varepsilon_s)=0$ where s $\neq$ t; s,t=1,...n ; disturbances (ε_t) are normally distributed and all characteristics of the ε_t are identical, including all moments, and not just the mean and variance.

[10] For a complete derivation of the link between the CAPM or zero-beta CAPM and market model, see Fama (1968, 1973b).

$$Total\ risk = Systematic\ Risk + Unsystematic\ Risk \tag{2.31}$$

It can be see from (2.30) that the variance of the return on security i can be spilt into two components. Total variance is made up of variance related with beta and the disturbance variance $\sigma^2(\varepsilon_{im})$. $\sigma^2(\varepsilon_{im})$ or, equivalently, the standard deviation of the disturbance, $\sigma(\varepsilon_{im})$ is a measure of the non-β_{im} risk of security i. ($\sigma(\varepsilon_{im})$) is a specific risk (unsystematic risk), which is independent of market fluctuations, provides no compensation to investors since it can virtually be eliminated by portfolio diversification. On the other hand, investors can expect to be rewarded for bearing β_{im} (systematic risk), since it is attributed to the stock's response to changes in the market and cannot, therefore be diversified away. The greater the systematic risk assumed by an investor, the higher his expected return.

2.3.2. MAIN HYPOTHESIS TO BE TESTED

If the CAPM is true then:

1. The parameter beta completely captures the cross sectional variation of expected returns.
2. This beta-return relation should be linear (positive) (the market risk premium, $(E(r_m)-r_f)$ in equation (2.23) is positive).
3. There should be no extra return for bearing non-market risk.
4. In the standard CAPM model, the intercept in return-beta space should be risk-free rate (it should be zero in statistical term), and the slope of (Rm-Rf) while in the zero-beta version of CAPM, there should be an intercept of Rz and a slope of (Rm-Rz) (it should be Rz (1-β_{im}) in statistical term).

2.4. EARLY TESTS OF CAPM

From theoretical point of view, CAPM represents an almost perfect blend of elegance and simplicity. Moreover, from an empirical point of view the model appears to be readily tested. From equation (2.29), tests of the CAPM can be formulated in an empirical model. Betas are easily estimated from the equation (2.29).

This section reviews the literature that tests the CAPM in the pre-1980 period. Early cross-sectional studies of stock returns (Nicholson (1960)) did not receive a great deal of attention, due to the small samples used to conduct the empirical tests. It was not until the CRSP and Compustat[11] databases became available that researchers could construct samples large enough (and of sufficient quality) to produce results.

One of the first empirical studies of the CAPM was performed by Lintner and reproduced in Douglas (1968) using the data[12] from the US stock market. Most of the early empirical test (like Lintner) involved the use of time series (first pass) regression to estimate the betas and the use of cross-sectional regression[13] (second pass) to test the hypothesis that was derived from the CAPM in the earlier section. Lintner used the following time-series model or the market model (first-pass regression) for estimating beta:

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[11] CRSP is the Center for Research in Security Prices at the University of Chicago. The CRSP database contains stock market data (prices, returns, shares outstanding, etc.) for New York Stock Exchange, AMEX, and NASDAQ common stocks. The Compustat database is produced by Standard and Poor's Corporation and contains accounting data for US (and some foreign) companies.

[12] The US data for most of the empirical studies mentioned in this chapter comes from CRSP and Compustat.

[13] Cross-sectional data are data on one or more variable collected at the same point in time. A time series is a set of observations on the values that a variable takes at different time.

$$R_{it} = \alpha_{it} + b_i R_{mt} + \varepsilon_{it} \tag{2.32}$$

where *Ri* is the return on individual security; *Rm* is the return on the market portfolio; α_i, b_i are the intercept and the estimate (the regression coefficient) of the true beta for stock i respectively and ε_i is the error term.

To estimate betas from equation (2.32), they regressed the returns of 301 US stocks against the average return for all stocks in the sample using data from 1954 to 1963. Lintner then performed the second-pass cross-sectional regression:

$$\bar{R} = a_1 + a_2 \hat{\beta}_i + a_3 \hat{\sigma}^2_{ei} + \mu_i \tag{2.33}$$

where $\hat{\sigma}^2_{ei}$ is the residual variance from the first-pass regression (the variance of ε_i in equation (2.32)). According to CAPM, the intercept term (a_1) was too large (estimated to be .11 but .04 in data). The coefficient value of a_2 was too small (estimated to be .06 but .08 in data) and the estimated value of a_3 was .24 and significant. The presence of residual risk and a lower value of the intercept seemed to violate the CAPM. Douglas (1968)[14] employed a similar methodology and found results that were similar to Lintner's.

[14] Douglas (1968) was the first to test directly the CAPM in its cross-sectional form, except for the market betas, Douglas also added the assets' own variance in the cross-sectional regression relationship as a regressor. He examined the period 1926 to 1960 (specifically, he tested seven separate five-year periods from 1926 to 1960). Douglas reported a significant positive relation between average realised returns and the variance of the securities' returns, but he did not found any relation for their covariance with the returns on the market index. The results indicated intercepts that were larger than the prevailing risk-free rate. These results appeared to be inconsistent with the relation given by CAPM because the coefficient of the variance term was not zero.

Miller and Scholes (1972) noted that the Douglas results could be caused by some of the econometrics problems. They pointed out four major econometrics problems in the methodology used by Douglas.

Omitted variable bias: Miller and Scholes (1972) argued that the time series first pass regression (equation (2.32)) may produce biased estimates of beta and that the following model:

$$R_{it} = (1-\beta_i)R_{ft} + \beta_i R_{mt} + \varepsilon_{it} \tag{2.34}$$

should be used. But, they suggest that, if the risk-free rate *(Rf)* is constant over time period, then equation (2.32) is correct. However if the risk-free rate fluctuates and is correlated with market portfolio *(Rm)* then equation (2.32) is a case of omitted variable and the estimate of beta is biased. Appendix 2.1 demonstrates the problem.

Distortions due to heteroskedasticity; which is an often encountered problem in econometrics test. It occurs when the variance of the error is larger for higher values of the independent variable than it is for smaller values. Basically, higher beta stocks usually have a higher variance of return unexplained by the market than lower beta stocks. In other words, the residuals are not normally distributed ($\mu \sim N(0, \sigma^2\beta)$ and not $N(0, \sigma^2)$) as initially assumed). This means that the variance of the error term in the cross-section test regression is not constant. Miller and Scholes found some evidence of heterscedasticity. This problem reduces the estimate of errors in the regression coefficients and so may lead us to conclude that a relationship is statistically significant when it, in fact, is not.

A feasible non-linearity in the risk-return relation: There might be a possibility of non-linearity in cross-sectional regression (equation (2.33)). This problem might bias the estimated results. Miller and Scholes tested for nonlinearity[15] by adding the squared value of beta to the cross-section test regression and found it to be statistically insignificant.

Errors-in-Variable (EIV) problem: The most direct approach to the tests of the CAPM would seem to be to obtain estimates b_i (in equation 2.32) of the true β_i of individual securities, plug these into equation (2.33), and then proceed. The problem with such a technique is that any estimate b_i differs from the true β_i by an estimation error (or measurement error). If the errors are typically large, there is a serious EIV problem. This problem was brought forward by Miller and Scholes. The problem is clearly demonstrated in Appendix 2.2. The main consequence of this problem is that if proxy explanatory variables are used in a least square regression (equation (2.33)) to place the unknown variables, the computed coefficients do not have the same properties as if the true explanatory variables are used. In particular, they are inefficient and biased. Moreover the EIV problem overstates the statistical significance of the second pass OLS estimate of $\hat{\beta} i's$ (in equation (2.33)). A direct solution to this problem is to reduce the errors in the estimates of the risk measures by computing beta from long time-series of monthly returns. This ensures that the errors in $\hat{\beta} i$ are relatively small. But still this approach depends heavily on the assumption that betas are stable. Miller and Scholes further suggested[16] that the true beta is positively correlated

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[15] While the inclusion of quadratic terms is suggestive of non-linear effects, this model is still, of course, "linear in the parameters".

[16] Miller and Scholes offered some other possible problems that had introduced biases into the empirical analysis of the Lintner and Douglas results: 1) The distribution of returns for the stocks was very skewed. 2) The use of an improper index as a proxy for the return on the market portfolio. They find that the results are reasonably insensitive to the choice of the stock market index. Roll (1977), as discussed later, questions this result.

with a residual variance. Hence the residual variance serves as a proxy of the true beta and the return will be positively correlated with residual risk. In this way, the cross-sectional regression will show an association between residual risk and return, even though there is no such association. They concluded that this is in fact the case in the Lintner tests.

To deal with EIV problem the following techniques have been suggested: One approach is to minimise the EIV problem by grouping the stocks into portfolios and increasing the precision of the beta estimate, as adopted by Black, Jensen and Scholes (1972). Black, Jensen and Scholes (1972) used all securities listed on the New York Stock Exchange (NYSE) during the period 1926-1966 for testing the time-series and cross-sectional regressions of CAPM. They firstly estimated the following time-series regression to test the CAPM:

$$R_{it}-Rft=\alpha_i+\beta_i(R_{mt}-Rft)+\varepsilon_{it} \qquad (2.35)$$

where the definitions of all the variables are same as before.

They could have estimated (2.35) for all the stocks and examined the distribution of the estimated intercept. But the errors in equation (2.35) for each stock return may not be independent across i. They therefore conducted the following to get rid of this problem:

In step 1, they estimated betas for each stock on the NYSE from first-pass regression (equation (2.32)) over five periods of monthly data using an equally-weighted portfolio of NYSE stocks as the market portfolio, e.g. they started with the 60-month period 1926-30. They ranked stocks by beta into deciles (each portfolio containing 10% of the stocks). These

portfolios were held for the next 12 months, e.g. portfolio ranked by beta for the period 1926-30 are held for 1931.

In step 2, they calculated the mean return and beta for the year, 1931 on each portfolio. The whole procedure was repeated by rolling over year forward. For example, stocks were again ranked for the year 1927-31, and the portfolios were held for the following year (1932). In this way, the portfolio returns and betas were calculated for 35 years. The returns from a portfolio of stocks were then regressed against the return of the market (using equation (2.35)). Black, Jensen and Scholes also divided the 35-year period into four sub-periods and for each sub-period, equation (2.35) was run again. The result showed that for the whole period, portfolios with high betas had positive values for intercept, while portfolios with low betas had negative values. These findings were consistent with the zero-beta CAPM model as

$$\alpha_i = (1-\beta_i)(Rz-Rf) \text{ where } Rz > Rf$$

For the sub-periods, Black, Jensen and Scholes again found some evidence, against the CAPM.

They further regressed the excess return of the ten portfolios on the portfolios beta using the following cross-sectional equation:

$$\bar{R}_i - Rf = \hat{\gamma}_0 + \hat{\gamma}_1 \beta_p + \mu_p \qquad (2.36)$$

They found a positive value of the intercept and their slope coefficient was significantly different from the excess return to the market proxy. There evidence was again in favour of the 'zero-beta' CAPM[17].

However one problem that arises with the approach of Black, Jensen and Scholes (1972) is the loss of information about the relationship between risk and expected return when securities are combined into portfolios. First, this method of annually reforming the portfolios yields biased betas, that is, the betas of the lowest beta portfolio tend to be too low and the betas of highest-beta portfolio tend to be too high. Such a naïve procedure could result in what is called a 'regression phenomenon'. This is again an EIV problem in the estimates of the beta. Second, in the Black, Jensen and Scholes study, there were differences in the results between the sub-periods. This may be due to the fact that the estimates used in the tests were not stationary.

However, according to Fama and Macbeth (1973, p.23) "If the errors in the beta are substantially less than perfectly correlated, the $\hat{\beta}\, p$ of portfolios can be much more precise estimates of the true betas for individual securities". Appendix 2.3 presents the econometrics for using the portfolios instead of securities. Fama and Macbeth (1973) came up with an interesting solution to this problem. Fama and Macbeth tried to cope with this phenomenon by forming portfolios from ranked βp computed from data for one time period and then using a subsequent period to obtain the $\hat{\beta}\, p$ for the portfolios that were used in the tests.

[17] Black Jensen and Scholes (1972) analyse the intercept of the second-pass regression over several subperiods. This analyses provides further

Fama and Macbeth used the exact data and market index as the Black, Jensen and Scholes study however they did not used the current beta on the portfolio to test the theory. Fama and Macbeth methodology involves the following test. In Step 1 (or Stage 1), betas were estimated for each stock on the NYSE from first-pass regression (equation (2.32)) for the 48-month period (1926-29) and 20 portfolios were formed. The betas were then estimated from 20 portfolios of securities from a first-pass regression starting 1930-34. In other words, to eliminate the bias that is mentioned above, the portfolio betas are estimated a second time using a later set of stock returns. This technique is called standard instrumental variables technique. In Step 2, the following cross-section test regression was estimated:

$$R_{it} = \gamma_{0t} + \gamma_{1t}\hat{\beta}_i + \gamma_{2t}\hat{\beta}_i^2 + \gamma_{3t}\hat{\sigma}_{ei} + \mu_i \tag{2.37}$$

for each month in the period 1935-38 where R_{it} is the return of the portfolio p at month t, $\hat{\beta}_i$ is the beta estimated from step 1, $\hat{\sigma}_{ei}$ is the estimated unsystematic risk of the portfolio from step 1 and μ_i is the error term. The $\hat{\beta}_i^2$ was included to test the linearity between returns and beta. Steps 1-2 was repeated by rolling forward 1 year. Fama and Macbeth (1973) repeated[18] this process using data from 1926-68 to obtain 390 estimates of each of the coefficients in (2.37).

The statistical modelling method used for estimating (2.37) is OLS. OLS is used to fit linear regression models for monthly returns (equation 2.37). Fama and Macbeth test the hypothesis that the time series average of the monthly regression coefficients is zero. The test

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evidence that the Black (1972) version of CAPM is a better description of security returns than the standard CAPM.

[18] This minimises the non-stationary issue in the estimates that prevailed in the Black Jensen and Scholes (1972) study.

is based on a t-statistic formed by dividing the time series average of the monthly regression coefficients by the time series standard error of this average, which properly accounts for any serial correlation among the estimated regression coefficients across months. Fama and Macbeth (1973) use the following t-statistic: $T=(\bar{\gamma}_i)=\bar{\gamma}_i/(S(\bar{\gamma}_i)/\sqrt{N})$, where $\bar{\gamma}_i$ is the time series average of the estimated coefficient, $S(\bar{\gamma}_i)$ is the standard deviation of the estimated coefficient and N is the number of observations (390 in the case of Fama and Macbeth). It should also be noted that, as n becomes larger the t distribution approaches the standard normal distribution (n>30) until they are approximately equal[19].

Fama and Macbeth estimate equation (2.37) and test the following. $E(\gamma_{3t})=0$ - residual risk does not affect return; $E(\gamma_{2t})=0$ - there are no nonlinearities in the CAPM; $E(\gamma_{1t})>0$ - there is a positive price of risk; $E(\gamma_{0t})=E(Rf)$ (Sharpe-Lintner Hypothesis) or $E(Rz)$ (Black (1972) model); Parameter estimates should not be autocorrelated and the residuals should not be autocorrelated.

The results of Fama and Macbeth study showed that for the whole period and all sub-periods the average value of γ_{1t} was positive and significant. However the average value was lower than the market risk return (average *Rm-Rf*) for the period under study. They further found that the parameter on residual risk is insignificant and independent for the sample and sub-periods. This result was different than that found by Lintner. They also found that the

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[19] In interpreting these t-statistics one should keep in mind the evidence of Fama (1965) and Blume (1970). They suggests that distributions of common stock returns are "thick-tailed" relative to the normal distribution and probably conform better to nonnormal symmetric stable distributions than to the normal. From Fama and Babiak (1968), this evidence means that when one interprets large t-statistics under the assumption that the underlying variables are normal, the probability or significance levels obtained are likely to be overestimates. Officer (1971) tested the hypotheses on monthly stock returns. Under the assumption that distributions of monthly returns are symmetric stable, he estimates that in the post-World War II period, the characteristic exponent for these distributions is about 1.8 (as compared with a value of 2 for a normal distribution). From Fama and Roll (1968), for values of the characteristic exponent so close to 2.0 stable nonnormal distributions differ noticeably from the normal only in their extreme tails-that is, beyond the .05 and .95 fractiles. Thus as long as one is not concerned with precise estimates of probability levels, interpreting t-statistics in the usual way does not lead to serious errors.

parameter on β_i^2 is insignificant and independent for the sample and sub-periods. Also Fama and Macbeth found the Sharpe-Lintner hypothesis to support the results of Black, Jensen and Scholes. Fama and Macbeth generally found the intercepts in their study to be greater then the risk free rate that prevailed during that period. The also found that the residuals were not autocorrelated. Overall, the evidences of Fama and Macbeth clearly supported the CAPM[20].

2.5. ANOMALIES DURING 1980s

2.5.1. EARLY TEST OF CAPM IN THE US EQUITY MARKET

Soon after the initial tests of CAPM, quite a few empirical regularities were found in the literature. An empirical regularity not predicted by CAPM was called an anomaly. The following section briefly presents some of the existing anomalies[21] in literature:

2.5.1.1. EARNINGS TO PRICE (E/P)

One of the early studies that contradicted the predictions of CAPM was Basu (1977). Using the sample period from April 1957 to March 1971, Basu showed that stocks with high Earning-Price (E/P) ratios (or low P/E ratios) earned significantly higher returns than stocks with low E/P ratios. His results indicated that differences in beta could not explain these return differences. A study by Jaffe, Keim and Westerfield (1989) confirmed these findings and also showed that the E/P effect does not just appear in the month of January, as had been

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[20] The studies above used actual data for testing the CAPM. Theoretically, however as stated earlier, the CAPM is based on expectations or ex-ante returns. Friend, Westerfield and Granito (1978) claimed to have used ex-ante measures of returns in testing the CAPM. These returns were the expected returns of a particular US stock as forecast by institutions for their investment purposes. Friend, Westerfield and Granito used individual securities rather than portfolio in their study due to limited availability of data. Their overall results did not seemed to support the validity of the CAPM.

claimed by Basu (1983). Aggarwal, Hiraki and Rao (1988) found something similar for the Japanese stock market. The E/P effect is a direct contradiction of the CAPM; beta should be all that matters.

2.5.1.2. FIRM SIZE

In 1981, the study by Banz suggested that CAPM might be missing something. Banz (1981) tests the CAPM by investigating whether the size of the firms involved can explain the residual variation in average returns across assets that is not explained by the CAPM's beta. He found that during the 1936-75 period, the average return to stocks of small firms (those with low value of market equity) was substantially higher than the average return to stocks of large firms after adjusting for risk using the CAPM. This observation has been known as size effect. Banz (1981) uses a procedure similar to the portfolio grouping procedure of Black Jensen and Scholes (1972). In Banz (1981) study, the stocks are sorted on the basis of size and then beta to get 25 portfolios. Banz then estimated the cross-sectional relation between return, beta, and relative size-that is, equation:

$$Rp = a + b\beta p + c\psi p + ep, \tag{2.38}$$

where Rp is the return of the pth portfolio, βp is the beta of the pth portfolio, ψp is equal to the relative size of the pth portfolio and ep is the error term. With this procedure then, b and c are risk premiums for beta and size risks, respectively. For the entire period, 1936-75, Banz obtains:

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[21] Most of the review discussed in this section is only related to US stock market. The review of the UK stock market will be discussed in the following sections.

$$Rp= \quad .0045-.0092\beta p-.00052\psi p \qquad (2.39)$$

$$\textit{t-statistics} \quad (2.76) \quad (-1.0) \quad (-2.92)$$

It can be seen that, the size coefficient (in Banz (1981)) is large in absolute value and statistically significant. The fact that the estimate for *c* is negative implies that stocks of firms with large market values have had smaller returns on average than stocks of small firms. From these results, relative size seems to explain a large fraction of cross-sectional variation in average returns unlike beta. Banz conclude that the CAPM is misspecified.

2.5.1.3. BOOK-TO-MARKET EQUITY (BE/ME)

Rosenberg, Reid and Lanstein (1985) provide yet another piece of evidence against the CAPM by showing that stocks with high ratios of BE/ME have significantly higher returns than stocks with low BE/ME. Since the sample period for this study is fairly short (1973-84), the empirical results did not receive as much attention as some of the other studies discussed above. However, when Chan, Hamao and Lakonishok (1991) found similar results in the Japanese market, BE/ME began to receive serious attention as a variable that could produce dispersion in average return.

2.5.1.4. PRIOR RETURN (REVERSAL AND MOMENTUM) EFFECT

There is an evidence that prior returns can explain the cross-sectional behaviour of subsequent stock returns. The literature documents two, seemingly, unrelated phenomena. The first is the existence of return reversals (past 'loser' becomes past 'winner' and vice-versa) over both long-term horizons (3 to 5 years) as well as very short-term periods (a

month and shorter). The second is the presence of an opposite effect over horizons of intermediate length: When prior return are measured over periods of 6 to 12 months, 'losers' and 'winners' retain their characteristic over subsequent periods. There is, in this case, return momentum rather then reversal.

The main finding of Debondt and Thaler (1985) was that losers have much higher average returns than winners over the next three to five years. Chopra, Lakonishok and Ritter (1992) show that beta cannot account for this difference in average returns. This tendency of returns to reverse over long horizons (e.g. losers become winners) is yet another contradiction of the CAPM. Losers should have much higher betas than winners in order to justify the return difference. Chopra, Lakonishok and Ritter show that the beta difference required to save the CAPM is not there.

Jagadeesh (1990) found that stock returns tend to exhibit short-term momentum. In Jagadeesh and Titman (1993), it is clearly shown that the buying past winners and selling past losers generates significant positive excess returns over the periods of 3 to 12 months.

2.5.1.5. SEASONAL EFFECT

This anomaly indicates that the stock returns over different calendar periods are predictable. This was first observed by Watchel (1942) and was then investigated more fully by Officer (1975) and Rozeoff and Kinney (1976). The latter paper found that returns to an equally-weighted portfolio tended to be higher in January than in other months. This is sometimes known as January effect. Basically, the January effect describes the empirical observation that stock returns appear to be higher in January than in other months of the year. Another

dimension to the January effect indicates that a substantial proportion of the January effect was caused by the performance of small firms, see for example, Ikenberry and Lakonishok (1989), who found that over the period 1926-1986, small firms outperformed large firms in the month of January by about 5.5%. Haugen and Lakonishok (1990) obtained similar results.

In addition to above findings, there are various other evidences found against the CAPM. Bhandari (1988) found that the firms with high leverage (high debt/equity ratios) have higher average returns than firms with low leverage for the 1948-79 period. This result persists after size and beta are included as explanatory variables. Reinganum (1981) showed that the positive relation between beta and return that was observed in earlier studies like Black, Jensen and Scholes (1972) and Fama and Macbeth (1973) had weakened in most recent years. Litzenberger and Ramaswamy (1979, 1982) and Miller and Scholes (1982) found a dividend yield effect in average returns. Some other anomalies like, transaction costs (Brown and Barry (1984)), neglect effect (Merton (1987)), low price effect (Blume and Husic (1973))[22] were also found in the literature.

2.5.2. EARLY TESTS OF CAPM IN THE UK STOCK MARKET

During the early 1980s, tests of the CAPM had mostly been done using the US data. Very few tests of the CAPM have been carried out on UK stocks during this period.

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[22] Neglect and Transaction cost effect: Proxies for differential information are the neglected and transaction cost effect. Under this hypothesis, firms neglected by analysts' investors, financial analyst, and other investment agencies suffer from lack of information or asymmetric information. Low price effect: Blume and Husic (1973) showed that the price per share of stock acted an indicator of changes in the levels of risk of individual securities.

Levis (1985) examined the stocks traded on London Stock Exchange (LSE) for the period January 1958-December 1982 using an approach similar to Fama and Macbeth. He constructed 10 portfolio on the basis of market values (in an ascending order) and then used the familiar Fama and Macbeth approach. OLS betas were obtained by regressing monthly portfolio returns against monthly returns of the Financial Times All Share (FTA) value-weighted index. His results showed that small firms appeared to be less risky than their larger counterparts, concluding that such evidence contradicts both the main premise of modern financial theory about the positive trade-off between risk and return and the empirical evidence from the capital markets outside US.

Corhay, Hawaini and Micheal (1987) examined the relationship between average monthly returns and risk for portfolios of common stocks traded on the LSE using a methodology similar to Fama and Macbeth (1973). They found that no relationship existed, on average, between monthly portfolio returns and systematic risk over the entire sample period (January 1955-December 1983). However, they were able to find a positive and significant systematic risk premium in the month of April. This came to be known as a monthly effect. In addition to this, they also found a negative but insignificant relationship between average returns and size. But the size effect was visible when the systematic risk factor (beta) was added to the regression.

In another study, Beenstock and Chen (1986) covered the period 1961 to 1981. The study used individual stocks in the regression rather then portfolios. They again found evidences, which were clearly against the CAPM. Poon and Taylor (1991) also used the Chen, Roll and

Ross (1986)[23] methodology and found the risk premium for the UK to be negative and significant, a result which was inconsistent with the CAPM.

The above results add to the growing number of empirical studies that cast doubt on the ability of the CAPM to explain equilibrium relationships in the financial markets. Inspite of all this negative evidence against the CAPM, the CAPM was still the default view for most financial economists and researchers going into the 1990s. But, it will now be seen, how this view has also changed.

2.6. INNOVATION IN THE 1990s

The anomalies discovered in the 1980s and the general failure of the CAPM became the subject of research in 1990s. In 1992, Fama and French pulled together most of the findings of the 1980s in one single cross-sectional study. Five variables were used in their study, namely, size, beta, leverage, BE/ME and E/P. These five variables were used to explain the cross-section of expected returns in the US stock market.

2.6.1. THE FAMA AND FRENCH (1992) STUDY

Fama and French (1992) looked at US stocks for the period 1963-90. Fama and French used all nonfinancial firms in the intersection of (a) the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association Of Securities Dealers Automated Quotations (NASDAQ) returns files from the Centre for Research in Security

[23] The procedure of Chen, Roll and Ross (1986) is similar to that of Fama and Macbeth except few differences. In the first-stage, time series regressions are run for each of a series of portfolios to estimate each portfolio's sensitivity to each macro economic variables using equation 2.22. The rest of the procedure is the same as Fama and Macbeth.

Prices (CRSP) and (b) the merged COMPUSTAT annual industrial files of income statement and balance sheet data, also maintained by CRSP. The CRSP returns cover NYSE and AMEX stocks until 1973 when NASDAQ returns also came in line. The COMPUSTAT data are from 1962-1989. Fama and French used on average 2,267 companies in the monthly regressions over the whole sample period.

Fama and French followed the same procedure as Fama and Macbeth (1973) but with a few adjustments to the methodology. Basically, Fama and Macbeth (1973) tried to cope with the Error In Variable (EIV) problem by forming portfolios from ranked beta computed from data for one time period and then using a subsequent period to obtain the beta for the portfolios that were used in the tests. This is standard instrumental variable technique. Fama and French (1992) use a multivariate instrument technique for forming portfolios with good reason. Fama and French (1992) were cautious of the multicollinearity problem found by Chan and Chen (1988). Chan and Chen (1988) documented a problem in estimated portfolio betas if size effect (Banz (1981)) existed in portfolio returns. In this way, either equation (2.39) mentioned in Section 2.5.1.2 is misspecified or the estimated portfolio betas contain substantial errors. Chan and Chen (1988) showed how size and the betas of size portfolios were highly correlated (small firms not only have higher returns; they also have high betas). Basically Chan and Chen (1988) shows that, if two independent variables move together, like the size and beta in the case of Fama and French, then there is a problem of multicollinearity. In such a case, it will be difficult to determine the separate influences of beta and size. In data, this problem will be reflected in imprecise estimates, that is, estimates with high

variances[24]. Chan and Chen (1988) proposed the use of an instrument that was highly correlated with risk, period by period, so those portfolios formed consistently on the basis of this instrumental variable could be assumed to have the same relative characteristics over time. Chan and Chen (1988) suggested that any instrument variable that is good instrument for expected return will be a good instrumental variable for the beta. From the size effect, they believed that firm size was such an instrument. Fama and French therefore rectified this problem by using their two-pass sort of stocks: sorting stocks into 10 size portfolios and then subdividing these portfolios according to pre-estimated betas. The purpose of this procedure was to allow beta to vary in a way, which was independent of size. Poon and Taylor (1991) point out, however that the positive size-beta correlation (with a rank coefficient of 0.977 in their sample) could be due to nonsynchrouous-trading or 'thin-trading' effect[25]. Although, estimated betas in Fama and French study had been adjusted for the thin-trading problem using the method of Dimson (1979), the relation between beta and firm size was still positive. The methodology of Dimson (1979) is clearly demonstrated in Appendix 2.4.

Fama and French divided the stocks according to basis of size. Fama and French then used equation (2.29) to calculate the pre-ranking beta to subdivide the size portfolios. Every firm was subsequently assigned a category based on the location of its two criteria (size and beta) in the NYSE deciles. Consequently, a firm was placed into one of the 100 portfolios (i.e., 10 times 10). Its location within 10x10 array changed from year to year. Sorting each

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[24] Estimates in the presence of multicollinearity problem are still Linear Unbiased Estimates, but have larger variances and covariances. As a consequence, the t-statistics of one or more coefficients tends to be statistically insignificant. Yet at the same time, the overall measure of goodness of fit can be very high.

[25] Non-synchronous trading in stock market exists when some stocks trade more frequently than others. Suppose that the two stocks i and j are independent but i trades less frequently than j. If some systematic news arrives in time t, it is more likely that stock j will reflect the news before stock i because it trades more frequently. Eventually, stock i will reflect the new information, but only when it trades. Because the price of stock i responds with a lag to the information, the price of stock i and j will be cross serially correlated. As a result, a portfolio containing both i and j will be serially correlated.
Nonsynchronous trading problem is often associated with small firms. Size is related to bid-ask spread. The speed of adjustment to new information is likely to be negatively related to bid-ask spread. Prices of high spread stocks respond more slowly to new information because it is not profitable for traders to act upon new information until the value of that information exceeds the costs of transacting. Therefore the returns of high spread firms are more like to exhibit positive autocorrelation.

firm by the 10 size and 10 Pre-ranking beta decile breakpoints created 100 portfolios for every year. Like Fama and Macbeth, the equally-weighted monthly stock returns for each portfolio were computed for the succeeding 12 months. These equally-weighted monthly stock returns for each portfolio were called post-ranking returns in Fama and French (1992). Again like Fama and Macbeth, the process was repeated by moving one year forward, the size and pre-ranking beta were recomputed for each available firm, the 100 portfolios were rebalanced according to the new decile breakpoints, and the monthly equally weighted portfolio returns throughout the succeeding 12 months were collected. This procedure was repeated till 1990.

In Fama and Macbeth, the betas in the first stage were computed for every year using the portfolio returns and market index. But in the case of Fama and French, the portfolio returns were stacked together for full-sample period. These time series returns were then regressed on the equally weighted portfolio to get the betas. Equation (2.32) was used for regression. These betas were called post-ranking betas in Fama and French (1992). In second stage of Fama and French (1992), a Fama and Macbeth cross-sectional regression similar to equation (2.37) was then performed using the individual stock returns as a dependent variable and portfolio beta, size, BE/ME, E/P and dividend yield as an independent variable. Fama and French also formed the portfolios on the basis of beta, size, BE/ME and E/P and investigated whether their results were sensitive to different types of portfolios.

Fama and French showed that, when portfolios were formed on size, there was a positive relation between return and beta as predicted by CAPM. It also appeared that the CAPM explained the higher returns that small firms had earned. The beta-sorted portfolios showed no obvious relation between beta and average returns. The size-beta portfolios showed that

the variation in beta that was tied to size was positively related to average return, but variation in beta unrelated to size was not compensated in the average returns of 1963-1990. Fama and French estimate the following equation using the size-beta portfolios:

$$Ri = \quad -.37 + .15\beta P \qquad (2.40)$$

$$\textit{t-statistic} \quad (.46)$$

Fama and French included only beta in the regression equation, and found an insignificant positive slope; their estimate of the risk premium was .15 (.15% per month or 1.8% p.a.) with a t-statistics of .46. They also tested the cross-sectional relationship between return and beta using a different sample period. Their estimate of expected return compensation based on data for the 1941-90 period was .24% per month, but, because the conventional t-statistic was thus only about 1.0, they could reject the CAPM. It was this aspect of the evidence that has received significant attention in finance world in the 1990s.

In the light of the flat relationship between expected returns and market betas, Fama and French also examined whether there are additional factors that explain the cross-section variation of average returns. Fama and French included accounting variables such as size, BE/ME, dividend yield, E/P and leverage in the original CAPM. This methodology forced the beta variable to compete as an explanatory variable with alternative explanatory variables. When size was included in the regression, the beta coefficient was estimated to be -.379 (t= -1.21) and coefficient on size was estimated to be -.17 (t= -3.41). Fama and French interpreted this as an evidence that the relation between beta and average return was flat and considered size as an important variable. Fama and French also considered the ability of other attributes to account for the cross-sectional variation. Unlike the simple relation

between beta and average return, the univariate[26] relations between average return and size, leverage, E/P and book-to-market equity (BE/ME) were strong. When they included the BE/ME as an explanatory variable in addition to size, they found that this ratio could account for substantial portion of the cross-sectional variation in average returns. In fact, BE/ME appeared to be more powerful than size. The positive relation between BE/ME and average returns also persisted in competition with other variables. However in multivariate tests, the negative relation between size and average return was present no matter what combinations were used in the regressions. This negative relationship implied that the small firm stocks had higher expected return. The t statistics for leverage and E/P were also significant. But, overall Fama and French found that the BE/ME and size were the two variables that had the strongest relation to return. An explanatory power of other variables was removed when BE/ME and size were included in the regressions.

Fama and French (1992) suggest that market overreaction may cause the BE/ME effect. To address this hypothesis, they estimated cross-sectional regressions of monthly returns on size, BE/ME, and three-year lagged returns, but found that prior returns have no explanatory power, even when used alone. Moreover, Fama and French (1992) study differ from finding reported by De Bondt and Thaler (1987), who found that the subsequent performance of prior winners and losers is positively related to BE/ME. Fama and French (1992) do not explore seasonal overreaction patterns documented by De Bondt and Thaler (1985, 1987), Zarowin (1990), and Chopra, Lakonishok, and Ritter (1992), or the seasonal aspects of the size effect reported by Keim (1983), Tinic and West (1984), and Jaffe, Keim, and Westerfield (1989). Thus it is unclear in the US whether the BE/ME effect and market overreaction and, in

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[26] Tests with one explanatory variable in regression models are known as univariate tests. On the other hand, tests with more then one explanatory variable in regression models are known as multivariate tests.

general whether prior returns represent distinct and important influence on return. Fant and Peterson (1995) find that overreaction is not subsumed by BE/ME, but instead that strong seasonal relations exist between returns and prior returns, even after accounting for effects associated with BE/ME and stocks.

What is surprising about the above results is that Fama and French (1992) uses the same procedure as Fama and Macbeth (1973) but reaches a different conclusion. Fama and Macbeth (1973) support the CAPM; but Fama and French (1992) do not. When Fama and French (1992) rerun their regressions for 1941-65, using the Fama and Macbeth sample, they find a positive relationship between average return and beta. So the different results are due to the different sample periods. It can be seen, therefore, that the relationship between beta and returns are very sensitive to the sample period.

Jagannathan and McGrattan (1995) shows that by applying CAPM to data sets from different subperiods, (1926-75, 1976-80, 1981-90, 1926-91) in US, the results of CAPM are quite weak for smaller subperiods (1976-80 & 1981-91) but are quite strong for longer subperiods (1926-75). Another point in the Jagannathan and McGrattan (1995) study is that, the excess returns on small stocks and large stocks have the same beta value with excess returns of 1.7% and 13.3% respectively. This fact is also counter to the prediction of CAPM. The intuition of their study is that there is empirical support for the CAPM over a longer horizon and in between that there are periods in which they do not find a CAPM prediction. This study suggests that the relationship between average returns and beta can be completely flat for some sample periods.

Chan and Lakonishok (1993) illustrate how difficult it is to make unambiguous inferences from the very noisy and ever-changing environment generating stock returns. Chan and Lakonishok test the CAPM using the technique of Fama and Macbeth for different types of market. They use this procedure using CRSP data from 1926-91 for 'up market' and 'down market'. They focus on whether it is indeed true that, stocks with high betas represent higher risk then stocks with low betas. They test that if the market in general falls, then the prices of high beta stocks should decline more that the prices of low beta stock. They concluded that beta fared very well in predicting stock returns, especially in 'down market'. Pettengill, Sundaram and Mathur (1995) repeated the Chan and Lakonishok (1993) study and found similar results as Chan and Lakonishok.

Other studies (Klein (2001), Brennan, Chordia and Subrahmanyam (1998), Amihud (2000), and Paster and Stambaugh (2001)) have argued that taxes and liquidity are the missing factors in a rationally based CAPM. For example, Klein (2001) introduces a capital gain lock-in effect while Brennan, Chordia and Subrahmanyam (1998), Amihud (2000), and Paster and Stambaugh (2001) present the case for higher expected returns in illiquid stocks. Jensen and Mercer (2002) found that the risk premiums on beta for the US stock market were sensitive to the monetary policies.

2.6.2. RECENT STUDIES OF THE UK STOCK MARKET

Soon after the Fama and French (1992) study, two similar studies on the cross-section of expected returns were done on the UK stock market.

Strong and Xu (1997) looked at the 1337 UK stocks for the sample period 1973-1992 and 4603 stocks for the sample period 1960-1992. They used the data from London Share Price Database (LSPD) and Exstat database. A difference between the Fama and French and the Strong and Xu (1997) study was the number of portfolios. They divided all the stocks into 25 portfolios[27] instead of 100 portfolios like Fama and French did for the US stocks.

The following Fama and Macbeth regressions are taken from Strong and Xu (1997) (*t-statistics are shown in brackets):*

$$Ri = .06 + .17\beta p \quad (2.41)$$

t-statistics ***(4.64) (.14)***

$$Ri = 2.22 - .06\beta p - .19(size) \quad (2.43)$$

t-statistics ***(4.64) (-.08) (-2.77)***

$$Ri = 1.88 + .51(BE/ME) \quad (2.42)$$

t-statistics ***(5.10) (1.81)***

$$Ri = 2.14 - .13(size) + .34(BE/ME) \quad (2.44)$$

t-statistics ***(3.92) (-4.49) (5.41)***

Equations (2.41) and (2.43) show that the βp (beta) is not positive and significant. By looking at equation (2.43), size emerges to be powerful then beta. But like Fama and French (1992), Strong and Xu (1997) also found that the BE/ME had the strongest relation to return (see equation (2.42) & (2.44)). But like Fama and French, Strong and Xu (1997) also found that the R-squared of all the cross-sectional models never exceeded 8%. The models may have been spurious due some econometrics problem discussed in the earlier sections.

Chan and Chui (1996) used the data for 1480 stocks from the LSPD and Exstat Company Accounts Database for the years 1971-90. The number of stocks included in Chan and Chui

[27] They replicated the results using 6x6, 7x7, and 8x8 classifications with no material effect on the results reported in their paper.

(1996) study was similar to the stocks included in the previous UK studies. For example, for the UK stock market, the two samples in Levis (1989) ranges from 770 to 1,920 and from 1,150 to 2,300 respectively, and the Poon and Taylor (1991) sample size ranges from 562 to 1,086 for the sample period July 1973-June 1990.

The following Fama and Macbeth regressions were taken from Chan and Chui (1996) (*t-statistics are shown in brackets)*:

$$Ri = (N/A) - .0144\beta p \qquad (2.45)$$

t-statistics ***(-1.80)***

$$Ri = (N/A) - .0120\beta p - .0006(size) \qquad (2.46)$$

t-statistics ***(-2.09)*** ***(-.94)***

$$Ri = (N/A) + .0040(BE/ME) \qquad (2.47)$$

t-statistics ***(4.82)***

$$Ri = (N/A) - .0005(size) + .0032(BE/ME) \qquad (2.48)$$

t-statistics ***(-.66)*** ***(4.45)***

Equations (2.45) to (2.48) also show more or less the same results as Strong and Xu (1997) except for one big difference. Size is never a significant variable in any of the regressions. Strong and Xu (1997)'s results showed some validity of size variable. When the beta and size were run together, Chan and Chui were able to find a negative estimate of beta. Although the estimate of beta was negative, the estimate was small, so it seemed unlikely to have any economic meaning. As with all other studies in the 1990s, BE/ME was the most important variable in this study as well.

In another study done of UK stock markets, Clare, Priestley and Thomas (1998), using FTSE 100 stocks quoted on the LSE between January 1980 and December 1993, explore the

relationship between beta and expected returns using an alternative testing methodology developed by Gibbon (1982) and extended by McElroy et al. (1985). This is a one-step procedure that they argued is more efficient then the Fama and Macbeth (1973) method.

The Fama and Macbeth (1973) estimation procedure is usually undertaken using OLS. The efficiency of the OLS estimator requires that there is no contemporaneous correlation between idiosyncratic returns. If this condition does not hold then, the resultant estimate of beta will be inefficient and the associated standard errors will be biased upwards.

McElory et al (1985) has proposed an alternative estimation procedure for the CAPM (and the APT) which can accommodate correlation between idiosyncratic returns. They use a Non-linear Seemingly unrelated regression technique[28] (NLSUR) which is asymptotically efficient when the variance-covariance matrix of returns is not diagonal.

This section will now summarise the steps of the one step estimation method used by Clare, Priestley and Thomas (1998). Let the time series of excess returns be determined by,

$$R_t = E_t + \beta RM_t + v_t \tag{2.50}$$

where R_t is an Nx1 matrix of returns; E_t is an Nx1 matrix of expected returns; β is an Nx1 matrix of beta coefficients; RM_t is scalar, which represent the excess return on the market

[28] Gibbons (1982) was one of the first to present a Seemingly Unrelated Regression (SUR) type multivariate framework for estimating the expected return on the 'zero-beta' portfolio and for testing a multivariate restrictions implied by CAPM for the period 1926-1975 for US stocks. The test that Gibbons employed to test the null hypothesis was a likelihood ratio test. While the likelihood ratio test used by Gibbons (1982) rejected the null hypothesis of a linear relationship between risk and expected return for the period from 1953-1976, Stambaugh(1982)'s later lagrange multiplier test, for the same period, accepted it. Stambaugh also argued that his methodology avoided an EIV problem and increased the precision of parameter estimates for the risk premium.

proxy; and v_t is the NxN variance-covariance matrix. And let the cross section of expected returns be determined by,

$$E_t = \lambda_m \beta \tag{2.51}$$

where λ_m is scalar, which represents the price of risk.

Then, substituting (2.51) into (2.50)

$$R_t = \lambda_m \beta + \beta RM_t + v_t \tag{2.52}$$

Equation (2.52) represents a system of non-linear regressions. The NLSUR estimators, which provide joint estimates of β and λ_m are those that solve the minimisation problem:

$$min\ v^1 [\ \hat{\sum}^{-2} \otimes I_t] v, \tag{2.53}$$

where $\hat{\sum}^{-2}$ is the N x N residual variance-covariance matrix. Equation (2.52) can be estimated with the restriction of a diagonal variance-covariance matrix (under the assumption that there is no contemporaneous correlation amongst the error terms in the system) or with the restriction removed, estimating a full variance-covariance matrix thus allowing for contemporaneous correlation. Estimating the system both with and without the restriction on the variance-covariance matrix allowed Clare, Priestley and Thomas (1998) to gauge the

impact on beta and price of risk estimates under the competing assumptions about idiosyncratic returns.

Clare, Priestley and Thomas observe that it is possible to add the Fama and French variables to this method, so that, for example, the following regression is obtained:

$$R_t = \lambda_m \beta + \beta RM_t + \gamma size_{t-1} + \delta(BE/ME)_{t-1} + v_t \qquad (2.54)$$

But, of course, this is not the hypothesis tested by Fama and French, as the size and Book-To-Market Equity factors are not explicitly incorporated.

Clare, Priestley and Thomas (1998) estimated the CAPM using the NLSUR estimator of the equation presented in expression (2.52). They obtained an insignificant beta coefficient (t=1.55). Their results indicate that when they use the one-step estimator, where it is assumed that there is no correlation between idiosyncratic returns, they reject the key cross-sectional conclusion of the CAPM. However in the Clare, Priestley and Thomas study[29], the results of unconstrained estimates of the CAPM were different. When they allowed for a full correlation structure between idiosyncratic returns, they found that the CAPM's cross-sectional restriction was accepted and thus they found a highly significant and positive relationship between beta and expected UK stock returns. The t-value of beta estimated by this method was 5.79. They found that Fama and French (1992) variables had little additional explanatory power for the cross-section of expected UK stock returns. In their study, the t-values for the Fama and French variables from this method were all less then 2.

[29] Paolo Pasquariello (1999) applied a similar methodology to the New York Stock Exchange (NYSE) for the period of 1935-1968. Their results are in favour of the null. In their study, on average, there is significant positive trade-off between return and risk and price of risk does play an important role in explaining the cross-sectional variability of expected returns.

Chelley-Steeley (1996) study introduced some interesting findings on the UK stock market. Monthly returns for 150 UK stocks for the sample period, 1976-1991 were gathered. She found that the risk is not priced every month of the year. According to her, investors received a systematic risk premium in only three months of the year, January, April and July. Moreover, in her study, when systematic risk is priced, large firms provide a higher systematic risk premium than small firms. Overall, her findings provide little evidence in support of the CAPM, at least on a month by month basis.

2.7. ECONOMETRIC AND DATA CONSIDERATIONS

The findings of Fama and French (1992) were further questioned by a number of other studies during the 1990s that examined a variety of econometrics and data issues. These will now be reviewed.

2.7.1. DATA MINING AND DATA SNOOPING EFFECT

When a researcher utilises many methods in a study, such as various combinations of explanatory factors, various periods, and various models, it can be said that the researcher is data mining. Through the data mining, a few variables are bound to show a statistical relation to returns, by chance.

Black (1993a, 1993b), suggested that the Fama and French results were likely to be the result of data mining. Since Fama and French chose their explanatory variables based on the results of earlier empirical studies, the observed explanatory power of these variables could

be due to a massive data mining exercise on the part of the authors of these earlier studies. For example, the small-firm effect soon vanished after the Banz (1981) was published. Fama and French find that in the period after the Banz study 1981-90, there was no size effect yet they claim that size is one of the variables that captures the cross-sectional variation in average returns. Black also criticises the use of the BE/ME variable. According to Black, Fama and French provides no theory for the size or BE/ME effect. Based on these findings, Black contended that some of the statistical tests in Fama and French study were not properly specified. He also suggested that, since the relations between returns and the Fama and French factors were likely a result of data mining, they would disappear if another time period or another data source were analysed. Mackinlay (1995) also mentions data mining[30] as a potential cause of the observed results.

Barber and Lyon (1997) also considered the issue of data mining pointed by Black (1993a, 1993b) in Fama and French study. They collected a sample of financial firms for the 1973-94 period and found a reliable BE/ME effect among those firms. Since financial firms were purposely excluded from the Fama and French sample, the results of Barber and Lyon provided independent evidence of the explanatory power of BE/ME. Further independent evidence came from Fama and French (1998), who found a reliable BE/ME effect in several developed countries for the 1975-95 period. Capaul, Rowley and Sharpe (1993) also found evidence of BE/ME effect in the US and five other developed countries for the 1981-92 period. Such findings were clearly in favour of the innovative findings of the early 1990s.

[30] Lovell (1983) had presented an excellent reasoning on data mining.

Data snooping might be another reason behind the Fama and French results. Lo and MacKinlay (1990, pg. 434) define data snooping as occurring "when the construction of test-statistics is influenced by empirical relations derived from the very same data to be used in the test". According to Lo and MacKinlay, the size effect was discovered as part of the evolution of empirical research performed largely on the same CRSP and COMPUSTAT data sets. Lo and Mackinlay (1990) also point out that if the sorting procedures used for portfolio construction is based on either a variable that is only known to be empirically correlated with returns or a variable measured within the sample, the test will again contain a data-snooping bias. Lo and Mackinlay argue that researchers choose to construct their portfolios in a sample in which other studies already detected the variation. Due to this problem, the researchers may lead to conclude that a relationship between risk and return is statistically significant when it, in fact, is not. Liang (2000) also argues that even if the sort is based on a variable estimated using prior data, measurement error in this variable can lead to false conclusions. Berk (2000) demonstrated that by sorting stocks into enough portfolios it is possible to reduce the variance of returns within the portfolios to a level such that no model has any explanatory power, so, it is possible to falsely reject a 'true' risk-pricing model.

Mikkelsen (1999) argues that a natural method to avoid data snooping effects and minimize the effects of biases in the data is to form portfolios in a non-systematic way avoiding the use of any information that may contaminate the results. In particular by randomly shuffling the universe of possible stocks into a given number of portfolios (say, one hundred) biases are likely distributed evenly across portfolios and no data snooping takes place. In his study, a bootstrap type method was used for randomly shuffling the stocks in

different portfolios. The drawback is that differences in relevant portfolio characteristics are less pronounced than for traditional size/beta based sorts. Mikkelson (1999) therefore randomly re-sample portfolios a sufficiently large number of times so that certain population characteristics are reasonably stable and reliable. Using this procedure any biases of the form discussed above would likely be present only in a very small number of replications with negligible effects on population statistics. Mikkelson (1999) shows for NYSE stocks that not only is it difficult to reject the CAPM, it also seems that it holds up very convincingly. Furthermore, size plays a minor role in their sample.

2.7.2. SURVIVORSHIP BIAS

According to Kothari, Shanken and Sloan (1995), the book-to-market effect discovered by Fama and French suffers from 'survivorship bias' or 'selection bias'. A data set suffers from selection bias when a selection rule other than random sampling determines whether a given observation on a firm enters the database. An econometrician who ignores the inherent selection rule is implicitly conditioning on the outcome of the selection process. This may lead to biased inference[31].

Fama and French (1992) used COMPUSTAT data for their cross-sectional analysis. Kothari, Shanken and Sloan (1995) suggested some aspects of COMPUSTAT selection procedure that appeared to impart a survivorship bias in COMPUSTAT data. Kothari, Shanken and Sloan (1995) argue that the potential source of the bias is in the COMPUSTAT "back-filling-in" procedure. As also described by Banz and Breen (1986) and Breen and Korajczyk (1994), firms are typically brought into the Compustat files with several years of

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[31] For a general discussion of selection bias, see Verbeek and Nijman (1995).

historical data. In the practice of back filling the missing data by COMPUSTAT, firms with relatively poor earnings (inducing low stock returns and high book-to-market ratio) in a given year, are more likely to be added to the COMPUSTAT database. However, firms with consistently poor earnings are much less likely to be added in the given year. For example, 31% of the 6433 firms, which were included in the early periods, but were then removed from COMPUSTAT in the given period. These 2109 firms were delisted from the stock exchanges because of the financial distress, exchange-forced delistings, and SEC-forced delisting. These companies delay filing the financial information due to financial distress and hence file their previously delayed financial statements and COMPUSTAT incorporates data on these firms. However COMPUSTAT might not include data for these firms if they still suffer from these problems. This selection procedure tends to include firms with high book-to-market and subsequently high returns, but tends to exclude firms with high book-to-market and subsequently low returns. Kothari, Shanken and Sloan (1995) and Breen and Korajczyk (1994) argue that this might induce a (positive) upward bias in the Fama and French coefficient of the book-to-market variable and provide some indirect evidence that a portion of the significant explanatory power of book-to-market equity to average stock returns might be due to the selection bias. Breen and Korajczyk (1994) follow up on this conjecture by using a COMPUSTAT sample that has the same set of firms for all years; no back-filled data are used. They find that the effect of the book-to-equity ratio is weaker in these data than that reported by Fama and French[32]. In a recent study by Kothari, Sabino, and

[32] Shumway (1997) and Shumway and Wather (1998) also criticise the findings of Fama and French (1992) on the basis of a critique similar to that of Kothari, Shanken and Sloan (1995). Shumway (1997) and Shumway and Wather (1998) demonstrate that the widespread missing information on delisting returns in CRSP NYSE/AMEX data may explain the size effect. Shumawy and Warther (1998) conclude that accounting for missing delisting returns in CRSP NASDAQ data eliminates size effect. More precisely, delisting returns are substantially negative on average due to, for example, bankruptcies and take-overs. They suggest that, ignoring what will make portfolios containing many delisted stocks appear to earn abnormal high returns. Companies with small market size are, of course, much more likely to be delisted and Shumway and Warther (1998) find that on substituting a negative return of 55% for all missing delisting returns there is no longer a size effect in the NASDAQ data.

Zach (2001), it is also shown that the results of empirical studies can be very sensitive to the problem of from 'survivorship bias'.

One of the early responses to the criticisms of Fama and French (1992) was Davis (1994), who constructed a database of book values for large US industrial firms for the 1940-63 period, a period for which the Compustat coverage was either poor or non-existent. This database was constructed to be free of survivorship bias, and it covered a period that preceded the period studied by Fama and French. The results of Davis (1994) generally confirmed those of Fama and French. The explanatory power of BE/ME was observed in 1940-63 period, although the magnitude of the return dispersion was somewhat smaller. Davis also found that, the annual beta could not improve the CAPM's performance during 1940-63. Chan, Jegadeesh and Lakonishok (1995) found something similar for 1968-91 period.

2.7.3. ANNUAL ESTIMATION

Rather than use monthly returns, Kothari, Shanken and Sloan (1995) also suggested using annual return observations, for equal-weighted market index for 1927-90 and 1941-90 in the US stock market, to estimate beta. They found that the beta is significantly and positively related to average returns, using annual returns to estimate beta. This result raised a question. If annual betas necessarily have a large estimation error, why, then, are these betas superior in 'explaining' the cross-section of expected returns? It has long been recognised that if there are delays in the complete incorporation of information in security prices, then betas estimated using high-frequency returns (e.g. daily returns) would be biased. Lo and Mackinlay (1990) and Mech (1993) suggest that the time it takes for security prices to

accurately incorporate available information is surprisingly long. For example, in the case of small firm stocks, the non-synchronous trading problem continues to be important using a monthly return measurement interval. A bias in estimated betas due to non-synchronous trading can be reduced, by increasing the length of return measurement interval used in forming returns. Thus, it maybe that the relative performance of annual and monthly betas is a situation in which noisy but less biased annual betas estimate is better than a less variable but biased monthly beta estimate.

An alternative explanation is that the relation to annual betas is spurious somehow reflecting a correlation between the measurement error in beta and average returns. This can be valid given that Kothari, Shanken and Sloan use full-period post ranking betas in order to increase the precision of their annual beta estimates. But they also experimented by computing beta using annual data. Thus, in their study, the betas are re-estimated each year, as opposed to using the full-period post-ranking estimates. They find that the significance of beta estimated in this manner is reduced only slightly.

By contrast, Fama and French (1996a) found that the simple regression t-statistics for the cross-sectional coefficients on monthly and annual betas were small and nearly identical. This was due to the fact that their post-formation betas (for decile portfolios based on past beta rankings) estimated from either monthly or annual returns were nearly perfectly cross-sectionally correlated. This might be because, Fama and French (1996a) compound equally-weighted monthly portfolio returns to obtain annual returns. That is, portfolios are still rebalanced each month, yielding annual returns that differ from Kothari, Shanken and

Sloan's buy-and-hold annual returns obtained by averaging the compounded annual returns on individual securities in portfolio.

2.7.4. VALUE WEIGHTED VERSUS EQUALLY WEIGHTED PORTFOLIOS

Kothari, Shanken and Sloan (1995) provide an interesting analysis on Book-to-Market Equity effect. They form deciles portfolio on the basis of BE/ME. They value weight the stock returns and use value-weighted returns in their study. They then compare the BE/ME effect by comparing the results for value-weighted BE/ME deciles to those for equal-weighted BE/ME deciles portfolios. The latter was done in Fama and French (1992).

TABLE 2.1: RETURNS ON VALUE-AND EQUAL-WEIGHTED PORTFOLIOS FORMED ON BOOK-TO-MARKET EQUITY (BE/ME); JULY 1963 TO 1990

Panel A: Value-weighted Book-to-Market Portfolios adapted from Kothari, Shanken and Sloan (1995)				Panel B: Equal-weighted Book-to-Market *Portfolios adapted from Fama and French (1992)*		
Portfolio	Book-to Market (BE/ME)	Average Market Capitalization	Value-weighted Portfolio Returns	Book-to Market (BE/ME)	Average Market Capitalization	Equal-weighted Portfolio Returns
1A	0.17	1328	11.4	0.11	93	3.70%
1B	0.29	1159	9.1	0.22	107	8.3
2	0.41	852	11.6	0.33	109	11
3	0.54	987	11.6	0.47	96	12.3
4	0.65	664	11.2	0.6	87	13.2
5	0.77	719	12	0.73	80	15
6	0.9	695	12.6	0.87	69	16.8

Table (Panel A), above shows that the average returns for the first six deciles are essentially flat at 11-12% with value-weighting BE/ME ratios for these deciles exhibit substantial range from .17 for portfolio 1A to .90 for portfolio 6 and firm size decile declines as well. Over a similar range of BE/ME values equal-weighting yields (see Panel B) average returns that increase from about 8% to 17%. In panel A, consistent with the weaker cross-sectional results for large firms, the first six BE/ME deciles have the largest average market capitalizations ranging from around $ 1.3 billion to $65 million. These flat returns in Panel A are quite surprising since these effects on expected returns of an increase in BE/ME and the decline in size lead one to expect a steep increase in average returns from decile 1 to 6, however this is not happening.

The overall results of Kothari, Shanken and Sloan (1995) cast considerable doubt on the BE/ME effect, but they do find some evidence of size effect[33]. Their analysis suggests that although beta is not the only relevant variable in explaining returns it certainly is not as redundant as Fama and French seem to believe. In addition to Kothari, Shanken and Sloan, Pontiff and Schall (1998) found that, for the US stock market, the BE/ME effect was period specific and was restricted to the 1926-60 period and was insignificant for the 1960-94 period.

2.7.5. MULTICOLLINEARITY

Munshi (1998) showed that when the linear combination of explanatory variables are correlated then the model might suffer from 'mulitcollinearity'. When Fama and French (1992) removed the size from the data before they tested the relationship between beta and return, they may have also removed that which they intended to measure. A failure to find a beta effect in the residuals of the size effect does not imply an absence of beta effect. There are better ways to find the unique contribution of two correlated variables. Munshi (1998) suggest that, one might first regress beta against size and use these residuals as the unique contribution of beta and then regress size against beta and use those residuals as the unique contribution of size.

2.7.6. CONTINUOUS OR DISCRETE RATES OF RETURN

The empirical evidence of Black, Jensen and Scholes (1972) was based on the discrete rates of return. The period covered by that study commenced shortly after the stock market crash of 1929 and finished in the 1960s. Their results were sensitive to the returns used in the test. In Black, Jensen and Scholes (1972) study, after converting the discrete returns to continuous returns, it appeared that the relationship between risk and return was not nearly as strong. Jensen (1972) attempted to fit a continuously compounded version of Sharpe-Lintner (1972) model to the Black, Jensen and Scholes data. His estimate for the mean continuously

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[33] There might be other reason to explain the differences between the Kothari, Shanken and Sloan (1995) and Fama and French (1992) results. Unlike Kothari, Shanken and Sloan, who include AMEX firms from July 1964, Fama and French restrict their sample to NYSE stocks. This has the effect of substantially reducing the range of estimated betas. For example, using equal-weighted annual index returns, the post-formation betas of NYSE decile portfolios formed by ranking stocks on past betas range from .78 to 1.27 in Fama and French (1992, Table 1). In comparison, the corresponding range is .52 to 1.35 in Kothari, Shanken and Sloan (1995, Table 1), an increase of nearly 70%.

compounded rate of return for the market portfolio was .0105 per month or 13.4% per annum. This figure was 5% less then what Black Jensen and Scholes found for their study. Jensen also concluded that the continuously compounded model does not fit the data. The Fama and French (1992) study was based on mean discrete returns rather than continuous compounding. In view of the foregoing discussion on continuous compounding return, it is difficult to interpret how the Fama and French study would have fared had they used continuous compounding.

Ashton and Tippett (1999) show that in the UK, the small firm effect disappears when they use continuously compounded returns. They gather data from the LSPD for the year 1961-1997 with a sample of 2,820 stocks. Their study shows that for discrete returns in UK stock market, the relative abnormal return increases as the size of the firm in the portfolio decreases. With continuous returns, the size effect disappears. The size effect in the UK seems to depend on the way they compute returns. They also proved that there is unsystematic risk in the average of the discrete returns that result in a size effect in observed returns. The percentage of unsystematic risk in the total variability of returns increases with decreasing size and this gives rise to the so-called size effect.

2.7.7. THE MARKET PORTFOLIO

Jagannathan and Wang (1993, 1996) used the same data set as of Fama and French (1992). They show that the lack of empirical support for the CAPM may be due to the inappropriateness of some assumptions made to facilitate the empirical analysis of the model. Such an analysis must include a measure of the return on the aggregate wealth portfolio of all agents in the economy. They include human capital in their measure of wealth. They used the growth of labour income as a proxy of human capital. In this way, their CAPM was able to explain 28% of the cross-sectional variation in average return in the 100 portfolios studied by Fama and French (1992). Roll and Ross (1994), Kandel and Stambaugh (1995), and Grauer (1999) suggested that the cross-sectional tests of the Fama and French were susceptible to the use of poor proxies for the market portfolio.

2.8. CONCLUSION

This chapter reviews the developments of the CAPM beginning right in 1960 to the end of the new millennium. In this chapter, one found out that, in general, the theoretical CAPM states that expected return was related to systematic risk and that this relationship was linear. This chapter then discussed the controversy surrounding the validity of CAPM. Early tests such as Black, Jensen and Scholes (1972) and Fama and Macbeth (1973) find that the market beta alone is sufficient to explain the cross-sectional variation in average excess returns. Using later data, Fama and French (1992) for US do not find a significant relation between return and beta. Cross sectional studies of the CAPM for the data from the UK stock market (Strong and Xu (1997) & Chan and Chui (1996)) have also produced similar results. These studies further found that other factors like size, earnings and dividend yield and especially book-to-market were very useful in explaining the cross-sectional variation in returns. It has been shown however that the test used by Fama and French (1992) suffers from a number of deficiencies like data-snooping (Black (1993a, 1993b)), survivorship biases (Kothari, Shanken and Sloan (1995)), sensitivity of results to different time-periods (Chan and Lakonishok (1993)), the return interval over which beta was estimated (Kothari, Shanken and Sloan (1995)), the form in which the CAPM is tested (Jagannathan and Wang (1996)), and statistical issues (Clare, Priestly and Thomas (1998)). Hence, the evidence of Fama and French (1992) for US stock market cannot be completely accepted.

The next chapter will test the cross-sectional relationships between the realized returns and beta and its competing factors using the most recent data from the UK stock market. This analysis will also go a step further by applying different types of statistical techniques to the current methodology and keeping other critical issues of Fama and French (1992) in mind.

APPENDIX 2.1

OMITTED VARIABLE BIAS

Consider the 'first-pass' regression:

$$R_{it} = \alpha_{it} + b_i R_{mt} + \varepsilon_{it} \tag{1}$$

where R_{it} is return of asset i; R_{mt} is market rate of return; α and b are the intercept and slope (beta) coefficient respectively and ε is the residual term.

The estimate of b from (equation (1)) is given by (lower case is in deviations from the mean)

$$\hat{b}_i = \sum_{t=1}^{T} x_t y_t / \sum_{t=1}^{T} x^2{}_t = \sum_{t=1}^{T} r_{mt} r_{it} / \sum_{t=1}^{T} r^2{}_{mt} \tag{2}$$

Miller and Scholes (1972) argue that the time series first pass regression (equation (1)) may produce biased estimates of beta. They consider the following equation (3) for estimation purpose:

$$R_{it} = (1-\beta_i) R_{ft} + \beta_i R_{mt} + \varepsilon_{it} \tag{3}$$

Substitute for the true r_{it} from (3) to get

$$\hat{b}_i = \sum_{T=1}^{T} r_{mt}((1-b_i) r_{ft} + b_i r_{mt} + e_{it}) / \sum_{t=1}^{T} r_{mt}^2 \tag{4}$$

Rearranging equation (4)

$$\hat{b}_i = b_i + [(1-b_i)\sum_{t=1}^{T} r_{mt} r_{ft} / \sum_{t=1}^{T} r_{mt}^2] + [\sum_{t=1}^{T} r_{mt} e_{it} / \sum_{t=1}^{T} r_{mt}^2] \tag{5}$$

and taking expectations of (5) to get

$$E(\hat{b}_i) = b_i + ((1-b_i)\sum_{t=1}^{T} r_{mt} r_{ft} / \sum_{t=1}^{T} r_{mt}^2) \tag{6}$$

If Rf fluctuates and is correlated with Rm, then the second term in (6) is not equal to zero. And if researchers estimate (1) when (3) is true then the estimate of b is biased and this biases the estimate from the cross section regression.

Source: [Miller and Scholes (1972) and Gujarati (1995)]

APPENDIX 2.2

ERROR IN VARIABLE PROBLEM

Consider the case of a single independent variable. Assume that the cross-sectional model one desire to estimate for month t is

$$r_{jt} = a_t + b_t \beta_{jmt} + \mu_{jt} \text{ where j=1,2,..., N.} \quad (1)$$

where r_j is the return on asset j; β_j is estimates of beta from the first pass regression (see equation 2.32 in text); a & b are the intercept and slope (second pass estimate) coefficients respectively and μ is the error term. Instead of using the unobservable true beta, β_{jmt}, an unbiased estimate $\hat{\beta}_{jmt}$ is used.

To simplify the discussion, assume that an equally weighted index of the N assets used in the test is used as the market proxy and that equation (1) satisfies the OLS assumptions that the variance is constant throughout the discussion about the measurement errors.

The OLS estimate of b_t is

$$\hat{b}_{t(OLS)} = \sum_{J=1}^{N} (r_{jt} - r_{mt})(\hat{\beta}_{jmt} - 1) / \sum_{j=1}^{N} (\hat{\beta}_{jmt} - 1)^2 \quad (2)$$

where r_{mt} is the equally weighted index.

The estimated beta , $\hat{\beta}_{jmt}$ may be expressed as the true beta, β_{jmt} plus a measurement error, ν_{jt},

$$\hat{\beta}_{jmt} = \beta_{jmt} + \nu_{jt} \quad (3)$$

Since $\hat{\beta}_{jmt}$ is unbiased,

$E[\nu_{jt}]=0$, j=1,2...,N.

Before proceeding further, substitute the right hand side of (3) for $\hat{\beta}_{jmt}$ in (2) to get

$$\hat{b}_{t(OLS)} = [\sum_{J=1}^{N}((r_{jt} - r_{mt})(\beta_{jmt} - 1)/N) + \sum_{J=1}^{N}((r_{jt} - r_{mt})v_{jt}/N)]/[\sum_{J=1}^{N}((\beta_{jmt} - 1)^2/N) + (\sum_{J=1}^{N} v_{jt}^2/N) + (\sum_{J=1}^{N} 2(\beta_{jmt} - 1)v_{jt}/N)] \quad (4)$$

The main purpose now is to show that even under a set of assumptions about the measurement error, $\hat{b}_{t(OLS)}$ is inconsistent. Probability limit of equation (4) is taken, when the number of assets included in the sample goes to infinity.

The following assumptions about v_{jt} are made:

$$1.\ E(v_{jt}, v_{kt}) = \begin{cases} = 0 & if\ \ j \neq k \\ \leq \sigma_{vt}^2 < \infty & if\ \ j = k \end{cases}$$

$$2.\ \mathrm{Cov}\,(v_{jt}, \mu_{jt}) = 0 \quad \forall j, k$$

3. The variance of the v_{jt} is constant

Relation 1 and 2 basically say that the measurement errors are cross sectionally uncorrelated and are uncorrelated with the disturbance terms. It is further assumed that

$$\lim_{n \to \infty} \sum_{j=1}^{N} \beta_{jmt}^2 / N^2 = 0 \quad (5)$$

That is, the sum of the squares of the true betas increases more slowly than the square of the sample size as the same size goes to infinity. Note that a sufficient condition for equation (5) is that the true betas are uniformly bounded as the number of assets in the sample goes to infinity.

Mathematically, the following relations imply that:

$$p\lim_{N\to\infty}\left(\sum_{J=1}^{N}(r_{jt}-r_{mt})v_{jt}/N\right) = 0 \tag{6}$$

$$p\lim_{N\to\infty}\sum_{J=1}^{N}\beta_{jmt}v_{jt}/N = 0 \tag{7}$$

$$p\lim_{N\to\infty}\sum_{J=1}^{N}v_{jt}/N = 0 \tag{8}$$

and

$$p\lim_{N\to\infty}\sum_{J=1}^{N}v_{jt}^{2}/N = \lim_{N\to\infty}\sum_{J=1}^{N}Var(v_{jt})/N \tag{9}$$

respectively. Now define

$$\bar{Var}(\beta_t) \equiv \lim_{N\to\infty}\sum_{J=1}^{N}(\beta_{jmt}-1)^2/N \tag{10}$$

the asymptotic sample variation of the true betas. It is assumed that $\bar{Var}(\beta_t)\neq 0$. Taking the probability of equation (4) by using (6) to (9) gives

$$p\lim_{N\to\infty}\hat{b}_{t(OLS)} = b_t/[1+(\bar{Var}(v_t)/\bar{Var}(\beta_t))] \tag{11}$$

where

$$\bar{Var}(\nu_t) \equiv \lim_{N \to \infty} \sum_{J=1}^{N} Var(\nu_{jt}) / N \tag{12}$$

Thus $\hat{b}_{t(OLS)}$ is not a consistent estimator of b_t. From equation (11), it can be seen that the magnitude of inconsistency can be improved either when $\bar{Var}(\nu_t)$ is small or $\bar{Var}(\beta_t)$ is large.

The OLS estimator of a_t is

$$\hat{a}_{t(OLS)} \equiv r_{mt} - \hat{b}_{t(OLS)} \tag{13}$$

Moreover, since $\hat{b}_{t(OLS)}$ is not consistent, $\hat{a}_{t(OLS)}$ is not either.

(Source: Huang and Litzenberger (1993), p.325-328)

APPENDIX 2.3

PORTFOLIO APPROACH TO AVOID ERROR-IN-VARIABLE PROBLEM

Consider a market model:

$$R_i = \alpha_i + \beta_{im} R_m + \varepsilon_i \quad \text{i=1, 2, 3..N} \tag{1}$$

where R_i, R_m and β_i are the excess return on individual stock, excess return on the market portfolio and the sensitivity of returns to the systematic risk factor respectively. ε_i is the error term.

The sampling variance (by definition) of b_{im} as an estimator of β_{im} is given by:

$$\sigma^2(b_{im}) = \sigma^2(\varepsilon_i) / \sum_{T=1}^{T} (R_{mt} - \overline{Rm})^2 \tag{2}$$

It would seem that one way to accomplish this goal is to compute b_{im} from long time series of monthly returns. This means that, the sum of square in the denominator of equation (2) is large, so that $\sigma^2(b_{im})$ is small. But this approach depends on the assumption that the value of β_{im} is stationary through time. The values of β_{im} do wander slightly through time, and the optimal period for estimation from monthly data is roughly 10-30 years. Well, one has seen in the text that the estimates of b_{im} leave substantial uncertainty about the true values; that is, the errors in the b_{im} of individual securities are likely to be large relative to the true β_{im}. Errors in estimates of risk measures can be reduced by working on the numerator of (2), that is, to reduce $\sigma^2(\varepsilon_i)$ the variance of the market model disturbance. The way to do this is to work with portfolios rather than individual securities. To see the basis of the approach, recall that multivariate normality of security returns implies that the joint distribution of the return on any portfolio p and the return on the portfolio m is bivariate normal, so that there are market model relationships like (1) for portfolios as well as for individual securities. For any portfolio p, one has:

$$R_{pt} = \alpha_{pm} + \beta_{pm} R_{mt} + \varepsilon_{pt} \tag{3}$$

The portfolio return disturbance ε_{pt} in (3) is however, just the weighted average of security return disturbances ε_{it}. To the extent that the ε_{it} for different securities are less than perfectly positively correlated, there is a "diversification effect", and $\sigma^2(\varepsilon_p)$ can be expected to be smaller than the $\sigma^2(\varepsilon_i)$ of individual securities. The result is that $\sigma^2(\beta_{pm})$ is generally smaller for portfolios than for individual securities. This means that the EIV problem is likely to be less serious if tests of CAPM are carried out in terms of portfolios rather than individual securities.

(Source: Fama (1976), p.344-351)

APPENDIX 2.4

ESTIMATION OF UNBIASED BETA

Dimson (1979) and Scholes and Williams (1977) are the first to recognise that non-synchronous trading will bias estimates of systematic risk. Estimates of beta are usually obtained from the market model (which provides an estimate of the correlation between the return of a security and the market return). The market model can be written as:

$$R_{i,t} = \alpha_i + \beta_i RM_t + \varepsilon_t \qquad (1)$$

where,

$R_{i,t}$ = the return to security i in time t

RM_t = the market return in time t, and

β_i = the estimate of systematic risk for stock i or portfolio i which indicates the extent to which stock i covaries with the market return, this can be calculated as $\sigma(R_i, RM)/\sigma^2(RM)$.

This equation measures the extent to which a variation in the market is also reflected in stock i. If a stock which is thinly traded, has a trade in time t, but not in time t-1 then the effects of a systematic shock in time t will not be observed in the security return until it trades. This means that the relationship between the market and an individual security will be understated in cases where stock i is thinly traded. In which case the beta estimate will be biased downwards.

If thin trading persists over time, these systematic biases will be serially correlated (see footnote: 22 of Chapter 2, and Lo and MacKinlay (1990b)), and hence autocorrelation will be greater than zero.

One way to avoid the thin trading problem is to adjust OLS estimates of (1) to make them unbiased. There are adjustment techniques that can be used. The Scholes-Williams (1977) betas are defined as:

$$\beta_i = \sum_{k=-1}^{k=+1} \beta_{ik} /(1+2\rho) \tag{2}$$

where ρ is the autocorrelation of a value-weighted daily market returns and β_{ik} are the slope coefficients from 3 separate regressions,

$$R_{i,t} = \alpha_i + \beta_{ik} RM_{t+k} \quad \text{for k= -1, 0, +1} \tag{3}$$

This allows the beta estimate to reflect the spill over of returns that often occur around non-trading.

Dimson (1979) proposed an aggregate coefficient model, which allows us to make unbiased estimates of betas in the presence of thin-trading. Beta estimates for each firm are obtained by summing the slope coefficients on the five lagged, five leading and contemporaneous returns on a market index using the aggregate coefficients model. The aggregate coefficient model can be written as:

$$R_{i,t} = \alpha_i + \sum_{k=-5}^{k=5} \beta_{i,k} RM_{t+k} \tag{4}$$

where,

RM_{t+k} = the market return in time $t+k$;

β_0 = the covariability of the return of stock i in time t with the market return in time t;

β_k = the covariability of the return of stock i in time t with the market return in time $t+k$;

If a stock fails to trade at time t, the effect on stock i of a change in the market index will only be observed when stock i trades. If stock i trades in time t+1, the effect of a systematic shock in time t will be captured by the relationship between the market return in time t-1 and the security return in time t. Dimson therefore, suggests using an aggregate coefficients model where lagged market returns are allowed to enter the market model. The coefficients associated with lagged market return will capture the effect of systematic changes, which are not observed in the security stock returns because a stock is thinly traded. For thinly traded

stocks, betas should be estimated as the sum of the contemporaneous betas that is β_0 and the β_k's from equation (4).

(Source: [Cohen, Maler, Schwartz, Whitcomb (1985, p.112-129) and Chelley-Steeley (1996)]

CHAPTER 3

AN EMPIRICAL EXAMINATION OF THE CROSS-SECTION OF UK EXPECTED STOCK RETURNS

3.1. INTRODUCTION

3.1.1. OBJECTIVE AND MOTIVATION

This chapter analyses the ability of beta and other factors, like size and book-to-market, to explain cross-sectional variation in average stock returns on the UK stock market for the period 1969-2001. The analysis focuses on beta, size[1] and book-to-market because of their rich history in the literature. Motivation of this study comes from the Fama and French (1992) and Strong and Xu (1997) study. Size and book-to-market are consistently found to be important in explaining the cross-sectional variation in stock returns (Fama and French (1992) and Strong and Xu (1997)). Size and book-to-market also appear to dominate the beta in the empirical explanation of cross-sectional returns. Beta has a rich theoretical foundation but lacks empirical support. This study, by using data from (1969-2001) will therefore update the previous findings for the UK. This study will further test the robustness of the results by using different methods for estimation, which have not been previously used for the UK stock market.

[1] This study will be using "size", "ME", "market size" or "market-value" interchangeably throughout this chapter.

3.1.2. BACKGROUND

A growing number of empirical studies have presented the presence of persistent cross-sectional pattern in stock returns that do not support one of the most fundamental assumptions of finance: expected returns are determined by their level of beta risk through a positive and linear relationship. The principal assumption was shown with the help of the simple Capital Asset Pricing Model (CAPM) (Sharpe (1964), Lintner (1965), Mossin (1966) and Treynor (1961)). One of the first empirical studies of the CAPM is that of Black Jensen, and Scholes (1972). They examine whether there is a positive linear relation between average return and beta. They find that the CAPM is an approximation to reality. Another famous empirical study of the CAPM is by Fama and Macbeth (1973). Using US return data for the period from 1926 to 1968, Fama and Macbeth (1973) find that the data generally supports the CAPM. The CAPM thus passed its first major empirical test. In 1981, however, a study suggested that it might be missing something. Banz (1981) challenges the CAPM by showing that size explains the cross-sectional variation in average returns. He finds that during the 1936-1975 period, the average return to stocks of small firms (those with low values of market equity) was substantially higher than the average return to stocks of large firms after adjusting for risk using the CAPM. This observation has become known as size effect. The earlier studies suggested that the market was not the only factor that is important in determining the return an asset is expected to earn. Beta is probably relevant to security pricing, but returns appear to be determined by beta and size. A decade later, a few other studies suggested that the CAPM might be missing everything, and hence began a puzzle. Factors such as the book-to-market (Stattman (1980), Rosenberg, Reig, and Lanstein (1985), and Chan, Hamao, and Lakonishok (1991)), leverage (Bhandari (1988)), earnings (Basu (1977, 1983)), momentum effect (Jegadeesh (1990)) and overreaction (Debondt and Thaler

(1985, 1987)) were found, which were related to returns. Since then, theoretically and empirically, one of the most troubling problems for academics and financial analyst has been that the CAPM's single source of risk is the market.

The empirical evidence before 1990 suggested that the data had some systematic deviations from the CAPM, but it was not economically meaningful enough to reject it. But, more recently, Fama and French (1992) highlighted several empirical contradictions of the CAPM. They found that the relationship between average return and beta is virtually non-existent from 1963 to 1990 and variables such as book value of a firm's common equity to its market value and size appears to explain cross-sectional variation in average returns. In fact, book-to-market equity appears to be more powerful than size.

The CAPM is considered one of the main contributions of academic research to financial managers yet Fama and French' s (1992) evidence is so contrary to the CAPM that it caused a big revolution in the financial community. Since the Fama and French (1992) study, a number of other studies[2] were undertaken for the US stock market. Chan & Chui (1996) were the first ones to investigate the cross-sectional relationships in UK stock market for the period of 1971-90. Strong and Xu (1997) did a similar study for the period of 1973-92. Both the studies made use of the Fama and French (1992) methodology. Strong and Xu found strong support for the Book-to-Market Equity and leverage effects, but only support beta in isolation. According to Chan and Chui, there is hardly any role of beta in explaining the cross-section of average returns in the UK. The Book-to-Market Equity variable also seems to be consistently significant in their study.

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[2] Amihud, Christensen, and Mendelson (1992) used the NYSE stocks for the year 1981-90 and found that when more efficient statistical methods were used, the estimated relation between average return and beta was positive and significant. They proposed two econometric methods to improve the efficiency of the estimation and provided more powerful test statistics: joint pooled cross-section and time-series estimation and generalized least squares. Using these techniques, they find a highly significant relationship between average portfolio returns and systematic risk.

This chapter proceeds in a sequential manner. First, the cross section of stock returns in the UK stock market for the period January 1969- December 2001 are investigated. Extension of the cross-sectional analysis complements the previous two UK studies (Chan and Chui (1996) & Strong and Xu (1997)) because the current study uses more recent data and applies various other cross-sectional techniques to the sample. To make results more comparable to the other UK studies, this study like Strong and Xu (1997) apply the methodology of Fama and French (1992) for testing the pricing of market risk and other factors like Book-to-Market Equity (BE/ME) and size. Second, earlier evidence suggests that the risk-return relationship is very sensitive to different sub periods (Fama and Macbeth (1973)). This study therefore investigates cross-sectional results for different sub-periods of sample. Two sub-sets of the sample are formed for different time periods on the basis that during each sub-set of the sample the UK economy experienced different economic conditions. Third, the effect of using different types of return and indexes, and different return-intervals is examined.

One, now, proceeds by examining data set and the standard methodology, which are used for testing the asset-pricing model. The subsequent sections present the empirical results and conclusion respectively.

3.2.DATA

The sample of this study includes most of the UK stocks traded on the London Stock Exchange (LSE) from January 1969 through December 2001. This study includes UK stocks for which adequate data on rates of return, market size and book-to-market values are available. The data in this study is obtained from two different sources: London Share Price Database (LSPD) and Datastream International. This study, like Strong and Xu (1997), has excluded all the property and financial companies. Fama and French (1992) provide a reason for the exclusion of financial companies. They argue that firms with higher leverage may have a higher possibility of displaying distress. Since financial firms typically have a higher leverage, high leverage for financial firms may not have the same meaning as for non-financial firms. The month-end, dividend-adjusted stock return data are therefore collected for 2108 non-financial firms (stocks) quoted on LSE for January 1969 to December 2001 from LSPD. By contrast, Strong and Xu (1997) collected the data from Exstat database and LSPD for the sample period: 1973-1992 (1337 stocks) and 1960-1992 (4603 stocks), while, Chan and Chui (1996) collected the data from LSPD and Exstat Company Accounts database for the sample period: 1973-1990 (1480 stocks).

The LSPD is the most important stock return database for risk measurement and the testing of asset pricing theories in the UK (Dimson (1979)), but it has its deficiencies ((Board and Smithers)(1989)). While almost all quoted companies since 1975 feature on it, this was not the case in earlier years. Prior to 1975, companies were included only on the basis of a 33% random sample of all UK companies in 1955, together with the largest 500 in 1955 and the largest 200 in 1972. The accuracy of data might be higher for post-1975 period

than for the pre-1975 one. Franks and Harris (1989) find that the LSPD is comprehensive from 1975 onwards, however, prior to 1975 the UK database is biased towards larger firms[3].

The continuous compounded monthly returns on the LSPD database are calculated as:

$$r_t = Log[(P_t + D_t)/P_{t-1}] \tag{3.1}$$

where: P_t is the last traded price in month t;

D_t is the dividend declared xd during month t adjusted to a month-end basis;

P_{t-1} is the last traded price in month t-1.

Prices are adjusted for scrip and right issues. These returns have been used by Levis (1985), Beenstock and Chan (1986), Levis (1989), Poon and Taylor (1991), and Chan and Chui (1996). Strong and Xu (1997) have used discrete rates of returns for their analysis as has been done in most US studies. In the current study, the effects of using different types of return are examined, which has been shown by Ashton and Tippett (1999) to be important in the UK.

The data for accounting variables like book value of equity and market size comes from Datastream International. In this study, the following definitions for book equity and market size are same as Strong and Xu (1997):

Market value of equity = Product of share price x number of share outstanding (3.2)

Book common equity = book value of stockholders' equity - the book value of preferred stock.

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[3] See Board et al (1991, p. 11-24, 49-59 and 112-121).

Book equity was measured at the fiscal year year-end in calendar year t-1, and market size of common equity was also measured at end of December of year t-1[4]. Book-to-Market Equity (BE/ME)[5] is equal to book common equity for the fiscal year ending in calendar year t-1, divided by market common equity at the end of December of calendar year t-1.

There are, however, a few problems with the Datastream data. The data has been backfilled in the mid-70s, as there is no information on dead companies in the database until this point. In addition, Datastream systematically misses small companies and certain industries in the 60s and 70s. This suggests that there is a serious danger of selection bias in the Datastream sample. Banz and Breen (1986) indicate that selection/survivor bias will be inherent in any database since that databases are likely to add firms that ultimately survive and to miss distressed firms that die. Levis (1987) investigated the impact of the survivorship bias and found that the detailed adjustment for missing companies resulted in changes to his results of less than 1%. Therefore, the problem of the survivorship bias in the current study sampling procedure is considered to be minimal.

The data set in this study includes firms that appear in both Datastream and LSPD. The Datastream firm codes with LSPD firm codes were matched for each firm from a file with matching code data. In some cases, LSPD company number had to be linked to two different Datastream codes in different time periods. This case arose, for example, if

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[4] Fama and French (1992) report that market equity is measured "in June" of each calendar year t from 1963 to 1991. Yet the measure of market equity in June is ambiguous because there is more than one trade date in June and thus more than one actual closing price or average closing bid/ask quote in June each year for actively-traded stocks. Fama and French report that market equity in the denominator of the book-to-market equity is measured "at the end of December" of each calendar year t-1 from 1963-1991. The measure of market equity at the end of December can be unique if it is the closing price or average closing bid/ask quote on the last trade date of the month. Individual common stock calendar year-end capitalization or market value of equity is provided in the CRSP monthly return file.

[5] According to Fama and French (1992, pg.430) "Our use of December market equity in the E/P, BE/ME, and leverage ratios is objectionable for firms that do not have December fiscal year-ends because the accounting variable in the numerator of a ratio is not aligned with the market value in the denominator. Using ME at fiscal year-ends is also problematic: then part of the cross-sectional variation of a ratio for a given year is due to market-wide variation in the ratio during the year. For example, if there is a general fall in stock prices during the year, ratios measured early in the year will tend to be lower then ratios measured later. We can report, however that the use of fiscal-year-ends MEs, rather than December MEs, in the accounting ratios has little impact on our return tests." In this study, a random sample from this data indicates that the majority of firms have December year-ends.

Datastream and the LSPD did not agreed on the company that "survived" in the merger. The accounting data for firms with fiscal year-ends in the calendar year t-1 were matched with returns for July of year t to June of year t+1. This 6-month gap between the accounting data and the returns is to ensure that the accounting data are available before the returns.

3.3. METHODOLOGY

Fama and Macbeth (1973) advocate the rolling method to form portfolios from ranked betas computed from data for one period, and then use a subsequent period for estimation. This study has adopted the approach used by Fama and French (1992) and Strong and Xu (1997). This approach is divided into two stages. The following section explains this methodology in detail.

3.3.1. FORMATION OF PORTFOLIOS (CONSTRUCTION OF DATA)

The first stage involves construction of the portfolios. All the stocks with missing values are excluded before the portfolio formation. In period t, to form portfolios, all firms with missing BE/ME values for 6 years preceding June t+1 were excluded from the sample[6]. Thus, firms that did not have missing BE/ME values for five years prior to the year of portfolio formation and also the year of portfolio formation are taken in account in the portfolios. Hence, this study excludes all possible missing information from the analysis. The sample of this study is large enough (see Table 3.1) to produce good estimates from the

[6] With respect to the book-to-market anomaly in the US stock market (Fama and French (1992)), it has been argued that the apparent superior performance is due to a subtle selection bias in a typical data source used to implement the tests of asset pricing models, the COMPUSTAT data. One of the main aims of our study is also to investigate the BE/ME effect. We therefore include the firms on the basis of BE/ME values. Firms with missing BE/ME values in the "construction and test periods" are excluded from the sample. But, this strict restriction excludes many firms appearing in the LSPD. This may again introduce a selection bias in our study. Later, in this chapter, tests are also conducted using all the 2108 securities. This will suggest whether our selection process leads to any biased inference.

cross-sectional methodology (mentioned below) without the information excluded from the analysis.

All the selected companies quoted on LSPD are then ranked on the basis of size (ME) for period t-1. The firms are then put into one of the 5 portfolios arranged in order of increasing size, each containing the same number of securities. For example, for the year 1979, firms in existence since 1974 that have market value information for December 1978 are ranked and put into a portfolio based on market value as of December 1978. The composition of the portfolio is then held constant through 1979.

According to Chan and Chen (1988), the size and the betas of size portfolios are highly correlated (-.988 in their data), so asset-pricing tests lacks power to separate size from beta effects in average returns. Each portfolio is therefore also subdivided on the basis of pre-ranking beta[7].

This study uses the following time-series model, the market model, for estimating beta using the 60 months data preceding the year of the testing period (e.g. July 74-June 79) and Ordinary Least Square (OLS):

$$R_{it} = \alpha_{it} + b_i R_{mt} + \varepsilon_{it} \tag{3.3}$$

[7] For example, let N be the total number of securities to be allocated to portfolios and let int (N/25) be the largest integer equal to or less then N/25. Using the sample period (1974-79), 25 portfolios are formed on the basis of size and beta. 25 portfolios of int (N/25) are formed, with a slight variation in the last portfolios if the number is odd.

where R_{it} is the return of the individual security, R_{mt} is an equal-weighted index[8] of all 2108 stocks, α_{it} and b_i are the intercept and the estimated pre-ranking beta of the security i respectively and ε_{it} is the error term.

Basically, the betas are estimated with a set of 'time-series regressions', one for each security. These betas are called pre-ranking beta in Fama and French (1992). Fama and French (1992) basically separates the construction period from testing period by naming it pre-rank and post-rank period respectively. The estimated pre-ranking betas might be sensitive to the problem of thin-trading. Thin and infrequent trading often appears for the smaller companies. All the previous studies of pricing present a serious problem when estimating betas for thinly traded securities. As shown in other studies, when shares are thinly traded, their beta estimates are biased downwards (e.g. Fisher (1966), Cohen et al. (1983), Dimson (1979) and Scholes et al. (1977)). To avoid the downward biases due to thin-trading, the Dimson (1979) method is used to adjust the pre-ranking betas for thin-trading problem. Hence instead of equation (3.3), the Dimson beta estimates for each firm are obtained by summing the slope coefficients on the five lagged, five leading and contemporaneous returns on a market index in the following OLS regression:

$$R_{it} = \alpha_{it} + \sum_{k=-5}^{k=+5} b_i R_{m,t+k} + \varepsilon_{it} \qquad (3.4)$$

[8] The choice for the market index however is an empirical dilemma. The CAPM implies that the value-weighted portfolio of all assets should be mean-variance efficient. It is sometimes suggested, therefore, that the value-weighted stock index is preferred as a market proxy over the equally-weighted index. Whether the value- or equally weighted index is a better proxy depends largely on whether the returns are more closely related to small- or large-firm stocks returns. Using an equally-weighted index may reduce any size effect as beta against an equally-weighted index will pick up more of the size effect. Hence, the results might be biased against finding size as a significant factor. The effect on beta coefficient will depend on the correlation between beta and size. However, Strong and Xu (1997) suggest that an equally-weighted index of all quoted stocks may be a better measure of the universe of capital assets than a value-weighted index constructed from a sample of quoted stocks. Moreover, early tests of the CAPM by Black, Jensen and Scholes (1972) and by Fama and Macbeth (1973) use an equally weighted index of stocks listed in New York Stock Exchange. In most of the tables below, the results for the equally-weighted index are reported. This is in line with Strong and Xu (1997). In order to test the sensitivity of the results, value-weighted index is also used later in this chapter.

where k is the number of lags.

The stocks in each size-portfolio are then reassigned to a portfolio subclass. The returns on these 25 portfolios are then determined for each of the next 12 months (e.g. July 79-June 80). This return is the equally-weighted average of the returns on the stock with available data in the particular month for each portfolio. The portfolio returns from July 1979-June 1980 are called post-ranking returns and the portfolio returns from July 1974 to June 1979 are called pre-ranking returns.

The procedure mentioned so far is rolled forward one year until a time series of returns on 25 size-beta sorted portfolios are constructed. By repeating this process for each year in the sample, twenty-nine consecutive post-rank periods are formed. For each year in the sample, moreover, the stocks are sorted according to the market size and the beta estimates for these stocks are calculated by incorporating the past year's returns. The size values and new beta estimates for each year in turn could change the old rankings of the stocks, thus causing the composition of the 25 portfolios to vary somewhat from year to year. Annual rebalancing of stocks in each portfolio is an attempt to obtain portfolios whose size/beta characteristics change relatively slowly over time. Table 3.1 presents the pre-rank and post-rank period in detail. From Table 3.1, it can be seen that initially there was a large sample, namely 2108 UK listed companies trading on the LSE during the period under consideration of which some 850 companies were analysed, the remainder failed to meet the criteria for remaining on the sample.

The portfolio returns for the full sample (29 consecutive sub-periods of 12 months each) are stacked together to get 342 time series observations for each portfolio. These time series returns were then regressed (market model (equation (3.3)) was used for this purpose) on equally weighted portfolio to get the betas. These betas were called full-period 'post-ranking' betas[9] in Fama and French (1992). These are the betas that will be used in the Fama and Macbeth (1973) cross-sectional regressions in the next step.

3.3.2. CROSS-SECTIONAL ANALYSIS

The second stage in the methodology is to use the 25 post-ranking betas of the 25 portfolio with different size/beta characteristics to test the CAPM. This study uses the post-rank period returns (12 months) for each consecutive sub-period and associate with each stocks its corresponding post-rank beta. For example, if security 1 comes from portfolio 1, then post-rank beta of portfolio 1 will be attached to security 1. In this way, one of the 25 post-rank betas is attached to all the securities in each post-ranking period. This means a stock's beta is the same for each 12-month period, July of year t to June year t+1, but its post-ranking beta can change from one 12-month period to the next if it switches among the 25 size-beta portfolios.

This study obtains estimates of the intercepts and slope coefficients of the (monthly) 'cross-sectional regressions' (Fama and Macbeth (1973)). Each post-rank period has 12

[9] Usually, the betas are re-estimated each year, as opposed to using the full-period post-ranking estimates. But to be in line with Fama and French (1992), full-period post-ranking betas are estimated in this study.

months and there are 29 post-ranked periods[10] in this study. This will result in 342 cross sectional regressions.

The following cross-sectional regressions (Equations (3.5)-(3.11)) are used:

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \mu_{it} \tag{3.5}$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \hat{\gamma}_{2t}ME_i + \mu_{it} \tag{3.6}$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{2t}ME_i + \mu_{it} \tag{3.7}$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \hat{\gamma}_{3t}(BE/ME)_i + \mu_{it} \tag{3.8}$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{3t}(BE/ME)_i + \mu_{it} \tag{3.9}$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{2t}ME_i + \hat{\gamma}_{3t}(BE/ME)_i + \mu_{it} \tag{3.10}$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \hat{\gamma}_{2t}ME_i + \hat{\gamma}_{3t}(BE/ME)_i + \mu_{it} \tag{3.11}$$

i=1,2....n ; t=1,2.....342

[10] This study has 29 post-ranked period. Hence 348 cross-sectional monthly regressions should be estimated in total. But 29th post-ranked period in this study ends in December 2001 instead of June 2002. So, 342 regressions are estimated.

where R_{it} is the return on individual security i in month t; β_i is the full period post-ranking beta of portfolio p, that is, the slope coefficient from a time-series regression of monthly post-ranking returns on the returns for an equally-weighted portfolio of all portfolios. ME_i [11] is the market value of equity of security i; $(BE/ME)_i$ is the ratio of book value of equity to its market value of security i; $\gamma_{0t}, \gamma_{1t}, \gamma_{2t}$ *and* γ_{3t} are regression coefficients and μ_{it} is the error term.

The regression models above are estimated 342 times for every month t between July 1973 till December 2001. Hence 342 estimates are obtained for each γ for every model. In other words, equations (3.5-3.11) allow γ to vary stochastically from period to period. The average value of each γ is computed by:

$$(1/T)\sum_{t=1}^{T} \gamma_{1t} \qquad (3.12)$$

where T=342 and the average value of each γ over 342 estimates are found and tested for significance via t-test.

A cross-sectional regression using stock returns as the dependent variable is likely to have heteroskedastic and correlated errors, the latter due to the substantial correlation across stock returns in a given month. The usual regression standard errors are therefore not reliable. To test the hypothesis that the expected coefficient is zero, Fama and Macbeth

[11] Many studies ((Strong and Xu (1997) and Chan and Chui (1996)) use natural logs of these variables and drop negative BE/ME stocks. But, here, in this study, negative BE/ME stocks are included in the sample. Hence, ME and BE/ME rather than natural logs of these variables are used in this study.

(1973) suggested forming a t-ratio as the time series average of the monthly cross-sectional coefficients divided by the standard error of mean, where the latter is computed from the time-series of the coefficient estimates. As shown in Fama and Macbeth (1973), these t-statistics are:

$$t(\gamma_i) = [\overline{\gamma_i}] / [s(\overline{\gamma_i}) / \sqrt{n}] \tag{3.13}$$

where $\overline{\gamma_i}$ is the time series average of the slope coefficient of 342 cross-sectional regression, $s(\gamma_i)$ is the standard deviation of 342 estimates of γ_i and n is the number of observations.

3.3.3. AN ALTERNATIVE PORTFOLIO FORMATION IN PROCEDURE

It is important to note that empirical results are likely to vary with different groupings of portfolios based on the same population of individual stocks. In addition to stocks sorted on 'size', 'beta', and 'size-beta', this study also uses a different kind of sorting procedure for this analysis. Stocks are sorted on the basis of beta and size. Stocks are first sorted on the basis of beta and divided into two portfolios. Each portfolio is further sliced up into five portfolios on the basis of size. In total, ten (2 x 5) beta-size portfolios are formed. This is done due to the following reason. Sorting entirely on beta, Fama and Macbeth (1973) confirm the validity of the CAPM. However, sorting first on size and then on beta and using the same method as Fama and Macbeth (1973), Fama and French (1992) strongly rejects the CAPM. Different methods of portfolio formation give different results. If CAPM holds perfectly, the average slope from a Fama and Macbeth regression using a certain set of portfolios can be interpreted as one possible draw from the distribution of the ex-post market

risk premium which itself is a random variable with a mean, and a standard deviation. Other groupings of stocks into portfolios will likely result in different draws from the distribution of that random variable. The likelihood that a positive return relationship is obtained in any given regression will then depend on the degree of statistical significance of the market risk premium. In the extreme cases, for statistical reasons it is always possible to obtain a negative or insignificant relation between risk and return from the left tail of the distribution even if the CAPM holds perfectly. It is also important to remember that the CAPM has a positive risk-return relationship for 'any' portfolio of individual stocks, not limited to just one portfolio formation. Any noises due to data-snooping present in Fama and Macbeth regression might have diversified away to a certain extent when different types of ranked portfolios are used.

3.4. CROSS SECTIONAL ANALYSIS

3.4.1. STATISTICAL CHARACTERISTICS OF THE VARIABLES

Before running the regressions, this study first summarises the statistical features of the variables by presenting their average descriptive statistics for the sample period: July 1973 through December 2001 in the Table 3.2[12] for the different sets of portfolios.

The descriptive statistics include:

(a) The arithmetic mean

(b) The Standard deviation

(c) The Skewness, which denotes the tendency for values to bunch at one end of a distribution, the values at the other end being relatively dispersed

[12] In this table, size (ME) and (BE/ME) are the simple averages of the values for stocks in each portfolio and for all the 29 annual periods.

(d) The Kurtosis of a frequency curve which is a measure of its peakedness

(e) The highest observation and the lowest observation for each variable

The OLS regression methodology employed in this study requires that in order to allow statistical inferences about the significance of explanatory variables, the error term in the regression model must follow a normal distribution. Normality in the data is assessed using the Skewness and Kurtosis statistics. For a normal distribution, Skewness and Kurtosis must have the values zero and three respectively. The values of these measures in the current data indicate the extent of any deviation from the normal distribution. Table 3.2 examines the average Skewness and Kurtosis statistics of current data. It can be clearly seen that, none of the variable passes the normality test with 'full faith'. For example, the average Skewness and Kurtosis for size variable for beta-ranked portfolio (in Panel A) is -.34 and -.65 respectively. On the hand, the Skewness and Kurtosis values of size changes to 1.85 and 3.08 respectively when the stocks are sorted on the basis of beta and size. By looking at all the Panels in Table 3.2, it can be seen that beta and BE/ME variables are also not normally distributed. Moreover, the distribution of monthly returns is different from a normal distribution[13].

The data is never without a normality problem. Non-normality in the accounting ratios could result from number of factors. First, if the relationship between the numerator and the denominator is not strictly proportional across firms then Skewness in the distribution can occur. Second, outlier observations in the data can severely change the characteristics of the underlying distribution. A number of transformations are available to deal with non-

[13] Claessens, Dasgupta and Glen (1995, 1996) examine market anomalies in emerging markets using data from the Emerging Markets Database (EMDB) published by the International Finance Corporation (IFC). They find that portfolio returns are non-normal in nearly all of the markets. Due to this problem, extreme observations (outliers) can drive the regression tests. Outliers are especially likely to be present when, as in the case of Claessens, Dasgupta and Glen (1995, 1996), the returns are extremely variable. This issue will be discussed later in this study.

normality resulting from these factors. These include natural logarithm, reciprocal and square root of reciprocal. However because of lot of ratios have negative values, these procedure cannot be easily applied. Additionally, Sundarsanam (1981) shows that when applied to UK data these procedures generally do not lead to major improvements in the departure from non-normality.

Table 3.2 also implies something interesting about the UK stock market. First, the average post-ranking beta values in all the panels are less then 1. Overall, the shares in the UK stock market tend to under-perform the return on the market portfólio (the return on the FTSE index). Th low beta shares can either be good or a bad thing, depending on what is happening to the return on the FTSE index. Second, if CAPM does not work very well, companies will make systematic and predictable mistakes in estimating cost of capital and evaluating portfolio managers. For example, companies with low betas will underestimate their cost of capital. Third, if small-firm effect (Banz (1991) exist in the UK stock market, then small stocks will have high betas and high average returns and big stocks will have low betas and low average returns. But, once we control for size, there is little relation between beta and return. The interpretation of beta values might not therefore mean anything. Fourth, an investor in the UK can make an average profit of around 10% on annual basis. The results, here, suggest that this profit opportunity can be exploited using CAPM or size anomalies.

3.4.2. PROPERTIES OF PORTFOLIOS

This study now investigates the various properties of the different portfolios constructed for this study. Table 3.3a, shows the average portfolio returns, portfolio betas, average size,

average book-to-market values, and the number of firms in each portfolio from, July 1973 to December 2001 for 10 portfolios each formed by sorting the portfolio values using the pre-ranking beta (Panel A), market size (Panel B), beta-size (2 x 5) (Panel C) and Book-to-Market Equity (BE/ME) (Panel D) respectively. The smallest 10% firms are in portfolio 1 and the 10% largest firms are in portfolio 10. Table 3.3b shows the correlation between the returns, beta, size and BE/ME. The portfolios are formed at the end of June each year and their market index is computed by using equally weighted returns.

Looking at Table 3.3a, Panel A, this study like Strong and Xu (1997) also found no clear relationship between average return and pre-ranking beta. The second smallest beta ranked portfolio gives the highest return of 0.972 %. However the next highest return comes from sixth beta ranked portfolio. The lowest return of 0.625% comes from the smallest beta ranked portfolio. The overall relationship looks to be uneven. The correlation (see Table 3.3b, Panel A) between average return and beta is also 0.019. The relationship is very weak but consistent with one of the basic assumptions of CAPM. The basic assumption is that, there should be a positive (linear) relationship between return and beta. Another aspect of beta-sorted portfolios recalls the Fama and French (1992) analysis. In the second column of Table 3.3a (Panel A), post-ranking betas for portfolios formed on pre-ranking betas almost perfectly reproduce the ordering of the pre-ranking betas. Like Fama and French (1992) study, where one beta was out of line, one of the estimated post-ranking beta (for the second lowest and the highest beta-sorted portfolio) in this study is also out of line. In other words, while the range of the estimated betas fluctuates, the pattern is almost always monotonic from large to small firms. It can be seen that the lowest market value comes from the highest beta ranked portfolio. Strong and Xu (1997) found the same results. The correlation (see

Table 3.3b, Panel A) between the beta and size (r=0.24) is weak and is not in line with the evidence produced by Chan and Chen (1988) (-0.988).

In Panel B of Table 3.3a, the portfolios are ranked according to the size. The results for these portfolios are somewhat similar to the earlier studies (Fama and French (1992), Strong and Xu (1997), Kothari and Shanken (1997)), but with an exception. The correlation between average returns and beta is negative (r = -.442). According to the CAPM, there should be a positive relationship between return and beta. Chan and Chui (1996) also found a rank correlation of -.81 between return and beta when the stocks were sorted according to the market size. There also seems to be some evidence of a size-effect (Banz (1981)). The correlation between return and size is negative (r=-.347) in the current study. The correlation in Chan and Chui (1996) was -.62 between return and size. It can be seen in Panel B, that the smallest portfolios are giving the highest returns of 1.26% (15.12% on an annualized basis). Strong and Xu (1997) found that the smallest market value portfolio provided an average return premium of around 36% on an annualized basis. But, the results of this study do not completely appear in line with the Banz study. This is because of the inconsistency in the return patterns of the size-portfolios. The average returns are falling from the lowest size-ranked portfolio to the highest size-ranked portfolio but with the exception of fourth, sixth, seventh, eighth and tenth portfolio. For size portfolio, Fama and French (1992) found a very strong negative relation between size and average return. From Table 3.3b, Panel B, it can also be seen that there is a positive relation between beta and size (r=.191). This beta-size relation shows that smaller the company the lower their beta coefficients will be. The lowest size ranked portfolio is associated with the lowest post-rank beta (.719). The post-ranking betas are rising with the portfolio level. Levis (1985), also

using Dimson beta estimates (like this study) and Risk Measurement Service, find that smaller firms in the UK appear to be less risky than their larger counterparts. Poon and Taylor (1991) suspect the positive size-beta correlation in such studies could possibly be due to a thin-trading effect. Although, estimated betas in this study have been adjusted for the thin trading problem using Dimson (1979), the relation between beta and size is still positive.

Table 3.3a, Panel C, presents the results of the portfolios sorted on beta and size (2 x 5). The average return appears to be negatively related to beta within each beta group (low and high beta portfolios). Small firms are associated with higher returns within each beta group. There seems to be some sign of a small-firm effect in these portfolios. This finding is in line with the Banz's (1981) study. Hence the small firm effect is sensitive to the way the portfolios are formed in the cross-sectional studies. This will be discussed later in this chapter.

The most interesting evidence is in Table 3.3a, Panel D, where the portfolios are sorted according to BE/ME[14]. There is a positive relationship between average returns and BE/ME. Average return do rise from .414% (for lowest BE/ME portfolio) to .875% for fifth BE/ME ranked portfolio and produces a highest return of 1.179% for the largest BE/ME ranked portfolio. This is in agreement with the findings of Fama and French (1992), Chan, Hamao and Lakonishok (US study) (1991) and Strong and Xu (1997). These studies find a strong positive relation between average return and BE/ME. According to Fama and French (1992), firms with low market equity are more likely to have poor prospects, resulting in low stock

[14] Fama and French do not use negative BE-firms when forming the BE/ME portfolios.

prices and high book-to-market equity. Conversely, large stocks are more likely to be firms with stronger prospects, higher stock prices, lower book-to-market equity, and lower average returns. Something like this is happening in this study. It can also be seen that the BE/ME is negatively related with size. This is clear in Table 3.3a, Panel D, where average size of BE/ME portfolios gets smaller with larger BE/ME portfolio. In addition, there is almost a perfect negative relationship (see Table 3.3b) between beta and size (r=-.950) when the stocks are ranked according to BE/ME. One point to note from this is that when using size, beta or BE/ME portfolios only, size and betas of the these portfolios are highly correlated, and as a result there will be a lack of power in regression tests to separate size from beta coefficients in average returns. In order to allow for variation in beta that is uncorrelated to size, this study also forms portfolios based on size and then beta and examines their properties.

Table 3.4, Panel A gives 25 portfolios, which are formed first, on size and then within each size portfolio, 5 sub-portfolios are formed on the basis of pre-ranking beta. This was done to test the relative contribution of the 'beta effect' and the 'size effect'. This two-pass sort will help us to give a clear picture of the different roles of beta and size in average returns. In Panel A, within each of the beta matrices, it can be seen that the returns are falling (with few exceptions) and at the same time in Panel B, post-rank betas are increasing. In Panel C, the market size is increasing in the columns of the beta matrices. The interpretation of all this is pretty clear. When the stocks within the beta matrices are tied to size, there seems to be negative relationship between average returns and size. This is because, the lowest size portfolio within the beta quintile generally produces highest return. By contrast, Fama and French (1992) for two-sort portfolios find a much stronger correlation between

return and size. Looking at the size quintiles (rows) and beta matrix, the average equally-weighted returns have a slight tendency to decline with increasing beta. It is difficult to interpret the beta-return relationship when the stocks are tied to beta within each size quartile. This is because the evidence suggests a negative relationship between return and beta. There is also a negative correlation (r=-.45) between the beta and average returns ((Chan and Chen (1996) also found this, and to some extent Strong and Xu (1997) also found similar results for two-sorts portfolios). It can also be seen in Table 3.4, Panel C that size is increasing in beta for small firms and decreasing in beta for large firms. Hence there seems to be some correlation between beta and size. There is a positive relationship between size and beta (r=.523). According to Fama and French (1992), variation in beta that is tied to size is positively related to average returns, but variation in beta unrelated to size is not compensated in the average returns of 1963-1990 for US stocks. The post-ranked beta in Panel B of Table 3.4 varies from .552 to 1.144 and generally rises within the beta-quartile portfolios. Hence post-ranking beta preserves the pre-ranking order of the portfolios. This again suggests that the pre-ranking beta sort mimics the order of the post-ranking beta. Strong and Xu (1997) found something similar for the UK stock market.

This study also computed the same measures for 'beta-size portfolios'. They are shown in Table 3.5. The Table is transposed to easily compare with the size-beta portfolios. There are three findings, when 'beta-size' ranked portfolios are used for analysis: First, the post-ranking betas are increasing and at the same time, the returns are falling within each size matrices. Hence, the results are similar to that of Table 3.4 (size-beta portfolios). Like the results in Table 3.4, the return-beta relation in Table 3.5 for this type of portfolio (beta-size) is again negative (r=-.463). Second, when market risk (beta) is increasing, the market value

is falling. Third, there is a positive relationship between size and return (r=.662) when the portfolios are sorted according to beta and then size. The results, here, suggest that is no stable small-firm effect for the UK stock market.

In Figure 3.1, it can be seen that the small-size and high BE/ME portfolios are the most successful portfolios. But, the relationship between returns and beta seems to be flat. This confirms the earlier findings of this study. In Figure 3.2, it can be seen that the highest return comes from 3^{th} (8^{th}) portfolio and lowest from 11^{th} (25^{th}) portfolio for size-beta (beta-size) portfolios. This again suggests a flat (or almost negative) relationship between beta and size.

3.4.3. FAMA-MACBETH REGRESSIONS

In this section, a more formal approach is adopted to test the factors (beta, size and BE/ME) that were examined in the previous analysis. This study employs the cross section regression method of Fama and Macbeth (1973). Seven different models (equations (3.5)-(3.11) mentioned above) are used for this purpose. Table 3.6 reports the cross-sectional regression results for each of the five portfolio-sorting procedure for the sample period: July 1973-December 2001. The regression coefficients are computed by taking an average of 342 monthly estimates obtained by 342 cross-sectional regressions.

If assets are priced rationally according to conventional asset pricing theory then investors only expect a higher return on assets when they expect higher risk. But the regressions in Table 3.6, Panel A says that when beta is the only explanatory variable, it has absolutely no role in explaining the cross-sectional average monthly returns. The estimated market risk premium for the period of 1969-2001 is only -.37% per month. The negative

sign of slope coefficient (-.003) is a complete contradiction to the theory. The null of the Sharpe-Lintner-Treynor CAPM is rejected, which states a positive and linear relationship between return and beta. The test has been done on the basis of 5% significance level. The overall p-value (not reported) of the slope coefficient at 5% level is also less then .05. The t-statistic of the slope coefficient (t= -.631) is so small, that the null is rejected at all significance levels. Chan and Chen (1988) also report the same sign but their t-static (-1.80) is also insignificant. Strong and Xu (1997) reported a positive and significant risk premium in equilibrium expected returns for the 1973-1992 sample period when they only used beta as an independent variable. Strong and Xu (1997) found an insignificant and positive coefficient of beta when they include both size and book-to-market variable in the regression (they also found a negative and insignificant risk premium when they included size as another independent variable for a different sample period of 1960-1992). Poon and Taylor (1991) found a negative risk-return relationship for the UK stock market. According to Poon and Taylor (1991), the negative risk-return relationship in their study could be due to the significant positive correlation between size and beta and the negative relationship between returns and size. The negative risk-return relationship in the UK stock market is also reported in the paper of Corhay, Hawaini and Michel (1987). They used the twenty-seven year period (1957-83). Their beta coefficient was negative (-.0041) but not statistically significant. They argued that this phenomenon was primarily the result of a significantly downward sloping risk-return relationship in the months of May and November. Fama and French (1992) found a positive and statistically significant coefficient of beta for the US. Their size variable had a significant effect in average returns.

The sign of size coefficient in this study is positive but insignificant, but all the earlier evidence including Banz (1981), Chan and Chen (1988), Fama and French (1992) and

Strong and Xu (1997 reported a negative but 'statistically significant' coefficient. This aspect of current study differs from previous studies. However, Chan and Chui (1996) also rejected the size coefficient for the UK.

It can also be seen that the explanatory power of the regressions is not very impressive. Table 3.6, Panel A and B, reports the Adjusted R-squared for all models. The R-squared measures the 'goodness-of-fit' of the regression equations. The adjusted R-squared in this study is the average of all adjusted R-squares of the 342 cross-sectional monthly regressions for 1969-2001. The average adjusted R-squared of risk-return model is only 1.60%. Hence 1.60% of the total variation in the security returns is explained by risk (beta). The rest of 98.4% remains unexplained. This might be due to 'other factors'[15] affecting the security returns (present in residuals). The Adjusted R-squared of all the other models is also very low. All this shows that our predicted CAPM does not fit the actual data. This might be due to the existence of measurement errors in estimating the beta coefficients from observations on individual stocks. This suggests that, the ability to explain the cross-section of returns with Fama and French (1992) variable (BE/ME) is very low.

The Fama and Macbeth regressions are also reported for the sorts based on 'beta-size', 'beta', 'size' and 'beta-size (2 x 5)' portfolios in Panels B, C, D and E of Table 3.6 respectively. There is hardly any change in the interpretation of the 'return-beta' relationship except the slight changes in the magnitude of the beta coefficient. But, in Table 3.6, Panel C, something different can be noticed. In 'beta' sorted portfolios, beta (in isolation) is still insignificant but 'positive' and hence matches with Fama and French (1992) study. For

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[15] It is perhaps possible that none of the factors mentioned in empirical models are not explained by risk at all: Brennan, Chordia and Subrahmanyam (1998) find that size and book-to-market variable are significant even after supposedly adjusting for risk. As they point either the risk adjustment method is incomplete or perhaps other factors than risk affect expected returns. Their work on trading volume suggests that perhaps liquidity is a factor in explaining returns: as the quantity traded of an asset decreases it generally becomes less liquid. Lower liquidity might mean that the investor cannot sell a current stock quickly enough, if he/she forecast a price fall, or if he wants to take advantage of another investment opportunity elsewhere. In a way this is a form of "timing risk": profitable trading opportunities may have to be foregone due to illiquidity. However, on most markets stocks can be brought or sold, instantly, so provisionally one can suspect that this source of "risk" is unimportant.

example, in Panel C, the monthly risk estimates for risk-return model (equation (3.5)) is .003. This is different from the results in Table 3.6, Panel A, but the null is still rejected (t=.0773). However t-statistic of beta coefficient for 'beta-sorted portfolio' is much higher then 'size-beta portfolios.' Overall for all the portfolios, the results statistically confirm that there is no relation between average return and beta. The story of adjusted R-squared for 'beta-size', 'beta', 'size' and 'beta-size' (2 x 5) portfolios in Table 3.6, is very similar to the 'size-beta' portfolio.

When both beta and ME (size) are included in the regression, the coefficients on size and beta are indistinguishable from zero. This is again reported in Table 3.6. But when Strong and Xu (1997) include beta and size together, beta becomes insignificant while the market value stays significantly negative. It has already been recognised that market beta and size are not a perfect explanation of average returns. Variable such as BE/ME might contain risk left unexplained by market beta and size. In Table 3.6, the statistical relationships between average return and BE/ME confirm the importance of BE/ME in explaining the cross-section of average returns. In Panel A, the average slope from the monthly regressions of returns on BE/ME is .11% with a (absolute value) t-statistic of 2.22. The t-statistics of BE/ME coefficients for all the regressions are greater then 1.96. The BE/ME slopes have impressive standard errors from zero. The sign of BE/ME is positive and is in line with what Fama and French (1992), Chan and Chui (1996) and Strong and Xu (1997) found in their studies. Out of all the independent variables, BE/ME has consistent explanatory power for average returns. But inspite of adding the BE/ME in the cross-sectional regressions, the adjusted R-squared still remains very low. This is puzzling and the test of beta, size and BE/ME factor requires further investigation. However, the regression method that is employed relies on estimates of beta, not the underlying or 'true' beta. Since BE/ME is likely to be strongly

(negatively) correlated with true beta as well as other measures like size, it is difficult to know exactly what the coefficient on BE/ME[16] is reflecting. In other words, BE/ME could be priced or could not be priced.

A TEST OF THE SHARPE LINTNER HYPOTHESIS

In the Sharpe-Lintner CAPM of market equilibrium discussed in Chapter 2, the intercept is a risk free rate. The work of Friend and Blume (1970) and Black, Jensen, and Scholes (1972) suggest that the intercept should be zero beta rate. In cross-sectional tests that include only beta, the intercept should be risk-free rate or the zero beta rate. To pass this test, the intercept should be significantly different from zero. Each of the seven different models (3.5-3.11) of Table 3.6 can be used to test the Sharpe-Lintner hypothesis. The most efficient test is however provided by the one-variable model (including return and beta) in Table 3.6, Panel A. The intercept is statistically very different from zero for all models. The studies like Fama and Macbeth (1973), Stambaugh (1982), and Kothari, Shanken & Sloan (1993), who tested the two parameter model assuming the Sharpe-Lintner hypothesis-the intercept being equal to the risk-free interest rate (Treasury Bills) –for the US found that on average the intercept is greater than risk-free rate. This study found similar results for the UK stock market.

3.4.4. SUB-PERIOD ANALYSIS

The whole period is divided into two sub-periods: the first sub-period is from January 1969 to June 1985 and the second sub-period is from July 1985 to December 2001. There are three good reasons for analysing sub-periods. First, the reason that the whole period (342 months

[16] There might be "multicollinearity" problem (refer to Section 2.7.5 in Chapter 2).

or 29 years) is divided into sub-periods (144 vs 198 months or 12 vs 17 years) is that, in the early years, LSPD has much more missing data than in the later years. Prior to 1975, companies were included only on the basis of a 33% random sample of all UK companies in 1955. Frank and Harris (1989) suggest that the LSPD is comprehensive from 1975 onwards. Although, there is no bias from the LSPD, but the accuracy of the data might be higher for the post-1975 period. Gregory, Harris and Michou (2002) suggested that by omitting the years 1975-80 from the sample, any "backfill" bias that may be present in Datastream during this period could be avoided too. Sub period analysis will therefore help to examine any possible bias from restricting the sample in earlier periods. Second, results regarding beta may be explained by inflation. The UK had a period of high inflation in the 1970s and early 1980s. Equities were seen as serving their traditional investment function as a hedge against inflation in the 1970s, a negative relationship between risk premium and inflation would have been found empirically. This means that a lower rate of return would be associated with shares with a high inflation beta. The inflation rates fluctuated between 22% to 5% between 1973 to 1982, which is in the first sub-period. The issue of whether risk premia appear to be causally related to inflation in the UK has been investigated by Yaansah and Peasnell (1994). They conclude that the observed relationship between ex-ante real risk premium and inflation does not appear to be a causal one. Third, Fama and Macbeth (1973) and Fama and French (1992) use the US stock returns for different sample period and finds different results. The former study shows that beta is "alive" during the 1926-68 period, while the latter shows that beta is "dead" during the 1963-90 period. This shows that the cross-sectional results are very sensitive to the sample periods. As most of the other cross-sectional studies (Strong and Xu (1997), Chan and Chui (1996) and Kothari, Shanken and

Sloan (1995)) have also experimented with the different sub-periods of their sample, this study should therefore do the same.

The post-ranked betas are estimated for different subperiods. In this way, there will be 25 new post-ranked betas for first sub-period (12 year post-ranked period) and 25 new post-ranked beta for second sub-period (17 year post-ranked period) (Table 3.1 has more information on sample dates). The rest of the procedure is same as above. Looking at Table 3.7, Panel A, it can be seen that sub-periods do not offer much prospect that the average premium for beta is economically important. The positive sign of beta changes to negative in the second sub-period (see Table 3.7, Panel B). The market risk also appears to be significant in the second sub-period. It looks in this study, that, there is not much stability of beta over time. The central prediction of the CAPM is that higher beta securities are more risky than low beta securities, and therefore should offer an investor higher expected returns. But, during the 1985-2001 period, this study finds opposite results for the UK stock market. This study also found less of a BE/ME effect over the 1969-1985 than over the 1986-2001 period. This shows that the BE/ME effect is also not stable over time. The results for market value remained the same as for original sample period.

Chan and Chui (1996) used two sub-periods: July 1973-December 1981 and January 1982-June 1990 for their analysis. They found results quite similar to the findings of this study. Their beta estimates in the first sample period were closer to zero while significantly negative for the second sub-period. Like this study, they also found a weak BE/ME effect in the first sub-period period but a very strong BE/ME effect in the second sub-period. They suggested that, their overall results are dominated by the results of a low–inflation period

(second sub-period). In the current study, the t-statistics on the mean of the parameter estimates rests on the assumption that the price of risk for each regressor is constant across the test sub-periods. According to Chan and Chui (1996) this assumption may be misleading in the presence of inflation in the UK. Strong and Xu (1997) used two sub-periods, July 1960 to June 1973 and July 1973 to June 1992 for their analysis. Their sub-period analysis did not alter their previous conclusions for the entire period (July 1973-June 1992). They still found some beta effect, size effect and a very strong BE/ME effect in stock returns.

3.5. MEASUREMENT ISSUES

Despite the existence of a large academic literature, which discusses implementation of CAPM, in particular in relation to estimation of the key parameter beta, there is no consensus in relation to how a best estimate should be obtained. There is no consensus with respect to the index, type of return: discrete or continuous, and the time frame that should be used for estimation. The next part of this chapter will, therefore, use a different index, a different type of return, and a different time frame for estimating beta, and then re-examine the Fama and Macbeth cross-sectional regressions.

3.5.1.CHOICE OF MARKET INDEX

Explanation of above findings could be provided by the theoretical argument of Roll and Ross (1994) and Kandel and Stambaugh (1995) that the equivalence between the mean-variance efficiency of an index and exact linearity of expected returns in the betas breaks down when the market index or market portfolio is only 'approximately' efficient. Roll and

Ross argue, for example, that given a sets of assets, it is conceivable that there are indices 'close' to the efficient frontier that produce no relation between beta and mean return. Kandel and Stambaugh, on the other hand, focus on the assets. They show that, when an index is approximately efficient with respect to a set of assets returns, the assets may be 'repackaged' into (potentially unusual looking) portfolios such that the return/beta relation is arbitrarily weak. In practice, there are no indices that measure or even come close to the market portfolio.

The underlying theory of CAPM is quite specific in its recommendation of index; it specifies that a value-weighted index consisting of all the assets in the world should be used. Since only a small fraction of all assets in the world trade on stock exchanges it is impossible to construct such an index so a proxy must be used instead. This study has so far used equally-weighted index for analysis. A value-weighted index can be another option for estimating the post-ranking beta. The following results will indicate whether the choice of market index makes a difference to the results[17] in Table 3.6.

In order to test the sensitivity of results to the index type, the Fama and Macbeth procedure mentioned in the previous section is repeated by using a value-weighted index. For this purpose, the FTSE All Share Index from 1969 to 2001 is employed. The post-ranking beta is re-estimated for all the 25 portfolios[18] by regressing the portfolio return

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[17] The table summarises betas estimated for Disney, using monthly data from January 1, 1993 to December 31, 1997, using a number of different indices:

Index used	Beta calculated
Dow 30	0.99
S & P	1.13
NYSE Composite	1.14
Whilshire 5000	1.05
MS Capital Index	1.06

Note that none of these indices include other asset classes, such as fixed income or real assets. (Souce: Damodaran (2001, pg.23)).

[18] In Table 3.6, it can be seen that the cross-sectional averages from 'size-beta', 'beta-size', 'size', 'beta' and 'beta-size (2x5)' ranked portfolios are quite similar. It can also be seen that the portfolios are formed on the basis of two dominating variables: size and beta. Hence size (beta) dominates beta (size) in 'size-beta' ('beta-size') ranked portfolios. Therefore, from now onwards, cross-sectional regressions are only run on 'size-beta' and 'beta-size' (or beta) ranked portfolios.

against the value-weighted index. The results, in Table 3.8 are similar to the results obtained by using the equally-weighted index, but with two exceptions. First, average coefficient of beta is found to be positive for the 'beta-size' sorted portfolios when the value-weighted index is used in the analysis. The sign was negative for 'beta-size' sorted portfolio when equally-weighted index was used. Strong and Xu (1997), suggest that using the value-weighted index has the effect of either reducing or reversing any positive beta-return relation that occurs with the equally-weighted index. Something similar appears to be happening in this study. The t-statistic of beta coefficient for 'beta-size sorted portfolio' with value-weighted index is much higher then the t-statistics computed so far for beta coefficient in this study. Second, surprisingly, size and BE/ME appears to have less influence. The BE/ME is less significant for 'size-beta portfolios' when the value-weighted index is used for analysis. Overall, these results may be due to the construction of value-weighted index. There is a strong influence of large firms on a value-weighted index. The results here, indicate that an value-weighted index captures the movement of small stocks and BE/ME[19] less better then an equally-weighted index.

In theory, the CAPM implies that the portfolio of stocks that has maximum correlation with the true market portfolio is efficient. But, market portfolio is the portfolio of all assets in the economy and it therefore cannot be observed. On the basis of this theory, one can accept CAPM model or a model with BE/ME variable and commit a "type 1"[20] error if the proxy index is efficient and true market portfolio is inefficient or reject CAPM and commit a "type 2" error if the proxy index is inefficient and true market portfolio is efficient. This is an interesting empirical question and left for future research.

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[19] In theory, these are high BE/ME. Like small firms, these "high BE/ME" firms are financially distressed firms.

[20] In type 1 error, one tends to falsely accept the null, when the null is false. In type 2 error, one tends to falsely reject the null, when the null is true.

3.5.2. CONTINUOUS OR DISCRETE RATE OF RETURN

Most of the empirical studies of the relationship between systematic risk premia and expected returns in cross-sectional studies have used 'continuous' rates of returns. By contrast, many of the apparently contradictory studies used 'discrete' rates of return. A great deal of controversy therefore lies in the definition of return, which has not been given much weight in this literature.

According to Strong and Xu (1997, pg.6); "The returns on the LSPD are monthly continuously compounded returns. By contrast US asset pricing studies have used discretely compounded monthly returns. In a portfolio model with a discrete investment horizon, as in CAPM the simple discrete return is the appropriate variable theoretically (see, for example Fama, 1976, p.27 ff.). Therefore to be consistent with the underlying theory of portfolio models, and to allow direct comparison with the US results that motivate this study, we use discrete monthly returns here."

They then add in an attached footnote; "A previous version of this paper used continuously compounded returns. These results confirmed concerns on the effect of very low returns assuming continuous compounding. However given, the use of both returns in the literature, the effect of switching between the two deserve attention."

It is clear therefore that the precise definition of rates of return is important in cross-sectional studies. So far this study has used continuous rates of returns for analysis. In the CAPM theory, the discrete return is the appropriate variable for analysis. To be consistent

with underlying theory of portfolio models, and to allow direct comparison with the Fama and French (1992), Ashton and Tippett (1999) and Strong and Xu (1997) results that motivate this study, discrete rates of returns are used here. The cross-sectional models are now re-estimated by using discrete rates of return for the UK stock market[21]. The same Fama and Macbeth (1973) procedure is used for this purpose. Hence different sets of pre-ranking beta, portfolio returns and post-ranking betas are estimated for the sample period.

Table 3.9 presents the results. Some of the estimates obtained using discrete returns for 'size-beta' portfolios (Panel A) are similar to the results obtained by using continuous returns and 'size-beta' portfolios. In fact, the results again suggest that there is a very strong and positive book-to-market effect for the current sample period. As the earlier evidences are supportive (see, Table 3.6) of the book-to-market effect, this discovery is no surprise. The coefficients on beta and BE/ME variables using 'beta-size ' portfolios (Panel B) are also similar to the results obtained by using continuous returns except for one difference. The t-statistics of all the variables including beta are much higher then the estimates obtained by using continuous rates of return. For example, this study (for continuous rates of return) estimated monthly average market risk premium of -.10% with a t-statistics of .2322 in absolute terms. But in the case of discrete rates of returns, this study estimated monthly average market risk premium of around .4% with a t-statistics of 1.070. However, the t-statistics of market risk premium is not large enough to change our earlier interpretation of CAPM. Overall, CAPM is again rejected. The sign on size coefficient is negative but statistically insignificant using discrete rates of return where as it is positive using

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[21] The monthly data for UK stock market for the period of January 1969 to December 2001 are used for analysis. In order to use the discrete rates of return, the continuous rates of return are converted to the discrete rates of return by using the following:

$r_t = EXP\{Log[(P_t + D_t)/P_{t-1}]\} - 1$ where EXP is the exponential value.

continuous rates of returns. It appears to us that the sign of size coefficient is sensitive to the 'type of return' used for analysis, but in all cases, it is not significant.

3.5.3. ANNUAL COMPOUNDING RETURNS

One choice that can affect the beta, size and BE/ME estimates is the return interval. Handa, Kothari, and Wasley (1989) and Kothari, Shanken and Sloan (1995) provides evidence that the test of CAPM are sensitive to the choice of the interval. Using shorter intervals increases the number of observations in the regression, for any given time period, but it does with a cost. Assets do not trade on a continuous basis, and when there is non-trading on the asset, the beta estimated can be affected. In particular, non-trading on an asset during a return period can reduce the measured correlation with the market index, and consequently the beta estimate. By using longer return interval like annual results, fewer observations are used in the regression.

For all these reasons, the risk-return relation is now investigated using annual data. Returns data are taken from LSPD monthly returns. The procedure mentioned in Section 3.3 is then used to obtain equally-weighted monthly portfolio returns. Monthly portfolio's returns are then compounded from July t to July t+1 to obtain annual portfolio returns. The annual returns are computed for 29 consecutive periods. Annual post-ranking betas are estimated using the full sample of 29 years (1973-2001) of equal-weighted annual returns on each of the 25 size-beta portfolios with the equally-weighted market annual return. Table 3.10a reports the properties of annual returns and annual betas estimated from size-beta ranked portfolios. There is a reasonable spread in betas and average returns among the 25 portfolios. The post-ranking period equally weighted beta ranges from .776 to 1.556 and are

consistent with previous findings on monthly returns (.516 to 1.144) data, which have a similar dispersion. Like Chan and Chui (1996), this study also find that, when the smallest size quintile portfolios are compared to the largest, the smaller size portfolios are now associated with higher beta (where previously, in Table 3.3, they were associated with lower beta). The spread in average returns across the 25 portfolios is about 10 % (13% in Chan and Chui study). The average return in the beta portfolios within a size decile does not exhibit considerable variation, which should be consistent enough with the assumption of positively-sloped risk-return relationship. For example, the lowest-beta portfolio in the largest size decile earns 8.24% (on annual basis) compared to just 7.04% earned by the highest-beta portfolio in the largest size decile. The returns for the high beta portfolio in the smallest size quartile are more variable but somehow closer to the earlier findings of Banz (1981). There again seems to be a strong small-firm effect in annual returns. So far, the findings of this study are quite different from the earlier findings of Kothari, Shanken & Sloan (1995) on the US stock market. Their lowest-beta portfolio in the largest quartile earned 11.5% average return compared to 15.3% earned by the highest beta portfolio in the largest size portfolio, which clearly favours the positive risk-return relation (the beta spread was .48 to 1.44 from the lowest to largest beta portfolio in the largest size portfolio).

The findings on the reversal of post-ranking betas for the smallest portfolios are interesting and require some investigation. The beta estimates for the smallest size portfolios could have been biased downwards to a greater extent due the presence of autocorrelation in the small firms. It is therefore not surprising to find that the differences between the monthly and annual post-ranking beta estimates for the smallest size portfolios is more evident than other portfolios. Handa, Kothari and Wasley (1989) also found that the betas of smallest-size

portfolios increase from 1.41 to 1.66 as the return interval is increased from one month to one year, while the betas of the largest-size portfolios decrease from .67 to .56. The betas of other portfolios do not experience much change. As mentioned above, the reversal of post-ranking betas is attributed in part to the beta sensitivity to the return interval for the smallest-size portfolio and the autocorrelation due to potential thin trading.

To investigate further, the relationship between annual returns and beta is also tested using 'beta-ranked portfolio' (shown in Table 3.10b). Annual returns using beta-ranked portfolio didn't produce anything different to the earlier results. In the monthly return case, the second smallest beta ranked portfolio gives the highest return of .972 % (shown in Table 3.3, Panel A). But in the annual return case, the highest returns are produced by fifth largest beta-ranked portfolio. Thus, like monthly return case, the return pattern again seems to be unstable across portfolios in the annual case. Also like the monthly case, the annual post-ranking beta's for portfolios formed on pre-ranking betas almost perfectly reproduce the ordering of the pre-ranking betas.

In the annual return case, two different types of Fama-Macbeth cross-sectional regressions are run. First, the compounded annual returns are regressed on individual securities (grouped into portfolios) against the annual post-ranked beta, size and BE/ME to examine the cross-sectional relationships. Second, the same regressions are run for individual monthly returns against the annual beta. Looking at Table 3.11, Panel A1, it can be seen that the beta variable is insignificant (t-statistic<2) and the annual risk premium is just about .1% when beta is the only regressor. Thus, the sign of beta changes from negative (in Table 3.6, Panel A) to positive for 'size-beta' ranked portfolios (Table 3.11, Panel A1).

Hence using an incorrect return interval can lead to incorrect conclusion about the risk-return relationship. But, it appears that even annual betas do not produce a statistically and economically significant risk premium in UK market. CAPM is again rejected. The results are again similar to that of Chan and Chui (1996).

The results of Strong and Xu (1997) for annual returns were not different from their monthly regressions, and Fama and French (1996a) also found that the simple regression t-statistics for the cross-sectional coefficients on monthly and annual betas were small and nearly identical. And, in their case, the post ranking betas of monthly and annual returns were identical. By contrast, Kothari, Shanken and Sloan (1995) show that annual betas are significantly priced for a variety of portfolios. One wonders then how Kothari, Shanken and Sloan (1995) found different results for monthly and annual betas when Fama and French (1996a) did not. The important difference between Fama and French (1996a) and Kothari, Shanken and Sloan (1995) study is that Fama and French compound equal-weighted monthly portfolio return to obtain annual returns. That is, the portfolios are rebalanced each month, yielding annual returns that differ from Kothari, Shanken and Sloan's buy-and-hold annual returns obtained by averaging the compounded annual returns on individual securities. Since the difference between Kothari, Shanken and Sloan's monthly and annual betas increases as the betas deviate from one, it is not surprising that the cross-sectional results in Kothari, Shanken and Sloan are much more sensitive to the horizon over which beta is estimated. Kothari, Shanken and Sloan's (1995) methodology has received more attention in finance literature. In this study, the methodology of Kothari, Shanken and Sloan (1995) is therefore used to obtain the results for the annual case.

The size and book-to-market variables seems to be generally insignificant too. The average coefficient of BE/ME is positive but only significant at 10% level of significance for two of the models. This is surprising because this study found a very strong BE/ME effect when monthly returns were used for the analysis.

The results of Table 3.11, Panel A2 (monthly returns against annual beta) are a little different to the case when annual returns are used against annual beta. The sign of beta switches from positive to negative when monthly returns are used against the annual betas. The BE/ME effect is once again visible for the UK stock market, while the size effect is insignificant, but less so then what was found for the case when annual returns were used for the analysis.

The analysis is also repeated using 'beta-ranked' portfolios. This is shown in Table 3.11, Panel B1. The beta coefficient is again sensitive to the way portfolios are formed. The sign of beta changes from positive to negative but remains insignificant. This was puzzling because, positive beta coefficient was found for beta-ranked portfolios when monthly returns were used against the monthly betas. The t-statistics of the size coefficient increases from around .939 for 'size-beta portfolios' to around 1.534 in absolute terms for 'beta case'. The results for monthly returns and annual betas for beta-ranked portfolios are similar to those for monthly returns and annual betas for 'size-beta' ranked portfolios.

3.6. AVERAGE RESIDUALS FROM ANNUAL REGRESSIONS

Following Fama and French (1996a), the average residuals are examined from annual cross-sectional regressions. Average residuals are the basis for evaluating whether betas or other factors completely capture cross-sectional variation in expected returns. Fama and French (1996a) point to the large "CAPM pricing error" for the extreme size and beta deciles and view their multivariate regression results (on size, BE/ME and beta), as well as those in Kothari, Shanken and Sloan (1999), as evidence that "size and BE/ME always adds substantially to beta's description of average returns." Yet no information is provided on the extent to which size and BE/ME actually reduces the average residuals.

Table 3.12 provides the average residuals from annual Fama and Macbeth return models that include size, BE/ME or annual beta as well as the model with annual beta, size and BE/ME.

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \mu_{it} \tag{3.14}$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{2t}ME_i + \mu_{it} \tag{3.15}$$

$$R_{it} = \gamma_{0t} + \gamma_{3t}(BE/ME)_i + \mu_{it} \tag{3.16}$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \hat{\gamma}_{2t}ME_i + \hat{\gamma}_{3t}(BE/ME)_i + \mu_{it} \tag{3.17}$$

The definitions of annual return, full period post-ranking annual beta, size and BE/ME are the same as mentioned in Section 3.5.3. After running the Fama and Macbeth cross-sectional regressions, the residual (μ_{it}) are assigned into the 25 size-beta portfolio matrix. For each portfolio, average residuals is calculated by averaging the estimated μ_{it} for portfolio p across 29 consecutive periods. One refers to a portfolio's average residual as its 'deviation' from the model. The basic properties of (cross-sectional) regression residuals guarantee that the average deviation across the 25 portfolios is zero.

By looking at Table 3.12, Panel A, B, C and D, it can be seen that for all the four models (3.14-3.17) respectively, two of the portfolios have deviations that exceed 4%. Most of these occur either in the lowest size portfolio or the smallest beta portfolio. These results are not surprising because Kothari, Shanken and Sloan (1999) found similar results for the US stock market. The standard deviation of the 25 portfolio average residuals from the beta-only model (equation 3.14) is 2.38%, compared to 2.40% for size-only model (equation 3.15), 2.20% for BE/ME only model (equation 3.16) and 2.22% for the combined model (equation 3.17).

Table 3.13, Panels A, B, C contains the differences between the value of the portfolio deviation from the model 3.14, 3.15, 3.16 from model 3.17 respectively. The difference is taken to test the incremental effect of size and BE/ME in asset-pricing model. In Panel A, there are around nine portfolios with the average residual of more then 0. In contrast, around fourteen and ten portfolios have an average residual of more then 0 when the difference between the models "3.15 and 3.17" and "3.16 and 3.17" are taken respectively. The

standard deviation of the differences in Panel C is .08% compared to .32% and .40% in Panel A and B. Using annual returns, the variability of the average residuals from BE/ME only model continues to be considerably smaller than that of the average residual from the size only and beta only model. These results clearly verify the earlier results obtained by simple Fama and Macbeth cross-sectional regressions[22]. The estimated incremental impact of BE/ME in explaining expected returns is again quite high, given its statistical significance.

3.7. DATA SNOOPING ISSUES

Lo and MacKinlay (1990, pg. 434) define data snooping as occurring "when the construction of test-statistics is influenced by empirical relations derived from the very same data to be used in the test.

Fama and French (1992) didn't discuss "data-snooping bias" in their tests of the market value of equity or "size" variable which is an often-specified data-instigated empirical variable that Lo and MacKinlay (1990) use to illustrate "data-snooping bias", Lo and Mackinlay (1990, pg.434) state "Perhaps the most common attribute by which securities are grouped is market value of equity or 'size'. The prevalence of size-sorted portfolios in recent tests of asset pricing models has not been precipitated by any economic theory linking size to asset prices. It is a consequence of a series of empirical studies demonstrating the statistical relation between size and the stochastic behaviour of stock returns. Therefore, we must allow for our foreknowledge of size-related phenomena in evaluating the actual

[22] Analysis was also done on the monthly residuals and similar results were found.

significance of tests performed on size-sorted portfolios. More generally, grouping securities by some characteristic that is empirically motivated may affect the size of the usual significance tests, particularly when the empirical motivation is derived from the very data on which test is based".

This study has tried to use the best data-set available. To some extent, by using a new data-set, this study has tried to overcome the problem of data-snooping. But it might be a good idea to additionally examine the sample periods used by earlier UK cross-sectional studies. A difference between the current data and that of Strong and Xu (1997) is that, they collected the accounting data from Exstat database and accounting data for this study was collected from Datastream. This study uses the Strong and Xu (1997) sample-period of July 1973-June 1992 (228 cross-sectional regressions) to see if there is any difference in the earlier results (Table 3.6). To be directly comparable to Strong and Xu (1997), this study like them uses discrete rates of return for their sample period. As usual, the post-ranked betas are re-estimated using 19 post-ranked period and the same second-stage procedure (see Section 3.3.2) is followed. Table 3.14, Panels A and B presents the results. There again seems to be a very strong BE/ME effect no matter whichever ranked-portfolios are used for analysis. There is some evidence of a beta effect in discrete returns when the stocks are sorted according to beta-size portfolio. The average slope from the monthly regressions of returns on beta is .7% with a (absolute value) t-statistic of 1.426 when used alone. Hence, the beta variable is statistically significant at 20% significance level. The market risk premium goes up to .8% with a t-statistics of 1.504 when size is added to the regression. Hence, there is some support for the traditional CAPM. Other than this, the earlier interpretations remain unchanged.

In addition, Chan and Chui (1996) sample-period of July 1973-June 1990 (204 cross-sectional regressions) is also used for analysis. To be directly comparable to the Chan and Chui (1996) study, this study like them used continuous rates of return for their sample period. Table 3.15, presents the results. The results from the Chan and Chui (1996) sample period are very much similar to the results for full sample period (Table 3.6).

3.8. ROBUST METHODS

In this section, the Fama and Macbeth cross-sectional regressions are used in situations where the regression estimator might be sensitive to 'extreme' observations, different market conditions and the sample-selection. Identifying and investigating these situations could deepen our understanding of the economic reasons for the risk premia associated with beta and BE/ME. This is also important because BE/ME is not directly related to any of the equilibrium asset-pricing models.

3.8.1. EXTREME OBSERVATIONS

Dybvig and Ross (1985) discuss problems associated with the estimation of the beta-return relation when changes in information shape ex-post returns. Downs and Ingram (2000) consider the unanticipated information events that corrupt the CAPM results for the US stock market. They try to get rid of the problem by using a 'trimmed methodology'. Their approach is that monthly stock returns deviating by more than 50% from market almost surely are induced by unanticipated information events. They therefore 'censor' the return data. They collect equally weighted portfolio returns for the 12 out-of-sample months

following each annual sorting of the data, and then they eliminate any monthly returns that deviate by more than 50% from the months market return. For example, if a particular month's market return is 2%, they eliminate monthly security returns greater than 52% or less than –48%. After eliminating extreme returns, they find that beta and total risk (variance) are statistically significant determinants for the cross-section of stock returns. The market size variable became insignificant in their study. This methodology has not been applied before to the UK stock market before.

Monthly returns were collected for each of the twenty-five portfolios throughout the 342 sample months. Monthly return data that deviated by more than 50% from the market return month was eliminated. Post-ranking betas were then estimated with the censored data, and 342 independent monthly Fama and Macbeth equations (see Section 3.3.2, equations (3.5) and (3.11)) were then estimated, the estimated coefficients were averaged and the time-series t-statistics were computed. Table 3.16 presents the results. By comparing the results of the trimmed observations (in Table 3.16, Panel A) with untrimmed observations (Table 3.4, Panel A), it can be seen that the values of small-firm portfolios are different for both types of observations. In Table 3.16, Panel A, it can be seen that when the stocks within the beta matrices are tied to size, there seems to be positive relationship between average returns and size. This is because; the lowest size portfolio within the beta quintile generally produces lower returns. Small-firm effect was found for untrimmed observations, but censoring extreme returns from a portfolio diminishes the average returns of small firm portfolios. Hence small-firms seem more affected by the noise in the data. Looking at the size quintiles (rows) and beta matrix, the average equally-weighted returns of the trimmed observations have a lesser tendency to decline with increasing beta. Like before, in Table 3.16, Panel B, it

can be seen that the post-ranking betas follow the order of the pre-ranking betas. The Fama and Macbeth equations estimated with censored data are shown in Table 3.16, Panel C. The coefficient on beta is positive and statistically significant from zero in the full equation (3.11), (row 2), at 10% level of significance but statistically insignificant in univariate equation (3.5) (row 1). BE/ME remains a strong variable and market size remains an insignificant variable.

The extreme returns, here, might be due to the small firms. This can be seen in Table 3.16, Panel D. Removal of these extreme observations eliminates about 5% of the small-firm observations. Therefore, most of the noisy observations comes from small-size portfolios.

Although, some interesting results have been obtained through the use of the trimming methodology, Fama[23] has argued that trimming is not a good procedure because the distributions of monthly returns are highly skewed. Hence, the results through trimming methodology cannot be accepted with full confidence.

3.8.2. CONDITIONAL RELATIONSHIPS

Asset-pricing models like CAPM are usually expressed in terms of expected returns while several tests are performed on realized values over several periods. The common explanation is to rely, explicitly or implicitly, on a period by period rational expectation equilibrium and thereby presuming that expectations are on average correct. Therefore, for positive stock

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[23] Fama in his one of the interviews suggest that, Knez and Reddy (1997), takes out the biggest manifestations of the risk effect through market returns. He suggests that, if the biggest manifestations of the market return are taken out, the market premium pretty much goes away as well. This can be done for anything and it's going to go away. According to Fama, this is not the way to trim. Fama suggest that when the data is trimmed, it has to be trimmed on both ends. And there's no way to implement a trimming strategy. If researchers knew in advance what were going to be biggest months, they could capitalize on that.
He further suggests that if the distribution is symmetric, trim should not effect the means. But if the distribution of monthly returns is not symmetric, and if the data is then trimmed, it effects the mean. For example, if the distributions of monthly returns are highly skewed to the right, trimming is not a good procedure. The positive values are more positive than the negative values are negative.
The above discussion was taken from an interview between Junior Fama and Senior Fama (interview was downloaded from the following website: http://www.indexfunds.com/articles/19991201_famaint_iss_int_GF.htm.

betas cross-sectional relations between realized stock returns should on average conform to a positive linear relation between stock returns and market portfolio return. It is obvious that this average may appear to be quite weak if the sample contains a substantial number of observations with negative market return, and these negative market returns are generally considered to be a very noisy approximation of expected returns (see Merton (1980)). The results from standard Fama and Macbeth methodology report that the average premium for market beta is statistically insignificant. Nevertheless, this conclusion, which is consistent with previous studies such as Fama and French (1992) for the US and Chan and Chui (1996) for the UK, may result from averaging a combination of negative and positive coefficients. From these perspective it is interesting to analyse separately the role of beta, size and BE/ME in situations where the market return is negative and vice-versa.

To reach a testable hypothesis, analysis starts from a one-factor asset-pricing model where the riskiness of stock is directly related to its covariance with market, which means that high-risk stocks have large outcomes in states where market wealth is high and vice-versa. In this model agents try to smooth consumption and the only source of risk is variation in aggregate wealth. Since CAPM can be deduced from this more general model it seems reasonable that by analogy a similar relation may be valid for CAPM: high beta stocks have large outcome in states where the value of the market portfolio is high and vice versa and the states are approximated by realized market return. This idea can be tested via the following hypothesis: there is a positive relation between realized stock return and beta, conditional on the market return being positive and a negative relation for a negative market return. This is not a equilibrium model that estimate the risk premium for beta, but an analysis of the factors driving returns in bad and good states respectively. Such an analysis is

of course important for an individual investor who changes his/her prior subjective beliefs for good and bad states.

The significance of beta, market size and BE/ME has been tested by investigating the relationship between return and beta, market size and BE/ME when the market return is positive or negative, or more simply stated, whether the market is up or down. This approach has been used by Chan and Lakonishok (1993), and Petengill, Sundaram and Mathur (1995) in the US. A down market month is defined as a month when the market return is negative. Between July 1973 to December 2001, there were 123 such months when a value-weighted index was used and 134 months when an equally-weighted index was used. An up-market month is defined as the month with positive market return. Between July 1973 to December 2001, there were 219 such months for a value-weighted index and 208 such months for an equally-weighted index.

The cross-sectional regression estimates and its associated t-tests of the conditional relationships can be obtained from the monthly regression coefficients estimates in the down and up market months using the methodology mentioned in Section 3.3 of this chapter. Table 3.17, Panel A presents the results of the average beta coefficient for the down and up-market month using the value and equally-weighted index. For the down-months, the value of beta coefficient was negative and significant at the 5% significance level. It is clear that in these months high-beta stocks suffered greater loss than low-beta stocks. There seems to be some size effect in down-market conditions when equally-weighted index is used for separating the down and up markets. But there seems to absolutely no size effect when

value-weighted index is used for analysis. The BE/ME effect is negative and insignificant when equally-weighted index is used.

For up-market conditions (shown in Table 3.17, Panel B), the average value of beta coefficient is positive and significant at 5% level of significance. Hence high beta stocks in these conditions give better results. Chan and Lakonishok (1993) for the US stock market found that the estimated coefficient almost moves in the same direction as the market premium. So, in their study, the slope is high (low) when market index is high (low). This view was confirmed by Petengill, Sundaram and Mathur (1995). The results for the average beta coefficient showed that the same behaviour could be detected in the UK market. There seems to be no size effect at all. A positive BE/ME effect is visible in up market when equally-weighted index is used for separating the up from down markets.

In Table 3.6, the average premium for market beta is statistically insignificant. Nevertheless, this conclusion, which is consistent with previous studies such as Strong and Xu (1997) and Fama and French (1992) in the UK and US respectively, may result from averaging a combination of negative and positive coefficients. This section reports a significant positive relation between return and beta when the market return is positive and a significant negative relation between return and beta when the market is negative. Our results suggest that taking average across up and down months is the cause of the flat relationship between beta and return reported in the Table 3.6. But, this finding can be a useful tool for investment strategies[24]. The evidence is mixed for BE/ME effects. BE/ME

[24] Investors can protect themselves in periods when the market return is below the risk-free rate by investing in stocks with low beta.

appears to have lowest correlation with market risk. That is, its coefficient remains positive in up and down periods when value-weighted index is used.

3.8.3. SAMPLE SELECTION

Strong, Liu and Xu (1999) suggested that it is impossible to state clearly whether excluding any stocks from the sample introduces any bias to the study of the UK stock returns. Banz and Breen (1986) examine how selection bias and look-ahead biases[25] effects in data sets affect studies of equity returns and firm characteristics. Banz and Breen (1986), for the US stock market, used the data sets from Compustat, that included all companies, which subsequently merged, liquidated, went bankrupt or disappeared in some periods. According to Banz and Breen (1986) sample containing all firms show, on average higher returns than the sample containing survivor-only firms.

This section examines the robustness of earlier results by using all the 2108 stocks simultaneously. The data set includes firms that appear in both Datastream and LSPD. Instead of using the varying samples in the post-ranking periods (see 1st column, 10th row of Table 3.1), all 2108 stocks (see 1st column, 8th column of Table 3.1) are used for every post-ranking period. The 2108 stocks include dead as well as live stocks in the sample. In other words, so far, securities that had insufficient history of accounting data were excluded from

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[25] **Selection bias** arises because data set contains only those firms that are currently viable entities-Firms, which filed for bankruptcy, merged or ceased to exist are excluded from sample. Also, new firms often enter the database later a full history thus introducing data not available at an earlier point in time.
Look ahead bias can arise due to the following reason:
-timing of information. Accounting data reported at the year-end may not be available to the investor till some time in the New Year. Bias lies in assuming that investors have some information, which they did not actually possess at the time: For example:
December 31, 1978: Actual price= £12.87, actual EP ratio (Earning-Price)=£.85
=Observed earnings yield (EY) =.85/12.87=6.6%.
Compustat File: Actual Price=£12.87, EP=£1.24=EY=9.6%

the sample data. But, now, these securities are added back to the sample data. New information is therefore added to the sample data.

Some of the Fama and Macbeth cross-sectional regressions are run using all 2108 stocks and the full-sample period. Table 3.18 presents the results. There is absolutely no difference in the results whether using varying stocks (like in Table 3.6) or the full 2108 stocks (in Table 3.18). The results are similar. Like before, there is again no beta and size effect and a very strong BE/ME effect. These findings are quite interesting. This is because, the results suggest that the sample of this study 'might be' free of selection biases. If there was a bias in earlier results (Table 3.6), there ought to some difference between 'full-sample' and 'varying-sample' stock.

3.9. SUMMARY AND CONCLUSION

The cross sectional relationship between risk factors and stock returns has attracted a massive amount of academic attention in the US market. In contrast, there is limited evidence for the UK stock market. In order to fill the gap, this study examines some of the issues surrounding empirical tests of the risk-return relation in the UK stock market. This study first analyses the ability of beta and other factors, like BE/ME and size, to explain the cross-sectional variation in average stock returns on the UK stock market for the sample period: 1969-2001. This study employed the same methodology as Fama and French (1992) employed on the US market, and replicated their results for the UK market. This study comes up with three main findings. First, overall interpretation of this study for the UK stock market is similar to the popular interpretation of Fama and French (1992) results, that there is absolutely no role for beta risk in explaining the variation in expected returns. The

relationship between beta and expected return is either negative or flat. Second, there is no relation between average return and size. Third, the only variable consistently significant in explaining the cross-section of UK expected stock returns is the BE/ME variable. The BE/ME effect dominates beta and market size in explaining average returns throughout the sample period. The positive sign of the BE/ME variable was in line with the previous findings for the US and also for the UK such as Strong and Xu (1997).

This study then investigates the cross-sectional results for different sub-periods of sample. When the risk-return relationship is tested for different sub-periods, results indicate a negative and significant relationship between beta and return across the 17 year period from 1985-2000, showing that the price behaviour on the London Stock Exchange is inconsistent with the CAPM. Interestingly, there is a weak BE/ME effect over the 1965-1985 period.

This study also tests the cross-sectional relationship under a variety of different conditions. When beta is estimated using annual data, discrete rates of return, different indexes and different sample size, the cross-sectional results are similar to main findings. This study still finds an insignificantly negative relationship between expected return and beta. However, significant coefficient on the beta variable is found, when censored data and conditional relationships are used in the standard Fama and French methodology. The findings from the censored data support the central proposition of the CAPM that average returns relate positively with beta. This study also finds that the beta is priced differently in periods with positive market return versus periods with negative market return period. Beta is significant in both states of the world and it is particularly influential in bad state. Thus,

beta is a very important variable for explaining cross-sectional differences among asset returns when conditioned on the sign of market return.

Interesting evidence is also found for the BE/ME effect, when it is tested under a variety of conditions. First, the BE/ME variable is weakly significant when annual returns are used in the cross-sectional regressions. Second, BE/ME is insignificant in different market conditions. Third, the BE/ME effect is also sensitive to the portfolio formation and market indexes. For example, this study finds a weak BE/ME effect using size-beta and a value-weighted index, but the opposite is found, when an equally-weighted index is used for analysis.

The evidence above heavily rejects the validity of the CAPM. Returns are not related to beta. The weight of evidence suggests that the CAPM is misspecified and the CAPM does not explain why BE/ME seems to explain cross-sectional variation in stock returns. The empirical evidence therefore requires that this study reject the CAPM as a theoretical model, but it does not mean that expected returns are unrelated to beta. In other words, validity of results of a test of the risk-return relation depend critically on the accuracy with which a researcher has measured the betas of the portfolios whose returns and risk are being correlated. The less precise the estimated betas as measures of the underlying or 'true' risk of the portfolios, the greater the likelihood that the researcher will end up concluding that the risk-return trade-off is non-existent. This might be the case with our method that has attempted to reduce but cannot remove these problems (e.g. Error-in-Variable problem). Different types of statistical methods are therefore useful in investigating further the risk-return relationship for the UK stock market.

No evidences have been offered why BE/ME is a good predictor of returns. With the availability of fast computers and easily accessible stock market data, it is not surprising that some statistically significant correlations between return and book-to-market have been found. Published work might be biased in favour of reporting controversial results rather than confirmations of true results. Thus, many of the predictable patterns that have been discovered in cross-sectional analysis may simply be the result of data mining-'the result of beating the data set in every conceivable way until it finally confesses'. Hence BE/ME effect might just be a result of 'data-mining' problem. Therefore at this point, it is very hard to make any judgements on such an effect on returns.

Overall, this study suggest that the results of cross-sectional models involving returns, beta, BE/ME and size variables on the current data-set indicate the sensitivity of inferences to model specification and to different periods of testing. On balance, the results in this study confirm for the UK the importance of book-to-market equity found previously for the US and UK. At this point, we are not sure why BE/ME works, however, an understanding this is an important topic for research. Later, this study will investigates the validity of these additional factors like BE/ME and size for the UK stock market. However such statistical inferences will still be made with caution since as will be seen, the correct risk model remains unknown. An issue whether beta can explain the cross-sectional variation in the risk premium is still unresolved. So far, on balance, observations in this chapter do not provide a ray of hope for those impressed with the compelling logic of modern portfolio theory. However, results from the conditional regressions suggest that a practical approach rather than an empirical approach may be useful in testing the CAPM.

TABLE 3.1
PORTFOLIO FORMATION, ESTIMATION AND TESTING PERIODS

COLUMN 1		2	3	4	5	6	7	8	9
Pre-rank period....	Jan' 69-June' 73	July' 69-June' 74	July' 70-June' 75	July' 71-June' 76	July' 72-June' 77	July' 73-June' 78	July' 74-June' 79	July' 75-June' 80	July' 76-June' 81
Months....	**7-60**	**13-72**	**25-84**	**37-96**	**49-108**	**61-120**	**73-132**	**85-144**	**97-156**
Post-rank and testing period....	July' 73-June' 74	July' 74-June' 75	July' 75-June' 76	July'76-June'77	July' 77-June' 78	July' 78-June' 79	July' 79-June' 80	July' 80-June' 81	July' 81-June' 82
Months...	**61-72**	**73-84**	**85-96**	**97-108**	**109-120**	**121-132**	**133-144**	**145-156**	**157-168**
Cross-sectional regressions (in sequence)	12	24	36	48	60	72	84	96	108
No of securities available...	2108	2108	2108	2108	2108	2108	2108	2108	2108
No. of securities meeting data requirement..... **(10TH ROW)**	670	668	697	711	782	811	822	829	829

10	11	12	13	14	15	16	17	18	19	20
July' 77-June' 82	July' 78-June' 83	July' 79-June' 84	July' 80-June' 85	July' 81-June' 86	July' 82-June' 87	July' 83-June' 88	July' 84-June' 89	July' 85-June' 90	July' 86-June' 91	July' 87-June' 92
109-168	**121-180**	**133-192**	**145-204**	**157-216**	**169-228**	**181-240**	**193-252**	**205-264**	**217-276**	**229-288**
July' 82-June' 83	July' 83-June' 84	July' 84-June' 85	July' 85-June' 86	July' 86-June' 87	July' 87-June' 88	July' 88-June' 89	July' 89-June' 90	July' 90-June' 91	July' 91-June' 92	July' 92-June' 93
169-180	**181-192**	**193-204**	**205-216**	**217-228**	**229-240**	**241-252**	**253-264**	**265-276**	**277-288**	**289-300**
120	132	144	156	168	180	192	204	216	228	240
2108	2108	2108	2108	2108	2108	2108	2108	2108	2108	2108
832	833	837	806	774	754	730	727	732	762	804

21	22	23	24	25	26	27	28	29
July' 88-June' 93	July' 89-June' 94	July' 90-June' 95	July' 91-June' 96	July' 92-June' 97	July' 93-June' 98	July' 94-June' 99	July' 95-June' 00	July' 96-June' 01
241-300	**253-312**	**265-324**	**277-336**	**289-348**	**301-360**	**313-372**	**325-384**	**337-396**
July' 93-June' 94	July' 94-June' 95	July' 95-June' 96	July' 96-June' 97	July' 97-June' 98	July' 98-June' 99	July' 99-June' 00	July' 00-June' 01	July' 01-Dec' 01
301-312	**313-314**	**325-336**	**337-348**	**349-360**	**361-372**	**373-384**	**385-396**	**397-402**
252	264	276	288	300	312	324	336	342
2108	2108	2108	2108	2108	2108	2108	2108	2108
854	889	913	865	924	852	784	730	746

TABLE 3.2
SUMMARY STATISTICS OF THE PORTFOLIOS

PANEL A: BETA PORTFOLIO								
	Mean	Standard Deviation	Minimum	Maximum	Sum	Variance	Skewness	Kurtosis
Return (%)	0.932	0.153	0.605	1.118	9.322	0.023	-1.040	1.093
Beta (β)	0.876	0.113	0.625	0.972	8.756	0.013	-1.431	1.567
Size (£ million (m))	344.785	174.217	51.055	598.816	3447.851	30351.729	-0.349	-0.652
BE/ME	1.508	0.185	1.316	1.828	15.077	0.034	0.914	-0.571

PANEL B: SIZE								
	Mean	Standard Deviation	Minimum	Maximum	Sum	Variance	Skewness	Kurtosis
Return (%)	0.944	0.173	0.719	1.196	9.442	0.030	-0.192	-1.407
Beta (β)	0.866	0.159	0.719	1.254	8.664	0.025	1.853	3.786
Size (£ m)	332.111	860.975	1.374	2769.175	3321.115	741277.593	3.101	9.700
BE/ME	1.512	0.972	0.770	4.019	15.119	0.945	2.244	5.529

PANEL C: BETA-SIZE (2 x 5) PORTFOLIOS								
	Mean	Standard Deviation	Minimum	Maximum	Sum	Variance	Skewness	Kurtosis
Return (%)	0.933	0.185	0.602	1.197	9.334	0.034	-0.371	-0.433
Beta (β)	0.863	0.154	0.652	1.169	8.629	0.024	0.815	0.546
Size (£ m)	341.008	562.064	2.813	1683.044	3410.076	315916.388	1.859	3.085
BE/ME	1.545	0.876	0.825	3.245	15.451	0.768	1.402	0.643

PANEL D: BOOK-TO-MARKET PORTFOLIOS								
	Mean	Standard Deviation	Minimum	Maximum	Sum	Variance	Skewness	Kurtosis
Return (%)	0.976	0.061	0.848	1.068	9.763	0.004	-0.707	1.323
Beta (β)	0.874	0.290	0.414	1.263	8.740	0.084	-0.293	-1.118
Size (£ m)	344.917	224.336	20.012	695.226	3449.171	50326.806	-0.031	-1.175
BE/ME	1.481	1.877	-0.148	6.557	14.805	3.525	2.604	7.490

PANEL E: SIZE-BETA PORTFOLIOS								
	Mean	Standard Deviation	Minimum	Maximum	Sum	Variance	Skewness	Kurtosis
Returns (%)	0.917	0.238	0.438	1.567	22.930	0.056	0.810	1.438
Beta (β)	0.882	0.170	0.516	1.144	22.052	0.029	-0.513	-0.406
Size (£ m)	356.616	649.162	2.377	1963.957	8915.396	421411.285	1.702	1.257
BE/ME	1.527	0.906	0.763	3.907	38.172	0.821	1.555	1.420

PANEL F: BETA-SIZE PORTFOLIOS								
	Mean	Standard Deviation	Minimum	Maximum	Sum	Variance	Skewness	Kurtosis
Returns (%)	0.746	0.166	0.328	1.007	18.643	0.028	-0.848	0.800
Beta (β)	0.921	0.121	0.637	1.077	23.018	0.015	-0.737	-0.341
Size (£ m)	342.096	186.988	56.795	748.367	8552.389	34964.660	0.217	-0.458
BE/ME	1.561	1.348	-4.734	2.680	39.036	1.816	-4.575	22.108

The table shows summary statistics of the portfolios based on the pre-ranking beta against an equally-weighted index (panel A), Size (ME) (panel B), Beta-Size (2 x 5) portfolios (panel C), Book-to-Market Equity (BE/ME) (panel D), Size-Beta (panel E) and Beta-Size (panel F). In panel A, for each year t, stocks are sort into 10 portfolios based on pre-ranking beta using 2-60 monthly observation over the 5-year period ending June, year t. Five lagged and five leading market returns are also used for estimating the pre-ranking beta. In panel B, for each year t, stocks are sort into ten portfolios based on SIZE at the end of year t-1. In panel C for each year t, stocks are sort into ten portfolios on the basis of pre-ranking beta and size. In panel D, for each year t, stocks are sort into ten portfolios based on (BE/ME) at the end of year t-1. In panel E, for each year t, stocks are sort into five portfolios based on size at the end of year t-1. Each size portfolios is sort into a further five portfolios according to pre-ranking beta, using 2-60 monthly observations over the 5-year period ending June, year t. In panel F, for each year t, stocks are sort into five portfolios based on pre-ranking beta, using 60 monthly observations over the 5-year period ending June, year t. Each beta portfolio is sort into a further five portfolios based on size at the end of year t-1.
Return is the time-series average of 342 equally-weighted monthly returns from July 1973 to December 2001 for each portfolio. β is the full period post-ranking beta estimated by running equally-weighted portfolio returns, against an equally-weighted index, estimated using monthly data from July 1973 to December 2001. Size and BE/ME are year-end values. Size and (BE/ME) are the average annual values of these variables for stocks in each portfolio.

TABLE 3.3a
PROPERTIES OF PORTFOLIO FORMED ON ONE-DIMENSION SORTS BASED ON PRE-RANKING BETA, MARKET VALUE, PRE-RANKING BETA /SIZE AND BOOK-TO-MARKET: JANUARY 1969-DECEMBER 2001

Panel A: Portfolios formed on Pre-Ranking Beta against an Equally Weighted Index					
	Post-ranking Beta (β)	Return (%)	SIZE (ME) (£ m)	BE/ME	Firms
Small-β	0.792	0.625	369.802	1.828	79
β-2	0.605	0.972	598.816	1.796	79
β-3	0.847	0.915	500.681	1.359	79
β-4	0.904	0.794	443.823	1.316	79
β-5	0.947	0.959	497.630	1.511	79
β-6	0.974	0.970	336.957	1.418	79
β-7	1.012	0.896	277.714	1.485	79
β-8	1.046	0.948	253.041	1.634	79
β-9	1.076	0.910	118.334	1.373	79
Large-β	1.118	0.769	51.055	1.359	83

Panel B: Portfolios formed on Size					
	Post-ranking Beta (β)	Return (%)	SIZE (ME) (£ m)	BE/ME	Firms
Small-ME	0.719	1.254	1.374	4.019	79
ME-2	0.730	0.956	3.638	2.096	79
ME-3	0.730	0.754	6.892	1.692	79
ME-4	0.877	0.847	11.938	1.431	79
ME-5	0.957	0.719	20.373	1.211	79
ME-6	1.005	0.756	35.225	1.003	79
ME-7	1.037	0.804	60.707	1.002	79
ME-8	1.115	0.809	116.976	1.089	79
ME-9	1.196	0.799	294.817	0.807	79
Large-ME	1.076	0.965	2769.175	0.770	83

Panel C: Portfolios formed on the basis of Pre-ranking Beta and Size (2x5)					
	Post-ranking Beta (β)	Return (%)	SIZE (ME) (£ m)	BE/ME	Firms
Small-β/ME	0.602	1.169	2.813	3.245	79
β/ME-2	0.726	0.754	12.447	1.750	79
β/ME-3	0.877	0.652	43.261	1.158	79
β/ME-4	0.989	0.865	641.158	0.977	79
Large-β/ME-5	1.063	0.863	1683.044	0.836	79
Small-β/ME-1	0.837	1.050	42.935	2.990	79
β/ME-2	0.879	0.888	9.501	1.430	79
β/ME-3	1.029	0.771	25.137	1.223	79
β/ME-4	1.134	0.728	83.261	1.016	79
Large-β/ME-5	1.197	0.889	866.520	0.825	83

Panel D: Portfolios formed on Book-to-market (BE/ME)					
	Post-ranking Beta (β)	Return (%)	SIZE (ME) (£ m)	BE/ME	Firms
Small-BE/ME	1.068	0.414	695.226	-0.148	79
BE/ME-2	1.031	0.542	496.688	0.447	79
BE/ME-3	0.993	0.564	558.765	0.594	79
BE/ME-4	0.959	0.847	510.505	0.728	79
BE/ME-5	1.020	0.875	400.647	0.872	79
BE/ME-6	0.945	0.921	286.434	1.031	79
BE/ME-7	1.000	0.974	270.850	1.236	79
BE/ME-8	0.953	1.161	131.159	1.509	79
BE/ME-9	0.946	1.263	78.886	1.979	79
Large-BE/ME	0.848	1.179	20.012	6.557	83

Table 3.3a (cont.)

The table shows summary statistics of the portfolios based on the pre-ranking beta against an equally weighted index (panel A), Size (ME) (panel B), Beta-Size portfolios (2 x 5) (panel C), and Book-to-Market Equity (BE/ME) (panel D). In panel A, for each year t, stocks are sort into 10 portfolios based on pre-ranking beta using 2-60 monthly observation over the 5-year period ending June, year t. Five lagged and five leading market returns are also used for estimating the pre-ranking beta. In panel B, for each year t, stocks are sort into ten portfolios based on SIZE at the end of year t-1. In panel C, for each year t, stocks are sort into ten portfolios on the basis of pre-ranking beta and size. In panel D, for each year t, stocks are sort into ten portfolios based on (BE/ME) at the end of year t-1.

Return is the time-series average of 342 equally-weighted monthly returns from July 1973 to December 2001 for each portfolio. β is the full period post-ranking beta estimated by running equally-weighted portfolio returns, against an equally weighted index, estimated using monthly data from July 1973 to December 2001. Size and BE/ME are year-end values. Size (ME) and (BE/ME) are the average annual values of these variables for stocks in each portfolio. Firms are the average number of stocks in each portfolio.

TABLE 3.3b
CROSS SECTIONAL CORRELATIONS FOR AVERAGE RETURNS, POST-RANKING BETA, AVERAGE SIZE AND AVERAGE BOOK-TO-MARKET EQUITY FOR DIFFERENT PORTFOLIOS: 1969-2001

Panel A: Portfolios formed on Pre-Ranking Beta against an Equally Weighted Index				
	Return	**Post-ranking Beta**	**Size (£ m)**	**BE/ME**
Return	1.000	0.019	-0.848	-0.624
Post-ranking Beta	0.019	1.000	0.247	-0.164
Size	-0.848	0.247	1.000	0.359
BE/ME	-0.624	-0.164	0.359	1.000

Panel B: Portfolios formed on Size				
	Return	**Post-ranking Beta**	**Size (£ m)**	**BE/ME**
Return	1.000	-0.442	-0.347	-0.761
Post-ranking Beta	-0.442	1.000	0.191	0.819
Size	-0.347	0.191	1.000	-0.314
BE/ME	-0.761	0.819	-0.314	1.000

Panel C: Portfolios formed on the basis of Pre-ranking beta and Size (2 x 5)				
	Return	**Post-ranking Beta**	**Size (£ m)**	**BE/ME**
Return	1.000	-0.450	0.527	-0.802
Post-ranking Beta	-0.450	1.000	0.012	0.765
Size	0.527	0.012	1.000	-0.492
BE/ME	-0.802	0.765	-0.492	1.000

Panel D: Portfolios formed on Book-to-market (BE/ME)				
	Return	**Post-ranking Beta**	**Size (£ m)**	**BE/ME**
Return	1.000	-0.764	0.799	-0.868
Post-ranking Beta	-0.764	1.000	-0.950	0.631
Size	0.799	-0.950	1.000	-0.744
BE/ME	-0.868	0.631	-0.744	1.000

Refer to the Table 3.3a, for the details relating to the portfolios and the variables used for cross-sectional correlations.

TABLE 3.4
PROPERTIES OF PORTFOLIOS FORMED ON TWO DIMENSION SORT: SIZE AND PRE-RANKING BETA: JANUARY 1969-DECEMBER 2001

	Low-β	β-2	β-3	β-4	β-5
Panel A: Portfolio Returns (%)					
Small-ME	1.237	1.278	1.567	1.095	0.922
ME-2	0.797	0.880	1.277	0.943	0.648
ME-3	0.438	0.903	0.768	0.847	0.677
ME-4	0.803	0.962	0.717	0.948	0.758
ME-5	0.735	1.045	0.869	0.870	0.945

Panel B: Full Period Post Ranking Beta	Low-β	β-2	β-3	β-4	β-5
Small-ME	0.552	0.516	0.708	0.661	0.875
ME-2	0.750	0.700	0.881	0.730	0.905
ME-3	0.798	0.844	0.879	0.943	1.047
ME-4	0.924	0.924	0.966	1.086	1.107
ME-5	0.988	1.010	1.039	1.073	1.144

Panel C: Average Size- (ME) (£ m)	Low-β	β-2	β-3	β-4	β-5
Small-ME	2.386	2.377	2.666	2.615	2.785
ME-2	9.008	9.621	9.700	9.430	10.368
ME-3	26.666	28.984	28.885	29.269	31.771
ME-4	84.600	90.484	90.573	206.144	235.347
ME-5	1963.957	1734.067	1712.091	1377.930	1213.671

Panel D: Average Book-to-Market-(BE/ME)	Low-β	β-2	β-3	β-4	β-5
Small-ME	3.907	3.573	3.124	2.666	2.537
ME-2	1.516	1.544	1.529	1.776	1.374
ME-3	1.061	1.137	1.131	1.121	1.118
ME-4	0.951	1.166	1.051	0.982	1.015
ME-5	0.780	0.763	0.778	0.778	0.796

Panel E: Cross sectional correlations				
	Return	**Post-ranking Beta**	**Size (£ m)**	**BE/ME**
Return	1.000	-0.455	-0.088	0.678
Post-ranking Beta	-0.455	1.000	0.523	-0.833
Size (£ m)	-0.088	0.523	1.000	-0.453
BE/ME	0.678	-0.833	-0.453	1.000

The table gives average returns in percentage (panel A), full period post-ranking betas (panel B), average size (ME) (panel C) and average BE/ME (panel D) for portfolios formed on a two dimension sort according to size, followed by pre-ranking beta against an equally weighted index. For each year t, stocks are sort into five portfolios based on (ME) at the end of year t-1. Each size portfolio is sort into a further five portfolios according to pre-ranking beta, using 60 monthly observations over the 5-year period ending June, year t. Pre-ranking beta is estimated with a Dimson (1979) estimator using five lagged, and five leading market returns. Portfolio's equally weighted monthly returns are calculated for period July, year t to June, year t+1. The process is repeated by rolling one year forward. Average monthly returns is the time series average of 342 equally-weighted monthly returns from July 1973 to December 2001. Full period post-ranking betas are against an equally weighted index estimated using equally-weighted monthly return's data. Average size and average Book-to-Market are firm's market value and Book-to-Market values (at the end of period t-1) averaged over each portfolio and over 29 annual periods. Panel E, reports the cross-sectional correlations between the variables.

TABLE 3.5
PROPERTIES OF PORTFOLIOS FORMED ON TWO DIMENSION SORT: PRE-RANKING BETA AND SIZE: JANUARY 1969-DECEMBER 2001

	Low-β	β-2	β-3	β-4	β-5
Panel A: Portfolio Returns (%)					
Small-ME	0.878	0.751	0.753	0.806	0.387
ME-2	0.776	0.703	0.928	0.711	0.629
ME-3	0.867	1.007	0.948	0.883	0.545
ME-4	0.714	0.676	0.751	0.777	0.568
ME-5	0.754	0.910	0.928	0.666	0.328

Panel B: Full Period Post Ranking Beta	Low-β	β-2	β-3	β-4	β-5
Small-ME	0.809	0.757	0.922	1.021	1.046
ME-2	0.715	1.021	0.921	1.028	1.031
ME-3	0.637	0.874	0.953	0.992	1.049
ME-4	0.898	0.767	0.907	0.988	1.077
ME-5	0.777	0.841	0.947	0.984	1.056

Panel C: Average Size- (ME) (£ m)	Low-β	β-2	β-3	β-4	β-5
Small-ME	642.418	440.030	291.898	209.497	90.241
ME-2	748.367	461.229	407.686	279.001	88.761
ME-3	342.496	552.606	599.232	301.201	87.043
ME-4	451.811	491.571	373.950	201.333	56.795
ME-5	245.031	421.529	390.451	301.974	76.238

Panel D: Average Book-to-Market-(BE/ME)	Low-β	β-2	β-3	β-4	β-5
Small-ME	1.801	2.680	2.004	1.673	1.994
ME-2	1.961	1.654	1.850	1.564	1.810
ME-3	2.051	1.866	2.047	1.520	2.014
ME-4	1.801	1.763	1.950	2.161	-4.734
ME-5	2.022	1.660	1.004	1.505	1.416

Panel E: Cross sectional correlations

	Return	Post-ranking Beta	Size (£ m)	BE/ME
Return	1.000	-0.463	0.662	0.217
Post-ranking Beta	-0.463	1.000	-0.642	-0.351
Size (£ m)	0.662	-0.642	1.000	0.330
BE/ME	0.217	-0.351	0.330	1.000

The table gives average returns in percentage (panel A), full period post-ranking betas (panel B), average size (ME) (panel C) and average BE/ME (panel D) for portfolios formed on a two dimension sort according to pre-ranking beta against an equally weighted index followed by size. For each year t, stocks are sort into five portfolios based on pre-ranking beta, using 60 monthly observations over the 5-year period ending June, year t. Each pre-ranking beta-portfolio is then sort into a further five portfolios according to (ME) at the end of year t-1. Pre-ranking beta is estimated with a Dimson (1979) estimator using five lagged, and five leading market returns. Each portfolio's equally weighted monthly return is calculated for period July, year t to June, year t+1. The process is repeated by rolling one year forward. Average monthly returns is the time series average of 342 equally-weighted monthly returns from July 1973 to December 2001. Full period post-ranking betas are against an equally weighted index estimated using equally-weighted monthly return's data. Average size and average Book-to-Market are firm's market value and Book-to-Market values (at the end of period t-1) averaged over each portfolio and over 29 annual periods. Panel E, reports the cross-sectional correlations between the variables.

TABLE 3.6
AVERAGE SLOPES (T-STATISTICS) FROM MONTH-BY-MONTH REGRESSIONS OF STOCK RETURNS ON (MONTHLY) BETA, SIZE AND BOOK-TO-MARKET EQUITY: JANUARY 1969-DECEMBER 2001

Panel A: Size-Beta Ranked Portfolios

Regressions no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	1.6000	0.0119	-0.0037		
		2.6697	*-0.6317*		
3.6	1.8900	0.0125	-0.0047	0.0000	
		2.8408	*-0.7831*	*0.5937*	
3.7	0.3500	0.0085		0.0000	
		2.7336		*0.7977*	
3.8	1.9800	0.0116	-0.0023		0.0009
		2.6257	*-0.3987*		*2.2252*
3.9	0.8100	0.0097		0.0000	0.0011
		3.1271		*0.9461*	*2.5759*
3.10	0.4700	0.0099			0.0011
		3.2115			*2.6076*
3.11	2.2600	0.0123	-0.0033	0.0000	0.0009
		2.8076	*-0.5678*	*0.7122*	*2.1656*

Panel B: Beta-Size Ranked Portfolios

Regressions no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	0.4500	0.0096	-0.0010		
		3.0551	*-0.2322*		
3.6	0.8000	0.0088	-0.0003	0.0000	
		2.7168	*-0.0813*	*0.7199*	
3.7	0.3500	0.0085		0.0000	
		2.7336		*0.7977*	
3.8	0.9100	0.0108	-0.0009		0.0011
		3.4214	*-0.2053*		*2.6108*
3.9	0.8100	0.0097		0.0000	0.0014
		3.1271		*0.9461*	*2.5759*
3.10	0.4700	0.0099			0.0011
		3.2115			*2.6076*
3.11	1.2400	0.0098	-0.0002	0.0000	0.0009
		3.0348	*-0.0501*	*0.8702*	*2.7123*

TABLE 3.6 (cont.)

Panel C: Beta Ranked Portfolios

Regressions no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	0.4400	0.0100 *3.4634*	0.0003 *0.0773*		
3.6	0.7700	0.0089 *2.8735*	0.0012 *0.3046*	0.0000 *0.6266*	
3.7	0.3300	0.0103 *3.4186*		0.0000 *0.6035*	
3.8	0.8600	0.0114 *3.8431*	0.0003 *0.0572*		0.0010 *2.3284*
3.9	0.7500	0.0113 *3.6998*		0.0000 *0.7469*	0.0001 *2.2788*
3.10	0.4300	0.0115 *3.7768*			0.0010 *2.3156*
3.11	1.1700	0.0099 *3.1958*	0.0012 *0.2925*	0.0000 *0.7554*	0.0009 *2.2969*

Panel D: Size Ranked Portfolios

Regressions no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	1.6400	0.0126 *2.5124*	-0.0023 *-0.4021*		
3.6	1.9000	0.0129 *2.5841*	-0.0029 *-0.4848*	0.0000 *0.2585*	
3.7	0.3300	0.0104 *3.4186*		0.0000 *0.6036*	
3.8	1.9900	0.0122 *2.4650*	-0.0012 *-0.2131*		0.0008 ** *1.7977*
3.9	0.7500	0.0113 *3.6998*	0.0000 *0.7469*		0.0010 *2.2788*
3.10	0.4300	0.0114 *3.7768*			0.0010 *2.3156*
3.11	2.2500	0.0126 *2.5471*	-0.0018 *-0.3151*	0.0000 *0.3848*	0.0008 ** *1.7079*

Portfolio E: Beta-Size Ranked Portfolios (2x5)

Regressions no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	1.5000	0.0117 *2.7813*	-0.0034 *-0.6502*		
3.6	1.7800	0.0123 *2.9475*	-0.0041 *-0.7897*	0.0000 *0.4766*	
3.7	0.3600	0.0086 *2.7336*		0.0000 *0.7977*	
3.8	1.8700	0.0111 *2.5200*	-0.0026 *-0.4907*		0.0000 *2.4213*
3.9	0.7400	0.0087 *2.7657*		0.0000 *0.8169*	0.0000 *2.7564*
3.10	0.3800	0.0000 *2.8263*			0.0000 *2.6216*
3.11	2.1400	0.0116 *2.6705*	-0.0033 *-0.6310*	0.0000 *0.4431*	0.0000 *2.2651*

TABLE 3.6 (cont.)

*Table reports the time series averages of estimated coefficients from the monthly cross-sectional regressions from July 1973-December 2001, associated t-statistics in bold (the underlined t-statistics indicates significance at 5 %, ** indicates significance at 10 % level), and Adjusted R-square values. Portfolios are formed in five different ways: (1) 25 portfolios by grouping stocks into 5 portfolios on size and then into 5 portfolios on pre-ranking beta within each size group; (2) 25 portfolios by grouping stocks into 5 portfolios on pre-ranking beta and then into 5 portfolios on size within each beta group; (3) 10 portfolios by grouping on pre-ranking beta alone; (4) 10 portfolios by grouping on size alone and (5) 10 portfolios by sorting the stocks by pre-ranking beta and size (2x5). Pre-ranking beta is estimated with a Dimson (1979) estimator using five lagged, and five leading market returns (equally-weighted index) using 60 monthly observations (stock returns) over the 5-year period ending in June, year t.* β_i *is the post-ranking betas and are estimated by running the equally-weighted portfolio returns on equally-weighted market index. ME is the market value of the firm equity at the end of t-1. BE/ME is the Book-to-Market Equity of the firm at the end of t-1. The average slope is the time series average from 342 monthly cross-sectional regressions from July 1973-December 2001. The t-statistic (in bold) is the average slope divided by its time-series standard deviation. Adjusted R-squared is computed by averaging the adjusted R-square values of 342 cross-sectional regressions.*

The seven regression models used for cross-sectional analysis are:

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\mu_{it} \qquad (3.5)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{2t}\hat{ME}_i+\mu_{it} \qquad (3.6)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{2t}\hat{ME}_i+\mu_{it} \qquad (3.7)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (3.8)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (3.9)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{2t}\hat{ME}_i+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (3.10)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{2t}\hat{ME}_i+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (3.11)$$

i=1,2....n ; t=1,2.....342

where R_{it} *is the return on individual security i in month t;* β_i *is the full period post-ranking beta of portfolio p, i.e., the slope coefficient from a time-series regression of monthly post-ranking returns on the returns for an equally-weighted portfolio of all portfolios.* ME_i *is the market value of equity;* $(BE/ME)_i$ *is the ratio of book value of equity to its market value:* $\gamma_{0t},\gamma_{1t},\gamma_{2t}$ *and* γ_{3t} *are regression coefficients and* μ_{it} *is the error term.*

The regression models above are estimated 342 times for every month t between July 1973 till December 2001. The average number of firms in 25 portfolio ranges from 26-42 in each portfolio as seen below:

	Lowest	*2*	*3*	*4*	*highest*
lowest	*31*	*31*	*31*	*31*	*33*
2	*30*	*31*	*31*	*31*	*34*
3	*28*	*31*	*31*	*31*	*36*
4	*26*	*31*	*31*	*31*	*38*
highest	*25*	*31*	*31*	*31*	*42*

TABLE 3.7
SUB PERIOD ANALYSIS

Panel A: July 1973-June 1985 (144 observations)

Regression no.	Adjusted R-square	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	1.39	0.012	0.003		
		2.826	***0.334***		
3.6	1.62	0.013	0.002	0.000	
		2.933	***0.252***	***0.173***	
3.7	.57	0.015		0.000	
		2.685		***0.776***	
3.8	2.55	0.012	0.004		0.002
		2.883	***0.495***		***1.640***
3.9	1.21	0.016		0.000	0.002
		3.014		***0.891***	***1.852*** **
3.10	.72	0.016			0.002
		3.028			***1.864*** **
3.11	2.87	0.013	0.003	0.000	0.002
		2.992	***0.397***	***0.274***	***1.561***

Panel B: July 1985-December 2001 (198 observations)

Regression no.	Adjusted R-square	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	.40	0.023	-0.015		
		4.452	***-2.297***		
3.6	.99	0.022	-0.014	0.000	
		4.196	***-2.162***	***0.277***	
3.7	.47	0.007		0.000	
		1.715 **		***0.378***	
3.8	1.35	0.024	-0.015		0.001
		4.573	***-2.260***		***2.422***
3.9	.88	0.008	0.000		0.001
		1.884 **	***0.642***		***2.531***
3.10	.65	0.008			0.001
		1.980			***2.512***
3.11	1.56	0.022	-0.014	0.000	0.001
		4.314	***-2.131***	***0.535***	***2.432***

In Panel A, slope coefficient is the time series average of 144 cross-sectional regressions. In Panel B, slope coefficient is the time series average of 198 cross-sectional regression. T-statistics are given in bold figures. Refer to Table 3.6, for the notes relating the cross-sectional regressions.

TABLE 3.8
AVERAGE SLOPES (T-STATISTICS) FROM MONTH-BY-MONTH REGRESSIONS OF RETURNS ON BETA, SIZE AND BOOK-TO-MARKET EQUITY USING VALUE WEIGHTED INDEX: JANUARY 1969-DECEMBER 2001

Panel A: Portfolio: Size-Beta

Regression no.	Adjusted R square (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	1.966	0.012 ***3.133***	-0.002 ***-0.256***		
3.6	2.187	0.012 ***3.425***	-0.003 ***-0.456***	0.000 ***0.096***	
3.8	2.332	0.012 ***3.151***	0.000 ***-0.066***		0.001 ***1.816*** **
3.11	2.549	0.012 ***3.449***	-0.002 ***-0.273***	0.000 ***0.186***	0.001 ***1.807*** **

Panel B: Portfolio: Beta-Size

Regression no.	Adjusted R square (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	0.388	0.009 ***2.730***	0.005 ***0.916***		
3.6	0.696	0.009 ***2.688***	0.005 ***0.931***	0.000 ***0.310***	
3.8	0.805	0.010 ***3.066***	0.005 ***0.886***		0.001 ***2.449***
3.11	1.097	0.010 ***3.013***	0.005 ***0.891***	0.000 ***0.466***	0.001 ***2.392***

Table reports the time series averages of 342 estimated coefficients from the monthly cross-sectional regressions from July 1973-December 2001, associated t-statistics in bold, and Adjusted R-square values for size-beta ranked and beta-size ranked portfolios respectively. Refer to Table 3.6 to see the details relating to the portfolio formation. β_i *is the post-ranking beta and is estimated by running the equally weighted portfolio returns on value weighted index. Refer to Table 3.6 for details relating to cross-sectional models.*

TABLE 3.9
AVERAGE SLOPES (T-STATISTICS) FROM MONTH-BY-MONTH REGRESSIONS OF STOCK RETURNS ON (MONTHLY) BETA, SIZE AND BOOK-TO-MARKET EQUITY: USING DISCRETE RETURNS: JANUARY 1969- DECEMBER 2001

Panel A: Size-Beta Portfolio

Regression no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	.44	.019	-.003		
		5.6065	*-.9794*		
3.6	.74	.019	-.003	-.000	
		5.432	*-.913*	*-.873*	
3.7	.30	.016		-.000	
		5.325		*-.906*	
3.8	.87	.020	-.003		.001
		5.893	*.896*		*3.338*
3.9	.75	.017		-.000	.000
		5.838		*-.673*	*3.396*
3.10	.46	.017			.001
		5.877			*3.310*
3.11	1.16	.020	-.002	-.000	.001
		5.697	*-.844*	*-.644*	*3.198*

Panel B: Beta-Size Portfolio

Regression no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	.36	.012	.004		
		3.802	*1.070*		
3.6	.65	.011	.004	-.000	
		3.642	*1.156*	*-.857*	
3.7	.30	.0162		-.000	
		5.327		*-.9030*	
3.8	.77	.013	.003		.001
		4.371	*.975*		*3.262*
3.9	.70	.017		-.000	.000
		5.825		*-.670*	*3.281*
3.10	.42	.017			.001
		5.859			*3.308*
3.11	1.04	.013	.004	-.000	.001
		4.139	*1.069*	*-.633*	*3.144*

Table reports the time series averages of estimated coefficients from the monthly cross-sectional regressions using discrete rates of returns from July 1973-December 2001, associated t-statistics (in bold), and Adjusted R-square values for size beta ranked and beta-size ranked portfolios respectively. Refer to Table 3.6 to see the details relating to the cross-sectional regressions.

TABLE 3.10a
ANNUAL POST-RANKING BETAS AND AVERAGE EQUALLY-WEIGHTED ANNUAL RETURNS ON 25 SIZE-BETA PORTFOLIOS: JANUARY 1969-DECEMBER 2001

	Low-Beta	Beta-2	Beta-3	Beta-4	Beta-5	Average
Panel A: Portfolio Returns (%)						
Small-ME	1.179	1.164	1.332	0.987	0.716	1.076
ME-2	0.748	0.775	1.031	0.787	0.513	0.771
ME-3	0.402	0.858	0.631	0.692	0.465	0.610
ME-4	0.653	0.786	0.529	0.685	0.537	0.638
Big-ME	0.451	0.800	0.650	0.645	0.704	0.650
Average	0.687	0.877	0.835	0.759	0.587	
Panel B: Annual Beta						
Small-ME	1.295	1.061	1.211	1.317	1.556	1.288
ME-2	1.241	1.130	1.202	1.304	1.532	1.282
ME-3	1.099	1.065	1.056	1.064	1.392	1.135
ME-4	1.007	0.938	0.952	1.166	1.179	1.048
Big-ME	0.902	0.776	0.824	0.785	0.932	0.844
Average	1.109	0.994	1.049	1.127	1.318	

The table gives average returns in percentage (panel A) and full period annual post-ranking betas (panel B) for portfolios formed on a two dimension sort according to size and then by pre-ranking beta.
25 Portfolios are formed each year on June 30 from 1973 to 2001 by ranking all stock on the basis of size (ME) and then sorting the stocks on the basis of pre-ranking beta within each size portfolio. Pre-ranking beta is estimated with a Dimson (1979) estimator using five lagged, and five leading market returns (equally-weighted index) using 60 monthly observations (stock returns) over the 5-year period ending in June, year t. Each year 25 Size-Beta portfolios are constructed by rolling one year forward. Portfolios are rebalanced every year. An annual, equally weighted return for each portfolio over the period of July 1 of year t to June 30 of year t+1 is calculated. In Panel A, the post-ranking return for each portfolio is a simple average of the time series of 29 annual returns. In Panel B, post-ranking beta for each portfolio is the slope coefficient from a time series regression of annual post-ranking returns on an equally weighted market portfolio consisting of the 25 Size-Beta portfolios.

TABLE 3.10b
ANNUAL POST-RANKING BETAS AND AVERAGE EQUALLY-WEIGHTED ANNUAL RETURNS ON 10 BETA-RANKED PORTFOLIOS: JANUARY 1969-DECEMBER 2001

	Returns (%)	Post-ranking beta
Low Beta	0.589	0.783
2	0.913	0.658
3	0.858	0.652
4	0.750	0.948
5	0.930	0.925
6	0.929	0.985
7	0.839	1.040
8	0.915	1.078
9	0.846	1.148
High Beta	0.739	1.210
Average	0.831	0.943

The table gives average returns in percentage (panel A) and full period annual post-ranking betas (panel B) for portfolios formed on one dimension sort according to pre-ranking beta. 10 Portfolios are formed each year on June 30 from 1973 to 2001 by ranking all stock on the basis of pre-ranking beta. Pre-ranking beta is estimated with a Dimson (1979) estimator using five lagged, and five leading market returns (equally-weighted index) using 60 monthly observations (stock returns) over the 5-year period ending in June, year t. Each year 10 Beta portfolios are constructed by rolling one year forward. Portfolios are rebalanced every year. An annual, equally weighted return for each portfolio over the period of July 1 of year t to June 30 of year t+1 is calculated. In Panel A, the post-ranking return for each portfolio is a simple average of the time series of 29 annual returns. In Panel B, post-ranking beta for each portfolio is the slope coefficient from a time series regression of annual post-ranking returns on an equally weighted market portfolio consisting of the 10 Beta portfolios.

TABLE 3.11
AVERAGE SLOPES (T-STATISTICS) FROM REGRESSION OF MONTHLY AND ANNUAL STOCK RETURNS ON ANNUAL BETA, SIZE AND BOOK-TO-MARKET EQUITY: JANUARY 1969-DECEMBER 2001

Panel A1: Portfolio: Size-Beta :		**Annual returns, Annual post-rank beta**			
Regression no.	**Adjusted R-square (%)**	γ_0 **(intercept)**	γ_1 **(Beta)**	γ_2 **(Size)**	γ_3 **(BE/ME)**
3.5	2.00	.101	.003		
		1.838 **	***.080***		
3.6	2.28	.090	.012	.000	
		1.685 **	***.280***	***.915***	
3.7	.56	.104		.000	
		2.535		***.676***	
3.8	2.82	.129	-.008		.012
		2.412	***-.194***		***1.602***
3.9	1.54	.119		.000	.012
		2.800		***.780***	***1.901*** **
3.10	1.03	.121			.013
		2.871			***1.953*** **
3.11	3.08	.116	.001	.000	.011
		2.238	***.020***	***.939***	***1.562***

Panel A2: Portfolio: Size-Beta :		**Monthly returns, Annual post-rank beta**			
Regression no.	**Adjusted R-square (%)**	γ_0 **(intercept)**	γ_1 **(Beta)**	γ_2 **(Size)**	γ_3 **(BE/ME)**
3.5	1.17	.009	-.0003		
		1.652 **	***-.105***		
3.6	1.38	.007	.000	.000	
		1.439	***.147***	***1.035***	
3.7	.35	.008		.000	
		2.733		***.797***	
3.8	1.57	.011	-.001		.001
		2.090	***-.417***		***2.363***
3.9	.81	.009		.000	.001
		3.127		***.946***	***2.575***
3.10	.47	.009			.001
		3.211			***2.607***
3.11	1.78	.010	-.000	.000	.001
		1.844 **	***-.142***	***1.090***	***2.276***

TABLE 3.11 (cont.)

Panel B1 : Portfolio: Beta		Annual returns, Annual post-rank beta			
Regression no.	Adjusted R-square (%)	γ_0	γ_1	γ_2	γ_3
3.5	2.71	.131 *2.878*	-.027 *-.397*		
3.6	2.76	.133 *2.883*	-.028 *-.407*	-.000 *-1.500*	
3.7	.05	.106 *2.604*		-.000 *-.016*	
3.8	3.49	.142 *3.128*	-.025 *-.371*		.011 *1.900***
3.9	1.08	.121 *2.879*		-.000 *-.070*	.012 *1.935***
3.10	1.03	.121 *2.871*			.013 *1.953***
3.11	3.54	.143 *3.214*	-.026 *-.382*	-.000 *-1.534*	.011 *1.861***

Panel B2: Portfolio: Beta		Monthly returns, Annual post-rank beta			
Regression no.	Adjusted R-square (%)	γ_0	γ_1	γ_2	γ_3
3.5	.46	.010 *4.305*	-.001 *-.620*		
3.6	.59	.010 *4.371*	-.001 *-.649*	-.000 *-.918*	
3.7	.13	.008 *2.812*		-.000 *-.649*	
3.8	.90	.011 *4.814*	-.001 *-.602*		.001 *2.600*
3.9	.60	.010 *3.225*		-.000 *-.704*	.001 *2.574*
3.10	.40	.009 *3.211*			.001 *2.607*
3.11	1.05	.011 *4.878*	-.001 *-.633*	-.000 *-.976*	.001 *2.562*

TABLE 3.11 (cont.)

Table reports the time series averages of estimated coefficients from the monthly cross-sectional regressions from July 1973-December 2001, associated t-statistics in bold, and adjusted R-square values.

Portfolios are formed in two different ways: (1) 25 portfolios by grouping stocks into 5 portfolios on size and then into 5 portfolios on pre-ranking beta within each size (ME) group; (2) 10 portfolios by grouping on pre-ranking beta alone; Pre-ranking beta is estimated with a Dimson (1979) estimator using five lagged, and five leading market returns (equally-weighted index) using 60 monthly observations (stock returns) over the 5-year period ending in June, year t.

The seven regression models used for cross-sectional analysis are:

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\mu_{it} \qquad (3.5)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{2t}\hat{ME}_i+\mu_{it} \qquad (3.6)$$

$$R_{it}=\gamma_{0t}+\gamma_{2t}ME_i+\mu_{it} \qquad (3.7)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (3.8)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (3.9)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{2t}\hat{ME}_i+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (3.10)$$

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{2t}\hat{ME}_i+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (3.11)$$

i=1,2....n ; t=1,2.....342

where R_{it} *is the return on individual security i in month t;* β_i *is the full period post-ranking beta of portfolio p, i.e., the slope coefficient from a time-series regression of monthly post-ranking returns on the returns for an equally-weighted portfolio of all portfolios.* $(ME)_i$ *is the market value of equity;* $(BE/ME)_i$ *is the ratio of book value of equity to its market value;* $\gamma_{0t},\gamma_{1t},\gamma_{2t}$ *and* γ_{3t} *are regression coefficients and* μ_{it} *is the error term.*

The definitions of post-ranking beta and returns are given in the following paragraph:
(1) In Panel A1, β_i *is the full-period post-ranking annual beta of size-beta portfolio and is the slope coefficient from time-series regression of annual equally-weighted security returns. The slope coefficient is the time-series average of 29 cross-sectional regression from July 1973-December 2001 (2) In Panel A2,* β_i *is the full-period post-ranking annual beta of size-beta portfolio and is the slope coefficient from the time-series regression of monthly security returns. The slope coefficient is the time series average of 342 cross sectional regression from July 1973-December 2001 (3) In panel B1,* β_i *is the full-period post-ranking annual beta of beta portfolio and is the slope coefficient from time-series regression of annual equally-weighted security returns. The slope coefficient is the time-series average of 29 cross-sectional regression from July 1973-December 2001. (4) In Panel B2,* β_i *is the full-period post-ranking annual beta of beta portfolio and is the slope coefficient from the time-series regression of monthly security returns. Time series averages of estimated coefficients is calculated from 342 monthly cross-sectional regressions from July 1973-December 2001.*

TABLE 3.12
AVERAGE RESIDUALS FROM FAMA-MACBETH CROSS-SECTIONAL REGRESSIONS: JANUARY 1969-DECEMBER 2001

	Low-β	β-2	β-3	β-4	β-5	Average
Panel A: Beta-only model (Model 3.14)						
Small-ME	4.581	0.803	5.309	2.805	0.117	2.723
ME-2	0.631	-1.222	2.156	1.280	-3.429	-0.117
ME-3	-4.895	1.899	-0.704	-0.922	-3.274	-1.579
ME-4	-1.618	0.829	-2.277	0.241	-2.293	-1.024
ME-5	-1.557	1.726	-0.611	-0.198	0.233	-0.081
Average	-0.571	0.807	0.775	0.641	-1.729	
Panel B: Size-only model (Model 3.15)						
Small-ME	4.793	1.474	4.751	2.854	0.932	2.961
ME-2	0.773	-1.123	2.281	1.445	-3.177	0.040
ME-3	-4.816	1.961	-0.646	-0.858	-3.085	-1.489
ME-4	-1.603	0.808	-2.289	0.318	-2.212	-0.996
ME-5	-2.742	1.080	-1.444	-0.624	0.086	-0.729
Average	-0.719	0.840	0.531	0.627	-1.491	
Panel C: Book-to-Market model (Model 3.16)						
Small-ME	4.228	0.969	4.142	2.502	0.423	2.453
ME-2	0.349	-1.476	1.875	1.177	-3.289	-0.272
ME-3	-4.911	1.709	-0.803	-0.838	-2.862	-1.541
ME-4	-1.130	1.118	-2.125	0.717	-1.835	-0.651
ME-5	-2.173	1.722	-0.873	-0.107	0.434	-0.199
Average	-0.727	0.809	0.443	0.690	-1.426	
Panel D: Beta-Size-Book-to-Market model (Model 3.17)						
Small-ME	4.189	1.026	4.259	2.638	0.457	2.514
ME-2	0.412	-1.401	1.908	1.212	-3.321	-0.238
ME-3	-4.873	1.771	-0.799	-0.873	-2.979	-1.551
ME-4	-1.185	1.121	-2.179	0.660	-1.931	-0.703
ME-5	-1.931	1.773	-0.824	-0.129	0.236	-0.175
Average	-0.678	0.858	0.473	0.702	-1.508	

Table provides the average residuals from the following annual (Fama and Macbeth) univariate models that include annual returns, annual beta, size (ME), Book-to-market (BE/ME), and as well as the multivariate model with annual return, annual beta, size and BE/ME together:

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \mu_{it} \qquad (3.14)$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{2t}\hat{ME}_i + \mu_{it} \qquad (3.15)$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{3t}(\hat{BE/ME})_i + \mu_{it} \qquad (3.16)$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \hat{\gamma}_{2t}\hat{ME}_i + \hat{\gamma}_{3t}(\hat{BE/ME})_i + \mu_{it} \qquad (3.17)$$

where R_{it} is the annual return on individual security i in month t; β_i is the full-period post-ranking annual beta of size-beta portfolio and is the slope coefficient from time-series regression of annual equally-weighted security returns; ME_i is the market value of equity; $(BE/ME)_i$ is the ratio of book value of equity to its market value; $\hat{\gamma}_{0t}, \hat{\gamma}_{1t}, \hat{\gamma}_{2t}$ and $\hat{\gamma}_{3t}$ are regression coefficients and μ_{it} is the residual term. Refer to Table 3.11 to see the details relating to the portfolio formation.

The average column at the right of each panel is the equal-weighted average of residuals for the beta decile portfolios within each size decile portfolio. The average row at the bottom of each panel is the equal-weighted average of residuals for the size decile portfolios within each beta decile portfolio.

TABLE 3.13
AVERAGE RESIDUALS FROM THE DIFFERENCES BETWEEN FAMA AND MACBETH UNIVARIATE AND MULTIVARIATE MODELS: JANUARY 1969-DECEMBER 2001

	Low-β	β-2	β-3	β-4	β-5	Average
Panel A: Beta-only model (3.14) minus Beta-Size-Book-to-market model (3.17)						
Small-ME	0.393	-0.223	1.050	0.167	-0.339	0.209
ME-2	0.219	0.179	0.248	0.068	-0.108	0.121
ME-3	-0.022	0.128	0.096	-0.050	-0.295	-0.028
ME-4	-0.433	-0.293	-0.098	-0.419	-0.362	-0.321
ME-5	0.374	-0.046	0.213	-0.069	-0.004	0.093
Average	0.106	-0.051	0.302	-0.061	-0.222	
Panel B: Size-only model (3.15) minus Beta-Size-Book-to-market model (3.17)						
Small-ME	0.604	0.448	0.492	0.216	0.475	0.447
ME-2	0.361	0.278	0.373	0.233	0.144	0.278
ME-3	0.057	0.190	0.154	0.014	-0.106	0.062
ME-4	-0.417	-0.313	-0.111	-0.342	-0.281	-0.293
ME-5	-0.811	-0.692	-0.620	-0.495	-0.150	-0.554
Average	-0.041	-0.018	0.058	-0.075	0.016	
Panel C: Book-to-market-only model (3.16) minus Beta-Size-Book-to-market model (3.17)						
Small-ME	0.040	-0.056	-0.117	-0.136	-0.034	-0.061
ME-2	-0.063	-0.074	-0.033	-0.035	0.033	-0.034
ME-3	-0.037	-0.061	-0.004	0.035	0.117	0.010
ME-4	0.055	-0.003	0.053	0.057	0.096	0.052
ME-5	-0.242	-0.050	-0.049	0.021	0.198	-0.024
Average	-0.050	-0.049	-0.030	-0.012	0.082	

Panel A, B and C provides the difference between residuals from the models 3.14, 3.15, 3.16 from model 3.17 respectively. Refer to Table 3.12 to see the details relating to the models.

The average column at the right of each panel is the equal-weighted average of residuals for the beta decile portfolios within each size decile portfolio. The average row at the bottom of each panel is the equal-weighted average of residuals for the size decile portfolios within each beta decile portfolio.

TABLE 3.14
CROSS SECTIONAL REGRESSIONS ON STRONG & XU PERIOD: JULY 1973-JUNE 1992 (228 OBSERVATIONS)

Panel A: Size-Beta portfolio

Regression no.	Adjusted R-square (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	.52	.0193 ***4.097***	-.0011 ***-.227***		
3.6	.86	.004 ***3.949***	-.001 ***-.194***	-.000 ***-.824***	
3.7	.34	.018 ***4.500***		-.000 ***-.847***	
3.8	1.01	.021 ***4.406***	-.000 ***-.140***		.002 ***3.286***
3.9	.85	.020 ***5.040***		-.000 ***-.617***	.003 ***3.182***
3.10	.53	.020 ***5.075***			.002 ***3.236***
3.11	1.33	.020 ***4.232***	-.006 ***-.121***	-.000 ***-.597***	.002 ***3.150***

Panel B: Beta-Size portfolio

Regression no.	Adjusted R-square (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	.31	.010 ***2.885***	.007 ***1.426***		
3.6	.53	.010 ***2.703***	.008 ***1.504***	-.000 ***-.798***	
3.7	.23	.018 ***4.498***		-.000 ***-.844***	
3.8	.65	.013 ***3.587***	.006 ***1.302***		.002 ***3.186***
3.9	.57	.020 ***5.040***		-.000 ***-.348***	.003 ***3.331***
3.10	.35	.020 ***5.001***			.002 ***3.141***
3.11	.86	.013 ***3.319***	.007 ***1.390***	-.000 ***-.5775***	.003 ***3.343***

Table reports the time series averages of 228 estimated coefficients from the monthly cross-sectional regressions using discrete rates of returns from July 1973-June 1992, associated t-statistics (in bold), and Adjusted R-square values for size beta ranked and beta-size ranked portfolios respectively. Refer to Table 3.6, for the notes relating to the cross-sectional regressions.

TABLE 3.15
CROSS SECTIONAL REGRESSIONS ON CHAN & CHUI (1996) SAMPLE PERIOD: JULY 1973-JUNE 1990 (204 OBSERVATIONS)

Panel A: Size-Beta portfolio

Regression no.	Adjusted R-square (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	1.02	.015	-.001		
		2.492	***-.214***		
3.6	2.37	.016	-.002	.000	
		2.578	***-.291***	***.476***	
3.7	.42	.014		.000	
		3.197		***.721***	
3.8	2.46	.015	.002		.001
		2.454	***.030***		***2.205***
3.9	.96	.016		.000	.001
		3.642		***.867***	***2.552***
3.10	.87	.016			.001
		3.682			***2.595***
3.11	3.08	.015	.005	.000	.001
		2.549	***.065***	***.593***	***2.136***

Panel B: Beta-Size portfolio

Regression no.	Adjusted R-square (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5		.011	.003		
	1.04	***2.539***	***.492***		
3.6	2.56	.010	.003	.000	
		2.298	***.553***	***.645***	
3.7	.32	.014		.000	
		3.197		***.721***	
3.8	2.67	.012	.003		.001
		2.896	***.561***		***2.597***
3.9	.99	.016		.000	.001
		3.642		***.867***	***2.552***
3.10	.76	.016			.001
		3.682			***2.595***
3.11	3.21	.012	.004	.000	.001
		2.602	***.622***	***.793***	***2.558***

Table reports the time series averages of 204 estimated coefficients from the monthly cross-sectional regressions using continuos rates of return from July 1973-June 1990, associated t-statistics (in bold), and Adjusted R-square values for size beta ranked and beta-size ranked portfolios respectively. Refer to Table 3.6, for the notes relating to the cross-sectional regressions.

TABLE 3.16
AVERAGE SLOPES (T-STATISTICS) FROM MONTH-BY-MONTH REGRESSIONS OF RETURNS ON BETA, SIZE AND BOOK-TO-MARKET EQUITY USING TRIMMING METHOD: JANUARY 1969-DECEMBER 2001

Panel A: Trimmed Returns (%)	Low-Beta	Beta-2	Beta-3	Beta-4	High-Beta
Small-ME	0.839	0.895	1.156	0.736	0.599
ME-2	0.784	0.867	1.161	0.908	0.709
ME-3	0.624	1.098	0.843	0.833	0.824
ME-4	0.810	1.002	0.792	0.973	0.794
Big-ME	0.832	1.065	0.972	0.939	1.039

Panel B: Post-ranking Beta (β_i)	Low-Beta	Beta-2	Beta-3	Beta-4	High-Beta
Small-ME	0.391	0.333	0.461	0.472	0.610
ME-2	0.487	0.503	0.584	0.604	0.634
ME-3	0.625	0.610	0.657	0.736	0.796
ME-4	0.801	0.781	0.809	0.873	0.919
Big-ME	0.907	0.955	0.994	0.989	1.068

Panel C: Regressions using Trimmed Data

Regression no.	Adjusted R square (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
(3.5)	.90	.005	.003		
		1.863 **	***1.027***		
(3.11)	1.63	.005	.007	-.000	.001
		1.652 **	***1.799*** **	***-.161***	***3.750***

Panel D:

Firms in each portfolio before using the trimming methodology

	Low-Beta	Beta-2	Beta-3	Beta-4	High-Beta
Small-ME	31	31	31	31	33
ME-2	30	31	31	31	35
ME-3	28	31	31	31	36
ME-4	26	31	31	31	38
Big-ME	24	31	31	31	42

Firms in each portfolio after using the trimming methodology

	Low-Beta	Beta-2	Beta-3	Beta-4	High-Beta
Small-ME	21	23	23	23	18
ME-2	25	27	28	27	26
ME-3	24	29	29	29	32
ME-4	24	30	30	29	34
Big-ME	23	30	30	30	40

TABLE 3.16 (cont.)

Panel A gives average returns after eliminating any monthly returns that deviates by more than 50% from the month's value-weighted index (in percentage). In panel B, full period post-ranking betas, (for portfolios formed on a two-dimension sort according to size, followed by pre-ranking beta) are given. The post-ranking betas (β_i) are obtained by running the equally-weighted trimmed returns for portfolios against the value-weighted index.

Panel C reports the time series averages of estimated coefficients from the monthly cross-sectional regressions from July 1973-December 2001, associated t-statistics in bold, and Adjusted R-squared. The following cross-sectional models are used:

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \mu_{it} \qquad (3.5)$$

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \hat{\gamma}_{2t}\hat{ME}_i + \hat{\gamma}_{3t}(\hat{BE/ME})_i + \mu_{it} \qquad (3.11)$$

i=1,2....n ; t=1,2.....342

where R_{it} is the return on individual security i in month t; β_i is the full period post-ranking beta of portfolio p, i.e., the slope coefficient from a time-series regression of monthly post-ranking returns on the returns for an equally-weighted portfolio of all portfolios. ME_i is the market value of equity; $(BE/ME)_i$ is the ratio of book value of equity to its market value; $\gamma_{0t}, \gamma_{1t}, \gamma_{2t}$ and γ_{3t} are regression coefficients and μ_{it} is the error term.

Any returns that deviate by more then 50% from the value-weighted index are eliminated from the regression.

Panel D gives firms in the portfolios before eliminating any monthly returns that deviates by more than 50% from the month's value-weighted index and the firms in the portfolios after eliminating any monthly returns that deviates by more than 50% from the month's value-weighted index respectively.

TABLE 3.17
CONDITIONAL RELATIONSHIPS

PANEL A:

DOWN MARKET USING VALUE WEIGHTED INDEX

Regression no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	**2.15**	.025 ***3.365***	-.063 ***-6.542***		
3.11	**2.96**	.026 ***3.652***	-.063 ***-6.429***	-.000 ***-.124***	.001 ***2.219***

DOWN MARKET USING EQUALLY-WEIGHTED INDEX

Regression no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	**2.16**	.009 ***1.40***	-.054 ***-7.167***		
3.11	**2.42**	-.0123 ***-1.926*** **	-.059 ***-7.823***	.000 ***1.679*** **	-.006 ***-1.220***

PANEL B:

UP MARKET USING VALUE-WEIGHTED INDEX

Regression no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	**1.29**	.004 **.805**	.029 ***4.577***		
3.11	**1.88**	.004 ***.771***	.030 ***4.701***	.000 ***1.222***	.000 ***.904***

UP MARKET USING EQUALLY-WEIGHTED INDEX

Regression no.	Adjusted R^2 (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	**1.80**	.013 ***2.273***	.029 ***3.798***		
3.11	**2.30**	.012 ***2.074***	.032 ***4.305***	.000 ***.150***	.001 ***3.083***

Panel A reports the time series averages of estimated coefficients from the monthly cross-sectional regressions for the down-market months using the value-weighted index (123 down-market months) and equally-weighted index (134 down-market months) respectively using the models 3.5 and 3.11. Associated t-statistics for each coefficients are given in bold numbers, and Adjusted R-squared for cross-sectional regressions in the down market months are also given for the models 3.5 and 3.11.
Panel B reports the time series averages of estimated coefficients from the monthly cross-sectional regressions for the up-market months using the value-weighted index (219 UP-market months) and equally-weighted index (208 UP-market months) respectively using the models 3.5 and 3.11. Associated t-statistic for each coefficient is given in bold numbers, and Adjusted R-squared for cross-sectional regressions in the up markets are also given for the models 3.5 and 3.11. Refer to the Table 3.6 to see the details relating to the models: 3.5 & 3.11.

TABLE 3.18
CROSS-SECTIONAL REGRESSIONS USING ALL 2108 SECURITIES: JANUARY 1969-DECEMBER 2001

Panel A: Portfolio: Size-Beta

Regression no.	Adjusted R square (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	.82	.009	-.002		
		2.413	***-.585***		
3.6	1.10	.0112	-.004	.000	
		2.761	***-.923***	***.302***	
3.8	1.24	.010	-.002		.000
		2.573	***-.590***		***2.496***
3.11	1.47	.011	-.005	.000	.000
		2.787	***-.733***	***.327***	***2.647***

Panel B: Portfolio: Beta-Size

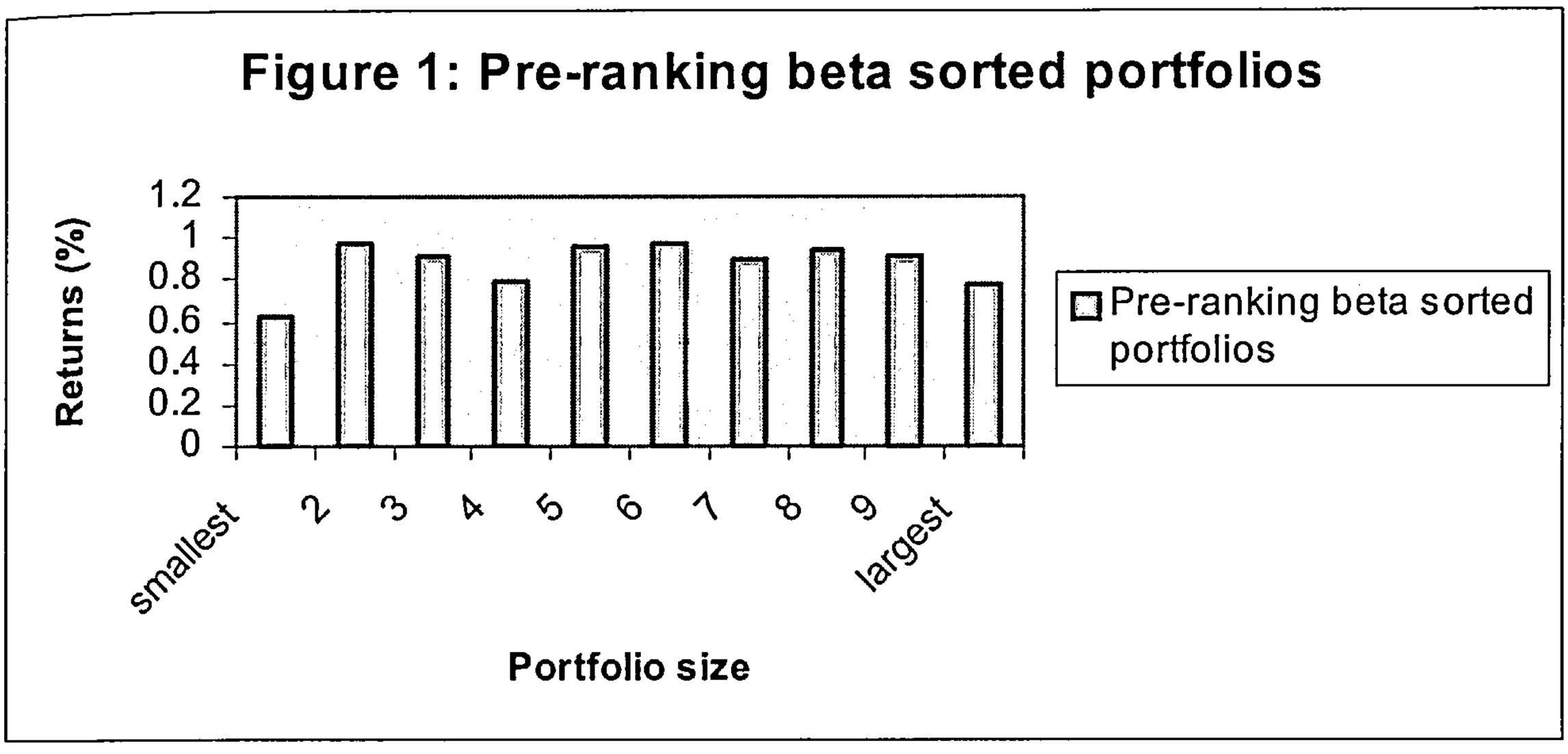
Regression no.	Adjusted R square (%)	γ_0 (intercept)	γ_1 (Beta)	γ_2 (Size)	γ_3 (BE/ME)
3.5	.33	.009	-.002		
		3.208	***-.547***		
3.6	.59	.009	-.002	.000	
		3.118	***-.550***	***.167***	
3.8	.73	.013	-.004		.000
		4.164	***-1.142***		***2.673***
3.11	1.00	.012	-.004	.000	.000
		3.846	***.957***	***.239***	***2.829***

Table reports the time series averages of estimated coefficients from the monthly cross-sectional regressions from July 1973-December 2001, associated t-statistics in bold, and Adjusted R-square values for size-beta ranked and beta-size ranked portfolios. All 2108 securities are included in the sample data. On average, around 84 firms are in each portfolio. The following table shows the number of firms in each portfolio:

	lowest	*2*	*3*	*4*	*Highest*
Lowest	*84*	*84*	*84*	*89*	*82*
2	*81*	*84*	*84*	*91*	*81*
3	*79*	*84*	*84*	*86*	*88*
4	*76*	*84*	*84*	*86*	*89*
Highest	*71*	*84*	*84*	*87*	*98*

Refer to Table 3.6 to see the details relating to the cross sectional models.

FIGURE 3.1
AVERAGE MONTHLY RETURNS FOR PORTFOLIOS SORTED BY EACH OF FOUR FUNDAMENTAL VARIABLES



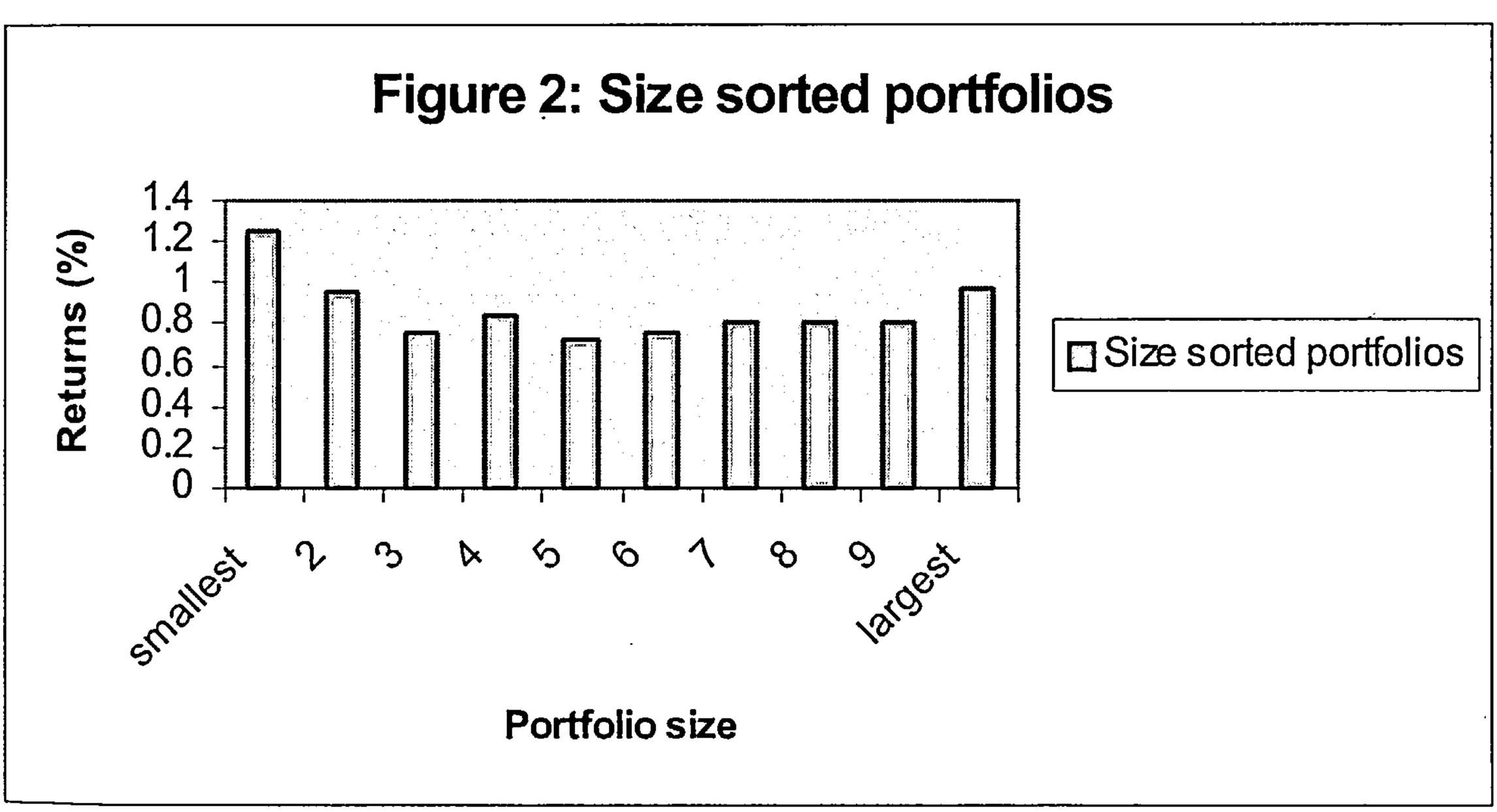
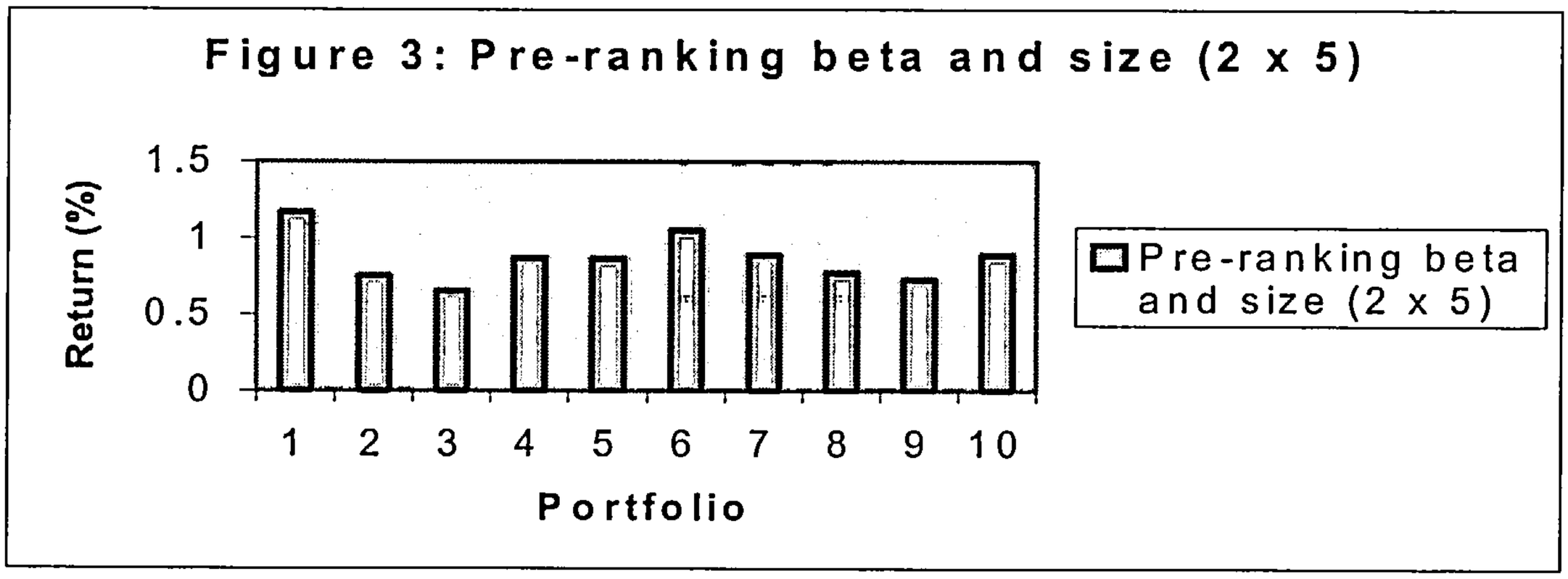
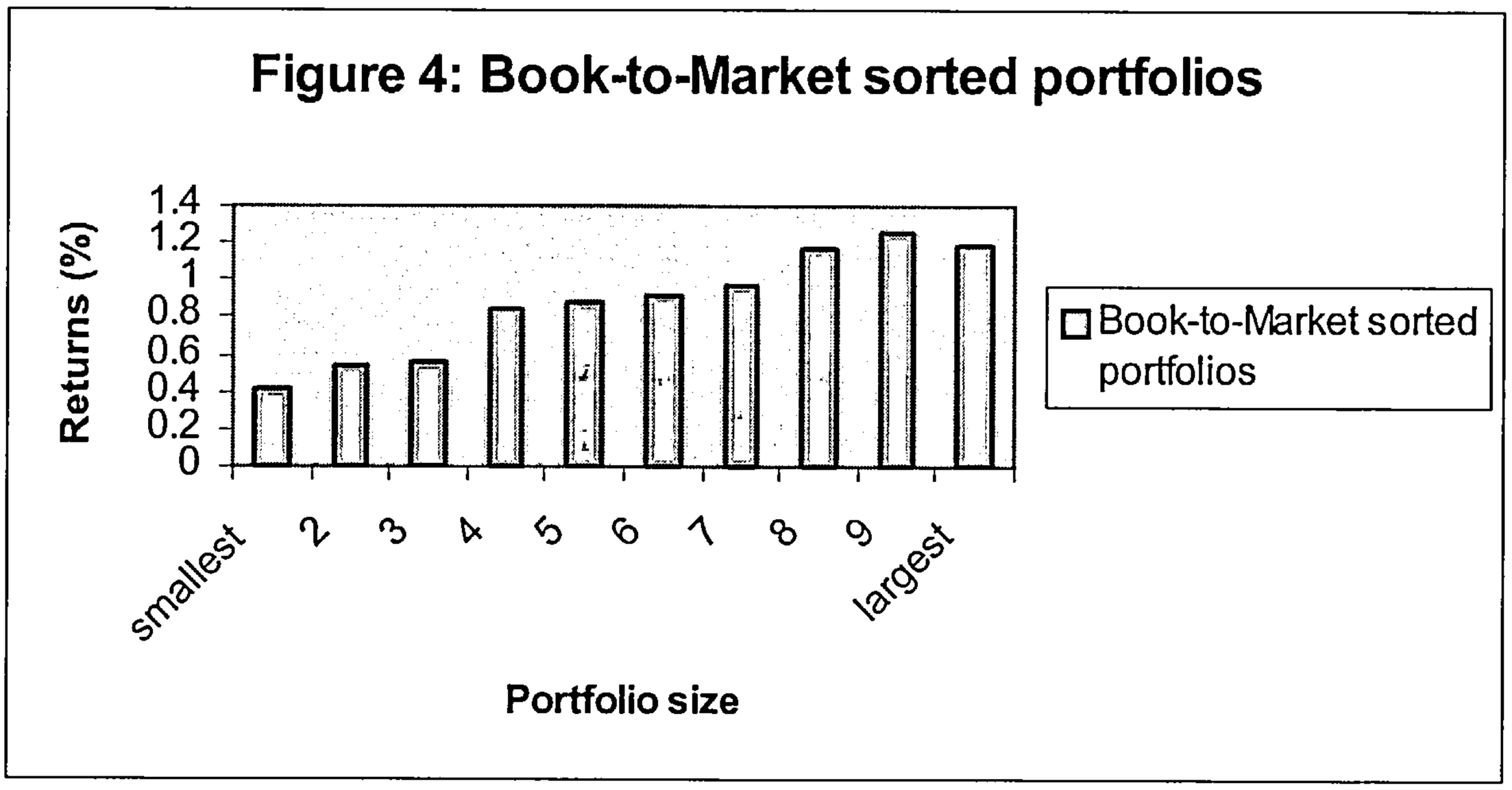


Figure 3.1 (cont.)

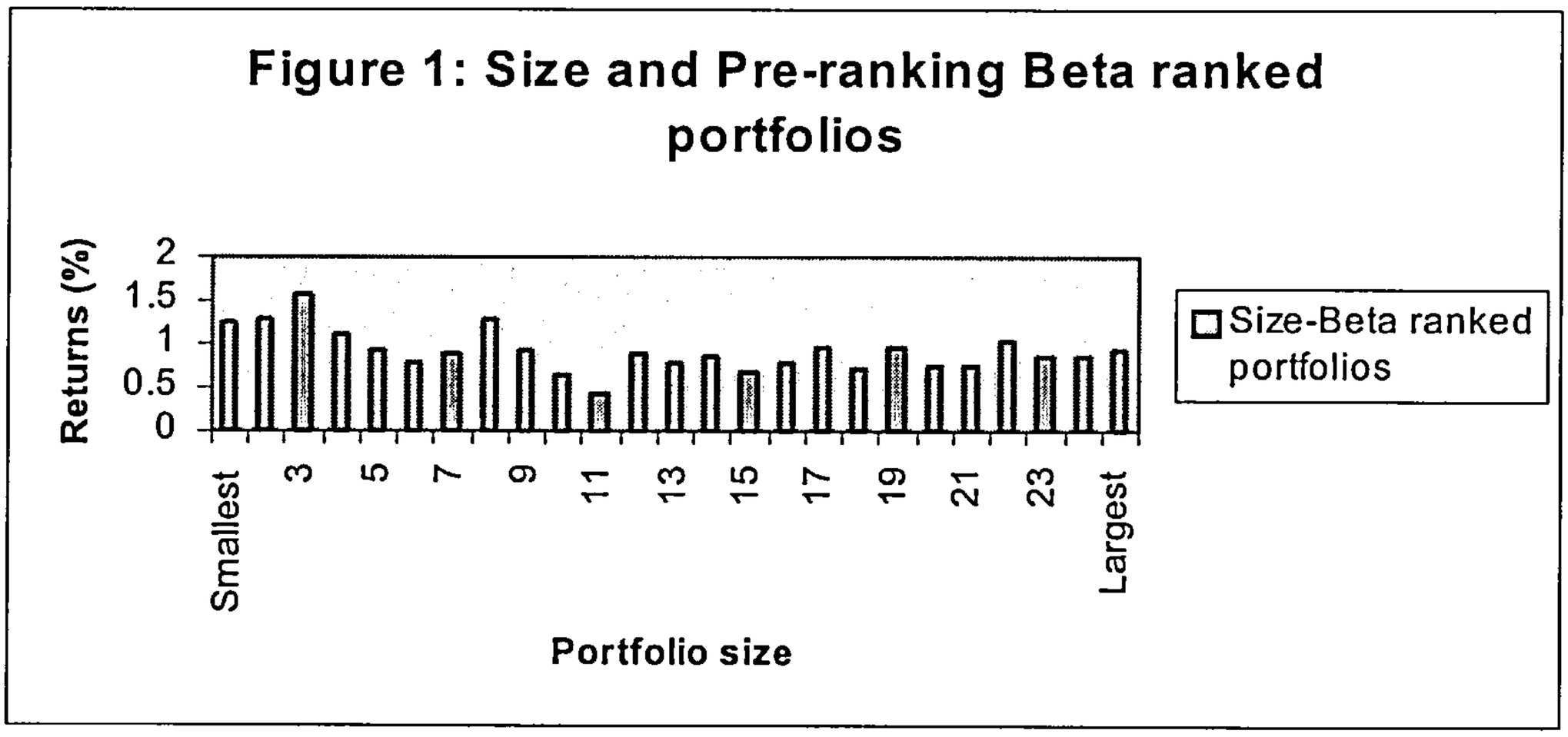


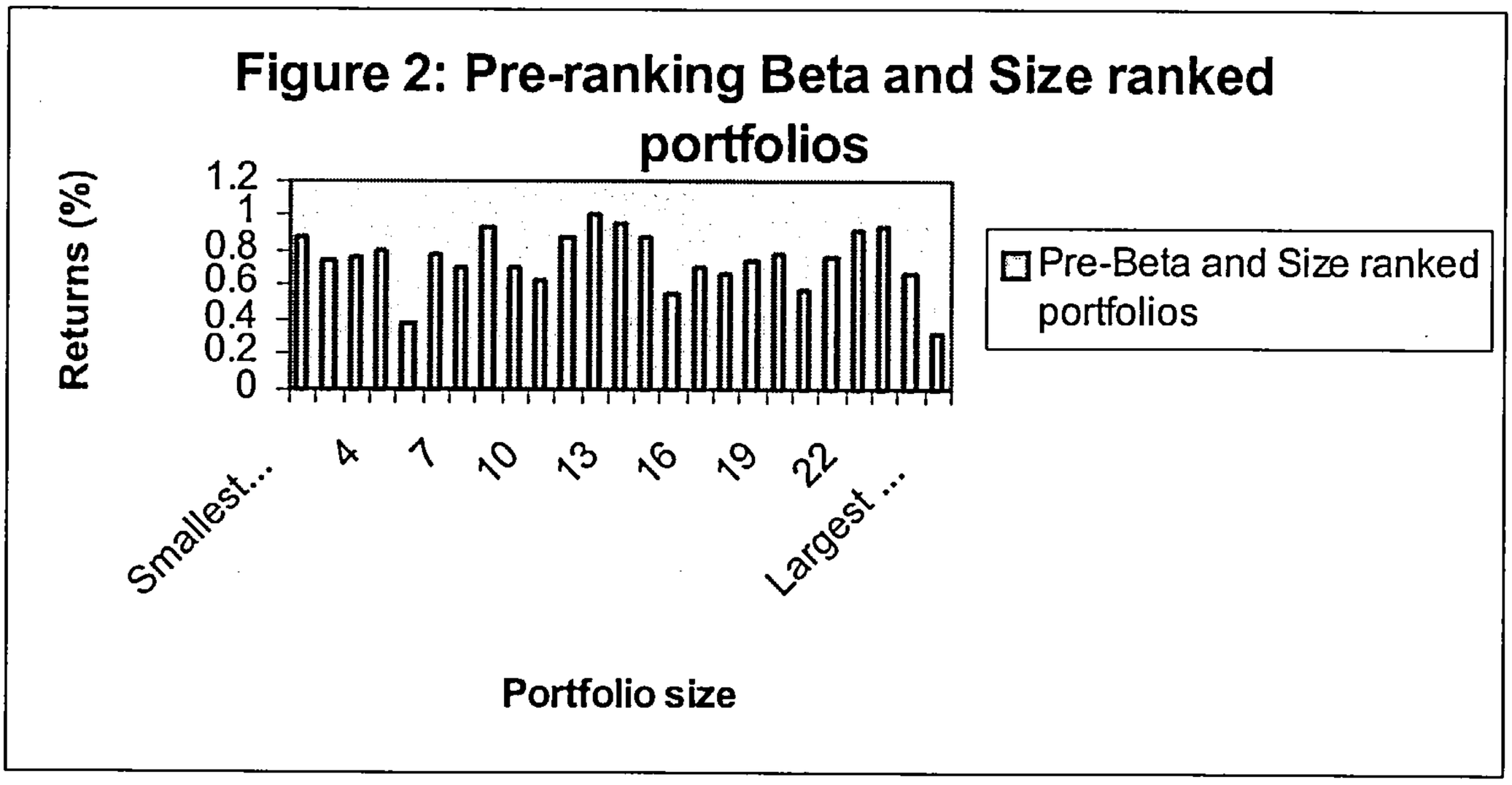
Note that in Figure 3, the stocks are divided into low and high beta portfolios. Each portfolio is then sliced up into five portfolios on the basis of size. Portfolios 1-5 are low beta/size stocks and Portfolios 6-10 are high beta/size stocks.



Refer to Table 3.3a to see the details relating to portfolio formation

FIGURE 3.2
AVERAGE MONTHLY RETURNS FOR PORTFOLIOS SORTED BY SIZE-BETA AND BETA-SIZE





Refer to the Table 3.4 to see the details relating to the portfolio formation.

Note that in Figure 1 and 2, the "first five (1, 2, 3, 4 & 5)" portfolios comes from the smallest size quintile, the "next five (6,7,8,9 & 10)" portfolios comes from the next largest size quintile and in this way the "last five (21,22,23,24 & 25)" portfolios comes from the largest size quintile.

CHAPTER 4

RISK, SEASONALITY AND SMALL-FIRM EFFECT

4.1. INTRODUCTION

It has been seen in the previous two chapters that the Capital Asset Pricing Model (CAPM) is not supported by UK data and that there are other factors besides beta that can, in certain circumstances explain the cross sectional variation in expected returns. In this chapter, the degree of influence of the seasonal factors upon the cross-sectional relationships found in the earlier chapters is considered. Specifically, this study analyses the nature and importance of seasonal fluctuations in the UK equity market during the period 1969 to 2001, and presents three different types of analysis. First, this study investigates the existence of monthly patterns or monthly effects in the returns of the UK stock market. This study tests the monthly relationship between risk and return, in a CAPM framework, using both a Fama and Macbeth and Seemingly Unrelated Regression (SUR). As with the earlier analysis, this study also uses discrete and continuous rates of returns and compares the results using both. Second, the return behaviour across the different months for both large and small firms is investigated. This study analyses whether seasonal effects in the UK data are due to seasonal movements in small firm stocks. Finally, Fama and French (1992) demonstrated that in the presence of the book-to-market ratio there is no relationship between beta and return. Similar results were found in the previous chapter (Chapter 3). This study therefore tests whether the relationship between book-to-market and return is influenced at all by calendar month. This is the first detailed test of such a relationship for the UK stock market, and, since more

recent data (1969-2001) is used, this chapter updates the previous findings of Chelley-Steeley (1996) that examined the relationship between the proxy of beta risk and seasonality.

The remaining of the paper is organised as follows: Section 4.2 reviews the literature on small firm effect and seasonality. Section 4.3 presents the methodology and data set employed. Section 4.4 discusses the results obtained from econometric analysis. Finally, the last section presents the conclusion of the chapter.

4.2. BACKGROUND

Seasonal patterns or calendar effects in stock prices have been of great importance to financial scholars and practitioners. These effects or anomalies have been regarded as strong evidence against Efficient Market Hypothesis (EMH) in financial economics. The existence of such anomalies is a contradiction of the weak form of the EMH. The weak form of the EMH states that the market is efficient if stock price movements cannot be predicted using the historical information. A large number of studies have tested the EMH by examining serial correlation in stock prices. An complementary approach is to test for seasonal patterns in stock returns. Evidence in favour of seasonality in returns implies that market efficiency does not hold. The literature in this field has presented abundant evidence of calendar anomalies such as day of the week, month of the year, turn of the month, holiday, and intraday effects.

The explanation that has also attracted most attention relates to the fact that seasonality appears to have significant interactions with 'small-firm effects'. According to the CAPM, the small-firm effect should be due solely to higher risks. The evidence however, suggests that this is not the case. Specifically the reported 'abnormal returns' from small-firm effect range from just a few percent per year to almost thirty percent per year (Reinganum (1981)). Such results, if true, are clearly inconsistent with the simple one period CAPM.

In the following section, some evidences concerning the small-firm effect and seasonality are presented.

4.2.1. SMALL FIRM EFFECT

The 'small firm effect' is the empirical regularity with which firms with smaller market value exhibit returns, that, on average significantly exceed those of large firms. Banz (1981) was the first to document a small firm effect. He documented a relation between market capitalization (firm size) and mean return. He used a methodology similar to that of Fama and Macbeth (1973), for the period from 1926 to 1975 for stocks on the NYSE. Banz's evidence showed that the CAPM is misspecified in the sense that the excess return from holding a portfolio of very small NYSE companies long and very large NYSE companies short was, on average, 1.52% per month or 19.8% on an annualized basis over a forty year period. Banz's results encouraged many other researchers to examine the size effect and so plentiful was the research that the entire June 1983 issue of the Journal of Financial Economics was devoted to this phenomenon. Reinganum (1981) also concluded "one can earn 'abnormal' returns that persist for at least two years by forming portfolios based on market value of the stock".

One possible explanation for this size effect, implied by the work of Levy (1978) is that the existence of various transaction costs results in shares of small firms being held in portfolios that on average are relatively undiversified. This lack of diversification in turn requires that investors in small firms be compensated for bearing total risk or unsystematic risk rather than systematic risk. However Lakonishok and Shapiro (1984), using monthly data from the period of 1962-1981 and a variety of procedures examined the relationship between returns and various measures of risk, and tested Levy's (1978) hypothesis. They concluded that neither beta nor the alternative risk measure (variance or residual standard deviation) could explain the cross-sectional variation in returns; only size appeared to matter as it turned out to be the only statistically significant variable. Christie and Hertzel (1981) argued that the size effect could be due to the non-stationarity of beta. But the adjustment for non-stationarity of beta in estimates of beta could not eliminate the size effect.

The presence of such anomaly is not confined at the US market alone. Comprehensive evidence[1] on the small firm effects for most of the different markets in the world confirmed the findings of Banz (1981). Analysis of stock returns on four major stock exchanges- Australia, Canada, Japan and United Kingdom has revealed a distinct size –return relation.

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[1] Brown, Keim , Kleidon and Marsh (1983) for Australia; Hawaini, Michel and Corhay (1989) for Belgium; Berges, McConnell and Schlarbaum (1984) for Canada; Wahlroos and Berglund (1986) for Finland; Stehle (1992) for Germany; Coghlan (1988) and Mckillop and Hutchinson (1983) for Ireland; Ziemba (1991) for Japan; Van den Burgh and Wessels (1983) for the Netharlands; Gillan (1990) for New Zealand; Rubio (1986) for Spain; Cornioley and Pasquier-Dorthe (1991) for Switzerland; Ma and Shaw (1990) for Taiwan and earlier work by Dimson and Marsh (1984, 1986) for UK.

The results are summarised in the following table:

Australia (1958-81) (a)		Canada (1951-80) (b)			Japan (1966-83) (c)		UK (1958-82) (d)	
Size Portfolio	**Return (%) (std. Error)**	**Size Portfolio**	**Return (%) (std. Error)**		**Size Portfolio**	**Return (%) (std. Error)**	**Size Portfolio**	**Return (%) (std. Error)**
			1971/72	**1973-80**				
Smallest	6.75 (.64)	smallest	2.02(.27)	1.67(.58)	Smallest	2.03(.35)	smallest	1.32(.20)
2	2.23 (.39)	2	1.48(.22)	1.66(.56)	2	1.50(.32)	2	1.18(.23)
3	1.74(.31)	3	1.14(.22)	1.41(.59)	3	1.38(.29)	3	1.22(.25)
4	1.32 (.27)	4	.99(.23)	1.39(.56)	4	1.17(.27)	4	1.16(.26)
Largest	1.02(.24)	Largest	.90 (.23)	1.23(.58)	Largest	1.14(.27)	Largest	.92(.31)

Note: monthly returns are reported for each country

Sources: a. Brown et al (1983); b. Berges et al (1984); c. Nakamura and Tereda (1984); d. Levis (1985).

It is difficult though to compare the results about the relative magnitude of the size effect across the four countries because of different time periods and research design. Nevertheless in each country there is an inverse relation between expected returns and market capitalization.

Recently, Perez-Quiros and Timmermann (2000) for the US stock market provide evidence that small firms have high average returns because they are more affected by tight credit conditions. Small firms do not have the same access to domestic and international bond markets that are enjoyed by large firms. Usually, the availability of credit is tied to economic conditions. If the credit contraction typically occurs near a recession, small firms will be more affected by the systematic variation in credit market conditions. Thus the high returns to small firms might be compensated for the high sensitivity to a credit-related risk factor.

Like its American counterpart, the UK size effect is also very marked as the study by Levis (1985) showed. Corhay, Hawaini and Michel (1987) also examined the relationship

between average monthly returns and size for securities traded on the London Stock Exchange (LSE). They found that over the twenty-seven year period (from 1957 to 1983) the relationship was negative, which indicated that small firms outperformed large firms but this relationship was not statistically significant. Poon and Taylor (1991) constructed 20 portfolios (sorted on market value) also found that the size premium for the UK market was about 8.2% per annum for the period from January 1965 to December 1984. They also found that smaller firms have smaller betas than that of larger firms. Fong (1992) analysed the period from January 1979 to December 1988 and got results similar to that of Poon and Taylor (1991). Dimson (1998) documented the long-term performance of smaller companies as compared to larger capitalisation equities in the UK. In their study, over the period from 1955 up to the 1987, smaller companies had outperformed the All Share index by an annual average of six percentage points. Over the subsequent decade (until the present), the performance of the small firms was much attenuated.

4.2.2. SEASONALITY

Richard N. Owens and Charles O. Hardy spent considerable time during the early 1920s conducting their own investigation of the seasonality pattern in the US stock market. After concluding that the greater part of the stock-price data available up to 1925 presented no evidence of seasonality, they wrote: "Seasonal variations of security prices are impossible". Some fourteen years later, the research department of Fenner and Beane (one of the country's larger investment houses) published the results of a survey showing that strong bull tendencies prevailed in security prices during fourteen of the fifteen summers from 1924 to 1939. After the publication of the Fenner and Beane studies, various other investigations of market seasonals appeared.

A large amount of international evidence has been covered to indicate a relationship between stock returns and the month of the year. Tinic and West (1984) have produced empirical results, which quite clearly shows that the return seasonalities have profound implications for the tests of equilibrium asset pricing models. Specifically they tested the Capital Asset Pricing Model (CAPM) with data on US stock returns and showed that the systematic risk was consistently positive only in January. They further reported that, when the data for the month of January was withheld from the analysis of risk-return trade off, the estimated monthly risk-premia was not significantly different from zero. A number of other studies have also provided evidence of January returns that are significantly higher than the returns during the rest of the year. This kind of effect is known as 'January effect' anomaly. Rozeff and Kinney (1976), for example, provided evidence for return seasonality in an equally-weighted index of New York Stock Exchange (NYSE) prices for the period 1904-1974. The authors found that the average January monthly return was approximately 3.5 percent while the average return over the other month was 0.5 percent. Gultekin and Gultekin (1983) examined the monthly value-weighted indices in seventeen countries with different tax laws and tax year-ends. They also found a persistent January effect in most of the countries including Japan and US. Rogalski and Tinic (1986) supported the finding of a January effect using the equally-weighted index of NYSE and the American Stock Exchange stocks for the period 1963-1982. The above studies, tries to explain the January effect by focussing their interest on market frictions that violate the CAPM assumptions.

4.2.3. SEASONALITY AND SMALL FIRM EFFECT

Various theories have been proposed to explain the January anomaly. The most widespread explanation is 'tax-loss-selling hypothesis'. Wachtel (1942), Branch (1977) and Dyl (1977) were among the first to attempt to explain the January effect by appealing to the tax-loss-selling hypothesis. According to this hypothesis, investors wait until the tax-year end to sell their common stock 'loser', in order to realise capital losses to be set against capital gains in order to reduce tax liability. Therefore, the heavy selling pressure (downward pressure) during this end-year period (December) depresses the prices of stocks. Consequently, at the beginning of the new tax year (January), in the absence of selling pressure, the downward pressure on stock prices disappears and is followed by buying pressure in January as investors return to desired portfolio compositions. The stock prices therefore regain their real market price. This phenomenon generates large abnormal stock returns at the turn of each tax year. Reinganum (1983) examined the US stock returns to investigate whether the tax-loss-selling hypothesis can fully explain January-size effects. He found that small firms exhibit high returns after controlling for tax-loss-selling pressures. Small firm stocks are likely candidates for tax-loss selling since these stocks typically have higher variance of price changes and therefore large probabilities of large price declines. Reinganum concluded that the January abnormal returns for small firms were consistent with tax loss selling; however, tax-loss-selling cannot explain the entire seasonality effect or the January effect anomaly.

Brown et al. (1983) claim that the Australian turn-of-the-month (December-January) seasonal is evidence against a tax-loss-selling explanation for the January seasonal since the tax year in Australia ends at the end of June. Brown et al. (1983) found that December,

January, July, and August have significantly higher raw returns than do the other months. Gultekin and Gultekin (1983) also found July seasonality in Australia (but not the validity of the tax-loss-selling hypothesis), April seasonality in UK, as well as a January effect in most of the industrial countries. Ho (1990) provides evidence that the tax-loss selling hypothesis does not receive considerable support in most of the Asia Pacific markets, since only in three out of the nine Asia Pacific markets, the return of the first month of the tax-year was significantly higher than that for all other months.

Berges, McConnel and Schlarbaum (1984) also tested whether the tax-loss-selling hypothesis explains January-size effects using Canadian stock return data. They focus on the fact that, until 1972, Canada had no taxes on capital gains. So, for the period prior to 1972, there should not be January-size effects according to the tax-loss-selling hypothesis. However, they found that January-size effects in Canada are similar to those in the US both before and after 1972. This evidence is either inconsistent with the tax-loss-selling hypothesis or consistent with an well-integrated market between Canadian and US investors[2]. Tinic, Barone and West (1987) have reported that, while taxes are not the sole explanation for the January size effect in Canada, the 1972 imposition of a capital gain tax did affect the behaviour of returns. Also consistent with the tax-loss-selling hypothesis, Shultz (1985) found no evidence of a US January seasonal prior to the levy of personal income taxes in 1917. But Jones, Pearce and Wilson (1987) analysed US stock returns extending back to 1871 and found evidence of a January seasonal prior the advent of the income tax code.

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[2] An integrated market means that US investors are active participants in the Canadian market and vice versa.

Another theory regarding the January effect anomaly is the 'information hypothesis'. The information hypothesis refers to fact that smaller firms have less publicly available information compare to the large firms. This lack of information leads to greater uncertainty and risk, resulting in higher returns. Brown and Barry (1984) attempted to test the information hypothesis as a possible explanation of the 'small firm effect'. Using 'time of listing on the exchange' as a proxy for the availability of information, Brown and Barry (1984) found that 'time of listing' does explain some of the small firm effect. They concluded that information uncertainty does play at least partial role in explaining the small firm effect. Keim (1983) suggests that the 'January effect anomaly' affects small-firm prices more than those of large firms for which the information cost is less. He reports that the small firm returns during January are significantly higher than large firm returns and that approximately fifty percent of size effect appears in January. Therefore, there appears to be a link between the January effect and the small firm effect. Other recent studies like Hawaini and Keim (2000) shows that "large stocks dominated indexes" do not exhibit seasonality and that the US turn-of-the-year effect is almost exclusively a small stock phenomenon.

A month to month analysis of Corhay, Hawawini and Michel (1987) also showed that the size effect is a seasonal phenomenon for UK stock market. But in their case, not January but May was the only month of the year for which there was a significant relationship between average returns and size. The relationship was negative indicating that most of the small size premium is earned during the month of May. Levis (1985) also found results similar to Corhay, Hawawini and Michel (1987). Reinganum and Shapio (1987) suggest that the UK equity market may have both a January and April Seasonal. The results of Chelley-Steeley (1996) are striking. Chelley-Steeley (1996) found January and April to be only significant

months for UK stock for the period from January 1976 to December 1991. She showed that the systematic risk premium for these months is higher for large firms. This means, that the large firm outperforms small firms in the months of January and April. In their study, there seems to be no link between seasonality and the small firm effect.

'Risk seasonality' might be another reason behind the January effect. Some studies shows that the betas and variance, which are both used to measure risk, take on above-average values in January. This applies above all, to small companies. The January effect would accordingly not be a genuine anomaly, but an indemnification of higher risk. Rogalski and Tinic (1986) found that small-size firms have significantly higher risk (total, systematic and residual) in the beginning of the year than in the rest of the year.

Finally the portfolio-rebalancing hypothesis developed by Haugen and Lakonishok (1988) might be another reason behind the interaction of the small firm effect and January anomaly. This hypothesis states that the high returns on risky securities in January are caused by systematic shifts in portfolio holdings of investors at the turn of the year. Haugen and Lakonishok (1988) argue that January seasonality could be induced by fund managers rebalancing their portfolios to either hedge or window dress their performance. In performance hedging, fund managers lock in their gains, especially from small stocks, and move into stocks that will closely replicate the features of their performance benchmark during the course of calendar year. They re-enter the market after the last reporting day of the year to acquire undervalued small stocks that consequently appreciate in price at the start of the calendar year. In "window dressing", fund-managers include stocks that have done well in the recent past and eliminate under-performing small stocks for year-end reporting

purposes. At the start of the new reporting period, managers choose stocks, especially those of small firms that are likely to provide higher returns during the year. The prices of small stocks therefore rebound at the start of the next reporting period. Ritter and Chopra (1989) and Porter et al. (1996) report evidence consistent with this hypothesis for the US as do Athannassakos (1992) and Athanassakos and Schnabel (1994) for Canada.

4.2.4. BOOK-TO-MARKET ACROSS FIRM SIZE AND SEASONALITY

Fama and French (1992) document that size and the book-to-market ratio "provide a simple and powerful characterization of the cross-section of average returns for the 1963-1990 period." They report that stocks with high book-to-market ratios have reliably higher returns than lower book-to-market stocks of the same size. Fama and French assert that their findings have powerful implications for portfolio formation and performance evaluations for investors. There is, however, a remarkable conflict between the finance literature (Fama and French study) and money manager performance. According to Fama and French, value firms (high book-to-market ratios) have reliably higher realized returns than growth firms (low book-to-market ratios). But, if the book-to-market effect has such strong power in predicting future returns, why have value money managers not been able to outperform growth money managers by an appreciable amount? This study therefore investigates whether book-to-market effect is driven by low returns on small stocks, which comprise a small proportion of the market's total capitalization. Usually, the large managers find it difficult to use these stocks on short side of their portfolios; a substantial portion of the book-to-market effect would not be available to them.

Small growth stocks represent less than 1% of the total market value of all publicly-traded equity in the US. In contrast, the largest size quintile accounts for 73% of the total market value of all publicly traded firms, on average. Loughran (1997) found that for largest size quintile, book-to-market has no significant explanatory power for the cross section of expected returns. That doesn't mean that young small firms are driving the entire book-to-market pattern. Loughran (1997) found that during 1963-1995, large firms exhibit much higher January returns than do small firms. The lack of consistent book-to-market effect outside the January for large firms is very important in understanding the cross section of returns. One possible explanation for the strong seasonal book-to-market pattern is found in Ritter and Chopra (1989). They find that small NYSE firms, which are strongly tilted toward value, have high January returns irrespective of whether or not the January value-weighted market return is positive or negative. Their finding is consistent with a window dressing explanation of the strong January pattern for 'small firms' mentioned in the last section. Thus, following December tax loss selling, investors rebalance their portfolios in early January, and value firms experience a bounce.

This study is not aware of any studies done on the book-to-market seasonality for the UK stock market, and so this chapter will make a new contribution in this regard.

4.3. DATA AND METHODOLOGY

4.3.1. DATA

In this chapter, this study uses the same monthly returns for 2108 firms obtained from London Share Price Database (LSPD) covering the period January 1969-December 2001. Monthly returns were calculated as logarithms of price relatives including dividend payments. The data for the market value and book value was collected from Datastream. Market value of common equity was measured at end of December of year t-1. Book-to-market equity (BE/ME), and is equal to book common equity for the fiscal year ending in calendar year t-1, divided by market common equity at the end of December of calendar year t-1. The data set includes firms that appear in both Datastream and LSPD. When forming portfolios, this study excludes from the sample all firms with missing BE/ME values in pre and post formation period. As a result, not all the 2108 firms might be included in any testing period. A survivorship bias is therefore possible in the estimated results. According to Chelley-Steeley (1996), it is possible that small firms are more influenced by survivorship problems as they are more likely to be taken over because financing a take-over or merger when a company is small is easier then for a large company. Negal (2001) also provides evidence on the effects of survivor biases in the existing UK databases. He also confirms that the firms with such a problems are small and have high book-to-market. According to Negal, the bias in the estimates (for e.g., betas, risk estimates and its relationship to returns) depends on the type of methodology undertaken for the study.

This study has adopted a methodology that can atleast help to reduce the biases arising from survivorship problem. This is because, it is necessary for a company in this study to exist for atlest five years to allow enough time to calculate betas and then test the relationship between risk and return. Individual stock estimates are grouped into 25 equally-weighted portfolios on the basis of 'size-beta' and 'beta-size'. Grouping returns into portfolios reduces estimation error of the estimates by decreasing firm-specific variation (which tends to cancel out in portfolios). Grouping on the basis of size and beta increases the power of tests based on the cross-sectional regression by assuring that the sample will have a good dispersion of risk and return across portfolios.

4.3.2. TEST PROCEDURE

The familiar Fama and Macbeth (1973) method is employed to test the monthly relationship between risk and return. The link between seasonality and the size effect on the UK stock market is also examined, and SUR methods and discrete returns further test the sensitivity of the results.

4.3.2.1. TESTING THE MONTHLY EFFECT

The estimation of the monthly risk premia for individual securities (using portfolio groupings described in Chapter 3) are performed over the entire sample period (342 months, July 1973-December 2001). 29 sets of cross-sectional estimates are obtained for each month[3]

[3] 342 cross-sectional estimates are obtained for the sample period: July 1973-December 2001. In this way, 29 cross-sectional estimates are obtained for the months: July 1973-December 2001 and 28 cross-estimates for the months: January 1974-June 2001.

for the full-sample period using the following model and with different combinations[4] of beta, size (ME), and book-to-market (BE/ME) variables:

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{2t}ME_i+\hat{\gamma}_{3t}(BE/ME)_i+\mu_{it}, \quad i=1,2....n; \quad t=1,2.....342 \tag{4.1}$$

where R_{it} is the return on individual security i in month t; β_i is the post-ranking beta of security i for month t (Post-ranking beta is the full period post-ranking beta of portfolio p, i.e., the slope coefficient from a time-series regression of monthly post-ranking returns on the returns for an equally-weighted portfolio of all portfolios); ME_i is the market value of equity for security i for month t; $(BE/ME)_i$ is the ratio of book value of equity to its market value for security i for month t; $\gamma_{0t},\gamma_{1t},\gamma_{2t}$ *and* γ_{3t} are regression coefficients and μ_{it} is the error term. The familiar Fama and Macbeth t-statistic (see Chapter 3, Section: 3.3.2.) is used for testing the monthly estimates.

4.3.2.2. TEST OF THE MONTHLY EFFECT FROM SUR ESTIMATES

This study now investigates the monthly effect with a change in the final stage of the Fama and French procedure. Instead of applying the usual OLS to each security for each post-rank period, the monthly coefficients are estimated using the Seemingly Unrelated Regression (SUR) procedure[5]. 29 x 12 monthly cross-sectional estimates are estimated for each month by using the SUR procedure in the last stage of the Fama and French methodology. Equation (4.1) is then tested using the Fama and Macbeth t-statistic.

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[4] Refer to Chapter 3, Section. 3.3.2 to see the cross-sectional models with all combinations.

[5] It is difficult to pre-specify theoretically the correct monthly cross-sectional relationships, it is important to verify that any relationships that are uncovered using standard cross-sectional methodology (Section 4.3.2.1) are not merely statistical artifacts. Moreover, SUR estimates are consistent and asymptotically normal, and, asymptotically more efficient if the residuals across portfolio groups are in general correlated (Clare, Priestley and Thomas (1998)). But, cross-correlation do not affect the unbiasedness of monthly cross-sectional estimates and Fama and Macbeth (1973) base their tests on the time-series average of coefficients (assuming independence of return over time).

With the help of the SUR technique this study also test the restriction that the monthly returns are same for all months in a given year.

4.3.2.3. SMALL FIRM AND MONTHLY EFFECTS USING THE DUMMY VARIABLES.

This section examines the small-firm effect using the entire sample period (January 1969-December 2001). Since the study aims to discover whether both calendar and small-firm effects exist in the risk-return relationship, the following model is tested:

$$R_{i,t}=\tilde{\alpha}_{1,t}+\tilde{\alpha}_{2,t}\hat{\beta}_{i,t}+\tilde{\alpha}_{3,t}MEi,t+\alpha_{4,t}\,BE/MEi,t+\sum_{j=1}^{2}\tilde{\gamma}_{i,t}\delta_{j,t}+\sum_{j=1}^{2}\tilde{\lambda}_{i,t}\,(\delta_{j,t}\hat{\beta}_{i,t})+ \quad (4.2)$$

$$\sum_{j=1}^{2}\tilde{\gamma}_{i,t}\,(\delta_{j,t}MEi,t)+\sum_{J=1}^{2}\tilde{\ell}_{i,t}(\delta_{j,t}\;BE/MEi,t)+\tilde{\mu}_{i,t}$$

where t=1,2….342, j=1,2, i=1,2,….n, $\tilde{\alpha}_{1,t},\tilde{\alpha}_{2,t},\tilde{\alpha}_{3,t},\alpha_{4,t}$ are the average coefficients associated with the intercept, systematic risk (β), Market Size (ME) and Book to Market effect (BE/ME) respectively. The δ_1 takes on the value of 1 if the pth portfolio consist of small sized firms, but a value of zero otherwise and where security i is in portfolio p in month t. δ_2 takes on the value of 1 if the pth portfolio consists of large firms and zero otherwise and where security i is in portfolio p in month t. $\tilde{\gamma},\tilde{\ell}$, are the average coefficients associated with the two size dummies[6]. The terms $\delta_1\,\delta_2$, $\tilde{\lambda}_1\,\tilde{\lambda}_2$, $\tilde{\gamma}_1\,\tilde{\gamma}_2$ & $\tilde{\ell}_1\tilde{\ell}_2$, are the average coefficients associated with the two slope (size) dummies for systematic risk, size and Book-to-Market respectively.

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[6] Note that the variable "size" has three classes, the small, medium and large size firms. Two dummy variables are used because we have three classes of the size. Large firms are those firms in the two largest market value quintiles and small firms are those in the smallest two market value quintiles. Influence of medium sized firms is picked up through the intercept term. If this is not followed, one shall fall into what might be called the dummy variable trap, this is, the situation of perfect multicollinearity (for additional discussion, see Gujarati (1995, pg.504)).

The above approach will allow us to establish whether firm size influences the magnitude of the systematic risk, size and BE/ME premium in any of the months. Before using this approach, securities are divided into portfolios on the basis of 'size and beta' and 'beta and size'. The model (4.2) is then tested for these securities, for each individual month of the year. For a given month, the beta, size and book-to-market of a security are regressed against the monthly return for a given month and dummy variable including if they are in either of the small or the large firms portfolios. The familiar Fama and Macbeth t-statistic is again used to test the hypothesis whether the seasonal and small firm effect exists together for any individual month of the year.

4.3.2.4. POOLED TIME SERIES CROSS SECTIONAL REGRESSION

In the above section, the monthly effects are tested by independently running the regressions using OLS and then averaging the coefficients, as Fama and Macbeth did. Here, pooled time-series cross-sectional regressions are estimated using the Seemingly Unrelated Regression (SUR) technique. The SUR technique takes into account any cross month correlation of the portfolio returns.

Specifically, monthly equally weighted portfolio returns are regressed on a January intercept dummy variable, the market index and a cross-product term, which produces a January slope dummy variable. The following time series SUR is used for this purpose. The following time-series models, basically says whether the estimate of post-ranking betas from the Fama and French method[7] are affected by the seasonal patterns:

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[7] In Fama and French (1992), there are arguably "two" steps:

Step 1 : Portfolio returns are created from pre-rank betas and sorting procedures
: Post-ranking betas are then estimated from a time-series regression (portfolio returns are regressed on equally weighted portfolio to get the post-ranking betas)

Step 2 : Risk premia on beta, size and BE/ME are then estimated using the cross-sectional models

$$R_{pt}=\gamma_{0p}+\gamma_{1p}D_t^{Jan}+\beta_{1P}RM_t+\beta_{2p}(D_t^{Jan}*RM_t)+\varepsilon_{pt} \quad (4.3)$$

where R_{pt} is the 342 x 25 matrix of portfolio returns obtained from the Fama and French method; the January dummy variable, D_t^{jan}, takes on the value of one in January and zero in other months, RM is the market index constructed as in Section 3.3.1 of Chapter 3, β_{1p} is the post-ranking beta for portfolio p; β_{2p} is the January slope dummy variable and ε_{pt} is the residual term.

Using the above approach, the following equation (4.4) is used to test for April seasonality:

$$R_{pt}=\gamma_{0p}+\gamma_{1p}D_t^{April}+\beta_{1P}RM_t+\beta_{2p}(D_t^{April}*RM_t)+\varepsilon_{pt} \quad (4.4)$$

25 time series estimates are obtained by running the above time-series regression ((4.3) and (4.4)). The coefficients are tested by via a t-statistic associated with each time series estimate.

4.4. EMPIRICAL RESULTS

4.4.1. STANDARD FAMA AND MACBETH METHODOLOGY

4.4.1.1. SYSTEMATIC RISK PREMIA SEASONALITY

Estimates of seasonality in the monthly estimates of the systematic risk premia are reported in Table 4.1, Panel A. It was found earlier[8] that no relationship exist, on average, between monthly security returns and systematic risk over the entire 29 year period from January 1969-December 2001. Expected return behaviour on the London Stock Exchange is not consistent with the CAPM. Here, this study reports the monthly results using portfolios with different sorts: the 'size-beta', 'beta-size', 'beta', 'size' and 'beta-size (2 x 5)'[9]. Previous studies done on the UK stock market have either used the 'size-beta' or 'size' ranked portfolios for this type of analysis.

Looking at the month-month results in Table 4.1, Panel A (basic CAPM), it can be seen that January, February, March, April, July, August and December are the months in which the systematic risk premium is positive. May, June and September are the only significant months in this study. But, for all these three months, there seems to be a negative and significant relationship between the price of risk and monthly returns. The month of April is significant at 10% level of significance where the systematic risk is positively priced. But due to a very high negative and significant risk-return effect in the months of May, June, September, October and November, this study finds that the overall relationship between return and systematic risk is on average, negative (see Chapter 3, Table 3.6). This

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[8] See Chapter 3, Section. 3.4.3 for more details.

[9] See Chapter 3, Section: 3.1 & 3.3 to see the details on portfolio construction and sorting procedures.

phenomenon is therefore primarily the result of a significantly downward ex-post sloping risk-return relationship in the months of May, June and September (the May risk premium is equal to minus 3.33%, that is, minus 39.60% on an annual basis. Similarly, the June and September risk premium is equal to minus 3.38% and minus 5.40% on an monthly basis respectively and minus 40.56% and minus 64.80% on an annual basis respectively). These results are quite similar to the monthly estimates obtained by Corhay, Hawawini and Micheal (1987) for the UK stock exchange over the period of 1955 to December 1983. In their case, only May and November appeared to be negatively priced. In their study, April was the only month in which systematic risk was positive and significant at 10% level. Chelley-Steeley (1996) also did similar analyses using UK stocks for the sample period: 1976-1991. In Chelley-Steeley (1996) study, only January and April appeared to be positively priced. For the other ten months of the year no persistent relationship between systematic risk and return appear to exist. To compare the results, here, with the earlier studies, sub-sample tests are done later in this chapter. But, overall, so far, the results from this study are similar to the other UK studies (Corhay, Hawaini and Micheal (1987) and Chelley-Steeley (1996)).

4.4.1.2. SENSITIVITY TO PORTFOLIO FORMATION

The results for 'beta-size', 'size', 'beta' and 'beta-size (2 x 5)' sorts are reported in Table 4.1, Panels B, C, D & E[10] respectively. Looking at the CAPM, this study finds some interesting results by using beta ranked portfolios. The results obtained by using 'beta-ranked' portfolios (see Panel C), show that April is the month of year in which the

[10] In Table 4.1, Panel A, it can be seen that the monthly estimates of cross-sectional regressions with different combinations are almost similar. Therefore, in Table 4.1, Panels B, C, D and E, estimates of four selected cross-sectional models are reported.

systematic risk premium is statistically significant (at 5% level of significance) and positive. Again a negative effect was found in the months of September and October. The positive impact of the systematic risk in the month of April is also found for the other models and portfolios sorting methods, except for size sorted. The positive April effect above may be tax-induced. The UK's tax year-ends on 5th April, thus the UK's March is roughly equivalent to the US's December and the UK's April is roughly equivalent to the US's January. The significant positive average returns, which this study finds in the month of April in the UK, may then be caused by tax-loss selling by UK investors or tax-loss-selling hypothesis. According to this hypothesis, as the end of the fiscal year approaches (March in United Kingdom), investors can reduce their taxes by selling the stocks on which they lost money during the year. In doing, so they realize capital losses that are deductible from their taxable income. The sale of securities at the end of the fiscal year depresses prices, which recover at the beginning of the next fiscal year (April) as stocks move back toward their equilibrium value. The linear and positive relationship between average returns and systematic risk in April is therefore consistent with the tax-selling hypothesis. If this is true, UK stocks might also be seem to be depressed in March. But, in this study, there was no significant risk-return effect in the month of March. But, March returns will not reflect the full effect of tax-loss selling if some of this selling occurs in the first few days of April (i.e. before 5th April). Also, the private investors in UK tend to load their pension schemes at the end of the tax year to reduce their personal tax liabilities. This practice could also lead to an increase in the flow of funds into capital markets during April.

4.4.1.3. BE/ME AND SIZE SEASONALITY

It was noted in Chapter 3 (see Table 3.6) that average relationship between security returns and the BE/ME variable is positive and significant for overall sample. Turning to the month-to-month results, it can be seen that the BE/ME effect is also a seasonal phenomenon. In Table 4.1, Panel A, one can see that March, April and May are three months in which the relationship is positive and significant. This suggests that the strong relationship between BE/ME and returns found in Chapter 3 is probably the result of the seasonal phenomenon. This is a new finding for the UK stock market that is not sensitive to the portfolio formation procedure (see Panels B-E).

Loughran (1997) did something similar for US stocks for the period from January 1963-December 1995. He found a positive and significant BE/ME effect in the month of January. He also found an average positive and significant BE/ME effect for the months of February-December. Loughran (1997)'s result was also consistent with the previous research by Keim (1988). Keim reports a strong January seasonal BE/ME effect for NYSE firms over the 1964-1982 period. Since Keim restricted his sample to just NYSE firms, no BE/ME effect was observed in his sample outside of January.

The overall relationship between average security returns and size was also reported in Chapter 3 (see Table 3.6). It was found that, over the whole sample period, the size-return relationship was almost positive (indicating that large firms outperformed, on average, small firms) but that it was not statistically significant. The month-to-month results would allow us to uncover any seasonality in size masked by the overall sample. By looking at Table 4.1

(Panels A-E), this study finds that, all the coefficients in size variables are almost positive and not significantly different from zero. So, monthly results from this study confirm the absence of a size effect found earlier. These results are different to the earlier findings. Corhay, Hawawini and Micheal (1987) and Levis (1985) for the UK, found a negative size effect in a month of May indicating that most of the small size premium is earned during the month of May. Strong and Xu (1997) found a significantly negative size coefficient in months of May, June, July, September, October and November. It will be seen later in this study whether the size-effect during the different months is sensitive to the sample period.

4.4.2. DISCRETE RETURNS

The importance of continuous and discrete rates of returns was discussed in the Chapter 2 and 3 of this thesis. So far, this study has used continuous returns for examining the monthly relationship between average returns and systematic risk premia and its competing variables (BE/ME and size) of common stocks traded on the LSE. This study now examines the results using discrete returns. These are shown in Table 4.2[11]. The results for discrete returns are extremely sensitive to the portfolio formation procedure. For the 'beta-size' sorted portfolio (Panel B), the results are similar to those for continuous returns. There is a significant positive coefficient on both beta and BE/ME variables in April and also on BE/ME variable in March. For the 'size-beta' ranked portfolios (Panel A), beta is not significantly positive priced in April, but appear significantly negative in May and June. This is similar to a typical continuous returns case of size sorted only portfolios (Table 4.1, Panel D). This suggests some interplay between portfolio sorting and existence of significant

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[11] It was noticed in the Section 4.4.1.1. that the results from the cross-sectional regressions are mainly sensitive to the first (or dominating) sorting variable used for forming the portfolios. From now onwards, this study therefore only uses 'size-beta' ranked and 'beta-size' ranked portfolios for analysis.

risk premium, which speaks to Lo & MacKinlay's (1990) data mining issues, and also Berk's (2000) findings. Lo and MacKinlay suggest that, if the sorting procedures used for portfolio construction is based on variables that are only known to be empirically correlated with returns or a variables measured within the sample, the test will might be suffering from data-snooping or data-mining biases. The results presented in Table 4.2 are suggesting something similar.

4.4.3. SUB-SAMPLE TEST

The results of this study might be sensitive to the data period. Chelley-Steeley's (1996) study covered the period from January 1976 to December 1991, while the current study covers the period from January 1969 to December 2001. Chelley-Steeley found both a January and an April effects, while this study found only an April effect. In addition to the April effect, this study also finds a negative beta-return relationship in the months of May, June and September in some instances. These results suggest that for UK stock market, seasonalities are not stable. Seasonality may exist for sometime and then disappear. In order to gain the better understanding of this issue, the analysis was repeated using the sample period (1976-1991) used by Chelley-Steeley (1996). The results are reported in Table 4.3[12]. It can be seen that there are no seasonal effects in beta for any months accept September (see Panel A), where the relationship with the systematic risk is negative. By contrast, the April seasonal found earlier (see Table 4.1) for BE/ME is still significantly positive (see Table 4.3, Panels A and B). The differences between the results here and that of Chelley-Steeley are

[12] Chelley-Patricia (1996) only uses portfolios, which were ranked according to the beta. But to avoid the "multicollinearity" problem, this study uses size-beta ranked portfolios for the sub-sample test. As the results from the different cross-sectional models are similar (see Table 4.1), this study only uses two important cross-sectional models for this purpose.

likely the result of the different number of stocks used, 2108 here, against 150 by Chelley-Steeley.

4.4.4. SUR PROCEDURE

This study now investigates the monthly effect with a modification in the final stage of the Fama and French procedure. Instead of applying the usual OLS to each security for each 342 post-rank period, the post-rank periods are estimated in blocks of 12 months using the SUR procedure. The results can be seen in Table 4.4. A significant or almost significantly positive beta risk premium is found in the month of April (Panels A & B). This study also found a significantly negative beta risk premium in September ('size-beta' ranked portfolios, Panel A) and October ('beta-size' ranked portfolios, Panel B). It can also be seen that, the result of monthly risk-return relationships is sensitive to the sort method. BE/ME effect also appears to be positive and significant in the month of April for 'size-beta' ranked portfolios but is also significantly positive in the month of October for 'beta-size' ranked portfolios. Overall, the findings from this section are similar to the previous ones (see Section. 4.4.1, 4.4.2 and 4.4.3) but some results are sensitive to estimation method: negative risk-return effect in October.

Table 4.5, Panel A, reports the results that tests the restriction that the coefficients on beta are the same for all months within a 12 month block. Using size-beta sorted portfolios, the restriction is rejected in 27 out of 29 years, while using beta-size sorted portfolios, the restriction is rejected in 16 out of 29 years. Both results confirm the existence of seasonal pattern in the pricing of beta risk.

The analysis was also repeated by testing the equality of 36 months one at a time (see Table 4.5, Panel B). The results in Panel B are almost similar to the results in Table A . There was again a solid evidence of seasonality in UK stock market.

4.4.5. SMALL FIRM EFFECT AND SEASONALITY

4.4.5.1. RELATION BETWEEN RISK AND RETURN ON BASIS OF MARKET CAPITALIZATION

It was seen earlier in Sections 4.4.1.1 and 4.4.1.2 that sorting by size first or alone, could mask the significance of the beta risk premium in April. It is possible that this interplay with size be uncovered if the Fama and Macbeth cross sectional regressions are augmented by dummy variables indicating the size ranked portfolio of securities, particularly if they are in the largest or smallest portfolio. The results of this procedure are in Table 4.6. This study finds a January effect evident in large firms (the risk premium in January for large firms is equal to .08 on monthly basis). There is some April effect (significant at 10% level of significance) for the small firms (the risk premium in April for small firms is equal to .03 on monthly basis). In UK, the tax year ends in April. The April effect for small firms may be due to the tax-selling hypothesis. The tax selling hypothesis implies that prices of stocks that depreciate towards the end of the tax year should rebound in the following years. This means that returns on small company stocks that depreciate in price before the end of the tax year will exhibit higher returns relative to those of large companies that had appreciated in price at the start of the tax year. This study finds that for the small firms. It is now reasonable to conclude that the tax-loss-selling hypothesis associated with small firm stocks at the beginning of the tax-year as proposed by Ritter (1988) is confirmed for the UK.

The results from this study are comparable to the previous results of Chelley-Steeley (1996) who also found a positive 'January' seasonality for large-stock firms for UK stock markets. Menyah (1999) also detected January seasonality in large-firms and found April seasonality in small firms for UK equity returns during the 1956-1992 period. But their January evidence was consistent with portfolio rebalancing hypothesis[13] and not the tax-loss-selling hypothesis. Overall, the results from this study are consistent with results reported in the earlier studies

The 'beta-size' ranked portfolios (see Table 4.6, Panel B) results also indicate that there is sensitivity to portfolio formation and that the Lo and MacKinlay (1990) and Berk (2000) issues mentioned in the Section. 4.4.2 are important.

The combined regressions for all the 342 months for the small and large firms are shown in Table 4.6, Panel A. A positive coefficient on beta is obtained for small and large firms respectively. But both the coefficients are statistically insignificant. But, there is some large firm effect when the portfolios are ranked according to 'beta-size' (see Table 4.6, Panel B). The coefficient on large firm beta is negative and statistically significant at 10% level of significance.

4.4.5.2. BOOK TO MARKET AND SIZE EFFECT IN SMALL AND LARGE FIRMS

This study now examines the BE/ME and size patterns across the different sizes of firm and calendar seasonality. Table 4.6, Panel A reports the results. The BE/ME effect is significant

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[13] Portfolio rebalancing hypothesis was explained in Section 4.2.3

and positive for small firms in the month of 'December' (at 10% significance level) and for the large firms in the months of January (at 10% significance level) and April' (5% significance level). The combined regressions for all the 342 months for the small and large firms are shown in Table 4.6, Panel A. In Panel A, one can see a strong BE/ME effect (average coefficient of .20% (t-statistic of 2.57)) from the small firm slope dummy and an insignificant and low BE/ME effect for the large firm slope dummy (average coefficient of .04% (t-statistic of .848)). Using 'beta-size' ranked portfolios (see Table 4.6, Panel B), a strong small-firm BE/ME effect is found. Clearly, small-firms have a very large impact on the BE/ME effect in the UK stock market. This is the first time this has been documented for the UK stock market.

Calendar effects for the size variable are also reported in Table 4.6, Panel A. There is an evidence of March seasonality for size variable in large firm group. This finding indicates that the large companies earn higher average returns then the small ones in the month of March. The same can be said for small firms in the month of May. The results for the average coefficients on size for small and large firms are given in Table 4.6, Panel A. There is a significantly negative relationship between size and large firm stock returns.

4.4.5.3. SUB-SAMPLE TEST

This study also re-examines the relation between seasonality of returns and size using the sub-period (January 1976-December 1991) sample to compare these results (for systematic risk premium) with the study of Chelley-Steeley (1996). The results are reported in Table 4.7. The results from using the sample period of Chelley-Steeley study are interesting. January and February are the two months, which provide the significantly positive returns

for the large firms (see Panel A). These results are similar to Chelley-Steeley, who found that large firms obtain a significantly positive systematic risk premium during the months of January[14] and April. Chelley-Steeley[15] suggested that the January effect during the early 1990s in the UK was consistent with an increased movement between the UK and US stock market.

The results are different, when the analysis is repeated using the 'beta-size' ranked portfolios. This study finds a significantly negative risk premiums for the small firms in the months of June and September and significantly positive and negative risk premiums for large firms in the months of April (at 10% significance level) and November respectively. The overall results from this section suggest that the systematic risk premium is dependent on the "month of year", "firm size", "sample-period" and "sample size".

4.4.5.4. ADDITIONAL FINDINGS

There is another way (and extension) of doing what Chelley-Steeley (1996) did (and what this study has done in Section 4.4.5.1, 4.4.5.2 and 4.4.5.3). This study re-examines the seasonality in risk premia using samples that (i) exclude the smallest 20% stocks (measured by size), (ii) exclude the lowest 20% beta-stocks, (iii) exclude the 20% extreme beta stocks, (iv) exclude both the smallest 20% of stocks and the 20% extreme beta stocks, and (v) only include the largest 20% of big stocks each year[16]. This methodology is arguably a better way to look at the link between size and seasonal risk pricing.

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[14] Limmack (1995) for the UK stock market, also found January effect, particularly for large firms.

[15] Chelley-Steeley suggested that during 1980s there was increased internationalisation of stock markets, which encouraged the removal of exchange controls. This encouraged an increased co-movement between national stock markets because of the additional pressure from the foreign investors on domestic markets.

[16] In step 1 of Fama and French methodology, the stocks are divided into 25 portfolios on the basis of 'size' and then on 'beta'. After estimating the post-ranking beta, the following stocks are excluded before running the standard cross-sectional regressions in step 2:
a) Without the small firm stocks (excluding portfolio no: 1-5); b) No low beta stocks (excluding portfolio no: 1, 6, 11, 16 and 21); c) No extreme beta stocks (excluding portfolio no: 1, 6, 11, 16, 21 and 5, 10, 15, 20, 25) ; d) No extreme beta and no small firm stocks (excluding portfolio no: same as c and also without 2, 3, 4) and e) Only big firm stocks (only including 21-25).

The results are reported in Table 4.8 (Panels A, B, C, D and E). The results obtained by using the full-sample stocks are very similar to the results obtained by excluding the stocks with different characteristics. For example, in Panel A (excluding the 20% small-firm stocks), a strong and negative relationship between the systematic risk premia and returns is found during the months of June and September. In addition to this, a weak April effect (significant at 10% level of significance) is again found. But the April effect disappears when, low-beta stocks, extreme beta-stocks and both low and extreme beta stocks are excluded from the sample. June is the only month in which this study finds a consistent relationship (negative) between systematic risk premia and returns. October is the only month for 'large-firm' stocks when the systematic risk premia is negatively related to monthly returns (see Panel E). But there is also some April effect for large firms (similar to Chelley-Steeley (1996)). There is no BE/ME effect for large firms (see Panel E). There seems to some BE/ME effect in the month of April for small firms (Panels B and C). But, when small firms are excluded, the BE/ME seasonal in April does not disappear (see Panels A and D). The BE/ME seasonal in April therefore cannot be associated easily with the size effect. As this is just another way of examining the relationship between size and seasonality, it is not surprising that the results are consistent with the earlier findings of this study (see Table 4.1).

4.4.6. SEASONAL ANALYSIS OF POST-RANK BETAS

This study now uses portfolio returns and a SUR procedure (equation (4.3) and (4.4) in Section 4.3.2.4) to examine seasonality in the post rank betas for the months of January and April. The results are reported in Table 4.9, Panel A and Panel B. The coefficient on January slope dummy variable is strongly negative and statistically significant for the first two

(small-size firms) and the fourth, ninth and twenty-first portfolio. Six out of twenty-five portfolios produce positive but insignificant relationship between systematic risk premia and returns for the month of January. Overall, post-rank betas for small firms are significantly lower in January. One can also say that the, investors are compensated with a lower return for the higher risk that they undertake when investing in stocks of small-size firms in January. April effect is also tested for small and large firms (see Table 4.9, Panel B). Only one portfolio (lowest size portfolio) produces a coefficient on April slope dummy variable, which is statistically significant at 10% level of significance. Overall, post-rank betas for small or large firms have no effect in April.

According to Ross (1977), CAPM results are sensitive to the choice of market index. The results from this analysis (Table 4.9, Panels A and B) might be due to the use of an incorrect proxy for the true market portfolio. The results of this study for the value-weighted index are similar to that of equally-weighted index. This is shown in Table 4.9, Panel C and Panel D. One can again see a significantly lower January effect and no April effect for post-rank betas of small firm portfolios.

4.5. CONCLUSION

This chapter has presented an examination of the nature and importance of seasonality in the pricing of risk in the UK stock market. This study mainly investigated the monthly calendar and small-firm effects in the UK stock market from January 1969-December 2001.

The Capital Asset Pricing Model is tested on a month by month basis to identify whether there are monthly differences in the systematic risk premium. The results from this study are quite similar to earlier findings (Menyah (1999), Chelley-Steeley (1996), Corhay, Hawawini and Micheal (1987), Levis (1985) and Strong and Xu (1997)) for the UK market. This study finds an April seasonal in the pricing of beta effect for the UK stock market, using cross-sectional analysis. Tax-selling hypothesis is considered one good reason behind the April effect in the UK stock market. When discrete rates of return, different portfolio sorting procedures, and different sample periods are used, this study finds that the average positive returns in April are robust to most of these changes. There are some interesting counter examples suggesting that the portfolio sorting procedure may be important.

The small firm regularity has been regarded as one of the most robust patterns in stock price behaviour. The findings of this study from cross-sectional regressions do not confirm the existence of a small-firm effect in the UK during the period from January 1969-December 2001. In this study, smaller companies of the UK stock market have an average beta, which is not statistically different from zero. This study also could not find a strong link between the small firm effect and January effect for the UK stock market. Using time series observations and Seemingly Unrelated Regressions (SUR), this study also examines seasonality in post-rank betas of portfolio returns and in this instance finds a January effect, where small firm betas are lower in January. This raises the question of why January/size effect appears to have been accepted by the academic community as a world-wide phenomenon. There can be two interesting reasons: First, stock market returns including small firms have exhibited January seasonal at least on an expost basis. Second, one possibility for the reversal of the UK small firm premium is that the premium estimated so

far might be overstated or perhaps non-existent. This might be due to the problems such as survivorship biases in the database, data-snooping issues and omission of transaction cost.

This study shows that the book-to-market variable is priced strongly in the months of April and May. In addition to this, it can also be seen that this seasonal book-to-market effect is a small firm phenomenon. But there are instances where seasonal book-to-market effects are found for large firms. Overall, the results from this chapter suggest that the BE/ME effect found in Chapter 3 might just be the result of seasonal or size phenomenon. This has not been documented before for the UK stock market.

Evidences in favour of return seasonality in this study have important implications for investment strategies, as it would attack the concept of the Efficient Market Hypothesis (EMH). According to EMH, security prices follow a random walk, thus making it impossible to predict future returns on the basis of any information. Evidences in favour of seasonality invalidate the paradigm of EMH. In the investor chooses an investment strategy based on seasonal patterns, he or she might able to make supernormal profits. But, the existence of significant differences in monthly returns in UK or other markets should not necessarily imply that supernormal profits could be made in these markets, because investors face borrowing constraints and transaction costs. Moreover, as Black (1993, 1993b) noted the out-of-sample return used for exploiting a market anomaly is expected to be zero.

TABLE 4.1
THE MONTHLY CROSS SECTIONAL RELATIONSHIP BETWEEN SYSTEMATIC RISK, SIZE, BOOK-TO-MARKET AND RETURN FOR THE PERIOD JANUARY 1969-DECEMBER 2001

PANEL A: SIZE-BETA PORTFOLIO

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.024	*1.028*	0.018	*0.529*				
Feb	0.007	*0.425*	0.019	*0.877*				
Mar	0.010	*0.832*	0.002	*0.133*				
Apr	0.005	*0.367*	0.030	*1.949* **				
May	0.040	*3.179*	-0.033	*-2.198*				
Jun	0.030	*2.176*	-0.038	*-2.313*				
Jul	-0.004	*-0.212*	0.009	*0.329*				
Aug	0.007	*0.586*	0.001	*0.068*				
Sep	0.031	*2.626*	-0.054	*-3.087*				
Oct	-0.006	*-0.418*	-0.002	*-0.088*				
Nov	0.000	*0.003*	-0.007	*-0.365*				
Dec	-0.001	*-0.035*	0.008	*0.498*				

	γ_0	t	γ_1	T	γ_2	t	γ_3	t
Jan	0.018	*0.529*	0.021	*0.621*	0.003	*0.058*		
Feb	0.019	*0.877*	0.021	*0.957*	0.105	*1.072*		
Mar	0.002	*0.133*	0.002	*0.099*	-0.144	*-1.647* **		
Apr	0.030	*1.949* **	0.030	*1.876* **	-0.013	*-0.541*		
May	-0.033	*-2.198*	-0.032	*-2.233*	-0.088	*-1.046*		
Jun	-0.038	*-2.313*	-0.039	*-2.394*	0.053	*1.547*		
Jul	0.009	*0.329*	0.007	*0.241*	0.039	*0.580*		
Aug	0.001	*0.068*	0.000	*0.014*	0.041	*0.922*		
Sep	-0.054	*-3.087*	-0.057	*-3.198*	-0.053	*-0.509*		
Oct	-0.002	*-0.088*	-0.004	*-0.234*	0.046	*1.066*		
Nov	-0.007	*-0.365*	-0.012	*-0.594*	0.120	*1.628*		
Dec	0.008	*0.498*	0.007	*0.446*	0.025	*0.467*		

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.042	*3.087*			0.017	*0.264*		
Feb	0.025	*3.069*			0.166	*1.216*		
Mar	0.011	*1.128*			-0.136	*-1.596*		
Apr	0.033	*4.615*			0.029	*0.783*		
May	0.011	*1.518*			-0.102	*-1.256*		
Jun	-0.005	*-0.507*			0.017	*0.350*		
Jul	0.005	*0.398*			0.070	*0.653*		
Aug	0.007	*0.620*			0.099	*0.916*		
Sep	-0.018	*-1.545*			-0.101	*-0.804*		
Oct	-0.007	*-0.602*			0.059	*0.747*		
Nov	-0.008	*-0.763*			0.119	*1.357*		
Dec	0.007	*0.767*			0.008	*0.103*		

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.022	*0.944*	0.023	*0.711*			0.003	*1.569*
Feb	0.007	*0.426*	0.021	*0.958*			0.002	*1.559*
Mar	0.010	*0.801*	0.006	*0.397*			0.003	*2.170*
Apr	0.005	*0.360*	0.034	*2.190*			0.003	*2.673*
May	0.039	*3.119*	-0.030	*-2.036*			0.002	*1.696* **
Jun	0.029	*2.112*	-0.037	*-2.262*			0.001	*0.451*
Jul	-0.004	*-0.173*	0.008	*0.281*			0.001	*0.281*
Aug	0.008	*0.701*	0.000	*-0.012*			0.001	*0.348*
Sep	0.032	*2.673*	-0.054	*-3.220*			0.001	*0.711*
Oct	-0.006	*-0.459*	0.000	*0.004*			0.001	*1.072*
Nov	0.000	*-0.024*	-0.006	*-0.332*			0.001	*1.038*
Dec	-0.001	*-0.068*	0.007	*0.432*			0.002	*1.348*

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.044	*3.307*			0.026	*0.419*	0.002	*0.954*
Feb	0.026	*3.238*			0.172	*1.257*	0.002	*1.502*
Mar	0.014	*1.489*			-0.130	*-1.565*	0.002	*1.852* **
Apr	0.035	*4.733*			0.036	*1.016*	0.003	*2.223*
May	0.014	*1.873* **			-0.094	*-1.201*	0.003	*2.707*
Jun	-0.003	*-0.357*			0.018	*0.358*	0.000	*0.260*
Jul	0.006	*0.384*			0.073	*0.645*	0.000	*0.211*
Aug	0.007	*0.584*			0.103	*0.905*	0.001	*0.355*
Sep	-0.017	*-1.494*			-0.095	*-0.771*	0.002	*1.187*
Oct	-0.005	*-0.449*			0.069	*0.860*	0.002	*1.706* **
Nov	-0.008	*-0.743*			0.114	*1.371*	0.001	*0.594*
Dec	0.005	*0.545*			0.001	*0.015*	0.002	*1.720* **

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.044	*3.294*					0.002	*0.951*
Feb	0.026	*3.239*					0.002	*1.406*
Mar	0.014	*1.491*					0.002	*1.820* **
Apr	0.035	*4.771*					0.002	*2.137*
May	0.014	*1.858* **					0.003	*2.661*
Jun	-0.003	*-0.320*					0.000	*0.310*
Jul	0.006	*0.419*					0.000	*0.179*
Aug	0.007	*0.589*					0.000	*0.239*
Sep	-0.016	*-1.502*					0.002	*1.188*
Oct	-0.005	*-0.394*					0.002	*1.710* **
Nov	-0.007	*-0.674*					0.001	*0.585*
Dec	0.005	*0.640*					0.002	*1.577*

TABLE 4.1, PANEL A (cont.)

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.020	*0.854*	0.026	*0.789*	0.009	*0.160*	0.003	*1.556*
Feb	0.005	*0.332*	0.023	*1.021*	0.110	*1.102*	0.002	*1.585*
Mar	0.010	*0.911*	0.005	*0.360*	-0.141	*-1.635*	0.002	*2.159*
Apr	0.006	*0.412*	0.033	*2.098*	-0.008	*-0.342*	0.003	*2.666*
May	0.039	*3.199*	-0.030	*-2.076*	-0.085	*-1.040*	0.002	*1.723* * *
Jun	0.030	*2.291*	-0.038	*-2.354*	0.051	*1.438*	0.001	*0.458*
Jul	-0.002	*-0.090*	0.006	*0.192*	0.046	*0.606*	0.001	*0.285*
Aug	0.008	*0.720*	-0.001	*-0.053*	0.047	*0.921*	0.001	*0.428*
Sep	0.033	*2.917*	-0.056	*-3.322*	-0.050	*-0.490*	0.001	*0.685*
Oct	-0.005	*-0.339*	-0.003	*-0.145*	0.049	*1.122*	0.001	*1.063*
Nov	0.003	*0.170*	-0.011	*-0.570*	0.115	*1.638*	0.001	*1.088*
Dec	-0.001	*-0.053*	0.006	*0.376*	0.020	*0.369*	0.002	*1.402*

Table reports the average and its associated Fama and Macbeth (1973) t-statistics (in bold), of the 29 (29 x 12) estimates obtained for each month. The underlined t-statistics indicates significance at 5%, * *indicates significance at 10% level.*

The 29 estimates for each month (or 342 estimates) are obtained by using the following model and other models (refer to section 4.3.2.1 of text) with different combinations of beta, size and book-to-market variable:

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{2t}\hat{ME}_i+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (4.1)$$

$i=1,2....n$; $t=1,2.....342$

where R_{it} *is the return on individual security i in month t;* β_i *is the post-ranking beta of security i for month t (Post-ranking beta is the full period post-ranking beta of portfolio p, i.e., the slope coefficient from a time-series regression of monthly post-ranking returns on the returns for an equally-weighted portfolio of all portfolios);* ME_i *is the market value of equity for security i for month t;* $(BE/ME)_i$ *is the ratio of book value of equity to its market value for security i for month t;* $\gamma_0,\gamma_1,\gamma_2$ *and* γ_3 *are regression coefficients and* μ_{it} *is the error term. The familiar Fama and Macbeth t-statistic (see Chapter 3, Section: 3.3.2.) is used for testing the monthly estimates.*

PANEL B: BETA-SIZE PORTFOLIO

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.009	*0.667*	0.034	*1.508*				
Feb	-0.005	*-0.418*	0.032	*2.076*				
Mar	0.009	*0.980*	0.003	*0.175*				
Apr	0.009	*0.864*	0.026	*1.868* **				
May	0.016	*2.008*	-0.006	*-0.501*				
Jun	0.021	*2.418*	-0.027	*-2.321*				
Jul	-0.002	*-0.162*	0.008	*0.323*				
Aug	0.004	*0.414*	0.004	*0.266*				
Sep	0.013	*1.204*	-0.033	*-2.202*				
Oct	0.017	*1.291*	-0.026	*-1.745* **				
Nov	0.000	*0.002*	-0.008	*-0.586*				
Dec	0.021	*2.251*	-0.014	*-1.489*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.007	*0.399*	0.037	*1.451*	0.051	*0.598*		
Feb	-0.004	*-0.419*	0.032	*2.100*	0.155	*1.233*		
Mar	0.008	*0.870*	0.004	*0.270*	-0.145	*-1.628*		
Apr	0.009	*0.871*	0.025	*1.850* **	0.030	*0.764*		
May	0.017	*2.082*	-0.006	*-0.526*	-0.107	*-1.247*		
Jun	0.023	*2.676*	-0.029	*-2.569*	0.013	*0.265*		
Jul	-0.005	*-0.297*	0.010	*0.389*	0.079	*0.664*		
Aug	0.004	*0.444*	0.003	*0.203*	0.075	*0.822*		
Sep	0.012	*1.212*	-0.032	*-2.219*	-0.107	*-0.886*		
Oct	0.014	*1.077*	-0.022	*-1.574*	0.041	*0.621*		
Nov	0.001	*0.111*	-0.010	*-0.718*	0.110	*1.247*		
Dec	0.017	*1.751* **	-0.012	*-1.196*	0.023	*0.317*		

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.010	*0.690*	0.035	*1.540*			0.002	*0.901*
Feb	-0.001	*-0.127*	0.030	*1.946* **			0.002	*1.562*
Mar	0.011	*1.173*	0.004	*0.254*			0.002	*2.113*
Apr	0.011	*1.065*	0.025	*1.879* **			0.002	*2.188*
May	0.018	*2.367*	-0.005	*-0.462*			0.003	*2.573*
Jun	0.023	*2.757*	-0.028	*-2.473*			0.000	*0.249*
Jul	-0.002	*-0.119*	0.007	*0.301*			0.000	*0.071*
Aug	0.003	*0.323*	0.004	*0.313*			0.001	*0.294*
Sep	0.014	*1.431*	-0.033	*-2.161*			0.002	*1.211*
Oct	0.017	*1.363*	-0.023	*-1.632*			0.002	*1.702* **
Nov	0.001	*0.081*	-0.008	*-0.623*			0.001	*0.690*
Dec	0.018	*1.936* **	-0.014	*-1.423*			0.002	*1.648* **

	γ_0	t	γ_1	t	γ_2	T	γ_3	t
Jan	0.007	*0.428*	0.038	*1.476*	0.059	*0.721*	0.003	*2.201*
Feb	-0.002	*-0.145*	0.030	*1.983*	0.161	*1.278*	0.002	*1.913* **
Mar	0.010	*1.035*	0.005	*0.358*	-0.138	*-1.587*	0.002	*1.786* **
Apr	0.011	*1.067*	0.025	*1.866* **	0.037	*0.985*	0.002	*1.937* **
May	0.019	*2.387*	-0.005	*-0.480*	-0.099	*-1.195*	0.001	*0.875*
Jun	0.025	*2.983*	-0.030	*-2.721*	0.014	*0.271*	0.000	*0.015*
Jul	-0.004	*-0.259*	0.009	*0.366*	0.082	*0.658*	0.002	*0.752*
Aug	0.004	*0.399*	0.003	*0.233*	0.079	*0.821*	0.001	*0.473*
Sep	0.014	*1.425*	-0.032	*-2.167*	-0.101	*-0.857*	0.001	*0.706*
Oct	0.013	*1.141*	-0.020	*-1.467*	0.050	*0.753*	0.001	*0.688*
Nov	0.002	*0.175*	-0.010	*-0.742*	0.105	*1.247*	0.001	*0.831*
Dec	0.015	*1.464*	-0.011	*-1.136*	0.016	*0.223*	0.002	*1.461*

TABLE 4.1, PANEL B (cont.)

*Table reports the average and its associated Fama and Macbeth (1973) t-statistics (in bold), of the 29 (29 x 12) estimates obtained for each month. The underlined t-statistics indicates significance at 5%, * * indicates significance at 10% level.*

The 29 estimates for each month (or 342 estimates) are obtained by using the following model and other models (refer to section 4.3.2.1 of text) with different combinations of beta, size and book-to-market variable:

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{2t}\hat{ME}_i+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (4.1)$$

i=1,2....n ; t=1,2.....342

where R_{it} *is the return on individual security i in month t;* β_i *is the post-ranking beta of security i for month t (Post-ranking beta is the full period post-ranking beta of portfolio p, i.e., the slope coefficient from a time-series regression of monthly post-ranking returns on the returns for an equally-weighted portfolio of all portfolios);* ME_i *is the market value of equity for security i for month t;* $(BE/ME)_i$ *is the ratio of book value of equity to its market value for security i for month t;* $\gamma_0,\gamma_1,\gamma_2$ *and* γ_3 *are regression coefficients and* μ_{it} *is the error term. The familiar Fama and Macbeth t-statistic (see Chapter 3, Section: 3.3.2.) is used for testing the monthly estimates.*

TABLE 4.1, PANEL C: BETA PORTFOLIO

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.019	1.749**	0.023	1.305				
Feb	0.003	0.390	0.023	1.793**				
Mar	0.011	1.354	0.001	0.048				
Apr	0.010	1.074	0.024	2.110				
May	0.014	2.266	-0.003	-0.364				
Jun	0.015	1.825**	-0.020	-1.861**				
Jul	-0.002	-0.134	0.007	0.288				
Aug	0.006	0.682	0.001	0.095				
Sep	0.010	1.039	-0.029	-2.062				
Oct	0.015	1.274	-0.023	-2.016				
Nov	0.007	0.569	-0.014	-1.135				
Dec	0.019	2.333	-0.013	-1.634				

	γ_0	t	γ_1	t	γ_2	T	γ^t
Jan	0.015	1.185	0.027	1.300	0.046	0.549	
Feb	0.004	0.436	0.022	1.766**	0.161	1.229	
Mar	0.010	1.277	0.002	0.123	-0.143	-1.646**	
Apr	0.011	1.085	0.023	2.092	0.028	0.750	
May	0.015	2.415	-0.004	-0.442	-0.105	-1.257	
Jun	0.015	1.919**	-0.021	-1.992	0.014	0.291	
Jul	-0.007	-0.368	0.011	0.415	0.116	0.749	
Aug	0.007	0.691	0.001	0.041	0.079	0.805	
Sep	0.010	1.024	-0.029	-2.050	-0.113	-0.922	
Oct	0.011	1.034	-0.020	-1.804**	0.051	0.706	
Nov	0.008	0.653	-0.017	-1.207	0.108	1.190	
Dec	0.016	1.710**	-0.010	-1.260	0.015	0.202	

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.021	1.777**	0.023	1.325			0.002	0.924
Feb	0.006	0.744	0.021	1.637			0.002	1.531
Mar	0.013	1.594	0.002	0.125			0.002	2.135
Apr	0.013	1.289	0.024	2.127			0.003	2.268
May	0.016	2.759	-0.003	-0.338			0.003	2.581
Jun	0.017	2.114	-0.021	-2.008			0.000	0.193
Jul	-0.002	-0.107	0.006	0.275			0.000	0.001
Aug	0.005	0.580	0.002	0.150			0.001	0.326
Sep	0.011	1.205	-0.029	-2.006			0.002	1.197
Oct	0.015	1.365	-0.021	-1.904**			0.002	1.695**
Nov	0.008	0.628	-0.015	-1.177			0.001	0.779
Dec	0.016	1.944**	-0.012	-1.559			0.002	1.609

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.017	1.217	0.027	1.3134	0.053	.667	0.002	0.933
Feb	0.007	0.760	0.021	1.6277	0.167	1.270	0.002	1.647**
Mar	0.012	1.491	0.003	0.2088	-0.136	-1.600	0.002	2.143
Apr	0.013	1.292	0.023	2.1141	0.035	.981	0.003	2.339
May	0.017	2.835	-0.003	-0.4048	-0.097	-1.207	0.003	2.629
Jun	0.017	2.167	-0.022	-2.1364	0.014	.297	0.000	0.145
Jul	-0.006	-0.358	0.011	0.4058	0.118	.741	0.000	0.069
Aug	0.006	0.630	0.001	0.0833	0.084	.807	0.001	0.430
Sep	0.011	1.176	-0.028	-1.9945	-0.107	-.893	0.002	1.196
Oct	0.012	1.120	-0.018	-1.6990**	0.060	.819	0.002	1.684**
Nov	0.009	0.694	-0.017	-1.2365	0.103	1.186	0.001	0.799
Dec	0.013	1.381	-0.009	-1.1851	0.009	.114	0.002	1.744**

TABLE 4.1, PANEL C (cont.)

*Table reports the average and its associated Fama and Macbeth (1973) t-statistics (in bold), of the 29 (29 x 12) estimates obtained for each month. The underlined t-statistics indicates significance at 5%, * * indicates significance at 10% level.*

The 29 estimates for each month (or 342 estimates) are obtained by using the following model and other models (refer to section 4.3.2.1 of text) with different combinations of beta, size and book-to-market variable:

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_i + \hat{\gamma}_{2t}\hat{ME}_i + \hat{\gamma}_{3t}(\hat{BE/ME})_i + \mu_{it} \qquad (4.1)$$

i=1,2....n ; t=1,2.....342

where R_{it} is the return on individual security i in month t; β_i is the post-ranking beta of security i for month t (Post-ranking beta is the full period post-ranking beta of portfolio p, i.e., the slope coefficient from a time-series regression of monthly post-ranking returns on the returns for an equally-weighted portfolio of all portfolios); ME_i is the market value of equity for security i for month t; $(BE/ME)_i$ is the ratio of book value of equity to its market value for security i for month t; $\gamma_0, \gamma_1, \gamma_2$ and γ_3 are regression coefficients and μ_{it} is the error term. The familiar Fama and Macbeth t-statistic (see Chapter 3, Section: 3.3.2.) is used for testing the monthly estimates.

PANEL D: SIZE PORTFOLIO

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.035	*1.525*	0.006	*0.198*				
Feb	0.007	*0.382*	0.018	*0.799*				
Mar	0.011	*0.690*	0.001	*0.060*				
Apr	0.009	*0.611*	0.024	*1.484*				
May	0.044	*2.822*	-0.035	*-2.169*				
Jun	0.029	*1.670* **	-0.035	*-1.913* **				
Jul	0.003	*0.171*	0.002	*0.095*				
Aug	0.001	*0.059*	0.007	*0.360*				
Sep	0.030	*1.984*	-0.051	*-2.735*				
Oct	-0.010	*-0.582*	0.003	*0.139*				
Nov	-0.008	*-0.395*	0.002	*0.074*				
Dec	-0.004	*-0.246*	0.011	*0.626*				

	γ_0	t	γ_1	t	γ_2	t	γ	t
Jan	0.032	*1.379*	0.009	*0.303*	-0.004	*-0.087*		
Feb	0.006	*0.319*	0.020	*0.853*	0.107	*1.039*		
Mar	0.012	*0.797*	0.000	*0.000*	-0.129	*-1.620*		
Apr	0.010	*0.658*	0.024	*1.427*	-0.012	*-0.513*		
May	0.044	*2.854*	-0.034	*-2.183*	-0.087	*-1.100*		
Jun	0.030	*1.769* **	-0.036	*-1.972*	0.057	*1.636*		
Jul	0.004	*0.202*	0.001	*0.035*	0.039	*0.556*		
Aug	0.002	*0.126*	0.006	*0.285*	0.038	*1.010*		
Sep	0.032	*2.191*	-0.053	*-2.887*	-0.046	*-0.477*		
Oct	-0.009	*-0.517*	0.001	*0.052*	0.036	*0.964*		
Nov	-0.005	*-0.240*	-0.002	*-0.118*	0.109	*1.717* **		
Dec	-0.004	*-0.238*	0.011	*0.584*	0.027	*0.554*		

	γ_0	t	γ_1	t	γ_2	γ_3	t
Jan	0.032	*1.399*	0.012	*0.419*		0.003	*1.702* **
Feb	0.006	*0.350*	0.021	*0.901*		0.002	*1.590*
Mar	0.010	*0.638*	0.005	*0.295*		0.002	*1.931* **
Apr	0.008	*0.563*	0.028	*1.729* **		0.003	*2.608*
May	0.043	*2.781*	-0.033	*-2.063*		0.001	*1.452*
Jun	0.028	*1.627*	-0.034	*-1.867* **		0.001	*0.579*
Jul	0.004	*0.230*	0.001	*0.035*		0.001	*0.322*
Aug	0.002	*0.158*	0.006	*0.276*		0.001	*0.443*
Sep	0.031	*2.009*	-0.051	*-2.856*		0.000	*0.421*
Oct	-0.010	*-0.615*	0.004	*0.217*		0.001	*1.003*
Nov	-0.008	*-0.405*	0.002	*0.095*		0.001	*1.115*
Dec	-0.004	*-0.258*	0.010	*0.550*		0.002	*1.184*

	γ_0	t	γ_1	t	γ_2	T	γ_3	t
Jan	0.029	*1.262*	0.015	*0.505*	0.002	*0.040*	0.003	*1.687* **
Feb	0.005	*0.299*	0.022	*0.937*	0.110	*1.062*	0.002	*1.539*
Mar	0.011	*0.745*	0.004	*0.233*	-0.126	*-1.606*	0.002	*1.928* **
Apr	0.009	*0.613*	0.027	*1.658* **	-0.007	*-0.335*	0.003	*2.605*
May	0.043	*2.818*	-0.032	*-2.083*	-0.084	*-1.094*	0.001	*1.443*
Jun	0.029	*1.721* **	-0.035	*-1.931* **	0.055	*1.525*	0.001	*0.591*
Jul	0.005	*0.267*	-0.001	*-0.028*	0.045	*0.577*	0.001	*0.326*
Aug	0.003	*0.220*	0.005	*0.216*	0.043	*0.995*	0.001	*0.494*
Sep	0.033	*2.211*	-0.053	*-3.007*	-0.045	*-0.467*	0.000	*0.355*
Oct	-0.009	*-0.549*	0.003	*0.129*	0.040	*1.036*	0.001	*0.977*
Nov	-0.005	*-0.250*	-0.002	*-0.105*	0.105	*1.715* **	0.001	*1.192*
Dec	-0.004	*-0.249*	0.009	*0.503*	0.023	*0.458*	0.002	*1.247*

TABLE 4.1, PANEL D (cont.)

Table reports the average and its associated Fama and Macbeth (1973) t-statistics (in bold), of the 29 (29 x 12) estimates obtained for each month. The underlined t-statistics indicates significance at 5%, indicates significance at 10% level.

The 29 estimates for each month (or 342 estimates) are obtained by using the following model and other models (refer to section 4.3.2.1 of text) with different combinations of beta, size and book-to-market variable:

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{2t}\hat{ME}_i+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (4.1)$$

i=1,2....n ; t=1,2.....342

where R_{it} is the return on individual security i in month t; β_i is the post-ranking beta of security i for month t (Post-ranking beta is the full period post-ranking beta of portfolio p, i.e., the slope coefficient from a time-series regression of monthly post-ranking returns on the returns for an equally-weighted portfolio of all portfolios); ME_i is the market value of equity for security i for month t; $(BE/ME)_i$ is the ratio of book value of equity to its market value for security i for month t; $\gamma_0,\gamma_1,\gamma_2$ and γ_3 are regression coefficients and μ_{it} is the error term. The familiar Fama and Macbeth t-statistic (see Chapter 3, Section: 3.3.2.) is used for testing the monthly estimates.

TABLE 4.1, PANEL E: BETA-SIZE (2 x 5) PORTFOLIO

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.033	1.815**	0.008	0.314				
Feb	0.004	0.218	0.022	1.035				
Mar	0.010	0.810	0.001	0.093				
Apr	0.007	0.570	0.027	1.914**				
May	0.044	3.406	-0.035	-2.504				
Jun	0.027	1.895**	-0.033	-2.156				
Jul	0.002	0.131	0.003	0.157				
Aug	0.005	0.406	0.003	0.179				
Sep	0.027	2.314	-0.047	-2.943				
Oct	-0.004	-0.283	-0.003	-0.174				
Nov	-0.011	-0.624	0.004	0.232				
Dec	-0.002	-0.116	0.009	0.555				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.031	1.691**	0.011	0.436	-0.004	-0.070		
Feb	0.003	0.162	0.023	1.099	0.090	0.941		
Mar	0.011	0.874	0.001	0.095	-0.129	-1.562		
Apr	0.007	0.581	0.027	1.873**	-0.024	-0.828		
May	0.043	3.475	-0.034	-2.542	-0.075	-1.006		
Jun	0.028	2.035	-0.035	-2.249	0.059	1.786**		
Jul	0.003	0.193	0.001	0.073	0.021	0.386		
Aug	0.006	0.473	0.002	0.096	0.035	1.072		
Sep	0.028	2.598	-0.049	-3.079	-0.044	-0.441		
Oct	-0.003	-0.199	-0.005	-0.289	0.034	1.025		
Nov	-0.008	-0.455	0.000	-0.002	0.110	1.692**		
Dec	-0.001	-0.086	0.008	0.490	0.024	0.525		

	γ_0	t	γ_1	t	γ^t	γ_3	t
Jan	0.032	1.703**	0.008	0.330		0.000	0.047
Feb	0.004	0.256	0.022	0.995		0.000	0.191
Mar	0.008	0.640	0.004	0.283		0.002	1.102
Apr	0.005	0.402	0.028	1.945**		0.003	2.140
May	0.043	3.286	-0.034	-2.411		0.001	2.609
Jun	0.027	1.813**	-0.032	-2.040		0.002	1.650**
Jul	0.002	0.109	0.003	0.149		0.003	1.048
Aug	0.003	0.245	0.004	0.239		0.002	1.418
Sep	0.026	2.227	-0.046	-2.957		0.003	1.951**
Oct	-0.005	-0.284	-0.003	-0.166		0.003	1.736**
Nov	-0.011	-0.619	0.005	0.276		0.003	0.658
Dec	0.001	0.039	0.007	0.454		0.001	0.319

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.030	1.582	0.011	0.437	-0.003	-0.059	0.000	0.089
Feb	0.003	0.197	0.023	1.061	0.090	0.935	0.001	0.209
Mar	0.009	0.682	0.004	0.303	-0.131	-1.596	0.002	1.090
Apr	0.006	0.407	0.028	1.903**	-0.025	-0.850	0.003	2.234
May	0.042	3.353	-0.033	-2.447	-0.076	-1.014	0.001	2.649
Jun	0.028	1.945	-0.033	-2.149	0.056	1.753**	0.003	1.806
Jul	0.003	0.169	0.001	0.066	0.022	0.406	0.003	1.051
Aug	0.004	0.313	0.003	0.155	0.035	1.068	0.002	1.518
Sep	0.028	2.513	-0.049	-3.109	-0.045	-0.447	0.003	1.993
Oct	-0.003	-0.205	-0.005	-0.279	0.034	1.044	0.003	0.309
Nov	-0.008	-0.462	0.001	0.046	0.109	1.684**	0.003	1.095
Dec	0.001	0.068	0.006	0.389	0.023	0.505	0.000	0.265

TABLE 4.1, PANEL E (cont.)

Table reports the average and its associated Fama and Macbeth (1973) t-statistics (in bold), of the 29 (29 x 12) estimates obtained for each month. The underlined t-statistics indicates significance at 5%, indicates significance at 10% level.

The 29 estimates for each month (or 342 estimates) are obtained by using the following model and other models (refer to section 4.3.2.1 of text) with different combinations of beta, size and book-to-market variable:

$$R_{it}=\hat{\gamma}_{0t}+\hat{\gamma}_{1t}\hat{\beta}_i+\hat{\gamma}_{2t}\hat{ME}_i+\hat{\gamma}_{3t}(\hat{BE/ME})_i+\mu_{it} \qquad (4.1)$$

i=1,2....n ; t=1,2.....342

where R_{it} is the return on individual security i in month t; β_i is the post-ranking beta of security i for month t (Post-ranking beta is the full period post-ranking beta of portfolio p, i.e., the slope coefficient from a time-series regression of monthly post-ranking returns on the returns for an equally-weighted portfolio of all portfolios); ME_i is the market value of equity for security i for month t; $(BE/ME)_i$ is the ratio of book value of equity to its market value for security i for month t; $\gamma_0,\gamma_1,\gamma_2$ and γ_3 are regression coefficients and μ_{it} is the error term. The familiar Fama and Macbeth t-statistic (see Chapter 3, Section: 3.3.2.) is used for testing the monthly estimates.

TABLE 4.2
THE MONTHLY CROSS SECTIONAL RELATIONSHIP BETWEEN SYSTEMATIC RISK, SIZE, BOOK-TO-MARKET AND DISCRETE RETURNS FOR THE PERIOD JANUARY 1969- DECEMBER 2001

PANEL A: SIZE-BETA PORTFOLIO

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.029	*1.144*	0.028	*0.796*				
Feb	0.031	*4.195*	0.002	*0.475*				
Mar	0.016	*1.863* **	0.001	*0.414*				
Apr	0.041	*5.031*	-0.002	*-0.500*				
May	0.022	*2.749*	-0.007	*-1.782* **				
Jun	0.013	*1.281*	-0.011	*-2.550*				
Jul	0.012	*1.044*	-0.011	*-2.106*				
Aug	0.024	*2.658*	-0.012	*-1.369*				
Sep	0.006	*0.628*	-0.013	*-1.925* **				
Oct	0.001	*0.046*	-0.001	*-0.073*				
Nov	0.017	*1.241*	-0.012	*-1.174*				
Dec	0.019	*1.736* **	-0.001	*-0.161*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.028	*1.039*	0.030	*0.812*	-0.013	*-0.186*		
Feb	0.031	*4.239*	0.003	*0.568*	-0.008	*-0.097*		
Mar	0.017	*1.929* **	0.001	*0.329*	-0.101	*-1.339*		
Apr	0.042	*5.103*	-0.002	*-0.742*	0.055	*1.185*		
May	0.022	*2.735*	-0.007	*-1.737* **	-0.085	*-1.373*		
Jun	0.013	*1.306*	-0.011	*-2.551*	-0.037	*-1.278*		
Jul	0.011	*0.977*	-0.010	*-1.983*	-0.044	*-1.428*		
Aug	0.024	*2.603*	-0.013	*-1.366*	0.103	*0.877*		
Sep	0.006	*0.634*	-0.013	*-1.871* **	-0.046	*-0.776*		
Oct	0.000	*0.013*	-0.001	*-0.059*	-0.036	*-0.886*		
Nov	0.017	*1.233*	-0.012	*-1.174*	-0.059	*-0.756*		
Dec	0.018	*1.617*	-0.001	*-0.130*	0.067	*1.111*		

	γ_0	t	γ_1	T	γ_2	t	γ_3	t
Jan	0.033	*1.276*	0.029	*0.826*			0.006	*1.924* **
Feb	0.032	*4.418*	0.003	*0.593*			0.003	*2.032*
Mar	0.018	*2.180*	0.002	*0.666*			0.002	*2.083*
Apr	0.043	*5.060*	-0.001	*-0.299*			0.002	*2.843*
May	0.024	*2.950*	-0.007	*-1.628*			0.002	*1.545*
Jun	0.013	*1.337*	-0.011	*-2.609*			0.001	*0.761*
Jul	0.011	*0.977*	-0.011	*-2.198*			0.001	*1.031*
Aug	0.023	*2.566*	-0.012	*-1.411*			0.000	*0.553*
Sep	0.007	*0.735*	-0.013	*-1.927* **			0.002	*1.324*
Oct	0.002	*0.190*	0.000	*-0.011*			0.003	*1.866* **
Nov	0.017	*1.302*	-0.011	*-1.159*			0.001	*0.768*
Dec	0.019	*1.734* **	-0.002	*-0.294*			0.000	*0.153*

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.032	*1.160*	0.031	*0.836*	0.006	*0.099*	0.006	*1.927* **
Feb	0.032	*4.435*	0.003	*0.663*	0.002	*0.022*	0.003	*2.019*
Mar	0.019	*2.239*	0.002	*0.558*	-0.096	*-1.286*	0.002	*2.140*
Apr	0.044	*5.139*	-0.002	*-0.551*	0.061	*1.314*	0.002	*2.866*
May	0.023	*2.909*	-0.006	*-1.601*	-0.081	*-1.309*	0.002	*1.297*
Jun	0.013	*1.357*	-0.010	*-2.613*	-0.042	*-1.451*	0.002	*0.837*
Jul	0.011	*0.912*	-0.010	*-2.065*	-0.047	*-1.625*	0.001	*1.150*
Aug	0.024	*2.529*	-0.013	*-1.400*	0.104	*0.872*	0.000	*0.309*
Sep	0.007	*0.737*	-0.013	*-1.873* **	-0.040	*-0.704*	0.002	*1.319*
Oct	0.002	*0.150*	0.000	*-0.002*	-0.025	*-0.660*	0.003	*1.849* **
Nov	0.018	*1.289*	-0.012	*-1.163*	-0.058	*-0.767*	0.001	*0.677*
Dec	0.018	*1.608*	-0.002	*-0.262*	0.067	*1.119*	0.000	*0.316*

TABLE 4.2 (cont.)

PANEL B: BETA-SIZE PORTFOLIO

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.018	*1.138*	0.041	*1.664* *				
Feb	0.010	*1.041*	0.024	*1.653* *				
Mar	0.002	*0.224*	0.016	*1.200*				
Apr	0.013	*1.211*	0.027	*2.240*				
May	0.026	*2.939*	-0.012	*-1.160*				
Jun	0.014	*1.563*	-0.013	*-1.107*				
Jul	0.010	*0.948*	-0.010	*-1.026*				
Aug	0.005	*0.553*	0.006	*0.540*				
Sep	-0.002	*-0.175*	-0.006	*-0.418*				
Oct	0.015	*1.280*	-0.015	*-1.296*				
Nov	0.008	*0.652*	-0.003	*-0.213*				
Dec	0.020	*1.778* *	-0.002	*-0.244*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.017	*0.965*	0.042	*1.594*	-0.013	*-0.186*		
Feb	0.011	*1.144*	0.023	*1.570*	-0.008	*-0.097*		
Mar	0.003	*0.269*	0.016	*1.251*	-0.101	*-1.339*		
Apr	0.014	*1.288*	0.026	*2.193*	0.055	*1.185*		
May	0.027	*3.090*	-0.013	*-1.291*	-0.085	*-1.373*		
Jun	0.015	*1.658* *	-0.014	*-1.222*	-0.037	*-1.278*		
Jul	0.010	*0.909*	-0.009	*-1.021*	-0.044	*-1.428*		
Aug	0.005	*0.511*	0.006	*0.561*	0.103	*0.877*		
Sep	-0.004	*-0.383*	-0.004	*-0.276*	-0.046	*-0.776*		
Oct	0.013	*1.125*	-0.013	*-1.125*	-0.036	*-0.886*		
Nov	0.007	*0.588*	-0.003	*-0.181*	-0.059	*-0.756*		
Dec	0.018	*1.588*	-0.001	*-0.126*	0.067	*1.111*		

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.021	*1.248*	0.041	*1.690* *			0.005	*1.580*
Feb	0.013	*1.415*	0.023	*1.545*			0.003	*1.884* *
Mar	0.006	*0.584*	0.015	*1.153*			0.002	*2.384*
Apr	0.015	*1.368*	0.028	*2.298*			0.002	*2.741*
May	0.028	*3.316*	-0.012	*-1.197*			0.002	*1.846* *
Jun	0.018	*2.138*	-0.016	*-1.407*			0.001	*0.678*
Jul	0.010	*0.861*	-0.009	*-1.026*			0.001	*0.967*
Aug	0.004	*0.432*	0.007	*0.597*			0.000	*0.336*
Sep	0.000	*0.038*	-0.006	*-0.460*			0.002	*1.404*
Oct	0.016	*1.453*	-0.014	*-1.257*			0.003	*1.790* *
Nov	0.011	*0.945*	-0.005	*-0.358*			0.001	*0.739*
Dec	0.018	*1.641*	-0.002	*-0.210*			0.000	*0.176*

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.020	*1.065*	0.043	*1.617*	0.037	*0.416*	0.005	*1.595*
Feb	0.014	*1.475*	0.022	*1.474*	0.004	*0.061*	0.003	*1.872* *
Mar	0.006	*0.620*	0.015	*1.206*	-0.096	*-1.318*	0.002	*2.445*
Apr	0.016	*1.437*	0.027	*2.260*	0.058	*1.333*	0.002	*2.783*
May	0.030	*3.403*	-0.013	*-1.316*	-0.081	*-1.350*	0.002	*1.554*
Jun	0.018	*2.155*	-0.016	*-1.500*	-0.041	*-1.459*	0.001	*0.748*
Jul	0.009	*0.820*	-0.009	*-1.020*	-0.053	*-1.808* *	0.001	*1.077*
Aug	0.004	*0.428*	0.007	*0.597*	0.091	*0.792*	0.000	*0.108*
Sep	-0.002	*-0.161*	-0.004	*-0.320*	-0.050	*-0.847*	0.002	*1.405*
Oct	0.014	*1.283*	-0.012	*-1.084*	-0.026	*-0.655*	0.003	*1.755* *
Nov	0.010	*0.851*	-0.004	*-0.311*	-0.064	*-0.793*	0.001	*0.640*
Dec	0.017	*1.449*	-0.001	*-0.101*	0.072	*1.170*	0.000	*0.302*

*Table reports the average and its associated t-statistics (in bold) of the 29 (29 x 12) estimates obtained for each month. 29 estimates are obtained for each month using the discrete rates of return. The underlined t-statistics indicates significance at 5%, * * indicates significance at 10% level. Refer to Table 4.1 for more details.*

TABLE 4.3
SUB-SAMPLE TEST: JANUARY 1976- DECEMBER 1991

PANEL A: ANALYSIS USING CONTINUOUS RATES OF RETURN

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.032	** *1.781*	0.009	*0.395*				
Feb	0.024	*1.348*	0.008	*0.313*				
Mar	0.023	** *1.658*	0.014	*0.870*				
Apr	0.024	** *1.865*	0.004	*0.303*				
May	0.042	*2.621*	-0.030	*-1.475*				
Jun	0.036	** *1.717*	-0.027	*-1.280*				
Jul	0.003	*0.093*	0.023	*0.471*				
Aug	-0.005	*-0.312*	0.026	*0.898*				
Sep	0.032	*2.194*	-0.044	*-2.492*				
Oct	0.012	*0.616*	-0.025	*-0.928*				
Nov	-0.019	*-0.711*	0.021	*0.936*				
Dec	0.013	*0.721*	0.003	*0.123*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.027	*1.629*	0.020	*0.988*	-0.069	*-1.383*	0.005	** *1.847*
Feb	0.023	*1.353*	0.012	*0.465*	0.119	*0.722*	0.002	*1.369*
Mar	0.022	** *1.653*	0.018	*1.096*	-0.132	*-1.184*	0.003	*1.580*
Apr	0.027	*2.156*	0.005	*0.394*	-0.008	*-0.253*	0.005	*2.520*
May	0.042	*2.592*	-0.027	*-1.332*	-0.169	*-1.371*	0.003	** *1.689*
Jun	0.034	** *1.748*	-0.027	*-1.345*	0.075	*1.321*	0.002	*0.807*
Jul	0.004	*0.127*	0.022	*0.435*	0.076	*0.581*	0.002	*0.351*
Aug	-0.003	*-0.190*	0.022	*0.754*	0.093	*1.021*	0.002	*0.541*
Sep	0.034	*2.421*	-0.046	*-2.716*	-0.123	*-0.675*	0.001	*0.563*
Oct	0.011	*0.616*	-0.022	*-0.810*	0.052	*0.687*	0.003	*1.458*
Nov	-0.017	*-0.658*	0.016	*0.731*	0.200	** *1.685*	0.004	** *1.767*
Dec	0.012	*0.654*	0.003	*0.131*	-0.065	*-0.991*	0.002	*0.899*

PANEL B: ANALYSIS USING DISCRETE RATES OF RETURN

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.021	*0.491*	0.056	*0.917*				
Feb	0.040	*3.768*	0.004	*0.612*				
Mar	0.036	*3.511*	0.003	*0.793*				
Apr	0.037	*3.426*	-0.002	*-0.491*				
May	0.026	*2.426*	-0.009	*-1.544*				
Jun	0.021	*1.422*	-0.010	*-1.509*				
Jul	0.025	*1.373*	-0.013	*-1.558*				
Aug	0.030	*2.407*	-0.019	*-1.238*				
Sep	0.008	*0.625*	-0.014	*-1.241*				
Oct	-0.010	*-0.454*	0.004	*0.258*				
Nov	0.015	*0.830*	-0.014	*-0.843*				
Dec	0.014	*0.914*	0.009	*0.824*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.025	*0.537*	0.059	*0.936*	-0.008	*-0.079*	0.009	** *1.828*
Feb	0.043	*4.067*	0.005	*0.791*	-0.011	*-0.085*	0.004	*2.000*
Mar	0.038	*3.576*	0.003	*0.908*	-0.155	*-1.254*	0.001	*1.207*
Apr	0.041	*3.536*	-0.003	*-0.580*	0.109	*1.390*	0.004	*2.659*
May	0.027	*2.429*	-0.008	*-1.503*	-0.094	*-0.935*	0.001	*0.624*
Jun	0.019	*1.277*	-0.010	*-1.621*	-0.086	** *-1.841*	0.004	*1.427*
Jul	0.024	*1.242*	-0.012	*-1.398*	-0.113	*-2.432*	0.001	*0.706*
Aug	0.031	*2.294*	-0.020	*-1.257*	0.190	*0.882*	0.001	*0.371*
Sep	0.010	*0.775*	-0.013	*-1.138*	-0.084	*-0.824*	0.004	** *1.715*
Oct	-0.007	*-0.308*	0.006	*0.348*	-0.054	*-0.806*	0.005	** *1.879*
Nov	0.016	*0.815*	-0.015	*-0.853*	-0.103	*-0.762*	0.000	*0.189*
Dec	0.013	*0.851*	0.009	*0.824*	0.067	*0.704*	0.000	*0.056*

*Panel A reports the average of 16 (16 x 12) estimates and its associated t-statistics (in bold) for each month using the continuous rates of returns. Panel B reports the average of 16 estimates and its associated t-statistics (in bold) for each month using the discrete rates of returns. The underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level.*

TABLE 4.4
THE MONTHLY CROSS SECTIONAL RELATIONSHIPS USING THE SUR PROCEDURE

PANEL A: SIZE-BETA PORTFOLIO

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.006	*0.351*	0.025	*1.006*				
Feb	0.022	*1.663* **	-0.005	*-0.309*				
Mar	0.009	*0.672*	0.028	*1.596*				
Apr	0.050	*4.290*	-0.040	*-2.878*				
May	0.029	*1.881* **	-0.040	*-2.213*				
Jun	-0.001	*-0.042*	0.011	*0.330*				
Jul	0.001	*0.091*	0.012	*0.484*				
Aug	0.029	*2.007*	-0.040	*-2.205*				
Sep	0.000	*-0.021*	-0.009	*-0.414*				
Oct	-0.003	*-0.171*	-0.008	*-0.411*				
Nov	-0.002	*-0.153*	0.010	*0.533*				
Dec	-0.001	*-0.188*	0.011	*0.268*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.013	*0.571*	0.035	*0.983*	0.001	*0.179*		
Feb	0.005	*0.277*	0.026	*1.104*	0.014	*1.287*		
Mar	0.022	*1.758* **	-0.004	*-0.278*	-0.015	*-1.569*		
Apr	0.009	*0.660*	0.028	*1.561*	0.000	*0.028*		
May	0.051	*4.515*	-0.042	*-3.047*	-0.013	*-1.313*		
Jun	0.030	*2.058*	-0.041	*-2.323*	0.006	*1.488*		
Jul	0.000	*0.022*	0.009	*0.255*	0.005	*0.665*		
Aug	0.003	*0.241*	0.009	*0.370*	0.004	*0.793*		
Sep	0.030	*2.183*	-0.041	*-2.333*	-0.008	*-0.677*		
Oct	0.000	*0.030*	-0.010	*-0.484*	0.004	*0.935*		
Nov	0.001	*0.030*	-0.013	*-0.646*	0.013	*1.611*		
Dec	-0.002	*-0.126*	0.009	*0.472*	0.003	*0.456*		

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.013	*0.564*	0.039	*1.127*			0.004	*1.594*
Feb	0.006	*0.352*	0.026	*1.068*			0.002	*1.375*
Mar	0.021	*1.591*	0.000	*-0.013*			0.002	*2.077*
Apr	0.009	*0.656*	0.032	*1.820* **			0.004	*2.264*
May	0.049	*4.237*	-0.038	*-2.744*			0.001	*1.648* *
Jun	0.028	*1.841* **	-0.039	*-2.194*			0.001	*0.502*
Jul	0.000	*0.010*	0.009	*0.252*			0.000	*0.160*
Aug	0.002	*0.116*	0.010	*0.424*			0.000	*0.016*
Sep	0.030	*2.042*	-0.040	*-2.358*			0.001	*0.741*
Oct	-0.001	*-0.077*	-0.007	*-0.339*			0.001	*0.757*
Nov	-0.003	*-0.195*	-0.009	*-0.465*			-0.003	*1.366*
Dec	-0.003	*-0.186*	0.010	*0.494*			-0.001	*0.968*

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.011	*0.499*	0.041	*1.170*	0.002	*0.319*	0.003	*1.581*
Feb	0.005	*0.287*	0.028	*1.155*	0.014	*1.314*	0.002	*1.384*
Mar	0.021	*1.678* **	0.000	*0.032*	-0.015	*-1.558*	0.002	*2.002*
Apr	0.009	*0.650*	0.032	*1.769* **	0.001	*0.443*	0.004	*2.270*
May	0.051	*4.466*	-0.040	*-2.925*	-0.012	*-1.309*	0.001	*1.489*
Jun	0.029	*2.018*	-0.040	*-2.313*	0.005	*1.312*	0.001	*0.491*
Jul	0.002	*0.080*	0.006	*0.178*	0.006	*0.693*	0.001	*0.194*
Aug	0.004	*0.279*	0.008	*0.313*	0.004	*0.815*	0.000	*0.110*
Sep	0.030	*2.215*	-0.041	*-2.478*	-0.008	*-0.669*	0.001	*0.694*
Oct	0.000	*-0.021*	-0.009	*-0.414*	0.005	*0.968*	0.001	*0.761*
Nov	0.000	*0.005*	-0.014	*-0.702*	0.012	*1.624*	0.003	*1.405*
Dec	-0.002	*-0.159*	0.009	*0.429*	0.002	*0.382*	0.001	*1.017*

TABLE 4.4 (cont.)

PANEL B: BETA-SIZE PORTFOLIO

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.021	*1.593*	0.026	*1.165*				
Feb	0.014	*1.097*	0.017	*1.512*				
Mar	-0.003	*-0.187*	0.019	*1.053*				
Apr	0.013	*1.533*	0.023	*1.935* **				
May	0.028	*2.194*	-0.015	*-1.031*				
Jun	0.006	*0.549*	-0.013	*-1.287*				
Jul	0.005	*0.406*	0.005	*0.186*				
Aug	0.010	*1.137*	0.002	*0.217*				
Sep	0.008	*0.738*	-0.015	*-1.171*				
Oct	0.020	*1.581*	-0.027	*-2.601*				
Nov	0.010	*0.691*	-0.022	*-1.492*				
Dec	0.016	*1.821* **	-0.010	*-1.313*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.021	*1.582*	0.026	*1.180*	0.000	*0.020*		
Feb	0.013	*0.976*	0.018	*1.527*	0.011	*0.853*		
Mar	-0.003	*-0.223*	0.020	*1.109*	-0.008	*-1.104*		
Apr	0.014	*1.699* **	0.022	*1.879* **	-0.002	*-0.652*		
May	0.031	*2.419*	-0.016	*-1.186*	-0.016	*-1.808* **		
Jun	0.006	*0.576*	-0.014	*-1.366*	0.005	*1.199*		
Jul	0.002	*0.104*	0.008	*0.316*	0.012	*0.851*		
Aug	0.009	*1.022*	0.002	*0.251*	0.007	*0.953*		
Sep	0.009	*0.923*	-0.016	*-1.270*	-0.014	*-1.044*		
Oct	0.018	*1.453*	-0.025	*-2.369*	0.001	*0.110*		
Nov	0.010	*0.663*	-0.022	*-1.521*	0.014	*1.813* **		
Dec	0.014	*1.495*	-0.009	*-1.127*	0.004	*0.441*		

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.025	*1.874* **	0.026	*1.182*			0.004	*1.700* **
Feb	0.017	*1.316*	0.015	*1.312*			0.002	*1.247*
Mar	0.000	*0.023*	0.019	*1.075*			0.002	*1.517*
Apr	0.016	*1.894* **	0.022	*1.932* **			0.003	*1.830* **
May	0.031	*2.494*	-0.014	*-1.015*			0.003	*3.817*
Jun	0.009	*0.834*	-0.015	*-1.523*			0.001	*0.401*
Jul	0.005	*0.426*	0.004	*0.165*			0.000	*0.054*
Aug	0.008	*0.865*	0.003	*0.294*			0.001	*0.759*
Sep	0.010	*1.063*	-0.016	*-1.220*			0.003	*1.156*
Oct	0.022	*1.867* **	-0.026	*-2.653*			0.003	*2.339*
Nov	0.009	*0.657*	-0.021	*-1.537*			0.002	*1.181*
Dec	0.015	*1.754* **	-0.011	*-1.449*			0.001	*1.257*

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.025	*1.839* **	0.026	*1.196*	0.001	*0.264*	0.004	*1.689* **
Feb	0.016	*1.172*	0.016	*1.348*	0.011	*0.901*	0.002	*1.320*
Mar	0.000	*-0.024*	0.020	*1.138*	-0.008	*-1.065*	0.002	*1.431*
Apr	0.017	*2.052*	0.021	*1.883* **	-0.001	*-0.296*	0.003	*1.860* **
May	0.033	*2.681*	-0.016	*-1.161*	-0.015	*-1.733* **	0.003	*3.784*
Jun	0.009	*0.849*	-0.015	*-1.598*	0.006	*1.201*	0.001	*0.405*
Jul	0.002	*0.128*	0.007	*0.291*	0.012	*0.835*	0.000	*0.030*
Aug	0.008	*0.808*	0.003	*0.300*	0.007	*0.928*	0.001	*0.450*
Sep	0.011	*1.229*	-0.017	*-1.302*	-0.013	*-1.033*	0.002	*1.161*
Oct	0.020	*1.742* **	-0.025	*-2.422*	0.002	*0.262*	0.003	*2.385*
Nov	0.009	*0.634*	-0.022	*-1.564*	0.013	*1.837* **	0.002	*1.187*
Dec	0.013	*1.410*	-0.009	*-1.254*	0.003	*0.375*	0.001	*1.498*

*Table reports the average and its associated t-statistics (in bold) of the 29 (or 29x12) estimates obtained for each month. The underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level. Instead of using the standard OLS, the SUR procedure is used in the last stage of Fama and French (1992) methodology to obtain the 29 estimates for each month. The rest of the details are the same as Table 4.1.*

TABLE 4.5
SEASONALITY WITH RESTRICTIONS

PANEL A: TESTING THE EQUALITY OF 12 MONTHS

		Wald test (a)	Probability	Wald test (b)	Probability
Jul-73	*Jun-74*	**52.7049**	**0.0000**	18.1820	0.0770
Jul-74	*Jun-75*	**81.6295**	**0.0000**	**28.4350**	**0.0030**
Jul-75	*Jun-76*	**72.4024**	**0.0000**	**21.7270**	**0.0270**
Jul-76	*Jun-77*	**76.5956**	**0.0000**	11.2570	0.4220
Jul-77	*Jun-78*	**103.4864**	**0.0000**	**46.5860**	**0.0000**
Jul-78	*Jun-79*	**69.7614**	**0.0000**	**39.0540**	**0.0000**
Jul-79	*Jun-80*	**111.4153**	**0.0000**	**35.3890**	**0.0000**
Jul-80	*Jun-81*	26.7317	0.0600	25.0840	0.0900
Jul-81	*Jun-82*	**44.8991**	**0.0000**	**21.4530**	**0.0290**
Jul-82	*Jun-83*	**72.5643**	**0.0000**	16.6710	0.1180
Jul-83	*Jun-84*	**44.5126**	**0.0000**	**49.0040**	**0.0000**
Jul-84	*Jun-85*	**73.3793**	**0.0000**	18.6880	0.0670
Jul-85	*Jun-86*	**43.5865**	**0.0000**	14.1480	0.2250
Jul-86	*Jun-87*	**119.3581**	**0.0000**	12.1880	0.3500
Jul-87	*Jun-88*	**330.4427**	**0.0000**	**43.2390**	**0.0000**
Jul-88	*Jun-89*	**83.2923**	**0.0000**	**45.2400**	**0.0000**
Jul-89	*Jun-90*	**77.2558**	**0.0000**	**29.4690**	**0.0020**
Jul-90	*Jun-91*	**31.9815**	**0.0008**	19.6640	0.0600
Jul-91	*Jun-92*	**63.4283**	**0.0000**	12.8570	0.3030
Jul-92	*Jun-93*	**124.6198**	**0.0000**	**26.7060**	**0.0050**
Jul-93	*Jun-94*	**48.2380**	**0.0000**	**36.7610**	**0.0000**
Jul-94	*Jun-95*	**74.9695**	**0.0000**	15.2210	0.1730
Jul-95	*Jun-96*	**48.4772**	**0.0000**	**32.5050**	**0.0010**
Jul-96	*Jun-97*	**32.5763**	**0.0006**	10.3770	0.4970
Jul-97	*Jun-98*	**30.8822**	**0.0011**	**21.8827**	**0.0253**
Jul-98	*Jun-99*	**95.9618**	**0.0000**	**39.2814**	**0.0000**
Jul-99	*Jun-00*	**107.2311**	**0.0000**	**20.6428**	**0.0373**
Jul-00	*Jun-01*	**29.9207**	**0.0016**	18.3410	0.0740
Jul-01	*Dec-01*	4.6480	0.4603	13.5612	0.0787

PANEL B: TESTING THE EQUALITY OF 36 MONTHS

		Wald test (a)	Probability	Wald test (b)	Probability
Jul-73	*Jun-76*	**214.3907**	**0.0000**	**66.4442**	**0.0010**
Jul-76	*Jun-79*	**266.3686**	**0.0000**	**65.2616**	**0.0014**
Jul-79	*Jun-82*	**156.9003**	**0.0000**	**81.1624**	**0.0000**
Jul-82	*Jun-85*	**213.8863**	**0.0000**	**69.4032**	**0.0005**
Jul-85	*Jun-88*	**493.7256**	**0.0000**	**111.1461**	**0.0000**
Jul-88	*Jun-91*	**347.5838**	**0.0000**	**103.2819**	**0.0000**
Jul-91	*Jun-94*	**235.4390**	**0.0000**	**87.6148**	**0.0000**
Jul-94	*Jun-97*	**166.0683**	**0.0000**	**83.0158**	**0.0000**
Jul-97	*Jun-00*	**156.5112**	**0.0000**	**115.3657**	**0.0000**
Jul-00	*Dec-01*	**37.6179**	**0.0028**	**31.6558**	**0.0166**

With the help of the SUR technique this study also test the restriction that the monthly returns are same for all months in a given year. Wald test is used for this purpose. The table reports the Wald test and its associated probability value. Bold coefficients denote Wald test statistics that are significant at 5% level of significance (or with a p-value less than .050).

(a) Analysis is done on size-beta ranked portfolio

(b) Analysis is done on beta-size ranked portfolio

TABLE 4.6
SEASONALITY AND SMALL FIRM EFFECT: JANUARY 1969-DECEMBER 2001

PANEL A: SIZE-BETA RANKED PORTFOLIOS

	α_1	t	ι_1	t	ι_2	t	λ_1	t	λ_2	t	γ_1	t	γ_2	t	ℓ_1	t	ℓ_2	t
Jan	0.040	**2.875**	-0.027	*-1.000*	-0.081	**-2.193**	0.035	*1.269*	0.080	**2.128**	-0.004	*-0.775*	0.008	*0.629*	0.005	*1.122*	0.003	*1.749* **
Feb	0.023	**2.131**	-0.002	*-0.152*	-0.044	*-1.902* **	0.003	*0.143*	0.048	*1.992* **	-0.002	*-0.331*	0.003	*0.254*	0.002	*0.878*	0.001	*1.179*
Mar	0.011	*0.972*	0.005	*0.454*	-0.010	*-0.397*	0.008	*0.469*	0.019	*0.771*	0.000	*-0.093*	-0.031	**-2.644**	0.007	*1.598*	0.001	*1.056*
Apr	0.033	**2.962**	-0.026	*-1.812* **	-0.008	*-0.336*	0.029	*1.689* **	0.020	*0.844*	0.004	*0.885*	-0.004	*-0.701*	0.000	*0.086*	0.004	**2.556**
May	0.009	*1.166*	0.003	*0.188*	0.017	*0.870*	0.011	*0.542*	-0.026	*-1.271*	-0.007	**-2.076**	-0.010	*-0.969*	0.001	*0.318*	0.000	*0.636*
Jun	0.003	*0.236*	0.011	*0.869*	0.045	**2.417**	0.000	*-0.009*	-0.045	**-2.285**	-0.002	*-1.079*	-0.009	*-0.715*	0.000	*0.294*	0.001	*0.454*
Jul	0.001	*0.058*	0.008	*0.370*	-0.008	*-0.302*	0.003	*0.095*	0.013	*0.458*	-0.004	*-0.611*	-0.014	*-1.191*	0.006	*1.037*	0.002	*1.119*
Aug	0.008	*0.859*	0.011	*0.683*	-0.006	*-0.274*	-0.008	*-0.465*	0.007	*0.288*	0.000	*0.140*	-0.017	*-1.733* **	0.003	*0.887*	0.000	*0.092*
Sep	0.000	*-0.019*	0.015	*1.128*	0.009	*0.345*	-0.006	*-0.341*	-0.019	*-0.702*	-0.003	*-1.742* **	0.001	*0.086*	0.002	*0.953*	0.001	*0.691*
Oct	-0.005	*-0.324*	0.024	*1.533*	0.027	*0.934*	-0.026	*-1.223*	-0.021	*-0.725*	-0.001	*-0.372*	0.000	*0.021*	0.000	*0.012*	0.001	*0.515*
Nov	0.004	*0.284*	0.004	*0.237*	-0.033	*-1.166*	0.012	*0.567*	0.039	*1.373*	-0.006	*-1.110*	-0.010	*-0.904*	0.001	*0.426*	0.002	*1.308*
Dec	0.006	*0.613*	0.016	*0.913*	-0.023	*-0.923*	-0.015	*-0.712*	0.027	*1.052*	0.002	*0.471*	0.003	*0.418*	0.004	*1.814* **	0.001	*0.902*
Combined	0.010	**2.974**	0.004	*0.856*	-0.008	*-1.100*	0.002	*0.489*	0.010	*1.357*	-0.002	*-1.548*	0.000	**-2.082**	0.002	**2.577**	0.004	*0.848*

*Table reports the average of 29 (29 x 12) estimates and its associated t-statistics (in bold) (the underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level) for each month using the following model:*

$$R_{i,t}=\tilde{\alpha}_{i,t}+\tilde{\alpha}_{2,t}\hat{\beta}_{i,t}+\tilde{\alpha}_{3,t}\hat{ME}i,t+\alpha_{4,t}\,\hat{BE/ME}i,t+\sum_{j=1}^{2}\tilde{\iota}_{i,t}\delta_{j,t}+\sum_{j=1}^{2}\tilde{\lambda}_{i,t}\,(\delta_{j,t}\hat{\beta}_{i,t})+\sum_{j=1}^{2}\tilde{\gamma}_{i,t}\,(\delta_{j,t}\hat{ME}i,t)+\sum_{J=1}^{2}\tilde{\ell}_{i,t}(\delta_{j,t}\,\hat{BE/ME}i,t) \qquad (4.2)$$
$$+\tilde{\mu}_{i,t}$$

where $\tilde{\alpha}_{1,t},\tilde{\alpha}_{2,t},\tilde{\alpha}_{3,t},\alpha_{4,t}$ (already reported in table 4.1) are the average coefficients associated with the intercept, systematic risk (β), Market Size (ME) and Book to Market effect (BE/ME) respectively. The δ_1 takes on the value of 1 if the pth portfolio consist of small sized firms, but a value of zero otherwise. δ_2 takes on the value of 1 if the pth portfolio consists of large firms and zero otherwise. $\tilde{\iota}_1,\tilde{\iota}_2$, are the average coefficients associated with the two slope dummies. δ_1 δ_2, $\tilde{\lambda}_1$ $\tilde{\lambda}_2$, $\tilde{\gamma}_1$ $\tilde{\gamma}_2$ & $\tilde{\ell}_1,\tilde{\ell}_2$, are the average coefficients associated with the two slope dummies for systematic risk, size and book-to-market respectively.

TABLE 4.6 (cont.)

PANEL B: BETA-SIZE RANKED PORTFOLIOS

	α_1	t	l_1	t	l_2	t	λ_1	T	λ_2	t	γ_1	t	γ_2	t	ℓ_1	t	ℓ_2	t
Jan	0.010	*0.406*	-0.006	*-0.125*	-0.038	*-0.728*	0.028	*0.423*	0.045	*0.900*	0.004	*0.860*	0.006	*0.606*	0.008	*1.073*	0.005	* * *1.867*
Feb	0.034	*2.271*	-0.015	*-0.749*	-0.013	*-0.323*	0.009	*0.405*	0.017	*0.434*	-0.006	*-0.582*	0.069	*0.837*	0.002	*1.045*	0.002	*1.529*
Mar	0.015	*1.616*	-0.004	*-0.301*	0.051	*1.417*	0.005	*0.354*	-0.051	*-1.461*	0.015	*1.098*	-0.025	*-0.636*	0.005	*3.080*	0.001	*0.668*
Apr	0.036	*5.443*	-0.015	*-1.206*	-0.021	*-0.622*	0.014	*1.184*	0.022	*0.654*	0.020	*1.223*	-0.008	*-0.803*	0.003	* * *1.929*	0.001	*0.732*
May	0.014	*1.358*	-0.014	*-0.915*	0.019	*0.436*	0.018	*0.950*	-0.017	*-0.421*	-0.006	*-0.528*	-0.086	*-1.277*	0.004	*1.219*	0.002	*2.851*
Jun	-0.003	*-0.275*	0.035	*2.175*	0.011	*0.284*	-0.039	*-2.383*	-0.013	*-0.367*	0.002	*0.639*	0.017	*0.705*	0.000	*0.055*	0.000	*0.093*
Jul	0.021	*1.581*	-0.011	*-0.399*	-0.017	*-0.419*	0.011	*0.296*	0.017	*0.415*	-0.003	*-0.329*	0.099	*0.953*	0.007	*0.705*	0.000	*0.274*
Aug	0.008	*0.514*	0.000	*-0.024*	-0.011	*-0.318*	-0.001	*-0.095*	0.012	*0.362*	-0.004	*-1.185*	0.076	*1.055*	0.003	*0.973*	0.000	*0.071*
Sep	-0.043	*-1.961*	0.040	*2.144*	0.044	*1.003*	-0.032	*-1.594*	-0.048	*-1.119*	-0.025	*-0.937*	-0.082	*-1.286*	0.001	*0.702*	0.000	*0.132*
Oct	0.009	*0.533*	-0.002	*-0.122*	0.100	*1.994*	0.008	*0.487*	-0.096	* * *-1.950*	0.013	*0.715*	0.009	*0.237*	0.006	* * *1.720*	0.002	*1.441*
Nov	-0.001	*-0.086*	0.014	*0.732*	0.051	*1.073*	-0.015	*-0.766*	-0.053	*-1.183*	0.002	*0.249*	0.047	*1.491*	0.001	*0.406*	0.002	*0.976*
Dec	-0.005	*-0.343*	0.020	*1.141*	0.081	*2.068*	-0.020	*-1.048*	-0.084	*-2.203*	0.019	*0.651*	-0.017	*-0.247*	0.001	*0.379*	0.004	* * *1.889*
Combined	0.008	* * *1.770*	0.031	*0.483*	0.022	* * *1.826*	-0.005	*-0.066*	-0.021	* * *-1.829*	.000	*0.556*	.000	*0.539*	0.003	*2.81*	0.006	*1.223*

*Table reports the average of 29 (29 x 12) estimates and its associated t-statistics (in bold) (the underlined t-statistics indicates significance at 5%, * * indicates significance at 10% level) for each month using the following model:*

$$R_{i,t}=\tilde{\alpha}_{i,t}+\tilde{\alpha}_{2,t}\hat{\beta}_{i,t}+\tilde{\alpha}_{3,t}\hat{ME}i,t+\alpha_{4,t}\,\hat{BE/ME}i,t+\sum_{j=1}^{2}\tilde{\iota}_{i,t}\delta_{j,t}+\sum_{j=1}^{2}\tilde{\lambda}_{i,t}\,(\delta_{j,t}\hat{\beta}_{i,t})+\sum_{j=1}^{2}\tilde{\gamma}_{i,t}\,(\delta_{j,t}\hat{ME}i,t)+\sum_{J=1}^{2}\tilde{\ell}_{i,t}(\delta_{j,t}\,\hat{BE/ME}i,t)+\tilde{\mu}_{i,t} \quad (4.2)$$

where $\tilde{\alpha}_{1,t},\tilde{\alpha}_{2,t},\tilde{\alpha}_{3,t},\alpha_{4,t}$ (already reported in table 4.1) are the average coefficients associated with the intercept, systematic risk (β), Market Size (ME) and Book to Market effect (BE/ME) respectively. The δ_1 takes on the value of 1 if the pth portfolio consist of small sized firms, but a value of zero otherwise. δ_2 takes on the value of 1 if the pth portfolio consists of large firms and zero otherwise. $\tilde{\iota}_1,\tilde{\iota}_2$, are the average coefficients associated with the two slope dummies. δ_1 δ_2, $\tilde{\lambda}_1\tilde{\lambda}_2$, $\tilde{\gamma}_1\tilde{\gamma}_2$ & $\tilde{\ell}_1,\tilde{\ell}_2$, are the average coefficients associated with the two slope dummies for systematic risk, size and book-to-market respectively.

TABLE 4.7
SUB-SAMPLE TEST (JANUARY 1976-DECEMBER 1991): SEASONALITY AND SMALL FIRM EFFECT

PANEL A: SIZE-BETA RANKED PORTFOLIOS

	α_1	t	ι_1	t	ι_2	t	λ_1	t	λ_2	t	γ_1	t	γ_2	t	ℓ_1	t	ℓ_2	t
Jan	0.043	*4.054*	-0.012	*-0.709*	-0.065	*-1.800* **	0.023	*1.183*	0.090	*2.333*	-0.004	*-0.593*	-0.001	*-1.597*	0.006	*0.740*	0.007	*2.483*
Feb	0.026	*3.004*	0.009	*0.561*	-0.090	*-3.157*	0.008	*0.350*	0.107	*3.094*	-0.014	*-1.549*	0.001	*0.647*	0.004	*0.883*	0.002	*0.731*
Mar	0.032	*3.406*	-0.006	*-0.428*	-0.012	*-0.444*	0.020	*0.904*	0.018	*0.615*	0.006	*0.892*	-0.002	*-1.426*	0.015	*2.075*	0.001	*0.289*
Apr	0.029	*4.248*	-0.010	*-0.761*	-0.010	*-0.379*	0.034	*1.706* **	0.021	*0.683*	-0.003	*-0.740*	0.000	*0.480*	0.001	*0.302*	0.007	*2.226*
May	0.016	*1.403*	0.000	*-0.016*	0.005	*0.208*	0.025	*0.786*	-0.018	*-0.698*	-0.011	*-2.269*	-0.002	*-1.675* **	0.000	*0.071*	0.001	*0.911*
Jun	0.011	*1.051*	0.013	*1.320*	0.021	*1.029*	0.000	*0.014*	-0.031	*-1.275*	-0.003	*-0.769*	0.001	*1.896* **	0.000	*0.152*	0.003	*0.635*
Jul	0.008	*0.850*	0.016	*1.272*	0.005	*0.184*	-0.014	*-0.988*	-0.012	*-0.435*	-0.002	*-0.538*	0.000	*-1.478*	0.003	*0.690*	0.003	*1.427*
Aug	0.016	*1.538*	0.002	*0.142*	-0.034	*-1.871* **	0.002	*0.142*	0.037	*1.932*	-0.004	*-1.524*	-0.001	*-1.006*	0.001	*0.208*	0.002	*1.624*
Sep	0.001	*0.098*	0.019	*1.353*	-0.004	*-0.110*	-0.019	*-1.116*	-0.007	*-0.195*	-0.004	*-1.702* **	0.001	*1.687* **	0.001	*0.396*	0.002	*0.685*
Oct	-0.008	*-0.390*	0.024	*1.594*	0.021	*0.537*	-0.013	*-0.593*	-0.034	*-0.810*	-0.008	*-2.963*	0.000	*0.232*	0.002	*0.383*	0.000	*0.198*
Nov	-0.001	*-0.049*	0.007	*0.466*	-0.028	*-1.099*	-0.002	*-0.080*	0.031	*1.280*	-0.004	*-1.304*	0.001	*1.810* **	0.001	*0.265*	0.003	*1.412*
Dec	0.016	*1.988*	0.003	*0.243*	-0.035	*-1.214*	-0.004	*-0.238*	0.047	*1.400*	0.004	*0.778*	-0.001	*-1.491*	0.005	*1.386*	0.000	*0.296*

PANEL B: BETA-SIZE RANKED PORTFOLIOS

	α_1	t	ι_1	t	ι_2	t	λ_1	t	λ_2	t	γ_1	t	γ_2	t	ℓ_1	t	ℓ_2	t
Jan	0.066	*2.868*	-0.080	*-0.859*	-0.022	*-0.285*	0.121	*0.949*	0.039	*0.535*	0.008	*0.962*	0.001	*0.397*	0.016	*1.043*	0.009	*1.761* **
Feb	0.042	*3.310*	-0.029	*-1.995*	0.043	*0.717*	0.029	*1.826* **	-0.035	*-0.611*	-0.019	*-0.929*	0.014	*0.854*	0.004	*1.138*	0.003	*1.147*
Mar	0.042	*3.984*	0.002	*0.134*	0.035	*0.789*	-0.002	*-0.107*	-0.034	*-0.797*	0.027	*0.982*	-0.006	*-0.695*	*0.008*	*2.540*	0.000	*0.012*
Apr	0.045	*5.290*	-0.023	*-1.367*	-0.060	*-1.720* **	0.026	*1.475*	0.063	*1.844* **	0.009	*1.403*	-0.001	*-0.651*	*0.007*	*2.551*	0.004	*1.152*
May	0.019	*1.478*	-0.006	*-0.390*	-0.018	*-0.287*	0.009	*0.487*	0.021	*0.350*	0.008	*0.687*	-0.018	-1.279	0.009	*1.433*	0.004	*2.298*
Jun	0.011	*0.862*	0.042	*2.871*	-0.005	*-0.071*	-0.049	*-3.237*	0.003	*0.046*	0.007	*1.260*	0.004	0.753	0.003	*0.586*	0.001	*0.415*
Jul	0.027	*1.155*	-0.021	*-0.916*	0.022	*0.442*	0.032	*1.033*	-0.017	*-0.335*	0.000	*-0.017*	0.020	*0.871*	0.016	*0.746*	0.001	*0.349*
Aug	0.031	*2.222*	-0.014	*-0.852*	-0.078	*-1.215*	0.010	*0.663*	0.076	*1.238*	-0.001	*-0.325*	0.016	*1.052*	0.004	*0.654*	0.000	*0.071*
Sep	-0.002	*-0.125*	0.031	*3.860*	0.038	*0.775*	-0.023	*-2.232*	-0.033	*-0.717*	-0.001	*-0.871*	-0.016	*-1.217*	0.004	*1.318*	0.000	*0.148*
Oct	-0.006	*-0.255*	0.006	*0.314*	-0.001	*-0.017*	0.001	*0.051*	0.007	*0.116*	-0.004	*-1.137*	0.001	*0.107*	0.007	*1.382*	0.004	*1.331*
Nov	0.006	*0.344*	-0.009	*-0.490*	0.105	*2.497*	-0.002	*-0.105*	*-0.106*	*-2.629*	0.005	*1.103*	0.010	*1.459*	0.004	*1.808* **	0.006	*1.507*
Dec	0.017	*1.533*	0.025	*1.285*	0.070	*1.117*	-0.023	*-1.122*	-0.067	*-1.082*	0.002	*1.026*	-0.006	*-0.379*	0.001	*0.118*	-0.005	*1.142*

*Table reports the average of 16 (16 x 12) estimates, its associated t-statistics (in bold) using the equation (4.2). The underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level. Refer to Table 4.6 for more details.*

TABLE 4.8
ADDITIONAL FINDINGS OF SEASONALITY AND SMALL FIRM EFFECT: JANUARY 1969-DECEMBER 2001

PANEL A: EXCLUDING 20% SMALL FIRMS

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.012	*0.634*	0.038	*1.198*				
Feb	0.011	*0.799*	0.020	*0.987*				
Mar	0.010	*1.096*	0.009	*0.719*				
Apr	0.011	*0.979*	0.026	*1.718* *				
May	0.037	*3.551*	-0.025	*-1.793* *				
Jun	0.032	*2.802*	-0.044	*-3.331*				
Jul	0.010	*0.509*	-0.005	*-0.149*				
Aug	0.009	*0.858*	0.002	*0.092*				
Sep	0.019	*2.172*	-0.027	*-2.027*				
Oct	0.004	*0.347*	-0.015	*-1.015*				
Nov	0.007	*0.472*	-0.024	*-1.294*				
Dec	0.005	*0.457*	-0.001	*-0.053*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.012	*0.577*	0.041	*1.348*	0.006	*0.237*	0.003	*1.311*
Feb	0.009	*0.663*	0.025	*1.225*	-0.009	*-0.526*	0.002	*1.028*
Mar	0.008	*0.868*	0.018	*1.327*	-0.027	*-1.660* *	0.004	*2.255*
Apr	0.014	*1.313*	0.025	*1.742* *	0.021	*1.917* *	0.003	*2.910*
May	0.033	*3.152*	-0.016	*-1.186*	-0.036	*-2.194*	0.002	*1.349*
Jun	0.030	*2.773*	-0.042	*-3.194*	-0.014	*-0.988*	0.002	*0.767*
Jul	0.013	*0.670*	-0.006	*-0.206*	0.000	*-0.014*	0.004	*0.714*
Aug	0.007	*0.714*	0.005	*0.296*	-0.028	*-1.456*	0.002	*0.597*
Sep	0.019	*2.326*	-0.026	*-1.914* *	-0.018	*-1.462*	0.002	*1.017*
Oct	0.005	*0.464*	-0.017	*-1.182*	-0.021	*-1.218*	0.001	*0.578*
Nov	0.007	*0.502*	-0.023	*-1.357*	-0.006	*-0.307*	0.001	*0.654*
Dec	0.007	*0.633*	-0.007	*-0.502*	0.034	*1.012*	0.002	*0.863*

PANEL B: EXCLUDING 20% LOW BETA PORTFOLIOS

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.018	*0.736*	0.031	*0.831*				
Feb	0.005	*0.239*	0.026	*1.028*				
Mar	0.022	*1.437*	-0.003	*-0.159*				
Apr	0.014	*0.923*	0.023	*1.272*				
May	0.045	*3.435*	-0.036	*-2.253*				
Jun	0.034	*2.370*	-0.045	*-2.515*				
Jul	-0.002	*-0.094*	0.012	*0.355*				
Aug	0.009	*0.650*	0.004	*0.163*				
Sep	0.023	*1.684* *	-0.033	*-2.014*				
Oct	-0.003	*-0.201*	-0.006	*-0.274*				
Nov	0.000	*0.019*	-0.012	*-0.561*				
Dec	-0.015	*-0.840*	0.022	*1.129*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.015	*0.624*	0.038	*1.079*	0.001	*0.919*	0.004	*1.562*
Feb	0.006	*0.293*	0.027	*1.101*	0.002	*1.427*	0.001	*1.265*
Mar	0.019	*1.401*	0.003	*0.162*	-0.002	*-1.530*	0.002	*1.711* *
Apr	0.014	*0.935*	0.027	*1.492*	0.000	*0.208*	0.004	*2.417*
May	0.045	*3.573*	-0.032	*-2.121*	-0.001	*-0.911*	0.002	*2.412*
Jun	0.033	*2.570*	-0.043	*-2.628*	0.000	*0.092*	0.000	*0.056*
Jul	0.000	*0.016*	0.008	*0.231*	0.000	*0.129*	0.001	*0.235*
Aug	0.013	*0.932*	-0.002	*-0.087*	0.002	*1.491*	0.000	*0.081*
Sep	0.024	*1.825* *	-0.035	*-2.200*	-0.001	*-0.787*	0.000	*0.235*
Oct	-0.003	*-0.195*	-0.007	*-0.332*	0.001	*1.075*	0.001	*0.326*
Nov	0.003	*0.166*	-0.016	*-0.747*	0.001	*1.293*	0.002	*1.021*
Dec	-0.015	*-0.883*	0.020	*1.004*	0.000	*0.330*	0.002	*1.472*

TABLE 4.8 (cont.)

PANEL C: EXCLUDING 20 EXTREME BETA PORTFOLIOS

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.014	*0.500*	0.033	*0.773*				
Feb	0.010	*0.499*	0.021	*0.799*				
Mar	0.016	*1.086*	0.002	*0.149*				
Apr	0.022	*1.575*	0.014	*0.829*				
May	0.041	*2.925*	-0.032	*-1.811* * *				
Jun	0.025	*1.620*	-0.036	*-2.109*				
Jul	-0.005	*-0.220*	0.016	*0.459*				
Aug	0.008	*0.618*	0.005	*0.220*				
Sep	0.025	*1.748*	-0.037	*-2.083*				
Oct	-0.007	*-0.389*	-0.001	*-0.051*				
Nov	-0.002	*-0.090*	-0.010	*-0.437*				
Dec	-0.012	*-0.694*	0.020	*0.970*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.015	*0.536*	0.037	*0.899*	0.001	*0.951*	0.004	*1.842* * *
Feb	0.011	*0.608*	0.023	*0.921*	0.002	*1.545*	0.002	*1.563*
Mar	0.010	*0.693*	0.014	*0.958*	-0.002	*-1.867* * *	0.003	*1.959* * *
Apr	0.022	*1.586*	0.020	*1.186*	0.000	*-0.054*	0.005	*2.927*
May	0.041	*2.972*	-0.028	*-1.649* * *	-0.001	*-0.942*	0.002	*1.326*
Jun	0.024	*1.726* * *	-0.034	*-2.135*	0.000	*0.558*	0.000	*0.027*
Jul	0.000	*-0.007*	0.008	*0.216*	0.000	*-0.409*	0.000	*0.084*
Aug	0.013	*0.986*	-0.001	*-0.041*	0.002	*1.732* * *	0.002	*0.575*
Sep	0.026	*1.902* * *	-0.037	*-2.334*	-0.001	*-0.677*	0.001	*0.469*
Oct	-0.004	*-0.282*	-0.005	*-0.232*	0.001	*0.831*	0.000	*0.069*
Nov	0.001	*0.057*	-0.014	*-0.626*	0.001	*1.186*	0.001	*0.969*
Dec	-0.011	*-0.679*	0.019	*0.869*	0.000	*0.592*	0.000	*0.174*

PANEL D: EXCLUDING BOTH 20% OF SMALLEST STOCKS AND 20% OF EXTREME BETA STOCKS

	γ_0	T	γ_1	t	γ_2	t	γ_3	t
Jan	0.013	*0.541*	0.036	*0.976*				
Feb	0.009	*0.590*	0.023	*1.065*				
Mar	0.002	*0.173*	0.020	*1.519*				
Apr	0.022	*1.731*	0.014	*0.872*				
May	0.036	*2.702*	-0.023	*-1.340*				
Jun	0.030	*2.306*	-0.042	*-3.078*				
Jul	0.006	*0.264*	0.001	*0.044*				
Aug	0.020	*1.509*	-0.010	*-0.453*				
Sep	0.018	*1.537*	-0.026	*-1.661* * *				
Oct	-0.006	*-0.454*	-0.001	*-0.074*				
Nov	0.016	*0.901*	-0.033	*-1.511*				
Dec	-0.001	*-0.079*	0.007	*0.356*				

	γ_0	t	γ_1	t	γ_2	t	γ_3	t
Jan	0.014	*0.588*	0.035	*0.925*	0.001	*0.313*	0.003	*1.185*
Feb	0.017	*1.422*	0.014	*0.933*	0.004	*0.591*	0.002	*0.770*
Mar	-0.005	*-0.369*	0.036	*2.197*	-0.011	*-1.616*	0.003	*1.484*
Apr	0.028	*2.455*	0.010	*0.727*	0.004	*0.979*	0.006	*3.211*
May	0.026	*1.893* * *	-0.005	*-0.282*	-0.005	*-0.998*	0.002	*1.026*
Jun	0.024	*2.217*	-0.034	*-2.710*	-0.002	*-0.373*	0.001	*0.314*
Jul	0.012	*0.598*	-0.006	*-0.190*	-0.002	*-0.570*	0.002	*0.440*
Aug	0.035	*3.149*	-0.032	*-1.782* * *	0.017	*1.101*	0.004	*1.047*
Sep	0.009	*0.910*	-0.012	*-0.800*	-0.010	*-1.500*	0.001	*0.240*
Oct	-0.011	*-0.808*	0.003	*0.205*	-0.001	*-0.131*	0.001	*0.479*
Nov	0.023	*1.583*	-0.046	*-2.425*	0.008	*0.786*	0.001	*0.760*
Dec	-0.003	*-0.224*	0.010	*0.679*	-0.001	*-0.164*	0.002	*0.722*

TABLE 4.8 (cont.)

PANEL E: ONLY INCLUDING 20% LARGE FIRM PORTFOLIOS

	γ_0	T	γ_1	t	γ_2	t	γ_3	t
Jan	0.003	*0.124*	0.050	*1.266*				
Feb	0.019	*1.410*	0.013	*0.620*				
Mar	0.014	*0.955*	0.003	*0.162*				
Apr	0.004	*0.349*	0.037	*1.846* **				
May	0.008	*0.641*	0.023	*1.160*				
Jun	0.020	*1.798* **	-0.020	*-1.269*				
Jul	0.008	*0.360*	0.000	*0.003*				
Aug	0.020	*1.318*	-0.011	*-0.436*				
Sep	0.018	*1.326*	-0.025	*-1.163*				
Oct	0.029	*1.658* **	-0.047	*-2.041*				
Nov	-0.010	*-0.525*	0.007	*0.275*				
Dec	0.019	*1.549*	-0.019	*-0.972*				

	γ_0	T	γ_1	t	γ_2	t	γ_3	t
Jan	0.010	*0.447*	0.052	*1.575*	-0.015	*-1.014*	0.008	*1.426*
Feb	0.013	*0.748*	0.010	*0.453*	0.011	*0.897*	0.003	*0.651*
Mar	0.022	*1.719* **	0.003	*0.144*	0.007	*0.421*	0.006	*1.442*
Apr	0.000	*-0.029*	0.033	*1.559*	0.006	*1.013*	0.000	*0.123*
May	0.018	*1.397*	0.026	*1.340*	-0.023	*-2.224*	0.003	*0.787*
Jun	0.013	*1.063*	-0.011	*-0.653*	0.002	*0.185*	0.001	*0.258*
Jul	0.028	*1.720* **	-0.011	*-0.407*	-0.017	*-0.766*	0.011	*1.260*
Aug	0.019	*1.077*	-0.010	*-0.431*	0.019	*1.103*	0.003	*0.476*
Sep	0.023	*1.687* **	-0.020	*-0.991*	-0.012	*-2.186*	0.002	*0.558*
Oct	0.046	*2.751*	-0.051	*-2.152*	-0.015	*-1.675* **	0.004	*0.687*
Nov	-0.002	*-0.087*	0.009	*0.353*	-0.009	*-1.651* **	0.000	*0.104*
Dec	0.031	*2.145*	-0.020	*-0.865*	0.001	*0.136*	0.009	*2.299*

*Table reports the average and its associated t-statistics of the 29 (29 x 12) estimates obtained for each month. The underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level. The 29 estimates for each month (or 342 estimates) are obtained by using the models mentioned in Table 4.1.*

The following stocks are excluded before running the standard cross-sectional regressions:
Panel A: Without the small firm stocks (portfolio no: 1-5);
Panel B: No low beta stocks (portfolio no: 1,6,11,16 and 21);
Panel C: No extreme beta stocks (portfolio no: 1,6,11,16,21 and 5,10,15,20,25);
Panel D: No extreme beta and no small firm stocks (portfolio no: same as Panel C and also without 2,3,4);
Panel E: Only big firm stocks (only include 21-25);

TABLE 4.9
THE TIME SERIES RELATIONSHIP BETWEEN SYSTEMATIC RISK (JANUARY AND APRIL) AND PORTFOLIO RETURNS FOR THE PERIOD JANUARY 1969- DECEMBER 2001

EQUALLY WEIGHTED INDEX:

PANEL A: TEST OF JANUARY EFFECT

Size-Beta Ranked Portfolio	γ_0	t-value	γ_1 (January dummy)	t-value	β_{1p}	t-value	β_{2p}	t-value
Smallest	0.007	*3.018*	0.027	*2.723*	0.617	*13.657*	-0.627	*-5.292*
2	0.006	*2.589*	0.028	*3.119*	0.582	*13.878*	-0.457	*-4.223*
3	0.009	*4.259*	-0.001	*-0.111*	0.718	*19.175*	-0.087	*-0.565*
4	0.004	* * *1.771*	0.018	* * *1.841*	0.691	*16.510*	-0.401	*-3.436*
5	0.002	*0.844*	0.015	*1.484*	0.873	*20.655*	-0.152	*-1.310*
6	0.002	*0.756*	0.011	*1.197*	0.727	*17.751*	-0.132	*-1.233*
7	0.001	*0.313*	0.005	*0.571*	0.664	*19.444*	0.164	*1.164*
8	0.001	*0.513*	0.008	*1.026*	0.900	*28.262*	-0.085	*-0.644*
9	0.003	* * *1.734*	0.016	*2.052*	0.729	*21.250*	-0.230	*-2.434*
10	-0.002	*-0.753*	0.017	* * *1.926*	0.906	*23.761*	-0.193	* * *-1.833*
11	-0.004	* * *-1.835*	0.022	*2.645*	0.780	*21.803*	-0.124	*-1.260*
12	0.002	*1.108*	-0.005	*-0.595*	0.811	*20.930*	0.159	*1.125*
13	-0.001	*-0.864*	0.004	*0.551*	0.882	*31.256*	-0.036	*-0.463*
14	-0.001	*-0.608*	0.009	*1.247*	0.919	*29.103*	0.054	*0.623*
15	-0.002	*-1.179*	0.016	*2.016*	1.022	*30.797*	-0.039	*-0.432*
16	-0.002	*-0.768*	-0.001	*-0.138*	0.886	*25.626*	0.140	*1.472*
17	0.000	*-0.073*	0.015	*2.097*	0.915	*30.082*	-0.140	* * *-1.667*
18	-0.002	*-0.912*	0.007	*0.968*	0.937	*29.719*	-0.008	*-0.089*
19	0.000	*-0.051*	0.007	*1.045*	1.051	*34.620*	0.044	*0.522*
20	-0.003	* * *-1.766*	0.016	*2.173*	1.065	*33.303*	-0.040	*-0.458*
21	-0.002	*-0.797*	0.009	*0.951*	1.025	*24.385*	-0.254	*-2.192*
22	0.001	*0.534*	-0.001	*-0.135*	1.018	*26.842*	-0.032	*-0.311*
23	-0.001	*-0.544*	0.002	*0.254*	1.008	*26.502*	0.118	*1.124*
24	-0.002	*-0.904*	0.004	*0.463*	1.053	*27.911*	0.035	*0.333*
Largest	-0.001	*-0.270*	0.003	*0.356*	1.131	*27.291*	-0.033	*-0.290*

PANEL B: TEST OF APRIL EFFECT

Size-Beta Ranked Portfolio	γ_0	t-value	γ_1 (April dummy)	t-value	β_{1p}	t-value	β_{2p}	t-value
Smallest	0.009	*3.388*	0.004	*0.389*	0.544	*12.494*	-0.360	* * *-1.772*
2	0.006	*2.858*	0.007	*0.767*	0.521	*13.081*	-0.073	*-0.408*
3	0.009	*4.191*	0.004	*0.487*	0.720	*19.648*	-0.220	*-1.361*
4	0.004	*1.617*	0.019	* * *1.852*	0.644	*16.289*	-0.304	*-1.593*
5	0.002	*0.952*	0.008	*0.696*	0.857	*21.628*	-0.034	*-0.175*
6	0.002	*0.925*	0.008	*0.847*	0.719	*18.919*	-0.209	*-1.180*
7	0.001	*0.697*	-0.007	*-0.852*	0.673	*20.003*	0.228	*1.540*
8	0.001	*0.681*	0.004	*0.544*	0.902	*28.858*	-0.105	*-0.765*
9	0.004	*2.159*	-0.001	*-0.067*	0.707	*21.801*	-0.045	*-0.287*
10	-0.002	*-0.812*	0.016	*1.602*	0.884	*24.719*	-0.077	*-0.437*
11	-0.003	*-1.256*	0.007	*0.794*	0.781	*23.128*	-0.155	*-0.940*
12	0.002	*0.908*	0.012	*1.277*	0.831	*21.989*	-0.244	*-1.512*
13	-0.001	*-0.491*	-0.004	*-0.579*	0.883	*33.550*	-0.043	*-0.333*
14	-0.001	*-0.300*	-0.001	*-0.174*	0.930	*31.371*	0.135	*0.934*
15	-0.001	*-0.474*	-0.001	*-0.125*	1.033	*33.110*	-0.090	*-0.588*
16	-0.001	*-0.709*	0.005	*0.553*	0.912	*28.132*	-0.125	*-0.791*
17	0.001	*0.536*	-0.005	*-0.589*	0.905	*31.589*	0.034	*0.245*
18	-0.001	*-0.507*	-0.001	*-0.154*	0.946	*32.048*	-0.060	*-0.416*
19	0.001	*0.583*	0.000	*-0.037*	1.075	*37.944*	-0.201	*-1.447*
20	-0.002	*-1.021*	-0.004	*-0.517*	1.073	*35.595*	0.026	*0.177*
21	-0.001	*-0.553*	-0.002	*-0.212*	0.996	*25.195*	-0.095	*-0.493*
22	0.001	*0.621*	-0.005	*-0.529*	1.013	*28.607*	0.020	*0.114*
23	-0.001	*-0.302*	-0.005	*-0.483*	1.027	*28.818*	0.093	*0.536*
24	-0.001	*-0.447*	-0.012	*-1.272*	1.063	*30.195*	0.125	*0.727*
Largest	0.000	*-0.068*	-0.008	*-0.723*	1.127	*29.115*	0.120	*0.634*

Table 4.9 (cont.)

VALUE-WEIGHTED INDEX:

PANEL C: TEST OF JANUARY EFFECT

Size-Beta Ranked Portfolio	γ_0	t-value	γ_1 (January dummy)	t-value	β_{1p}	t-value	β_{2p}	t-value
Smallest	0.008	2.882	0.037	3.329	0.391	8.242	-0.609	-5.356
2	0.007	2.717	0.040	3.924	0.368	8.062	-0.479	-4.654
3	0.012	4.094	0.022	1.744 **	0.459	9.056	-0.472	-2.146
4	0.006	1.978	0.031	2.710	0.505	10.080	-0.486	-4.203
5	0.004	1.207	0.027	2.016	0.565	10.010	-0.181	-1.340
6	0.002	0.762	0.026	2.348	0.508	10.850	-0.263	-2.353
7	0.002	0.766	0.024	2.236	0.522	12.016	-0.189	-1.004
8	0.004	1.478	0.024	1.799 **	0.574	10.742	-0.222	-0.955
9	0.005	1.745 **	0.027	2.577	0.527	11.941	-0.294	-2.779
10	0.000	0.043	0.030	2.399	0.619	11.568	-0.254	-1.980
11	-0.003	-1.145	0.032	3.099	0.617	13.907	-0.229	-2.160
12	0.003	1.117	0.007	0.616	0.575	12.234	0.029	0.143
13	0.000	0.000	0.013	1.290	0.639	14.308	-0.085	-0.793
14	0.000	0.135	0.019	1.708 **	0.662	13.789	0.003	0.024
15	0.000	-0.057	0.024	1.922 **	0.692	12.852	-0.002	-0.018
16	-0.001	-0.259	0.008	0.788	0.705	15.447	0.032	0.291
17	0.001	0.246	0.023	2.329	0.739	17.470	-0.205	-2.019
18	0.000	-0.118	0.016	1.422	0.697	14.781	-0.040	-0.352
19	0.001	0.490	0.016	1.363	0.775	15.504	0.029	0.245
20	-0.002	-0.608	0.027	2.231	0.802	15.790	-0.093	-0.767
21	-0.001	-0.458	0.015	1.291	0.859	16.941	-0.282	-2.320
22	0.002	0.620	0.000	0.008	0.853	18.502	0.012	0.107
23	-0.001	-0.351	0.007	0.638	0.875	19.583	0.063	0.589
24	-0.001	-0.444	0.007	0.617	0.868	18.121	0.058	0.502
Largest	0.000	0.011	0.008	0.686	0.940	17.994	-0.046	-0.364

PANEL D: TEST OF APRIL EFFECT

Size-Beta Ranked Portfolio	γ_0	t-value	γ_1 (April dummy)	t-value	β_{1p}	t-value	β_{2p}	t-value
Smallest	0.010	3.316	0.008	0.628	0.303	6.656	-0.262	-1.108
2	0.009	3.175	0.010	0.883	0.283	6.608	0.038	0.179
3	0.012	4.150	0.008	0.636	0.441	8.661	-0.116	-0.516
4	0.006	2.037	0.023	1.808 **	0.424	9.115	-0.240	-1.020
5	0.005	1.348	0.013	0.881	0.539	10.378	0.059	0.220
6	0.003	1.002	0.014	1.142	0.474	10.951	-0.153	-0.680
7	0.003	1.221	-0.002	-0.224	0.508	11.677	0.229	1.189
8	0.005	1.670 **	0.009	0.675	0.567	10.606	0.010	0.042
9	0.006	2.140	0.005	0.380	0.485	11.804	-0.009	-0.043
10	0.000	0.081	0.022	1.532	0.580	11.769	-0.004	-0.015
11	-0.002	-0.637	0.014	1.146	0.597	14.482	-0.176	-0.823
12	0.003	0.988	0.018	1.537	0.585	12.502	-0.216	-1.002
13	0.001	0.262	0.002	0.208	0.632	15.405	-0.022	-0.105
14	0.001	0.347	0.006	0.440	0.667	15.115	0.154	0.674
15	0.001	0.355	0.006	0.445	0.709	14.284	-0.037	-0.142
16	-0.001	-0.226	0.013	1.037	0.722	17.265	-0.173	-0.800
17	0.002	0.693	0.003	0.256	0.714	18.218	-0.011	-0.056
18	0.000	0.145	0.006	0.490	0.701	16.193	-0.063	-0.282
19	0.002	0.833	0.008	0.614	0.801	17.437	-0.208	-0.873
20	0.000	-0.143	0.004	0.306	0.800	17.068	0.018	0.075
21	-0.001	-0.262	0.006	0.468	0.818	17.484	-0.179	-0.735
22	0.002	0.594	0.004	0.322	0.859	20.339	-0.091	-0.417
23	-0.001	-0.233	0.005	0.397	0.894	21.788	-0.042	-0.196
24	-0.001	-0.180	-0.003	-0.232	0.886	20.149	0.024	0.106
Largest	0.000	0.116	0.002	0.158	0.935	19.532	0.017	0.068

*Table reports the 25 time series estimates and its associated t-statistics (in bold) by using the model mentioned in the next paragraph. The underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level. Panel A and B reports the results using equally-weighted index. The results for value-weighted index are demonstrated in panel C and panel D. The following time series SUR is used for this purpose. The following time-series models, basically says whether the estimate of post-ranking betas from the Fama and French method are affected by the seasonal patterns.*

$$R_{pt} = \gamma_{0p} + \gamma_{1p} D_t^{Jan} + \beta_{1P} RM_t + \beta_{2p}(D_t^{Jan} * RM_t) + \varepsilon_{pt} \qquad (4.3)$$

where R_{pt} is the 342 x 25 matrix of portfolio returns obtained from the Fama and French method; the January dummy variable, D_t^{jan}, takes on the value of one in January and zero in other months, RM is the market index constructed as in Section 3.3.1 of chapter 3, β_{1p} is the post-ranking beta for portfolio p; β_{2p} is the January slope dummy variable and ε_{pt} is the residual term. Similarly, April effect is tested.

CHAPTER 5

A MULTIFACTOR MODEL EXPLANATIONS OF THE SIZE AND BOOK-TO-MARKET EFFECT IN THE CROSS-SECTION OF EXPECTED STOCK RETURNS

5.1. INTRODUCTION

In the Chapter 3, it was found that the main prediction of the Capital Asset Pricing Model (CAPM), a linear cross-sectional relationship between mean returns and the market factor loading, was violated for the UK stock market. This study show that, in this model, the market return does not completely capture the relevant risks in the economy, and additional factors are required to explain expected returns. A positive cross-sectional relationship between average stock returns and the ratio of a firm's Book Equity to Market Equity (BE/ME) was found for the UK stock market. Previous empirical[1] has also found two other factors associated with average returns: the firm's market size[2] and stock price momentum.

In this chapter, the question as to whether the factors such as book-to-market and size, that are found to be priced in Chapter 3 represent risk or mispricing is investigated. There are four main components in this chapter. First, this study attempts to explain the validity of risk factors found in the UK stock market. To do this, one attempts to distinguish between the factor models of Fama and French (1993) and characteristic based models of Daniel and Titman (1997). Only one such type of study (unpublished) is done on the UK stock market

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[1] UK evidences includes Strong and Xu (1997) and Strong, Liu and Xu (1999).

[2] This study will be using the words 'size' or 'market-value' interchangeably throughout this chapter.

(Strong, Liu and Lee (2001))[3]. Second, this study test whether it is the time variation in expected premiums as measured by characteristics or time variation in the risk loadings as measured by the risk factors arising from characteristics. This is done, using the conditional asset-pricing models or methodology of Shankan (1990). This methodology allows both expected returns and factor loadings to vary over time with BE/ME and size. Such an analysis has not been done before for the UK stock market. Third, this study checks whether the results are robust to different statistical procedures. Fourth, as this study uses a previously untested returns dataset, one can again visit the issue of data snooping.

In Section 5.2 of this chapter, the current literature relating to the above components is reviewed. In Section 5.3, the data set is explained in detail. In Section 5.4, the methodology used for constructing the three factors is briefly described and also the Fama and French (1993) three-factor model is empirically examined for the UK stock market from January 1973-December 2001. This study analyses whether the market, size and value factors are pervasive in the cross-section of average stock returns. In Section 5.5, a characteristic based model is developed and its results are compared with the models estimated in Section.5.4. In Section 5.6, the conditional multivariate regression is developed and used to explore the role of time variation in explaining the results obtained from Sections 5.4 and 5.5. Section 5.7 concludes.

[3] This is at the time when I started writing up this chapter.

5.2. LITERATURE REVIEW

5.2.1. RISK BASED EXPLANATIONS

Different explanations have been offered for the recent empirical evidence of a relationship between the BE/ME and size factors and average stock returns. Some authors have argued that the factors like BE/ME and size are proxies for exposures to a systematic risk factor. If these factors are priced, a relationship between proxy exposure and expected returns fits a rational asset-pricing model. Evidence consistent with this interpretation can be found in Fama and French (1993) where common time variation in returns not related to market returns is documented. They examined a three-factor model consisting of market, size and book-to-market factors, where the size and book-to-market factors are stock portfolios constructed to *mimic* the underlying risk factors in returns. According to these authors, if the stocks are priced rationally, the market, size and book-to-market must proxy for sensitivity to pervasive risk factors in returns. Fama and French sees high returns as a reward for taking on high risk: in particular that means, for example, if returns increase with BE/ME, then stocks with a high BE/ME must be more risky than average. By contrast a high BE/ME would traditionally have been seen as an indication of a buying opportunity because the stock looks cheaper; it is offering a value premium. Fama and French confirmed that, for the US stock markets, portfolios constructed to *mimic* risk factors related to market, size, and book-to-market all help to explain the random returns to well-diversified stock portfolios. They also found a strong association between a stock's BE/ME ratio and its loading on the book-to-market factor.

Fama and French (1996b) used a market excess return factor, and size (small firm) and BE/ME (value) factors for the US sample for the period 1963 to 1993 and showed that their model explains the average returns of portfolios constructed on many variables that challenge the CAPM, that is, size, BE/ME, earnings-to-price, cashflow-to-price, past sales growth, and long-term past return. Although, Fama and French are not particular about why variables like value and size factors measure risk, they, and others, have suggested some possible reasons. For example, a high BE/ME could mean a stock is "distressed", temporarily selling low because future earnings look doubtful. Investors rationally attach a high discount rate to these firms. In other words, if risk goes up and BE is constant, BE/ME increases, and hence expected return goes up. These are poor firms and a distress factor that explains the common variation in returns. Alternatively, a high BE/ME could mean a stock is capital intensive, making it generally more vulnerable to low earnings during slow economic times. Chan and Chin (1991) also suggested that poor performing, or distressed firms are likely to have high BE/ME. According to them, these firms are especially sensitive to economic conditions, and their returns might be driven by many of the macroeconomic factors (such as variation over time in bankruptcy costs and access to credit markets).

Dichev (1998) also finds that financially distressed firms with weak fundamentals tend to have low average stock returns and that measures of financial distress have low correlations with BE/ME. If the book-to-market return premium is driven by differences in relative distress as suggested by Fama and French (1993, 1995), and if firm's BE/ME ratio and O-score[4] both capture unique information related to distress, the risk-based model predicts that average returns should be increasing in both O-score and BE/ME.

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[4] O-score (Ohlson's (1980)) measure of probability of financial distress (O-score) is calculated using accounting values from the previous December for the June rankings).

Griffin and Lemmon (2001) independently sort the cross-section of stock returns by O-score and book-to-market equity to examine the competing predictions of the risk and mispricing hypotheses. They examine whether firms with high O-score and BE/ME are rewarded with higher returns as predicted by the risk model, or whether patterns in returns are more consistent with investor mispricing. Their sample is similar to that of Fama and French (1996b) from June 1965-June 1996. Stocks are ranked each June according to their previous December book-to-market equity ratio and June market capitalization. They show that annual size-adjusted percentage return differential between the portfolio of high and low BE/ME securities is 3.87, 3.25, 5.49, 10.62 and 14.44 within the O-score quintiles one through five, respectively. Similar patterns hold for both the small and large firm portfolios separately. These findings reveal that the distressed firms earn low average returns and are largely driven by the underperformance of low BE/ME stocks (Dichev (1998)). If firms with high BE/ME earn high returns because they are more risky, then the large return differential between high and low BE/ME firms in the highest O-score quintile suggests that any differences in risk should be most apparent in this group of firms. They find little evidence that distressed firms are awarded with higher returns. This is inconsistent with the Fama and French (1993, 1995)) view that distressed firms are riskier and these firms tend to have low return on assets, high leverage and high loadings on the market, size and BE/ME factors then their non-distressed counterparts.

Fama and French (1993) have suggested that the Fama-French factor portfolios may be related to the investment opportunity set and that their risk premia may therefore be justified by appeal to the ICAPM. Under the Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM) explanation, covariances of asset returns with state variables other than the

market portfolio may affect expected returns, if the investment opportunity set varies over time[5]. Fama and French argue that their BE/ME and size factors are state variables that describe changes in investment opportunity set. Liew and Vassalou (2000) argue that if the Fama and French factors are state variable, then they should be related to fundamental risk in the economy. In other words, they should be related to economic growth. Liew and Vassalou (2000) support the risk-based story by showing that Fama and French factors are able to predict future GDP growth in some countries. However, the relation between these variables and GDP growth is weak in several countries, and it is non-existent in the US for the 1957-1998 period. Liew, Vassalou and Xing (2001) then argued that the GDP could be decomposed into consumption and investment. They focussed on investment side of the economy. Liew, Vassalou and Xing (2001) explained that the expected excess return of a risky asset is a linear function of its covariance with five sector investment growth rates. They showed that the components of GDP growth could successfully explain the cross-section of equity returns. They conclude that a model that includes only the investment component of GDP outperforms the Fama-French model, although it includes only macro factors and not return-based factors as the Fama-French does.

A study by Elton, Gruber, Agrawal and Mann (2001) reports a potentially important link between equity and fixed income markets. This study was similar to that of Fama and French (1993). If certain risk factors are pervasive enough to explain common variation in stock returns, it is reasonable to expect that these same risk factors would be at work in the bond market as well. Elton et al. provide evidence that BE/ME and size factors do just that.

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[5] In it's standard form, the ICAM delivers a 3-factor model, although the interpretation of the factors is arguably different.

Vassalou and Xing (2002) examine the relationship between default risk (bankruptcies and liquidation) and Fama and French factor portfolios. Fama and French argue that their size and book-to-market factors may proxy for financial distress. Vassalou and Xing (2002) test whether default risk affects equity returns. They estimate the default probabilities for individual firms for their test. They find a risk premium for bearing default risk but the risk premium is not the same as what can be earned for having exposure to the Fama and French BE/ME and size factor. They conclude that only small components of BE/ME and size factor are related to default risk.

Pastor and Stambaugh (2001) provide evidence that sensitivity to a market-wide shift in liquidity might be priced risk factor. Stocks that are highly sensitive to shifts in market liquidity (they have a high "liquidity beta") have high average returns. The liquidity factor appears to be distinct from size and BE/ME factor of Fama and French suggesting an independent source of risk. However, it appears that liquidity betas are highly unstable, and there is substantial variation in the corresponding premium. It is too early to conclude that there is a systematic liquidity factor in stock returns.

An indication of the acceptance of the three-factor model is the frequency with which it is now used as a benchmark for performance measurement. For example, Quigley and Sinquefield (2000) use a three-factor benchmark to analyse the performance of UK unit trusts, and Carhart (1997) and Davis (2001) use the three-factor model in studies of US mutual fund performance[6].

[6] Carhat (1997) adds a fourth factor in the three-factor model to reflect momentum. This is discussed later in this chapter.

Further support for the risk hypothesis comes from Fama and French (1995), who showed that there are size and value factors in earnings as well as in returns. This suggests that systematic variation in firms' cash flow streams may be associated with systematic variation in stock returns.

5.2.2. NON-RISK BASED EXPLANATIONS

Lakonishok, Shleifer, and Vishny (1994) argue that the value premium in average returns arises not because of risk factors, but because of security mispricing. The mispricing view takes the perspective of a contrarian investor. A firm with poor stock price performance tends to be underpriced and have a low market value relative to book value. As a result, high BE/ME value predicts high future returns as underpricing is eliminated. Lakonishok, Shleifer, and Vishny (1994) and Haugen (1995) offer a rationale for the association between past performance and mispricing. They argue that the investors naively extrapolate past growth[7] when evaluating a firm's prospects. For example, investors tend to be overly pessimistic about a firm, which has had low or negative earnings. Investors overreact to such performances and assign irrationally low values to weak firms and irrationally high values to strong firms. In this way, the market undervalues distressed stocks (firms with low earnings) and overvalues growth stocks (firms with high earnings). But, when some of these value (poorly performing) firms get things turned around, investors are surprised, and the stocks of these firms experience high returns. In other words, when pricing errors or overreaction is corrected, distressed or weak (value) stocks have high returns and growth or strong stocks have low returns. In the Lakonishok, Shleifer, and Vishny (1994) study, value stocks significantly outperform glamour stocks in the US market over their sample period, 1968-

[7] The evidence presented in Chan, Karceski, and Lakonishok (2002) supports the notion that investors rely too heavily on recent earnings when trying to estimate future earnings.

1990. An implication of this is that investor can increase returns without increasing risk, simply by buying value stocks and selling (or not buying) growth stocks. Thus, the mispricing argument says that BE/ME captures biases in investor expectations.

While Fama and French (1996b) showed that their three-factor model could explain most of the departures from the CAPM, a notable exception being contrarian and momentum effect[8]. Contrarian Strategies were first examined by Debondt and Thaler (1985), who found that portfolios of past losers (stocks with low returns in the past three to five years) have higher average returns than those of past winners (stocks with high returns in the past three to five years), the "contrarian" effect. By contrast, Jegadeesh and Titman (1993) found that recent past winners (portfolios formed on the last year of past returns) out-performed recent past losers, a "continuation" or "momentum" effect. Using their three-factor model, Fama and French (1996b) captures the reversal of long-term returns documented by DeBondt and Thaler (1985), that they had been unable to explain in terms of size and beta factor. But, Fama and French were not able to explain the short-term momentum effects found by Jegadeesh and Titman (1993) using their three-factor model.

To date, the strongest attack on the Fama and French three-factor model comes from Daniel and Titman (1997). Daniel and Titman (1997) argue in favour of a characteristic-based model, consistent with the mispricing view. Daniel and Titman doubt the risk-based explanation. They contend that it is "characteristics" (growth and distress), not "covariances", that produce return dispersion. The risk-based story says that high BE/ME stocks have high average returns because they are sensitive to common variation in stock

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[8] The results which are corroborated by Fama and French (1996b), Chan, Jegadeesh and Lakonishok (1998), and Jegadeesh and Titman (2001) for the US, apply equally well to developed markets (see Rouwenhorst (1998) for European markets, Chui, Titman and Wei (2000) for Asian markets with the exception of Japan and Korea) and emerging markets (Rouwenhorst, 1999).

returns. In other words, the high returns are due to a high sensitivity to BE/ME factor loading. In contrast, Daniel and Titman argue that high BE/ME stocks have high returns due to some other reasons (possibly overreaction), so that the high returns have nothing to do with systematic risk. In their opinion, it is characteristic (high BE/ME) rather than the covariance (high sensitivity to BE/ME factor loading) that is associated with high returns. For example, suppose there are some strong firms in distressed industries. In the characteristics model, these firms have low returns because they are strong. But they can have high loadings on a distress risk factor if the factor is in part due to covariation of return with industries. Thus, the returns on these firms will be to low, given their risk loadings. Conversely, there are distressed firms in strong industries. Because they are distressed, they have high returns, but in terms of risk loadings they look like strong firms. If characteristics drive prices, their returns will be too high given their risk loadings. They also found that the cross-sectional correlation between BE/ME and its factor loading is quite high, so it was difficult to see which of these variables has more explanatory power for returns. Nevertheless, Daniel and Titman provide results suggesting that the characteristics-based story is more valid for the US stock market for 1973-1993 period. They found a stronger relation between expected returns and BE/ME than between expected returns and factor loadings. Daniel, Titman, and Wei (2001) also confirm characteristic based story for the Japanese stock market. However Davis, Fama and French (2000) show that the Daniel and Titman results are confined to their relatively short sample period. When the longer 1929-1997 period is examined, covariances show more explanatory power than characteristics. It is not clear why shorter periods produces different results, but the longer period should produce more reliable results, and these results favour the risk-based story.

Berk (2000) questioned the findings of Daniel and Titman (1997). According to Berk (2000), the result of Daniel and Titman is basically the result of earlier studies that have used same factors to derive their results. They argued that the characteristics-based model of Daniel and Titman takes account of one Fama-French factor at a time. The contribution of the other two Fama-French factors is therefore missing in the model. Berk (2000) suggests that the missing factors are sources of measurement error. In other words, under their null hypothesis, all three factors are hypothesised to explain returns, so by leaving out two factors, Daniel and Titman (1997) are implicitly ensuring that the measurement error is larger under the null. This problem might be a reason why Daniel and Titman (1997) fail to support the three-factor model in the data-set (1927-1997 and 1963-1993) in which these three-factors were identified.

Griffin (2002) examined the Fama-French three-factor model, which incorporate both foreign and domestic factors. Their findings do not support the notion that there are benefits to extending the Fama and French three-factor model to a global context. However their country-specific three-factor models were more useful in explaining average stock returns than are world and international versions.

5.2.3. DATA ISSUES

Some authors argue that the empirical relationship between returns and Fama and French factors is due to data biases. Indeed, most papers on these studies have studied US stock returns and use the CRSP files to compute stock returns and COMPUSTAT to derive ratios based on accounting data, such as the BE/ME ratio. It is well known that both data sources contain biases. Kothari, Shanken and Sloan (1995) suggest that the high returns found for

high book-to-market firms stem from the omission from the data sample of firms that failed to survive. It is considered that the inclusion of failing firms, and the negative returns associated with failure, would probably reduce the estimated returns on portfolios of high book-to-market shares.

Berk, Green and Naik (1999) and Gomes, Kogan, and Zhang (2000) develop models that explain the Fama-French results on the basis of problems in measurement of beta. In these models, firm betas are stochastic, and there is a statistical relation between average returns, unconditional betas and other firm characteristics such as size and BE/ME ratios, which could be captured by a model such as the Fama-French three-factor model[9].

The past empirical results may also be due to data-snooping. According to Black (1993a, 1993b) and Mackinlay (1995), the positive relation between BE/ME and average returns (the so-called value premium) is a chance result unlikely too be observed out of sample. This is because ninety percent of the current evidence of Fama and French three-factor model comes from US stock market. When the three-factor model has been tested using differently-formed portfolios, the results are quite different[10]. Berk (1995) argues that high BE/ME and small firms will, by construction, earn high mean returns whether they are related to mispricing or risk. Ferson, Sarikissian, and Simin (1999) caution against using empirical regularities as "explanatory risk factors". They explain how a factor derived empirically from company-specific attributes unrelated to risk might still explain cross-sectional variation of stock returns. They basically create an "alphabet" effect in which stock returns are related to the first letter of a company's name and completely unrelated to systematic risk. Through this

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[9] Measurement error in factor loadings affects the performance of the three-factor model (there was a discussion on measurement error in Chapters 2 and 3 of this thesis).

[10] This is shown in Toms and Hussain (2002, UK study). This study is mentioned in the Section 5.2.5.

example, they suggest that the practice of using attribute-sorted portfolios as risk factors can result in a genuine anomaly being converted into a spurious risk measure.

The data-snooping critique was strongly responded by studying other samples of data, for example, Chan, Hamao and Lakonishok (1991) (Japan), Capaul, Rowley and Sharpe (1993) (France, Germany, Switzerland, the UK, Japan and the US) and Fama and French (1998) (Europe, Australia and the Far East). Davis (1994) and Davis et al. (2000) study earlier time periods than Fama and French (1993), yet find similar results. Overall, all these papers conclude that international data also support the Fama and French factors.

Barber and Lyon (1997) presented a clever way to address the issue of data mining. They formed a sample of financial firms for the 1973-1994 period and found reliable evidences supporting the Fama and French factors. Since financial firms were purposely excluded from the Fama and French sample, these results of Barber and Lyon provide independent evidence of the explanatory power of book-to-market risk factor.

5.2.4. TIME VARIATION ISSUES

According to Daniel and Titman (1997), a given stock will sometimes vary positively and sometimes negatively with the loading on the BE/ME factor. Depending on the type of firms that are currently under-and overpriced, the loading on the BE/ME factor will be related to constantly changing micro-and macroeconomic factors. For example, the loading on BE/ME factor will be sensitive to interest rates and inflation risk when it is weighted towards underpriced financial firms, but will be negatively related to these risks when financial firms are overpriced. Corresponding to changes in the loading on the BE/ME factor, a stock will

tend to covary positively with the loading when similar firms are underpriced, but negatively when similar firms are overpriced. Over time, however, a firm's average loading on the BE/ME factor should be close to zero under the mispricing story, unless firms are persistently under-and overpriced (which seems unreasonable).

Evidences by Fama and Schwert (1977), Keim and Stambaugh (1986), Fama and French (1989), and Kothari and Shanken (1997) has shown that the factors like size and BE/ME predict time-variation in expected returns. Lettau and Ludvigson (2001) show that a Consumption-oriented CAPM (CCAPM) that allows expected returns to vary over time provides a good cross-sectional explanation of equity returns. They showed that BE/ME and size capture common variation in returns because they seem to be related to variation in a consumption-based risk premium that changes over time.

Lewellen (1999) uses Shanken (1990) methodology (conditional regressions) to highlight the interaction between BE/ME and risk, as measured by time-variation in market betas and the loadings on the Fama and French (1993) size and BE/ME factors. This framework was then used to test whether the three-factor model explains time-varying expected returns better than the characteristic-based model. Lewellen (1999) used monthly returns for US stocks for May 1968 to December 1994 for their analysis. Their results from the conditional multifactor regressions indicated that the BE/ME captured time-variation in risk, as measured by the Fama and French (1993) three-factor model. No evidence was found in favour of the characteristic based model for the US stock market. The current study uses the Lewellen (1999) based model to test the interaction between the characteristics and risk by

using the time-variation in market betas and the loadings on the Fama and French (1993) size and BE/ME factors in the UK stock market.

5.2.5. UK EVIDENCE

Guidi and Davies (1997) applied the Fama and French three-factor model on the UK stocks for the period 1969-1993. Their results showed that size and book-to-market explains strong variation in stock returns and help explain the time-series of average returns as found by Fama and French (1993, 1995) in the US. Overall, their study supported the risk-based explanation of Fama and French and rejected the irrational-pricing story of Lakonishok, Shleifer, and Vishny (1994).

Later, Guidi and Davies (2000) took a slightly different approach in understanding the risk versus characteristics analysis on the UK stock market. They gathered the data from London Share Price Database and Datastream for the sample period: 1969-1993 and constructed the portfolios on the basis of different characteristics, such as newly listed and high leveraged firms that were very sensitive to macroeconomic conditions. They then applied the three-factor model on these portfolio returns. They found that the, three-factor model seemed to be a more accurate description of expected returns than the Daniel and Titman (1997) characteristic based model.

Toms and Hussain (2002) gathered the data from the Datastream and also attempted to apply the Fama and French three-factor model on the UK stock market. In their study, the three-factor model only captures the returns to portfolios formed on the basis of earnings-price. In their study, the book-to-market and size effects remain as market anomalies for the

three-factor model in the UK. The loading on their book-to-market factor is high implying that relative distress is captured for this portfolio by the three-factor model. But, the risk in this portfolio is not compensated by systematically higher returns. They show that potentially financially distressed firms (highest BE/ME) are generously compensated in returns but the highest financially distressed firms (negative BE/ME) are not as well compensated. Overall, the three-factor model in their study performs better than the CAPM on the size and book-to-market portfolios. They concluded that the distress premium for the UK is weak but real. Their results could be different because in the past UK (three-factor model) studies have used data from London Share Price Database to compute returns, but, they gather the data from DataStream.

The study by Strong, Liu and Xu (1999) for the UK stock market explores the application of the three-factor model to explaining the returns of momentum portfolios. Like Fama and French (1996b), they also show that the three-factor model predicts a reversal for the post-formation returns of short-term losers and winners, and hence misses the observed continuation.

Gregory, Harris and Michou (2001) investigate whether the value strategies can be explained using the three-factor model. They came up with mixed results. Using one way portfolio sort, they support the three-factor model. However, for two-way portfolio sort, they reject the three-factor model. Later, Gregory, Harris and Michou (2002) analyse value strategies using three-factor model in different market conditions and further prove this point. They conclude that some value strategies in the UK are able to generate excess returns that do not appear to be related to currently priced risk factors. Their results are therefore

more consistent with mispricing story than a rational pricing one. They found no evidence that value strategies do worse in adverse states of the world suggesting that they are not fundamentally riskier. They conclude that the factors used as proxies for unobserved risk factors are statistically insignificant.

Strong, Liu and Lee (2001) arguably undertake the most detailed study of the three-factor model. Their paper provides evidence as to whether size and value premiums are due to risk-based or non-risk based reasons for data from 1977 to 2000 for the UK stock market. Their results are consistent with the studies, such as Daniel and Titman (1997) and Daniel, Titman and Wei (2001) that indicate that a factor explanation cannot fully explain the size or BE/ME premiums. They found convincing evidence that stock returns had a stronger relationship with characteristics than with loadings on the factors suggested by Fama and French (1993, 1996b).

Overall, some UK studies support the three-factor model and some don't. It is difficult to compare the results of Guidi and Davies (1997), Guidi and Davies (2000), Toms and Hussain (2002), and Strong, Liu and Lee (2001) because different data sources, sample-periods and methodologies are used in each study. Later, this study will discuss these issues further.

5.3. DATA DESCRIPTION

As in the earlier chapters, the sample data for the analysis in this chapter includes 2108 UK stocks traded on the London Stock Exchange (LSE) from January 1969 through December 2001. The data on BE/ME and market value (or size) were obtained from the Datastream database. The monthly returns were obtained from the London Share Price Database (LSPD). This study included UK stocks for which, there is adequate data of rates of return, market value (or size) and BE/ME. The data set therefore includes firms that appear in both Datastream and LSPD. The Datastream firm codes are matched with LSPD firm codes for each firm from a file with matching code data. Thus after finding the appropriate LSPD code, the collected month-end dividend-adjusted stock return data is collected for 2108 stocks quoted on LSE for January 1969 to December 2001 from LSPD[11] and year-end BE/ME and size values from Datastream for the same period.

The data of this study differs from the study of Strong, Liu and Lee (2001) in two ways: First, this study only includes non-financial companies whereas Strong, Liu and Lee (2001) include financial[12] as well as non-financial companies. Second, study of Strong, Liu and Lee (2001) covers a 23-year period from July 1977 to June 2000, while this study examines the 29-year period from July 73 to December 2001.

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[11] The issues relating to firm selection and selection/survivor biases were explained in detail in Chapters 2 and 3.

[12] Financial companies are often excluded from studies of this kind on the grounds that some accounting variables present problems of comparability across financial and non-financial companies. Strong, Liu and Lee (2001) prefer to include financial companies, first because they are an important sector of the UK market and second because excluding them imposes an arbitrary constraint on the investment strategies considered here. However to ensure that their results are not driven by including the financial sector, as a robustness check, they have replicated the empirical analysis on a sub-sample that excludes financial and property sector companies and obtained similar quantitatively identical results.

5.4. APPLYING THE FAMA AND FRENCH (1993) MODEL

5.4.1. THE SIZE AND VALUE SORTED PORTFOLIOS

The first task in applying the Fama and French three-factor model is to construct the portfolios to be explained by the model. The construction of the basis of the portfolios follows Fama and French (1993). This study takes all UK stocks in the sample and ranks them on basis of size and BE/ME value. Based on these rankings, a 50% breakpoint is calculated for size and 30%, 40% & 30% break points for BE/ME. All UK stocks are then placed into two size groups and three BE/ME groups based on these breakpoints. Firms above the 50% size breakpoint are designated B (for big), and the remaining 50% S (for small). Also the stocks above the 70% BE/ME breakpoint are designated H, the middle 40% of firms are designated M, and the firms below the 30% BE/ME breakpoint are designated L.

Six portfolios (S/L, S/M, S/H, B/L, B/M and B/H) are constructed from the intersection of the two size and three BE/ME groups. For example S/L portfolio contains stocks that are in the small size group and also in the low BE/ME group while B/H consists of big size stocks that also have high BE/ME ratios. Monthly returns on the six portfolios are calculated from the July of year t to June of year t+1, and the portfolios are re-formed in June of year t+1. The six size-BE/ME portfolios are constructed to be "value-weighted[13]" as suggested by Fama and French (1993); that is,

$$R_{p,t} = \sum_{i=1}^{n} w_{i,t} * Ri,t \qquad (5.1)$$

[13] Using value-weighted components results in mimicking portfolios that capture the different return behaviour of small and big stocks, or high and low BE/ME stocks, in a way that corresponds to realistic investment opportunities.

where:

$R_{p,t}$: is the value-weight monthly return of portfolio p in month t.

Ri,t: is the monthly return of stock i of portfolio p in month t.

$w_{i,t}$: is the ratio of market value of stock i on total value market of portfolio p in month t.

n: is the number of stocks of portfolio p.

The value-weighted returns for each portfolios are calculated from January 1969-December 2001. Like all the other chapters, first post-rank period, here, begins in July 1973 and so value-weighted portfolio returns are calculated for 342 months. Table 3.1, in Chapter 3, has the details on the post-rank and pre-rank periods. Also, as before, the end of June is used as the portfolio formation data because the annual report containing the book-equity value for the preceding year is virtually certain to be public information by that time.

5.4.2. THE THREE-FACTOR MODEL

For a specific firm or portfolio i, the expected excess return are assumed to be given by,

$$E(R_i)-R_f = b_i[E(R_m)-R_f]+s_iE(SMB)+h_iE(HML) \qquad (5.2)^{14}$$

where

$E(R_i)$ is the expected return on asset i or portfolio.

Rf is the return on the risk-free asset.

E(Rm) is the expected return on the market portfolio.

E(SMB) is expected return on a mimicking portfolio for size factor.

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[14] This is the unconditional version of the three-factor model. The conditional version of the model authorizes a temporal variation of the rate of stock returns and coefficients of the factors of risk. This is discussed later in this chapter.

E(HML) is the expected return on a mimicking portfolio for BE/ME factor.

But, the empirical counterpart for this model is, (also see Fama and French (1996b, pg.56)):

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i \quad (5.3)$$

where

R_i, R_f, *and* R_m are the realized return on asset i, risk-free asset and market portfolio;

the excess return on a broad market portfolio (Rm-Rf) where Rf is one-month Treasury bill rate and Rm is the market portfolio return or market index. For the value-weighted market index, the FTSE-AllShare index is used for analysis;

SMB: (Small Minus Big) is meant to mimic the risk factor in returns related to size. SMB is the difference each month between the simple average of the returns of three small stock portfolios (S/L, S/M and S/H) and the average of the return on three big portfolios (B/L, B/M, B/H). It is the difference between the returns on small and big stocks portfolios with about the same weighted-average BE/ME. Hence SMB is largely clear of BE/ME effects, focussed on the different behaviour of small and big stocks;

HML: (High Minus Low) is meant to mimic the risk factor in return related to value (this is book-to-market ratios). HML is the difference each month between the simple average of the returns on two high BE/ME portfolios (S/H and B/H) and the average returns on two low BE/ME portfolios (S/L and B/L); it is constructed to be relatively free of the size effect and

ε_i is the error term.

The parameters of this model will be estimated using the time-series regressions approach of Black, Jensen, and Scholes (1972) as in Fama and French (1993, 1996b). Thus monthly returns on portfolios are regressed on the market (Rm-Rf), size (SMB) and book-to-market (HML) factor. The factor sensitivities or loadings, b_i, s_i and h_i (in equation (5.3)), measure the sensitivity of the portfolios return to the market, small-minus-big and high-minus-low factors, respectively. It is expected that portfolios of value stocks (high BE/ME) will have a high value for h, while growth portfolios (low BE/ME) will have a negative h. Similarly, large size portfolios will load negatively on SMB (s_i will be negative), and small size portfolios will have a large positive value for s.

The most robust way to test the Fama and French model, or any asset-pricing model is by testing its implications for the cross-section of average returns. Fama and French (1993) argue that the multi-factor asset pricing models of Merton (1973) and Ross (1976a, 1976b) imply a simple test of whether the set of explanatory variables suffice to describe the cross-section of average returns: that is, that the intercepts of time-series regressions should be close to zero[15].

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[15] Suppose that the statistical model that describes realized excess returns through time is

$$R_{it}-R_{ft}=\alpha_i+\beta_i(R_{mt}-R_{ft})+\varepsilon_{it}$$

Assuming that the expected value of error is zero and it is uncorrelated with the independent variable, and taking expectations of each side this model, given

$$E(R_{it}-R_{ft})=\alpha_i+\beta_i E_i(R_{mt}-R_{ft})$$

which looks like the Capital Asset Pricing Model (CAPM). However, the CAPM imposes the following constraint on expected returns:

$$E(R_{it}-R_{ft})=\beta E_i(R_{mt}-R_{ft})_{it} \quad \text{or}$$

$\alpha_i=0$ for all securities i,

that is, that the intercept, alpha, is zero. A similar argument follows for the three-factor model.

If the standard assumption is made that the ε_is are Identically and Independently Distributed (IID)-normal, this study can test the standard zero intercept restriction that the null hypothesis: Ho: a_i=0 (in equation (5.3)), i=1,2, N, using a Wald test based on the statistic:

$$W=(a'\{\text{var}(a)\}^{-1}a) \tag{5.4}$$

where a is the vector of estimated intercepts which has a covariance matrix var(a). If var (a) is replaced by a consistent estimator, W is asymptotically χ_2-distributed with N degrees of freedom under Ho. Here, an alternative to the Wald test is used, which is the GRS test due to Gibbon, Ross and Shanken (1989). They demonstrated that an adjusted version of W has an exact F distribution under Ho and the Independently and Identically Distributed-normal assumptions:

$$F=[(T-N-1)/(TN)]W\sim F_{(N,T-N-1)} \tag{5.5}$$

where T is the time-series observation and N is the number of variable.

Using the GRS (1989) test, the CAPM can be easily compared with the Fama and French three-factor model.

5.4.3. EMPIRICAL ANALYSIS

5.4.3.1. SUMMARY STATISTICS OF THE SIX FAMA AND FRENCH PORTFOLIOS

Table 5.1, Panel A provides summary statistics for the set of six portfolios (S/L, S/M, S/H, B/L, B/M and B/H). The value-weighted averages of market value and value-weighted averages of BE/ME in Table 5.1, Panel A indicate that the independent sorts achieve their purpose, namely to create variation of size holding BE/ME constant and vice-versa. The results in Table 5.1, Panel A suggests that the value weighted BE/ME averages are rising within the size portfolios. It can also be seen that the low value-weighted size averages are associated with small-size portfolios (S/L, S/M and S/H) and vice-versa. All this suggests that, the sorting has achieved its purpose that is to clearly separate the value and size portfolios. The results in Table 5.1, also suggest that value firms with high BE/ME are associated with low market weights. Dimson, Nagel and Quigley (2003) have shown that, value firms with high BE/ME exhibit persistently low earnings and this is consistent with low market weights. This basically indicates that the BE/ME factor proxies for some kind of relative financial distress (Fama and French (1995)).

Table 5.1, Panel B shows the first four moments and the first three autocorrelations of the six size and value sorted portfolio returns and the three factor portfolio returns for the full 29-year period (January 1969-December 2001) for the UK stock market. These are the dependent and explanatory returns in the time series regressions respectively. The six size-BE/ME portfolios exhibit an average excess return ranging from .73% to 1.04% per month. All the six portfolios produce average excess returns that are more than two standard errors from 0. According to Merton (1980): because stock returns have high standard deviations

(average standard deviation of returns is around 5.5% per month in this study), large average returns often are not reliably different from zero. In Table 5.1, Panel B, it can be seen that the average excess returns are strong enough to offset the impact of market volatility. But, it was mentioned in previous chapters that the trading was often thin for many small companies. In Table 5.1, Panel B, the autocorrelation for small cap portfolio is significant at a 95% confidence level. Thus the, simple standard deviations as reported in Table 5.1 may understate the true variation in portfolio returns, and so exaggerate the significance of the mean returns.

The average value of the market premium is 1.10% per month. This is large from an investment perspective (about 13.2% per year) and is also 3.37 standard errors from 0 (t-statistic=3.37). There is therefore a strong market premium in returns.

There is hardly any value premium in returns. The average HML returns is positive (.08% per month, t-statistic=.80) and is less than 1 standard error from 0. But, Table 5.1, Panel B confirms that the value premium for large stocks (average B/H-average B/L) for Jan 1969 to December 2001 for the UK stock market is -.04% per month, and is lower than the value premium for small stocks (the average S/H-S/L), .22% per month. In other words, the relation between value and average return is positive for small stocks, but negative for big stocks. This is different from the US findings (Fama and French (1992, 1993)) of a strong positive relation between value and average return irrespective of size. But presumably it's the same general effect: there is a big value premium for small stocks and small value premium for big stocks. Dimson, Nagel and Quigley (2003) for the UK market, found that the value premium exist within the small-firms as well as the large firms. Gregory, Harris and Michou (2002) for the UK stock market shows that the portfolio returns are 'always'

positive from the value-minus-growth stocks using different types of market conditions (up and down). They further showed that the excess returns to the value portfolios were always greater than the excess returns to growth portfolios. Overall, their results were similar, when the analysis was repeated using different types of value portfolios[16] except Earning-Price sorted portfolios. Arshanapalli, Coggin, and Doukas (1998) for the US, find that the superior performance of value stocks over growth stocks is positively and significantly associated with the firm size variable (small-big).

In contrast to the worldwide evidence, which shows a negative relation between size and average returns, here, the results indicate a weak positive relation between size and average return. Firms in the big portfolios earn higher excess returns than in small size portfolios. The average SMB returns is negative (-.13%, t-statisitic=-.55). The weak size effect may be due to the fact that the six components of SMB are value-weighted portfolios. It can also be seen that, without the control for BE/ME, the average difference between the returns on value-weight portfolios of stocks below and above 50% is -.30% per month. The simple size premium (S/L-B/L) is .20% lower than the average SMB return. It is also noted that there is autocorrelation in SMB returns at lag 3.

In summary, it seems that the UK stock market displays a strong market effect, no size effect and a conditional value effect, the latter being present only for small stocks. Fama and French (1995), on the contrary cite, a strong value effect and a conditional size effect for the US market.

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[16] In the study of Gregory, Harris and Michou (2002), the value portfolios were formed using different characteristics like Book-to-Market (BE/ME), Cash Flow-to-Price (CP), Earnings-to-Price (EP) and three-year Sales Growth (SG).
In their study, there was little evidence to suggest that value portfolios are more risky than growth portfolios.

In Table 5.1, Panel B, the value, size and factor portfolio returns show departures from a normal distribution. In large samples of normally distributed data, the estimates of skewness and kurtosis are normally distributed with means 0 and 3 and variances 6/T and 24/T respectively. The excess kurtosis estimates for portfolio returns are generally less for small-stocks and HML portfolio, but they are slightly larger for other portfolios. The skewness estimates are negative for all the small-stock, SMB and HML portfolios and ranges from .13 to .69 for other portfolios.

Table 5.1, Panel C shows the correlation coefficients between the MKT (Value (Rm) and Equally weighted index (Rem)), SMB and HML factors, which serve as the independent variables in the regression model. Like Fama and French (1993), this study also finds that the HML portfolio returns have a negative correlation with the excess market return (-.24 for value-weighted index and -.16 for equally weighted index). Unlike Fama and French (1993), the SMB and HML factors have a positive correlation (.29), while there is a negative correlation between SMB and the excess market return. In Table 5.1, Panel C, when this study considers an equally-weighted index, the correlation becomes positive (.35). The low correlation between "excess market return and SMB" and "excess market return and HML" are desirable as the returns on the SMB and HML factors should be independent of the market returns. This reflects the fact that, their construction is controlled to get the differences in the betas of the underlying stocks. In other words, the procedure used for constructing the SMB and HML factors appears to successfully control each factor for the influence of the other[17]. Overall, the correlation coefficients between the independent

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[17] The CAPM and most empirical studies examine the relation between simple regression market betas and expected returns. To enhance comparison with cross-sectional studies, some studies have used size and BE/ME factors that are orthogonal to market factor. These factors SMBO and HMLO, are constructed by adding the intercepts to the residuals when SMB and HML are regressed on a constant and the excess market return. From regression analysis (e.g., Johnston, 1984, p.238), the coefficients in the three-factor model will be unaffected by the changes in variables, except that the market betas will now be the simple-regression betas of CAPM.

variables suggest that the standard errors of the regression estimates may not be large due to problems of "multicollinearity" between the independent variables.

The performance of factors (SMB and HML) is analysed by looking at Figures 5.1 and 5.2. Figure 5.1 shows annual returns on the SMB (small minus big size) zero-investment portfolio. The payoff on SMB has been very variable in the UK. The time-series patterns documented here for a BE/ME-neutral long-short size strategy are very similar to those reported by Dimson, Nagel and Quigley (2003). One can see (in Figure 6.1) a pre-1989 premium on size, and the subsequent reversal in 1990s. Dimson, Nagel and Quigley (2003) found an extraordinary rebound of SMB in 1999 (annual excess return of around 40%), whereas this study (Figure 6.1) found a lower premium on size (annual excess return of around 15%). The annual performance of HML (high minus low BE/ME) is depicted in Figure 5.2. Like SMB, the payoff on HML is also quite variable in the UK. This study, like Dimson, Nagel and Quigley, also found a persistent value premium until mid 70s and same pattern during the mid 80s. The mid 1990s has seen a highly volatile performance of HML in the UK. The highest absolute returns and lowest returns on the HML factor also occurred during this period[18] .

5.4.3.2. THREE FACTOR MODEL

The main objective of this chapter is to test a characteristics model against the risk model given in equation (5.3). But the exercise might be of no use if equation (5.3) is not a good

[18] Dimson, Nagel and Quigley (2003) suggest that the persistent performance of value stocks during the 70s and 80s might be due to some look-ahead bias. They have taken care to rule out this possibility. For example, their portfolio formation mechanism requires that accounting data be at lest six months old before they use it. This is meant to ensure that the formation mechanism uses only public information. One might want to question whether this assumption really reflects circumstances in the UK during the 1950s and 1960s when financial reporting was slower than today. To check this, they formed their portfolios with the requirement that accounting data be at least 18 months old. The results were almost the same.

approximation for expected returns. Thus, this study begins by testing the three-factor model (5.3) on portfolios formed on size and BE/ME.

Actually, the role of common factors in returns has been explored in five related models: (a) regressions that use market, SMB and HML factors (the Fama-French model), (b) regressions that use only the market factor (Rm-Rf) as explanatory variable (Sharpe-Lintner CAPM), (c) regressions that use SMB and HML as explanatory factors, (d) regressions that use market and SMB factors and (e) regressions that use market and HML factors.

Market, SMB and HML – It can be seen in Table 5.2a that the three-factor model explains about 70% of stock returns for the six size and value sorted portfolios. Interestingly, the three-factors are explaining different things, that is, the market factor explains the large difference between average return of the portfolios and one-month Treasury bills while the other two factors, SMB and HML, explain the average return variation between the portfolios. For all the portfolios, market factor loadings are about the same magnitude and are more then 22 standard error from zero. The slopes on the SMB factor are highly significant for all the 6 portfolios, with positive value of around 0.6 for all small firms and negative values of around 0.4 for all large firms. The HML factor loading increases from strong negative values for S/L to strong positive values for B/H portfolios. There is therefore a strong positive correlation between the BE/ME characteristic and the HML risk loading. The implication of this finding is that an investor can earn a maximum premium from value strategy. The results, here, suggest that an investor can get a premium of around .48% per month (for small stocks) and .90% per month (from big stocks) from value strategy.

This study examines whether the three risk factors fully explain the cross-section of mean returns on stocks by focussing on the intercept estimates of the three-factor model. If the pricing theory holds, the true intercepts equal zero. This study tests the restriction that the intercept is zero in two ways. The t-statistic is examined for each individual intercept, and the adjusted Wald test statistic proposed by Gibbons Ross and Shanken (1989) (GRS) is used to test all the intercepts jointly. This is presented in Table 5.2 again. It can be seen in Table 5.2a that the intercepts of the three-factor model are very close to zero. Intercept values for all sample portfolios are also indistinguishable from zero at 95% level. The results show the ability of the three-factor model to capture the cross-section of average return. The GRS test statistic or multivariate F-statistic cannot reject the hypothesis (asset-pricing restriction) that all intercepts are zero.

The Market- Table 5.2b shows that the market factor does explain a fair proportion of the common variation in stock returns. Market factor loadings for all the portfolios are more than 13 standard error from 0. The R-squared values range from 36% to 74% for all the portfolios. Not surprisingly, the R-squared values are relatively lower for small stock portfolios and the value portfolio (S/H and B/H) showing the failure of standard CAPM in explaining the size and value effects in returns. Used alone, the market factor produces a mean R-squared of 55%; the mean R-squared only increases to 71% when two factors are used with the market factor (see Table 5.2a). Overall, the market factor clearly ranks first in explanatory power, but it will be seen in the following paragraphs that, there is no clear ranking of the other two factors. In Table 5.2b, the intercepts for all the portfolios are indistinguishable from zero except small-value portfolio. The results support the CAPM predictions in isolation. But, the GRS test statistic testing whether all intercepts are zero is

not significant (p-value=.053) suggesting that the CAPM also holds for the UK data. The CAPM restriction is therefore accepted: all intercepts are zero.

SMB and HML – Table 5.2c shows the power of size and value factors in stock returns. The SMB slopes are puny. The estimated size loading increases monotonically with size ranking, and estimated BE/ME factor loading increases steadily within the BE/ME ranking. In other words, HML factor loading increase with BE/ME, and the spread between the HML slopes for high and low BE/ME portfolios is approximately .209. The size factor loadings are statistically significant for the large stock portfolios. But the HML factor loading is significant for 4 out of 6 portfolios. The value portfolios are significant for both small and big portfolios and are positively related to the HML risk premium. The regression results also indicate that the returns on glamour portfolios are negatively related to the HML risk premium. Thus, in the absence of competition from market factor, the SMB and HML do capture some of the common variation in stock returns. This is again demonstrated by the fact the R-squared for some of the portfolio is more then 40%. But R-squared for small-stock portfolios are around 6% on average. Hence, size variable fails to perform but there is some value-effect. It can also be noted that given the strong factor loadings on SMB and HML, it is not surprising that adding the two returns to the three-factor regressions results in large increases in R-squared values (in Table 5.2a). In Table 5.2c, all the intercepts are distinguishable from zero and are also statistically significant at 95% level.

Market and SMB- Table 5.2d shows that the market and SMB factor capture a greater proportion of common variations in returns compared to one-factor CAPM, and the market factor loadings for all the portfolios are more than 19 standard error from 0. The size factor

loadings are also significant for all the portfolios. The positive and significant return for small-stock portfolio shows that, there does seem to be some size effect in average returns. It can be clearly see that the size effect is influenced by the market factor in returns. The R-squared ranging from 62% to 81% is also amongst the best in compare to the models discussed above. Statistically insignificant intercepts are obtained if the market factor is added to the model with SMB in Table 5.2d.

Market and HML- Table 5.2e demonstrates the presence of value factors in stock returns. While the market factor loading continue to be statistically significant at 5% level, the significance of HML factor loading has improved compared to the model with HML and SMB factor. The HML factor loading becomes steeper and R-squared values improve for the value portfolios. Adding HML to the market model decreases the R-squared for 5 portfolios when compared to the model with SMB and market. Statistically insignificant intercepts are again obtained when the market factor is added to the model with HML factor in Table 5.2e. In Table 5.2d and 5.2e, one can again see the dominance of the market factor over the SMB or HML factor. The significance of the intercepts is highly influenced by the addition of the market factor to the model with just SMB or HML.

In summary, of the models considered here, the three-factor model provides the most suitable description of pervasive risk in these size and value-sorted portfolios. Moreover, the sub-models of three-factor model also tend to indicate that certain risk factors are missing in those models.

5.4.3.3. ROBUSTNESS TESTS

To examine the robustness of Fama and French three-factor model results, five different types of tests are done: First, the portfolios are constructed using a different sorting order. Second, seasonality issues are investigated. Third, this study uses one set of stocks in the explanatory returns and another, disjoint set in the dependent returns. These tests address the concern of MacKinlay (1995) that the evidence of size and BE/ME factors in the regressions above may be spurious, arising only because this study uses size and BE/ME portfolios for both the dependent and explanatory variables. Fourth, a sub-period analysis is done to see whether there are any differences in the results across different sub-periods. Finally, momentum portfolios are used to further test the Fama and French three-factor model.

5.4.3.3.1. DIFFERENT PORTFOLIO FORMATION AND EQUALLY WEIGHTED RETURNS

In cross-sectional analysis in the earlier chapters, it was seen that, different sets of portfolios often produce quite different estimates of risk. The time-series regressions in this chapter might also be sensitive to the way in which portfolios are formed. Table 5.3 shows the results of a one factor and a three-factor model, using 25 portfolios sorted dependently[19] on size and BE/ME. The excess returns used in these portfolios are "equally-weighted returns".

In Table 5.3, Panel A, the results from the one-factor model suggests that the t-statistics associated with the market betas for stocks are all greater then 8. In Panel B, the results from the three-factor model suggest that the t-statistics on the market slopes even gets bigger.

[19] Quintile breakpoints for size and BE/ME are used to form 25 portfolios.

These findings are similar to that of Table 5.2, Panels A and B. Like in Table 5.2, Panels A and D, it can also be seen that the SMB, the mimicking return for the size factor, clearly captures shared variation in stock returns that is missed by market and by HML. The slopes on HML are systematically related to BE/ME (like in Table 5.2, Panel A). In every size quintile of stocks, the HML slopes increases from negative values for the lowest BE/ME quintile to strong positive values for the highest-BE/ME quintile. But, again like in Table 5.2, Panel A, the factor loadings on HML factor are only significant for high BE/ME portfolios (with an exception of one portfolio: high size and low BE/ME portfolio).

In Table 5.3, Panels A and B, it can be seen that the excess return on the market portfolio of stocks (RM-Rf), captures more common variation in stock returns then other factors (SMB and HML). Used alone, the market factor produces a mean R-squared of 48%; the mean R-squared increases to 56% when two factors are used with the market factor. So, addition of two factors to one-factor model does not increase the R-square from a large amount.

One can again see the superiority of three-factor model over the CAPM. This is because, the intercepts are insignificant for both the models but the intercepts for the three-factor models are much lower then the one-factor model. There is not much difference in the results, when the regressions are run on 25 dependent-portfolios instead of 6 independent-portfolios. The GRS test statistic has a p-value of more then .05 (shown in Table 5.3, Panel C) for both the models and therefore the hypothesis that all intercepts are zero for both the models is not rejected. Overall, the results from this analysis are similar to that found in Table 5.2.

5.4.3.3.2. SEASONALITY IN RETURNS

In this section, the January and April effect in the UK stock market are briefly examined through the Fama and French three-factor model. The following time-series models, basically says whether the Fama-French three factor model is affected by seasonal patterns:

$$R_{pt}=\gamma_{0p}+\gamma_{1p}D_t^{January}+\beta_{1P}RM_t+\beta_{2p}(D_t^{January}*RM_t)+s_{1p}SMB_t+s_{2p}(D_t^{January}*SMB_t)+ h_{1p}HML+h_{2p}(D_t^{January}*HML)+\varepsilon_{pt} \quad (5.6)$$

where R_{pt} is the 342 x 6 matrix of portfolio returns, the January dummy variable, D_t^{jan}, takes on the value of one in January and zero in other months; RM, SMB and HML are the market (value-weighted index), size factor and BE/ME factor respectively as previously described. The coefficients β_{1p}, s_{1p} *and* h_{1p} are those associated with market, SMB and HML factors respectively, while β_{2p}, s_{2p} *and* h_{2p} are those associated with the January slope dummy variables and also associated with market, SMB and HML factors respectively. In the same way, the following equation (5.7) is tested for April Seasonality:

$$R_{pt}=\gamma_{0p}+\gamma_{1p}D_t^{April}+\beta_{1P}RM_t+\beta_{2p}(D_t^{April}*RM_t)+s_{1p}SMB_t+s_{2p}(D_t^{April}*SMB_t)+ h_{1p}HML+h_{2p}(D_t^{April}*HML)+\varepsilon_{pt} \quad (5.7)$$

Table 5.4, Panel A provides the results relating to January effect. There is evidence of a January effect in the sensitivity to the size factor but not for the HML factor. Fama and French (1993), for the US market, found a January seasonal for both the SMB and HML factors. Table 5.4, Panel B indicates no evidence of an April effect. None of the three factors seems to be of any importance in the month of April. The results from Table 5.4 are

comparable to those in Chapter 4 (see Table 4.9). In Chapter 4, time series regressions were run using a January and April dummy variables associated with market index. In Chapter 4, this study found a weak evidence of January effect and no effect in the month of April. Some small firm effect (in Table 4.9) (similar to SMB factor in Table 5.4) was also found in January but there was no small firm effect in the month of April. Overall, the results from one-factor (Table 4.9) and three-factor model (Table 5.4) do not offer much difference, when the seasonal factors are taken into account.

5.4.3.3.3. SPLIT SAMPLE REGRESSIONS

It has been pointed out by MacKinlay (1995) that the regression results may be spurious as a result of the explanatory risk factors (SMB and HML) being constructed from the six size-BE/ME portfolios. To overcome this problem the values of SMB and HML need to be derived independently of the data used to run the regressions that test the ability of these factors to explain returns[20]. Fama and French (1995) for the US contend that this is not a serious problem, but split their sample to allow the factors to be determined from data not used in the regressions to ensure that the results from the full sample regression are not spurious. To achieve the split sample regressions, the stocks in each of the six size-BE/ME portfolios are 'randomly' divided into two groups. The new dependent portfolios (S/L, S/M, S/H, B/L, B/M, B/H) value-weighted returns from one group are regressed against the explanatory factors (Market, SMB, HML) from the other group and vice-versa.

The results are presented in Table 5.5. Return patterns reported in Table 5.5, suggest that the coefficients of value portfolios (S/H and B/H) are significant (t-statistics>2) for both sets

[20] Raw returns and not excess returns are used in this section. The results, here, are therefore not directly comparable to the results in Table 6.1.

of split sample data (shown in Panel A (1) and Panel B (1)). There seems to be some value premium in average returns. The results also support the three-factor model (shown in Panel A (3) and Panel B (3)). The intercepts in the three-factor regressions for both the split samples are close to 0.0. The market factor seems to again dominate all the other factors. But, the slopes of SMB and HML factor loading are not similar to those of in Table 5.2. The SMB factor loading is significant for three portfolios (S/L, S/H and B/M) in first group of split sample regression and (S/L, B/L, B/M) for the second group. These results suggest that the size effect is weak. Again, similar to the full sample regressions, this study finds that the coefficients to the HML factor for the six dependent portfolios are uneven. The t-statistics for SMB and HML factors also shows less power to reject the hypothesis: the three factors capture cross-section of average stock returns (like the full-sample regression in Table 5.2). The three-factor split regressions produce reasonable values of R-square (average of 35%), they are quite lower than those in Table 5.2 (around 70% on average). Overall, the results[21] are not good news. The size effect in Table 5.2 seems to have gone but the market effect is still there. The HML effect seems to have reversed. This could be because the 6 portfolios in the split-sample regressions use half the available stocks and portfolios here are less diversified than those in Table 5.2. It could also be due to the MacKinlay's (1995) spurious regression problem mentioned earlier.

5.4.3.3.4. SUB-PERIOD ANALYSIS

This study uses four sub-periods for this analysis. The four periods are (1) January 1998-December 2001, (2) July-1973-October 1987, (3) November 1987-December 2001 (4) May 1969-December 1993. The first one is chosen to see the efficiency of the three-factor model

[21] The results in this section are from just one random set of data. If 1000 random sets of data are used, one may get different results.

during recent market downturn, which has been caused by a number of events. The first and one of the most obvious reasons for this is the effect of the 11th September attack in the World Trade Centre in 2001. Second, accounting scandals such as frauds in Enron, World.com, Global crossing, AOL, Big Marshall etc. have also been a feature of recent market events. Third, the asset bubble in late 1990s that was driven by tech stocks in UK has also appeared to bust. Overall, the market has fallen by around 10% from 1998 to 2002. The second and third set of sub-period are analysed to see the effect of the stock market crash in 1987. The results in the third sub-period will be compared to the results of the second sub-period. The fourth sub-period matches one used in a previous study done of the UK stock market. The motivation for choosing the fourth sub-period comes from Guidi and Davies (1997) study on the UK stock market.

The results for the sub-periods are presented in Table 5.6. The three-factor model appears to be weak in the new millennium. The mean of R-square for all the portfolios is also over 80%. The betas are much closer to one now. There seems to be some value premium and size effect in returns. But, the intercepts of two portfolios (small-growth (S/L) and big-value (B/H)) are significant at 5% and one portfolio (B/M) at 10%. It can be seen that the three-factor model does not work very well in the period of crises (1998-2001). The investors should use the three-factor model with caution in the new millennium.

The results in Table 5.6b and 5.6c will suggest whether the three-factor model works well before or after the stock market crash of October 1987. The R-squared has vastly gone up from an average of around 67% (in Table 5.6b) to an average of around 87% (Table 5.6c) for all the portfolios. Again, the interesting result is the almost doubling of the betas. But, the

intercept values for all the sample portfolios in both the sub-periods (July 1973- October 1987 and November 1987-December 2001) are distinguishable from zero at 95% level. The results show the inability of the three-factor model to explain the cross-section of average return.

The results presented in Table 5.6d allow a close comparison with the study done on the UK by Guidi and Davies (1997). That study was done from May 1969-December 1993, but due to unavailability of data, this study starts in July 1973. The overall impression from the results obtained by the sample of this study is not the same as Guidi and Davies (1997)[22]. First, the values of market beta and its associated t-statistics in their study are quantitatively higher than this study. In contrast to the results in this study, where one found coefficients on market factor with less then 1 and around 19 standard error from zero, the coefficients on market factor obtained in their sample are more then 1 and around 80 standard error from 0. In their study, the coefficients on HML and SMB factors are also more strongly statistically significant. Second, the average Adjusted R-square values are all above 95% in their case, but, here, this study found an average Adjusted R-square value of about 75%. Third, intercepts for all the sample portfolios are indistinguishable from zero in Guidi and Davies (1997). Here, four portfolios have intercepts, which are distinguishable from zero at 5% and one at 10% significance level. Overall, the regression results of three-factor model in Guidi and Davies (1997) explain variations in return better than this study[23].

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[22] Their data set contains over 700 Firms from 1970 onwards. The data set in their study is therefore quantitatively similar to ours.

[23] Strong, Liu and Lee (2003) for the UK stock market reject the hypothesis that the Fama and French model completely explains the cross-sectional return regularities examined in their study- most notably, effects attributable to market value, earnings-to-price, sales growth, return momentum, return reversal and to two-dimensional sorts of book-to-market, earnings-to-price, or cash-to-price and sales growth.

Using sub-period samples, the three-factor model accounts for a large proportion of the cross-sectional variation in average returns across UK stocks. But, the significant intercept indicates that the model does not explain the cross-section of expected stock returns.

5.4.3.3.5. THE THREE FACTOR MODEL AND MOMENTUM PORTFOLIOS

This study adopts the methodology used by Jegadesh and Titman (1993) to form momentum portfolios using the UK stock returns for the period July 1973-December 2001. This study tests whether the three-factor model of Fama and French (1996b) could explain the returns to these momentum portfolios. Like Strong, Liu and Xu (1999), this study considers the ranking period of r=6 months and subsequent holding period of h=6 months (6 x 6 momentum strategy). In addition, 12 x 12 strategy is also used for the same purpose[24]. Unlike Jegadeesh and Titman study, where portfolios involved overlapping periods, this study, like Strong, Liu and Xu (1999), examines non-overlapping periods.

To select stocks for different portfolios at the start of each holding period, t, the ranking period r-month returns for each of the stock is computed as,

$$CR_{j,t} = \sum_{t=1}^{r} R_{j,t} \tag{5.8}$$

where $R_{j,t}$ is the monthly return of stock j, CR_j is the cumulative return of security j and r is the number of months (6 or 12 months). Stocks are then ranked into 10 portfolios on the basis of CR_j.

In the following 6 or 12 months, described here as the test period (TP), the CR for all stocks in the winner and losers portfolios are calculated. The mean of CR represents the cumulative return for an equally weighted portfolio and is measured as,

$$CR_{r+1} = (1/N)\sum_{j=1}^{N}(\sum_{t=r+1}^{2r} R_{j,t}) \tag{5.9}$$

where N is the number of stocks in the portfolio and where the test period returns for stock j in the portfolio are $R_{j,t}$, t=r+1, r+2,.....$2r^{25}$.

The momentum portfolio is constructed by going long in the winner portfolio and going short in the loser portfolio.

Table 5.7, (Panel A) clearly indicates that the difference between the winner and the loser portfolios is positive (1.028%) and is strongly (statistically) significant (t=8.021). Hence, the investors can use a momentum strategy, based on this result to make profits. Overall, for 6 x 6 strategy, the estimates of returns are significant for all portfolios (winner, momentum and intermediate portfolios) except loser portfolio. For 12 x 12 strategy (in Panel B), the estimates of returns for winner and momentum portfolios are similar to that of 6 x 6 strategy and less for intermediate portfolios and different for a loser portfolio.

The issue for this section is, whether Fama-French three-factor model explains this potentially anomalous pattern in average returns. If the three-factor model can explain the

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[24] One could consider a number of other momentum strategies, but the purpose of this section is not to test the momentum strategies but to test the three-factor model on momentum portfolios. This study therefore considers only a few strategies for analysis.

returns of the portfolios, the intercept in equation (5.3) should not be significantly different from zero. Table 5.7, Panels A2 and B2 presents the results of equation (equation 5.3) for each decile portfolio and the momentum (Winner-Loser) portfolio for the 6 x 6, and 12 x 12 respectively. Intercepts in both the Panels are significantly different from zero. The results suggest that the three-factor model cannot explain momentum portfolios, therefore it is not a complete model of risk. Fama and French (1996b) noted that their three-factor model also does not explain the momentum effect, since their estimate of abnormal returns were strongly positive for short-term winner portfolio. Hence, the results from this study are similar to that of Fama and French (1996b) study. Strong, Liu and Xu (1999) found a negative and significant intercept for the loser portfolio (-.61%, t=-3.35), a positive and significant for winner portfolio (.81%, t=-7.06) and a positive and significant intercept for momentum portfolio (1.42%, t=6.22). So, here, the results are also not much different from the Strong, Liu and Xu (1999) study. It can also be seen in Panel A2 that all decile portfolios and the momentum portfolio load insignificantly on SMB factor and load insignificantly on HML factor. This is in sharp contrast with the Strong, Liu and Xu (1999) results, where the coefficients on SMB and HML, using their decile and momentum portfolios indicated a small-stock effect and high BE/ME effect. There are two possibilities behind these differences: First, Strong, Liu and Xu (1999) use small sample, 1977-1998, and this study uses 1973-2001. Hence, the recent market downturn has had an impact. Second, Strong, Liu and Xu (1999) use weekly Wednesday data to form monthly returns, and since Wednesdays are not always in the month end, this may cause the effect. Like Strong, Liu and Xu (1999), the loser and winner portfolios obtained from this study have similar market exposure. But, overall results of this study indicate that neither the winner or loser portfolios

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[25] The test period for the final month begins from July 2001 and ends in December 2001. So, although, this study has the data for 342 months (ending December 2001), in this section, returns are only estimated for 336 months. Also, note that this study will only use non-overlapping 6-month

are riskier in terms of the Fama-French three factors. This is because none of the two portfolios are sensitive to any of the Fama-French three factors. The overall evidence indicates that the cross-sectional differences in expected returns under the Fama-French three-factor model cannot account for the momentum profits[26].

FOUR-FACTOR MODEL (USING MOMENTUM AS A FOURTH FACTOR)

A few studies have augmented the Fama and French three-factor model with a momentum factor (Carhart (1997), Brav, Geczy and Gompers (2000), Jegadeesh (2000) and Liew and Vassalou (2000)). Following these studies, this study also uses a Four-Factor Pricing Model (FFPM). In addition to the market, SMB and HML factor, a momentum factor: WML (Winner Minus Loser) is added. This has not previously been done for the UK stock market.

According to a FFPM, a stock's excess return is given by:

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + w_i WML + \varepsilon_i \qquad (5.10)$$

where the definition of R_i, R_f, R_m, SMB, HML *and* ε are same as in Section 5.4.2 and WML is a momentum factor and w_i is the factor loading associated with the momentum factor.

To construct the WML factor, the following steps in spirit of forming the HML and SMB factors were undertaken: For each month t from July of year t-1 to June of year t, the stocks are ranked based on their size in December t-1 and their performance (lagged returns)

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periods.

[26] Lewellen (2002) has presented evidence that portfolios of stocks sorted on size and BE/ME characteristics have similar momentum effects as those seen by Jegadeesh and Titman (1993, 2001) and Fama and French (1996b). He argues that the existence of momentum in large diversified portfolios make it unlikely that behavioural bias in information processing are likely to explain the evidence on momentum. The results of Strong, Liu and Xu (1999) however, do lend some support to the behavioural theories. According to Strong, Liu and Xu (1999) behavioural theories attempt to explain the simultaneous effects of underreaction at medium-term horizons and overreaction at long-term horizons.

between t-12 and t-2. These two rankings are then used to calculate a 50 percent breakpoint for size, and 30 and 70 percent breakpoints for lagged returns. The stocks are subsequently sorted into two size groups and three prior performance groups based on these breakpoints. The stocks above the 50 percent are designated B (for big) and the remaining 50 percent S (for small). Moreover, stocks above the 70 percent prior performance breakpoint are designated W (for winner), the middle 40 percent are designated N (for neutral) and firms below the 30 percent prior performance breakpoint are designated L (for loser). As previously, the six value-weight portfolios, 'S/L, S/N, S/W, B/L, B/N and B/W' are formed as the intersection of size and prior performance groups. WML (Winners Minus Losers) is the equal-weight average of the returns on the winner stock portfolio minus the returns on the loser stock portfolios: WML= ((S/W-S/L)+(B/W-B/L))/2.

For "four-factor regression", here, this study first uses the six-value-weighted portfolios (S/L, S/N, S/W, B/L, B/N and B/W) sorted on the basis of size and performance. Table 5.8, Panel A presents the results. First, the coefficients on WML factor are statistically significant for all portfolios except small size-neutral portfolio. These results suggest that the momentum effect is visible in the UK stock market. Second, intercepts for the four portfolios (S/N, S/W, B/N and B/W) are indistinguishable from zero. So, the four-factor model works well here. Third, there is again an evidence of strong small-firm effect from using the four-factor model (coefficients on the SMB factor is strongly positive and statistically significant for small firms). Fourth, there is again a strong market effect in returns (the coefficients on the market factor is positive and statistically significant for all the portfolios).

Four-Factor regression is also run on Fama and French portfolios (S/L, S/M, S/H, B/L, B/M and B/H) (see Table 5.8, Panel B). Three interesting findings are noted here. First, intercepts for all the portfolios are indistinguishable from zero. Second, coefficients on WML factor for all portfolios are statistically insignificant. Third, book-to-market factor is significant for value portfolios (S/H and B/H) and big size-growth portfolio (B/L). The results, here, are similar when the three-factor model is run on Fama and French factor portfolios. Addition of fourth factor to the three-factor model does not make any difference the results found in Table 5.2a. These results again suggest that the three-factor model works perfectly well in the UK stock market. The results in Table 5.8 also suggest that the loadings on momentum factor (WML) are extremely sensitive to the portfolios used for analysis. Table 5.8 presents some mixed results. Momentum effect may be a result of design in methodology. But, evidence of momentum effect in different stock markets and time periods reduces the likelihood that the effect is due to data-snooping[27] or methodology.

5.4.3.4. DISCUSSION AND SUMMARY

The Fama and French (1993) three-factor model showed that beta matter less than either size or BE/ME value. They derived factors from these size and value/growth effects. But, the size effect and the value/growth effect had been written before, so neither phenomena were new. What was new, was that Fama and French got a very strong support for their model, at least for their sample period of the mid-1970s, which was a very good for value stocks in US, which arguably drove their results. In my view, because there are different time periods, different markets and different countries, this chapter taking one alternative sample has so

[27] Ericsson and Gonzalez (2003) suggest that data snooping bias can be very substantial in momentum studies. The data in their study consist of all NYSE, AMEX and NASDAQ stocks on the CRSP database. Their analysis considers the period July 1963 to December 2002. They split the sample in two parts, 1963:07 to 1981:12 and 1982:01 to 2002:12. They found that the momentum effect was visible in the first period and not during the second period. The overall significance in their study was thus driven by events in the earlier part of the sample.

far suggested that the model will not always work so well. This study suggests that there are market, size and value factors in UK equity returns for the period January 1969-December 2001. Sub period analysis suggests that the Fama-French three-factor model is unable to explain the cross-sectional of expected stock returns. Moreover, the three-factor model failed to explain stock price momentum. It is therefore possible that this model omits some priced risk factors and hence provides inadequate adjustments for differences in risk. The following section will consider this issue further.

5.5. CHARACTERISTIC BALANCED PORTFOLIOS VS FACTOR PORFOLIOS

A competing model of the three-factor model of Fama and French (1993) is the model of the characteristics of the firm by Daniel and Titman (1997). Daniel and Titman gave a different interpretation for the relation between Fama and French risk factors and stock returns. Daniel and Titman (1997) argue that the construction of risk factors, which are designed to mimic an underlying risk factor in returns related to BE/ME, could induce 'spurious' correlation between a portfolio's BE/ME and its factor loading. Daniel and Titman (1997) suggest that the value or size premium traces to the value or size characteristics respectively and not to the risk. They show the superiority of their model in comparison to that of three factors of Fama and French.

5.5.1. METHODOLOGY

This test examines a characteristic and factor model that assumes that asset returns (R_{it}) are generated by the following process (for simplicity, this study assumes a single priced factor f_t and β_i is the coefficient associated with this factor; the argument is equivalent when there are multiple factors):

$$R_{i,t}=E(R_{i,t})+\beta_{i,t}f_t+\varepsilon_{i,t} \tag{5.11}$$

where ε_i is the error term and where expected returns are determined by,

$$E_{t-1}(R_{i,t})=\alpha+\delta\theta_{i,t-1}+\lambda\beta_{i,t-1} \tag{5.12}$$

where $\theta_{i,t-1}$ is a characteristic of security i (such as its size or BE/ME) observable at t-1.

The traditional factor model assumes that δ in equation (5.12) equals zero, implying that expected returns are a linear function of just the factor loading. In contrast, the characteristic model restrict λ to be zero, implying that expected returns are determined exclusively by the characteristic. Of course, it is possible that both δ and λ could be nonzero, meaning that expected returns would be function of both factor loading and the characteristic.

Distinguishing between the factor and characteristic models can be difficult, because θ_i and β_i are likely to be cross-sectionally correlated[28]. In other words, in a firm-by-firm cross-sectional regression,

$$\beta_{i,t-1} = \gamma\theta_{i,t-1} + \nu_{i,t-1} \tag{5.13}$$

both γ and the regression R^2 are likely to be significantly different from zero.

This multicollinearity problem is likely to occur in the Fama and French (1993, 1996b) test procedure that forms diversified test portfolios based on a characteristic sort. For example, a portfolio of all stocks with (roughly) the same BE/ME will have a portfolio β equal to $\gamma\theta$, as expressed in equation (5.13), because the positive and negative γs of individual securities will average out to zero. This will result in a set of test portfolios for which the average factor loading is almost perfectly correlated with the average characteristic, and a test of equation (5.12) with such portfolios will have almost no power to discriminate between the risk and non-risk based explanation. To eliminate this multicollinearity problem, Daniel and Titman (1997) point out the need to somehow create test portfolios with β s that are substantially different from $\gamma\theta$ (that is, with both substantially positive and negative γ s). For example, to test the Fama and French three factor model against the characteristic based model that the BE/ME characteristic is priced, one should form a set of high BE/ME (high θ) portfolios with both high and low loadings (β s) on the HML factor, as well as a set of low θ portfolios with both high and low

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[28] There are several arguments, why characteristics and factor loadings should be corrleated. Under a rational model, firms with a high loading on a priced factor will tend to have lower prices because their future cash flows are discounted at higher rates; this will induce a correlation between factor loadings and characteristics like size and BE/ME.

loadings (β s) on HML. This is essentially the Daniel and Titman approach, which forms two sets of test portfolios: characteristic-balanced portfolios and factor-balanced portfolios.

Characteristic-balanced portfolios are zero-cost portfolios with long and short positions in high or low factor loading stocks on one of the three factors (HML, SMB, or Market), but with similar levels of size and BE/ME. In other words, characteristic-balanced portfolios have a high sensitivity to factor loadings. It consists of the purchase and the sale of high BE/ME stocks (the purchase and the sale are made for the same amount). According to factor model explanation, expected returns of the characteristic balanced portfolios compensate for risk, unrelated to characteristics. According to the characteristic model, it is not the level of factor loadings but the level of characteristics that determines expected returns. Thus, the characteristic model would only be valid if the expected return of any characteristic-balanced portfolio is zero.

Factor-balanced portfolios are zero-cost portfolios with long and short positions in stocks with characteristics that relate to higher or lower returns but zero loadings on each of the three factors. In other words, such factor-balanced portfolios consists the purchase of portfolio of stocks of high ratio of BE/ME and low sensitivity to factor loading and the sale of portfolio of stocks of low BE/ME and of the same sensitivity to factor loading. According to the factor model, it is not the level of characteristics but the level of factor loadings that determine expected returns. Thus, the factor model would only be valid if the expected return of any factor-balanced portfolio is zero.

By forming such portfolios, appropriate "null hypotheses" can easily be defined to test the factor model and characteristic based model. Under the "factor null", the expected return of a factor-balanced portfolio is zero, and under the "characteristic model null", the expected return of a characteristic balanced portfolio is zero. If the factor model is valid, then the factor-balanced portfolios should yield average returns close to zero, because the long and short positions have similar risk exposures or characteristic-balanced portfolios should yield positive average returns for their long positions in risky stocks. If the characteristic based model is correct, then the factor-balanced portfolios should yield positive average returns since the average returns are related to the levels of characteristics or characteristic-balanced portfolios should yield around zero average returns because of the zero investment on the level of characteristics.

Finally, if the factor model is correct, then the intercepts obtained from regressing the characteristic-balanced portfolio returns on the three-factor portfolios:

$$(R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i) \tag{5.14}$$

should be zero. This is done using the Fama and French three-factor model (equation 5.14). By contrast, the characteristic model predicts that the intercepts from these regressions are negative, to offset the positive return premiums implied by the product of the positive HML loadings and the positive expected HML return (same applies for SMB and market loadings). This is because, the intercepts represent the returns of a portfolio that is factor-balanced but not characteristic-balanced, and this study will sometimes refer to the intercepts as the mean returns on factor-balanced portfolios. One can also directly evaluate each of

these two hypotheses by testing whether average returns of these two portfolios are indeed zero.

5.5.2. PORTFOLIO CONSTRUCTION

It was mentioned in the earlier section, that to distinguish between the factor and characteristic based models, one should form portfolios with low correlation between their factor loadings and characteristics. The portfolios are formed by using the UK stocks meeting the data requirements for the sample period of January 1969-December 2001. To do this, stocks are first ranked in one period by their BE/ME at the end of December of year t-1 and their market value at the end of December of year t-1. The sorting takes place before the end of December t-1. All the stocks are placed into three BE/ME groups and three size groups. At the end of June of year t (t=0), each of these nine portfolios is then subdivided equally into five value-weighted portfolios based on pre-formation values of risk loading (HML, SMB and Market). The following regression is used for the purpose:

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i, \quad t = -7 \text{ to } -42 \quad (5.15)$$

Daniel and Titman (1997) and Davis, Fama and French (2000) use special SMB and HML factors to estimate pre-formation risk loadings. When portfolios are formed on pre-formation risk loadings in June each year, the weights of securities in the pre-formation factors are fixed at their June values; security weights do not evolve with market values. The advantage of this approach is that it is likely to produce a wider spread in post-formation risk loadings (and thus more precise asset pricing tests) if the covariance matrix of security

[29] The slopes in these studies are estimated with five years (three-year minimum) of monthly returns ending in December of year t-1. In this chapter, 36 months from the five-year period are used to estimate the pre-factor loadings.

returns is relatively constant. To be consistent with the other UK study (Strong, Liu and Lee (2001)), this study uses variable-weight factors to estimate pre-formation risk loadings. Specifically these are the Fama and French (1993) variable-weight versions of SMB and HML to estimate the three-factor model on post-formation returns. According to Davis, Fama and French (2000), using the variable-weight factors to estimate pre-formation loadings have little effect on the results compare to the fixed-weight factors.

The result of this process is 45 portfolios constructed to produce variation in risk loading independent of the size and BE/ME characteristics of the portfolios. After holding these 45 portfolios for 12 months, the value-weighted returns are calculated for July of year t to June of year t+1. The whole procedure is repeated of all the periods. Hence value-weighted returns of each of these 45 portfolios are then calculated for each month between July 1978-December 2001. In total, the value-weighted returns are computed for 282 months[30]. Within each of the size and BE/ME groupings, a spread of factor loadings is obtained in quintiles (HB1 to HB5). These are basically the 'factor-loading portfolios' for the sample data.

The test of the characteristics model against the risk model focuses on the return of an arbitrage portfolio, the characteristic-balanced portfolios. The nine size and BE/ME portfolios groups are used for this purpose. Within each of the nine size-BE/ME groupings, portfolios are formed that have a one-dollar position in the high (fourth and fifth quintile) expected factor loading portfolios and short one dollar position in the low (first and second quintile) expected factor loading portfolios. Basically, this portfolio is the difference

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[30] In the study of Fama and French three-factor model, (Section.5.4), the sample period of July 1973-December 2001 is used. But in the 'characteristic-based study', this study is using the Fama and French (1993) variable-weight versions of SMB and HML which were initially used in estimating the three-factor model on post-formation returns. Using pre-formation returns, the pre-factor loadings are estimated with three to five years of monthly returns ending in December of year t-1. Hence, this study is using the pre-formation returns from July 1973. The post-formation returns were then calculated for the following 12 months. Hence the post-formation returns for 45 factor loading were estimated from July 1978-December 2001.

between the sum of the realised returns on two high factor loading portfolios (HB5 and HB4) minus the sum of the returns on the two low factor loading portfolios (HB1 and HB2) of the same size, group and then dividing it by two. The combined 'characteristic-balanced portfolio' is formed by averaging the 9 characteristic balanced portfolios across the nine size-BE/ME groups.

5.5.3. RESULTS

5.5.3.1. BE/ME VERSUS HML RISK LOADING

Table 5.9, Panel A shows the ex-ante HML loadings, average sizes, BE/ME characteristics and number of companies in each of the factor-loading portfolios. It can be clearly seen that, in each of the nine size-BE/ME groups, there is a steady increase of ex-ante HML risk loading, h_i from quintile 1 to quintile 5 (column 1 being the lowest and column 5 being the highest factor loading). With the help of these 'ex-ante HML risk loading', characteristic-balanced portfolios are constructed with long positions in stocks with extremely high sensitivity to the HML risk loading relative to the short positions. Overall, the three-pass sort succeeds in producing substantial variation in ex-ante HML risk loadings that is independent of the size and BE/ME characteristics.

Table 5.9, Panel B presents the mean excess returns and t-statistics of the 45 factor-loading portfolios. Each of the five columns provides the monthly excess returns (in percentage) of portfolios of stocks that are ranked in the particular quintile with respect to the HML factor loading. The results reveal a weak positive relation between average mean excess returns and ex-ante factor loading rankings. This shows that stocks with high

covariance with HML risk loading in the past are not rewarded by higher return in the future even before risk-adjustment. The results do not support the three-factor model. This is because generally the average return for the high HML risk loading is not necessarily higher than the average return on the low HML risk loading.

Table 5.9, Panel C presents the estimates for the three-factor regression (equation 5.14) for 45 triple sorted portfolios for full sample of January 1969-December 2001. The Panel basically shows the values of intercepts (Panel C1), its associated t-statistics (Panel C2), ex-post HML risk loading (Panel C3) and its associated t-statistics (Panel C4) respectively. The last row of Panel Table 5.9, Panel C3 shows a weak spread in average ex-post factor loadings from quintile 1 to quintile 5 (the average loadings for HB3 and HB4 are lower than the loadings for HB1 and HB2), and is not really corresponding to the ex-ante loading. This implies that ex-ante HML loading does not perform very well in predicting ex-post factor loading[31]. But, like Strong, Liu and Lee (2001), here, ex-post HML factor loading for quintile 5 exceeds that for quintile 1. The intercepts in Table 5.9, Panel C1, appear to provide some evidence against the three-factor model. Around 15 intercepts out of 45 have t-statistics with an absolute value greater than 2. The characteristic alternative implies the low-factor-portfolios should have positive intercepts and the high-factor loading portfolios should have negative intercepts. These intercepts are required by the characteristic model to offset negative intercepts for low-factor-portfolios and positive intercepts for high-factor portfolios by the factor alternative. This is not what this study finds here.

[31] Strong, Liu and Lee (2001) shows that ex-ante HML factor loading performs less well than SMB in predicting ex-post factor loading.

Now, a more conclusive (or powerful) test is required to examine the characteristic and factor based models. Like the study of Daniel and Titman (1997) and the other studies mentioned above, the test of the risk model in this study is based on the intercepts in estimates of the regression equation (5.14) for the arbitrage portfolios (which again, are the difference between the sum of the realised returns on two high factor loading portfolios (HB5 and HB4) minus the sum of the returns on the two low factor loading portfolios (HB1 and HB2) of the same size group, and then dividing it by two). The three-factor model (equation 5.14) says that the intercept should be indistinguishable from zero and the returns should be positive. In contrast, these intercepts should be negative and the returns should be zero under the characteristic model. The average returns of the characteristic-balanced portfolios as well the regression results testing the equation (5.14) are reported in Table 5.9, Panel D. Four out of the nine portfolios have positive mean returns, but none of these returns are significantly different from zero at the one or five percent level. In fact none of the returns are statistically significant.

The regression results of a single portfolio (combined characteristics-balanced portfolio) are also presented in Table 5.9, Panel D. The average return of a single portfolio (combined characteristic-balanced portfolio), formed by equally weighting the nine characteristic-balanced portfolios, is negative (-.0308%) and is not reliably different from zero (t=-.3299). So far, the tests cannot reject the null of the characteristic based model. The regressions results of the characteristic based portfolios formed on HML risk loading also favour the characteristic-based model, but to a lesser extent. Three out of the nine intercepts are negative and none of them are statistically significant. The intercept of the combined characteristic-balanced portfolio is also negative (-.0007) but statistically insignificant (-

.7432). It was mentioned earlier that the intercept can be used to proxy the factor-balanced portfolio returns and it appears that the BE/ME based factor-balanced portfolios yields an insignificant return. The insignificant intercept also shows that characteristic-balanced portfolios based on HML loading have lower power to discriminate between the factor and characteristic explanations.

This study also uses an alternative strategy to test the characteristic and factor based models. This study like Strong, Liu and Lee (2001) also examines the returns to zero-cost portfolio strategies that, for each of the nine size-BE/ME groupings, a long and short positions are taken in the highest (fifth quintile) and lowest (first quintile) expected factor loading portfolios respectively (as opposed to the (5,4-1,2) strategy discussed above). This portfolio (see Table 5.9, Panel E) also yields weaker evidence against the factor model: the average return of the combined characteristic balanced portfolio is positive but statistically[32] insignificant.

Overall, the results for characteristic balanced portfolios sorted on HML loadings have lower power to discriminate between the factor and characteristic-based model and the factor model therefore cannot be rejected in favour of its characteristic alternative unless there exists a significant premium unrelated to the factor loading.

5.5.3.2. SIZE VERSUS SMB RISK LOADING

Table 5.10, Panel A shows the ex-ante SMB loadings, average sizes, BE/ME characteristics and number of companies in each of the factor-balanced portfolios. Table 5.10, Panel B

[32] Thereafter, results from an alternative strategy will only be discussed if one finds a difference in the results from using an alternative strategy.

presents the mean excess returns and its associated t-statistics for the 45 portfolios. Table 5.10, Panel C presents the regression results for 45 factor loading portfolios. Table 5.10, Panel D presents the results of characteristic-based portfolios formed on SMB loading.

It can be seen that the spreads in ex-ante SMB factor loading increase from the lowest to the highest quintile in Panel A, and the similar pattern can also be seen in ex-post SMB loading (except the second quintile) in Panel C. A wide spread in factor loadings is therefore obtained in each size-BE/ME grouping and the post-formation SMB slopes do reproduce the ordering of the pre-formation slopes. This is different from what this study found in the HML loading case.

The variation in mean excess returns, in Panel B, is not supportive of the factor-based explanation. The relationship between the ex-post SMB loading's and excess return is weak even before the risk adjustment, that is, stocks with higher exposure to SMB are not necessarily compensated with higher returns. This gives direct evidence against the factor explanation, which predicts that exposure to factor risk should be rewarded by return. Strong, Liu and Lee (2001) obtained the similar result.

In Panel D, it can be seen that the combined characteristic-balanced portfolio has an insignificantly negative mean excess return (-.1450, t=-1.16) inspite of the significantly positive ex-post SMB loading (.296, t=8.250) obtained from the Fama and French three-factor model. The combined characteristic-balanced portfolios with high sensitivity to SMB loading fail to produce significant returns. This also shows that the evidence in favour of a size-effect is definitely not due to a factor model. In Panel D, the intercept for the combined characteristic-based portfolio is negative and statistically significant (-.003, t-statistic=-

3.174). The Fama-French three-factor model predicts that the intercepts of the combined characteristic-balanced portfolio should be zero and negative for the characteristic alternative. The combined characteristic-balanced portfolio's intercept, which also mimics the factor-balanced return, is statistically significant implying that even after controlling for the factor loadings, the size-characteristic produce a significant premium. All this also shows that the average return differential between the high-loading and low-loading portfolio is very low, relative to what would be predicted by the Fama and French (1993) model, and this large different allows this study to reject the three-factor model.

5.5.3.3. MARKET PREMIUM LOADING

Table 5.11a, Panel A shows the ex-ante market loadings (using value-weighted index), average sizes, BE/ME characteristics and number of companies in each of the factor-balanced portfolios. Table 5.11a, Panel B presents the mean excess returns and its associated t-statistics for the 45 portfolios. Table 5.11a, Panel C presents the regression results of 45 factor loading portfolios. Table 5.11a, Panel D presents the results of characteristic-based portfolios formed on market loading.

Table 5.11a, Panels A and C shows a steady increase in ex-anted factor loading and ex-post factor loading in each size-BE/ME combination. There is also a steady increase in average excess returns from quintile 1 to quintile 5 in Table 5.11a, Panel B. It can also be seen that the variation in mean excess returns in Panel B, is supportive of the factor-based explanation. The relationship between the ex-post market loading's and excess return is strong, that is, stocks with higher exposure to market are compensated with higher returns.

These result gives some evidence of the factor explanation, which predicts that exposure to factor risk should be rewarded by return.

In Table 5.11a, Panel D, the combined characteristic-balanced portfolio generates an insignificant and negative return (-.209, t-stat=-1.57) despite its significantly positive loading on market premium ex-post (.330, t-stat=14.744). One can also notice that the intercept for the combined characteristic-based portfolio is negative and statistically significant (-.006, t-statistic=-5.618). The factor model can be definitely rejected in favour of characteristic based model.

It was mentioned in the earlier chapters that sometimes the test of asset-pricing models is spuriously rejected due to poor proxies of the market portfolio. The whole procedure is therefore repeated (see Table 5.11b) by sorting the stocks on the basis of size, BE/ME and an equally-weighted index. This study (see Table 5.11b, Panel D) could not find any difference from the results obtained by using the equally-weighted index as an instrument for estimating market factor loading.

5.5.3.4. ROBUSTNESS TEST

As, Strong, Liu and Lee (2001) divided the stocks into 20 portfolios, this study also re-estimates the results by forming 20 portfolios as a robustness check. To do this, the stocks are first ranked in one period by their BE/ME at the end of December of year t-1 and their market value at the end of December of year t-1. The sorting takes place before the end of December t-1. All the stocks are then placed into two BE/ME groups and two size groups. Each of these four portfolios is then subdivided equally into five value-weighted portfolios

based on basis of risk loading (HML, SMB and Market). The results are reported in Table 5.12. The three-factor model is rejected in those cases in which the characteristic-balanced portfolios are formed on the basis of market and SMB loadings (Table 5.12, Panels A and B respectively). The positive returns and an insignificant intercept for the single characteristic-balanced portfolio formed on the basis of HML loading (Table 5.12, Panel C) show some support for the three-factor model.

5.5.3.5. SUB-PERIOD ANALYSIS

This study further tests the sensitivity of the above results (Tables 5.9, 5.10, 5.11a, 5.11b and 5.12) using different sub-periods. To do this, sample period is divided into two equal groups: July 1978-March 1990 and April 1991-December 2001. Table 5.13 presents the results. The results for the two sub-periods are very similar to each other and the overall results of the sub-period analysis are similar to the results for the full sample period. In the previous analysis, one could not discriminate between the factor and characteristic-based model for HML loading. Here, this study finds a similar result for the HML loading for both sub-periods. An insignificant intercept is found for one of the sub-periods for SMB loadings, so there is less evidence, which can be used to reject the factor model based on SMB loading. The overall sub-period results for the market factor support the characteristic-based model.

5.5.4. DISCUSSION

Overall, the results in this section suggest that the value premium or the size premium (if it exists at all) can be well explained by the three-factor model for some cases. In this, the results are comparable to other studies done on the major stock markets, such as Daniel and

Titman (1997) and Davis, Fama and French (2000) for the US, Daniel, Titman and Wei (2001) for Japan, and Strong et al (2001) for the UK. Strong, Liu and Lee (2001) found that the SMB loading was better able to discriminate between the two models compared to the HML and market loadings. In this chapter, unlike Daniel, Titman and Wei (2001), but like Strong, Liu and Lee (2001), the value premium was less able to discriminate between the two models. Strong, Liu and Lee (2001) reject the three-factor model for SMB loading. In this chapter, the three-factor model is rejected in those tests that form characteristic-balanced portfolios that load on the SMB and the market factor. Daniel, Titman and Wei (2001) reject the three-factor model in only those tests that form characteristic-balanced portfolios that load on the HML factor. Daniel and Titman (1997) reject the three-factor model with characteristic-balanced portfolios that load on HML, SMB, and Market factors. But Davis, Fama and French (2000) gives a new dimension to this study. They reject the factor model for market loading factor and only for a "different sub-period" in the US market. Here, in this chapter, when the analysis is done using sub-periods, factor model is accepted for SMB loading using sub-period sample. Surprisingly, in this chapter, the factor model is also accepted with the characteristic-balanced portfolios that load on HML loading when the portfolios are formed with a different classification (2 x 2 x 5).

Overall, this study is very important because it is only the fourth (Daniel and Titman (1997), Davis, Fama and French (2000), and Daniel, Titman and Wei (2001)) of its kind globally and second of its kind in the UK (Strong, Liu and Lee (2001)). The results in this section can be used to solve many of the existing problems such as data-snooping and measurement issues. If results in this section are true, one can exploit the profit opportunities

by following the pattern of a particular industry and not by following the pattern of the state variables like HML and SMB.

In this section, a very specific characteristic-based model is analysed. In the next section, the Lewellen (1999) model is used to obtain a stronger and comparative test of the characteristics-based model and three-factor model.

5.6. THE LEWELLEN BASED MODEL

Suppose that temporary overreaction explains deviation from the CAPM, and the HML, because of its construction, absorbs this mispricing (ignore size factor for simplicity). So, HML is constructed to explain the deviations from the CAPM. Therefore in the following equation:

$$R_i(t)=a_i+b_iRm(t)+h_iHML(t)+e_i(t) \qquad (5.16)$$

the unconditional factor loading on HML, hi will be equal to zero if assets are correctly priced on average over time. This result reflects the idea that temporary mispricing should not explain unconditional deviations from CAPM. In general, many firms have large unconditional loadings on both SMB and HML factors, which therefore suggests that the factors do not simply capture mispricing in returns. The result requires that there should be some time-variation in factor loading (hi) which should be uncorrelated with the factor's

expected returns[33]. The time-variation can be taken account using conditional regressions. This study therefore uses conditional regressions for this purpose.

5.6.1. METHODOLOGY

The empirical tests initially examine the simple relation between expected returns and characteristics. This study will use BE/ME as one of the characteristics to explain the entire methodology. The same methodology will apply to other competing factor (size characteristic) of CAPM model.

According to a risk-based view, BE/ME should capture information about changes in risk, and consequently, expected returns. The mispricing view says that BE/ME is related to biases in investor expectations, and will contain information about under- and overpricing (Lakonishok, Shleifer and Vishny (1994), Haugen (1995), DeBondt and Thaler (1987) and Daniel and Titman (1997)). Thus, both the explanations predict a positive slope coefficient in the regression:

$$R_i(t)=\alpha_{i0}+\alpha_{i1}BE/ME_i(t)+e_i(t) \qquad (5.17)$$

where R_i is the portfolio's excess return and BE/ME_i is its book-to-market portfolio's value.

This regression only picks time-series relation between expected returns and BE/ME like the time-series tested in the earlier sections. This regression makes no attempt to understand the source of time-varying expected returns. To distinguish between the factor-based model

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[33] This assumption seems reasonable since, here, one is interested in the factor loadings changing over time with firm-specific variables, like BE/ME, not with macroeconomic variables.

and characteristic based model, the predictive power of BE/ME in competition with the Fama and French (1993) three-factor model is examined. The regression framework to be used will employ the conditional time-series methodology of Shanken (1990). These regressions will combine the three-factor model with the simple regressions above. Fama and French estimate the unconditional model:

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i \qquad (5.18)$$

where Rm-Rf is the excess market return, and SMB and HML are the size and BE/ME factor mimicking portfolios. Unconditional here refers to the implicit assumption that the coefficients of the model are constant over time. If this assumption is not satisfied, the estimates from equation (5.18) can be misleading. The unconditional intercepts and factor loadings could be close to zero, but might vary considerably over time.

The conditional regressions allow both expected returns and factor loadings to vary with BE/ME. Suppose, for simplicity, that the coefficients of the three-factor model are linearly related to the firms BE/ME ratio:

(5.19)

$$a_{it} = a_{i0} + a_{i1} BE/ME_i(t)$$

$$b_{it} = b_{i0} + b_{i1} BE/ME_i(t)$$

$$s_{it} = s_{i0} + s_{i1} BE/ME_i(t)$$

$$h_{it} = h_{i0} + h_{i1} BE/ME_i(t)$$

Substituting these equations into the unconditional regressions yields a conditional version of the three-factor model:

$$R_i - R_f = a_{i0} + a_{i1} BE/ME_i + (b_{i0} + b_{i1} BE/ME_i)*Rm + (s_{i0} + s_{i1} BE/ME_i)*SMB + \quad (5.20)$$
$$(h_{i0} + h_{i1} BE/ME_i)*HML + e_i$$

where the time subscripts have been dropped to reduce clutter. The conditional regressions contain not only an intercept and three factors, but also four interactive terms with the portfolios BE/ME values.

Equation (5.20) breaks the predictive power of BE/ME into risk and non-risk components. The coefficient a_{i1}, the interactive term with the intercept, measures the predictive ability of BE/ME that is incremental to its association with risk in the three-factor model. A non-zero coefficient says that changes in the factor loading, captured by the coefficients b_{i1}, s_{i1} and h_{i1}, do not fully explain the time-series relation between BE/ME and expected return. Thus, the rational asset-pricing theory predicts that a_{i1} will be zero for all stocks, assuming that the factors are adequate proxies of priced risk. The mispricing, or characteristic-based, view implies that BE/ME will forecast returns after controlling for risk and, consequently, a_{i1} should be positive.

5.6.2. RESULTS

The empirical analysis uses size and BE/ME sorted portfolio returns for conditional regressions. The BE/ME portfolios allow us to examine how the expected returns and risk of distressed, or high-BE/ME firms change over time. Size portfolios have the advantage that they control for changes in market value, which has been shown to be associated with risk and expected returns in the previous sections.

Two sets of ten BE/ME (on the basis of BE/ME value of previous fiscal year) and ten size portfolios (on the basis of market value of the previous fiscal year) are formed. For all the two sets of portfolios, value-weighted returns are calculated. The time-series regressions use excess returns, calculated as returns minus one-month T-bill rate, and the values of BE/ME and size.

This study firstly investigates the simple time-series relation between expected returns and BE/ME. The simple regressions help evaluate the economic importance of BE/ME, without regard to changes in risk or mispricing, and provide a simple benchmark for the conditional three-factor regressions.

For each portfolio, the following equation is estimated:

$$R_i(t)=\alpha_{i0}+\alpha_{i1}BE/ME_i(t)+e_i(t) \tag{5.21}$$

The evidence in Table 5.14, Panel A1 provides some support for a positive association between expected returns and BE/ME when the portfolios are formed on BE/ME. The slopes range from .0025 to .003 and 6 of 10 coefficients are significantly different from zero at 10% significance level. A very strong evidence of the BE/ME effect is provided by the chi-squared test of the slope coefficients. Hence BE/ME does seem to capture the variation in expected returns. The same result (shown in Table 5.15, Panel A1) is found when the equation (5.21) is run on size-portfolios. A powerful test of the conditional regressions based on the BE/ME factor is now expected.

In Table 5.14, Panel A2, equation (5.21) is run using the size factor. There is absolutely no relationship between size and expected returns. This evidence potentially reduces the power of the tests of conditional regressions based on the size-factor, when the BE/ME portfolios are used. When equation (5.21) is estimated using the size portfolios and size factor (Table 5.15, Panel A2), one can see a clear size-effect in portfolio returns. So, reasonably robust results can be expected from running the conditional regressions on size-portfolios using both the size-factor and the BE/ME factor.

Table 5.14, Panel B1, reports OLS estimates of the following conditional model for the BE/ME factor on BE/ME sorted portfolios:

$$R_i - R_f = a_{i0} + a_{i1}BE/ME_i + (b_{i0} + b_{i1}BE/ME_i)*Rm + (s_{i0} + s_{i1}BE/ME_i)*SMB + \quad (5.22)$$

$$(h_{i0} + h_{i1}BE/ME_i)*HML + e_i$$

For brevity, the constant components of the coefficients on the intercept and factor loadings (a_{i0}, b_{io}, s_{i0} *and* h_{i0}) are not reported here. The interactive terms (a_{i1}, b_{i1}, s_{i1} *and* h_{i1}) with BE/ME are more interesting as will be discussed. The Table 5.14, Panel B1 shows that BE/ME directly predicts expected returns. The chi-square statistic can reject the hypothesis that all coefficients on BE/ME are zero, with a p-value of 0.01. There seems to be very strong evidence that BE/ME explains economically or statistically significant variation in the intercepts. Most of the interactive terms (a_{i1}) with the intercepts are significantly positive. Thus risk doesn't appear to explain any association between BE/ME and expected returns. The chi-squared statistics also cannot reject the hypothesis that BE/ME is unrelated to the loadings on Rm (p-value of 0.00), SMB (p-value of 0.00) and HML (p-value of .04). But, BE/ME tends to be negatively related to the loadings on the Rm, SMB and HML factor. This study therefore cannot interpret positive relationship in BE/ME as an evidence of distress. According to this result, there seems to be no link between Fama and French factor (HML) and distress firms. This evidence is consistent with the argument that the BE/ME factor proxies for mispricing in stock returns. Overall, there seems to be some support of characteristic-based model.

Using the size factor, equation (5.22) is run on the BE/ME portfolios. In Table 5.14, Panel B2, it can be seen that the chi-square statistics (p-value=.21) can easily accept the hypothesis that all the coefficients (a_{i1}) on size factor are zero. These results do not support the characteristic-based model. But the chi-square statistic cannot reject the hypothesis that size is unrelated to the loadings on Rm, SMB and HML factors with the p-value of 0.00, 0.00 and .001 respectively. The signs are in line with theory. This is because the size tends to

be positively related to the loadings on the three factors. The results suggest that, there is a time-varying relationship between the behaviour of size and Fama and French factors.

Using the BE/ME factor, equation (5.22) is run on the size portfolios (shown in Table 5.15). The BE/ME factor is not able to capture a proper variation in risk. The signs of the coefficients of the interactive terms on Fama and French factors (market, SMB and HML) are not in line with the theory. The results, here, suggest that the BE/ME variable has very little power to directly predict expected returns. The chi-squared can accept the hypothesis that all coefficients on BE/ME are zero with the p-value of .06. The evidence is not as strong as one achieved when the conditional regression is run using the BE/ME factor on BE/ME sorted portfolios. On the basis of these results, it is not easy to choose an appropriate model.

The results for the conditional regressions using the size-factor and size-portfolios (shown in Table 5.15, Panel B2) are a little bit different to the results when the conditional regressions were run using the size-factor on BE/ME portfolios (shown in Table 5.14, Panel B2). The chi-square statistic can reject the hypothesis that all coefficients (a_{i1}) on size are zero, with a p-value of 0.01. There seems to be some evidence that size explains economically or statistically significant variation in the intercepts. There are some evidences that the size factor is related to the Fama and French factors (p-value of 0.00, 0.00 and 0.00 for market, SMB and HML factor respectively). The signs of the coefficients of the interactive terms on Fama and French factors (market, SMB and HML) are also in line with the theory. On the basis of these results, one can neither accept nor reject the Fama-French three-factor model or the characteristic-based model. The power of test is not strong enough to accept either model in full confidence.

Given that, this study is the first one to use the conditional regressions to test characteristic-based and Fama and French factor model in the UK stock market, the evidence in this chapter might be useful if similar analysis is again done on the UK stock market.

5.7. CONCLUSION

This chapter has presented a mixed evidence regarding the three-factor and characteristic-based models. A key contribution of this chapter is to illustrate the many ways in which the Fama and French factors can be tested. Using samples of monthly data (January 1969-December 2001), this study analyses the sensitivity of a set of portfolio to the proxy-mimicking portfolios and perform a set of asset-pricing tests of the Fama and French model based on the proxy factors. The three-factor model results show that the size and BE/ME explain strong variation in stock returns and help explain the time-series of average returns as found by Fama and French (1993, 1996b).

However, there was some evidence against the three-factor model. For example, the Fama-French three-factor model was not able to account for the momentum effects. But this problem alone cannot be considered strong enough to discard the Fama-French three-factor model. This is because, factors like transaction costs and taxes can significantly erode the momentum profits. Furthermore, in practical sense, most of the returns to the winner minus loser portfolio are due to the poor performance of the losers. Hence to make profits from momentum strategies, it is very important for the investors to be able to take short-positions in the market. This is not possible for all the investors.

There were other reasons for not fully accepting the Fama-French three-factor model. The model was also invalid in different sub-periods. Mispricing in the spirit of Lakonishok, Shleifer, and Vishny (1994) might explain deviations from the CAPM, or the Fama and French factors might be empirically motivated. The main criticisms of the factor model came from Daniel and Titman (1997). They argued that the premium gained by investing in value stocks or size stocks is due to characteristics and not risk. This study therefore went one step further and tested this 'so-called' characteristic-based model. To do this, zero-cost portfolios are formed that are characteristic-balanced but are sensitive to at least one of the Fama and French factors. Overall, in this chapter, factor-based models based on SMB and market factor are rejected but not the characteristic-based model. Hence, the rational-pricing story by Fama and French (1993, 1996b) is not supported by the evidence in this chapter while the irrational pricing story by Daniel and Titman (1997) is supported to some extent. However, this conclusion cannot be fully accepted for 2 reasons. First, because of the low power of some of the tests (results based on HML loading), this study couldn't draw a definitive conclusion. Second, Daniel and Titman's (1997) arguments do not fully account for the relation between characteristics and risk. They only provided a justification for the BE/ME characteristics. In particular, their argument suggests that the loadings on HML (the BE/ME factor) will tend to vary with BE/ME due to growth and distress characteristics and not due to a common distress factor. They did not however say anything about the loadings on the market and SMB factor. Therefore, evidence in support of their characteristics model does not provide a complete argument against the Fama and French three-factor model.

This study then used the conditional regression framework of Lewellen (1999) to further test the Fama and French three-factor model and characteristic-based model. This study tested whether the risk loadings explain time-varying expected returns better than the characteristic-based model in the UK stock markets. One still couldn't get a definite answer using this methodology. The conditional regressions indicated that BE/ME can be directly predicted and without the support of the time-variation in risk. The general impression conveyed by the conditional regressions regarding the Fama and French factors is mixed. First, results from this methodology suggest that after controlling for changes in risk, BE/ME seems to contain information about expected returns. The BE/ME factor is due to a characteristic-based theory. Second, there are some results, which support the risk-based story of Fama and French. There seems to be a strong support for the Fama and French size factor when the conditional regressions are run using size factor. But, overall, the results of the conditional regressions are sensitive to the way the portfolios are formed in this study. This is bound to happen because these types of test are always influenced by the correlation between the characteristics and factor loadings. For example, a test of the size factor, will have greater power if size is not used in the portfolio formation process. Having said that, none of the tests (Fama and French (1993) and Daniel and Titman (1997)) are always entirely conclusive. These tests have been concerned primarily with changes in expected returns over time, not with their average levels. But always, in rational pricing framework, average levels are used for such test. In some cases, this study found that the unconditional intercepts supported either model. As a result, either of the models (Fama and French (1993) and Daniel and Titman (1997)) failed to explain average returns. It is therefore not easy to properly identify the validity of risk factors in asset-pricing theory. The story of asset-pricing theory will remain incomplete until some more discoveries are made about the risk factors.

The findings in this chapter do not really support the notion that the CAPM can be extended to the three-factor model. CAPM was and is a theory of equilibrium. The key insight of the CAPM is that higher expected returns go with the greater risk of doing badly in bad times. Beta is a measure of that. The three-factor model is a richer way of measuring the probability of doing badly in bad times. This is because, in any state (good or bad) of the world, CAPM only holds if the hedging demands like small-size or value-growth strategies of various investors are equally distributed across different types of securities so that deviations of portfolios weights from those of the market portfolios are offsetting. But if hedging demands are common to many investors, the prices of securities with desirable hedging characteristics will be bid up and the expected return reduced, which will invalidate the CAPM. Moreover, there's a lot of confusion and inconsistency in how some people take the Fama and French results to market and advocate a big value tilt and a big small tilt in their portfolios. If those tilts are just measures of an unrealized but future-looking beta, then the investors shouldn't have those tilts unless the investor happen to be one of those people who doesn't care how badly he does when the times are bad. We do care when times are bad. Otherwise, there shouldn't be a risk premium for anything.

Overall, there are some evidences in this chapter, supporting the significance of value and size variables. But it is too early to say whether the evidences comes for the irrational or rational asset-pricing framework.

There are numerous questions left unanswered by this study. Are the size and value factors pervasive in explaining the risk of a wider range of portfolios (such as industry

portfolios) for the UK stock market? Is there evidence of any other pervasive factor in returns? These questions are still left answered in the rational asset-pricing theory.

TABLE 5.1
SUMMARY STATISTICS OF VALUE, SIZE AND FACTOR PORTFOLIOS: JANUARY 1969 TO DECEMBER 2001, 342 MONTHLY OBSERVATIONS.

PANEL A: AVERAGES

	Value weights	% Value weights	Average firms	BE/ME average	BE/ME (value-weight average)	Size average (£ m)	Size (value-weight average)
S/L	0.0061	0.6081	117	-9.6927	0.1808	1145.2366	5.7474
S/M	0.0063	0.6263	157	191.0750	1.2519	1397.8031	7.8723
S/H	0.0036	0.3572	122	557.2020	1.7059	1053.6528	4.5737
B/L	0.5345	53.4504	113	-70.6771	-33.9002	125925.5313	62821.8672
B/M	0.2457	24.5720	157	118.5471	27.5472	84908.1797	28222.8203
B/H	0.2039	20.3860	127	238.7168	63.2039	60466.0898	16176.0693

PANEL B: MOMENTS

	Excess Return (%)	t-statistics (Excess Returns)	Standard deviation (%)	Skewness	Kurtosis	AR1	AR2	AR3
S/L	0.733	***2.6923***	5.035	-0.6296	2.4619	**0.3513**	0.1092	0.0537
S/M	0.8434	***3.2164***	4.8493	-0.6886	3.0356	**0.3262**	0.0779	-0.0162
S/H	0.9513	***3.7754***	4.6599	-0.8168	3.6822	**0.3666**	0.0929	**0.0264**
B/L	1.0453	***2.9195***	6.6215	0.6845	8.1738	0.0972	-0.1165	0.1568
B/M	0.8802	***2.5021***	6.5054	0.4575	6.3708	0.0982	-0.068	0.0986
B/H	1.0002	***2.8739***	6.4362	0.6944	9.2135	**0.1649**	-0.0649	**0.1137**
Rm-Rf	1.1088	***3.37***	6.0795	0.2294	9.0065	0.1002	-0.0947	0.0522
Rem-Rf	0.9101	***2.87***	5.859	0.1353	5.4704	**0.2491**	0.0053	0.0951
SMB	-0.1326	***-0.556***	4.4122	-1.3111	8.1495	0.097	-0.1037	**0.2263**
HML	0.0866	***0.8012***	1.9988	-0.0229	1.2434	0.0406	-0.0073	0.0211

PANEL C: CORRELATION COEFFICIENTS

	Rm-Rf	Rem-Rf	SMB	HML
Rm-Rf	1.0000	0.8032	-0.5559	-0.2492
Rem-Rf	0.8032	1.0000	-0.3517	-0.1642
SMB	-0.5559	-0.3517	1.0000	0.2942
HML	-0.2492	-0.1642	0.2942	1.0000

*In Panel A, BE/ME and size are value-weighted and are averages of annual values for the time-period shown. The average number of firms in each portfolio is equally-weighted. In Panel B, excess returns, its associated t-statistics (bold) and the other three moments are shown. The underlined t-statistics indicates significance at 5 %, * * indicates significance at 10% level.*

The autorcorrelations are also shown in panel B (bold numbers are statistically significant at 5% level of significance). Panel C shows the correlation coefficients of value, size and factor portfolios.
At the end of June of each year t (1969 to 2001), stocks are allocated to two groups (S or B) based on the market value on December t-1. Stocks are independently sorted to three Book-to-Market Equity (BE/ME) groups (L, M, or H) based on breakpoints for the bottom 30%, middle 40% and top 30% of the values of BE/ME for the UK stocks in current sample. BE/ME and size are based on BE/ME and market value at the end of December t-1. Six portfolios (S/L, S/M, S/H, B/L, B/M and B/H) are formed as the intersections of the two size and the three BE/ME groups. Value-weighted monthly returns on the portfolios are calculated from July of year t to June of t+1.

SMB: (Small Minus Big) is meant to mimic the risk factor in returns related to size. SMB is the difference each month between the simple average of the returns of three small stock portfolios (S/L, S/M and S/H) and the average of the return on three big portfolios (B/L, B/M, B/H). It is the difference between the returns on small and big stocks portfolios with about the same weighted-average BE/ME. Hence SMB is largely clear of BE/ME effects, focused on the different behavior of small and big stocks; HML: (High Minus Big) is meant to mimic the risk factor in return related to value (this is book-to-market ratios). HML is the difference each month between the simple average of the returns on two high BE/ME portfolios (S/H and B/H) and the average returns on two low BE/ME portfolios (S/L and B/L); it is constructed to be relatively free of the size effect; Rf is the one-month Treasury bill rate (from DataStream); Rm is the value-weighted index (FTSE-ALLSHARE INDEX) and Rem is the equally-weighted index on all stocks in our sample.

TABLE 5.2
EXCESS RETURN ON THE SIX SIZE-BE/ME PORTFOLIOS REGRESSED ON FACTOR PORTFOLIOS: JANUARY 1969 TO DECEMBER 2001, 342 OBSERVATIONS

Models		a	*t(a)*	b	*t(b)*	s	*t(s)*	h	*t(h)*	Adjusted R-square	GRS Test Statistics
Panel 2A											
	S/L	0.000	*-0.227*	0.781	*23.476*	0.613	*13.195*	-0.150	*-1.706* **	0.6275	2.084
	S/M	0.001	*0.430*	0.769	*24.404*	0.638	*14.505*	0.074	*0.888*	0.6402	*0.081*
	S/H	0.002	*1.102*	0.742	*25.279*	0.601	*14.647*	0.482	*6.210*	0.6612	
	B/L	0.002	*1.422*	0.735	*24.813*	-0.417	*-10.077*	-0.465	*-5.932*	0.8295	
	B/M	0.000	*-0.176*	0.784	*23.387*	-0.328	*-7.008*	-0.032	*-0.362*	0.7732	
	B/H	0.000	*0.064*	0.773	*22.934*	-0.404	*-8.585*	0.903	*10.125*	0.7659	
Panel 2B											
	S/L	0.001	*0.612*	0.546	*16.171*					0.435	2.208
	S/M	0.003	*1.371*	0.505	*15.090*					0.401	*0.053*
	S/H	0.004	*2.149*	0.461	*13.859*					0.361	
	B/L	0.000	*0.013*	0.941	*31.580*					0.746	
	B/M	-0.001	*-0.760*	0.919	*30.966*					0.738	
	B/H	0.000	*0.215*	0.862	*25.882*					0.663	
Panel 2C											
	S/L	0.008	*2.847*			0.044	*0.690*	-0.373	*-2.632*	0.0200	1.276
	S/M	0.009	*3.298*			0.078	*1.257*	-0.145	*-1.057*	0.0061	*0.279*
	S/H	0.009	*3.735*			0.060	*1.012*	0.271	*2.064*	0.0206	
	B/L	0.010	*3.917*			-0.951	*-16.081*	-0.674	*-5.163*	0.519	
	B/M	0.008	*2.875*			-0.899	*-13.928*	-0.256	*-1.796* **	0.4063	
	B/H	0.008	*3.005*			-0.967	*-15.080*	0.682	*4.821*	0.4017	
Panel 2D											
	S/L	-0.001	*-0.355*	0.787	*23.732*	0.598	*13.076*			0.6243	2.155
	S/M	0.001	*0.498*	0.766	*24.458*	0.645	*14.963*			0.6393	*0.073*
	S/H	0.002	*1.491*	0.723	*23.486*	0.650	*15.326*			0.6225	
	B/L	0.002	*0.934*	0.753	*24.401*	-0.464	*-10.903*			0.8118	
	B/M	0.000	*-0.204*	0.786	*23.593*	-0.331	*-7.223*			0.7732	
	B/H	0.001	*0.724*	0.736	*19.273*	-0.312	*-5.926*			0.6949	
Panel 2E											
	S/L	0.001	*0.546*	0.552	*15.824*			0.074	*0.701*	0.4356	2.786
	S/M	0.002	*1.115*	0.530	*15.517*			0.308	*2.959*	0.4162	*0.020*
	S/H	0.003	*1.646* **	0.518	*16.194*			0.702	*7.218*	0.4461	
	B/L	0.001	*0.649*	0.890	*30.945*			-0.617	*-7.054*	0.7783	
	B/M	-0.001	*-0.611*	0.907	*29.655*			-0.152	*-1.638*	0.7403	
	B/H	-0.001	*-0.472*	0.924	*29.149*			0.755	*7.829*	0.7149	

Panel 2A to Panel 2E presents the slope coefficients, its associated t-statistics (in bold) and Adjusted R-square values for different combinations of the Fama-French factors using the following model:

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i \qquad (5.3)$$

Panel 2A to Panel 2E also presents GRS test-statistics and its associated probability values for different combinations of the Fama-French Factors. Standard zero intercept restriction that the null hypothesis: Ho: $a_i = 0$, i=1,2, N, is tested using a GRS test statistics.

*The underlined t-statistics indicates significance at 5 %, ** indicates significance at 10% level.*

At the end of June of each year t (1969 to 2001), stocks are allocated to two groups (S or B) based on the market value on December t-1. Stocks are independently sorted to three Book-to-Market Equity (BE/ME) groups (L, M, or H) based on breakpoints for the bottom 30%, middle 40% and top 30% of the values of BE/ME for the UK stocks in current sample. BE/ME and size are based on BE/ME and market value at the end of December t-1. Six portfolios (S/L, S/M, S/H, B/L, B/M and B/H) are formed as the intersections of the two size and the three BE/ME groups. Value-weighted monthly returns on the portfolios are calculated from July of year t to June of t+1.

SMB: (Small Minus Big) is meant to mimic the risk factor in returns related to size. SMB is the difference each month between the simple average of the returns of three small stock portfolios (S/L, S/M and S/H) and the average of the return on three big portfolios (B/L, B/M, B/H). It is the difference between the returns on small and big stocks portfolios with about the same weighted-average BE/ME. Hence SMB is largely clear of BE/ME effects, focused on the different behavior of small and big stocks; HML: (High Minus Big) is meant to mimic the risk factor in return related to value (this is book-to-market ratios). HML is the difference each month between the simple average of the returns on two high BE/ME portfolios (S/H and B/H) and the average returns on two low BE/ME portfolios (S/L and B/L); it is constructed to be relatively free of the size effect; Rf is the one-month Treasury bill rate (from DataStream) and Rm is the value-weighted index (FTSE-ALLSHARE INDEX).

TABLE 5.3
ONE FACTOR AND THREE-FACTOR REGRESSIONS FOR PORTFOLIOS FORMED FROM DEPENDENT SORTS ON SIZE AND BE/ME: JANUARY 1969 TO DECEMBER 2001, 342 MONTHLY OBSERVATIONS

PANEL A	BE/ME Quintiles									
Size Quintile	Low	2	3	4	5	Low	2	3	4	5
			a					*t(a)*		
Small	0.0064	0.0031	0.0067	0.0071	0.0039	***2.3709***	***1.1428***	***2.6049***	***2.5886***	***1.3281***
2	0.0021	0.0019	0.0019	0.0009	0.0022	***0.8666***	***0.7473***	***0.7815***	***0.4015***	***0.8268***
3	-0.0020	0.0008	-0.0001	-0.0018	-0.0004	***-0.8521***	***0.2978***	***-0.0287***	***-0.7248***	***-0.1674***
4	-0.0033	-0.0019	-0.0003	0.0004	-0.0027	***-1.4379***	***-0.8249***	***-0.1116***	***0.1724***	***-1.2344***
Big	-0.0024	-0.0027	-0.0025	-0.0029	-0.0007	***-1.1972***	***-1.2920***	***-1.1770***	***-1.3164***	***-0.3011***
			b					*t(b)*		
Small	0.3611	0.5392	0.4423	0.4629	0.5933	***8.2464***	***12.2244***	***10.5683***	***10.4351***	***12.3252***
2	0.5299	0.5505	0.5631	0.6180	0.5088	***13.4062***	***13.6941***	***13.9768***	***16.3107***	***11.8612***
3	0.7288	0.7162	0.7271	0.7000	0.6953	***19.1181***	***17.4290***	***19.0656***	***17.3840***	***17.8340***
4	0.8825	0.8547	0.8380	0.8269	0.8214	***23.7645***	***22.9989***	***21.7609***	***21.5432***	***23.3220***
Big	1.0011	0.9727	1.0044	1.0180	0.9790	***31.0668***	***28.3451***	***28.8413***	***28.6197***	***26.9827***
			Adjusted R-square							
Small	0.1667	0.3053	0.2473	0.2426	0.3088					
2	0.3458	0.3555	0.3649	0.4390	0.2927					
3	0.5181	0.4719	0.5167	0.4706	0.4833					
4	0.6242	0.6087	0.5821	0.5772	0.6153					
Big	0.7395	0.7027	0.7099	0.7067	0.6817					

PANEL B	BE/ME Quintiles									
Size Quintile	Low	2	3	4	5	Low	2	3	4	5
			a					*t (a)*		
Small	0.0045	0.0009	0.0045	0.0047	0.0023	***1.8594*** **	***0.3724***	***1.9952***	***1.8995*** **	***0.7907***
2	0.0006	0.0001	-0.0003	-0.0011	-0.0002	***0.2708***	***0.0243***	***-0.1223***	***-0.5539***	***-0.0784***
3	-0.0031	-0.0004	-0.0013	-0.0034	-0.0020	***-1.3485***	***-0.1506***	***-0.5616***	***-1.4701***	***-0.8570***
4	-0.0043	-0.0023	-0.0007	-0.0006	-0.0035	***-1.9178*** **	***-1.0023***	***-0.2932***	***-0.2468***	***-1.6556***
Big	-0.0013	-0.0018	-0.0020	-0.0022	-0.0003	***-0.6529***	***-0.8682***	***-0.9313***	***-1.0299***	***-0.1558***
			b					*t(b)*		
Small	0.6008	0.8370	0.6980	0.7149	0.7639	***12.6178***	***18.7501***	***15.7316***	***14.9272***	***13.6498***
2	0.7350	0.7864	0.8455	0.8576	0.7439	***16.9537***	***18.3566***	***21.0309***	***21.5905***	***15.9925***
3	0.8677	0.8600	0.8660	0.8780	0.8546	***19.6461***	***17.9790***	***19.5474***	***19.2014***	***19.1385***
4	0.9941	0.9120	0.8921	0.9307	0.9146	***22.7195***	***20.3891***	***19.2114***	***20.4670***	***21.8919***
Big	0.8876	0.8570	0.9160	0.9201	0.8777	***23.6860***	***21.3713***	***22.2348***	***21.9215***	***21.0458***
			s					*t(s)*		
Small	0.5953	0.7495	0.5997	0.5435	0.3614	***8.9532***	***12.0267***	***9.6807***	***8.1283***	***4.6251***
2	0.5239	0.5915	0.7015	0.5584	0.4858	***8.6552***	***9.8896***	***12.4971***	***10.0694***	***7.4802***
3	0.3497	0.3555	0.3216	0.3945	0.3378	***5.6716***	***5.3239***	***5.1986***	***6.1796***	***5.4188***
4	0.2516	0.1487	0.1322	0.2261	0.2060	***4.1181***	***2.3810***	***2.0382***	***3.5620***	***3.5315***
Big	-0.2387	-0.2785	-0.2423	-0.2593	-0.3314	***-4.5616***	***-4.9745***	***-4.2117***	***-4.4249***	***-5.6911***
			h					*t(h)*		
Small	-0.0057	-0.0570	0.1674	0.3988	0.3025	***-0.0449***	***-0.4826***	***1.4266***	***3.1478***	***2.0434***
2	-0.0773	-0.0344	-0.0070	0.1750	0.4772	***-0.6737***	***-0.3036***	***-0.0658***	***1.6654*** **	***3.8782***
3	-0.0274	0.0034	0.1112	0.2295	0.2807	***-0.2342***	***0.0271***	***0.9489***	***1.8971*** **	***2.3762***
4	0.1230	-0.0300	0.0090	0.1530	0.1230	***1.0700***	***-0.2800***	***0.0800***	***1.2700***	***1.1100***
Big	-0.2108	-0.0410	0.1138	0.0817	0.3958	***-2.1265***	***-0.3862***	***1.0444***	***0.7356***	***3.5878***
			Adjusted R-square							
Small	0.3311	0.5170	0.4257	0.4007	0.3658					
2	0.4658	0.5032	0.5706	0.5814	0.4354					
3	0.5609	0.5143	0.5573	0.5366	0.5399					
4	0.6400	0.6100	0.5800	0.5900	0.6300					
Big	0.7609	0.7244	0.7244	0.7227	0.7145					

TABLE 5.3
(cont.)

PANEL C: GRS TEST STATISTICS

Model	GRS TEST-STATISTICS	P-value
One factor model	1.730	.140
Three factor model	1.899	.092

Dependent variable: Excess Returns on 25 dependent stock portfolios formed on size and BE/ME

The 25 size-BE/ME stock portfolios are formed as the intersections of five size and five BE/ME groups. Equally-Weighted monthly returns on the portfolios are calculated from July of year to June of t+1.

Panel A presents the regression results of one-factor model, its associated t-statistics (in bold) and Adjusted R-square values.
Panel B presents the regression results of three-factor model, its associated t-statistics (in bold) and Adjusted R-square values.

*The underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level.*
(Refer to the notes in Table 5.1 and Table 5.2 to see the details relating to size, value and factor portfolios)
Panel C presents the GRS test statistics and its associated probability-value of the models.

TABLE 5.4
SEASONALITY ANALYSIS OF FAMA AND FRENCH FACTORS FOR THE SAMPLE PERIOD: JANUARY 1969-DECEMBER 2001

PANEL A: JANUARY SEASONALITY

	γ_0	t-value	γ_1	t-value	β_1	t-value	β_2	t-value	s_1	t-value	s_2	t-value	h_1	t-value	h_2	t-value
S/L	-0.001	***-0.378***	-0.008	***-0.854***	0.793	***22.570***	0.177	***1.168***	0.555	***11.355***	0.545	***2.733***	-0.092	***-1.008***	-0.395	***-1.259***
S/M	0.000	***0.136***	-0.002	***-0.209***	0.782	***23.515***	0.091	***0.637***	0.581	***12.558***	0.442	***2.340***	0.120	***1.384***	-0.244	***-0.821***
S/H	0.002	***0.991***	-0.002	***-0.283***	0.757	***24.178***	0.023	***0.168***	0.566	***13.010***	0.254	***1.429***	0.526	***6.467***	-0.299	***-1.068***
B/L	0.002	***1.307***	-0.001	***-0.095***	0.749	***23.664***	-0.013	***-0.097***	-0.445	***-10.101***	0.181	***1.008***	-0.432	***-5.253***	-0.192	***-0.680***
B/M	-0.001	***-0.458***	-0.005	***-0.531***	0.798	***22.672***	0.163	***1.074***	-0.397	***-8.110***	0.588	***2.942***	0.035	***0.381***	-0.457	***-1.454***
B/H	0.000	***-0.082***	-0.006	***-0.675***	0.785	***21.950***	0.141	***0.915***	-0.456	***-9.174***	0.472	***2.326***	0.950	***10.233***	-0.288	***-0.903***

PANEL B: APRIL SEASONALITY

	γ_0	t-value	γ_1	t-value	β_1	t-value	β_2	t-value	s_1	t-value	s_2	t-value	h_1	t-value	h_2	t-value
S/L	-0.001	***-0.448***	0.008	***0.968***	0.777	***22.642***	-0.008	***-0.052***	0.602	***12.751***	0.293	***1.021***	-0.170	***-1.880*** **	0.151	***0.349***
S/M	0.000	***0.101***	0.005	***0.733***	0.759	***23.337***	0.098	***0.636***	0.630	***14.070***	0.164	***0.602***	0.061	***0.711***	0.078	***0.191***
S/H	0.001	***0.657***	0.006	***0.811***	0.726	***24.150***	0.179	***1.249***	0.586	***14.160***	0.278	***1.105***	0.448	***5.652***	0.370	***0.978***
B/L	0.002	***0.989***	0.004	***0.576***	0.718	***23.634***	0.212	***1.462***	-0.429	***-10.269***	0.239	***0.940***	-0.494	***-6.161***	0.304	***0.796***
B/M	-0.001	***-0.500***	0.009	***1.089***	0.776	***22.461***	0.033	***0.202***	-0.339	***-7.114***	0.243	***0.839***	-0.055	***-0.603***	0.210	***0.483***
B/H	0.000	***-0.145***	0.006	***0.756***	0.768	***22.051***	0.024	***0.145***	-0.413	***-8.619***	0.254	***0.871***	0.888	***9.662***	0.085	***0.194***

*Panel A report the estimates and associated t-statistics (bold and italic numbers) using the January dummy variable (equation (5.6)). Panel B reports the estimates and associated t-statistics (bold and italic numbers) using the April dummy variable (equation (5.7)). The underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level.*

The seasonal patterns in the Fama and French factors are tested through the following time-series model:

(5.6)

$$R_{pt}=\gamma_{0p}+\gamma_{1p}D_t^{January}+\beta_{1p}RM_t+\beta_{2p}(D_t^{January}*RM_t)+s_{1p}SMB_t+s_{2p}(D_t^{January}*SMB_t)+h_{1p}HML+h_{2p}(D_t^{January}*HML)+\varepsilon_{pt}$$

where R_{pt} is the 342 x 6 matrix of portfolio returns; the January dummy variable, D_t^{jan}, takes on the value of one in January and zero in other months; RM, SMB and HML are the market (value-weighted index), size factor and BE/ME factor respectively. β_{1p}, s_{1p} and h_{1p} are the coefficients associated with market, SMB and HML factors respectively; β_{2p}, s_{2p} and h_{2p} are the January slope dummy variables associated with market, SMB and HML factors respectively and ε_{pt} is the residual term. In the same way, the following equation (5.7) is tested for April Seasonality.

(5.7)

$$R_{pt}=\gamma_{0p}+\gamma_{1p}D_t^{April}+\beta_{1p}RM_t+\beta_{2p}(D_t^{April}*RM_t)+s_{1p}SMB_t+s_{2p}(D_t^{April}*SMB_t)+h_{1p}HML+h_{2p}(D_t^{April}*HML)+\varepsilon_{pt}$$

(Refer to the notes in Table 5.1 and Table 5.2 to see the details relating to size, value and factor portfolios)

TABLE 5.5
EXCESS RETURNS ON THE SIX SIZE-BE/ME PORTFOLIOS REGRESSED ON RM-RF, SMB AND HML: JANUARY 1969 TO DECEMBER 2001: SPILT SAMPLE.

PANEL A: REGRESSION OF SPILT-A DEPENDENT RETURNS ON SPILT-B EXPLANATORY RETURNS

(A1) RETURN BEHAVIOUR

	MEAN (%)	t
S/L	1.7708	***4.0474***
S/M	1.8406	***1.8884*** **
S/H	0.1199	***2.2846***
B/L	1.9182	***4.8323***
B/M	2.3396	***5.1854***
B/H	1.8471	***4.2400***
Rm-Rf	1.1088	***3.3727***
Rem-RF	0.9101	***2.8726***
SMB	0.3816	***1.6459*** **
HML	0.4593	***1.5969***

(A2) ONE FACTOR MODEL: $R_i - R_f = a_i + b_i[R_m - R_f] + \varepsilon_i$

	a	t(a)	B	t(b)	Adjusted R-square
S/L	0.0087	***.5612***	0.8161	***14.3130***	0.3760
S/M	0.0089	***.5991***	0.8571	***13.6600***	0.3543
S/H	-0.0055	***.3414***	0.6006	***9.7840***	0.2197
B/L	0.0109	***.9314***	0.7493	***14.5928***	0.3851
B/M	0.0149	***.8092***	0.7676	***12.4400***	0.3128
B/H	0.0096	***.8117***	0.8032	***14.0521***	0.3674

(A3) THREE-FACTOR MODEL: $R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i$

	a	t(a)	b	t(b)	s	t(s)	h	t(h)	Adjusted R-square
S/L	0.0096	***.7169***	0.7962	***13.9605***	-0.2425	***-2.6898***	0.0553	***0.7668***	0.3895
S/M	0.0087	***.2225***	0.8618	***13.5889***	0.0571	***0.5699***	-0.0123	***-0.1540***	0.355
S/H	-0.0033	***.8882***	0.5749	***9.6109***	-0.2282	***-2.4127***	-0.2241	***-2.962***	0.2755
B/L	0.0108	***.3674***	0.7480	***14.4178***	-0.0294	***-0.3581***	0.0502	***0.7641***	0.3862
B/M	0.0140	***.6663***	0.7851	***12.6732***	0.2047	***2.0900***	-0.0196	***-0.2500***	0.3227
B/H	0.0094	***.6487***	0.8110	***14.0673***	0.1106	***1.2137***	-0.0773	***-2.061***	0.3708

PANEL B: REGRESSION OF SPILT-B DEPENDENT RETURNS ON SPILT-A EXPLANATORY RETURNS

(B1) RETURN BEHAVIOUR

	MEAN (%)	t
S/L	2.2403	***5.3707***
S/M	2.1721	***5.5254***
S/H	2.2163	***5.0508***
B/L	1.3549	***2.2979***
B/M	1.8313	***4.1025***
B/H	2.2975	***5.3605***
Rm-Rf	1.1088	***3.3727***
Rem-RF	0.9101	***2.8726***
SMB	-0.7912	***-3.6143***
HML	-0.8610	***-3.8735***

TABLE 5.5 (cont.)

(B2) ONE FACTOR MODEL: $R_i - R_f = a_i + b_i[R_m - R_f] + \varepsilon_i$

	a	t(a)	b	t (b)	Adjusted R-square
S/L	0.0138	***1.1067***	0.7778	***14.3070***	0.3758
S/M	0.0137	***.2991***	0.7254	***14.0699***	0.3680
S/H	0.0131	***.7080***	0.8209	***14.3820***	0.3782
B/L	0.0028	***1.5554***	0.9690	***11.8382***	0.2919
B/M	0.0101	***.6480***	0.7435	***12.0661***	0.2998
B/H	0.0133	***.1035***	0.8750	***16.6934***	0.4504

(B3) THREE-FACTOR MODEL: $R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i$

	a	t(a)	b	t(b)	s	t(s)	h	t(h)	Adjusted R-square
S/L	0.0132	***.8460***	0.7833	***14.3474***	-0.1778	***-2.0215***	0.1014	***1.1621***	0.3836
S/M	0.0136	***.1903***	0.7343	***14.1811***	-0.1442	***-1.7276*** **	0.1376	***1.6623*** **	0.3757
S/H	0.0117	***.2442***	0.8095	***14.1043***	-0.0450	***-0.4869***	-0.1323	***-1.4427***	0.3843
B/L	0.0061	***.1936***	0.9796	***12.0256***	0.3647	***2.7779***	0.0618	***0.4750***	0.3131
B/M	0.0120	***.0884***	0.7482	***12.1323***	0.2307	***2.3212***	0.0134	***0.1360***	0.3132
B/H	0.0115	***.5101***	0.8579	***16.3809***	-0.0150	***-0.1773***	-0.2094	***-2.5017***	0.4627

In Panel A, the following is reported:

(1) the return behaviour of the explanatory returns and its associated t-statistics (in bold) of the SPILT sample B

(2) the coefficients, its associated t-statistics (in bold) and Adjusted R-square values for the regression of SPILT -A dependent returns on SPILT -B explanatory returns using one factor model

(3) the coefficients, its associated t-statistics (in bold) and Adjusted R-square values for the regression of SPILT -A dependent returns on SPILT -B explanatory returns using three-factor model

In Panel B, the following is reported:

(1) the return behaviour of the explanatory returns and its associated t-statistics (in bold) of the SPILT sample A

(2) the coefficients, its associated t-statistics (in bold) and Adjusted R-square values for the regression of SPILT-B dependent returns on SPILT-A explanatory returns using one factor model

(3) the coefficients, its associated t-statistics (in bold) and Adjusted R-square values for the regression of SPILT-B dependent returns on SPILT-A explanatory returns using three-factor model

*The underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level.*

Refer to Table 5.1 and Table 5.2 to see the details relating to the value, size and factor portfolios. In the spilt sample regressions, the stocks in each of the six size-BE/ME portfolios are divided randomly into two groups, and dependent variables constructed from one group are regressed on the explanatory variables constructed from the other.

TABLE 5.6
SUB-PERIOD ANALYSIS OF ONE-FACTOR MODEL AND FAMA AND FRENCH THREE–FACTOR MODEL

PANEL 5.6A: JANUARY 1998 TO DECEMBER 2001

Models		a	*t(a)*	b	*t(b)*	S	*t(s)*	h	*t(h)*	Adjusted R-square
One-factor	S/L	-0.012	*-2.165*	0.752	*5.980*					0.437
	S/M	-0.008	*-1.418*	0.695	*5.023*					0.354
	S/H	-0.005	*-0.930*	0.656	*4.814*					0.335
	B/L	-0.004	*-0.949*	1.038	*10.815*					0.718
	B/M	-0.006	*-1.603*	1.033	*11.444*					0.740
	B/H	-0.006	*-1.391*	0.900	*8.903*					0.633
Three-Factor	S/L	-0.008	*-2.936*	1.004	*14.410*	0.945	*10.871*	-0.181	*-1.668***	0.853
	S/M	-0.006	*-1.618*	0.973	*11.594*	0.944	*9.022*	0.038	*0.292*	0.798
	S/H	-0.004	*-1.364*	0.952	*14.998*	0.865	*10.924*	0.391	*3.967*	0.877
	B/L	-0.003	*-1.026*	0.924	*13.331*	-0.122	*-1.409*	-0.672	*-6.243*	0.875
	B/M	-0.007	*-1.724***	1.028	*10.641*	-0.082	*-0.682*	0.164	*1.094*	0.747
	B/H	-0.008	*-2.428*	0.976	*12.533*	-0.042	*-0.429*	0.756	*6.253*	0.815

PANEL 5.6B: JULY 1973 TO OCTOBER 1987

Models		a	*t(a)*	b	*t(b)*	S	*t(s)*	h	*t(h)*	Adjusted R-square
One-factor	S/L	0.012	*4.333*	0.478	*13.030*					0.500
	S/M	0.012	*4.577*	0.423	*11.734*					0.448
	S/H	0.014	*5.331*	0.383	*10.804*					0.407
	B/L	0.003	*0.864*	0.932	*20.978*					0.721
	B/M	0.001	*0.293*	0.907	*20.533*					0.713
	B/H	0.006	*1.486*	0.819	*16.829*					0.625
Three-Factor	S/L	0.010	*3.609*	0.573	*11.845*	0.251	*3.609*	-0.190	*-1.392*	0.537
	S/M	0.009	*3.515*	0.574	*12.515*	0.344	*5.211*	-0.060	*-0.461*	0.524
	S/H	0.010	*4.101*	0.568	*13.026*	0.312	*4.973*	0.405	*3.285*	0.524
	B/L	0.011	*4.424*	0.556	*12.757*	-0.710	*-11.338*	-0.489	*-3.974*	0.857
	B/M	0.008	*2.696*	0.598	*12.102*	-0.612	*-8.613*	-0.272	*-1.950*	0.809
	B/H	0.011	*3.857*	0.561	*11.473*	-0.771	*-10.973*	0.916	*6.636*	0.799

TABLE 5.6 (cont.)

PANEL 5.6C: NOVEMBER 1987 TO DECEMBER 2001

Models		a	*t(a)*	b	*t(b)*	s	*t(s)*	h	*t(h)*	Adjusted R-square
One-factor	S/L	-0.010	*-3.610*	0.733	*11.197*					0.427
	S/M	-0.008	*-2.760*	0.737	*11.287*					0.431
	S/H	-0.007	*-2.264*	0.677	*10.346*					0.389
	B/L	-0.003	*-2.002*	0.960	*28.545*					0.829
	B/M	-0.004	*-2.625*	0.951	*27.857*					0.822
	B/H	-0.005	*-3.002*	0.983	*25.051*					0.789
Three-Factor	S/L	-0.006	*-4.688*	0.982	*32.825*	1.012	*26.764*	-0.203	*-3.081*	0.893
	S/M	-0.004	*-2.878*	0.976	*29.630*	0.948	*22.784*	0.125	*1.726***	0.870
	S/H	-0.003	*-2.616*	0.912	*33.167*	0.912	*26.249*	0.487	*8.036*	0.903
	B/L	-0.003	*-2.481*	0.925	*32.558*	-0.106	*-2.962*	-0.526	*-8.397*	0.891
	B/M	-0.004	*-2.734*	0.950	*26.588*	-0.015	*-0.325*	0.150	*1.909***	0.825
	B/H	-0.006	*-4.551*	0.995	*32.623*	-0.007	*-0.184*	0.785	*11.679*	0.886

PANEL 5.6D: JULY 1973 TO DECEMBER 1993

Models		a	*t(a)*	b	*t(b)*	s	*t(s)*	h	*t(h)*	Adjusted R-square
One-factor	S/L	0.003	*2.236*	0.742	*32.797*					.431
	S/M	0.004	*2.506*	0.681	*27.494*					.441
	S/H	0.006	*3.382*	0.632	*23.741*					.510
	B/L	0.000	*0.237*	1.036	*32.845*					.782
	B/M	-0.001	*-0.672*	1.048	*41.034*					.789
	B/H	0.001	*0.606*	1.000	*32.104*					.791
Three-Factor	S/L	0.002	*1.952***	0.883	*58.952*	0.443	*21.767*	-0.154	*-3.320*	.786
	S/M	0.002	*2.129*	0.848	*53.387*	0.477	*22.068*	0.052	*1.051*	.754
	S/H	0.003	*3.426*	0.819	*50.628*	0.442	*20.108*	0.484	*9.675*	.796
	B/L	0.004	*3.446*	0.808	*44.635*	-0.578	*-23.491*	-0.417	*-7.441*	.787
	B/M	0.001	*1.245*	0.871	*54.197*	-0.484	*-22.136*	-0.146	*-2.941*	.740
	B/H	0.002	*2.027*	0.872	*48.880*	-0.577	*-23.785*	0.945	*17.124*	.786

Panel A to Panel D presents the coefficients, t-statistics (in bold) and Adjusted R-square values for one-factor and three-factor model respectively for the four different sub-periods.

*The underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level.*

Refer to Table 5.1 and Table 5.2 to see the details relating to the factor models, value, size and factor portfolios.

TABLE 5.7
RETURN BEHAVIOUR AND ESTIMATES OF THREE FACTOR MODEL USING MOMENTUM PORTFOLIOS FOR THE SAMPLE PERIOD: JANUARY 1969-DECEMBER 2001

PANEL A: 6 x 6 STRATEGY

PANEL A1: Return behaviour of the decile portfolios

	Loser Portfolio	2	3	4	5	6	7	8	9	Winner Portfolio	Momentum Portfolio (Winner-Loser)
Return (%)	0.144	0.509	0.767	0.821	0.867	0.894	0.926	1.173	1.225	1.172	1.028
t-statistics	*0.704*	*2.912*	*4.597*	*5.167*	*5.760*	*6.063*	*6.636*	*8.841*	*8.636*	*7.098*	*8.021*

PANEL A2: Estimates of the three- factor model using the decile portfolios

	Loser Portfolio	2	3	4	5	6	7	8	9	Winner Portfolio	Momentum Portfolio (Winner-Loser)
A	0.001	0.005	0.007	0.008	0.008	0.009	0.009	0.011	0.012	0.011	0.010
t (a)	*0.429*	*2.617*	*4.243*	*4.891*	*5.372*	*5.766*	*6.267*	*8.224*	*8.100*	*6.575*	*7.729*
b	0.053	0.039	0.038	0.023	0.038	0.022	0.031	0.051	0.044	0.061	0.008
t (b)	*1.289*	*1.109*	*1.136*	*0.726*	*1.265*	*0.751*	*1.094*	*1.943***	*1.546*	*1.858***	*0.320*
s	0.016	0.007	0.000	-0.013	0.007	0.003	0.024	-0.006	0.008	0.021	0.005
t (s)	*0.284*	*0.147*	*-0.005*	*-0.296*	*0.172*	*0.084*	*0.612*	*-0.152*	*0.197*	*0.454*	*0.127*
h	-0.055	-0.047	-0.031	-0.053	-0.051	-0.049	-0.043	0.007	-0.011	-0.055	0.000
t (h)	*-0.490*	*-0.496*	*-0.346*	*-0.611*	*-0.628*	*-0.609*	*-0.568*	*0.102*	*-0.149*	*-0.616*	*-0.006*

PANEL B: 12 x 12 STRATEGY

PANEL B1: Return behaviour of the decile portfolios

	Loser Portfolio	2	3	4	5	6	7	8	9	Winner Portfolio	Momentum Portfolio (Winner-Loser)
Return (%)	0.297	0.587	0.113	-0.686	0.509	0.309	0.693	0.930	1.010	0.902	0.605
t-statistics	*2.152*	*3.939*	*0.545*	*-2.200*	*1.392*	*2.051*	*8.747*	*11.747*	*11.560*	*8.004*	*6.166*

PANEL B2: Estimates of the three- factor model using the decile portfolios

	Loser Portfolio	2	3	4	5	6	7	8	9	Winner Portfolio	Momentum Portfolio (Winner-Loser)
a	0.003	0.006	0.001	-0.007	0.006	0.003	0.007	0.009	0.010	0.009	0.006
t (a)	*1.863***	*3.928*	*0.448*	*-2.152*	*1.699***	*1.850***	*8.356*	*11.233*	*11.124*	*7.479*	*5.912*
b	0.041	-0.004	0.026	0.009	-0.119	0.037	0.017	0.015	0.022	0.045	0.005
t (b)	*1.481*	*-0.142*	*0.634*	*0.146*	*-1.630*	*1.242*	*1.093*	*0.975*	*1.257*	*2.023*	*0.233*
s	0.022	-0.005	-0.007	0.023	-0.083	0.076	0.038	0.014	0.012	0.013	-0.009
t (c)	*0.568*	*-0.128*	*-0.125*	*0.265*	*-0.812*	*1.827***	*1.721***	*0.615*	*0.496*	*0.420*	*-0.315*
h	-0.088	-0.102	-0.139	-0.042	-0.072	-0.080	0.033	0.035	-0.061	-0.050	0.038
t (h)	*-1.207*	*-1.299*	*-1.270*	*-0.257*	*-0.375*	*-1.003*	*0.795*	*0.833*	*-1.329*	*-0.842*	*0.727*

TABLE 5.7 (cont.)

Panel A1 reports the equally-weighted average returns using the 6 x 6 momentum strategy adopted by Jegadesh and Titman (1993). Panel A2 reports the estimates of the three-factor model using the decile portfolios and momentum portfolio using the 6 x 6 strategy. Panel B1 reports the equally-weighted average returns using the 12 x 12 momentum strategy adopted by Jegadesh and Titman (1993). Panel B2 reports the estimates of the three-factor model using the decile portfolios and momentum portfolio using the 12 x 12 strategy.

*The bold and italic numbers are the associated t-statistics of the equally-weighted portfolio returns and Fama-French three factor estimates respectively. The underlined t-statistics indicates significance at 5%, * * indicates significance at 10% level.*

To see the details relating to the Fama and French factors (Market, SMB and HML), see Table 5.2.

To form momentum portfolio, this study considers the ranking period of r=6 and subsequent holding period of h=6 (6 x 6 momentum strategy). To select stocks for different portfolios at the start of each holding period, t, the ranking period r-month returns for each of the stock is computed as,

$$CR_{j,t} = \sum_{t=1}^{r} R_{j,t} \qquad (5.8)$$

where R_{jt} is the monthly return of stock j, CR_j is the cumulative return of security j and r is the number of months (6 or 12 months). Stocks are then ranked into 10 portfolios on the basis of CR j. Like Fama and French (1996b), this study forms 10 portfolios and obtains monthly returns (using equation (5.9)) for each decile for 336 months. The momentum portfolio is formed by going long in the winner portfolio and going short in the loser portfolio.

In the following 6 or 12 months, described here as the Test Period (TP), the CR for all stocks in the winner and losers portfolios are calculated. The mean of CR represents the cumulative return for an equally weighted portfolio and is measured as

$$CR_{r+1} = (1/N)\sum_{j=1}^{N}\left(\sum_{t=r+1}^{2r} R_{j,t}\right) \qquad (5.9)$$

where N is the number of stocks in the portfolio and where the test period returns for stock j in the portfolio are $R_{j,t}$, t=r+1,r+2,.....2r.

TABLE 5.8
ESTIMATES FROM THE FOUR-FACTOR PRICING MODEL FOR THE SAMPLE PERIOD: JANUARY 1969- DECEMBER 2001

PANEL A: SIZE AND PERFORMANCE PORTFOLIOS

	a	t (a)	b	t (b)	S	t (s)	h	t (h)	w	t (w)
S/L	-0.009	***-2.935***	0.745	***21.151***	0.642	***12.566***	0.233	***2.487***	-0.393	***-8.574***
S/N	0.004	***1.666*** **	0.708	***24.935***	0.644	***15.640***	0.088	***1.166***	-0.057	***-1.556***
S/W	-0.001	***-0.162***	0.866	***23.676***	0.687	***12.952***	-0.082	***-0.843***	0.546	***11.486***
B/L	0.008	***2.319***	0.883	***21.921***	-0.252	***-4.311***	-0.308	***-2.879***	-0.665	***-12.701***
B/N	-0.004	***-1.310***	0.730	***23.405***	-0.410	***-9.074***	-0.068	***-0.822***	0.089	***2.194***
B/W	0.000	***-0.119***	0.763	***22.455***	-0.296	***-6.013***	0.007	***0.072***	0.397	***8.991***

PANEL B: FAMA AND FRENCH PORTFOLIOS

	a	t (a)	b	t (b)	S	t (s)	h	t (h)	w	t (w)
S/L	-0.005	***-1.628***	0.781	***23.545***	0.637	***13.241***	-0.166	***-1.881*** **	0.079	***1.830*** **
S/M	-0.001	***-0.458***	0.768	***24.389***	0.648	***14.190***	0.067	***0.800***	0.035	***0.861***
S/H	0.000	***-0.183***	0.742	***25.272***	0.612	***14.370***	0.475	***6.084***	0.038	***0.997***
B/L	0.001	***0.207***	0.734	***24.792***	-0.408	***-9.492***	-0.470	***-5.973***	0.029	***0.744***
B/M	-0.003	***-1.117***	0.784	***23.397***	-0.312	***-6.415***	-0.043	***-0.481***	0.054	***1.242***
B/H	-0.004	***-1.263***	0.773	***22.975***	-0.383	***-7.852***	0.889	***9.946***	0.069	***1.588***

*Panel A reports the estimates from the Four- Factor Pricing Model (FFPM) on size and performance portfolios (S/L, S/N, S/W, B/L, B/N and B/W). The bold and italic numbers are the associated t-statistics of the four factor estimates. The underlined t-statistics indicates significance at 5%, * * indicates significance at 10% level.*

According to the FFPM, stock's excess returns are equal to:

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + w_i WML + \varepsilon_i \qquad (5.10)$$

where the definition of R_i, R_f, R_m, SMB, HML *and* ε *are same as in Table 5.2 and WML is the momentum factor (constructed as UMD (Up minus Down)) and* W_i *is the factor loading associated with the momentum factor.*

The construction of WML as follows:
For each month t from July of year t-1 to June of year t, the stocks are ranked on the basis of their size in December t-1 and their performance (lagged returns) between t-12 and t-2. These two rankings are then used to calculate a 50 percent breakpoint for size, and 30 and 70 percent breakpoints for lagged returns. The stocks are subsequently sorted into two size groups and three prior performance groups based on these breakpoints. The stocks above the 50 percent are designated B (for big) and the remaining 50 percent S (for small). Moreover, stocks above the 70 percent prior performance breakpoint are designated W (for winner), the middle 40 percent are designated N (for neutral) and firms below the 30 percent prior performance breakpoint are designated L (for loser). As previously, six value-weight portfolios (S/L, S/N, S/W, B/L, B/N and B/W) are formed as the intersection of size and prior performance groups. WML (Winners Minus Losers) is the equal-weight average of the returns on the winner stock portfolio minus the returns on the loser stock portfolios: WML= ((S/W-S/L)+(B/W-B/L))/2.

Panel B reports the estimates from the FFPM on Fama and French portfolios (S/L, S/M, S/H, B/L, B/M and B/H). Refer to Table 5.2 for the details relating to Fama and French portfolios.

TABLE 5.9
SUMMARY STATISTICS AND REGRESSIONS FOR PORTFOLIOS FORMED FROM SORTS ON SIZE, BE/ME AND using HML LOADING: JULY 1973 TO DECEMBER 2001, 282 MONTHLY OBSERVATIONS

Panel A: Ex-ante h								Market Value (£ m)						BE/ME						Number of Companies					
Characteristics		Factor Loading						Factor Loading						Factor Loading						Factor Loading					
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	-1.76	-0.33	0.19	0.70	2.20	0.20	7.50	8.07	7.85	8.10	7.64	7.83	-0.99	-1.88	-0.28	-0.73	-0.19	-0.81	13	8	6	6	13	9
1	*2*	-1.67	-0.34	0.18	0.70	1.95	0.17	8.17	7.95	7.91	8.25	7.64	7.98	0.87	0.89	0.88	0.89	0.87	0.88	18	14	12	12	15	14
1	*3*	-1.47	-0.33	0.18	0.70	1.90	0.19	7.26	7.27	7.29	7.37	7.21	7.28	2.42	3.02	2.71	2.61	2.82	2.72	35	28	27	28	35	31
2	*1*	-1.47	-0.32	0.18	0.71	1.71	0.16	46.97	48.31	50.72	48.98	45.67	48.13	0.32	-0.77	0.27	-0.20	-0.56	-0.19	22	18	17	17	19	18
2	*2*	-1.28	-0.33	0.18	0.69	1.66	0.18	42.53	46.19	45.94	45.44	45.04	45.03	0.85	0.85	0.85	0.85	0.85	0.85	19	20	21	21	20	20
2	*3*	-1.25	-0.31	0.18	0.70	1.70	0.20	37.69	42.19	41.88	41.26	41.67	40.94	1.72	1.98	2.14	1.77	1.90	1.90	13	15	15	16	20	16
3	*1*	-1.09	-0.32	0.18	0.67	1.47	0.18	11066.28	9868.67	7057.12	4544.19	2821.76	7071.60	0.13	0.28	0.09	0.25	0.04	0.16	24	31	32	28	18	26
3	*2*	-1.18	-0.33	0.17	0.70	1.55	0.18	5435.97	5366.56	4883.54	7678.09	1775.30	5027.89	0.81	0.84	0.82	0.83	0.81	0.82	12	21	25	24	17	20
3	*3*	-1.18	-0.31	0.20	0.74	1.67	0.22	2369.51	1827.43	1288.66	1283.91	572.11	1468.33	2.06	1.67	1.63	1.59	1.60	1.71	7	8	8	9	8	8
Avg		-1.37	-0.32	0.18	0.70	1.76		2113.54	1913.63	1487.88	1518.40	591.56		0.91	0.76	1.01	0.87	0.90		18	18	18	18	18	

Panel B: Mean Excess Return (%)								t-statistics					
	Characteristics		Factor Loading										
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	0.566	0.495	0.813	0.675	0.622	0.634	***1.996***	***-0.341***	***0.301***	***-0.583***	***0.359***	***0.346***
1	*2*	0.997	0.823	1.037	0.919	0.830	0.921	***1.555***	***1.494***	***2.227***	***1.728*** **	***1.502***	***1.701*** **
1	*3*	0.149	0.356	0.877	0.400	0.303	0.417	***3.195***	***2.671***	***3.578***	***3.216***	***2.647***	***3.061***
2	*1*	0.528	0.719	0.670	0.879	0.764	0.712	***0.401***	***1.143***	***2.650***	***1.243***	***0.688***	***1.225***
2	*2*	0.806	0.939	0.797	0.803	0.794	0.828	***1.575***	***2.373***	***2.064***	***2.733***	***2.353***	***2.220***
2	*3*	0.812	0.691	0.824	0.425	0.514	0.653	***2.179***	***2.644***	***2.437***	***2.507***	***1.977***	***2.349***
3	*1*	0.402	0.967	0.968	0.950	0.983	0.854	***2.492***	***2.012***	***2.401***	***1.223***	***1.297***	***1.885*** **
3	*2*	0.596	1.480	1.366	1.016	0.987	1.089	***0.935***	***2.754***	***2.887***	***2.861***	***2.407***	***2.369***
3	*3*	0.647	0.702	0.833	0.624	0.664	1.222	***1.346***	***3.551***	***3.403***	***2.572***	***2.119***	***2.598***
Avg		0.612	0.797	0.909	0.743	0.718		***1.741*** **	***2.033***	***2.439***	***1.944*** **	***1.705*** **	

TABLE 5.9 (Cont.)

Panel C1: Intercept								Panel C2: t-statistics					
	Characteristics			Factor Loading									
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	-0.003	-0.011	-0.008	-0.016	-0.010	-0.010	*-0.910*	*-3.175*	*-1.936***	*-2.101*	*-2.967*	*-2.218*
1	*2*	-0.005	-0.004	-0.001	-0.004	-0.004	-0.004	*-1.948***	*-2.047*	*-0.313*	*-1.670***	*-1.389*	*-1.474*
1	*3*	0.000	0.000	0.002	0.002	-0.001	0.000	*0.001*	*-0.024*	*0.914*	*0.849*	*-0.481*	*0.252*
2	*1*	-0.012	-0.006	-0.002	-0.006	-0.010	-0.007	*-5.865*	*-3.371*	*-1.043*	*-3.274*	*-3.597*	*-3.430*
2	*2*	-0.006	-0.003	-0.005	-0.002	-0.003	-0.004	*-3.355*	*-1.565*	*-2.547*	*-1.421*	*-1.788***	*-2.135*
2	*3*	-0.003	-0.002	-0.002	-0.002	-0.005	-0.003	*-1.099*	*-0.943*	*-0.725*	*-0.885*	*-1.774***	*-1.085*
3	*1*	-0.003	-0.005	-0.004	-0.008	-0.008	-0.006	*-1.822***	*-2.862*	*-2.630*	*-3.830*	*-3.368*	*-2.902*
3	*2*	-0.007	-0.002	-0.002	-0.002	-0.003	-0.003	*-2.032*	*-1.097*	*-1.113*	*-1.005*	*-1.173*	*-1.284*
3	*3*	-0.005	0.001	0.002	-0.002	-0.003	-0.001	*-1.274*	*0.439*	*0.617*	*-0.863*	*-0.895*	*-0.395*
Avg		-0.005	-0.004	-0.002	-0.005	-0.005		*-2.034*	*-1.627*	*-0.975*	*-1.578*	*-1.937***	

Panel C3: Ex-post h								Panel C4: t-statistics					
	Characteristics			Factor Loading									
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	0.038	-0.077	-0.031	0.237	-0.028	0.028	*0.190*	*-0.381*	*-0.127*	*0.567*	*-0.143*	*0.021*
1	*2*	0.031	0.070	0.162	-0.020	0.320	0.113	*0.229*	*0.569*	*1.096*	*-0.131*	*1.816***	*0.716*
1	*3*	0.185	0.205	0.182	0.115	0.024	0.142	*1.915***	*1.723***	*1.771***	*1.090*	*0.216*	*1.343*
2	*1*	-0.087	-0.037	0.047	-0.024	0.090	-0.002	*-0.788*	*-0.349*	*0.439*	*-0.214*	*0.566*	*-0.069*
2	*2*	0.233	0.170	0.076	-0.049	0.075	0.101	*2.223*	*1.667***	*0.752*	*-0.515*	*0.709*	*0.967*
2	*3*	0.474	0.376	0.304	0.130	0.397	0.336	*3.212*	*2.952*	*2.374*	*1.094*	*2.667*	*2.460*
3	*1*	-0.094	-0.098	-0.141	-0.168	-0.088	-0.118	*-0.954*	*-0.961*	*-1.559*	*-1.523*	*-0.633*	*-1.126*
3	*2*	-0.089	0.310	0.138	0.338	0.021	0.144	*-0.460*	*2.665*	*1.301*	*3.112*	*0.138*	*1.351*
3	*3*	0.396	0.255	-0.023	0.372	0.687	0.338	*1.868***	*1.609*	*-0.134*	*2.396*	*3.362*	*1.820***
Avg		0.121	0.130	0.079	0.103	0.166		*0.826*	*1.055*	*0.657*	*0.653*	*0.967*	

TABLE 5.9 (Cont.)

Panel D: Characteristic-Balanced Portfolio												
SIZE	***BE/ME***	Return	t	intercept	t	b	t (b)	s	t(s)	h	t(h)	R-square
1	*1*	-0.547	*-1.165*	-0.006	*-1.172*	0.026	*0.243*	0.057	*0.357*	0.124	*0.454*	0.002
1	*2*	0.118	*0.485*	0.000	*0.063*	0.086	*1.566*	0.009	*0.114*	0.100	*0.708*	0.010
1	*3*	-0.035	*-0.223*	0.000	*0.215*	-0.056	*-1.594*	0.013	*0.253*	-0.126	*-1.376*	0.016
2	*1*	0.099	*0.553*	0.001	*0.350*	0.043	*1.079*	0.129	*2.154*	0.095	*0.925*	0.024
2	*2*	0.198	*1.296*	0.002	*1.061*	0.029	*0.858*	0.024	*0.473*	-0.189	*-2.148*	0.021
2	*3*	-0.074	*-0.341*	-0.001	*-0.347*	0.012	*0.249*	0.075	*1.034*	-0.161	*-1.284*	0.008
3	*1*	-0.282	*-1.376*	-0.004	*-1.768***	0.091	*1.980*	0.138	*2.008*	-0.032	*-0.269*	0.021
3	*2*	0.282	*1.176*	0.002	*0.825*	0.081	*1.518*	0.146	*1.820***	0.069	*0.499*	0.017
3	*3*	-0.036	*-0.125*	-0.001	*-0.347*	0.066	*1.008*	0.089	*0.909*	0.204	*1.214*	0.011
Single Portfolio		**-0.031**	*-0.330*	-0.001	*-0.743*	0.042	*2.017*	0.076	*2.429*	0.009	*0.176*	0.027

Panel E: Characteristic-Balanced Portfolio with a different strategy												
SIZE	***BE/ME***	Return	t	intercept	t	b	t (b)	s	t(s)	h	t(h)	R-square
1	*1*	-0.794	*-1.692***	-0.007	*-1.495*	-0.031	*-0.297*	0.231	*1.463*	-0.066	*-0.244*	0.011
1	*2*	0.056	*0.161*	0.000	*0.084*	0.014	*0.176*	-0.060	*-0.513*	0.289	*1.425*	0.007
1	*3*	-0.166	*-0.789*	-0.001	*-0.433*	-0.059	*-1.257*	0.000	*-0.001*	-0.161	*-1.317*	0.011
2	*1*	0.154	*0.534*	0.001	*0.479*	0.048	*0.754*	0.318	*3.359*	0.177	*1.085*	0.053
2	*2*	0.236	*1.031*	0.003	*1.231*	-0.049	*-0.961*	-0.034	*-0.442*	-0.158	*-1.194*	0.008
2	*3*	-0.012	*-0.037*	-0.002	*-0.539*	0.155	*2.108*	0.121	*1.105*	-0.077	*-0.404*	0.017
3	*1*	-0.298	*-0.972*	-0.005	*-1.649***	0.212	*3.155*	0.315	*3.119*	0.007	*0.037*	0.050
3	*2*	0.581	*1.461*	0.004	*0.918*	0.200	*2.255*	0.253	*1.905***	0.110	*0.481*	0.024
3	*3*	0.391	*0.855*	0.002	*0.330*	0.214	*2.102*	0.172	*1.125*	0.292	*1.106*	0.020
Single Portfolio		**0.016**	*0.127*	-0.001	*-0.443*	0.078	*2.746*	0.146	*3.431*	0.046	*0.624*	0.054

TABLE 5.9 (Cont.)

Panel A reports descriptive statistics and the number of companies in each of the 45 factor loading portfolios over the sample period (January 1973-December 2001). The portfolios are constructed as the intersection of stocks independently sorted on Market value, Book-to-Market (BE/ME), and HML Loading (3x3x5). BE/ME is based on December t-1. Market value is also based on December t-1. The ex-ante factor loading is estimated using 36 monthly returns before December t-1. HB1 is the lowest factor loading portfolios, and similarly for other portfolios. Market value, BE/ME and HML Loading given in panel A are value-weighted averages and the number of companies are equally-weighted averages. Panel B reports the mean monthly excess returns for each of the 45 factor-loading portfolio and its associated t-statistics. Panels C report the intercept (its associated t-statistics) and ex-post HML factor loading (its associated t-statistics) of the 45 factor loading portfolio (formed after the portfolio formation) from the Fama-French three-factor model:

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i \tag{5.3}$$

*The underlined t-statistics indicates significance at 5%, * * indicates significance at 10% level.*

Refer to the notes in Table 5.2 for the construction of SMB and HML factors. Panel D presents the summary statistics and regression results of characteristic-balanced portfolios. These portfolios are formed, in each category, by subtracting the sum of the returns on the first and second quintile factor-loading portfolios from the sum of the returns on the fourth and fifth factor-loading portfolio, and then dividing by 2. The first nine rows of the panel gives the mean monthly excess returns (in percent) and the regression coefficients for the characteristic-balanced portfolio that has a long position in the high expected factor loading portfolios and a short position in the low expected factor loading portfolios that have the same size and BE/ME rankings. The bottom row of the panel D provides the coefficients estimates as well the t-statistics for this regression for a combined-portfolio that consists for an equally weighted combination of the above zero-investment portfolios. Panel E provides the summary statistics and regression results of the characteristic-balanced portfolios formed with a different strategy. These characteristic-balanced portfolios in Panel E are formed with long (short) position in factor loading quintile HB5 (HB1).

TABLE 5.10
SUMMARY STATISTICS AND REGRESSIONS FOR PORTFOLIOS FORMED FROM SORTS ON SIZE, BE/ME AND using SMB LOADING: JULY 1973 TO DECEMBER 2001, 282 MONTHLY OBSERVATIONS

Panel A: Ex-ante s								Market Value (£ m)						BE/ME						Number of Companies					
Characteristics				Factor Loading				Factor Loading						Factor Loading						Factor Loading					
SIZE	*BE/ ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	-0.48	0.17	0.52	0.93	2.06	0.64	7.33	7.54	8.38	7.96	7.57	7.75	-2.28	0.30	-1.07	-0.51	-0.72	-0.86	7	5	6	7	14	8
1	*2*	-0.43	0.17	0.53	0.93	1.84	0.61	7.62	8.00	8.37	8.15	8.07	8.04	0.90	0.89	0.87	0.87	0.88	0.88	9	9	11	12	17	12
1	*3*	-0.41	0.18	0.53	0.91	1.73	0.59	7.10	7.11	7.42	7.61	7.12	7.27	2.85	2.90	2.82	2.72	2.51	2.76	18	23	23	28	34	25
2	*1*	-0.42	0.19	0.52	0.90	1.80	0.60	46.76	48.89	51.15	48.98	44.08	47.97	-1.68	0.03	0.26	-0.15	-0.19	-0.34	8	12	17	18	21	15
2	*2*	-0.36	0.17	0.52	0.89	1.64	0.57	45.91	46.65	45.38	45.09	42.50	45.11	0.84	0.85	0.85	0.86	0.84	0.85	10	15	19	20	18	16
2	*3*	-0.42	0.18	0.52	0.89	1.62	0.56	42.11	44.97	43.51	38.40	35.39	40.87	1.82	1.86	2.14	1.79	1.88	1.90	8	12	14	17	14	13
3	*1*	-0.37	0.13	0.50	0.86	1.52	0.53	12410.34	4339.94	1985.97	1562.19	1199.24	4299.54	0.24	0.14	0.12	-0.05	0.33	0.16	36	27	21	15	10	22
3	*2*	-0.39	0.14	0.50	0.87	1.53	0.53	6528.44	7969.85	1650.64	649.24	429.04	3445.44	0.82	0.83	0.83	0.82	0.79	0.82	28	22	16	12	5	16
3	*3*	-0.36	0.17	0.52	0.89	1.61	0.57	2472.08	1451.63	1260.52	295.30	393.33	1174.57	1.45	1.85	1.71	1.75	1.69	1.69	11	9	7	4	3	7
Avg		-0.29	0.39	0.85	1.34	2.26		2396.41	1547.18	562.37	295.88	240.70		0.55	1.07	0.95	0.90	0.89		27	27	27	27	27	

Panel B: Mean Excess Return (%)								t-statistics					
	Characteristics	Factor Loading											
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	1.152	-0.268	1.241	0.318	-0.194	0.450	*1.961*	*-0.634*	*2.415*	*0.683*	*-0.426*	*0.800*
1	*2*	0.906	0.464	0.351	1.267	0.405	0.679	*2.380*	*1.259*	*0.961*	*3.705*	*1.013*	*1.864***
1	*3*	0.594	0.955	0.948	1.019	0.888	0.881	*1.777***	*3.309*	*3.363*	*3.434*	*2.658*	*2.908*
2	*1*	0.592	0.593	0.487	0.411	-0.011	0.414	*1.551*	*1.915***	*1.530*	*1.137*	*-0.028*	*1.221*
2	*2*	0.155	0.681	0.959	0.687	0.651	0.627	*0.447*	*2.379*	*3.007*	*2.262*	*1.793***	*1.978*
2	*3*	0.851	1.072	0.911	0.630	0.721	0.837	*1.956*	*3.367*	*2.890*	*1.771***	*1.820***	*2.361***
3	*1*	0.717	0.766	0.277	0.083	0.397	0.448	*2.260*	*2.222*	*0.714*	*0.181*	*0.788*	*1.233*
3	*2*	1.119	0.965	0.667	0.438	0.882	0.814	*3.474*	*2.658*	*1.814***	*0.954*	*1.582*	*2.096*
3	*3*	1.169	1.006	0.901	1.052	1.235	1.073	*3.465*	*2.477*	*1.989*	*1.955***	*1.951***	*2.367*
Avg		0.806	0.693	0.749	0.656	0.553		*2.141*	*2.106*	*2.076*	*1.787***	*1.239*	

TABLE 5.10 (cont.)

Panel C1: Intercept								Panel C2: t-statistics					
Characteristics		Factor Loading											
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	-0.001	-0.011	0.002	-0.007	-0.015	-0.004	*-0.237*	*-3.121*	*0.462*	*-1.870***	*-5.004*	*-1.954***
1	*2*	0.000	-0.005	-0.007	0.003	-0.008	-0.002	*-0.082*	*-1.805*	*-2.935***	*1.272*	*-2.942*	*-1.298*
1	*3*	-0.002	0.001	0.002	0.001	-0.002	0.000	*-0.733*	*0.582*	*0.853*	*0.587*	*-0.898*	*0.078*
2	*1*	-0.005	-0.004	-0.006	-0.008	-0.013	-0.004	*-1.776***	*-1.895***	*-3.586*	*-4.254*	*-5.864*	*-3.475*
2	*2*	-0.009	-0.002	-0.002	-0.004	-0.006	-0.003	*-3.692*	*-1.369*	*-1.053*	*-2.319*	*-3.651*	*-2.417*
2	*3*	-0.002	0.001	-0.001	-0.005	-0.005	-0.001	*-0.743*	*0.430*	*-0.339*	*-2.332*	*-2.136*	*-1.024*
3	*1*	-0.004	-0.004	-0.011	-0.013	-0.011	-0.005	*-3.024*	*-2.257*	*-5.319*	*-4.117*	*-2.883*	*-3.520*
3	*2*	0.000	-0.003	-0.006	-0.010	-0.006	-0.003	*-0.715*	*-1.303*	*-2.408*	*-3.102*	*-1.372*	*-1.780***
3	*3*	0.001	-0.003	-0.004	-0.002	-0.005	-0.001	*0.319*	*-0.913*	*-1.292*	*-0.464*	*-0.943*	*-0.659*
Avg		-0.003	-0.003	-0.004	-0.005	-0.008		*-1.187*	*-1.295*	*-1.735***	*-1.844***	*-2.855*	

Panel C3: Ex-post s								Panel C4: t-statistics					
Characteristics		Factor Loading											
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	1.346	0.880	1.027	1.194	1.392	1.168	*8.411*	*7.405*	*7.034*	*9.696*	*14.395*	*9.388*
1	*2*	0.887	0.955	1.162	0.956	1.207	1.034	*8.996*	*10.706*	*15.577*	*12.644*	*14.424*	*12.469*
1	*3*	1.025	0.818	0.834	0.912	1.021	0.922	*12.666*	*13.287*	*13.491*	*16.058*	*16.606*	*14.422*
2	*1*	0.942	0.698	0.858	0.962	1.123	0.916	*10.581*	*10.549*	*15.546*	*15.180*	*15.555*	*13.482*
2	*2*	0.716	0.708	0.841	0.716	0.951	0.786	*9.021*	*12.260*	*16.051*	*13.390*	*16.418*	*13.428*
2	*3*	1.017	0.678	0.652	0.810	0.991	0.830	*9.298*	*9.511*	*9.437*	*11.096*	*12.179*	*10.304*
3	*1*	0.197	0.151	0.350	0.693	0.543	0.387	*-4.409*	*1.024*	*5.046*	*6.684*	*4.423*	*2.349*
3	*2*	0.965	0.133	0.224	0.379	0.719	0.484	*1.710***	*-1.929***	*2.904*	*3.588*	*5.009*	*2.256*
3	*3*	0.122	0.185	0.352	0.511	0.708	0.375	*1.167*	*1.961*	*3.160*	*3.357*	*4.267*	*2.782*
Avg		0.802	0.578	0.700	0.793	0.962		*11.488*	*12.750*	*17.649*	*18.339*	*20.655*	

TABLE 5.10 (cont.)

Panel D: Characteristic-Balanced Portfolio												
SIZE	*BE/ME*	Return	t	intercept	t	b	t (b)	s	t(s)	h	t(h)	R-square
1	*1*	-0.380	*-1.037*	-0.005	*-1.241*	0.094	*1.150*	0.180	*1.466*	-0.322	*-1.521*	0.016
1	*2*	0.151	*0.589*	0.000	*0.111*	0.119	*2.078*	0.161	*1.872***	0.062	*0.421*	0.022
1	*3*	0.179	*0.929*	0.000	*0.013*	0.151	*3.563*	0.045	*0.709*	0.062	*0.561*	0.045
2	*1*	-0.392	*-1.989*	-0.006	*-3.239*	0.221	*5.244*	0.222	*3.516*	-0.123	*-1.128*	0.102
2	*2*	0.251	*1.470*	0.001	*0.330*	0.175	*4.726*	0.121	*2.186*	0.033	*0.349*	0.075
2	*3*	-0.286	*-1.243*	-0.005	*-1.914***	0.142	*2.787*	0.053	*0.694*	0.007	*0.056*	0.028
3	*1*	-0.502	*-1.727***	-0.008	*-2.884*	0.308	*5.261*	0.709	*8.086*	-0.159	*-1.051*	0.205
3	*2*	-0.382	*-1.190*	-0.007	*-2.165*	0.308	*4.636*	0.664	*6.670*	-0.485	*-2.826*	0.160
3	*3*	0.056	*0.149*	-0.003	*-0.675*	0.313	*3.858*	0.511	*4.195*	-0.127	*-0.604*	0.079
Single Portfolio		-0.145	*-1.166*	-0.003	*-3.174*	0.203	*8.497*	0.296	*8.250*	-0.117	*-1.887***	0.272

Panel E: Characteristic-Balanced Portfolio with a different strategy												
SIZE	*BE/ME*	Return	t	intercept	t	b	t (b)	s	t(s)	h	t(h)	R-square
1	*1*	-1.346	*-2.491*	-0.014	*-2.450*	0.025	*0.205*	0.046	*0.254*	-0.470	*-1.497*	0.009
1	*2*	-0.501	*-1.339*	-0.007	*-1.921***	0.226	*2.736*	0.320	*2.583*	0.215	*1.007*	0.042
1	*3*	0.293	*1.026*	0.000	*0.044*	0.232	*3.698*	-0.004	*-0.040*	0.161	*0.994*	0.055
2	*1*	-0.603	*-1.929***	-0.008	*-2.547*	0.195	*2.815*	0.181	*1.736***	0.033	*0.186*	0.030
2	*2*	0.496	*1.789***	0.003	*0.895*	0.230	*3.780*	0.235	*2.578*	0.027	*0.174*	0.054
2	*3*	-0.130	*-0.344*	-0.003	*-0.728*	0.125	*1.473*	-0.026	*-0.208*	-0.180	*-0.821*	0.015
3	*1*	-0.321	*-0.805*	-0.007	*-1.749***	0.376	*4.495*	0.740	*5.905*	0.068	*0.313*	0.133
3	*2*	-0.237	*-0.517*	-0.006	*-1.327*	0.388	*4.001*	0.816	*5.611*	-0.683	*-2.724*	0.124
3	*3*	0.066	*0.122*	-0.006	*-1.043*	0.591	*5.137*	0.696	*4.036*	-0.039	*-0.131*	0.102
Single Portfolio		-0.254	*-1.513*	-0.005	*-3.441*	0.265	*7.959*	0.334	*6.677*	-0.096	*-1.118*	0.223

TABLE 5.10 (cont.)

Panel A reports descriptive statistics and the number of companies in each of the 45 factor loading portfolios over the sample period (January 1973-December 2001). The portfolios are constructed as the intersection of stocks independently sorted on Market value, Book-to-Market (BE/ME), and SMB Loading (3x3x5). BE/ME is based on December t-1. Market value is also based on December t-1. The ex-ante factor loading is estimated using 36 monthly returns before December t-1. HB1 is the lowest factor loading portfolios, and similarly for other portfolios. Market value, BE/ME and SMB Loading in panel A are value-weighted averages and the number of companies are equally-weighted averages. Panel B reports the mean monthly excess returns and its associated t-statistics for each of the 45 factor-loading portfolio. Panels C report the intercept (its associated t-statistics) and ex-post SMB factor loading (its associated t-statistics) of the 45 factor loading portfolio (after the portfolio formation) from the Fama-French three-factor model:

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i \tag{5.3}$$

*The underlined t-statistics indicates significance at 5 %, * * indicates significance at 10% level.*

Refer to the notes in Table 5.2 for the construction of SMB and HML factors. Panel D presents the summary statistics and regression results of characteristic-balanced portfolios. These portfolios are formed, in each category, by subtracting the sum of the returns on the first and second quintile factor-loading portfolios from the sum of the returns on the fourth and fifth factor-loading portfolio, and then dividing by 2. The first nine rows of the panel gives the mean monthly excess returns (in percent) and the regression coefficients for the characteristic-balanced portfolio that has a long position in the high expected factor loading portfolios and a short position in the low expected factor loading portfolios that have the same size and BE/ME rankings. The bottom row of the panel D provides the coefficients estimates as well the t-statistics for this regression for a combined-portfolio that consists for an equally weighted combination of the above zero-investment portfolios. Panel E provides the summary statistics and regression results of the characteristic-balanced portfolios formed with a different strategy. These characteristic-balanced portfolios in Panel E are formed with long (short) position in factor loading quintile HB5 (HB1).

TABLE 5.11a
SUMMARY STATISTICS AND REGRESSIONS FOR PORTFOLIOS FORMED FROM SORTS ON SIZE, BE/ME AND MARKET FACTOR LOADING: JULY 1973 TO DECEMBER 2001, 282 MONTHLY OBSERVATIONS

Panel A: Ex-ante b								Market Value (£ m)						BE/ME						Number of Companies					
Characteristics		Factor Loading						Factor Loading						Factor Loading						Factor Loading					
SIZE	*BE/ ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	0.05	0.62	0.92	1.19	1.88	0.93	7.72	8.01	7.79	8.50	7.59	7.92	-1.59	-0.34	0.25	-1.10	-0.62	-0.48	13	6	5	4	9	8
1	*2*	0.13	0.63	0.91	1.20	1.81	0.94	7.42	8.28	8.59	8.11	8.11	8.10	0.88	0.87	0.89	0.87	0.89	1.28	20	13	9	7	10	12
1	*3*	0.13	0.64	0.92	1.19	1.72	0.92	7.09	7.44	7.11	7.64	7.34	7.32	2.65	2.48	2.43	3.46	2.91	3.39	42	27	19	18	20	26
2	*1*	0.10	0.64	0.92	1.19	1.80	0.93	45.67	47.83	49.02	50.29	45.87	47.74	-1.00	0.05	0.12	0.38	-0.65	0.58	15	17	15	13	16	16
2	*2*	0.22	0.65	0.93	1.19	1.74	0.94	42.35	43.09	47.77	49.05	43.62	45.18	0.84	0.85	0.86	0.84	0.85	1.85	15	19	17	15	15	17
2	*3*	0.18	0.65	0.92	1.20	1.73	0.94	38.25	41.10	41.27	38.68	43.90	40.64	1.96	2.06	1.81	1.83	1.91	3.11	12	12	13	13	15	14
3	*1*	0.29	0.67	0.93	1.18	1.56	0.93	8073.92	12415.69	9331.42	4929.02	3064.12	7562.83	0.32	0.07	0.31	0.13	0.21	1.61	9	20	28	30	22	23
3	*2*	0.27	0.66	0.92	1.19	1.59	0.92	3692.13	11436.99	5921.22	2428.99	1197.63	4935.39	0.72	0.84	0.81	0.82	0.83	2.40	5	14	21	23	20	18
3	*3*	0.16	0.67	0.92	1.18	1.61	0.91	1548.25	2157.57	2275.36	862.92	501.11	1469.04	2.12	1.67	1.56	1.58	1.67	3.52	3	5	8	9	9	8
Avg		0.17	0.65	0.92	1.19	1.72		1495.87	2907.33	1965.50	931.47	546.59		0.88	1.17	1.34	1.42	1.44		15	15	15	15	16	

Panel B: Mean Excess Return (%)								t-statistics					
Characteristics		Factor Loading											
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	0.314	0.903	0.321	0.009	0.046	0.319	*0.851*	*1.780***	*0.497*	*0.015*	*0.085*	*0.645*
1	*2*	0.493	0.765	0.924	0.415	0.715	0.662	*1.549*	*2.419*	*2.177*	*0.917*	*1.558*	*1.724***
1	*3*	1.108	0.890	0.638	0.692	1.138	0.893	*4.683*	*3.053*	*1.981*	*2.076*	*2.862*	*2.931*
2	*1*	0.640	0.548	0.444	0.211	0.015	0.372	*2.079*	*1.806***	*1.312*	*0.503*	*0.038*	*1.147*
2	*2*	0.598	0.963	0.535	0.693	0.768	0.711	*2.341*	*3.204*	*1.658***	*2.027*	*2.097*	*2.265*
2	*3*	1.090	0.807	0.900	0.580	0.899	0.855	*3.977*	*2.710*	*2.515*	*1.486*	*2.098*	*2.557*
3	*1*	0.959	0.715	0.563	0.805	0.720	0.752	*2.418*	*2.328*	*1.611*	*2.263*	*1.742***	*2.072*
3	*2*	0.698	0.892	1.118	0.901	0.694	0.861	*1.780***	*2.710*	*3.139*	*2.519*	*1.710***	*2.372*
3	*3*	1.145	1.479	1.376	0.965	0.971	1.187	*2.641*	*3.445*	*3.512*	*2.228*	*2.075*	*2.780*
Avg		0.894	1.107	1.091	1.030	1.218		*2.591*	*2.828*	*2.378*	*2.004*	*2.140*	

TABLE 5.11a (cont.)

Panel C1: Intercept								Panel C2: t-statistics					
Characteristics		Factor Loading											
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	-0.006	-0.004	-0.010	-0.013	-0.013	-0.009	*-1.980*	*-0.919*	*-1.828***	*-2.529*	*-2.892*	*-2.030*
1	*2*	-0.004	-0.001	-0.002	-0.008	-0.005	-0.004	*-1.702***	*-0.352*	*-0.514*	*-2.312*	*-1.653***	*-1.306*
1	*3*	0.005	0.000	-0.003	-0.003	-0.001	0.000	*3.147*	*-0.020*	*-1.514*	*-1.308*	*-0.221*	*0.017*
2	*1*	-0.003	-0.005	-0.007	-0.012	-0.013	-0.008	*-1.284*	*-2.585*	*-3.854*	*-4.665*	*-5.481*	*-3.574*
2	*2*	-0.002	-0.001	-0.006	-0.005	-0.005	-0.004	*-1.340*	*-0.470*	*-3.283*	*-2.324*	*-2.693*	*-2.022*
2	*3*	0.004	-0.002	-0.002	-0.007	-0.005	-0.002	*1.757***	*-0.819*	*-0.866*	*-2.646*	*-1.631*	*-0.841*
3	*1*	0.000	-0.002	-0.007	-0.005	-0.007	-0.004	*0.107*	*-1.193*	*-3.908*	*-2.759*	*-2.674*	*-2.085*
3	*2*	-0.001	-0.001	0.000	-0.004	-0.007	-0.003	*-0.350*	*-0.407*	*-0.170*	*-2.093*	*-3.140*	*-1.232*
3	*3*	0.001	0.004	0.002	-0.004	-0.006	0.000	*0.382*	*1.039*	*0.746*	*-1.225*	*-1.910***	*-0.194*
Avg		0.111	0.221	0.329	0.438	0.549		*-0.029*	*-0.414*	*-1.355*	*-1.985*	*-1.922***	

Panel C3: Ex-post b								Panel C4: t-statistics					
Characteristics		Factor Loading											
SIZE	BE/ME	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	1	0.841	1.184	1.266	1.252	1.236	1.156	*13.496*	*13.596*	*10.583*	*10.911*	*13.057*	*12.329*
1	2	0.824	0.796	1.023	1.119	1.182	0.989	*17.540*	*16.153*	*14.758*	*15.417*	*16.673*	*16.108*
1	3	0.633	0.839	0.893	0.913	1.121	0.880	*20.160*	*21.926*	*20.333*	*18.801*	*20.768*	*20.398*
2	1	0.845	0.921	1.060	1.265	1.183	1.055	*19.080*	*24.296*	*26.344*	*23.235*	*23.480*	*23.287*
2	2	0.747	0.948	1.015	1.049	1.170	0.986	*21.364*	*26.959*	*26.302*	*23.926*	*27.771*	*25.264*
2	3	0.676	0.874	1.009	1.132	1.229	0.984	*15.077*	*21.513*	*19.868*	*20.622*	*19.936*	*19.403*
3	1	0.767	0.762	1.051	1.079	1.169	0.965	*10.545*	*18.055*	*26.761*	*27.777*	*21.565*	*20.941*
3	2	0.653	0.805	0.961	1.070	1.193	0.936	*8.757*	*15.938*	*18.946*	*26.201*	*23.454*	*18.659*
3	3	0.825	0.935	0.990	1.142	1.327	1.044	*10.185*	*12.117*	*15.349*	*16.893*	*19.831*	*14.875*
Avg		0.757	0.896	1.030	1.114	1.201		*15.134*	*18.950*	*19.916*	*20.420*	*20.726*	

TABLE 5.11a (cont.)

Panel D: Characteristic-Balanced Portfolio												
SIZE	BE/ME	Return	t	intercept	t	b	t (b)	s	t(s)	h	t(h)	R-square
1	1	-0.581	*-1.362*	-0.008	*-1.898***	0.232	*2.439*	0.218	*1.531*	-0.209	*-0.853*	0.025
1	2	-0.064	*-0.231*	-0.004	*-1.591*	0.341	*5.773*	0.313	*3.532*	-0.148	*-0.970*	0.116
1	3	-0.084	*-0.425*	-0.004	*-2.116*	0.281	*6.865*	0.178	*2.900*	0.137	*1.293*	0.148
2	1	-0.481	*-2.407*	-0.009	*-4.678*	0.341	*8.505*	0.209	*3.473*	0.044	*0.420*	0.207
2	2	-0.050	*-0.306*	-0.003	*-2.281*	0.262	*7.876*	0.124	*2.476*	-0.018	*-0.207*	0.185
2	3	-0.209	*-0.868*	-0.007	*-3.000*	0.405	*8.348*	0.202	*2.778*	0.088	*0.705*	0.201
3	1	-0.075	*-0.255*	-0.005	*-1.665***	0.359	*5.710*	0.195	*2.066*	0.048	*0.295*	0.105
3	2	0.003	*0.010*	-0.005	*-1.787***	0.403	*7.247*	0.194	*2.332*	0.179	*1.246*	0.160
3	3	-0.344	*-1.077*	-0.007	*-2.338*	0.355	*5.153*	0.230	*2.228*	-0.086	*-0.481*	0.089
Single Portfolio		**-0.209**	*-1.574*	-0.006	*-5.618*	0.331	*14.744*	0.207	*6.149*	0.004	*0.067*	0.440

Panel E: Characteristic-Balanced Portfolio with a different strategy												
SIZE	*BE/ME*	Return	t	intercept	t	b	t (b)	s	t(s)	h	t(h)	R-square
1	*1*	-0.268	*-0.537*	-0.007	*-1.375*	0.395	*3.614*	0.374	*2.280*	-0.316	*-1.118*	0.052
1	*2*	0.222	*0.558*	-0.002	*-0.427*	0.358	*4.108*	0.280	*2.140*	-0.062	*-0.277*	0.059
1	*3*	0.030	*0.107*	-0.005	*-1.728***	0.489	*8.646*	0.367	*4.332*	0.035	*0.238*	0.215
2	*1*	-0.625	*-2.336*	-0.010	*-3.864*	0.338	*5.962*	0.173	*2.030*	-0.034	*-0.230*	0.115
2	*2*	0.170	*0.676*	-0.003	*-1.319*	0.424	*8.381*	0.256	*3.381*	0.058	*0.445*	0.202
2	*3*	-0.191	*-0.546*	-0.008	*-2.507*	0.553	*7.726*	0.239	*2.225*	0.168	*0.911*	0.178
3	*1*	-0.240	*-0.548*	-0.007	*-1.598*	0.402	*4.207*	0.159	*1.110*	-0.031	*-0.124*	0.062
3	*2*	-0.003	*-0.009*	-0.006	*-1.601*	0.539	*6.469*	0.294	*2.352*	0.199	*0.925*	0.131
3	*3*	-0.174	*-0.380*	-0.007	*-1.618*	0.503	*5.123*	0.357	*2.424*	-0.447	*-1.763***	0.100
Single Portfolio		**-0.120**	*-0.654*	-0.006	*-4.268*	0.445	*14.128*	0.278	*5.883*	-0.048	*-0.586*	0.421

TABLE 5.11a (cont.)

Panel A reports descriptive statistics and the number of companies in each of the 45 factor loading portfolios over the sample period (January 1973-December 2001). The portfolios are constructed as the intersection of stocks independently sorted on Market value, Book-to-Market (BE/ME), and market Loading (value-weighted index) (3x3x5). BE/ME is based on December t-1. Market value is also based on December t-1. The ex-ante factor loading is estimated using 36 monthly returns before December t-1. HB1 is the lowest factor loading portfolios, and similarly for other portfolios. Market value, BE/ME and Market factor loading given in panel A are value-weighted averages and the number of companies are equally-weighted averages. Panel B reports the mean monthly excess returns and its associated t-statistics for each of the 45 factor-loading portfolio. Panels C report the intercept (and its associated t-statistics) and ex-post Market factor loading (its associated t-statistics) of the 45 factor loading portfolio (after the portfolio formation) from the Fama-French three-factor model:

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i \tag{5.3}$$

*The underlined t-statistics indicates significance at 5 %, * * indicates significance at 10% level.*

Refer to the notes in Table 5.2 for the construction of SMB and HML factors. Panel D presents the summary statistics and regression results of characteristic-balanced portfolios. These portfolios are formed, in each category, by subtracting the sum of the returns on the first and second quintile factor-loading portfolios from the sum of the returns on the fourth and fifth factor-loading portfolio, and then dividing by 2. The first nine rows of the panel gives the mean monthly excess returns (in percent) and the regression coefficients for the characteristic-balanced portfolio that has a long position in the high expected factor loading portfolios and a short position in the low expected factor loading portfolios that have the same size and BE/ME rankings. The bottom row of the panel D provides the coefficients estimates as well the t-statistics for this regression for a combined-portfolio that consists for an equally weighted combination of the above zero-investment portfolios. Panel E provides the summary statistics and regression results of the characteristic-balanced portfolios formed with a different strategy. These characteristic-balanced portfolios in Panel E are formed with long (short) position in factor loading quintile HB5 (HB1).

TABLE 5.11b
SUMMARY STATISTICS AND REGRESSIONS FOR PORTFOLIOS FORMED FROM SORTS ON SIZE, BE/ME AND MARKET FACTOR LOADING using EQUALLY-WEIGHTED INDEX: JULY 1973 TO DECEMBER 2001, 282 MONTHLY OBSERVATIONS

Panel A: Ex-ante b								Market Value (£ m)						BE/ME						Number of Companies					
Characteristics		Factor Loading						Factor Loading						Factor Loading						Factor Loading					
SIZE	*BE/ ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB 4	HB5	Avg
1	*1*	0.04	0.63	0.93	1.21	1.86	0.93	7.52	8.91	8.04	7.04	7.76	7.85	-1.35	-0.50	0.15	-0.32	-1.94	-0.79	13	6	5	5	9	8
1	*2*	0.10	0.64	0.94	1.20	1.81	0.94	7.47	8.40	8.39	8.21	8.43	8.18	0.88	0.87	0.90	0.87	0.88	0.88	19	12	9	7	11	12
1	*3*	0.16	0.64	0.93	1.21	1.73	0.93	7.06	7.31	7.40	7.60	7.20	7.31	2.70	2.44	2.50	2.93	3.20	2.75	42	26	19	18	21	25
2	*1*	0.10	0.65	0.93	1.19	1.83	0.94	44.18	49.58	49.67	49.69	45.51	47.73	-0.97	-0.07	0.24	0.41	-0.82	-0.24	15	16	15	13	16	15
2	*2*	0.22	0.65	0.92	1.20	1.73	0.94	42.24	43.38	47.02	47.74	44.36	44.95	0.84	0.85	0.85	0.85	0.86	0.85	14	19	17	17	16	16
2	*3*	0.20	0.64	0.93	1.21	1.76	0.95	38.20	39.64	41.15	39.89	43.42	40.46	2.06	1.88	1.83	1.79	1.92	1.89	11	11	13	13	16	13
3	*1*	0.28	0.65	0.93	1.21	1.59	0.93	15086.74	10439.09	8903.86	5064.14	2237.32	8346.23	0.27	0.26	0.24	0.14	0.24	0.23	10	22	28	30	18	22
3	*2*	0.28	0.65	0.93	1.20	1.61	0.93	9846.43	6326.30	5280.25	1818.49	818.39	4817.97	0.83	0.81	0.83	0.82	0.84	0.83	5	16	19	22	20	16
3	*3*	0.24	0.67	0.93	1.21	1.66	0.94	1176.03	2902.27	1586.20	604.82	462.83	1346.43	2.12	1.51	1.59	1.66	1.63	1.70	3	6	8	8	9	7
Avg		0.18	0.65	0.93	1.20	1.73		2917.32	2202.77	1770.22	849.74	408.36		0.82	0.89	1.01	1.02	0.76		15	15	15	15	15	

Panel B: Mean Excess Return (%)								t-statistics					
Characteristics		Factor Loading											
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	0.341	0.718	0.444	-0.008	0.061	0.311	*0.953*	*1.267*	*0.651*	*-0.012*	*0.121*	*0.596*
1	*2*	0.279	0.949	0.753	0.699	0.524	0.641	*0.830*	*2.404*	*2.074*	*1.616*	*1.187*	*1.622*
1	*3*	1.073	0.743	0.808	0.849	1.032	0.901	*4.501*	*2.707*	*2.392*	*2.571*	*2.811*	*2.996*
2	*1*	0.632	0.616	0.368	0.335	-0.073	0.376	*1.978*	*1.969*	*1.073*	*0.897*	*-0.173*	*1.149*
2	*2*	0.643	0.778	0.773	0.682	0.685	0.712	*2.462*	*2.634*	*2.417*	*2.074*	*1.810***	*2.279*
2	*3*	1.231	0.678	0.818	0.721	0.843	0.858	*4.526*	*2.091*	*2.312*	*1.880***	*1.989*	*2.560*
3	*1*	0.843	0.534	0.863	0.822	0.256	0.664	*2.418*	*1.637*	*2.511*	*2.342*	*0.514*	*1.884***
3	*2*	0.738	1.076	1.032	0.884	0.463	0.839	*1.849***	*3.136*	*2.948*	*2.399*	*1.119*	*2.290*
3	*3*	1.653	1.315	1.147	0.950	1.028	1.219	*3.476*	*3.658*	*2.776*	*2.133*	*2.207*	*2.850*
Avg		0.826	0.823	0.779	0.659	0.536		*2.555*	*2.389*	*2.128*	*1.767***	*1.287*	

TABLE 5.11b (cont.)

Panel C1: Intercept								Panel C2: t-statistics					
Characteristics		Factor Loading											
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	-0.005	-0.008	-0.011	-0.012	-0.012	-0.009	*-1.714***	*-1.702***	*-1.919***	*-2.382*	*-3.031*	*-2.150*
1	*2*	-0.006	-0.001	-0.002	-0.004	-0.008	-0.004	*-2.228*	*-0.451*	*-0.884*	*-1.218*	*-2.509*	*-1.458*
1	*3*	0.004	-0.001	-0.002	-0.002	-0.001	0.000	*2.761*	*-0.557*	*-0.877*	*-0.940*	*-0.328*	*0.012*
2	*1*	-0.003	-0.004	-0.008	-0.009	-0.015	-0.008	*-1.353*	*-2.317*	*-4.265*	*-4.386*	*-5.696*	*-3.603*
2	*2*	-0.002	-0.002	-0.003	-0.005	-0.006	-0.004	*-1.296*	*-1.454*	*-1.999*	*-2.593*	*-3.093*	*-2.087*
2	*3*	0.006	-0.003	-0.003	-0.005	-0.005	-0.002	*2.653*	*-1.511*	*-1.076*	*-2.009*	*-1.781***	*-0.745*
3	*1*	0.000	-0.006	-0.004	-0.005	-0.012	-0.005	*0.109*	*-3.075*	*-2.823*	*-3.006*	*-3.460*	*-2.451*
3	*2*	-0.002	-0.001	-0.002	-0.005	-0.010	-0.004	*-0.517*	*-0.248*	*-0.919*	*-2.363*	*-4.552*	*-1.720***
3	*3*	0.005	0.003	-0.001	-0.004	-0.005	-0.001	*1.335*	*1.015*	*-0.441*	*-1.301*	*-1.771***	*-0.232*
Avg		0.000	-0.003	-0.004	-0.006	-0.008		*-0.028*	*-1.145*	*-1.689***	*-2.244*	*-2.913*	

Panel C3: Ex-post b								Panel C4: t-statistics					
Characteristics		Factor Loading											
SIZE	*BE/ME*	HB1	HB2	HB3	HB4	HB5	Avg	HB1	HB2	HB3	HB4	HB5	Avg
1	*1*	0.791	1.356	1.442	1.213	1.177	1.196	*12.800*	*14.020*	*11.763*	*10.822*	*13.845*	*12.650*
1	*2*	0.798	1.018	0.919	1.035	1.194	0.993	*14.851*	*17.258*	*15.714*	*14.403*	*18.346*	*16.114*
1	*3*	0.635	0.787	0.942	0.962	1.036	0.872	*19.510*	*22.190*	*20.735*	*22.265*	*20.351*	*21.010*
2	*1*	0.866	0.952	1.068	1.157	1.269	1.062	*18.724*	*24.498*	*26.541*	*24.888*	*22.881*	*23.507*
2	*2*	0.778	0.925	1.013	1.040	1.196	0.991	*22.673*	*26.227*	*26.648*	*26.393*	*27.193*	*25.827*
2	*3*	0.624	0.918	0.983	1.108	1.211	0.969	*13.503*	*19.611*	*19.174*	*20.503*	*19.632*	*18.485*
3	*1*	0.655	0.889	1.070	1.083	1.272	0.994	*10.913*	*22.545*	*32.220*	*30.711*	*16.582*	*22.594*
3	*2*	0.745	0.922	1.004	1.110	1.260	1.008	*10.128*	*19.928*	*23.292*	*26.391*	*25.455*	*21.039*
3	*3*	0.916	0.874	1.087	1.157	1.336	1.074	*10.244*	*14.595*	*16.762*	*16.510*	*20.265*	*15.675*
Avg		0.757	0.960	1.059	1.096	1.217		*14.816*	*20.097*	*21.428*	*21.432*	*20.506*	

TABLE 5.11b (cont.)

Panel D: Characteristic-Balanced Portfolio												
SIZE	*BE/ME*	Return	t	intercept	t	b	t (b)	s	t(s)	h	t(h)	R-square
1	*1*	-0.503	*-1.189*	-0.006	*-1.357*	0.121	*1.296*	0.470	*3.351*	-0.221	*-0.916*	0.039
1	*2*	-0.002	*-0.007*	-0.002	*-0.809*	0.207	*3.202*	0.078	*0.809*	-0.075	*-0.448*	0.038
1	*3*	0.032	*0.180*	-0.003	*-1.735***	0.288	*7.835*	0.159	*2.888*	0.087	*0.921*	0.181
2	*1*	-0.493	*-2.480*	-0.008	*-4.485*	0.304	*7.420*	0.110	*1.789***	0.061	*0.576*	0.168
2	*2*	-0.027	*-0.167*	-0.003	*-2.212*	0.266	*8.261*	0.148	*3.066*	0.148	*1.784***	0.201
2	*3*	-0.173	*-0.687*	-0.006	*-2.621*	0.388	*7.524*	0.138	*1.783***	0.117	*0.874*	0.172
3	*1*	-0.150	*-0.500*	-0.006	*-2.047*	0.406	*6.466*	0.353	*3.755*	0.032	*0.194*	0.137
3	*2*	-0.233	*-0.886*	-0.006	*-2.510*	0.352	*6.414*	0.187	*2.278*	0.439	*3.103*	0.149
3	*3*	-0.494	*-1.637*	-0.009	*-2.997*	0.352	*5.435*	0.189	*1.947*	0.098	*0.585*	0.096
Single Portfolio		-0.227	*-1.678***	-0.006	*-4.928*	0.298	*12.094*	0.204	*5.511*	0.076	*1.197*	0.348

Panel E: Characteristic-Balanced Portfolio with a different strategy												
SIZE	*BE/ME*	Return	t	intercept	t	b	t (b)	s	t(s)	h	t(h)	R-square
1	*1*	-0.280	*-0.584*	-0.007	*-1.438*	0.386	*3.654*	0.347	*2.194*	0.031	*0.115*	0.049
1	*2*	0.245	*0.659*	-0.002	*-0.541*	0.396	*4.919*	0.233	*1.928***	-0.085	*-0.410*	0.082
1	*3*	-0.041	*-0.156*	-0.005	*-1.940***	0.401	*7.299*	0.252	*3.065*	-0.077	*-0.540*	0.164
2	*1*	-0.706	*-2.362*	-0.012	*-4.031*	0.402	*6.405*	0.188	*1.999*	0.180	*1.110*	0.130
2	*2*	0.042	*0.170*	-0.004	*-1.826***	0.417	*8.330*	0.298	*3.971*	0.261	*2.012*	0.209
2	*3*	-0.388	*-1.084*	-0.011	*-3.218*	0.586	*8.110*	0.179	*1.654***	0.099	*0.532*	0.197
3	*1*	-0.587	*-1.211*	-0.013	*-2.662*	0.617	*6.042*	0.578	*3.774*	-0.238	*-0.901*	0.126
3	*2*	-0.275	*-0.677*	-0.009	*-2.185*	0.515	*6.009*	0.264	*2.053*	0.522	*2.355*	0.126
3	*3*	-0.624	*-1.313*	-0.011	*-2.274*	0.420	*4.047*	0.318	*2.042*	-0.293	*-1.091*	0.062
Single Portfolio		-0.290	*-1.496*	-0.008	*-5.154*	0.460	*13.554*	0.295	*5.802*	0.045	*0.507*	0.399

TABLE 5.11b (cont.)

Panel A reports descriptive statistics and the number of companies in each of the 45 factor loading portfolios over the sample period (January 1973-December 2001). The portfolios are constructed as the intersection of stocks independently sorted on Market value, Book-to-Market (BE/ME), and market Loading (equally-weighted index) (3x3x5). BE/ME is based on December t-1. Market value is also based on December t-1. The ex-ante factor loading is estimated using 36 monthly returns before December t-1. HB1 is the lowest factor loading portfolios, and similarly for other portfolios. Market value, BE/ME and Market factor loading given in panel A are value-weighted averages and the number of companies are equally-weighted averages. Panel B reports the mean monthly excess returns and its associated t-statistics for each of the 45 factor-loading portfolio. Panels C report the intercept (and its associated t-statistics) and ex-post Market factor loading (its associated t-statistics) of the 45 factor loading portfolio (after the portfolio formation) from the Fama-French three-factor model:

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i \tag{5.3}$$

*The underlined t-statistics indicates significance at 5 %, ** indicates significance at 10% level.*

Refer to the notes in Table 5.2 for the construction of SMB and HML factors. Panel D presents the summary statistics and regression results of characteristic-balanced portfolios. These portfolios are formed, in each category, by subtracting the sum of the returns on the first and second quintile factor-loading portfolios from the sum of the returns on the fourth and fifth factor-loading portfolio, and then dividing by 2. The first nine rows of the panel gives the mean monthly excess returns (in percent) and the regression coefficients for the characteristic-balanced portfolio that has a long position in the high expected factor loading portfolios and a short position in the low expected factor loading portfolios that have the same size and BE/ME rankings. The bottom row of the panel D provides the coefficients estimates as well the t-statistics for this regression for a combined-portfolio that consists for an equally weighted combination of the above zero-investment portfolios. Panel E provides the summary statistics and regression results of the characteristic-balanced portfolios formed with a different strategy. These characteristic-balanced portfolios in Panel E are formed with long (short) position in factor loading quintile HB5 (HB1)

TABLE 5.12
REGRESSIONS RESULTS FOR CHARACTERISTIC-BALANCED PORTFOLIOS USING 20 FACTOR LOADING PORTFOLIOS: JULY 1973 TO DECEMBER 2001, (282 MONTHLY OBSERVATIONS)

PaneL A: Characteristic-Balanced Portfolio using MARKET LOADING

SIZE	BE/ME	Excess Return	t	intercept	t	b	t(b)	s	t(s)	h	t(h)	R-square
1	1	-0.195	*-0.822*	-0.005	*-2.351*	0.316	*6.365*	0.287	*3.862*	0.136	*1.063*	0.138
1	2	-0.178	*-0.793*	-0.007	*-3.486*	0.451	*10.537*	0.260	*4.049*	-0.039	*-0.357*	0.288
2	1	-0.369	*-1.008*	-0.009	*-2.440*	0.446	*5.714*	0.223	*1.902***	-0.015	*-0.072*	0.106
2	2	-0.273	*-0.746*	-0.009	*-2.450*	0.520	*6.857*	0.323	*2.841*	-0.266	*-1.356*	0.154
Single Portfolio		-0.254	*-1.318*	-0.007	*-4.631*	0.433	*12.496*	0.273	*5.256*	-0.046	*-0.512*	0.363

Panel B: Characteristic-Balanced Portfolio using SMB LOADING

SIZE	BE/ME	Excess Return	t	intercept	t	b	t (b)	s	t(s)	h	t(h)	R-square
1	1	-0.209	*-0.779*	-0.005	*-1.799***	0.251	*4.297*	0.202	*2.312*	-0.103	*-0.683*	0.066
1	2	-0.123	*-0.576*	-0.004	*-1.878***	0.242	*5.267*	0.131	*1.910***	0.086	*0.722*	0.091
2	1	-0.478	*-1.433*	-0.008	*-2.514*	0.342	*5.057*	0.789	*7.778*	-0.195	*-1.115*	0.192
2	2	0.304	*0.934*	-0.001	*-0.333*	0.412	*6.209*	0.667	*6.706*	0.076	*0.441*	0.185
Single Portfolio		-0.126	*-0.724*	-0.004	*-2.945*	0.312	*9.573*	0.447	*9.167*	-0.034	*-0.406*	0.317

Panel C: Characteristic-Balanced Portfolio using HML LOADING

SIZE	BE/ME	Excess Return	t	intercept	t	b	t (b)	s	t(s)	h	t(h)	R-square
1	1	0.309	*1.315*	0.003	*1.254*	-0.001	*-0.020*	-0.033	*-0.421*	0.113	*0.828*	0.003
1	2	-0.074	*-0.452*	-0.001	*-0.451*	0.000	*0.008*	-0.016	*-0.294*	-0.011	*-0.114*	0.001
2	1	0.208	*0.692*	0.004	*1.457*	-0.220	*-3.318*	-0.210	*-2.111*	-0.100	*-0.584*	0.042
2	2	-0.179	*-0.491*	-0.001	*-0.277*	-0.093	*-1.138*	-0.270	*-2.214*	-0.151	*-0.720*	0.023
Single Portfolio		0.066	*0.476*	0.001	*1.011*	-0.078	*-2.556*	-0.133	*-2.880*	-0.037	*-0.471*	0.040

The portfolios are constructed as the intersection of stocks independently sorted on Market value, Book-to-Market (BE/ME), and Factor Loadings (2x2x5). BE/ME is based on December t-1. Market value is also based on December t-1. The ex-ante factor loading is estimated using 36 monthly returns before December t-1. HB1 is the lowest factor loading portfolios, and similarly for other portfolios (factor loading portfolios are not shown in this table).
Panels presents excess returns (its associated t-statistics) and regression results using (5.3) of characteristic-balanced portfolios formed by using three risk loadings (Market Loading (Panel A), SMB Loading (Panel B) and HML Loading (Panel C)) respectively.

$$R_i - R_f = a_i + b_i[R_m - R_f] + s_i SMB + h_i HML + \varepsilon_i \tag{5.3}$$

Refer to the notes in Table 5.2 for the construction of SMB and HML factors. These characteristic-balanced portfolios are formed with long (short) position in factor loading quintile HB5 (HB1). The first four rows of the panels gives the mean monthly excess returns (in percent) and the regression coefficients for the characteristic-balanced portfolio that has a long position in the high expected factor loading portfolios and a short position in the low expected factor loading portfolios that have the same size and BE/ME rankings. The bottom row of the each panel provides the coefficients estimates as well the t-statistics for the three-factor model (5.3) for a combined-portfolio that consists for an equally weighted combination of the above zero-investment portfolios.

*The underlined t-statistics indicates significance at 5%, ** indicates significance at 10% level.*

TABLE 5.13
REGRESSIONS FOR CHARACTERISTIC-BALANCED PORTFOLIOS USING SUB-PERIOD ANALYSIS

PANEL A: CHARACTEISTIC BALANCED PORTFOLIOS BASED ON MARKET LOADING

SUB-PERIOD 1

SIZE	BE/ ME	Mean	*t*	Intercept	*t*	b	*t (b)*	s	*t(s)*	h	*t(h)*	R-square
1	1	-0.426	*-0.900*	-0.008	*-1.541*	0.160	*1.606*	0.303	*1.674***	-0.460	*-1.390*	0.040
1	2	-0.168	*-0.490*	-0.006	*-1.702***	0.252	*3.652*	0.090	*0.718*	-0.190	*-0.830*	0.116
1	3	0.045	*0.178*	-0.004	*-1.400*	0.231	*4.592*	0.159	*1.741***	0.035	*0.208*	0.136
2	1	-0.363	*-1.670***	-0.007	*-3.075*	0.191	*4.507*	-0.028	*-0.364*	-0.038	*-0.270*	0.185
2	2	0.175	*0.829*	-0.002	*-1.132*	0.235	*5.768*	0.170	*2.303*	0.059	*0.435*	0.197
2	3	0.002	*0.008*	-0.004	*-1.554*	0.285	*5.356*	-0.058	*-0.598*	0.244	*1.384*	0.223
3	1	0.293	*0.872*	0.001	*0.171*	0.171	*2.452*	-0.093	*-0.734*	0.227	*0.982*	0.067
3	2	0.371	*1.038*	-0.001	*-0.213*	0.283	*3.929*	0.040	*0.304*	0.078	*0.324*	0.120
3	3	-0.031	*-0.080*	-0.005	*-1.301*	0.336	*4.042*	0.042	*0.277*	0.503	*1.828***	0.123
Single Portfolio		-0.011	*-0.080*	-0.004	*-3.197*	0.238	*9.628*	0.069	*1.546*	0.051	*0.619*	0.435

SUB-PERIOD2

SIZE	BE/ ME	Mean	*t*	Intercept	*t*	b	*t (b)*	s	*t(s)*	h	*t(h)*	R-square
1	1	-0.735	*-1.030*	-0.009	*-1.282*	0.348	*1.920***	0.177	*0.805*	-0.124	*-0.340*	0.027
1	2	0.039	*0.089*	-0.001	*-0.173*	0.446	*4.254*	0.495	*3.904*	-0.153	*-0.730*	0.155
1	3	-0.212	*-0.700*	-0.004	*-1.443*	0.352	*4.908*	0.200	*2.301*	0.168	*1.177*	0.165
2	1	-0.598	*-1.780***	-0.008	*-2.912*	0.526	*7.245*	0.380	*4.321*	0.043	*0.297*	0.297
2	2	-0.276	*-1.110*	-0.005	*-2.196*	0.329	*5.711*	0.086	*1.237*	-0.082	*-0.710*	0.196
2	3	-0.420	*-1.070*	-0.007	*-1.973*	0.559	*6.328*	0.374	*3.490*	-0.023	*-0.130*	0.237
3	1	-0.443	*-0.920*	-0.008	*-1.693***	0.615	*5.444*	0.372	*2.715*	-0.102	*-0.450*	0.183
3	2	-0.365	*-0.910*	-0.007	*-1.858***	0.539	*5.880*	0.288	*2.592*	0.205	*1.124*	0.215
3	3	-0.657	*-1.340*	-0.008	*-1.687***	0.408	*3.399*	0.330	*2.267*	-0.395	*-1.650***	0.097
Single Portfolio		-0.407	*-1.880***	-0.006	*-4.062*	0.458	*11.704*	0.300	*6.331*	-0.051	*-0.660*	0.513

PANEL B: CHARACTEISTIC BALANCED PORTFOLIOS BASED ON SMB LOADING

SUB-PERIOD 1

SIZE	BE/ ME	Mean	*t*	Intercept	*t*	b	*t (b)*	s	*t(s)*	h	*t(h)*	R-square
1	1	-0.334	*-0.724*	-0.003	*-0.571*	-0.013	*-0.135*	-0.127	*-.127*	-0.088	*-0.268*	0.006
1	2	0.226	*0.675*	0.003	*0.781*	-0.048	*-0.663*	0.044	*0.339*	-0.161	*-0.676*	0.007
1	3	0.261	*1.079*	0.001	*0.236*	0.116	*2.274*	0.073	*0.789*	-0.027	*-0.158*	0.040
2	1	-0.540	*-2.449*	-0.009	*-3.996*	0.197	*4.431*	0.192	*2.384*	0.100	*0.677*	0.127
2	2	0.067	*0.314*	-0.002	*-0.679*	0.121	*2.699*	0.119	*1.462*	-0.037	*-0.251*	0.054
2	3	-0.187	*-0.744*	-0.004	*-1.546*	0.153	*2.968*	-0.026	*-.281*	0.413	*2.416*	0.091
3	1	-0.172	*-0.529*	-0.003	*-1.004*	0.042	*0.627*	0.400	*3.316*	0.103	*0.467*	0.098
3	2	-0.206	*-0.790*	-0.004	*-1.617*	0.117	*2.143*	0.233	*2.346*	0.098	*0.542*	0.054
3	3	0.001	*0.002*	-0.003	*-0.679*	0.175	*1.975*	0.177	*1.103*	0.350	*1.192*	0.036
Single Portfolio		-0.098	*-0.845*	-0.003	*-2.326*	0.096	*4.070*	0.121	*2.833*	0.083	*1.072*	0.121

SUB-PERIOD 2

SIZE	BE/ME	Mean	*t*	Intercept	*t*	b	*t (b)*	s	*t(s)*	h	*t(h)*	R-square
1	1	-0.427	*-0.746*	-0.004	*-0.684*	0.228	*1.584*	0.385	*2.212*	-0.467	*-1.629*	0.050
1	2	0.076	*0.194*	-0.001	*-0.237*	0.345	*3.621*	0.254	*2.199*	0.114	*0.601*	0.100
1	3	0.097	*0.322*	-0.001	*-0.230*	0.208	*2.757*	0.030	*0.332*	0.087	*0.583*	0.057
2	1	-0.244	*-0.746*	-0.004	*-1.106*	0.307	*3.885*	0.270	*2.813*	-0.277	*-1.756***	0.124
2	2	0.434	*1.638*	0.003	*1.080*	0.277	*4.327*	0.156	*2.012*	0.028	*0.217*	0.124
2	3	-0.384	*-0.997*	-0.005	*-1.163*	0.156	*1.581*	0.092	*0.771*	-0.204	*-1.039*	0.025
3	1	-0.832	*-1.728***	-0.009	*-2.418*	0.721	*7.451*	0.925	*7.893*	-0.410	*-2.130*	0.394
3	2	-0.558	*-0.949*	-0.005	*-1.012*	0.608	*4.674*	0.960	*6.101*	-0.862	*-3.332***	0.267
3	3	0.111	*0.178*	0.001	*0.110*	0.547	*3.679*	0.759	*4.216*	-0.439	*-1.484*	0.150
Single Portfolio		-0.192	*-0.871*	-0.003	*-1.651***	0.377	*9.044*	0.426	*8.425*	-0.270	*-3.250*	0.463

PANEL C: CHARACTEISTIC BALANCED PORTFOLIOS BASED ON HML LOADING

SUB-PERIOD 1

SIZE	BE/ ME	Mean	*t*	Intercept	*t*	b	*t (b)*	s	*t(s)*	h	*t(h)*	R-square
1	1	0.340	*0.757*	0.005	*1.021*	-0.091	*-0.948*	-0.043	*-0.249*	0.037	*0.115*	0.008
1	2	0.194	*0.644*	0.000	*0.028*	0.085	*1.327*	0.162	*1.393*	-0.271	*-1.277*	0.030
1	3	-0.049	*-0.234*	0.000	*0.028*	-0.047	*-1.053*	0.071	*0.882*	0.023	*0.153*	0.030
2	1	-0.051	*-0.249*	-0.001	*-0.575*	0.043	*0.990*	0.066	*0.838*	0.222	*1.531*	0.029
2	2	0.324	*1.652* **	0.002	*1.012*	0.055	*1.310*	0.095	*1.252*	-0.023	*-0.166*	0.017
2	3	-0.088	*-0.341*	-0.001	*-0.394*	0.005	*0.093*	0.074	*0.740*	0.138	*0.754*	0.013
3	1	-0.038	*-0.164*	0.001	*0.263*	-0.053	*-1.070*	-0.039	*-0.431*	0.277	*1.683* **	0.037
3	2	0.630	*1.704* **	0.004	*1.078*	0.108	*1.366*	0.157	*1.098*	0.140	*0.534*	0.018
3	3	0.269	*0.674*	0.004	*0.886*	-0.087	*-1.022*	0.109	*0.708*	0.053	*0.188*	0.025
Single Portfolio		0.170	*1.524*	0.002	*1.278*	0.002	*0.085*	0.072	*1.699* **	0.066	*0.847*	0.043

SUB-PERIOD 2

SIZE	BE/ ME	Mean	*t*	Intercept	*t*	b	*t (b)*	s	*t(s)*	h	*t(h)*	R-square
1	1	-1.433	*-1.752* **	-0.015	*-1.804* **	0.131	*0.619*	0.047	*0.185*	0.171	*0.408*	0.004
1	2	0.042	*0.109*	-0.001	*-0.210*	0.077	*0.786*	-0.084	*-0.714*	0.287	*1.476*	0.024
1	3	-0.021	*-0.090*	0.000	*0.015*	-0.034	*-0.559*	-0.027	*-0.363*	-0.217	*-1.806* **	0.029
2	1	0.249	*0.852*	0.003	*1.003*	0.056	*0.751*	0.186	*2.068*	0.023	*0.153*	0.033
2	2	0.071	*0.305*	0.000	*0.194*	0.023	*0.391*	-0.036	*-0.499*	-0.278	*-2.367*	0.049
2	3	-0.060	*-0.171*	-0.001	*-0.179*	0.070	*0.793*	0.076	*0.708*	-0.340	*-1.925* **	0.030
3	1	-0.525	*-1.566*	-0.007	*-2.029*	0.322	*3.961*	0.239	*2.427*	-0.252	*-1.555*	0.119
3	2	-0.066	*-0.216*	0.000	*-0.116*	0.031	*0.397*	0.111	*1.170*	0.056	*0.362*	0.013
3	3	-0.341	*-0.807*	-0.006	*-1.351*	0.300	*2.835*	0.066	*0.514*	0.213	*1.012*	0.064
Single Portfolio		-0.232	*-1.566*	-0.003	*-1.941* **	0.108	*2.927*	0.064	*1.432*	-0.037	*-0.507*	0.061

Panels A, B, and C presents the excess returns, its associated t-statistics and regression results using equation (5.3) (see Tables 5.9-5.12) and characteristic-balanced portfolios formed by using three risk loadings (Market, SMB and HML) respectively and for two different (and equal) subperiods (Sub-period 1: July 1978- March 1990 and Sub-period 2: April 1990-December 2001) respectively.

*The underlined t-statistics indicates significance at 5 % , ** indicates significance at 10% level.*

Refer to the notes in Table 5.2 for the construction of SMB and HML factors. Refer to Tables 5.9-5.12 for the construction of the characteristic-balanced portfolios.
The bottom row of the each panel provides the coefficients estimates as well as the t-statistics for the regression (5.3) for a combined-portfolio that consists for an equally-weighted combination of the zero-investment portfolios.

TABLE 5.14
CONDITIONAL THREE-FACTOR REGRESSIONS ON BE/ME PORTFOLIOS: FULL SAMPLE: JANUARY 1969 TO DECEMBER 2001

Panel A1: Equation (5.21) using BE/ME as a characteristic factor

	α_0	t(α_0)	α_1	t(α_1)	R-square
Lowest	0.009	*2.321*	0.003	*1.283*	0.002
2	-0.002	*-0.320*	0.025	*1.818***	0.007
3	0.006	*1.074*	0.004	*0.399*	-0.002
4	0.000	*0.048*	0.017	*2.180*	0.011
5	-0.008	*-1.124*	0.026	*3.478*	0.032
6	0.003	*0.451*	0.010	*1.262*	0.002
7	-0.004	*-0.750*	0.019	*3.976*	0.042
8	0.000	*0.016*	0.024	*2.319*	0.013
9	0.009	*1.441*	0.013	*0.974*	0.000
Highest	0.005	*0.828*	0.018	*1.884***	0.007
Chi-square	12.040		19.580		
(p-value)	0.210		0.020		

Panel B1: Equation (5.22) using BE/ME as a characteristic factor

	a0	*t(a0)*	a1	*t(a1)*	b1	*t(b1)*	s1	*t(s1)*	h1	*t(h1)*	R-square
Lowest	0.001	*0.285*	0.003	*2.067*	-0.070	*-1.634*	-0.151	*-3.608*	-0.091	*-0.885*	0.766
2	-0.015	*-4.320*	0.039	*5.022*	-1.082	*-7.640*	-1.645	*-9.406*	-0.480	*-1.324*	0.775
3	-0.004	*-1.343*	0.009	*1.773***	-0.425	*-4.059*	-1.001	*-4.644*	-0.476	*-1.835***	0.743
4	-0.007	*-2.500*	0.015	*4.087*	-0.570	*-7.971*	-1.022	*-12.556*	-0.155	*-0.961*	0.817
5	-0.007	*-2.199*	0.013	*3.471*	-0.444	*-6.083*	-0.762	*-9.771*	0.106	*0.519*	0.775
6	-0.007	*-1.913***	0.012	*2.800*	-0.510	*-6.121*	-0.728	*-6.390*	-0.418	*-1.630*	0.720
7	-0.009	*-3.558*	0.012	*4.447*	-0.307	*-6.481*	-0.355	*-9.333*	-0.428	*-3.152*	0.757
8	-0.005	*-1.304*	0.013	*2.371*	-0.701	*-6.983*	-1.235	*-11.185*	0.166	*0.566*	0.737
9	0.000	*0.042*	0.003	*0.397*	-1.317	*-7.299*	-2.410	*-9.451*	0.207	*0.402*	0.630
Highest	0.000	*-0.003*	-0.001	*-0.086*	-0.509	*-4.956*	-0.958	*-9.843*	0.052	*0.144*	0.622
Chi-square	19.770		34.020		75.920		166.610		17.100		
(p-value)	0.010		0.000		0.000		0.000		0.040		

Panel A2: Equation (5.21) using SIZE as a characteristic factor

	α_0	t(α_0)	α_1	t(α_1)	R-square
Lowest	0.012	*2.695*	-0.033	*-1.859***	0.007
2	0.012	*2.423*	-0.087	*-1.422*	0.003
3	0.012	*2.825*	-0.054	*-1.917***	0.008
4	0.014	*3.214*	-0.051	*-1.298*	0.002
5	0.015	*3.072*	-0.056	*-0.796*	-0.001
6	0.011	*2.333*	-0.082	*-0.560*	-0.002
7	0.009	*2.473*	0.014	*0.295*	-0.003
8	0.014	*3.092*	-0.183	*-0.448*	-0.002
9	0.014	*3.219*	-0.095	*-0.261*	-0.003
Highest	0.015	*3.050*	-0.001	*-1.049*	0.000
Chi-square	10.530		11.250		
(p-value)	*0.300*		*0.250*		

TABLE 5.14 (cont.)

Panel B2: Equation (5.22) using SIZE as a characteristic factor

	a0	*t(a0)*	a1	*t(a1)*	b1	*t(b1)*	s1	*t(s1)*	h1	*t(h1)*	R-square
Lowest	0.001	*0.306*	0.003	*3.232*	0.001	*0.523*	0.006	*2.268*	0.002	*0.558*	0.759
2	-0.007	*-2.154*	0.017	*2.392*	0.052	*6.936*	0.066	*7.962*	-0.035	*-2.549*	0.754
3	-0.001	*-0.303*	0.002	*0.449*	0.012	*3.519*	0.014	*2.869*	0.004	*0.755*	0.731
4	-0.004	*-1.112*	0.009	*2.229*	0.005	*0.909*	0.006	*1.137*	0.008	*1.088*	0.728
5	-0.007	*-1.810* **	0.015	*3.547*	0.013	*1.387*	0.044	*4.297*	0.024	*1.175*	0.716
6	-0.002	*-0.557*	0.003	*0.686*	0.034	*1.352*	0.075	*2.375*	0.011	*0.210*	0.673
7	-0.009	*-2.978*	0.016	*4.988*	-0.009	*-0.823*	-0.019	*-1.516*	-0.024	*-1.870* **	0.603
8	-0.004	*-0.908*	0.015	*2.255*	0.011	*0.187*	0.168	*2.045*	0.094	*0.427*	0.626
9	0.002	*0.379*	0.006	*0.656*	-0.065	*-0.647*	0.057	*0.532*	-0.088	*-0.263*	0.522
Highest	0.000	*-0.083*	0.009	*1.271*	0.451	*0.119*	0.102	*1.441*	0.095	*0.819*	0.454
Chi-square	6.530		11.830		78.690		80.570		27.140		
(p-value)	0.680		0.220		0.000		0.000		0.001		

In Panel A1 and Panel B1, the regression results of (5.21) and (5.22) are reported for Book-to-Market (BE/ME) characteristic. In Panel A2 and Panel B2, the regression results of (5.21) and (5.22) are reported for size characteristic.

*The underlined t-statistics indicates significance at 5 %, ** indicates significance at 10% level.*

Each month from January 1969 through December 2001, value-weighted portfolios are formed on the basis of BE/ME. BE/ME is calculated as the ratio of book equity in the previous fiscal year to market equity in the previous fiscal year.

The following unconditional regression is used:

$$R_i(t)=\alpha_{i0}+\alpha_{i1}BE/ME_i(t)+e_i(t) \tag{5.21}$$

where R_i *is the portfolio's excess return,* BE/ME_i *is its book-to-market portfolio's value,* α_{i0} $and\alpha_{i1}$ *are the intercept and slope coefficient and* e_i *is the residual term. Note that the equation (5.21) is used in the same way for size characteristic.*

The following conditional regression is then used:

$$R_i-R_f = a_{i0}+a_{i1}BE/ME_i+(\ b_{i0}+b_{i1}BE/ME_i)*Rm+(\ s_{i0}+s_{i1}BE/ME_i)*SMB+ \tag{5.22}$$

$$(\ h_{i0}+h_{i1}BE/ME_i)*HML+e_i$$

where Ri is the portfolio's monthly return, Rf is the one-month Treasury bill rate (from Datastream), Rm is the FTSE-ALLSHARE INDEX, BE/ME is its book-to-market portfolio's value, SMB is the return on small stocks minus the return on big stocks, and HML is the return on high BE/ME minus the return on low-BE/ME. The table reports Ordinary Least Square (OLS) estimates of the interactive terms a_{i1}, b_{i1}, s_{i1} $and\ h_{i1}$, *which measures the time-variation in the intercept and loadings.*

Note that the equation (5.22) is used in the same way for size characteristic.

The Chi-square is also reported for both types of regressions. Chi-square $(\chi_2)=c'\sum c^{-1}$, *where c is the vector of coefficients and* $\sum$ *is the estimate of the covariance of matrix of c. Under the null that all coefficients are zero, this statistic is asymptotically distributed as chi-square (degrees of freedom (d.f).10). The Wald test is used for chi-square test.*

TABLE 5.15
CONDITIONAL THREE-FACTOR REGRESSIONS ON SIZE PORTFOLIOS: FULL SAMPLE: JANUARY 1969 TO DECEMBER 2001

Panel A1: Equation (5.21) using BE/ME as a characteristic factor

	α_0	t(α_0)	α_1	t(α_1)	R-square
Smallest	0.007	** *1.877*	0.373	*2.090*	0.013
2	0.004	*0.956*	0.319	*2.159*	0.014
3	0.005	** *1.665*	0.141	*2.228*	0.014
4	0.006	** *1.878*	0.100	*2.226*	0.014
5	0.002	*0.595*	0.118	*2.757*	0.022
6	0.004	*1.089*	0.064	*2.123*	0.013
7	-0.001	*-0.176*	0.079	*2.580*	0.019
8	-0.001	*-0.149*	0.039	*2.507*	0.018
9	0.006	*1.498*	0.006	*1.446*	0.006
Largest	-0.004	*-0.647*	0.003	*2.838*	0.023
Chi-square	13.040			*25.140*	
(p-value)	*.121*			*.001*	

Panel B1: Equation (5.22) using BE/ME as a characteristic factor

	a0	*t(a0)*	a1	*t(a1)*	b1	*t(b1)*	s1	*t(s1)*	h1	*t(h1)*	R-square
Smallest	0.003	*1.505*	0.229	*1.981*	-13.219	*-5.070*	-31.771	*-10.362*	1.629	*0.221*	0.635
2	-0.001	*-0.414*	0.193	*2.432*	-14.348	*-9.186*	-20.491	*-11.425*	4.506	*0.946*	0.743
3	-0.002	*-1.012*	0.091	*2.560*	-5.573	*-6.110*	-8.438	*-11.174*	1.509	*0.576*	0.769
4	0.000	*0.003*	0.042	*1.328*	-3.270	*-3.241*	-6.687	*-6.820*	-0.189	*-0.080*	0.689
5	-0.003	*-1.603*	0.058	*2.136*	-4.236	*-5.097*	-8.321	*-10.923*	1.960	*0.899*	0.735
6	-0.004	** *-1.781*	0.039	** *1.830*	-3.292	*-4.798*	-5.541	*-9.462*	1.762	*1.001*	0.705
7	-0.009	*-3.388*	0.058	*3.106*	-3.284	*-5.971*	-4.899	*-10.266*	3.180	*2.208*	0.737
8	-0.006	*-2.453*	0.016	** *1.936*	-1.204	*-5.313*	-2.362	*-11.728*	0.762	*1.293*	0.790
9	-0.003	*-1.251*	0.002	*0.594*	-0.224	*-2.001*	-0.607	*-7.025*	0.007	*0.027*	0.746
Largest	-0.005	*-3.256*	0.002	*4.948*	-0.070	*-10.690*	-0.111	*-17.226*	-0.022	*-1.110*	0.936
Chi-square	32.460		15.890		80.340		182.330		7.510		
(p-value)	0.000		0.060		0.000		0.000		0.580		

Panel A2: Equation (5.21) using SIZE as a characteristic factor

	α_0	t(α_0)	α_1	t(α_1)	R-square
Smallest	0.026	*6.679*	-3.294	*-4.570*	0.055
2	0.024	*6.100*	-0.466	*-4.518*	0.054
3	0.022	*5.540*	-0.125	*-4.394*	0.051
4	0.020	*5.080*	-0.038	*-3.852*	0.039
5	0.018	*4.344*	-0.012	*-3.446*	0.031
6	0.017	*3.686*	-0.004	*-2.748*	0.019
7	0.017	*3.456*	-0.001	*-2.565*	0.016
8	0.015	*2.890*	0.000	** *-1.930*	0.008
9	0.017	*2.971*	0.000	*-2.140*	0.010
Largest	0.015	*3.487*	0.000	** *-1.805*	0.007
	0.014	*4.183*	0.000	*-2.679*	0.018
Chi-square					
(p-value)	*12.500*		*37.980*		
	0.180		0.000		

TABLE 5.15 (cont.)

Panel B2: Equation (5.22) using SIZE as a characteristic factor

	a0	*t(a0)*	a1	*t(a1)*	b1	*t(b1)*	s1	*t(s1)*	h1	*t(h1)*	R-square
Smallest	0.006	*2.430*	0.155	*1.252*	32.092	*2.970*	82.885	*5.599*	-6.670	*-0.233*	0.539
2	0.000	*0.117*	0.221	*2.429*	5.667	*4.101*	10.145	*5.297*	1.520	*0.420*	0.642
3	0.000	*0.136*	0.115	*3.154*	1.760	*4.833*	3.181	*6.321*	0.362	*0.414*	0.685
4	0.001	*0.408*	0.066	*2.596*	0.720	*5.864*	1.285	*7.592*	0.254	*0.898*	0.698
5	-0.002	*-0.905*	0.080	*3.361*	0.257	*6.149*	0.568	*9.685*	0.095	*1.019*	0.707
6	-0.001	*-0.577*	0.045	*2.686*	0.094	*5.870*	0.221	*9.989*	0.010	*0.298*	0.698
7	-0.005	*-2.106*	0.059	*3.583*	0.033	*5.836*	0.076	*9.904*	-0.006	*-0.546*	0.715
8	-0.005	*-2.168*	0.025	*3.310*	0.010	*7.012*	0.021	*10.614*	0.001	*0.499*	0.768
9	-0.001	*-0.729*	0.006	*2.817*	0.002	*7.712*	0.003	*9.992*	0.001	*1.831* **	0.781
Largest	-0.007	*-2.821*	0.002	*4.769*	0.000	*3.351*	0.000	*4.305*	0.000	*1.241*	0.858
	-0.007	*-2.983*	0.016	*4.622*	0.000	*3.500*	0.000	*5.575*	0.000	*0.521*	0.724
Chi-square											
(p-value)	18.210		23.270		42.420		98.810		23.110		
	0.030		0.005		0.000		0.000		0.005		

In Panel A1 and Panel B1, the regression results of (5.21) and (5.22) are reported for Book-to-Market (BE/ME) characteristic. In Panel A2 and Panel B2, the regression results of (5.21) and (5.22) are reported for size characteristic.

*The underlined t-statistics indicates significance at 5 %, ** indicates significance at 10% level.*

Each month from January 1969 through December 2001, value-weighted portfolios are formed on the basis of SIZE. Size is market equity in the previous fiscal year.

The following unconditional regression is used:

$$R_i(t)=\alpha_{i0}+\alpha_{i1}BE/ME_i(t)+e_i(t) \tag{5.21}$$

where R_i *is the portfolio's excess return,* BE/ME_i *is its book-to-market portfolio's value,* α_{i0} $and\alpha_{i1}$ *are the intercept and slope coefficient and* e_i *is the residual term. Note that the equation (5.21) is used in the same way for size characteristic.*

The following conditional regression is then used:

$$R_i-R_f = a_{i0}+a_{i1}BE/ME_i+(b_{i0}+b_{i1}BE/ME_i)*Rm+(s_{i0}+s_{i1}BE/ME_i)*SMB+ \tag{5.22}$$

$$(h_{i0}+h_{i1}BE/ME_i)*HML+e_i$$

where Ri is the portfolio's monthly return, Rf is the one-month Treasury bill rate (from Datastream), Rm is the FTSE-ALLSHARE INDEX, BE/ME is its book-to-market portfolio's value, SMB is the return on small stocks minus the return on big stocks, and HML is the return on high BE/ME minus the return on low-BE/ME. The table reports Ordinary Least Square (OLS) estimates of the interactive terms a_{i1}, b_{i1}, s_{i1} and h_{i1}, *which measures the time-variation in the intercept and loadings.*

Note that the equation (5.22) is used in the same way for size characteristic.

The Chi-square is also reported for both types of regressions. Chi-square $(\chi_2)=c'\sum c^{-1}$, *where c is the vector of coefficients and* $\sum$ *is the estimate of the covariance of matrix of c. Under the null that all coefficients are zero, this statistic is asymptotically distributed as chi-square (d.f.10). The Wald test is used for chi-square test.*

FIGURE 5.1
ANNUAL PERFORMANCE OF SMB, 1973-2001

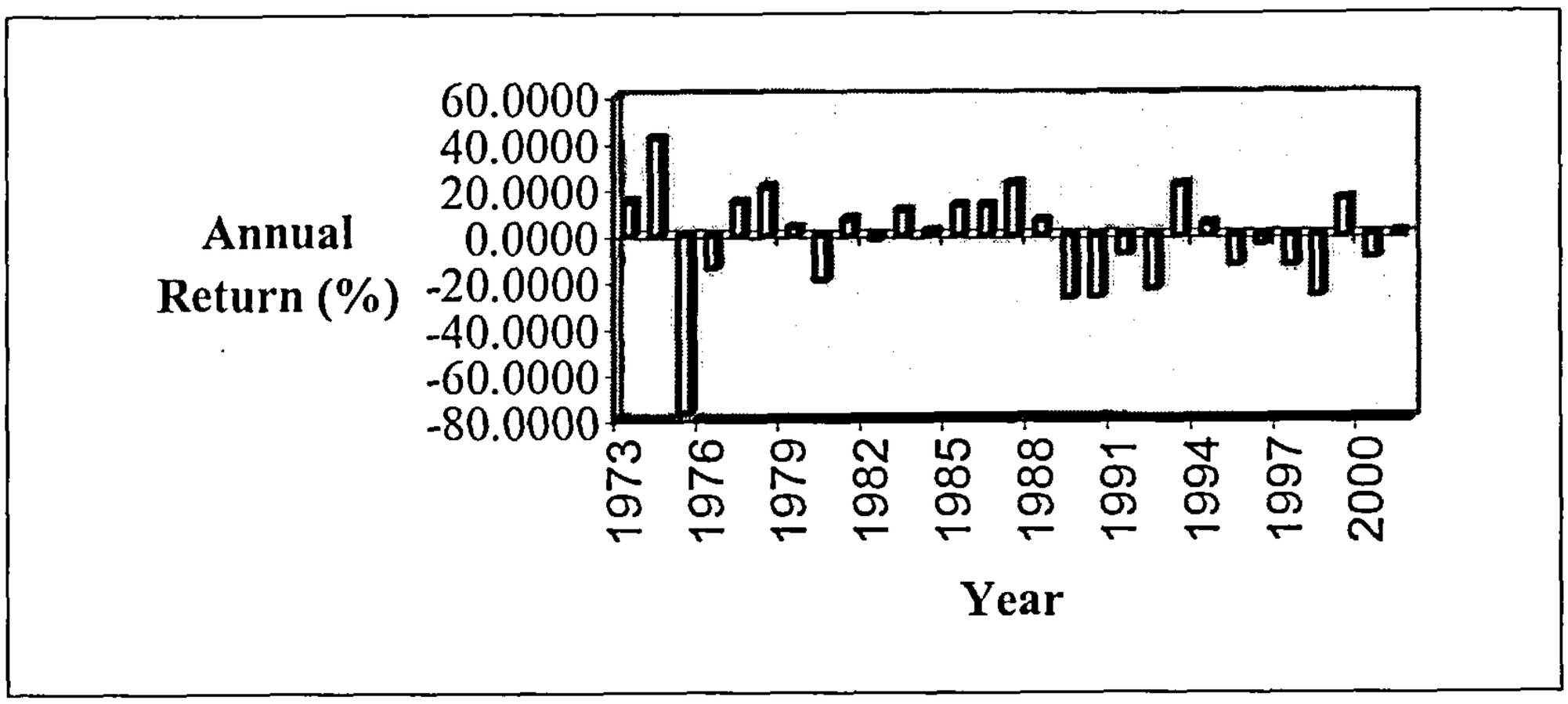
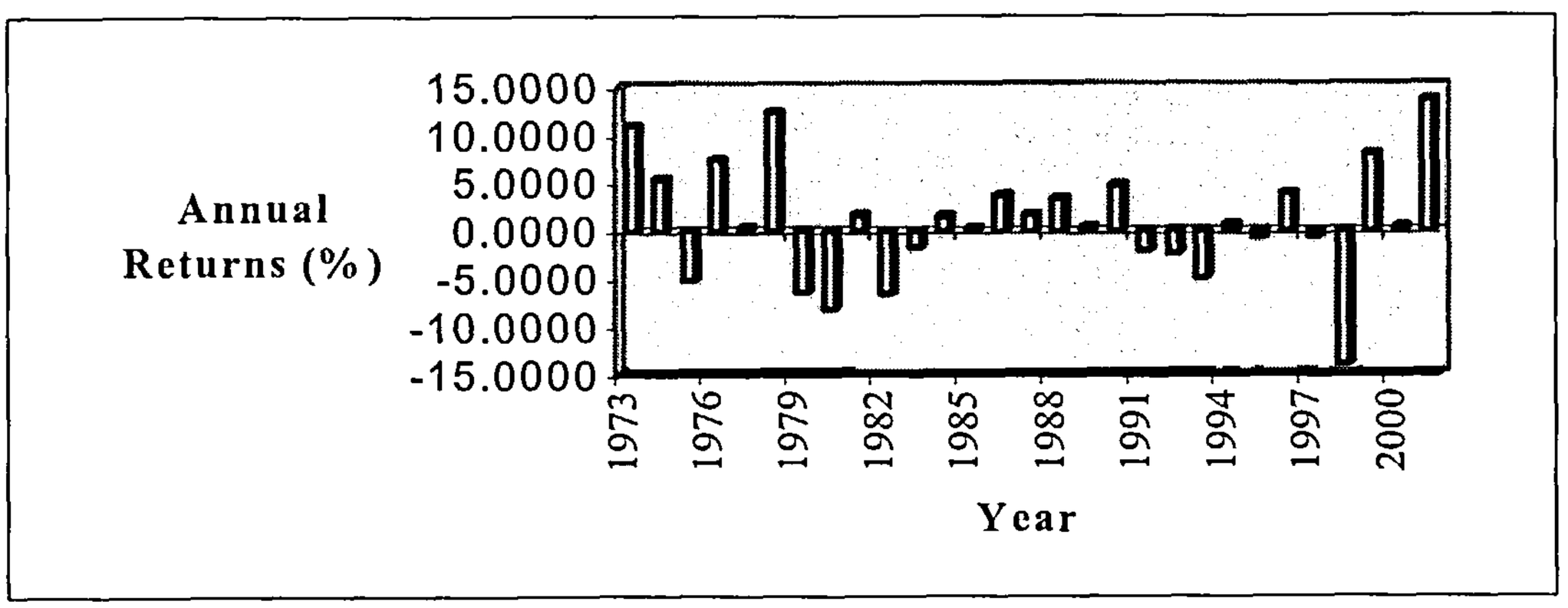


FIGURE 5.2
ANNUAL PERFORMANCE OF HML, 1973-2001



Refer to the notes in Table 5.2 for the construction of SMB and HML factors.

CHAPTER 6

A RE-EXAMINATION OF THE BOOK-TO-MARKET AND SIZE USING A RISK ADJUSTMENT PROCEDURE

6.1. INTRODUCTION

6.1.1. OBJECTIVES AND MOTIVATION

The main objective of this chapter is to investigate the explanatory power of the fundamental factors or non-risk characteristics (size, Book-to-Market (BE/ME) and momentum) relative to a Principal Component Analysis (PCA), the Capital Asset Pricing Model (CAPM) and the Fama and French three-factor model. In other words, this chapter complements the earlier studies by further investigating the ability of non-risk characteristics to explain the cross-section of returns after accounting for the effects of the factors through PCA, the Fama and French three-factor model and the traditional based CAPM. In this way, one investigates whether these non-risk characteristics are explained by risk at all.

In the earlier chapters, many applications of a two-stage[1] cross sectional regressions were used to test for the non-risk characteristics such as size, BE/ME and momentum. It was found that the risk characteristics of securities, as measured by betas or factor loadings, were also affected by non-risk characteristics like size and BE/ME. It was therefore argued in the earlier chapters, that one single risk-factor in not enough to explain UK stock returns. More factors are needed to have a perfect model. This study also found that the Fama and French three- factor

[1] This is discussed in Chapter 3, Section 3.3.

model had some power in explaining the variation in the UK stock returns. In this chapter, a different approach is applied for testing the non-risk characteristics. The factors, here, are estimated through a PCA procedure. But, the PCA procedure cannot be applied directly to test the non-risk characteristics, since there is no obvious way to incorporate nonfactor risk premia in the procedure. The approach, here, would be to use PCA to estimate factor portfolio returns and then use these factor estimates to risk adjust the returns used as dependent variables in the cross-sectional regression [as in Brennan, Chordia, and Subrahmanyan (1998) for the US stock market)]. Such a technique has not been applied before in the cross-sectional studies for the UK stock market. Most of the research applying a general factor model for the UK stock market has been done using macroeconomic factors. In these studies (e.g. Beenstock and Chen (1986) and Poon and Taylor (1991)) (pioneered by Chen, Roll and Ross (1986)), PCA allows the data to define the factors, and then the two-pass cross sectional regression requires the researcher to take a stance on the nature of the economic factors. In this chapter, the PCA is again used to define the factors. But, this chapter then attempts to find new evidence on non-risk characteristics by assessing the ability of non-risk characteristics to predict monthly returns after risk adjustment by the PCA. This approach is therefore quite different from the study related to Chen, Ross and Roll (1986). The returns are also adjusted using the Fama and French factors[2] and CAPM for testing the non-risk characteristics for the UK stock market. In total, three different sets of risk factors are used to adjust the returns for risk. The Fama and Macbeth (1973) cross-sectional regressions are then run using the risk-adjusted returns and fundamental factors such as size, BE/ME and momentum. From this analysis, one can find out whether it is the characteristics such BE/ME, size or momentum or risk that affects expected returns. The next section explains this further.

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[2] See Chapter 5, Section 5.4.2 to see the details relating to the Fama and French factors.

6.1.2. BACKGROUND

Multi factor models attempt to describe asset price returns and their covariance matrix as a function of a limited number of risk factors and are thus based on one of the fundamental areas of financial theory: no reward without risk. But in the finance literature, it is not easy to decide which factors to use in the factor models. To overcome this problem, some innovative asset-pricing models in addition to CAPM have been developed. Of these models, the Fama and French three-factor model proposed by Fama and French (1993) and the Arbitrage Pricing Model (APT)[3] proposed by Ross (1980) have attracted the most attention because of their promise for practical application, and their potential for unambiguous empirical validation. More recently, a characteristics-based model by Daniel and Titman (1997) was also inspired by the Fama and French (1993) three-factor model.

The Fama and French, characteristics-based and APT model are typically tested in different ways. The first two models are tested using a set of factors based on firm characteristics, while the third one is tested using a set of unspecified factors. Earlier in this study (Chapter 5), Fama and French (1993) three-factor model and the Daniel and Titman (1997) model were tested for the UK stock market. There was some support for both the models. This study, like Daniel and Titman (1997) found for some cases, that it is characteristics and not the loadings on the Fama-French factors that determine expected returns. But, in Chapter 5, it can also be seen that inspite of using methods to separate the Fama and French factors from each other, there is still some dependence between them.

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[3] The readers should note that a statistical APT is discussed in this chapter. This is different from the macro-economic APT. To determine the identity of K factors, one has to choose K macro-economic variables from the database. Most of the empirical literature on APT is based on macroeconomic variables. Chen et al. (1986) first analysed a number of macroeconomics innovations in the US stock market from 1953-1983. Poon and Taylor (1991) applied the same methodology as Chen et al. on the UK stock market from 1965-1984 and found that none of the macroeconomic factors priced in Chen et al. paper were priced in UK. Both of them used Maximum likelihood factor analysis (MLFA) to estimate the factor model.

In this chapter, a statistical-based factor model is used. In theory, these separated (statistical) factors truly reflect the underlying economic factors. In other words rather than specifying the risk factors a priori, this study follows the intuition of APT, that the risk factors should be those which capture the variation in large well-diversified portfolios. The model is constructed through the application of Principal Component Analysis (PCA)[4]. This methodology was developed by Connor and Korajczyk (1988) to estimate risk factors. The statistical factor model obtains both the factors and the sensitivities to these factors simultaneously. The advantage of this approach is its "objectivity", as neither the factors nor the sensitivities are defined in advance, but rather estimated from the data. This chapter illustrates how the factors are selected through the PCA. The use of PCA is particularly useful for determining the number of relevant risk factors. The UK stocks are again used in the analysis.

The notion of Principal Components of a sample was introduced as statistical tool in order to reduce the number of variables being studied without losing too much information in the covariance matrix. The objective of PCA as described by Lawley and Maxwell (1971) is a linear transformation of a set of variables into a new set that has the property of being uncorrelated with each other. The number of original variables transformed is exactly the same as the number of new variables. The principal components are not dependent on pre-specification of the nature of the economic factors but are the factor portfolios that explain the common movements across assets. In other words, this procedure determines the factors, which are uncorrelated with each other but also explain most of the variability in stock returns. Each of these factors is a linear combination of the stock returns. The principal component analysis

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[4] Some of the papers (Ross (1980) and Chen et al. (1986)) have used 'Factor analysis or MLFA' instead of PCA for extracting the factors for the APT influenced statistical based model. Factor analysis is well suited for the APT with strict factor structure. Chamberlain and Rothschild (1983) first suggested the suitability of PCA for empirical research. They extended the APT by suggesting that assets' return follow an approximate factor structure as contrast to a strict factor structure. In an approximate factor structure, the idiosyncratic residuals between stocks need not be correlated.

considers the total variance in the process of deriving the new factors. In computing the factors, one is interested in the best linear combination in the sense that the particular combination of original variable accounts for more of the variance in the data as a whole than other linear combination of variables. In other words, the first factor may be viewed as the single best summary of the linear relationship exhibited in the data. The second factor is defined as the second best linear combination of the variables, subject to the constraint that is orthogonal to the first factor. To be orthogonal to the first factor, the second factor must be derived from the variance that remains after extraction of the first factor. Thus, the second factor may be defined as the linear combination of the variables that accounts for the most residual variance after the effect of the first factor has been removed from the data. Subsequent factors are defined similarly, until the variance in the data is exhausted. Because each consecutive factor is defined to maximize the variability that is not captured by the preceding factor, consecutive factors are independent of each other. Therefore, consecutive extracted factors are uncorrelated or orthogonal to each other. PCA is an appropriate model because through this method, a perfect risk model is obtained. This chapter attempts to answer one principal question using this risk model: Are the non-risk characteristics such as Book-to-Market Equity (BE/ME), size and momentum influenced by risk factors using PCA at all?

It was also seen in the earlier chapters, that most applications of cross-sectional relations required portfolio groupings in order to eliminate (or at least mitigate) the Errors-In-Variable[5] problems from using estimated betas in the cross-sectional regressions. Portfolios are formed either to avoid problems caused by using estimated betas as independent variables in a two-step procedure or, when a one-step procedure is used, to allow estimation of a covariance matrix of residual returns. The second stage of Fama and Macbeth (1973) methodology is then

[5] See Chapter 2, Section 2.4 and Appendix 2.2, for the detailed discussion of the Errors-In-Variable problem.

followed, averaging the time series of coefficients from cross-sectional regressions of returns on the beta and firm characteristics for all individual securities grouped into the number of portfolios. The use of portfolios rather than the individual securities in the tests of asset-pricing models has been criticised from an opposing perspective by Roll (1977), and by Lo and Mackinlay (1990). Roll argues that the portfolio formation process, by concealing possibly return relevant security characteristics within portfolio averages, will make it difficult to reject the null hypotheses of no effect on returns. According to Lo and Mackinlay (1990), if the researchers forms portfolios on the basis of characteristics which prior empirical research has found to be related to average returns, he will be inclined to reject the null too often due to a 'data-snooping' bias. Lo and Mackinlay (1990) also suggests that the portfolio grouping procedure approach may bias test statistics and spuriously exaggerates the relationship between portfolio excess returns and the fundamental factors. Moreover Friend, Westerfield and Granito (1978) argued that tests of CAPM that rely on grouped data, to the exclusion of tests based on individual assets are not completely satisfactory since it is the returns on individual assets which the theory is trying to explain and individual asset deviations from linearity may cancel out in the formation of portfolios. Another advantage of conducting the analysis at the level of individual securities is that arbitrary decisions on the order of grouping securities into portfolios do not have to be made and as a result the explanatory variables are all assigned equal importance before hand. According to Connor and Korajczyk (1986), one of the advantages of PCA that it can be applied to individual asset returns and does not require portfolio grouping. This is because, in this chapter, a restricted form of PCA (no non-factor characteristics, no estimation of the zero-beta return) is used. In the restricted form of PCA, there is no error-in-variables bias from using estimated betas. With non-factor characteristics included, or with estimation of the zero-beta return, portfolio grouping is required. In this

chapter, the risk-adjusted returns on individual securities are therefore examined. It would be interesting to see whether the statistical significance of security characteristics for the expected returns is sensitive when the test is done using the individual securities[6].

The rest of the chapter as proceeds: Section 6.2 provides a brief view of past relevant empirical studies. Section 6.3 presents the data. Section 6.4 presents the methodology employed in this study. Section 6.5 provides the empirical results. Section 6.6 concludes.

6.2. REVIEW OF PAST EMPIRICAL STUDIES

There are no prior studies for the UK stock market, which combines the principal component factors with the cross-sectional methodology for testing the fundamental factors like size, BE/ME and momentum. Chamberlain and Rothschild (1983) originally proposed the PCA technique in literature, and Connor and Korajczyk (1986, 1988) were the first ones to use the PCA technique in an asset-pricing test. Brennan, Chordia, and Subrahmanyan (1998) used the PCA to examine the risk versus characteristics debate in the US stock market.

Connor and Korajczyk (1988) used monthly stock returns for four non-overlapping subperiods, 1964-1968, 1969-1973, 1974-1978 and 1979-1983 for the US stock market. They used the individual security returns and individual securities through portfolio grouping for PCA. They regressed the equally-weighted and value-weighted index portfolios on the first principal component factor, first five principal component factors and first ten principal component factors. Their first factor generally explained over 99% of the variance of the equal-

[6] Chan, Hamao and Lakonishok (1991) and Lakonishok and Shapiro (1986) applied the Fama and MacBeth procedure to data on individual securities as well to data on portfolio basis and found no essential differences between results using individual securities and those using portfolios.

weighted portfolio. The remaining factors had statistically significant explanatory power but obviously explained much less of the variance. For the value-weighted portfolio, the explained variance is lower then what was found for the equally-weighted index. To test the robustness of the results, they further tested the factors by using a simulation method[7]. Their simulation results indicated that the PCA[8] provides accurate estimates of the pervasive economic factors. Basically they used the PCA technique to compare the CAPM and APT. Overall, their five-factor version of the APT seemed to perform better than the value-weighted CAPM and about as well as the equally-weighted CAPM. In their study, the five-factor model also performed much better than CAPM in explaining the January-specific mispricing related to firm size. This result was due to the seasonality in the estimated risk premium of the multi-factor model that was not captured by the single-factor CAPM relations, even though the premium in the latter model also exhibited seasonality.

Brennan, Chordia, and Subrahmanyan (1998) uses the US stocks for the period January 1966 to December 1995. They used both PCA and the Fama and French (1993) technique to determine the relevant factors for the both statistical based model and the Fama and French three-factor model respectively. Stock returns were then adjusted for these sets of risk factors. They performed a test of the fundamental factors through cross-sectional regressions, but using risk-adjusted returns. Instead of examining the returns on portfolios, they examined the risk-adjusted returns on individual securities. This approach allowed them to consider the effects of a large number of firm characteristics simultaneously and also it helped them to avoid the data-

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[7] They use the bootstrapping procedure similar to Efron (1982) for the simulations.

[8] Trzcinka (1986) also focused on the Principal Component Analysis using the US data. The data selected in this study was weekly security returns for the period 1963 to 1983. In his study, the covariance matrix for 50 securities was constructed, and 50 additional stocks were added each time to the matrix to create a sequence where the matrix was expanded up to a maximum of 865 stocks. From the covariance matrix of each sequence, the eigen values were calculated and subjected to a combination of tests. The first eigen value had the largest value and this value increased as the number of securities were increased. The study therefore found that there might have been more than twenty factors present in the model. But, after performing the chi-square test on eigen values, the study suggested that five eigen value were enough to dominate the covariance matrix, and the five factors were sufficient to explain returns.

snooping biases that are inherent in the portfolio-based approaches discussed above. They found that excess returns are strongly related to size, BE/ME and lagged returns. Their cross-sectional estimates from using the unadjusted returns were similar to that of risk-adjusted returns. They again found a strong negative size effect and a positive BE/ME effect through both the PCA method of risk-adjustment and the Fama-French three-factor model. The dividend yield variable was also significant with PCA adjustment but not with the Fama and French three-factor model adjustment. They pointed out that, either their risk-adjustment method is incomplete or perhaps other factors than risk affect expected returns.

6.3. DATA

The sample of this study includes 2108 UK stocks traded on the London Stock Exchange (LSE) from January 1969 through December 2001. The monthly return data was obtained from London Share Price Database (LSPD). The data on size and Book-to-Market Equity (BE/ME) were obtained from Datastream database. This study included UK stocks for which adequate data of rates of return, market value (or size) and Book-to-Market Equity (BE/ME) are available. The data set therefore includes firms that appear in both Datastream and LSPD. The definitions of the return, size and BE/ME are the same as used in all the previous chapters. In this study, the equally-weighted index is used as the representative market portfolio and the one month Treasury Bill-rate is used as the proxy for the risk free rate of return. The one-month Treasury Bill-rate was also obtained from the Datastream.

6.4. METHODOLOGY

Asset returns are assumed to be generated by following process:

$$\tilde{R}_{jt} = E(\tilde{R}_{jt}) + \sum_{k=1}^{m} \beta_{jk}\, \tilde{f}_{kt} + \tilde{\varepsilon}_{jt} \tag{6.1}$$

where $\tilde{R}_j$ is the return on security j, β_{jk} is the loading of security j on factor k and f_k are return attributed to this factor and m is the number of factors.

The equilibrium version of APT, in which the market portfolio is well-diversified with respect to factors (Connor (1984); Shanken (1985, 1987)), implies that expected returns may be written as,

$$E[\tilde{R}_{jt}] - R_{ft} = \sum_{k=1}^{m} \lambda_{kt} \beta_{jk} \tag{6.2}$$

where R_f is the risk free interest rate, and λ_{kt} is the risk premium for factor k. Substituting from equation (6.2) into equation (6.1), the APT implies that realized returns are given by,

$$\tilde{R}_{jt} - R_{ft} = \sum_{k=1}^{m} \tilde{F}_{kt} \beta_{jk} + \tilde{\varepsilon}_{jt} \tag{6.3}$$

where $\tilde{F}_{kt} = \lambda_{kt} + \tilde{f}_{kt}$ is the sum of the return attributed to the factor k and its associated risk premium.

The first estimation step is to see whether the factors estimated through PCA[9] are statistically significant or not. The next objective is to test whether fundamental factors have any explanatory power for returns relative to the five factors from PCA procedure. The procedure is similar to the two-step procedure used by Fama and French (1992) to investigate the CAPM and will now be explained.

Each year from January 1969 to December 2001, factor loadings β_{jk} were estimated for all securities chosen over the prior 60 months. The first estimation period begins from January 1969 and ends till June 1973. The second estimation period begins from July 1969 and ends in June 1974. In this way, the factor loading is estimated for all the estimation periods. In order to be in line with the earlier methodology, to avoid thin-trading, the Dimson (1979) procedure is again used with five lags to adjust the estimated factor loading. After estimating the factor loadings in the first-stage regression, in the second stage, the estimated risk-adjusted returns or post-ranking security returns for each of the securities are computed by using the return data for the following 12 months for every estimation periods. The first test period begins from July 1973 till June 1974. By rolling one year forward and using the same procedure for the rest of the sample period, 29 test periods (like in Chapter 3) are obtained. The estimated risk-adjusted returns or the residuals are computed by using the following equation:

[9] See Appendix 6.1 for the construction of the PCA factors.

$$\tilde{R}^{*}_{jt} = \tilde{R}_{jt} - R_{ft} - \sum_{k=1}^{m} \hat{\beta}_{jk} \tilde{F}_{kt} \qquad (6.4)$$

where R^{*}_{jt} is the risk-adjusted return

Thus the null hypothesis is that the expected returns are determined by the statistical factor model with risk factors obtained using PCA. The returns are also adjusted for risk relative to the CAPM and Fama-French three-factor model and therefore the process mentioned above is repeated again.

MAIN HYPOTHESIS TO BE TESTED

After adjusting for risk, the following equation is used for testing the characteristics for all the securities for all the 29 test periods:

$$\tilde{R}^{*}_{jt} = c_0 + \sum_{m=1}^{M} c_m Z_{mjt} + \tilde{\varepsilon}_{jt} \qquad (6.5)$$

where Z_{mj} (m=1,…,M) is the value of (non-risk) characteristics m for security j, and c_m is the premium per unit of characteristic m. Our null hypothesis is that c_m=0 (m=0,1,….M). This study includes five (size, BE/ME and three momentum-based lagged return[10] variables) as possible determinants (non-risk characteristics) of expected returns. The variables are defined as follows:

[10] This study cannot use the momentum portfolios (constructed in Chapter 5) directly in this analysis. The lagged returns are therefore used as a possible indicator of the momentum effect in security returns.

Size- market value of the equity of the firm as of the end of the December t-1.

BE/ME- the ratio of book value of equity to the market value of equity, using the end of the December t-1.

lgrt1- the natural logarithm of the cumulative returns over the two months ending at the beginning of the previous month.

lgrt2-the natural logarithm of the cumulative returns over the five months ending at the beginning of the previous month.

lgrt3-the natural logarithm of the cumulative returns over the 11 months ending at the beginning of the previous month.

After estimating the coefficients for the equation (6.5) for 342 months (or 29 test periods), the time-series average of the coefficients associated with the characteristics is computed: it is simply the cross-sectional estimator except that the dependent variable is the risk-adjusted return, calculated using either the PCA, CAPM and Fama and French (1993) approach. The Fama and Macbeth (1973) t-statistics will be used to test the statistical significance of the fundamental variables. Under the null hypothesis, the risk-adjusted returns ($\tilde{R}^*_{jt}$) in the equation (6.5) (computed by the above method) should be independent of other (non-risk) security characteristics.

MEASUREMENT ERROR

The factor loading estimates for individual securities are subject to estimator error which will cause an Error-In-Variable bias in any regression in which the factor loading are included as independent variables. Two approaches were discussed in the earlier chapters to get rid of this problem. First, to group the assets into portfolios and second, to use the instrumental variable approach to form portfolio. To address this issue of Error-In-Variables, modified Fama-Macbeth (1973) approach for individual securities as suggested above was adopted. The individual securities are used because, the risk-adjusted returns should be completely free of non-risk characteristics like BE/ME and size. It also helps us to avoid the data-snooping biases that are inherent in the portfolio-based approaches as discussed in this and previous chapters.

It is assumed that, in equation (6.5) security characteristics are measured largely without error, there is no Error-In-Variable problem induced by this procedure, despite the fact that individual securities return data is used in this chapter. Although this procedure should ensure that errors in the estimated factor loadings are uncorrelated with security characteristics, to the extent that they are correlated, the coefficients in the cross-sectional regressions will be biased by an amount that is proportional to the factor realizations. One can see the difference between the error term in equation (6.5) and error term in equation (6.3). The error term in the equation (6.5) is due to the measurement error associated with factor loadings. In the presence of the measurement error, the estimators (c_m) from equation (6.5) are downward biased of the true estimators (c_m). Brennan, Chordia, and Subrahmanyan (1998) came up with a clever way of estimating an alternative estimator, which had less measurement error. This estimator was obtained for each of the characteristics as the constant term from the regression of the monthly

coefficient estimates on the time series of the PCA, Fama and French and CAPM factor realizations. These monthly coefficients which are used, as an independent variables are the original 342 coefficients estimated by using the cross-sectional regression (equation (6.5)). The coefficients estimated from this time-series regression are called purged estimates (the estimates in the presence of the measurement error are 'raw' estimates[11]).

6.5. EMPIRICAL RESULTS

6.5.1. CHOOSING THE RISK FACTORS

The PCA technique was applied to returns in excess of the risk-free rate on all securities listed continuously over the entire period, a total of 147 securities. One important reason for using a small number of stocks as opposed to a larger number was the limitation of the statistical package in handling the missing returns in the sample data. Out of the 2108 securities, only total of 147 stocks were found to be without any missing returns during the full-sample period. Although, only 147 securities could be used to define the PCA[12] factors, risk-adjusted returns on a full set[13] of 2108 securities is used in the cross-sectional regressions. Brennan, Chordia, and Subrahmanyan (1998) for the US stock market took a slightly different approach. They estimated the factors separately over the two over-lapping subperiods: July 1963 to December

[11] The standard error of the estimate is taken from the time series of monthly estimates in the case of the raw estimate (standard Fama-Macbeth estimator), and from the standard error of the intercept from the OLS regression in the case of the purged estimator. As Shanken (1992) points out, the standard errors of the coefficients yielded by the standard Fama-Macbeth approach are understated because they ignore the additional variation induced by the estimation error in the factor loadings. Applying the results of Shanken (1992, Theorem 2), consideration of this estimator error requires the variance of the estimate to be multiplied by one plus the squared Sharpe ratio (ratio of the mean excess return of a factor to its standard deviation) of the factor portfolio formed by the factors (PCA or Fama and French factors). However, Brennan et al. (1998) shows that the magnitude of this understatement is small for their sample, and does not affect their basic conclusions.

[12] Same set of sample data is used in all the chapters. The sample used for constructing the PCA factors also comes from the same set of data. The firms in the PCA are therefore represented on both the LSPD and Datastream. But, applying this approach over a long sample period (like in our case) necessarily increases the survivorship bias. The potential bias is real if there is a liquidity factor present in the data (see for example, Brennan and Subrahmanyam (1996), Brennan, Chordia and Subrahmanyam (1998) and Chordia, Subrahmanyam and Anshuman (2001) for the US). The UK stock market is plagued by illiquidity with trading being very infrequent (Dimson, Negal and Quigley (2003)). The liquidity effect is less likely to be picked up in a PCA restricted to stocks that survived an extended period of time.

[13] For more detail on data, refer to Chapter 3, Section 3.2.

1979 and January 1975 to December 1995. In this way, they were able to use around 2000 securities for estimating the factors. In this case, only 296 and 463 stocks were continuously listed over the first sample period[14] (January 1969-May 1986) and second sample period (May 1987-December 2001) respectively.

The first stage in determining a multi-factor model was an estimation of the number of factors that might be present. The objective of this study was to determine the number of factors, which would sufficiently describe the variation in returns without too much complexity. The matrix x (in equation (1) of Appendix 6.1) in the test is the (342, 147) matrix formed by the 147 share return vectors (each vector has 342 components, corresponding to the 342 monthly observations).

Table 6.1A shows the "eigen values", which represent the proportion of total variance in all the variables that is accounted for by that factor. To decide the number of factors to retain, both the Percentage of variance criterion and Scree test[15] were used. Here, the "the total variance explained table" (Table 6.1A) shows that there are seven dominant factors whose eigen values are more than two. But, in particular the first five factors account respectively for the 31.5%, 3%, 2.1%, 1.5% and 1.4% of the total variance. Looking at the Scree plot (Figure 6.1) (that plots the eigenvalues for each component) it can be seen that after the fifth factor, the eigenvalues are getting flat. Using the prediction components from PCA, at least 5 risk factors can be specified that can be measured from the UK financial data. But, there has been debate in literature as to the number of factors that drive stock returns. The appropriate number of factors

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[14] This study is only left with just a small number of stocks for the full period and sub-periods because of the large number of missing returns in the data. There are several reasons for this: First and most important of all, only 33% of random sample from LSPD were available till 1980. Second, the data set in this study included firms that appeared in both Datastream and LSPD . Therefore, this study was bound to have large number of missing returns. Third, at the beginning of this study (October 2001), the data was available till December 1998. In 2003, a new set of data (December 1998-January 2001) was added to the data. Hence, there were firms, which existed in the first set of data but were missing, in the most recent set.

[15] For the explanation of the Scree Test, see Appendix 6.1.

ranges from one (Trzcinka (1986)) to five (Roll and Ross (1980)) and there may be many as fifteen (Korajczyk and Viallet (1989)) or even more (Dhrymes, Friend and Gultekin (1984)). The evidences in this study tend to come down on the side of those who find a relatively small number of statistical factors. In the APT model, only certain factors are relevant and should be priced by the market while other factors can be diversified away. This study has therefore only selected five factors for constructing the APT influenced statistical based model. The eigenvalue analysis suggests that there are five dominant factors affecting the behaviour of share prices in the UK stock market and that one of these factors has prominent importance, explaining nearly 31% of the total variance.

The second step then regresses the (sample) mean returns on the factor loadings of the components. In other words, to get an understanding of the behaviour of the factors in relation to standard market portfolio, the excess return of an equally-weighted portfolio of stocks are regressed on the first five factors. The time-series regression of the equally-weighted index on the estimated factor loadings ($\hat{\alpha}$) as independent variables (Connor and Korajczyk (1988)) is given by:

$$R_e = \alpha_0 + \alpha_1 P1 + \alpha_2 P2 + \alpha_3 P3 + \alpha_4 P4 + \alpha_5 P5 + \varepsilon_i \qquad (6.6)$$

where the dependent variable (R_e) is the returns on the equally-weighted index; the five regressors (P1, P2, P3, P4 & P5) are the five principal components; the αs are parameter estimates from (6.6) and ε is the error term.

The results of the regression (6.6) are shown in Table 6.1B. The regression results indicate that the five principal components together explain 78% of the changes in an equally-weighted index. The first four components are significant at 5% and 1% level of significance. The fifth component is not significant at any level. The overall model is also significant at the 5% level as indicated by the F-statistic. The Table also shows the correlation coefficient. The first component is highly correlated with the market with a correlation coefficient of 86%. This suggests that a weighted average of the 147 companies in the component could work as an indicator of the overall activities of the market. The second component has a correlation coefficient of 17% with the market index, which indicates some level of association. The third, fourth and fifth component has an average of 5% correlation with the market. Overall, results here, suggest that there are five major significant components impacting the general market return in UK.

6.5.2. USE OF RISK ADJUSTED RETURNS IN CROSS-SECTIONAL MODELS

Equation (6.5) is now estimated using the 'risk-unadjusted' returns for individual securities. The results are reported in Table 6.2, Panel A. The evidence suggests that the size and BE/ME are not able to exert any independent effect on security returns. Like in all the other types of studies, the size variable is almost negative but an insignificant variable. Similar results were found, when the size factor was tested using the traditional cross-sectional methods (Chapter 3, Table 3.6). But some of the other results in Table 6.2, Panel A are quite interesting. The BE/ME was found to be the most important variable in the cross-sectional studies for the UK and the US stock market (see, Fama and French (1992), Strong and Xu (1997) and Chapter 3 of this thesis). But in this study, the book-to-market effect is positive and statistically insignificant at 5% level of significance but significant at 10% level of significance. Hence, there is no

strong evidence that investors expect high BE/ME stocks to generate higher returns than low BE/ME stocks, as this argument implies. The evidence indicates that when the regressions are done using individual securities (without portfolio grouping), the BE/ME is positively but insignificantly related to stock returns. This result[16] contrast with the evidence using portfolio grouping, where BE/ME was found to be a very important variable (see Table 3.6). While it is tempting to interpret these results as supportive of the standard factor model like CAPM or matter of fact APT since there is no evidence against the null, there is a reason to doubt these results. Econometric issues like Error-In-Variable problems, which were discussed, in great detail in the earlier chapters could be a possible reason to doubt the results in Table 6.2, Panel A. It can also be seen in Table 6.2, Panel A that three of the lagged variables are positive but only two of them are strongly significant. Brennan, Chordia, and Subrahmanyan (1998) found a strong size, BE/ME and momentum effect from the Fama-Macbeth regressions using the unadjusted returns for individual securities. So, using unadjusted returns[17] and individual securities in cross-sectional regressions, the results of Brennan, Chordia, and Subrahmanyan (1998) are consistent with Fama and French (1992), but the results from this chapter are not consistent with Strong and Xu (1997) and the cross-sectional analysis done in the Chapter 3 of this thesis.

Having shown that the security returns using the 'unadjusted returns' are not significantly affected with some of the firm characteristics, the cross-sectional relationships between 'risk-adjusted returns' and firm-characteristics are now tested. One effect of using risk-adjusted return rather than raw returns in the cross-sectional regression (equation (6.5)) is to reduce the

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[16] In this thesis, something similar was found when cross sectionals were run using annual observations (see Chapter 3, Table 3.11).

[17] Papers that use risk-unadjusted returns for cross-sectional analysis on individual securities include Litzenberger and Ramaswamy (1979b), Miller and Scholes (1982), and Lehmann (1990b).

correlation between the errors[18] in the monthly cross-sectional regressions. This increases the efficiency of the monthly estimates of the coefficients. This chapter starts with the risk adjusted using the PCA procedure. The results are presented in Table 6.2, Panel B. The economic significance of each of the non-risk characteristics is essentially unchanged by the risk-adjustment procedure of PCA except BE/ME effect. The raw estimates are presented in the first column of each Panel. There seems to be no book-to-market effect in UK stock returns at all. This result is different to the unadjusted series: now there is no evidence of a BE/ME effect (not at any level of significance) and this means that PCA does a good job[19]. It can also be seen in Table 6.2, Panel B that the signs and the significance of the lagged variables are unchanged. There still seems to be strong momentum effect whether the returns are adjusted for risk or not. There is little difference between the raw and purged estimate (shown in column 2 of Panel B), as one would expect if the factor loadings were uncorrelated with the non-risk characteristics.

In sum, this study finds that, after accounting for PCA factors, the only non-risk characteristics that have a significant effect on expected returns are the two lagged returns. Brennan, Chordia, and Subrahmanyan (1998) found that the size and BE/ME variables are significant even after supposedly adjusting for risk using PCA. This study found that, the size and BE/ME variables are not statistically significant at any levels of significance using PCA. These results suggest that the size and BE/ME effects are not explained by risk. This also suggests that the characteristics like BE/ME and size might not be risk factors but something else other then risk. The momentum factor on the other hand gives an indication that an important risk factor might be missing from the risk model (APT influenced). The results of

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[18] This was also discussed in Chapter 4.

[19] BE/ME variable was significant using the unadjusted returns (Table 6.2, Panel A) and portfolio grouping procedure (Chapter 3, Table 3.6). But the BE/ME effect disappeared using the PCA factors. This change might be due to the data-snooping or data-mining problem.

the momentum factor, here, are dissimilar to that found in the Chapter 5. In Chapter 5 (see Table 5.7), the overall evidence using time-series analysis indicates that the cross-sectional differences in expected returns under the Fama-French three-factor model cannot account for the momentum profits. Inconsistency of the momentum factor using different estimation methods increases the likelihood that the effect is due to data-mining[20].

For comparison purposes, the analysis is repeated using the factors proposed by Fama and French to risk adjust the returns; the results appear in Table 6.2, Panel C. The results are qualitatively similar except one big difference. Book-to-market effect is again visible in the UK stock market. The difference in the results is probably because the factors through PCA were selected on the basis of their ability to describe the variance-covariance matrix, while the Fama and French were selected on their ability to explain the cross-sectional structure of expected equity returns. According to Daniel and Titman (1997), Fama and French factors reflects the fact that they represent the covariance matrix less well than do the factors through PCA. Hence, the parameter estimates appear to be less efficient when the Fama and French factors are used. It is also worth noting one more point in these results. Like Brennan, Chordia, and Subrahmanyan (1998)[21], the magnitudes of most of the coefficients increases after the risk-adjustment using the Fama and French factors. There is also a difference between the raw and purged estimate (shown in column 2 of Panel C). The book-to-market effect gets weaker when the purged estimates are obtained.

The analysis is also repeated using the risk-adjusted returns from a CAPM (see Table 6.2, Panel D). The book-to-market effect seems to be present again. The role of size is insignificant

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[20] Also see Chapter 5, Section.5.4.3.3.5.

[21] Strong, Liu and Lee (2003) also did similar analysis on the UK stock market (July 1977 to June 2000, 4627 stocks). Their findings from the cross-sectional regressions are similar to that of Brennan et al. (1998). In Strong et al. (2003) study, even after "risk" control by the Fama-French model, the coefficients on BE/ME and size factors are significant. They suggest that the Fama and French model is deficient as a risk benchmark.

but the level of significance is not as low as it was found when the variables were estimated through the PCA and Fama and French procedure. The most consistent finding in this study is the strong momentum effect, which is also associated with the risk-adjusted returns using the CAPM procedure. The different types of risk-adjusted return make relatively little difference to the results for lagged returns.

Overall, the findings are quite interesting. First, the fact that 'non-risk' firm characteristics such as lagged returns are significant explanatory variables of the 'risk-adjusted' returns implies either that the risk adjustment is incomplete, or that returns are affected by other factors than risk. Second, book-to-market effect is robust to the way the returns ('unadjusted or adjusted') are used in the cross-sectional regressions (individual securities or portfolio grouping). This is puzzling for the supporters of BE/ME variable.

6.5.3. ROBUSTNESS TEST

This study has used risk-adjusted through PCA procedure and presented some very interesting results regarding the book-to-market effect in UK stock returns. So, PCA procedure has played a very important role in this study. But this procedure has many limitations. First of all, the major assumption that the PCA procedure makes is that the covariance matrix remains constant over time. Second, in a PCA procedure, the factors are orthogonal, that is, they are independent of each other. In reality however, it may not be possible to obtain factors, which are completely independent of each other. Typically, the statistical factor models do not provide a good fit to data out of sample in those periods when the company characteristics are subject to change. Only if the companies remain unchanged over time, will a statistical factor model, estimated on basis of long data series, provide a better fit. This implies that a pure statistical factor model

may be lead to over fitting of the parameters to the data. Third, the models formed through PCA are extremely general. This generality is both strength and a weakness. Although, it allows us to describe equilibrium in terms of multi-factor model, it gives us no evidence as to what might be an appropriate multi-factor model. Furthermore, this model tells us nothing about the size and sign of the factor loadings. This makes interpretation of test difficult. Finally, the r principal components retained from the original m variables are the ones that explain most of the variation in x, but these components might not be the most useful as explanations for log returns. These limitations suggest that further investigation of the results in Table 6.2 is required. This study therefore examines the robustness of the results in Table 6.2. Two different types of tests are done. First, seasonal factors (monthly effects) are analysed to confirm the earlier results using PCA. Second, a sub-period analysis is done to see whether there are any differences in the results across different sub-periods.

Table 6.3 presents the results using seasonal factors. The results clearly support the earlier findings of this study (Table 6.2, Panels B and C). There seems to be no BE/ME and size effect in any of the months. There is some evidence of seasonal patterns, for the lagged returns.

Table 6.4 reports the results of regressions (equation (6.5)) for two equal and different sub-samples. The first sub-sample begins from July 1973 and ends in September 1987 (results for the first sub-sample are shown in Table 6.4, Panels A1, B1 and C1) and the second sub-sample begins from October 1987 and ends in December 2001 (results for the second sub-sample are shown in Table 6.4, Panels A2, B2 and C2). The results of the sub-period analysis are more interesting than the results, from the full-sample period (see Table 6.2). By looking at all the Panels in Table 6.4, the significance of the size variables differs in the two-sub-period. There seems to be no size-effect during the first sub-period (July 1973-September 1987), but there

seems to be a strong size effect during the October 1987-December 2001. Ball (1978) suggests that the firm size may appear as a determinant of expected returns because of imperfect risk adjustment in the empirical analysis[22]. It is therefore important to assess whether size has any residual explanatory power for expected returns, after all the risk-factors are taken into account. Size seemed to be a strongly significant variable in the second sub-period after adjusting for risk using all the three procedures. It is perhaps possible that size effects are explained by risk in the second sub-period (October 1987-December 2001). The results are again mixed for BE/ME variable. For the first sub-period[23], the BE/ME variable is only significant for the risk-adjusted returns using the CAPM and Fama and French factor model. For the second sub-period, there seems to be no BE/ME effect in any risk-adjusted returns. The results for lagged returns are the same as before but with the exception of the regressions using the risk-adjusted returns for the PCA procedure for the first sub-period. Here, there is no momentum effect in returns either.

6.5.4. A COMPARISON OF THE THREE SETS OF FACTOR

In the previous sections, it was seen that the significance of the fundamental variables was different for the different sets of risk factors. But the question is, which set of risk factor can be considered economically better then the other?

The analysis, here, suggest whether the two sets of model: statistical based model (PCA) and Fama-French three factor model, are economically equivalent in terms of explaining the non-risk characteristics. Table 6.5 reports the results. In Panel A, when the Fama-French factors

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[22] This is formalized with mathematical proof in Berk (1995).

[23] In the sub-period analysis of Brennan, Chordia, and Subrahmanyan (1998), the BE/ME effect is attenuated considerably (the size of the coefficient is reduced by more than 50%) and its significance is also reduced considerably, when the risk-adjustment is done with the Fama and French factors. They obtain similar results when the returns are adjusted through PCA factors.

are regressed on the Principal Component factors, the market factor is strongly associated with the first principal component factor. Overall, the principal component factors explain 78% of the variance in market. However, as expected from the previous analysis (Table 6.2, Panel B), the PCA factors are less able to explain the HML and SMB factor returns. In Table 6.5, Panel B, when the principal component factors are regressed on the Fama-French factors, it can be seen that with the exception of the strong relation of first principal component factor and the market factor, the Fama and French factors are less well able to explain the variation in the PCA factors.

Overall, the evidence gives us a mixed result regarding the pricing of factors. Neither set of factors[24] is sufficient to price the other, though there is evidence that the PCA factors price the Fama and French factors better than the Fama and French factors price the PCA factors.

Here, this study also compares the three competing models: statistical based, Fama and French three-factor or CAPM using the method of 'residual analysis' (Chen (1983)). The residuals from these models are of interest as they are used for performance measurement. If the models are not misspecified, the expected returns of an asset i would be captured by its factor loadings, and the residual will behave like white noise with zero mean across time. This section demonstrates the methodology by comparing the CAPM and the statistical-based model.

In CAPM model,

$$E(R_i)-R_f=b_i[E(R_m-R_f] \tag{6.7}$$

[24] Brennan, Chordia, and Subrahmanyan (1998) found that the pricing of PCA factors by the Fama and French factors is better than that of Fama and French factors by the PCA factors, neither set of factors is sufficient to price the other.

where the (Rm)-Rf , is the expected premium, and the factor sensitivity or loading, b_i is the slope in the OLS time-series regression and ε_i is distributed N(0, σ_2) .

If expectations in the market are rational, the realized return can be written as:

$$R_i = E_i + \varepsilon_i \tag{6.8}$$

where E_i is the market rational expected return and ε_i is the error term. If the CAPM is not misspecified, R_i can also be written as:

$$R_i = E_i(CAPM) + \eta_i \tag{6.9}$$

Thus,

$$\eta_i = [E_i - \hat{E}_i(CAPM)] + \varepsilon_i \tag{6.10}$$

where $E_i(CAPM)]$ is the expected return from the CAPM with the market proxies. If the CAPM is correct then $E_i = \hat{E}_i(CAPM)$ and $\eta_i = \varepsilon_i$ should behave like white noise and should not be priced by any other models. If η_i is priced by any other models, E_i contains information that is not captured by $\hat{E}_i(CAPM)$ and the CAPM is misspecified. Therefore a logical method to test the CAPM is to run regression with η_i (the residuals of the CAPM) as dependent variable and the factor loadings of the APT influenced statistical based model as independent variables. An analogous regression of the APT influenced statistical based model

is then run on the CAPM factor loading beta to check if the CAPM prices information missed by the APT based statistical based model.

Table 6.6 presents the results. The results in Table 6.6, Panel A and Panel B, are clearly in favour of the statistical-based model. The APT influenced statistical-based model explains around 37% of the variance unexplained by the CAPM and the CAPM explains only 1% of the variance unexplained by the statistical-based model. This shows that, the CAPM fails to explain the variance of the statistical-based model residuals. It can be said that, the CAPM is misspecified and the missed priced information is being picked up by the APT influenced statistical model. The results from the cross-sectional regressions from the risk-adjustment method also gave us this interpretation. The same cannot be said when the statistical-based model is compared with the Fama-French factor model (see Panels C and D). The statistical-based model explain around 21% of the variance unexplained by the Fama-French factor model and the 20% of the variance unexplained by the statistical-based model is explained by Fama-French factor model. Here, on the basis of R-square values, the model with PCA factors appears to be best.

It can be noticed from the above analysis that the statistical-based model (PCA factors) and the Fama-French factor model are qualitatively similar. Hence the earlier findings using both the sets of factors are equally important, that is, for both the sets of factors: PCA and Fama-French three-factor model, non-risk characteristics appear to be something else other then the risk factors. Overall, if the choice has to be made between these sets of factors, the results from Table 6.6 again suggest that the model with the PCA factor again appears to be slightly better then the Fama and French three-factor model.

6.6. CONCLUSION

This chapter makes several contributions to the growing literature on the determinants of the cross-section of security returns for the UK stock market. First, risk-adjusted returns were obtained using the Principal Component Analysis, Fama and French three-factor model and CAPM. Second, the role of fundamental factors was explained using these risk-adjusted returns. Third, to avoid data-snooping problem, data on individual securities was used to test a given asset-pricing model against a specific alternative hypothesis. Finally, the three risk models: PCA, Fama and French three-factor and CAPM are also compared.

The examination of the factor loadings matrix through the PCA procedure suggested that five factors were very successful in providing a meaningful explanation for UK stock returns. In practice, models based on a large number of statistical factors are widely available to investment managers for risk analysis and management. But, one could see that in a predictive sense there was no benefit of adding statistical factors beyond the first three to six principal components. This study used PCA procedure for a good reason. Statistical factors like principal component factors have generated a lot of attention. Most of the existing literature estimates the factors and examines their usefulness within the sample. But PCA is considered optimal because, it has an ability to provide the most precise measure of the population factors given in a fixed sample of returns.

In this chapter, it was found that before adjustment for risk, the BE/ME variable was found to be positive, but was insignificantly related to individual security returns. Hence the results in the Chapter 3 might be suffering from the data-snooping biases suggested by Lo and

Mackinlay (1990). In this chapter, it was found that, after adjustment for risk using the PCA and Fama and French, security returns were not related to some of the non-risk based characteristics like size and BE/ME, but were significantly related to momentum returns. However, BE/ME and momentum returns appeared to be very strong variables using the CAPM procedure. This study observes that only momentum factors are likely to influence the returns of assets consistently during the study period. Overall, this study found that the size and BE/ME do not explain differences in average returns, given the Fama and French three-factor model and PCA model. It also appears to us that the momentum factor can be considered a risk factor in this study. But, the results in Chapter 5 suggested us something opposite. One can say that the momentum effect is sensitive to estimation methods.

The results were different, when the estimation was done using the sub-sample periods. During one of the sub-samples, size was a strong and a statistically significant variable. This shows that, the either risk-adjustment method is incomplete in some periods or size can be considered a risk factor for some periods. The sub-period analysis also confirmed the results for the BE/ME variable when PCA and Fama and French procedures were used.

This study further found that the three-set of factors were not economically equivalent. It was found that one set of factors is not strong enough to offset the importance of another set of factors. But, this study comes up with two facts from this analysis. First, the reward for risk implied by the PCA factors is slightly better than to that implied by the Fama and French factors. Second, model with PCA factors looks better in explaining the cross-sectional results of the fundamental factors.

Overall, most of the results found in this chapter are to some extent consistent with the several earlier empirical findings regarding the cross-section of UK equity returns. The role of BE/ME and size is important in explaining the cross-section of UK equity returns. But it is not clear whether these characteristic factors are the result of risk or non-risk based explanations. The study of risk-adjusted returns through PCA and other sets of factor enables us to gain crucial insights on the fundamental factors in the UK stock market. None of the models discussed in this study can be discarded completely from explaining the cross-sectional variation in average asset returns. But, these models also cannot be fully accepted. The results using PCA and Fama and French factor model can be accepted to some extent because, there is also evidence (using unadjusted returns), that suggests that BE/ME and size are insignificant variables. These findings are supportive of the CAPM. But, the evidence in that chapter also suggests that the CAPM is misspecified. Overall, this study can be regarded as one of the steps toward solving the problem of what determines the expected return of assets.

Since our candidate factors like size, BE/ME and momentum factors are drawn from a long list of previous research, there is still a danger of collective data-snooping. But, the study of the fundamental factors like size, BE/ME and momentum through different methodologies suggested, here, might help the policy makers and the investors to design the investment strategies meaningfully.

The above methodology should also be replicated with the data on other larger equity markets outside UK and US like Japan or China.

TABLE 6.1
RISK FACTORS THROUGH PRINCIPAL COMPONENT ANALYSIS

PANEL 6.1A

	Component Name (P)	Eigenvalue	Cumulative R-squared
1	P1	46.311	0.315
2	P2	4.484	0.346
3	P3	3.153	0.367
4	P4	2.373	0.383
5	P5	2.209	0.398
6	P6	2.122	0.413
7	P7	2.037	0.426
8	P8	1.878	0.439
9	P9	1.852	0.452
10	P10	1.795	0.464
11	P11	1.723	0.476
12	P12	1.688	0.487
13	P13	1.664	0.499
14	P14	1.639	0.510
15	P15	1.570	0.520
16	P16	1.547	0.531
17	P17	1.481	0.541
18	P18	1.455	0.551
19	P19	1.433	0.561
20	P20	1.378	0.570
21	P21	1.328	0.579
22	P22	1.296	0.588
23	P23	1.260	0.596
24	P24	1.247	0.605
25	P25	1.236	0.613
26	P26	1.220	0.622
27	P27	1.189	0.630
28	P28	1.178	0.638
29	P29	1.129	0.645
30	P30	1.119	0.653
31	P31	1.105	0.661
32	P32	1.092	0.668
33	P33	1.062	0.675
34	P34	1.041	0.682
35	P35	1.029	0.689
36	P36	0.996	0.696

PANEL 6.1B

	intercept	α_1 (P1)	α_2 (P2)	α_3 (P3)	α_4 (P4)	α_5 (P5)
Coefficient	0.009	0.051	-0.01	0.004	-0.004	0.002
t-statistics	***6.21***	***34.521***	***-6.869***	***3.043***	***-2.877***	***1.181***
R-squared	0.79		Adjusted R-squared	0.78		
F-statistic	***251.55***					
Correlation between market and each PC		0.86	0.17	0.07	0.06	0.02

TABLE 6.1A: PRINCIPAL COMPONENT ANALYSIS
Table 6.1A presents the Eigen values and its associated cumulative R-square values of principal component factors (P). Eigen value presents the proportion of total variance in all the variables that is accounted for by that principal component. Also refer to Appendix 6.1 for more details on the construction of Principal Component Factors.

TABLE 6.1B: MULTI-FACTOR MODEL THROUGH PRINCIPAL COMPONENT ANALYSIS
Table 6.1B presents the regression results of the following equation (6.6):

$$R_e = \alpha_0 + \alpha_1 P1 + \alpha_2 P2 + \alpha_3 P3 + \alpha_4 P4 + \alpha_5 P5 + \varepsilon_i \quad (6.6)$$

*where the dependent variable (R_e) is the returns on the equally-weighted index; the five regressors (P1, P2, P3, P4 & P5) are the five principal components; the α's are parameter estimates (associated t-statistics in bold) from (6.6) and ε is the error term. The underlined t-statistics indicates significance at 5 %, ** indicates significance at 10% level.*

TABLE 6.2
CROSS SECTIONAL REGRESSIONS USING RISK ADJUSTED RETURNS AND INDIVIDUAL SECURITIES

PANEL A: ESTIMATES WITH UNADJUSTED RETURNS

	Estimates
Constant	0.004 *1.744***
Size	0.000 *0.680*
BE/ME	0.000 *1.910***
lgrt1	0.015 *5.494*
lgrt2	0.007 *2.784*
lgrt3	0.001 *0.720*
Adjusted R-squared	2.48%

PANEL B: RISK ADJUSTED RETURNS USING THE PCA PROCEDURE

	Raw	Purged
Constant	0.004 *2.846*	
Size	0.000 *0.668*	0.000 *0.696*
BE/ME	0.000 *0.912*	0.000 *0.923*
lgrt1	0.017 *5.162*	0.017 *5.237*
lgrt2	0.007 *2.446*	0.007 *2.534*
lgrt3	0.004 *2.023*	0.004 *2.030*
Adjusted R-squared	1.929%	

PANEL C: RISK ADJUSTED RETURNS USING THE FAMA AND FRENCH PROCEDURE

	Raw	Purged
Constant	0.004 *3.292*	.
Size	0.000 *0.748*	0.000 *0.239*
BE/ME	0.001 *2.019*	0.006 *1.680***
Lgrt1	0.018 *5.987*	0.019 *6.508*
Lgrt2	0.007 *2.575*	0.008 *3.078*
Lgrt3	0.003 *1.709***	0.003 *1.733***
Adjusted R-squared	1.999%	

TABLE 6.2 (Cont.)

PANEL D: RISK ADJUSTED RETURNS USING THE CAPM PROCEDURE

	Raw	Purged
Constant	0.005 ***3.204***	
Size	0.000 ***0.072***	0.000 ***-1.438***
BE/ME	0.001 ***2.179***	0.897 ***2.070***
lgrt1	0.020 ***6.421***	0.019 ***6.352***
lgrt2	0.013 ***3.422***	0.017 ***4.531***
lgrt3	0.000 ***-0.107***	0.002 ***0.876***
Adjusted R-squared	3.418%	

*Panel A presents the estimates for risk-unadjusted returns through standard Fama and Macbeth (1973) methodology. Panel B, C and D presents the estimates for risk-adjusted returns through Principal Component Analysis (PCA), Fama & French (1993) and CAPM procedure respectively. The bold and italic figures are t-statistics. The underlined t-statistics indicates significance at 5 %, ** indicates significance at 10% level.*

The following equation is used for regressions:

$$\bar{R}^{*}_{jt} = c_0 + \sum_{m=1}^{M} c_m Z_{mjt} + \tilde{\varepsilon}_{jt} \qquad (6.5)$$

where R^{*}_{jt} is the risk adjusted return and where Z_{mj} (m=1,...,M) is the value of (non-risk) characteristics m for security j, and c_m is the premium per unit of characteristic m and ε_{jt} is the error term. The non-risk characteristics are Size, Book-to-Market (BE/ME) and lag returns (lgrt1, lgrt2 and lgrt3). The definitions of size, BE/ME, lgrt1, lrgt2 and lgrt3 are given in the text (Section 6.4).

Coefficient estimates are time-series averages of cross-sectional Ordinary Least Square (OLS) regressions. The time-series average relate to an average of 800 securities over 342 months from January 1973-December 2001. The estimates in the column labelled as 'Raw' are the coefficients estimated using the above equation (6.5). The purged estimator is obtained for each of the characteristics as the constant term from the regression of the monthly coefficient estimates on the time series of the PCA, Fama and French and CAPM factor realizations. These monthly coefficients which are used, as an independent variables are the original 342 coefficients estimated by using the cross-sectional regression (6.5). The Adjusted R-squared is the time-series average of the Adjusted R-squared for 342 months.

TABLE 6.3
SEASONALITY IN FUNDAMENTAL FACTORS USING THE RISK-ADJUSTED RETURNS FROM THE PRINCIPAL COMPONENT ANALYSIS

Factors	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
Intercept	0.004 *0.591*	0.000 *-0.080*	0.000 *0.107*	0.008 *1.897***	0.001 *0.215*	-0.003 *-1.039*	0.009 *1.344*	0.011 *1.688***	0.005 *1.596*	0.005 *1.008*	0.005 *1.127*	0.002 *0.496*
Size	0.000 *0.886*	0.000 *0.611*	0.000 *-0.906*	0.000 *1.035*	0.000 *0.532*	0.000 *-0.370*	0.000 *0.507*	0.000 *1.167*	0.000 *-1.730***	0.000 *1.719***	0.000 *-0.416*	0.000 *-0.056*
BE/ME	0.000 *0.207*	0.000 *0.248*	0.002 *1.545*	0.002 *1.841***	0.001 *0.790*	0.002 *1.878***	0.000 *0.033*	0.001 *0.574*	0.001 *1.445*	0.001 *0.867*	0.001 *1.400*	0.000 *0.091*
lgrt1	0.002 *0.158*	0.026 *3.058*	0.031 *2.782*	0.020 *1.614*	0.021 *2.001*	0.007 *0.710*	-0.011 *-0.904*	0.007 *0.671*	0.030 *2.862*	0.024 *2.035*	0.025 *1.873***	0.019 *1.481*
lgtr2	0.002 *0.163*	0.010 *1.058*	0.013 *1.670***	0.007 *0.727*	0.001 *0.069*	0.014 *1.664***	0.002 *0.119*	0.016 *1.638*	0.011 *0.847*	-0.015 *-2.027*	0.013 *1.463*	0.010 *1.135*
lgrt3	0.018 *2.565*	0.016 *3.171*	0.023 *3.399*	0.009 *1.431*	0.002 *0.280*	0.005 *0.814*	-0.012 *-1.313*	-0.007 *-0.968*	0.007 *0.860*	-0.008 *-1.354*	-0.011 *-2.804*	0.003 *0.550*
Adjusted R square (%)	2.276	1.849	1.784	2.093	1.931	1.722	2.075	1.999	2.380	1.534	1.495	1.807

*Table presents the monthly estimates for risk-adjusted returns through Principal Component Analysis (PCA). The bold and italic figures are t-statistics. The underlined t-statistics indicates significance at 5 %, ** indicates significance at 10% level.*

The following equation is used for regressions:

$$\tilde{R^*}_{jt} = c_0 + \sum_{m=1}^{M} c_m Z_{mjt} + \tilde{\varepsilon}_{jt} \qquad (6.5)$$

where R^*_{jt} is the risk adjusted return and where Z_{mj} (m=1,...,M) is the value of (non-risk) characteristics m for security j, and c_m is the premium per unit of characteristic m and ε_{jt} is the error term. The non-risk characteristics are Size, Book-to-Market (BE/ME) and lag returns (lgrt1, lgrt2 and lgrt3). The definitions of size, BE/ME, lgrt1, lrgt2 and lgrt3 are given in the text (Section 6.4). Monthly estimates are the time-series average of the slope coefficient of 29 (29 x 12) cross-sectional monthly regression by using the risk-adjusted returns through PCA factors as dependent variable and the fundamental factors as independent variable.

TABLE 6.4
CROSS SECTIONAL REGRESSIONS USING RISK ADJUSTED RETURNS AND INDIVIDUAL SECURITIES FOR TWO EQUAL SUB-SAMPLES

FIRST SUB-SAMPLE (JULY 1973-SEPTEMBER 1987)

PANEL A1

	Raw	Risk adjusted returns using the CAPM procedure
Size	0.000 *-0.058*	
BE/ME	0.305 ***2.111***	
lgrt1	2.886 ***3.901***	
lgrt2	2.655 ***2.181***	
lgrt3	-0.308 *-0.339*	

PANEL B1

	Raw	Risk adjusted returns using the PCA procedure
Size	0.000 *0.502*	
BE/ME	0.113 *0.672*	
lgrt1	2.269 *0.950*	
lgrt2	0.867 *0.736*	
lgrt3	0.542 *0.749*	

PANEL C1

	Raw	Risk adjusted returns using the Fama and French (1993) procedure
Size	0.000 *0.677*	
BE/ME	0.001 *1.973***	
lgrt1	0.014 ***3.118***	
lgrt2	0.004 *0.851*	
lgrt3	0.004 *1.640*	

TABLE 6.4 (Cont.)

SECOND SUB-SAMPLE (OCTOBER 1987-DECEMBER 2001)

PANEL A2

	Risk adjusted returns using the CAPM procedure
	Raw
Size	0.000 ***2.190***
BE/ME	0.014 ***0.722***
lgrt1	3.897 ***5.165***
lgrt2	1.958 ***3.363***
lgrt3	0.199 ***0.439***

PANEL B2

	Risk adjusted returns using the PCA procedure
	Raw
Size	0.000 ***2.767***
BE/ME	0.000 ***0.196***
lgrt1	0.021 ***4.588***
lgrt2	0.010 ***2.625***
lgrt3	0.005 ***1.760*** **

PANEL C2

	Risk adjusted returns using the Fama and French (1993) procedure
	Raw
Size	0.000 ***2.146***
BE/ME	0.000 ***0.531***
lgrt1	0.022 ***5.510***
lgrt2	0.011 ***3.170***
lgrt3	0.002 ***0.796***

*Panel A1, B1 and C1 presents the estimates for risk-adjusted returns using CAPM, PCA and Fama and French (1993) procedure for the first sub-sample respectively. Panel A2, B2 and C2 presents the estimates for risk-adjusted returns using CAPM, PCA and Fama and French (1993) procedure for the second sub-sample respectively. The bold and italic figures are t-statistics. The underlined t-statistics indicates significance at 5 %, ** indicates significance at 10% level. Refer to Table 6.2 to see the details relating to the cross sectional-regressions.*

TABLE 6.5
REGRESSIONS OF THE FAMA-FRENCH FACTOR PORTFOLIOS ON THE ESTIMATED PRINCIPAL COMPONENT FACTORS AND REGRESSIONS OF THE ESTIMATED PRINCIPAL COMPONENT FACTORS ON FAMA-FRENCH FACTOR PORTFOLIOS

PANEL A: Regressions of the Fama-French factors on Principal Component factors

	constant	P1	P2	P3	P4	P5	R-square
Market factor	0.009	0.051	-0.010	0.004	-0.004	0.002	
	6.210	*34.521*	*-6.869*	*3.043*	*-2.877*	*1.181*	0.789
SMB	-0.001	-0.019	-0.026	0.009	-0.001	0.003	
	-0.850	*-11.937*	*-16.697*	*5.757*	*-0.947*	*2.221*	0.578
HML	0.001	-0.003	-0.004	0.001	0.001	-0.002	
	0.828	*-3.107*	*-3.800*	*1.118*	*0.673*	*-1.530*	0.077

PANEL B: Regressions of the Principal Component factors on Fama-French factors

Factor	Constant	Market	SMB	HML	R-square
P1	-0.184	16.691	2.844	2.661	
	-9.691	*45.217*	*5.517*	*2.725*	0.884
P2	0.023	-3.787	-15.984	-2.455	
	0.527	*-4.467*	*-13.506*	*-1.095*	0.387
P3	-0.010	1.557	5.768	0.366	
	-0.183	*1.474*	*3.910*	*0.131*	0.048
P4	0.007	-1.000	-1.818	2.188	
	0.122	*-0.927*	*-1.206*	*0.766*	0.006
P5	-0.006	1.378	3.542	-5.267	
	-0.110	*1.288*	*2.370*	*-1.860* **	0.023

Panel A presents the estimates (with its associated t-statistics (in italic and bold)), and R-square values of the regressions of three Fama and French (1993) factors on five PCA factors (P1, P2, P3, P4 and P5).

Panel B presents the estimates (with its associated t-statistics (in italic and bold)), and R-square values of regressions of five PCA factors on three Fama and French (1993) factors.

*The underlined t-statistics indicates significance at 5 %, ** indicates significance at 10% level.*

The market factor is the excess return on the Fama-French market portfolio. SMB is the difference between the returns of a small and a large firm portfolio. HML is the difference between the returns on a high book-to-market ratio portfolio and a low book-to-market ratio portfolio. P1-P5 denotes the principal component factor portfolio returns.

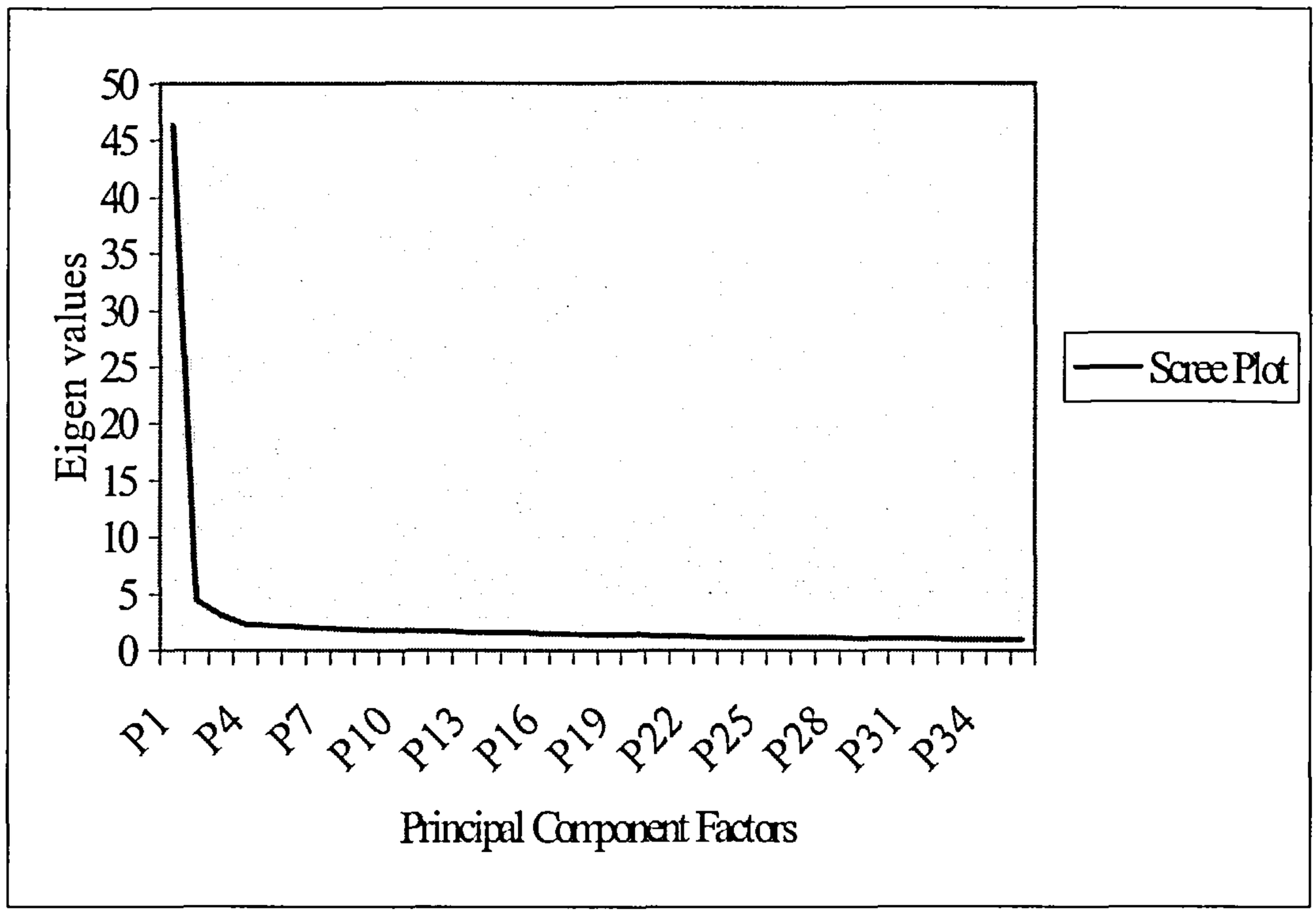
TABLE 6.6
RESIDUAL ANALYSIS

Dependent variable	Independent variable						
	c	**P1**	**P2**	**P3**	**P4**	**P5**	**R-squared**
Panel A: Residuals of CAPM	0.000	0.007	-0.018	0.007	-0.003	0.001	
	0.000	*4.465*	*-11.968*	*4.424*	*-1.929* **	*0.421*	0.357
	c	**Market factor**					**R-squared**
Panel B: Residuals of Principal Component Factors	0.000	0.027					
	-0.206	*1.147*					0.001
	c	**P1**	**P2**	**P3**	**P4**	**P5**	**R-squared**
Panel C: Residuals of Fama & French	0.000	0.012	0.006	-0.002	0.001	0.001	
	0.000	*7.955*	*4.213*	*-1.482*	*0.565*	*0.890*	0.201
	c	**Market factor**	**SMB**	**HML**			**R-squared**
Panel D: Residuals of Principal Component Factors	-0.001	0.196	-0.045	-0.043			
	-1.379	*8.297*	*-1.417*	*-0.642*			0.211

*The table presents the regression results of the residuals of one set of factor model on another set of factor model where the three types of factor models are CAPM, Fama-French three-factor model and statistical-based model (PCA factors). T-statistics are given in bold and italic figures. The underlined t-statistics indicates significance at 5 % , ** indicates significance at 10% level.*

See text (Section 6.5.4. in text), for details relating to the computation of residuals.

FIGURE 6.1
SCREE TEST



The Scree test is derived by plotting the Eigenvalues against the number of principal component factors (P) in their order of extraction. The shape of the resulting curve is used to evaluate the cut-off point. The first point when then curve begins to flatten out is considered as indicating the maximum number the factors to extract.Eigen value presents the proportion of total variance in all the variables that is accounted for by that principal component.
Refer to Appendix 6.1 for more details on the construction of Principal Component Factors.

APPENDIX 6.1

PRINCIPAL COMPONENT ANALYSIS (PCA) FACTORS

PCA FACTORS

The objective of this section is not a mathematics description of the methodology but to give only an idea about the steps that the computer is doing in order to obtain the results.

Most empirical work on the statistical factor models is based on the use of PCA to identify the factors. The m principal components of an (n, m) X matrix of n observations of m variables (log returns for each security) can be expressed by the (n, m) matrix Z:

$$Z=XA \tag{1}$$

where A is the eigen vectors matrix[1] .

From the above equation (1) one can reconstruct X as:

$$X=Z\,A' \tag{2}$$

being A orthogonal. One can thus reconstruct the original vector space, spanned by the m column vectors in matrix X with the vector space spanned by the column vectors (factors) of matrix Z with coefficients in A (eigenvectors matrix). Thus the number of eigenvalues will be equal to the number of variables, m. If the ordered eigenvalues are denoted $\lambda_i (i=1,....m)$, the ratio:

$$\phi_i = \lambda_i / \sum_{i=1}^{m} \lambda_i$$

gives the proportion of the total variation in the original data explained by the principal components i. Suppose the only the first r(0<r<m) principal components are deemed

[1] The eigen values can be interpreted as the respective variances of the different principal components. Each eigenvalue is paired with a corresponding so-called eigen vector.

sufficiently useful in explaining the variation (XX'), and that they are to be retained, with the remaining m-r components being discarded. Equation (2) would have to be replaced by

$$X=\tilde{Z}\,\tilde{A}'+U \tag{3}$$

where $\tilde{Z}$ and $\tilde{A}$ denote the submatricies of Z and A relative to the retained components and corresponding eigenvectors, and U is a matrix of errors. The factor vectors in matrix $\tilde{Z}$ calculated from either the covariance or correlation matrix represent directions in a subspace with the original vector space. This contains a large portion of the total variability in the original set. If a relatively small number of principal components account for a substantial portion of the variance, then equation (3) is a convenient and useful way to express X with a reduced number of variables. The reader should also note that, constructing the components is a purely mathematical exercise and thus no assumption is made concerning the structure, distribution, or other properties of the variables.

EXTRACTING THE OPTIMAL NUMBER OF FACTORS FROM PCA

How many factors one has to extract for having a perfect reconstruction? To arrive at a specific number of factors to extract one can use the following criterions such as: Percentage of variance Criterion and Scree test Criterion.

Percentage of variance criterion is based on achieving a specified cumulative percentage of total variance extracted by successive factors. The number of principal components is chosen so that the components explain 60% of the cumulative variance. Hair et al. (1998) report that it is common in social science where the data is often less precise to consider 60% as satisfactory. This specification has no theory in it. This is a standard practice in PCA procedure. The purpose is to ensure practical significance for the derived factors by ensuring that they explain at least a specified amount of variance.

Scree test Criterion suggested by Raymond B. Cattel (1966) remind that with PCA model the later factors extracted contain both common and specific (unique) variance. Although all factors contain at least some specific variance, the proportion of unique variance is

substantially higher in the later than in the earlier factors. The Scree test is used to identify the optimum number of factors that can be extracted before the amount of specific variance begins to dominate the common variance structure. The Scree test is derived by plotting the eigenvalues against the number of factors in their order of extraction. The shape of the resulting curve is used to evaluate the cut-off point. The first point when then curve begins to flatten out is considered as indicating the maximum number the factors to extract. The multivariate literature mention as a general rule suggest that the Scree test[2] results in at least one and sometimes two or three more factors than does the percentage of variance criterion. In this way, the principal components are argued to keep most of the important information contained in the original explanatory variables, but are orthogonal.

The regression finally estimated, after the principal components have been formed, would be only log returns (R_t) on the r principal components (p).

$$R_t = \gamma_0 + \gamma_1 p_{it} + ... + \gamma_r p_{rt} + \mu_t \tag{4}$$

The principal components estimates will be biased estimates although they will be more efficient than the Ordinary Least Square (OLS) estimators since redundant information has been removed. In fact, if the OLS estimator for the original regression of log returns on x is denoted b, it can be shown that

$$\hat{\gamma} = P_r' \hat{b} \tag{5}$$

where $\hat{\gamma}$ are the coefficient estimates for the principal components, and P_r is a matrix of the first r principal components. The principal component coefficient estimates are thus simply linear combinations of the original OLS estimates.

---

[2] Few other competing criterions like Latent Root Criterion and A Priori Criterion are not used because of its drawbacks towards this study. Latent Root Criterion proposed by Henry Kaiser (1960) is the most commonly used technique. The rationale for the latent root criterion is that any individual factor should account for variance of at least a single variable if it is to be retained for interpretation. Each variable contributes a value of 1 to the total eigen value. Thus, only factors with eigenvalues greater than 1 are considered significant. It doesn't make sense to add a factor that explains less variance that contained in one variable. There are some drawbacks of this criterion and are linked with the number of the variables used in the analysis. The criterion is reliable for establishing a cut-off when the number of variables is between 20 and 50. If the number is less than 20, there is a tendency that using this method to extract too few number of factors; whereas if more than 50 are involved there is tendency to extract too many factors.

Priori Criterion is used when one already knows how many factors to extract before undertaking the factor analysis. In this thesis, one is not sure about the number of factors to be chosen for analysis.

CHAPTER 7
CONCLUSION

7.1. SUMMARY AND IMPLICATIONS

The relationship between factors such as beta, firm size, Book-to-Market Equity ratio and stock returns has attracted a considerable amount of research attention in the US equity market. By contrast, there is limited evidence for the UK stock market. This study presents some new and interesting findings that have emerged from wide-ranging tests of the role of beta, size and Book-to-Market Equity (BE/ME) in explaining the variation in stock returns in the UK stock market for the sample period: 1969-2001.

This thesis begins by presenting a survey of the existing literature relating to the cross-sectional relationship between beta, size and Book-to-Market Equity (BE/ME) and return. Early evidence (Fama and Macbeth (1973) and Black, Jensen and Scholes (1973)) supported the notion that market beta alone is sufficient to explain the cross-sectional variation in average stock returns. The recent evidence (Fama and French (1992) and Strong and Xu (1997)) supported the notion that BE/ME and size, rather than beta can explain the cross section of returns. A number of academic papers, such as Lo and Mackinlay (1990), Black (1993a, 1993b), and Mackinlay (1995) suggested that the findings of Fama and French and others could be a result of data-snooping or data mining; while, Kothari, Shanken and Sloan (1995) found that the BE/ME effect in previous research was due to sample selection biases, and that CAPM was valid for annual returns and annual betas. Most other studies had used a monthly return interval. Overall, this chapter suggested that the CAPM cannot be discarded completely and that some of the empirical results rejecting the CAPM are not wholly conclusive.

Chapters 3 to 6 form the main body of the study and comprise an extensive empirical analysis. These chapters document a number of previously undiscovered findings for the UK stock market. In Chapter 3, empirical test commences by testing the basic proposition of the Capital Asset Pricing Model (CAPM) that is beta can explain the cross-section of expected stock returns. The findings in Chapter 3 indicate that the relationship between beta and expected returns is either negative or flat and there is absolutely no role for beta in explaining expected returns for the UK stock market. It was also found that BE/ME was consistently statistically significant in explaining the cross-section of expected stock returns. By contrast to the US evidence provided by Fama and French (1992) and the UK evidence of Strong and Xu (1997), this study found that the size has no significant effect on average returns. Overall, this study suggested that the cross-section of average stock returns is adequately described by the BE/ME variable.

Given the strong theoretical background for market beta and the lack of valid explanations for the explanatory power of BE/ME, this study then set out to undertake an extensive validation of these empirical findings. In Chapter 3, the cross-sectional relationships based on different sub-periods, using a residual analysis, comparing discrete and continuous rates of return, using a different market index, using annual returns, using trimmed observations, isolating different market conditions and using a different sample of firms are tested. This wide ranging analysis differentiates this study from previous work by focusing heavily on the robustness of the results. On analysing with conditional regressions, it was found that there was a negative and significant beta coefficient in down-market conditions but a positive and significant beta coefficient in up-market conditions. When the analysis was repeated using annual intervals, an insignificant beta effect in returns was again found, but now, a very weak BE/ME effect in returns was also found. In some

respects, this result is similar to the result of Kothari et al. (1995) who found a statistically significant, yet economically small role for BE/ME with annual betas for the US stock market. It is possible that the standard cross-sectional regression tests could be driven by outliers, that is, extreme observations will tend to have a large effect on the outcomes. A robust regression procedure was used to control for the effects of such outliers. Although, some support for the CAPM was found from robust regression, the beta effect was not strong enough to offset the importance of BE/ME variable. Overall, by estimating the cross-sectional regressions under the different settings, interesting conclusions are presented: there does exist a strong BE/ME effect, a very weak beta effect, but no size effect in UK stock returns. The results from Chapter 3, then became the foundation for the empirical work done in the Chapters 4 to 6.

As previous work in the US has associated small firm premium with monthly return regularities, Chapter 4 considered whether there were such regularities in the stock returns of UK firms. In this chapter, the empirical tests commenced by the investigation of monthly seasonality of UK equity returns during the 1969-2001 period. This study found evidence of an April seasonality for the UK stock market from the monthly cross-sectional regressions. In addition to this, a negative risk-return relationship was also observed in the months of May, June and September. April seasonality in the UK stock market was linked to a tax year effect. It was also found that the results of the seasonality tests were sensitive to the methodology used in the analysis. The April effect disappeared when the analysis was done using portfolio regressions and a Seemingly Unrelated Regression (SUR) framework. Like Chelley-Steeley (1996), this study, using cross-sectional analysis, found some evidence of a January effect in the returns of large firms. But again, this study found no January effect for large firms when the analysis was repeated using portfolio regressions. This again brings us back to the issue raised in Chapters 2 and 3, that is, most

of the controversial findings in the asset-pricing literature might be the result of data-snooping and data-mining. This study also shows that a Book-to-Market effect is quite evident in the months of April and May. In addition to this, this study also finds that the Book-to-Market only affects small size firms. Thus, the so-called 'Book-to-Market' effect discovered in the literature might be the result of a seasonality or small-firm effect. This has not been documented before for the UK stock market. The existence of significant differences for BE/ME for different firm size and months of the year should not necessarily imply that excess profits can be made by trading on this behaviour, as investors will be subject to borrowing constraints and transaction costs.

The next issue of this study was no longer whether size and BE/ME are able to explain cross-section of average stock returns, but why. The evidence from Chapters 2, 3 and 4 suggested that the CAPM is inappropriate and must be modified. There are two classes of explanation; risk and mispricing. The risk-based story came from Fama and French (1993), who showed that the factors related to size and BE/ME are able to explain a significant amount of the common variation in stock returns. According to Fama and French, if assets are priced rationally, then stock risks are multidimensional. One dimension of risk is proxied by market and other dimensions of risk are proxied by BE/ME and size. They presented this through their innovative three-factor model: the three factors are the excess return on the market portfolio (Market), the return on a portfolio long in high BE/ME stocks and short in low BE/ME stocks (HML), and the return on a portfolio long in small stocks and short in big stocks (SMB). In Chapter 5, it was found that a three-factor model explained most the cross-sectional variation in the average returns of size and BE/ME sorted portfolios. Hence, the existence of the relationship between BE/ME and return was also supported in Chapter 5. These results are consistent with some of the other studies of the UK stock market (Gregory, Harris and Michou (2001), Toms and Hussain (2002) and

Guidi and Davies (1997)), but not consistent with Strong, Liu and Lee (2001). Strong, Liu and Lee (2001) were unable to support the three-factor model using the UK data. But, the results from the three-factor model in Chapter 5 suggest that high BE/ME firms (value firms) are risker then low BE/ME firms (growth stocks) and investors would get a higher return by investing in value stocks. Return differentials between value and growth portfolios were successfully explained by the three-factor model. The only area of concern relating to the three-factor model was the momentum effect. Jegadeesh and Titman (1993) were first to examine the momentum effect. They find that there is a momentum effect when recent past winners (portfolios formed on the last year of past returns) out-performs recent past losers. Here, in Chapter 5, the three-factor model failed to explain the momentum effect in returns. Hence the momentum effect is a direct challenge to the three-factor model. Fama and French (1996b) suggests that their three-factor model is just a simple model and it surely cannot explain expected returns on all portfolios (one of them is momentum). To investigate the momentum effect further, four-factor model (including momentum) is investigated in Chapter 5. In this study, a four-factor model (using market, SMB, HML and a momentum factor) is not able to explain the momentum effect in returns. But, there were instances in which momentum factor (fourth factor) appeared to be significant. The results using the four-factor models brings us back to the debate by Fama (1998). It is argued that the momentum anomalies are due to chance and designs in methodology (Fama (1998)). Overall, these results are interesting because this is the first time four-factor model has been examined for the UK market.

The impressive performance of the Fama and French three-factor model has caused a debate in the finance literature over what underlying economic interpretation to give to the HML and SMB factors. The next step of this study was to explore an alternative explanation proposed by Daniel and Titman (1997). Daniel and Titman (1997) argued in

favour of a characteristics-based model, consistent with the mispricing view. They suggested that the Fama and French model appeared to explain average returns only because the factor loadings were correlated with firm characteristics (size and BE/ME). They concluded that the firm characteristics, in particular BE/ME, and not covariances determined expected stock returns. In Chapter 5, the results using the characteristics based model of Daniel and Titman (1997) are also explained and presented. This study follows Daniel and Titman (1997) and forms zero cost portfolios that are characteristic-balanced but are sensitive to at least one of the Fama and French (1993) factors. The result from this analysis is consistent with the earlier studies of Daniel and Titman (1997) and also Strong, Liu and Lee (2001), that the three-factor model cannot fully explain size premiums. This study found that the relationship between the ex-post SMB loadings and excess return is weak even before the risk adjustment, that is, stocks with higher contemporaneous exposure to SMB are not necessarily compensated with higher returns. This gives direct evidence against the factor explanation, which predicts that exposure to factor risk should be rewarded by return. One could definitely reject the factor model in favour of the characteristics-based model for SMB factor. This study also rejects the three-factor model in those tests that form characteristic-balanced portfolios that load on market factor. But like Strong, Liu and Lee (2001), this study also found that the results for characteristic balanced portfolios sorted on HML loadings have lower power to discriminate between the factor and characteristic-based model. This study therefore could not reject the factor model in favour of its characteristic alternative when the analysis is done using HML factor.

The above analysis is complemented by using conditional multifactor regressions to test the three-factor model against the characteristics based model, also in the Chapter 5 of this thesis. This study addresses one specific question: For a given portfolio, do BE/ME and size captures time-variation in risk, as measured by the Fama and French factor model. This

study found that BE/ME tends to be negatively related to the loadings on the Fama and French factors and size tends to be positively related to the loadings on the Fama and French factors, when the analysis was done using BE/ME portfolios. Time-variation in the intercepts of the conditional three-factor regressions measures the incremental explanatory power of BE/ME and size. This study found that, after controlling for changes in risk, BE/ME contained information about expected returns (significant intercepts) but size contained no information for expected returns (insignificant intercepts). The evidence from the size ranked portfolios was striking. Using size ranked portfolios, this study found that BE/ME had less power to directly predict expected returns and also BE/ME was negatively related to loadings on the Fama and French factors. Size seemed to explain economically or statistically significant variation in the intercepts and size was positively related to the loadings on Fama and French factors. Hence, through the conditional regressions, this study again found mixed results. This study could neither reject nor accept any model with full confidence. One can now agree with Fama (1998). Fama (1998) defends his three-factor model by suggesting that, due to the empirical problems measuring the factor associated with size, the Fama and French factor model might be better off with just the market factor and a factor derived from BE/ME.

This study made some further contributions by testing the risk-based asset-pricing model against non-risk alternatives using data on individual securities, in the Chapter 6 of this thesis. It is shown in Chapter 6, that the use of individual securities is important, because Lo and Mackinlay (1990) have shown that the use of portfolios is likely to give rise to a data-snooping bias. In Chapter 6, an insignificant BE/ME effect is found using individual securities. Hence, the results in Chapter 3 (cross-sectional analysis) might be the result of data-snooping biases. To test the sensitivity of the characteristics relative to different sets of risk factors, a risk model exploiting Principal Component Analysis (PCA) ((Connor and

Korajczyk)(1988)) is used. The results of the PCA show that a five-factor model is appropriate for explaining the returns in the UK. In this chapter, the cross-sectional approach of Fama and French (1992), and the factor models of Connor and Korajczyk (1988), Fama and French (1993) and the CAPM are brought together to examine the relationship between risk and return. When individual security returns are risk-adjusted using the 5 factors of the statistical based (Principal Component Analysis (PCA)) (or APT influenced) model, the significance of BE/ME disappears. The size effect also remains insignificant while the momentum factor appears to be significant. A weak BE/ME effect, an insignificant size effect and a significant momentum effect are found, when the analysis is repeated using Fama and French factors. In Chapter 6, when risk-adjusted returns are tested using CAPM, the significance of BE/ME appears to be quite visible. The size effect from the CAPM risk-adjusted returns is also stronger, but it is insignificant when the analysis is done using other types of risk-adjusted returns. Overall, the premium associated with size is also not strong enough. Momentum also remained significant for the CAPM adjusted returns. After fully adjusting the returns for risk using PCA and Fama and French model, the insignificance of BE/ME and size and the significance of momentum presents some puzzles. Either the risk-adjustment method is not complete or the BE/ME and size effects are not explained by risk. Overall, using time series analysis in Chapter 5, BE/ME and size can be considered to be risk factors but using modified cross sectional analysis in Chapter 6, BE/ME and size appear as non-risk factors. Momentum might be a risk factor, but not a characteristic in explaining returns. But, in Chapter 5, using time series analysis, momentum effect appears to be insignificant. These findings are again something new for the UK stock market.

What conclusions can one draw from this study? The BE/ME factor provides stronger evidence in support of the misspecification of the CAPM than does firm size. There is some

evidence in this study that supports the risk-based side of the debate on the economic nature of the size factor and especially the BE/ME factor. That is, there is evidence that investors expect high BE/ME stocks to generate higher returns than low BE/ME stocks. However, some evidence is also in support of the mispricing stories. Hence, the present study is still unable to add any specific economic interpretation to these factors. It is therefore too early to conclude that the three-factor model can be interpreted as a rational-asset pricing model. Overall, the combined evidence from the risk and mispricing stories suggest that the BE/ME is an important factor in literature. If one considers Fama and French are correct that SMB and HML reflect priced risk factors, then reducing a firm's exposure to these types of risk factors would lower the expected returns on its stock, and therefore, its cost of capital. Such a change would not increase the value of the firm, however, so there is no obvious prescription for managerial behavior. On the other hand, if Daniel and Titman (1997) are correct that firms with lower BE/ME have lower expected returns, holding risk constant, then corporate policies designed to lower BE/ME would improve value by lowering the cost of capital. Of course, holding book value constant, that is equivalent to increasing the market value of the stock, which is generally good for shareholders (and not a new insight). The fact that the same empirical proxy has been used in quite different ways raises serious questions about interpreting any of this evidence in a normative way to give firms or managers advice about financial policies. In addition to this, both the arguments are largely based on statistical comparisons and little is known about how important each of the two explanations matters to an investor's investment decisions in general and portfolio optimization in particular. If, all the claimed features of an anomaly matter little in the investor's decision and corporate policies one may take a somewhat extreme view of Black (1993a, 1993b) that "most of the so-called anomalies that have plagued the literature on investments seem likely to be the result of data-mining". Moreover, a possible cause for the existence of the BE/ME, size and momentum effect in the empirical studies may due to

"multicollinearity" problem. The financial data used in the asset-pricing test is often correlated. For example, empirical studies in the asset pricing literature are complicated by a high collinearity between price and accounting variables. If this is a case, the academic results from statistical techniques are unlikely to be helpful to the investors.

Overall, our results do not enable us to determine clearly whether the BE/ME, size and momentum effects in returns are a result of market inefficiency or deficiencies in the asset-pricing model. But, this study attempts to improve on previous empirical studies, in the process, to resolve the existing differences of opinion. Moreover, despite the arguments in the earlier paragraph, the findings in this study can be used to identify and control for differences in expected returns by investors and corporate managers. Further research on theoretical issues might help us to distinguish more confidently between the two competing explanations.

7.2. LIMITATIONS

Like every study, this study is not without limitations. These limitations are discussed in the following paragraph:

This study used two databases for analysis: LSPD and Datastream. Returns were collected from LSPD and accounting values (size and BE/ME) were collected from Datastream. LSPD has data for more than 6000 stocks, but this study had to match the Datastream firm codes with LSPD firm codes, and this left 2108 firms. Even though the conclusions of this study are obtained with dataset containing a large number of firms and covering around 30 years, it cannot be guaranteed that the conclusions of this study will be the same if one uses a much larger data-set. In addition to this, limitations relating to survivorship biases in these databases, which were discussed in the previous chapters might

introduce bias in this study. But, as Banz and Breen (1986) have noted, almost all databases suffer from this problem.

All of the models studied in this chapter are aimed at explaining cross-sectional variation in expected returns. However researchers have been forced to use realized returns as a proxy for expected returns. While this working assumption can be justified by an appeal to rational expectations, the focus on realized returns is also due to the absence of data concerning market's expectations of future outcomes. But, Elton (1999) in his presidential address, observes

"The use of average realized returns as a proxy for expected returns relies on the belief that information surprises tend to cancel out over the period of study and realized returns are therefore an unbiased estimated of expected return. However, I believe that there is ample evidence that this belief is misplaced"

The choice of variables such as size and BE/ME was chosen on the basis of their popularity among researchers. There might be substantial differences in the results if the risk factors were constructed using other variables such as Earning/Price ratio, leverage and Debt-to-Equity ratio.

Multicollinearity seems to be one of the crucial problems in this study and generally in asset pricing analysis. In Chapter 3 and 5, BE/ME and size seems to be strongly related to size. One cannot therefore be sure whether the BE/ME coefficients are not proxying for size. Moreover, the problem of multicollinearity can lead to unreasonable coefficient estimates, large standard errors, and consequently bad interpretation and inference.

The criticism of Black (1993a and 1993b) is worth mentioning again, because it applies to all the asset-pricing studies in general. Black (1993a and 199b) observes that although there are many researchers in finance, perhaps thousands, there is only one history, and therefore, pretty much just one set of data. Researchers use past studies to formulate new hypotheses and models. They then test these models on the same data that were used to test the past hypotheses. Recall that classical hypothesis testing is formulated on the basis of a priori hypotheses and the probability of the data given the null. In finance we therefore find ourselves repeatedly testing the probability of the data given the hypothesis given the data, that is, testing for patterns. In this sense classical statistics is a failure in financial research and re-evaluation of the research agenda and methodology is required in such studies.

Finally, a special characteristic of this research might limit the inference drawn from the statistical tests. The relevant characteristic is the choice of broad market portfolio (Roll (1977) and Ross (1994)) used as proxies for share price index. Alternative indexes are used in this study to examine the effects of this.

7.3. FUTURE WORK

The empirical results and the conclusions presented in this study have pointed to a number of possibilities where further research can be carried out. The aim of this section is to mention it briefly in the following section:

This study found a very weak BE/ME effect in annual returns. Hence, given the observed sensitivity of asset pricing empirical results to return interval employed, a deeper understanding of the source of the differences is clearly called and may prove relevant to other research questions as well. As discussed in Chapter 2 and Chapter 3, two of the current issues relating to annual intervals are trading frictions and risk estimation issues.

Future research is required to explore these issues in detail. In addition to this, more theoretical reasoning involving investment horizon is also required in such types of studies.

This study has limited the full analysis to non-financial UK securities over the period 1969 to 2001. It would be interesting to extend the study to a broader cross-section of securities and a longer sample period. The analysis should also be reviewed or replicated in a future period (say next 5 years) in order to find out whether or not the assumptions and implications of this study will hold.

It was mentioned earlier that the problem of multicollinearity could cause severe damage to the interpretations of the coefficients. An empirical study[1] can be conducted to investigate the possible causes of multicollinearity in asset-pricing tests. Efforts can also be made to overcome the problems of multicollinearity. Collecting more data with better information and performing robustness checks can reduce multicollinearity. Further work should also extend the cross-section analysis to different statistical techniques in the presence of multicollinearity to improve the quality of the estimates and establish if the results we get here are not due to multicollinearity problem.

Ali, Hwang and Trombley (2003) showed that BE/ME effect is greater for stocks related to high volatility, high transaction costs and with less ownership by sophisticated investors. They find that when the arbitrage cost of exploiting the profit from BE/ME strategies is higher then arbitrage benefits, any systematic mispricing would not be quickly and completely traded away. They further add that, risk associated with the volatility of arbitrage returns deters arbitrage activity and is an important reason for the existence of the BE/ME-related mispricing. Investigation for these issues for the UK stock market will

provide new evidence that should help readers revise their beliefs about the mispricing and risk explanations for the BE/ME anomaly.

Jensen and Mercer (2002) found that the Fama and French (1993) factors depend heavily on the monetary policy conditions of the US market e.g., high BE/ME effects are significant in both expansive and restrictive policy periods and small-firm is visible in expansive monetary policy periods. Overall, they suggest that risk premiums vary with monetary policy developments and its suggests that asset pricing models should consider the influences of monetary sectors. They suggest that the monetary policies are one of the intertemporal considerations that must be used to identify the state variables that tie the Fama and French (1993) results to the Merton's (1973) intertemporal CAPM. Future work on the cross-sectional studies for the UK stock market should therefore be done by allowing variation linked to the monetary sector.

In the earlier section, this study mentioned about one possible limitation arising from using realized returns as a proxy of expected returns. A direct measure of market expectations might improve the explanatory power of models. A natural line of extension is the inclusion of analysts' expectations in these types of studies.

The tests in this study are done using data from the UK stock market. A natural application of this study is to repeat the analysis using data from emerging countries. By looking closely at the other developed and developing markets like Japan, China, etc., a researcher might able to fully understand why the results for the traditional CAPM differ in so many ways from the earlier studies like Black, Jensen and Scholes (1972) and Fama and

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[1] Farrar and Glauber (1967) treated in an article a number of tests on multicollinearity which are very easy to apply. Test has been designed for: a. Detecting multicollinearity; b. Localising the multicollinearity; c. Finding the multicollinearity pattern. For an additional treatment of tests of multicollinearity, see Belsley and Welsch (1980).

Macbeth (1973). This step is required to evaluate the generality of the results of this study.

All these extensions are left for future research.

BIBLIOGRAPHY

Agarwal R., T.Hiraki and R.Rao (1988), 'Earning/Price Ratios, size, and seasonal anomalies in the Japanese Securities Market', Unpublished working paper, (John Caroll University).

Ajili S. (2001), 'The capital asset pricing model and the three factor model of Fama and French revisited in the case of France', Unpublished working paper, (University of Paris Dauphine).

Alexander G. and J.Francis (1986), 'Portfolio Analysis', 3rd edition, Prentice-Hall.

Ali A., L. Hwang, and A.M.Trombley (2003), 'Arbitrage risk and the book-to-market anomaly', *Journal of Financial Market*, Vol.69, p.355-373.

Amihud Y., B.J.Christensen and H.Mendelson (1992), 'Further Evidence on the risk-return relationship', *Working paper*, Salomon Brothers Center for the Study of Financial Institutions, Graduate School of Business Administration, (New York University).

Arrow K.J. and G. Debreu (1954), 'Existence of an equilibrium for a competitive economy', *Econometrica*, Vol.22, p.265-90.

Arshanapalli B., T.Coggin, and T.Daniel. (1998), 'Multifactor asset pricing analysis of international value investment strategies', *Journal of Portfolio Management*, Vol.24, p.10-23.

Ashton D.J. and M.J.Tippett (1999), 'Mean, myths and the size effect', Unpublished working Paper, (University of Exeter).

Athanassakos G. (1992), 'Portfolio-rebalancing and the January Effect in Canada', *Financial Analysts Journal*, Vol.48, p.67-78.

Athanassakos G. and J.A. Schnabel (1994), 'Professional portfolio managers and the January Effect: Theory and evidence', *Review of Financial Economics*, Vol.4, p.79-91.

Ball R. (1978), 'Anomalies in relationships between securities yield and yield-surrogates', *Journal of Financial Economics*, Vol.6, p.103-126.

Ball R. and P. Brown (1980), 'Risk and return from equity investments in the Australian minning industry: January 1958 to February 1979', *Australian Journal of Management*, Vol.5, p. 45-66.

Ball R., P. Brown and R.R.Officier (1976), 'Asset pricing in the Australian equity market', *Australian Journal of Management*, Vol.1, p.1-132.

Banz R. W. and Breen W.J. (1986), 'Sample dependent results using accounting and market data: Some evidence', *Journal of Finance*, Vol.41, p.779-793.

Banz R.F. (1981), 'The relation between return and market value of common stocks', *Journal of Financial Economics*, Vol.9, p.3-18.

Barber M.B. and J. D. Lyon (1997), 'Firm size, book-to-market ratio, and security returns: A Holdout Sample of Financial Firms', *Journal of Finance*, Vol.52, p.875-883.

Bartholdy J. and P. Peare (2002), 'Estimation of expected return: CAPM vs Fama and French', Unpublished working paper, (Aarhus School of Business).

Basu S. (1977), 'Investment performance of common stocks in relation to their price/earnings ratios: A test of the efficient market hypothesis', *Journal of Finance*, Vol. 32, p.663-682.

Basu S. (1983), 'The relationship between earning, yield, market value and the returns for NYSE stocks: Further evidence', *Journal of Financial Economics*, Vol.12. p.129-156.

Beckett S. (1938), '*Murphy*' , G. Routledge and Co. London.

Beenstock M. and Kam-Fai Chan (1986), 'Testing the Arbitrage Pricing Theory in the United Kingdom', *Oxford Bulletin of Economics and Statistics*, Vol.48, p.121-141.

Belsley E.K and R.E.Welsch (1980) 'Regression diagnostics: Indentifying influential data and sources of collinearity', (New York: Willey).

Berges A., J.J.McConnell, and G.G.Schlarbaum (1984), 'The Turn-of-the-Year in Canada', *Journal of Finance*, Vol. 39, p.185-192.

Berk J. (1995), 'A critique of size-related anomalies', *Review of Financial Studies*, Vol.8, p.275-286.

Berk J. (2000), 'Sorting out sorts', *Journal of Finance*, Vol.1, p.407-427.

Berk J., R.C. Green and V. Naik (1999), 'Optimal investment, growth options, and security returns', *Journal of Finance*, Vol.54, p.1553-1608.

Bernoulli D. (1738), trans. S. Louise (1954), 'Exposition of a new theory on the measurement of risk', *Econometricia*, Vol.22, p.23-36.

Bernstein P. (1992), 'If beta is dead, where is the corpse?' *Forbes Magazine*, Vol.15, p.343.

Bhandari and L. Chand (1988), 'Debt/Equity ratio and expected common stock returns: Empirical evidence', *Journal of Finance*, Vol.43, p.507-529.

Black F. (1993a), 'Beta and return', *Journal of Portfolio Management*, Vol. 20, p.8-18.

Black F. (1993b), 'Estimating expected return', *Financial Analyst Journal*, Vol.49, p.36-38.

Black F. and M.Scholes (1974), 'The effects of dividend yield and dividend policy on common stock prices and returns', *Journal of Financial Economics*, Vol.1, p.1-22.

Black F. (1972), 'Capital market equilibrium with restricted borrowing', *Journal of Business*, Vol.45, p.444-454.

Black F., M.C. Jensen and M.Scholes (1972), 'The Capital Asset Pricing Model: Some empirical tests', In Jensen (ed.), *Studies in Theory of Capital Markets'*, (NewYork: Praeger Publishers, 1972).

Blume M. (1975), 'Betas and their regression tendencies', *Journal of Finance*, Vol.30, p.785-95.

Blume M. and F. Husic (1973), 'Price, beta and exchange listing', *Journal of Finance*, Vol.28, p.283-299.

Blume M.E. (1970), 'Portfolio theory: A step toward its practical application', *Journal of Business*, Vol.43, p.152-73.

Board J. and J. Smither (1989), 'London Share Price Database-comments', *ICAEW Research Board Conference on UK Database for Accounting Research,* September.

Board J., P.F.Pope and L.C.L.Skerratt (1991), 'A consistency check on share price data from Datastream and the London Business School Share Price Database', by P.F.Pope and P.K.Yadav in *Databases for Accounting Research, ICAEW*, edited by J Board, P F Pope and L C L Skerratt.

Branch B. A. (1977), 'Tax-Loss-Selling Trading Rule', *Journal of Business*, Vol.50, p.198-207.

Breeden D.T. (1979), 'An intertemporal asset pricing model with stochastic consumption and investment opportunities', *Journal of Financial Economics*, Vol.7, p.265-296.

Breen W.J and A.R. Korajczyk (1994), 'On selection biases in book-to-market based tests of asset pricing models', Working Paper no. 167, (North-Western University).

Brennan J.M., T.Chordia and A.Subrahmanyan (1998), 'Alternative factor specification, security characteristics, and the cross-section of expected stock returns', *Journal of Financial Economics*, Vol.1, p.345-363.

Brennan J.M. and A.Subrahmanyan (1998) 'Market microstructure and asset pricing: On the compensation for illiquidity in stock returns', *Journal of Financial Economics*, Vol.41, p.441-464.

Brown P., W.A.Kleidon and T.A.Marsh (1983), 'Stock return seasonalities and the tax-loss selling hypothesis: Analysis of the arguments and Australian evidence', *Journal of Financial Economics*, Vol.12, p.35-56.

Brown S. and C. Barry (1984), 'Differential information and the small-firm effect', *Journal of Financial Economics*, Vol.13, p.283-294.

Campbell J.Y., W.A..Lo and A.C. Mackinlay (1997), 'The econometrics of financial markets', First edition, (Princeton University press).

Capaul C., I.Rowley and W.Sharpe (1993), 'International value and growth stock returns', *Financial Analyst Journal*, Vol.49, p.27-36.

Carhart M.M. (1997), 'On persistence in mutual fund performance', *Journal of Finance*, Vol.52, p.57-82.

Chamberlain G. and M.Rothschild (1983), 'Arbitrage and mean variance analysis on large asset markets', *Econometrica*, Vol.51, p.1281-1304.

Chan A. and L.P. Chui (1996), 'An empirical re-examination of the cross-section of expected returns: UK evidence', *Journal of Business Accounting and Finance*, Vol.23, p.1435-453.

Chan K.C and N. Chen (1991), 'Structural and return characteristics of small and large firms', *Journal of Finance*, Vol.46, p.1467-1484.

Chan K.C. and J. Lakonoshok (1993), 'Are the reports of beta's death premature?' *Journal of Portfolio Management*, Vol.19, p.51-63.

Chan K.C. and Nai-fu Chen (1988), 'An unconditional asset-pricing test and the role of firm size as an instrumental variable for risk', *Journal of Finance*, Vol.2, p.309-325.

Chan K.C., K.Louis, Y.Hamao and J.Lakonishok (1991), 'Fundamentals and stock returns in Japan', *Journal of Finance*, Vol.46, p.1739-1789.

Chan L., Y.Hamao and J. Lakonishok (1991), 'Fundamentals and stock returns in Japan', *Journal of Finance*, Vol.46, p.1739-1789.

Chan L.K.C, Karceski, and J.Lakonishok (2002), 'The level and persistence of growth rates', *Journal of Finance*, Vol.2, p.643-684.

Chan L.K.C., Karceski and J. Lakonishok (1998), 'The risk and return from factors', *Journal of Financial and Quantitative Analysis*, Vol.33, p.159-188.

Chan L.K.C., N. Jegadeesh and J.Lakonishok (1995), 'Evaluating the performance of value versus glamour stocks: The impact of selection bias', *Journal of Financial Economics*, Vol.38, p.269-296.

Chatfield C. and A. Collins (1980), 'Introduction to Multivariate Analysis', Chapman & Hall, (Great Britain).

Chelley-Steeley, Patricia, L. (1996), 'Risk, seasonality and the asymmetric behaviour of stock returns', *Journal of Business Finance and Accounting,* Vol.23, p.145-54.

Chen N. (1983), 'Some empirical tests of the theory of Arbitrage Pricing', *Journal of Finance*, Vol.38, p.1393-1414.

Chen N., R.Roll and S.A.Ross (1986), 'Economics forces and the stock market', *Journal of Business*, Vol.59, p.383-403.

Chen N.F. and F. Zhang (1998), 'Risk and return of value stocks', *Journal of Business*, Vol.71, p.501-535.

Chopra N., J.Lakonishok and J.Ritter (1992), 'Measuring abnormal performance: Do stocks overreact?' *Journal of Financial Economics*, Vol.31, p.235-68.

Chordia T., A.Subrahmanyam and V.R.Anshuman (2001) 'Trading activity and expected stock returns', *Journal of Financial Economics*, Vol.59, p.3-32.

Christie A. and M.Hertzel (1981), 'Capital Asset Pricing Anomalies', Unpublished working Paper, (University of Rochester).

Chui A., S. Titman and J. Wei (2000), 'Momentum, legal systems and ownership structure: An analysis of Asian stock markets', Working paper.

Claessens S., S. Dasgupta and J.Glen (1995), 'Return behaviour in emerging stock markets', The *World Bank Economic Review*, Vol.9, p.131-151.

Claessens S., S. Dasgupta and J.Glen (1996), 'The cross-section of stock returns: Evidence from the emerging markets', Working paper, World Bank.

Clare A.D., R.Priestley and S.H.Thomas (1998), 'Reports of beta's death are premature: Evidence from the UK', *Journal of Banking & Finance*, Vol.22, p.1207-1299.

Coghlan H. (1988), 'Small firms versus large on the Irish stock exchange: An analysis of the performances 1977-86', *Irish Business and Administrative Research*, Vol.9, p.10-20.

Cohary A., G.Hawaini and P.Michel (1987), 'Seasonality in the risk-return relationship: Some international evidence', *Journal of Finance*, Vol.42, p.49-68.

Cohen K.J., K.G.Hawawini, S.F.Maier, R.A.Schwartz and D.K.Whitcomb (1983), 'Frictions in the trading process and the estimation of systematic risk', *Journal of Financial Economics*, Vol.12, p.263-278.

Cohen K.J., S.F.Maier, R.A. Schwartz and D.K.Whitcomb (1985), 'The microstructure of securities markets', Prentice Hall.

Coleman R. D. (1997), 'Critique of asset pricing circularity', *Journal of Financial Abstracts*, C-WPS98-16.

Conarad J., M.Copper and G.L.Kaul (1999), 'Value versus glamour', Unpublished working paper, (University of Michigan).

Connor G. (1984), 'A unified beta pricing theory', *Journal of Economic theory*, Vol.34, p.13-31.

Connor G. and R. Korajczyk (1986), 'Performance measurement with the arbitrage pricing theory: a new framework for analysis', *Journal of Financial Economics*, Vol.15, p.373-394.

Connor G. and R.Korajczyk (1988), 'Risk and return in an equilibrium APT: Application of a new set of methodology', *Journal of Financial Economics*, Vol.21, p.255-290.

Connor G. and S. Sehgal (2001), 'Test of the Fama and French Model in India', Unpublished working Paper, (London School of Economics).

Cornioley, Claude and J.P.Dorthe (1991), 'CAPM, risk premium seasonality and the size anomaly: The Swiss case', *Journal of Finance*, Vol.12, p.23-44.

Damodaran A. (2000), 'Estimating risk parameters', Unpublished working paper, (Stern School of Business).

Daniel K., and S. Titman (1997), 'Evidence on the characteristics of cross sectional variation in stock returns', *Journal of Finance*, Vol.52, p.1-33.

Daniel K., S. Titman and J. Wei (2001), 'Explaining the cross-section of stock return in Japan: factors or characteristics?' *Journal of Finance*, Vol.55, p.743-766.

Davis J. L. (1994), 'The cross-section of realized stock returns: The Pre-COMPUSTAT evidence', *Journal of Finance*, Vol.49, p.1579-1593.

Davis J., E.Fama, and K.French (2000), 'Characteristics, covariances, and average returns: 1929-1997', *Journal of Finance*, Vol.55, p.389-406.

Davis J.L. (2001), 'Mutal fund performance and manager style', *Financial Analysts Journal*, Vol.57, p.19-27.

De Bondt W. and R. Thaler (1985), 'Does the stock market overreact?' *Journal of Finance,* Vol.40, p.793-805.

DeBondt W. and R. Thaler (1987), 'Further evidence on investor overreaction and stock market seasonality', *Journal of Finance*, Vol.42, p.557-581.

Demos A., E.Sentana E and M.Shah (1993), 'Risk and return in January: Some UK evidence', *FMG Discussion Papers*, Financial Markets Group and ESRC.

Dhymes P. J., I.Friend and B.N.Gultekin (1984), 'A critical examination of the empirical evidence on the Arbitrage Pricing Theory', *Journal of Finance*, Vol.39, p.323-346.

Dichev I.D. (1998), 'Is the risk of bankruptcy a systematic risk?' *Journal of Finance*, Vol.53, p.1131-1147.

Dimson E. (1979), 'Risk Measurement when shares are subject to infrequent trading', *Journal of Financial Economics*, Vol.7, p.197-226.

Dimson E. (1982), 'Friction in the trading process and risk measurement: A note', Working Paper, (London Business School).

Dimson E. (1984), 'Hedging the market: The performance of the FTSE 100 share index', *Journal of Institute of Actuaries,* Vol.111:2, p.403-430.

Dimson E. (2000), 'UK financial market returns 1955-2000', Unpublished working paper, (London Business School).

Dimson E. and P.R.Marsh (1983), 'The stability of U.K risk measures and the problem of thin trading", *Journal of Finance*, Vol.38, p.753-783.

Dimson E. and P.Marsh (1986), 'Event study methods and the size effect: the case of UK press recommendations', *Journal of Financial Economics*, Vol.17, p.1-29.

Dimson E. and P.Marsh (1998), 'Murphy's Law and Market Anomalies', Unpublished working paper, (London Business School) (Forthcoming in Journal of Portfolio Management).

Dimson E., S.Negal and G.Quigley (2003), 'Capturing the value premium in the UK: 1955-2001', Unpublished working paper, (London Business School) (forthcoming in the Journal of Financial and Quantitative Analysis).

Douglas G.W. (1968), 'Risk in the equity markets: An empirical appraisal of market efficiency', (Ann Arbor, Mich.: University Microfilms, Inc.,1968).

Downs W.T. and W.Ingram (2000), 'Beta, size, risk and return', *Journal of Financial Research*, Vol.23, p.245-261.

Dybvig P.H. and S.A. Ross (1985), 'Differential information and performance measurement using a security market line' *Journal of Finance*, Vol.40, p.383-99.

Dyl E. (1977), 'Capital gain, taxation and year-end stock market behaviour', *Journal of Finance*, Vol. 32, p.165-175.

Easley D., S. Hvidkjaer and M.O'Hara (2002), 'Is Information risk a determinant of asset returns?' *Journal of Finance*, Vol.57, p.2185-2223.

Efron B. (1982), 'The jackknife, the bootstrap, and other resampling plans', Monograph, no.38, (Philadelphia: society for Industrial and Applied Mathematics).

Elton E.J. (1999), 'Expected return, realized return, and asset pricing tests', *Journal of Finance*, Vol.54, p.1199-1220.

Elton J.E., J.Martin, D.Gruber, D.Agrawal and C. Mann (2001), 'Explaining the rate spread on corporate bonds', *Journal of Finance*, Vol.56, p.247-277.

Ericsson J. and A.Gonzalez (2003) 'Is Momentum due to data-snooping?' Unpublished Working Paper (Stockholm School of Economics).

Fama F.E. (1965), 'The behaviour of stock market prices', *Journal of Business*, Vol.38, p.34-105.

Fama F.E. (1968), 'Risk, return and equilibrium: some clarifying comments', *Journal of Finance*, Vol.23, p.29-40.

Fama F.E. (1970), 'Efficient capital markets: A review of theory and empirical work', *Journal of Finance,* Vol.25, p.383-416.

Fama F.E. (1973b), 'A note on the market model and the two-parameter model', *Journal of Finance*, Vol.28, p.1181-1185.

Fama F.E. (1976), 'Foundations of Finance', London, Basic Books.

Fama F.E. (1998), 'Market efficiency, long-term returns, and behavioural finance', *Journal of Financial Economics*, Vol.49, p.283-306.

Fama F.E. and G.W.Schwert (1977), 'Asset returns and inflation', *Journal of Financial Economics*, Vol.5, p.115-146.

Fama F.E. and H.Babiak (1968), 'Dividend policy: An empirical analysis', *Journal of American Statistical Association,* Vol.63, p.1132-61.

Fama F.E. and J.D.MacBeth (1973), 'Risk, return and equilibrium: Empirical test', *Journal of Political Economy*, Vol.81, p.607-636.

Fama F.E. and K.R. French (1989), 'Business conditions and expected returns on stocks and bonds', *Journal of Financial Economics*, Vol.25, p.23-49.

Fama F.E. and K.R.French (1988), 'Permanent and temporary components of stock prices', *Journal of Political Economy*, Vol.96, p.246-273.

Fama F.E. and K.R.French (1992), 'The cross-section of expected stock returns', *Journal of Finance*, Vol.47, p.427-465.

Fama F.E. and K.R.French (1993), 'Common risk factors in the returns on stocks and bonds', *Journal of Financial Economics*, Vol.33, p.3-56.

Fama F.E. and K.R.French (1995), 'Size and book-to-market factors in earnings and returns', *Journal of Finance*, Vol.50, p.131-155.

Fama F.E. and K.R.French (1996a), 'The CAPM is wanted, dead or alive', *Journal of Finance*, Vol.51, p.1947-1958.

Fama F.E. and K. R. French (1996b), 'Multifactor explanation of asset pricing anomalies', *Journal of Finance*, Vol.51, p.55-84.

Fama F.E. and K.R. French (1998), 'Value vs growth: the international evidence', *Journal of Finance*, Vol.53, p.1975-2000.

Fama F.E. and R.Roll (1968), 'Some Properties of Symmetric Stable Distributions', *Journal of American Statistical Association*, Vol.63, p.817-36.

Fant F. and D.Peterson (1995), 'The effect of size, book-to-market, equity, prior returns and beta on stock returns: January versus the reminder of the year', *Journal of Financial Research*, Vol.18, p.129-43.

Farrar D.E. and R.R.Glauber (1967) 'Multicollinearity in regression analysis: the problem revisited', Review of Economics and Statistics, Vol.49.

Ferson W. and R.H.Campbell (1991), 'The variation of economic risk premium', *Journal of Political Economy*, Vol.99, p.385-415.

Ferson W., S.Sarkissian and T. Simin (1999), 'The alpha factor asset pricing model: A parable', *Journal of Financial Markets*, Vol.2, p.49-68.

Ferson W.E. and C.R.Harvey (1990), 'The variation of economic risk premiums', *Journal of Political Economy,* Vol.99, p.385-415.

Fisher L. (1986), 'Some new stock market indexes', *Journal of Business*, Vol.39, p.191-225.

Fitzherbert R. (2001), 'Volatility, beta and return: Was there ever a meaningful relationship?' *Institute of Actuaries of Australia.*

Fong M.W. (1992), 'The size-effect: A multiperiod analysis', *Applied Financial Economics*, Vol.2, p.87-92.

Fowler D.J. and C.H.Rorke (1982), 'A bias correcting procedure for beta estimation in the presence of thin trading and risk measurement when shares are subject to infrequent trading: Comment', Unpublished Working Papers, (McGill University).

Frank J.R. and R.S.Harris (1989), 'Shareholder wealth effects of corporate takeovers: The UK experience', *Journal of Financial Economics*, Vol.23, p.225-249.

French R.K., W.Schwert and R.F.Stambaugh (1987), 'Expected stock returns and volatility', *Journal of Financial Economics*, Vol.19, p.3-29.

Friend I. and M.Blume (1970), 'Risk and long run rate of return on NYSE common stocks', Unpublished working paper, (Wharton School of Commerce and Finance).

Friend I., R.Westerfield and M.Granito (1978), 'New evidence on the Capital Asset Pricing Model', *Journal of Finance*, Vol.3, p.903-920.

Gallant R.A. (1975), 'Seemingly unrelated nonlinear regressions', *Journal of Econometrics*, Vol.3, p.35-50.

Gibbon R. M. (1982), 'Multivariate tests of financial models: A new approach', *Journal of Financial Economics*, Vol.10, p.3-27.

Gibbons R.M., S.R.Ross and J.Shanken (1989), 'A test of the efficiency of a given portfolio', *Econometrica*, Vol.57, p.1121-1152.

Gillian S. (1990), 'An Investigation into CAPM anomalies in New Zealand: The small firm and price earnings ratio effects', *Asia Pacific Journal of Management*, Vol.7 (special issue), p. 63-78.

Gomes J., L.Kogan, and L.Zhang (2000), 'Equilibrium cross-section of returns', Unpublished working paper, (University of Pennsylvania).

Grauer R.R. (1999), 'On the cross-sectional relation between expected returns, betas and size', Journal of Finance, Vol.54, p.773-789.

Gregory A., R.D.F.Harris and M.Michou (2001), 'An analysis of contrarian investment strategies in the UK', *Journal of Business Finance and Accounting*, Vol.28, p.1193-1228.

Gregory A., R.D.F.Harris and M.Michou (2002), 'Contrarian and Macroeconomic Risk', Unpublished working paper, (University of Exeter).

Griffin M.J. (2002), 'Are the Fama and French Factors global or country specific?' *The Review of Financial Studies*, Vol.15, p.783-803.

Griiffin M. and M.Lemmon (2001), 'Does book-to-market proxy for distress or mispricing?' Unpublished working Paper, (Arizona State University).

Guidi M. and D.Davies (2000), 'The structural characteristic evidence on risk factors: Characteristics, risk factors and risk premia', Unpublished working paper, (University of Glasgow).

Guidi M. and D.Davies (1997), 'UK evidence on the 3-factor model and the glamour versus value controversy', Unpublished working paper, (University of Glasgow).

Gujarati D.N. (1995), 'Basic Econometrics', Third edition, McGrawHill.

Gultekin M. and B.N.Gultekin (1983), 'Stock market seasonality: International evidence', *Journal of Financial Economics*, Vol.12, p.469-489.

Hair J., R.Anderson, R.Tatham and W.Black (1998), 'Multivariate data analysis', 5th edition, Prentice-Hall International, (Inc. New Jersey).

Hall H.B. and C.Cummins (1999), 'TSP user's guide: Version 4.5', TSP International, CA.

Handa P., S.Kothari and C.Wasley (1989), 'The relation between return interval and betas: Implications for the size-effect', *Journal of Financial Economics*, Vol.23, p.79-100.

Haugen R. (1995), 'The New Finance: The case against efficient markets', Prentice hall, Englewood Cliffs, (New Jersey).

Haugen R. and J.Lakonishok (1988), 'The incredible January effect: The stock market's unsolved mystery', Homewood IL: Dow Jones-Irwin.

Haugen R.A. and J.Lakonishok (1990), 'The incredible January effect: The stock market's unsolved mystery', Dow-Jones Irwin.

Hawawini G. and D.Keim (2000), 'The cross-section of common stock returns: a review of the evidence and some new findings', *In Keim D. and W.Ziemba (eds) Security market imperfections in world wide equity markets*, Cambridge University Press.

Hawawini G., P.Michel and A.Corhay (1989), 'A look at the Validity of the Capital Asset Pricing Model in light of equity market anomalies: The case of Belgian common stocks' in Guimaraes.

Henry K. (1960), 'The application of electronic computers to factor analysis', *Educ. Psychol. Meas.*, Vol.20, p.141-151.

Ho Y. K. (1990), 'Stock return seasonalities in Asia Pacific Markets', *Journal of International Financial Management and Accounting,* Vol.2, p.47-77.

Huang C. and R.Litzenberger (1993), 'Foundation of financial economics', Prentice-Hall, Inc.

Hulbert M. (1992), 'Beta is dead', *Forbes*, Vol.149, p.239.

Ikenberry D. and J.Lakonishok (1989), 'Seasonal anomalies in financial markets: A survey in a reappraisal of the efficiency of financial markets', edited by Rui M.C, Guimares B Kingsman and Stephan Taylor.

Jaffe J., B.D.Keim and R.Westerfield (1989), 'Earnings yields, market values, and stock returns', *Journal of Finance*, Vol.1, p.135-148.

Jagannathan R. and R.E.McGrattan (1995), 'The CAPM debate', (Federal Reserve Bank of Minneapolis Quarterly Review).

Jagannathan R. and Z.Wang (1993), 'The CAPM is alive and well', Working Paper, (Federal Reserve Bank of Minneapolis).

Jagannathan R. and Z.Wang (1996), 'The conditional CAPM and the cross-section of expected returns', *Journal of Finance*, Vol.51, p.3-53.

Jegadeesh N. (1990), 'Evidence of predictive behaviour of security returns', *Journal of Finance*, Vol.45, p.881-898.

Jegadeesh N. and S.Titman (1993), 'Returns to buying winners and selling losers: Implication for stock market efficiency', *Journal of Finance*, Vol.50, p.185-224.

Jegadeesh N., and S.Titman (2001), 'Profitability of momentum strategies: an evaluation of alternative explanations', *The Journal of Finance*, Vol.56, p.699-720.

Jensen G.R. and J.M.Mercer (2002), 'Monetary policy and the cross-section of expected returns', *Journal of Financial Research*, Vol.25, p.125-140.

Jensen M.C. (1972), 'The foundations and current state of capital market theory', *Studies in the Theory of Capital Markets*, Praeger Publishing, New York, p.3-43.

Jones C., D.K.Pearce and J.W.Wilson (1987), 'Can tax -loss selling explain the January effect? A note', *Journal of Finance*, Vol.42, p.453-461.

Judge G., E.W.Griffiths, C.R.Hill, H.Lutkepohl and L.T. Chao (1984), 'The theory and practice of econometrics', John Wiley and Son Publishers, 2nd edition.

Kamdel S. and R.F.Stambaugh (1995), 'Portfolio inefficiency and the cross-section of mean returns', *Journal of Finance*, Vol.50, p.157-85.

Kato K. and J.S.Schallheim (1985), 'Seasonal and size anomalies in the Japanese stock market', *Journal of Financial and Quantitative Analysis*, Vol.20, p.243-260.

Keim D.B. (1983), 'Size-related anomalies and stock return seasonality: Further empirical evidence', *Journal of Financial Economics*, Vol.12, p.13-32.

Keim D.B. (1988), 'Stock market regularities: A synthesis of the evidence and explanations', *In Stock Market Anomalies*, Elroy Dimson, ed. Cambridge, England: Cambridge University Press.

Keim D.B., Donald and R.F.Stambaugh (1986), 'Predicting returns in the stock and bond markets', *Journal of Financial Economics*, Vol.17, p.357-390.

Klein P. (2001), 'The capital gain lock-in effect and long horizon return reversal', *Journal of Financial Economics*, Vol.59, p.33-62.

Knez P.J. and M.J.Ready (1997), 'On the robustness of size and book-to-market in cross-sectional regressions', *Journal of Finance*, Vol.52, p.1355-82.

Korajczyk R.A. and C.J.Viallet (1989), 'An empirical investigation of international asset pricing', *Review of Financial Studies*, Vol.2, p.553-585.

Kothari S.P. and J.Shanken (1997), 'Book-to-market, dividend yield, and expected market returns: A time-series analysis', *Journal of Financial Economics*, Vol.44, p.169-203.

Kothari S.P., J.Shanken and R.G.Sloan (1995), 'Another look at the cross-section of expected returns', *Journal of Finance*, Vol.50, p.185-224.

Kothari S.P. and J.Shanken (1999), 'Beta and book-to-market: Is the glass half full or half Empty?' Unpublished working Paper, (University of Rochester).

Kothari S.P., J.S.Sabino and T.Zach (2001), 'Implications of data restrictions on performance measurement and tests of rational pricing', Unpublished working paper, (MIIT).

La Porta R., J.Lakonishok, A.Shleifer and R.W.Vishny (1997), 'Good news for value stocks: Further evidence on market efficiency', *Journal of Finance*, Vol.52, p.859-874.

Lakonishok J. and A.Shapiro (1984), 'Stock returns, beta, variance and size: An empirical analysis', *Financial Analysts Journal*, Vol.40, p.36-41.

Lakonishok J. and A.Shapiro (1986), 'The systematic risk, total risk and size as determinants of stock market returns', *Journal of Banking and Finance*, Vol.10, p.115-132.

Lakonishok J., A. Shleifer and R. Vishny (1994), 'Contrarian investment, extrapolation, and risk', *Journal of Finance*, Vol.49, p.1541-1578.

Lawley D.N. and A.E.Maxwell (1971), 'Factor analysis as a statistical method', Butterworth and Company, London.

Leamer E.F. (1983), 'Lets take the con out of econometrics', *American Economic Review*, Vol.73, p.31-43.

Lehmann B.N. (1990), 'Residual risk revisited', *Journal of Econometrics*, Vol.45, p.71-97.

Lehmann B.N. (1990), 'Fads, martingales and market efficiency', *Quarterly Journal of Economics*, Vol.105, p.1-28.

Lettau M. and S. Ludivgson (2001), 'Resurrecting the (C) CAPM: A cross-sectional test with risk premia are time-varying', *Journal of Political economy*, Vol.109, p.1238-1287.

Levhari D. and H. Levy (1977), 'The Capital Asset Pricing Model and the investment horizon', *Review of Economics and Statistics*, Vol.59, p.92-104.

Levis M. (1985), 'Are small firms big performers?' *The Investment Analyst Journal*, Vol.76, p.21-27.

Levis M. (1987), 'Size related anomalies and trading activity of U.K institutional investors' *In Stock Market Anomalies*, Elroy Dimson, ed. Cambridge, England: Cambridge University Press.

Levis M.(1989), 'Stock market anomalies: A re-assessment based on the U.K evidence', *Journal of Banking and Finance*, Vol.13, p.675-696.

Levy H. (1978), 'Equilibrium in an Imperfect Market: A Constraint on the number of securities in the portfolio', *American Economic Review*, Vol.68, p.643-58.

Lewellen J. (1999), 'The time series relations among expected return, risk, and book-to-market', *Journal of Financial Economics*, Vol.54, p.5-43.

Lewellen J. (2002), 'Momentum and autorcorrelation in stock returns', *Review of Financial Studies*, Vol.15, p.533-563.

Liang B. (2000), 'Portfolio formation, measurement error, and beta shifts: A random sampling approach', *Journal of Financial Research*, Vol.23, p.261-284.

Liew J. and M. Vassalou (2000), 'Can book-to-market, size and momentum be risk factors that predict economic growth', *Journal of Financial Economics*, Vol.57, p.221-245.

Liew J., M.Vassalou and Y.Xing (2001), 'An Investment growth asset pricing model', Unpublished working paper, (University of Columbia).

Limmack R. (1995), 'Firm size, monthly seasonalities and tax loss selling: Further evidence from the UK', *Conference paper from European Accounting Association*, Birmingham.

Lintner J. (1965), 'The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets', Review of Economics and Statistics, Vol.47, p.13-37.

Litzenberger R. and K.Ramaswamy (1979), 'The effects of personal taxes and dividends on capital asset prices: Theory and empirical evidence', *Journal of Financial Economics*, Vol.7, p.163-195.

Litzenberger R. and K.Ramaswamy (1979b), 'Dividends, short-selling restrictions, tax-induced investor clienteles, and market equilibrium', *Journal of Financial Economics*, Vol.7, p.163-196.

Litzenberger R. and K.Ramaswamy (1982), 'The effects of dividends on common stock prices tax effects or information effects?' *The Journal of Finance*, Vol.37, p.429-443.

Lo A.W. and A.C.Mackinlay (1990), 'Data-snooping biases in tests of financial asset pricing models', *Review of Financial Studies*, Vol.3, p.431-468.

Lo A.W and A.C.Mackinlay (1990b), 'An econometric analysis of non-synchronous trading', *Journal of Econometrics*, Vol.45, p.181-211.

London Share Price Database (1989), 'Reference Manual', London Business School.

Loughran T. (1997), 'Book-to-market across firm size, exchange, and seasonality: Is there an effect?' *The Journal of Financial Quantitative Analysis*, Vol.32, p.249-268.

Lovell M.C. (1983), 'Data mining', *Review of Economics and Statistics*, Vol.65, p.1-12.

Ma T. and T.Y.Shaw (1990), 'The relationship between market value, P/E ratio, trading volume and the stock return of Taiwan Stock Exchange', *in Rhee, Ghon, and Rosita Chang (Eds), Pacific-Basin Capital Markets Research*, Vol.1, North Holland, Amsterdam.

Mackinlay A. (1995), 'Multifactor models do not explain deviations from the CAPM', *Journal of Financial Economics*, Vol.38, p.3-28.

Mackinlay A. and M. Richardson (1991), 'Using generalized method of moments to test mean-variance efficiency', *Journal of Finance*, Vol.46, p.511-527.

Markowitz H.M. (1959), 'Portfolio selection: Efficient diversification of investments', *New York: Wiley.*

McElory M.B. and E.Burmeister (1988), 'Arbitrage Pricing Theory as a restricted nonlinear multivariate regression model', *Journal of Business and Economics Statistics*, Vol.6, p.29-42.

McElory M.B., and E.Burmeister (1977), 'Goodness of fit for seemingly unrelated regressions: Glahn's $R^2_{y,x}$ and Hooper's $\bar{r}_2$', *Journal of Econometrics*, Vol.6, p.381-387.

McElroy M.B., E.Burmeister and K.D.Wall (1985), 'Two estimates for the APT model when factors are measured', *Economic letters*, Vol.19, p.271-275.

Mckillop D. and R.Hutchinson (1983), 'The small firm effect, seasonality and risk in Irish equities', *Irish Business and Administrative Research*, Vol.9, p.21-29.

Mech, Timothy S. (1993), 'Portfolio return autocorrelation', *Journal of Financial Economics*, Vol. 34, p.307-344.

Menyah K. (1999), 'New evidence on the impact of size and taxation on the seasonality of UK equity returns', *Review of Financial Economics*, Vol. 8, p.11-24.

Merton R. (1973), 'An Intertemporal Capital Asset Pricing Model', *Econometrica*, Vol.41, p.867-887.

Merton R.C. (1980), 'On estimating the expected return on the market', *The Journal of Financial Economics*, Vol.8, p.323-361.

Merton R.C. (1987), 'A simple model of capital market equilibrium and incomplete information', *Journal of Finance*, Vol.42, p.483-510.

Mikkelsen O.H. (1999), 'The general cross-sectional relation between expected return and beta', Unpublished working Paper, (USC Marshall School of Business).

Miller M.H. and M.Scholes (1972), 'Rates of return in relation to risk: A re-examination of some recent findings', *in Jensen M. (ed.), Studies in the Theory of Capital Markets* (New York: Praeger).

Miller M.H. and M.Scholes (1982), 'Dividends and taxes: Some empirical evidence', *Journal of Political Economy*, Vol.90, p.1118-1141.

Modigliani F. and M.H.Miller (1958), 'The cost of capital, corporation finance, and the theory of investment', *American Economic Review*, Vol.48, p.261-297.

Moloay E. (1999), '*le modele de rentabilite a trois facteurs de fama et french: le cas francasis*', p.1-27.

Mossin J. (1966), 'Equilibrium in a capital asset market', *Econometrica*, Vol.24, p.763-83.

Munshi J. (1996), 'The Beta Puzzle', Unpublished working Paper, (Sonoma State University).

Munshi J. (1998), 'Confusing Results of Empirical Studies in Finance', Unpublished working Paper, (Sonoma State University).

Nakamura T. and N.Terada (1984), 'The size effect and seasonality in Japanese stock return', Unpublished working paper, (Southern Methodist University).

Negel S. (2001), 'Accounting information free of selection bias: A New UK database 1953-1999', Unpublished working Paper, (London Business School).

Neumann V. and O.Morgenstern (1944), 'Theory of games and economic behaviour', *NJ: Princeton University Press. (1947).*

Nicholson S.F. (1960), 'Price/Earning ratios', *Financial Analyst Journal*, Vol.16, p.43-45.

Officer R.R. (1971), 'A time series examination of the market factor of the New York Stock Exchange', Unpublished Ph.D. dissertation, (University of Chicago).

Officer R.R. (1975), 'Seasonality in Australian capital markets Market efficiency and empirical issues', *Journal of Financial Economics*, Vol.2, p.675-696.

Ohlson J.A. (1980), 'Financial ratios and the probabilistic prediction of bankruptcy', *Journal of Accounting Research*, Vol.19, p.109-131.

Pasquariello P. (1999), 'The Fama-Macbeth approach revisited', Unpublished working paper, (New York University-Stern School of Business).

Pasta L. and R.F.Stambaugh (2001), 'Liquidity risk and expected stock returns', Unpublished working paper, (University of Chicago and the Wharton School, University of Pennsylvania).

Perez-Quiros G. and A.Timmermann (2000), 'Firm size and cyclical variations in stock returns', Journal *of Finance*, Vol.55, p.1229-1262.

Pettengill G.N., S.Sundaram and L.Mathur (1995), 'The conditional relation between beta and returns', *Journal of Financial and Quantitative Analysis*, Vol.30, p.102-116.

Pontiff J. and L.Schall (1998), 'Book-to-market as a predictor of market return', *Journal of Financial Economics*, Vol.49, p.141-60.

Poon S. and S.J.Taylor (1991), 'Macroeconomics factors and the UK stock market', *Journal of Finance and Accounting*, Vol.18, p.619-37.

Porter D.C., G.E.Powell and D.G.Weaver (1996), 'Portfolio rebalancing, institutional ownership, and the small firm-January Effect', *Review of Financial Economics*, Vol.5, p.19-29.

Quigley G. and R. A. Sinquefield (2000), 'Performance of UK equity unit trusts', *Journal of Asset Management*, Vol.1, p.72-92.

Raymond C.B. (1966), 'The scree test for the number of factors', *Multivariate Behavioural Research*, Vol.1, p.140-161.

Reinganum M.R. (1981), 'Misspecification of capital asset pricing: Empirical anomalies based on earnings, yield and market values', *Journal of Financial Economics*, Vol.16, p.439-462.

Reinganum M.R. (1983), 'The anomalous stock market behaviour of small firms in January: Empirical tests for tax loss selling effects', *Journal of Financial Economics*, Vol.12, p.89-104.

Reinganum M.R. and A.C.Shapiro (1987), 'Taxes and stock return seasonality: Evidence from London Stock Exchange', *Journal of Business*, Vol.60, p.281-295

Ritter J.R. (1988), 'The buying and selling behaviour of individual investors at the turn of the year', *Journal of Finance*, Vol.43, p.701-17.

Ritter J.R. and N.Chopra (1989), 'Portfolio rebalancing and the turn-of-the-year effect', *Journal of Finance*, Vol.44, p.149-166.

Rogalski R. and S.Tinic (1986), 'The January size effect: Anomaly or risk mismeasurement?' *Financial Analyst Journal*, Vol.42, p.63-70.

Roll R. (1977), 'A critique of the asset pricing theory's tests: On past and potential testability theory', *Journal of Financial Economics*, Vol.4, p.129-176.

Roll R. (1981), 'A possible explanation of the small firm effect', *Journal of Finance*, Vol.35, p.879-88.

Roll R. and S.A.Ross (1994), 'On the cross-sectional relation between expected returns and betas', *Journal of Finance*, Vol.49, p.101-121.

Roll R. and S.Ross (1980), 'An empirical investigation of arbitrage pricing theory', *Journal of Finance*, Vol.35, p.1073-1103.

Rosenberg B., K.Reid and R.Lanstein (1985), 'Persuasive evidence of market inefficiency', *Journal of Portfolio Mangement*, Vol.11, p.9-17.

Ross S.A. (1976a), 'The arbitrage theory of capital asset pricing', *Journal of Economic Theory*, Vol.13, p.341-360.

Ross S.A. (1976b), 'Risk, return and arbitrage', *In Risk and Return in Finance*, edited by Irwin Friend and James Bicksler, (Cambridge, Mass.: Ballinger), p.189-218.

Rouwenhorst K.G. (1998), 'International momentum strategies', *The Journal of Finance*, Vol.53, p.267-284.

Rouwenhorst K.G. (1999), 'Local return factors and turnover in emerging stock market', *The Journal of Finance*, Vol.54, p.1439-1464.

Rozeff M.S. and M.A.Zaman (1998), 'Overreaction and insider trading: Evidence from growth and value portfolios', *Journal of Finance*, Vol.53, p.701-716.

Rozeoff M.S. and W.R.Kinney Jnr. (1976), 'Capital market seasonality: The case of stock returns', *Journal of Financial Economics*, Vol.13, p.379-402.

Rubio G. (1986), 'Size, liquidity and valuation', Unpublished working Paper, Southern European Discussion Series (Universidad del Pais Vasco, Lejona).

Schmidt P. (1977), 'Estimation of seemingly unrelated regressions with unequal numbers of observations', Journal of Econometrics, Vol. 5, p.365-377.

Scholes M. and J.Williams (1977), 'Estimating beta from nonsynchronous data', *Journal of Financial Economics*, Vol.5, p.309-327.

Schultz P. (1985), 'Personal income taxes and January effect, small firm, stock return before the War Revenue Act of 1917: A note', *Journal of Finance*, Vol.40, p.333-343.

Shanken J. (1985), 'Multibeta CAPM or equilibrium-APT? : A reply', *Journal of Finance*, Vol.40, p.1189-1196

Shanken J. (1987), 'Multivariate proxies and arbitrage pricing relations: living with the Roll critique', *Journal of Financial Economics*, Vol.18, p.91-110.

Shanken J. (1990), 'Intertemporal asset pricing: An empirical investigation', *Journal of Econometrics*, Vol.45, p.99-120.

Sharpe W.F. (1963), 'A simplified model of portfolio analysis', *Management Science*, Vol.9, p.277-293.

Sharpe W.F. (1964), 'Capital asset pricing: A theory of market equilibrium under conditions of risk', *Journal of Finance*, Vol.19, p.411-425.

Shumway T. (1997), 'The Delisting bias in CRSP data', *Journal of Finance*, Vol.52, p.327-340.

Shumway T. and V.A.Warther (1998), 'The Delisting Bias in CRSP's NASDAQ data and its implications for the size effect', *Journal of Finance*, Vol.54, p.2361-2379.

Siegel S. and N.J. Castellan Jr. (1988), 'Nonparametric statistics for the behavioural sciences', Second Edition, McGraw-Hill Book Company.

Skinner D. and R.Sloan (2002), 'Earnings surprises, growth expectations, and stock returns, or, don't let an earnings torpedo sink your portfolio', *Review of Accounting Studies*, Vol.7, p.289-312.

Stambaugh R. (1982), 'On the exclusion of asset from the two-parameter model: A sensitivity analysis', *Journal of Financial Economics*, Vol.10, p. 237-268.

Stattman D. (1980), 'Book values and stock returns', *The Chicago MBA: A journal of selected papers*, Vol.4. p.25-45.

Steeley J. M. (2001), 'Estimating time-varying risk premia in UK long term government bonds', Unpublished working Paper (University of Stirling).

Stehle R. (1992), 'The Size Effect in the German Stock Market', Unpublished working paper, (University of Augusburg).

Strong N., W.N.Liu and E. Lee (2003), 'Characteristics or covariance: UK evidence', Unpublished working paper, Manchester School of Accounting and Finance, *Revised Version*.

Strong N., W.N.Liu and E. Lee (2001), 'Characteristics or covariance: UK evidence', Unpublished working paper, Manchester School of Accounting and Finance.

Strong N., W.N.Liu and G.X.Xu (1999), 'The profitability of momentum investing', *Journal of Business Finance and Accounting*, Vol.26, p.1043–1091.

Strong N. and G.X.Xu (1997), 'Explaining the cross-section of UK expected stock returns', *British Accounting Review*, Vol.29, p.1-23.

Sundersanam P.S. (1981), 'Inter Industry differences in the accounting numbers of UK-quoted companies: A multivariate analysis', Unpublished Doctoral dissertation, (City University Business School).

Swamy P.A.V.B and J.S.Mehta (1975), 'On Bayesian estimation of seemingly unrelated regressions when some observations are missing', *Journal of Econometrics*, Vol.3, p.157-169.

Theil H. (1971), 'Principles of Econometrics', Wildey Publishers, New York.

Tinic S. and R. West (1984), 'Risk And return: January versus the rest of the year', *Journal of Financial Economics*, Vol.13, p.561-74.

Tinic S., G.Barone-Adesi and R.West (1987), 'Seasonality in Canadian stock prices: A test of the tax-loss-selling hypothesis', *Journal of Financial and Quantitative Analysis*, Vol.22, p.51-63.

Tobin J. (1958), 'Liquidity preference as a behaviour toward risk', *Review of Economics Studies*, Vol. 25, p.65-86.

Toms S. and I.Hussain (2002), 'Financial distress, single and multifactor tests and comparison of asset pricing anomalies: New evidence', Unpublished working Paper, (University of Nottingham).

Treynor J.L. (1961), 'Unpublished working paper on capital asset pricing'.

Trzcinka C. (1986), 'On the number of factors in the arbitrage pricing model', *Journal of Finance*, Vol.41, p.347-368.

Van den Bergh, Willem and R.Wessels (1983), 'Stock market seasonality and taxes: An examination of the tax-loss selling hypothesis', *Journal of Business Finance and Accounting*, Vol.12, p.515-530.

Vassalou M. (2002), 'News related to future GDP growth as a risk factor in equity returns', Unpublished working paper, (Columbia University), (Forthcoming in Journal of Financial Economics).

Vassalou M. and Y.Xing (2002), 'Default risk in equity premium', Unpublished working paper, (Columbia University).

Verbeek M. and T.Nijman (1995), 'Incomplete panels and selection bias', *In: Matyas L. and Sevestre P. (eds.),* The econometrics of panel data: handbook of theory with applications, (2nd ed), Kluwer, Dordrecht, Netherlands, p.449-90.

Wachtel B.S. (1942), 'Certain observations on seasonal movements in stock prices', *The Journal of Business of the University of Chicago*, Vol.15, p.184-193.

Wahlroos B., Willem and R. Wessels (1986), 'Risk, return and equilibrium returns in small stock market', *Journal of Business Research*, Vol.14, p.423-440.

White H. (2000), 'A reality check for data-snooping', *Econometrica*, Vol.68, p.1097-1026.

Yaansah R.A and K.V.Peasnell (1994), 'Expectations, security yields, and inflation: Ex-ante risk premia on UK shares, corporate bonds and gilts', *Journal of Business Finance and Accounting*, Vol.21, p. 155-74.

Zarowin P. (1990), 'Size, seasonality, and stock market overreaction', *Journal of Financial and Quantitative Analysis*, Vol.25, p.113-25.

Zellner A. (1962), 'An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias', *Journal of the American Statistical Association*, Vol.57, p.348-368.

Ziemba W. (1991), 'Japanese security market regularities, monthly, turn-of-the-month and year, holiday and golden week effects', *Japan and the World Economy*, Vol.3, p.119-146.

http://www.indexfunds.com/articles/19991201_famaint_iss_int_GF.htm.