A Re-examination of the Size and Value Effects in the UK: Evidence, Explanations and Implications for Style Rotation Strategies

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To my family

Declaration of Copyright

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Abstract

There is a lot of evidence in the academic literature that stock returns are predictable especially when various fundamental variables are used as predictors. Firm - specific variables, such as market value, book - to - price, cash flow - to - price, earnings yield or earnings growth have been extensively used either directly in static asset pricing models, as instruments in a conditional pricing framework, or as important factors in the construction of investment strategies. Whether the relationship between firm-specific variables reflects compensation for risk or some sort of market inefficiency is not yet clear. This thesis examines the characteristics and performance of various investment strategies constructed using fundamental variables, and investigate whether the difference in returns between portfolios can be attributed to differences in sensitivity to market industry and macroeconomic risk factors. Furthermore, market overreaction to past growth and analysts' earnings projections is examined as alternative explanation for existence of the value-growth premium.

The second part of the thesis focuses on the short-term return variability of portfolio strategies constructed using market value and book-to-price variables. The volatility of the size and value premiums suggests that a consistent bet to a certain investment philosophy or style might not be the ideal investment choice. The thesis explores the feasibility of style rotation strategies after taking account different levels of forecasting skill and transaction costs and tests out-of-sample a model that utilises mainly macroeconomic factors to predict the next months' size and value premium. Finally, the thesis analyse the volatility characteristics of style portfolios and proposes volatility specifications to predict future variances at different horizons.

Papers Published from the Thesis

- The Profitability of Style Rotation Strategies in the United Kingdom, with professor Mario Levis, *Journal of Portfolio Management*, Fall 1999.
- Investors' Expectations and the Performance of Contrarian Investment Strategies (The UK Evidence), with Professor Mario Levis, *City University Business School Working Paper*, December 1998.
- Time Varying Volatility in Time Series of UK Style Index Returns: Evidence and Forecasts using GARCH Models, with Professor Mario Levis, *City University Business School Working Paper*, May 1998.

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CHAPTER 1

"Introduction"

1.1 Introduction and Research Motivation

After the foundation of the notion of market efficiency and the development of equilibrium asset pricing models, such as the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT), a voluminous number of studies appeared to emphasise various irregular or anomalous patterns in common stock returns. A substantial number of variables or composite factors were compared with the CAPM beta and tested for their ability to explain the cross-section of stock returns. Furthermore, the profitability of numerous investment strategies, constructed on the basis of these fundamental variables, was assessed over time.

The findings of these studies point towards two major stock market anomalies; the size and value effect. Empirical research has shown that the market value of equity is an important characteristic of common stocks that is able to explain the cross-sectional variation of their returns, and strategies that invest in small capitalisation stocks earn significant abnormal returns in the long term. Similarly, valuation ratios, such as dividend, earnings and cash flow yield and more recently book-to-price have been found statistically and economically significant in cross-sectional and time series asset pricing applications.

Despite the fact that explanations for the existence of size and value effects have divided academics, almost all of them agree that significant profits can be earned by constructing investment strategies on the basis of these effects. Furthermore, a new asset pricing model, which includes a size and a value premium besides the market risk premium seems to be more effective compared to the CAPM, not just in the US, but in the majority of international capital markets as well (see Fama and French, 1996, 1998).

The early academic developments on this issue and the increasing need for specialisation in equity investment management have introduced the so called *investment style management*. The process of deciding on the best industrial sector at every point in time has gradually been enhanced by the selection of the most appropriate equity segment or investment "style". Investment styles represent families of stocks with unique characteristics that create underperformance or overperformance. Thus, it involves implicit links between equity characteristics and subsequent performance. Although a number of investment styles have been extensively used by the investment community, the most dominant and frequently used are four; value, growth, small-cap and large-cap investing.

Examining the four styles in more detail we observe that value managers usually search for stocks that sell below the worth of a company's assets, or below the value of its future growth prospects. According to Macedo (1995) the idea behind value investing is to buy assets that are cheap relative to some underlying value, such as the book value, earnings, or dividend stream. Bernstein (1995) argue that value managers are defined as low expectations managers because they tend to search for investments among stocks that are out of favour. It makes sense that, if a company is experiencing bad times, the market will often place a lower value on its current assets, or earnings to reflect the poorer future prospects of the firm. But, investors tend to be too pessimistic in such cases, sometimes failing to take into account the limited downside and greater potential for recovery. Thus, value investing can prove successful, whenever a market tends to be overly pessimistic about the prospects of low-rated companies.

The investment flip side of value is growth. Growth stock managers are defined as high-expectation managers, who prefer to search for investments among stocks that have a proven superior track record of earnings, or sales growth. Growth stock investors pay a high premium to hold such stocks, because the market realises the superior qualities of the company. Growth investing is usually considered as the opposite investment philosophy of value investing. Growth stocks are stocks with high ratios of price to fundamentals, high earnings growth and good future prospects. The growth investor is willing to pay a high price for some stocks, because he expects that earnings will grow fast enough in the future to more than justify the higher price. This style of investing should prove successful, if the particular manager's ability to assess the growth potential of a company is better, than that of the market in general.

The two other popular investment styles are associated with company size. A significant number of fund managers specialises in either small or large capitalisation stocks. Small stocks behave differently than large stocks because of structural differences between small and large companies and their securities. Rosenberg (1995) argues that small companies tend to be heavily dependent on a single product line in a single industry, and are thus more sensitive to changes in product demand and input prices. As a result, small stocks tend to have greater total volatility, specific volatility, and higher betas than large stocks. The relative neglect of small stocks also distinguishes them from large stocks. A fewer number of analysts follow small companies and less public information is available about them. Some small stocks are also thinly traded, which increases the chance of their being misspriced. Market value, however, is not the only variable that can be used to define small stocks. The size of sales or revenues, total assets, or number of employees can also be used, but most institutional investors prefer to use market capitalisation because it is a traditional proxy for a stock's trading liquidity.

The analysis of investment styles has other important applications, apart from use in active equity management. Interest in investment style is part of a growing need by consultants and investors to better understand manager performance and specialisation. Sharpe (1992), using a 12 asset class factor model, observed that the decision of how much to allocate to distinct styles (i.e. growth, value, large, small) may explain as much as 98% of the return performance of the diversified fund. He finds that on average, approximately 90% of a portfolio's return variability is explained by its exposure to the intra-asset classes or styles with the remaining 10% arising from individual stock selection. Therefore, he concludes that style analysis is the most important element in performance attribution.

The recent evidence on outperformance of large and growth stocks in the US and other markets has shed some light to another aspect of style investment. A number of academics and practitioners observed that, although in the long run small and value stocks outperform their counterparts, there have been many subperiods in which the opposite investment approach has been more rewarding. So, the market rewards styles at different times for different reasons. As a consequence, just as asset mix drift creates a need for active asset allocation, style drift creates a need for style management and becomes an important part of the portfolio manager's job. In other words, because style management (allocation) is recognised as the key driving force behind relative equity performance, plan sponsors and consultants need to reassess the practice of neutralising style in the equity class. For active-portfolio managers, switching or rotating among different style segments, may provide an excellent opportunity to enhance portfolio returns. If indeed style drives returns, as Sharpe suggests, then an active bet on a particular style can significantly improve portfolio returns.

Whether used for performance attribution or active and passive management, the analysis of equity investment styles has become a necessity among academics and financial practitioners. Despite being a relatively new research area, a number of important developments have taken place. However, various questions have been left unanswered and a few empirical results are still considered puzzling. This thesis re-examines the size and value effect in the UK and attempts to shed some light on various aspects of style investment.

1.2 Objectives and Contributions of the Thesis

The long term performance of size and value investment strategies have been researched extensively for a variety of capital markets and data frequencies. Almost all of the studies on the early 80's agree that strategies based on buying small or value stocks and short selling large or growth stocks earn statistically significant returns. However, recent evidence casts some doubt on the effectiveness of these strategies. This thesis re-examines the size and value effects in UK and the performance of strategies based on market value and various fundamental ratios, using a recent sample period and a methodology which allows segregation of one effect from the other.

As there is no accepted definition of value and growth investment style among academics and professionals, many different variables and techniques are employed to proxy value and growth stocks. In this thesis we use the book-to-price, earnings-to-price, cash flow-to-price, and historical earnings growth to define value and growth and construct relevant equity portfolios \ indices. Recording the performance of different size and value portfolios is not as important as understanding what drives that performance.

Even though there seems to be an agreement among academics on the outperformance of small-cap and value strategies, the origins of those historically observed return differentials are not yet clear. Some researches argue that differences in returns across investment styles are statistical aberrations. Data mining, selection bias and other data aberrations may be responsible for the reported return patterns. Therefore, they do not reflect differences in expected returns and are thus not likely to be repeated. Others, believe that style return differentials are risk premiums, or simply compensation for risk. This risk is reflected either on marker beta, or on the sensitivities of those stocks to macroeconomic factors, or on the behaviour of their earnings and cash flows. Another school of thought, rely on behavioural finance theories and market inefficiency to explain this phenomenon. Systematic errors in expectations about the future, resulting from either past extrapolation, analysts' forecasts errors, cognitive errors or insider trading, may explain the high returns earned by value stocks

The empirical contribution of the thesis is separated in two major parts. In the first part, we record the performance and characteristics of various size and value portfolios in UK and resolve the issue of whether it is risk differences or market overreaction that can explain their performance. One of the major objectives of the thesis is to evaluate and compare the risk characteristics of style portfolios and examine whether differences in sensitivities to risk factors can justify differences in returns. We examine whether the size and value premium remains (or becomes) significant after controlling for market, macroeconomic, or industry risk differences among portfolios.

Another objective of the thesis is to evaluate the validity of the overreaction hypothesis for explaining the difference in performance between value and growth stocks. According to existing research, the extreme expectations of investors about the future prospects of value and growth stocks make them overreact and underprice the former, whilst overpricing the latter. We examine two sources of overreaction; extrapolation of past earnings growth and price performance and reaction to analysts' earnings forecasts.

Existing literature attributes the difference in performance between value and growth portfolios to investors' extrapolation of earnings and cash flow growth. We re-examine this hypothesis using a new and much wider sample and investigate another aspect of extrapolation: past price performance. Using different definitions of value and growth, we look at how earnings growth and price performance is evolving around portfolio formation for all the different value and growth portfolios and investigate whether the earnings and returns of those portfolios display the relative reversion patterns predicted by the naïve extrapolation model. Moreover, we test whether investors are deluded by the previous record of value (growth) companies and underprice (overprice) them to an extend that can explain their subsequent return differential.

Some studies have also examined whether overreaction comes from analysts' earnings forecasts. We extend that literature by testing the relationship between earnings surprises and the performance of value and growth portfolios. Using a robust econometric methodology we assess the impact of positive and negative surprises to the returns of value and growth stocks.

The second part of the thesis focuses on the variability of size and value effects and emphasises the importance and effectiveness of style rotation strategies. Although, a lot of attention has been given to the magnitude of the size and value premiums (or the return spread between small - large and value - growth), very little research has been conducted towards monitoring and understanding the variability of these premiums across time. The volatility of size and value premiums suggest that even the most successful investment strategies sometimes experience extended underperformance. Therefore, just as the variability of the equity risk premium leads to tactical asset allocation and market timing, the variability of style premiums leads to tactical equity allocation or style rotation.

An objective of this thesis is to explore the efficacy of style rotation strategies and test the potential rewards and risks from switching between size portfolios and between value and growth stocks. Moreover, we investigate the sensitivity of these strategies' profitability to transaction costs, and the manager's level of forecasting skill using a number of simulation experiments. Our results contribute to the debate of active versus passive equity management, which is a major decision among managers, plan sponsors and trustees.

The accuracy of the manager's forecasts directly depend on the effectiveness of the forecasting model used. We test various forecasting models based mainly on market and economic variables, for the two style return spreads. Moreover, we implement these forecasting models to trading strategies and test their performance out-of-sample. Whereas, some research has been directed towards modelling and forecasting the returns of equity portfolios, to the best of our knowledge there is no study that attempts to forecast the direction (sign) of the style return spread. Identifying the factors that are important to predict which style will outperform next period and building style rotation strategies based on those predictions is another important innovation of this thesis.

Although the focus of style investment strategies is the modelling and forecasting of portfolio returns, some research has been conducted towards measuring and analysing the variance of those returns. Modelling and comparing the volatility of style portfolios can lead to a better understanding of asset pricing and more efficient construction of dynamic rotation strategies.

The final objective of this thesis is to analyse the volatility characteristics of the four most important style indices and develop a model that can forecast future volatility in different time horizons. An increasing amount of research deals with modelling and forecasting stock market volatility, specially after the development of GARCH models in the early 80's. This literature however, does not distinguish between different equity (style) portfolios, but usually uses the returns of an aggregate market index as the representative index. Testing whether some of the characteristics of conditional stock market volatility (high persistence, asymmetry, sensitivity to interest rates, etc.) can be generalised and applied to all equity indices is another contribution.

In summary, the main objectives of this thesis are the following:

1. Examine the fundamental characteristics and return performance of various size and value investment strategies in the UK using a recent sample, four different definitions of value and growth and a methodology which allows to disentangle one effect from the other (Chapter 6).

2. Investigate whether differences in returns between size and value portfolios can be explained by adjusting for differences in sensitivity to market, industry and macroeconomic risk factors (Chapter 6).

3. Test whether investors' extrapolation of past earnings growth and price performance cause misspricing in value and growth stocks, which justify the differences in their subsequent returns (Chapter 7).

4. Assess the impact of positive and negative analysts' earnings forecast errors to the one year holding period returns of different value and growth portfolios (Chapter 7).

5. Examine the consistency of size and value spreads over time and evaluate the opportunities for profit enhancement from monthly equity style rotation (Chapter 8).

6. Develop and test a style rotation model based on a set of market and economic variables, selected for their ability to predict the direction of the style spread in a given month (Chapter 8).

7. Model the conditional variance of small, large, value and growth style index returns using various symmetric and asymmetric GARCH models, and compare the properties of volatility of different style indices (Chapter 9).

8. Forecast the variance of style index returns for different investment horizons and implement these forecasts in style rotation using a quadratic minimum variance optimisation (Chapter 9).

The main theoretical and empirical issues associated with the above objectives, as well as the technical tools and methods used in order to achieve them, form the basis of all subsequent chapters and are briefly summarised in the following section.

1.3 Overview of the Thesis

This thesis is divided in two main parts. The first part (chapters 2-4) provides the theoretical framework and review of the main developments and applications in cross sectional and time series predictability of stock returns. The second part (chapters 5-9) presents the research design and the empirical findings and provide answers to the research questions addressed in the previous section.

Chapter 2, reviews the literature that documents a statistically and economically significant relation between common stock returns and various fundamental ratios, but more importantly scrutinises the theories that underpin these empirical findings. The chapter is divided into three parts. The first part focuses on the empirical evidence and explanations for the size effect. In the second part we review the studies that present a significant cross-sectional relationship between stock returns and earnings yield, cash flow yield and book-to-price. Furthermore, a lot of emphasis is given to the theories that explain this relationship. A number of risk-based explanations, consistent with rational pricing theory and market efficiency, are competing against behavioural-based explanations and irrational pricing theories. Finally, the studies that attribute the value effect to a number of research design biases, such as data snooping and survivorship bias are also presented. The final part of the chapter reviews the studies that consider the interaction between size and the value effects and examine which one is predominant in explaining the cross section of stock returns.

Chapter 3, presents the literature on the time - series predictability of returns and variances of common stocks. This chapter will set the necessary theoretical background for the construction of market timing and style rotation strategies, which is the subject of chapter 4 and one of the objectives of this thesis. The question of whether stock market returns are predictable at various time horizons is addressed by looking at previous returns, certain firm specific ratios, such as dividend yield, earnings yield and book-to-price, and various economic variables (interest rates, industrial production, inflation, etc.). The implications and explanation of this predictability are also emphasised. The rest of the chapter concentrates on modelling and forecasting the second moment of the distribution of stock returns. An evaluation and comparison of the most well known volatility forecasting techniques, with a particular emphasis on GARCH models, is presented in the second part of the chapter.

Chapter 4 is based on the conclusions of the two previous chapters, and reviews the studies, which examine whether predictability can be translated into profitable trading strategies. The chapter presents the literature on both tactical asset allocation and style rotation. The potential rewards and risks as well as the most important models and techniques that have been employed for both types of active strategies are reviewed.

The next chapter describes the data sample in detail and explains the procedure that is followed to organise the main dataset of the thesis. The sources from which each data item was collected are also described. Moreover, chapter 5 presents the methodology that is employed to construct portfolios or indices and reviews a number of alternative approaches. The advantages and drawbacks of each portfolio construction approach are outlined. Portfolios are formed on the basis of market value and one of book-to-price, earnings-to-price, cash flow-to-price and three years past earnings growth, using a variant of the Fama and French (1995) independent groups method. Finally, some preliminary characteristics for each of the resulting portfolios are outlined in the appendix at the end of the chapter.

Chapter 6, is the first and one of the central empirical chapters of the thesis, since it examines the size and value effects and tests whether differences in performance between equity style portfolios can be attributed to specific risk factors. A number of fundamental ratios are initially reported for each of the style portfolios and the aggregate style indices, in order to verify the definition of value and growth and understand the characteristics of different style investment strategies. The chapter also presents unconditional equal and value weighted returns for each portfolio for the entire period under study (July 1968 - June 1997) and three sub-periods.

The most important part of the chapter however is the second, where we test the conditional performance of different size and value portfolios. Using a pooled time series - cross section regression methodology with dummy variables that are adapted to classify returns along style dimensions, we estimate the statistical significance of style index returns. Furthermore, we adjust for various sources of risk and examine whether style return spreads remain significant after adjusting for market, industry and macroeconomic risk differences between portfolios. Using eleven broad industry groups, we identify the industrial composition of each style portfolio and investigate the sensitivity of relative style returns to industry factors. Moreover, we test whether there are important differences in the return sensitivities of size and value portfolios to five macroeconomic variables, using a Seemingly Unrelated Regression (SUR) estimation procedure, which corrects for cross-sectional dependence in the residuals of style index returns. Whether these differences are sufficient to explain the size and value effects, is another research question that we address.

Chapter 7, tests the overreaction hypothesis as another potential candidate for explaining the return differential between value and growth stocks. The purpose of this chapter is to examine two different versions of overreaction hypothesis; extrapolation and reaction to earnings surprises. We look at the returns and earnings per share of various value and growth portfolios for five years before and after portfolio formation. We test if the error in expectations hypothesis holds, by looking at whether value stocks were bad performers, with low earnings growth relative to growth stocks for several years before portfolio formation and whether these patterns are reversed after stocks are classified into portfolios. Furthermore, we use the portfolio approach suggested by LaPorta (1996) to test whether investors extrapolate past earnings growth and past price performance and if this extrapolation can justify the return differential between value and growth stocks.

Extrapolation however is not the only source of overreaction. Investors' overreaction may be reflected in analysts' earnings forecasts. The second part of chapter 7, focuses on earnings surprises, and evaluates their impact to the returns of value and growth portfolios, using I\B\E\S analysts' earnings forecast estimates from 1987 to 1997. If the error in expectations hypothesis is correct then positive surprises should have a significantly more positive impact to the returns of value compared to growth portfolios over the next year. Negative surprises, on the other hand, must suppress relatively more the returns of growth compared to value stocks. We test this asymmetric impact of positive and negative earnings surprises using a multivariate Generalised Method of Moments (GMM) regression framework.

After understanding what drives the performance of size and value portfolios, the next chapter explores the variation of the style premiums over time and introduces the idea of style rotation. Style rotation is implemented either by switching between small and large-cap stocks, or by independently switching between high and low book-to-price securities. We introduce the need for style rotation by examining the variability of the size and value style spreads using monthly, quarterly and semi-annually non-overlapping returns and calculating the number of periods when one style index performs better than the other by a specified amount. We then ask whether monthly equity style rotation should be preferable to a passive buy-and-hold strategy, by evaluating it's potential gains and losses after adjusting for transaction costs and assuming both perfect and a range of intermediate levels of forecasting skills. In this case, forecasting skill is synonymous to the hit ratio, or the percentage of months when someone predicts correctly which equity style will outperform. However, being generally accurate in style rotation is important, but not as important as being accurate at certain months. Therefore, a series of simulation experiments are conducted in order to identify the entire distribution of rotation profits for each different level of forecasting skill and evaluate the effect of forecasting skill to the profitability of style rotation.

In the second part of chapter 8, we test a number of market and macroeconomic variables for their ability to predict the direction of next month's style spread. Using a logit regression methodology, we estimate the probability that small-cap (value) stocks will outperform large (growth) for the next month, over a large out-of-sample period. Based on these probabilities, we develop three different trading rules and test their effectiveness compared to various passive benchmarks.

Chapter 9, which is the most technical chapter of the thesis, focuses on modelling and comparing the characteristics of volatility of style indices, using various GARCH specifications. After testing for the existence of conditional heteroskedasticity in time series of weekly style index returns, we implement an AR(2)-GARCH(1,1) model and test whether it can adequately describe conditional volatility. Furthermore, we investigate whether short term interest rates can affect the conditional volatility of equity portfolios by fitting a modified GARCH(1,1) model. Another question we address is whether style index volatility is asymmetric in the way it responds to positive and negative past unexpected events. We shed some light to this issue by employing the sign and size bias tests proposed by Engle and Ng (1993) and estimating a Threshold GARCH (TGARCH) and an Exponential GARCH (EGARCH) model for all four style indices.

The second part of chapter 9, concentrates on predicting the volatility movements of equity style indices. Using a large out-of-sample period and a rolling sample methodology, we compare the ability of various GARCH specifications against two simple models (Random Walk, Homoskedastic) to forecast future variance at different horizons. The forecasts are evaluated using ME, MAE, RMSE and by conducting a standard forecast efficiency test. Finally, the economic importance of these forecasts is emphasised. Value and growth volatility forecasts from different models are used into a quarterly minimum variance optimisation to suggest specific style allocations across time from 1983 to 1997. The average volatility and reward-to-variability ratio of the minimum variance portfolio are then compared for each different forecasting model.

The last chapter summarises the empirical findings from the thesis and draws the main conclusions. Some implications and generalisations from our results are also offered. Finally, the limitations of this study are emphasised and some suggestions for further empirical research are provided.

CHAPTER 2

THEORETICAL BACKGROUND I

"*Cross Sectional Predictability of Stock Returns - The Size and Value Effects*"

2.1 Introduction

In recent years, tests of various asset pricing models have uncovered a variety of anomalies or irregularities in the data. Two of the most popular anomalies that have attracted considerable attention among academics and practitioners are the size and value effects. Empirical research in finance has shown that strategies that buy stocks with low market value, or stocks with high book-to-price, earnings yield, or cash-flow yield can be rewarding in the long term.

The abnormal returns that are generated from these strategies have been interpreted by many market observers as evidence of market inefficiency or failure of the standard Capital Asset Pricing Model (CAPM) to explain the cross section of stock returns. In an efficient market, according to Fama (1965), information is widely and cheaply available to investors and all relevant and ascertainable information is already reflected in security prices. Under this regime, no particular market operation can earn abnormal profits without bearing high risk.

In an efficient market, price changes are random. Because information arrives randomly, changes in prices that occur as a consequence of that information will appear to be random. In other words, the condition for the existence of market efficiency is that the expected value of excess returns equals zero. Therefore, the actual asset returns fluctuate randomly about the expected equilibrium return. Testing this proposition is equivalent to examining whether investors set the actual return to its equilibrium value efficiently. Hence, market efficiency and equilibrium pricing issues are inseparable. The study of the efficient market hypothesis involves joint tests of equilibrium price determination and efficiency.

Market efficiency *per se* is not testable. It must be tested jointly with some model of equilibrium; an asset pricing model. In other words, we can only test whether information is properly reflected in prices, in the context of a pricing model that defines the meaning of "properly." As a result, it is very difficult to distinguish and attribute anomalous evidence to either market inefficiency or a bad model.

There are two possible explanations for the presence of those anomalies and the failure of the CAPM to detect them and explain the cross section of stock returns. According to the first, those variables measure the riskness of stocks and the correlation between the variables and returns reflect compensation for bearing risk. A correctly specified asset pricing model should be able to explain these anomalies. Misspecifications of the model can be attributed to omitted risk factors, or due to the failure to account for the stochastic behaviour of betas and the risk premium. According to another approach, these variables help identify stocks that are misspriced due to systematic misjudgements of investors.

This chapter presents the literature that documents the existence of those effects, but more interestingly, scrutinises the theories that underpin these empirical findings. Various rational and irrational pricing theories are presented as possible candidates for explaining the size and value effects. Some academics believe that small-cap and value stocks perform better simply because they carry higher risk compared to large-cap and growth stocks. This risk is either reflected on market beta, or on the sensitivities of those stocks to macroeconomic or various other risk factors, or on the behaviour of their earnings and dividends. Another school of thought relies on behavioural finance and irrational pricing theories to explain this phenomenon. Systematic errors in expectations about the future resulting from either past extrapolation, analysts' earnings forecasts, insider trading or various cognitive errors, may explain the high returns earned by value stocks.

2.2 Size effect: Evidence and Explanations

2.2.1 Empirical Evidence

The relationship between returns and the market value of common equity has received a lot of attention in the finance literature. Banz and Reinganum, were the first to document this "anomaly". Banz (1981), estimates for the period 1931 to 1975 a model of the form:

$$E(R_i) = \alpha_0 + \alpha_1 \beta_i + \alpha_2 S_i ,$$

where β_i is the CAPM beta and S_i is a measure of the relative market capitalisation for firm i. He finds a strong negative relationship between returns and the market value of equity, much stronger than the relationship between returns and beta. Reinganum (1981), using daily data over the period from 1963 to 1977, shows that portfolios of small firms have significantly higher average returns than large firms. He reports an annual difference in returns, between the smallest and largest portfolio of about 30%.

Basu (1983), re-examining Reinganum's results, using a different sample period and a different procedure for creating portfolios, finds that returns to stocks of firms with low market value are riskier than the stocks of large firms. Keim (1983), confirms the previous findings, but reports a significant January seasonality, associated with the size effect. He shows that approximately 50% of the return difference between small and large firm stocks, found by Reinganum (1981), is concentrated in January. Keim further reports that 50% of this January effect is concentrated in the first five trading days of the year. This turn-of-the-year return behaviour is also documented by Roll (1983), who notes that, in addition, small firms have abnormally large returns on the last trading day in December. Roll attribute this phenomenon to the year-end tax-loss selling pressure. According to the tax-loss selling hypothesis, there is a downward pressure in the prices of those stocks which have declined during the year, as investors attempt to realise their losses against their taxable income. As soon as the tax and calendar year ends, the selling pressure disappears and the stock prices quickly rebound to their "equilibrium" levels.

Recent evidence however, shows a disappearing, or even reversal of the size effect for US and other international markets. Ragsdale, Rao and Fochtman (1993) defined small-caps as the smallest-capitalisation quintile of all stock with data available in the Compustat database and compared their return to the returns of the S&P500 from 1973 to 1992. Although small-caps were on average more profitable than large-caps, the authors document a pronounced underperformance of small stocks relative to large, from mid-1983 to the end of 1990.

Following the discovery of a size premium in US equity markets, numerous studies have documented its existence in UK and other international capital markets. Levis (1985) and Corhay, Hawawini and Michel (1988) examine the performance of size strategies in the UK market. The first study documents an average 6.5% annual premium for smaller firms over the period January 1958 to December 1982. The premium, though not stable over time, has been evident more strongly during the late sixties and throughout the seventies, with the exception of 1975. In addition, Levis observes that the relatively higher returns of small firms can not be justified by higher risk in the context of CAPM.

The second study of Corhay, Hawawini and Michel examines the size effect in the UK market from 1955 to 1983. Using Fama-MacBeth (1973) regressions, they find that the relationship between average portfolio returns and the logarithm of market capitalisation over the twenty sever year period is negative (indicating that small firms on average outperformed large firms), but not statistically significant. They observe that the size effect is a seasonal phenomenon and May is the only month of the year for which there is significant relationship between average returns and size. The relationship is negative, indicating that most of the small size premium is earned during the month of May.

Dimson and Marsh (1987) presented results using a broad value - weighted small companies index which covers the smallest tenth, by equity capitalisation, of the UK market (Hoare Govett Smaller Companies - HGSC) and a companion index the Hoare Govett 1000 (HG1000) which includes the 1000 companies with the lowest market value. The HGSC index shows a size premium of 6.3% over the FTALL Share for the period 1955 to 1988, but it documents a dramatic reversal of small companies' performance in recent years. Two recent review papers by Levis (1999) and Dimson and Marsh (1999) provide evidence on the reversal of the size effect, although they attribute it to different reasons. The FTALL Share outperformed the HGSC and the HG1000 by 6% and 9% respectively, over the period 1989 - 1997.

Similar patterns in the performance of size portfolios have been identified for the Australian, Canadian, Japanese and several European markets. Hawawini and Keim (1995), in a comprehensive review of the size effect world -wide, point out that it is positive in all countries under study for long periods before 1989. A more recent study of European equity markets however, by Levis and Steliaros (1999), documents a reversal in the performance of small versus large companies for the majority of the markets examined.

2.2.2 Explanations

A variety of explanations have been offered for Banz's (1981) finding that the average risk-adjusted returns for small firms are higher than for large firms.

a. Risk Factors

Asset Pricing theories (such as CAPM or APT) suggest that one possible explanation of why the observed average returns are different for two classes of securities is their risk characteristics and consequently their response to risk factors. Jegadeesh (1992) and Berk (1995) found that market risk, as expressed by beta cannot explain the size effect but there may be alternative risk factors that are responsible for it. Jegadeesh argues that, while it is possible for the size effect to be a statistical artefact, attributable to measurement errors in betas, like Chan and Chen (1988) and Handa, Kothari and Wasley (1989) claim, it is also possible that the explanations for the size effect in the above papers are spurious. The results in the Jegadeesh paper indicate that the size effect cannot be explained by betas and a search for risk based explanations should consider the effects of non-market risk factors. Berk (1995) has shown that, far from being either an anomaly or a proxy for some more basic underlying risk, size measured by equity market value necessarily reflects the risks priced in the equity returns, whatever their source. Hawawini and Keim (1999) provide evidence from other equity markets outside the US, which confirms that the higher market beta of small firms cannot explain the size premium; the risk adjusted risk premium remains significantly different from zero.

Chan, Chen and Hsieh (1985) examine whether the size effect can be attributed to other factors apart from market risk, using the Chen, Roll and Ross framework, and taking into account a number of macroeconomic variables. Twenty portfolios, with roughly equal number of securities, are formed according to firm size and their returns are regressed cross-sectionally, using a variant of the Fama Mac Beth (1973) procedure, on betas of six variables: an equally weighted market index (EWNY), the seasonally adjusted monthly growth rate of industrial production (IPISA), the change in expected inflation (DEI), unexpected inflation (UITB), a measure of the changing risk premium (PREM) and a measure of the change in the slope of the yield curve (UTS). The exact model that they used is:

$$R_i = \lambda_0 + \lambda_1\beta_{i\,(EWNY)} + \lambda_2\beta_{i\,(IPISA)} + \lambda_3\beta_{i\,(DEI)} + \lambda_4\beta_{i\,(UITB)} + \lambda_5\beta_{i\,(PREM)} + \lambda_6\beta_{i\,(UTS)} + \varepsilon_i$$

The basic conclusion is that, the higher returns of smaller firms are compensations for higher risks, and the variable most responsible for explaining the difference in returns between small and large size firms is the sensitivity of asset returns to the changing risk premium. The inability of market betas to capture these risks led to the multifactor framework, which can explain most of the size effect. The economic reasoning linking the changing risk premium to the size effect is quite straightforward. During economic expansions and contractions, both the aggregate risk premium and the cash flows of many firms fluctuate. Since small firms tend to be marginal firms, they fluctuate more with business cycles and thus have higher risk exposure to the changing aggregate risk premium. By using an additional variable to measure business expansions and contractions, they found that smaller firms are riskier because they suffer a disproportionately higher bankruptcy rate[1] during economic contractions. When this risk exposure is priced in an equilibrium asset pricing model, small firms would have higher expected returns than large firms to compensate investors for this additional dimension of risk beyond the market factor risk.

A number of other studies provide alternative explanations. Chan and Chen (1991) attributed the size effect to a distress factor in average returns. They characterise small firms as marginal firms in the sense that their prices tend to be

[1] Queen and Roll (1987) found a strong negative relationship between unfavourable mortality and size. Their evidence shows that about 25% of the smallest firms are halted, delisted or suspended from trading within a decade, and about 5% actually meet this fate within one year. On the other hand, firms in the largest-size decile are mush more likely to be around for a long time. Only about 1% expire in the fist year, and about 80% survive for more than 20 years.

more sensitive to changes in the economy and they are less likely to survive adverse economic conditions. In addition they showed that small firms tend to be firms that have not been performing well, they have lost market value because of poor performance, they are inefficient producers, and they are likely to have high financial leverage and cash flow problems. For all these reasons, small firms tend to be riskier than large firms, and the risk of the smaller firms is not likely to be captured by a market index heavily weighted toward large firms. Therefore, they suggest two additional factors. The first one intends to capture the return behaviour of firms in distress, as inferred from recent dividend payout reductions, while the other represents the return differences between a portfolio of high leverage firms and a portfolio of low leverage firms. Their results indicate that these two factors are responsible for the return differences between small and large firms.

Finally He and Ng (1994), examine whether size and BM are proxies for risks associated with the Chen, Roll and Ross (1985) macro-economic factors, or measures of a stock's sensitivity to relative distress. Using a multifactor pricing model they find that the βs on the term and default factors are subsumed by size, but not by BM. Instead they found that size, BM and relative distress are related.

Another ex-ante measure of risk that has been examined is the quality rankings for stocks provided by Standard and Poor. Friend and Lang (1988) test whether quality rankings can be used to explain the variation in stock returns among different size groups. The authors find that when quality ranking is used as the appropriate risk measure, the anomalous size effect largely disappears. Moreover, the size effect seems attributable to the difference in January returns, between small and large firms, and this difference in turn can be explained almost completely by the subjective quality measure of risk.

The sensitivity of different UK market value portfolios to macro-economic risk factors has been examined by Levis (1995). He uses a conditional APT model for the period 1970-1991, in an attempt to account for the differences in risk characteristics between size portfolios. The standard Fama MacBeth methodology (1973) is employed to examine the sensitivity of 20 size portfolios to five macro-economic factors; an equally weighted market index, the monthly growth in industrial production, changes in expected inflation, changes in the yield difference between long corporate bonds and long government Gilts and changes in the yield difference between 20 year Gilts and 3 month treasury bills. The study points out that larger firms are more sensitive to unexpected changes in industrial production, unexpected inflation and default premium than their smaller counterparts. On the other hand, there is little variation in the beta coefficients for changes in term structure across different size portfolios.

b. Risk and Return Missestimation

A number of researchers have put forward the argument that the size effect was observed because either average returns or market betas and consequently abnormal returns were measured imprecisely.

Roll (1983) demonstrates that the computed average returns of small firm portfolios decline as the length of the interval for rebalancing the portfolio increases, and stabilise when the interval length is a month or longer. Blume and Stambaugh (1983) show that the returns computed over short rebalance intervals may be upwards biased due the bid-ask effect, especially for small firm portfolios. Since, the return of a buy-and-hold strategy is best mimicked by the return computed using a rebalance interval of at least one month, returns computed using shorter rebalance intervals may overstate the difference between small and large firms.

Roll (1981) was one of the first researchers who argued that, the size effect may be a statistical artefact of improperly measured risk, due to the infrequent trading of small stocks[2]. Reinganum (1981), however, estimating betas according to methods designed to account for thin trading (Scholes and Williams, 1977; Dimson, 1979[3]), found that the magnitude of the size effect is not very sensitive to the use of these estimates.

[2] Keim (1989) found that on average 27% of the firms in the smallest decile do not trade on the first trading of the year. By the second day, 12% of these firms have still not traded, and by the end of the fourth day 3% of the smallest firms have yet to trade. For the larger firms, the level of non trading is minimal and the author found no apparent patterns in the data

[3] Dimson (1979) suggested a method of estimating betas and consequently abnormal returns, taking into account infrequent trading of securities. According to the Aggregated Coefficients (AC) method, an unbiased estimator for beta would be the sum of the slope coefficients in a regression of security returns on lagged matching and leading market returns.

Chan and Chen (1988), on the other hand, argue that the size effect can be observed only in the case where they use five years of data to estimate betas, in the Fama Mac Beth (1973) cross sectional regressions. They show that the explanatory power of the firm-size variables disappears, when data from a longer period of time are used to estimate β's. They conclude, therefore, that the observed size effect is at least due to the imprecision with which betas were estimated in the past.

Handa, Kothari and Wasley (1989) and Kothari, Shanken and Sloan (1995) claim that abnormal returns to portfolios ranked by firm size are sensitive to the return measurement interval (daily, monthly, or longer) used to estimate systematic risk. Their analysis is motivated by the statistical observation that for any asset, it's covariance with the market return and the market return's variance may not change proportionately, as the return interval changes. Specifically, the beta of assets riskier than the market increases with return interval, whereas betas for assets less risky than the market decreases with the return interval. Thus, for longer return intervals, the spread between high and low risk securities will increase. Using this argument they show that the spread in systematic risk between extreme firm size portfolios increases, and consequently, small firms do not continue to earn superior abnormal returns.

There are at least three reasons that led those academics to re-examine the risk-return relation using longer-interval returns. First, the CAPM does not provide explicit guidance on the choice of horizon in assessing whether beta explains cross-sectional variation in average returns. Inferences from cross-sectional regressions of average returns on beta can be sensitive to the return measurement interval because true betas themselves vary systematically and non-linearly with the length of the interval used to measure returns. Second, beta estimates are biased due to trading friction and non-synchronous trading or other phenomena that induce systematic cross-temporal covariances in short-interval returns. These biases are reduced when longer interval returns are used. Third, using annual returns is one way of overcoming the statistical complications that arise from seasonality in returns.

Roll (1981) shows that performance mismeasurement arises when the selected surrogate market portfolio, or benchmark, is not ex ante mean variance efficient. Banz (1981) and Reinganum (1983) have acknowledged that their findings could be due to benchmark error. Banz, however, uses several different alternatives for the market portfolio and finds that the size effect is robust in every case. Booth and Smith (1985) used an errors-in-variables method and demonstrated that the size effect is robust over the feasible range of true coefficients. Therefore, they conclude that the small-firm effect cannot be explained by measurement errors caused by benchmark error, or infrequent trading.

Another source of possible miss-estimation is documented by Ball and Kothari (1989), who argue that the use of time varying risk parameters greatly diminishes the profitability of strategies that select stocks on the basis of firm size. They report that, returns in the five years post-ranking period decline almost monotonically with firm size, which is consistent with previous evidence that firm size is a good proxy for expected return or systematic risk. Total returns in the ranking period are an approximate parabolic function of size, being a mixture of two processes: the decreasing relation between expected return and size at the start of the ranking period and the increasing relation between ex post returns (during the ranking period) and size (at the end of the ranking period). The market betas change slightly from the ranking to the post-ranking period, with small stock portfolios increasing in risk and large stock portfolios decreasing.

A time varying risk model is also used by Bhardwaj and Brooks (1993). The authors document statistically significant differences in both systematic risk and abnormal returns of firm-size-based portfolios in recessions and expansions. Systematic risk of small firm stocks is larger in bull than in bear months, whereas large firm stocks have higher risk in bear than bull months. They suggest that earlier reported performance of small firm (large firm) stocks may have been overstated (understated) because of an implied assumption of constant risk in bull and bear periods. When this assumption is relaxed small-cap stocks actually underperform large-cap stocks and the size effect is reversed. Ferson, Kandel and Stambaugh (1987) examine the weekly returns on ten portfolios of NYSE and AMEX securities ranked by market value over the 1963-1982 period. They find that an asset pricing model with both time varying betas and risk premiums is capable to explain the return differences across size ranked portfolios

Foerster and Porter (1992) suggest an alternative approach to adjust for differences in risk between small and large stocks and properly measure the size effect. They use dual class shares to form two market value portfolios, each containing the same firms. Although the significance levels decrease substantially, size and January effects in similar magnitudes to previous studies are found. When, however, only dual class shares having equal dividend and liquidation treatment are examined and when returns are calculated using the mean of the closing bid and ask, the size effect disappears. Their findings imply that the size effect may result from unequal comparison of total risk, where total risk includes both market-wide and trading related risk factors.

c. Transaction Costs

Blume and Stambaugh (1983), Stoll and Whaley (1983) and Schultz (1983), were the first to examine the magnitude of transaction costs for firms in different size categories. They observe that, small firms' stocks tend to have lower prices and higher bid-ask spreads, so transaction costs are relatively high for these stocks. Stoll and Whaley (1983) using monthly returns of New York Stock Exchange listed stocks from 1960 to 1979, estimate risk-adjusted returns to the small firm portfolio, net of transaction costs, and find that a round trip transaction every three months is sufficient to eliminate the size effect. Adding together estimates of the bid-ask spread and the commission rate, round trip transaction costs average 6.8% for the smallest decile and 2.7% for the largest decile of firms.

Similar conclusions are drawn from the more recent studies of Keim (1989), Bhagat (1993) and Knez and Ready (1996). Keim (1989) reports that small firms have, on average, eleven times the percentage spread of large firms. Bhagat (1993) estimates that the total round - trip trading costs can range from 200 to 300 basis points under normal implementation conditions and could even be higher in the case of unfavourable market impact or opportunity costs. The author concludes that with an annual turnover of 150%, the performance barrier to simply break-even with the passive benchmark would be as high as 300 to 450 basis points.

Blume and Stambaugh (1983) observe that studies using daily returns tend to overstate the small-firm effect because of the bid-ask effect. Amihud and Mendelson (1986) argue that investors demand compensation for illiquidity and that that size effect proxies for an illiquidity premium. They find that stock returns are positively correlated with the bid-ask spread, which is used as a measure of market thinness, and that the effect of firm size was negligible after controlling for liquidity.

On the contrary, Schultz (1983) concludes that transaction costs cannot explain the high average returns to small stocks. Examining daily returns of New York and American Stock Exchange stocks from 1963 though 1979, he finds that for holding periods of one year, the small firm portfolio earns 31% average risk adjusted returns net of transaction costs. On the same line is a study by Sinquefield (1991), who argues that although trading costs in managing small-caps portfolios can undermine their performance, small company portfolio management strategies can overcome completely the obstacle of trading costs.

The implication, however, of the difference in transaction costs to the observed average returns of small and large firms is difficult to determine. For investors, who simply want to buy and hold small stocks and do not require immediacy in executing the orders, the effective bid-ask spread is probably different from the quoted bid-ask spread. Differential transaction costs will probably induce a clientele effect: investment that is anticipated to turn over frequently is more likely to be placed with low transaction cost assets. Thus, the implication for the observed average returns cannot be fully assessed without knowing the market equilibrium induced by differential transaction costs.

d. Other Explanations

One of the central factors that contributed to small-stock relative market performance is dividend and earnings growth. Dimson and Marsh (1999) concentrate on the relative dividends and dividend growth of HGSC compared to non-HGSC companies and rely on the simple Gordon constant growth model to explain the return differences over time between the two indices. They find that both in the UK and the US market the size premium over certain periods of time can be explained by the difference in the dividend levels and growth rates between the small and large-cap indices. Specifically, they show that the small-cap premium of 5.7%, over the 1955-1988 period, is supported by a difference in dividend levels of 3.6% and a difference in dividend growth of 1.9%. They also observe that for the period 1989-1997 dividends and growth for small companies were 1.4% and 3.4% lower than for large companies respectively. On the basis of this evidence they conclude that the size premium is mainly driven by dividends.

Ragsdale, Rao, and Fochtman (1993) argue that the most crucial factor driving the small stock relative performance is earnings growth, whether measured by pre-tax income or net income. They show that in the period 1975-1981, when small-caps clearly outperformed their counterparts in US, their aggregate net income grew at a compound annual rate of 18.5%, while that of the largest capitalisation quintile grew at only 9.1%. During the 1984-1990 period of small-cap underperformance the smallest stocks reported a negative aggregate net income for the period, while the largest quintile reported a positive aggregate net income and grew 4.3% on a compound annual basis. Similar supporting evidence on the ability of earnings growth to explain the size return differentials in UK is offered by Levis (1999).

The difference in performance of small firms may be perceived as being linked to the performance of certain industries. The argument is based on the fact that small and large firms are not evenly distributed across all industrial sectors. Dimson and Marsh (1999) support this argument and document that the HGSC and All Share indices have very different sector weightings for a number of important sectors. The HGSC is severely under-represented in sectors such as retail banks, integrated oil companies, pharmaceuticals and utilities, while it is over-represented in closed-end funds, support services, real estate and construction. These differences show clearly that a bet on smaller companies is also a bet on relative sector performance. The authors estimated the returns that would have been achieved on the All Share Index had each industrial sector been held in its HGSC weighting rather than its All Share return for the sample period 1989 to 1997. Their results show that sector weightings can explain a sizeable portion of smaller companies' poor relative performance over the last decade in UK.

Small companies stocks are generally regarded less efficient, because there are fewer analysts paying attention to them. Kellogg (1993) shows that less than five analysts on average research the stocks in the smallest quintile while more than 20 analysts on average are following large companies. Arbel and Strebel (1983) are the first to suggest that the relative neglect of smaller companies makes them problematic as portfolio holdings, thereby depressing price and enhancing expected returns.

Investors in small and neglected firms[4] face both higher monitoring costs and a greater likelihood of larger wealth transfers to managers and insiders than do investors in well-followed firms. Therefore, the neglected stocks would have to earn a sufficient return premium to cover their higher monitoring costs and expected losses from unanticipated wealth transfers. Bhardwaj and Brooks (1992) provide convincing evidence that the size effect disappears after controlling for the neglect effect.

[4] The number of analysts following a firm's stock is the most commonly used proxy measure of degree of neglect.

2.3 Value / Growth effect: Evidence and Explanations

2.3.1 Introduction

One other stock market anomaly, that has received a lot of attention, is the impressive performance of value strategies. These strategies call for buying stocks with low prices relative to value measures such as earnings, cash flows, book values or dividends. Several recent studies have documented that strategies based on those variables produce superior returns. Some of these are Basu (1977), Ball (1978), Chan, Hamao and Lakoniskok (1991), Rosenberg, Reid and Lanstein (1985), Fama and French (1992, 1995), Lakoniskok, Shleifer and Vishny (1994), etc.

Jacobs and Levy (1988), summarising the importance of those equity attributes, note that there are several reasons why they might be related to subsequent returns. First, they have long been recognised as important determinants of investment risk. Attributes associated with greater riskness should command higher expected returns. Consider the Dividend Discount Model, according to which the value of a security equals the present value of all future dividends D, discounted at a rate r, as follows:

$$P = \frac{D_1}{1+r} + \frac{D_2}{(1+r)^2} + \frac{D_3}{(1+r)^3} + \ldots\ldots\ldots\ldots\ldots + \frac{D_n}{(1+r)^n}$$

If dividends are assumed to grow at a constant rate, g, the previous formula reduces to:

$$P = \frac{D_1}{r-g}$$

Assuming the denominator (r-g) is the same for all firms, value is just a constant multiple of dividends. In this simplified world, high yielding stocks sell below fair value, while low-yielding stocks are overpriced. Modigliani and Miller (1961) demonstrated the equivalence of discounting dividends, earnings or cash flow. Thus, valuation models can be defined in terms of alternative accounting measures.

Second, the effects of macroeconomic forces may differ across firms, depending on the form of equity attributes. For instance, change in inflation affect growth stocks differently from utility stocks. Finally, like the overall market, equity attributes may be misspriced. Misspricing may be the result of investors overreaction or underreaction to dividends, earnings or other financial information, or it may be, just as fads in the stock market, psychological motivated, hence mean reverting overtime.

In this section we review all the recent studies that document a significant cross-sectional relation between stock returns and fundamentals, but more importantly we give more emphasis to the theories that explain this phenomenon.

2.3.2 Empirical Evidence

Basu (1977) introduced the notion that P/E ratios may explain violations of the CAPM and found that for his sample of NYSE firms, there is a significant negative relation between P/E ratios and risk adjusted average returns. If one had followed the strategy, of buying the quintile of lowest P/E stocks and selling short the quintile of highest P/E stocks, the average annual abnormal return, before commissions and other transaction costs would had been 6.75%. Ball (1978), as well, argues that earnings related variables, like P/E, are proxies for expected returns and that portfolios of stocks with low P/E ratios outperform portfolios of stocks with high P/E ratios. He argues that P/E is a proxy for omitted factors in asset pricing models. Thus, if two stocks have the same current earnings but different risks, the riskier stock has a higher expected return, and it is likely to have a lower price and consequently lower P/E. P/E is then a general proxy for risk and expected returns. A number of other studies examine the profitability of P/E strategy and relate it with the size or January effect [Reinganum (1981), Basu (1983), Cook and Rozeff (1984), Banz and Breen (1986), Jaffe, Keim and Westerfield (1989), etc.][5].

An alternative of the P/E ratio is the ratio of the cash flow to price, where cash flow is usually defined as reported accounting earnings plus depreciation. Accounting earnings may be misleading and biased estimate of the economic earnings, but cash flow per share is less maniputable and, therefore, possibly a less biased estimate of economically important flows accruing to the firm's shareholders. This distinction between reported earnings and cash flow is important when examining these effects across countries with different standards regarding the reporting of earnings, like Japan and U.S. for example.

[5] For detail discussion of these studies see the section " Interaction between size and value effects"

One of the few studies in that direction is the work of Chan, Hamao and Lakoniskok (1991), who investigate the cross-sectional relationship between returns on Japanese stocks and four fundamental variables: earnings yield, size, book-to-market ratio and cash flow yield from January 1971 to December 1988. They conclude that out of the four variables, the book-to-market ratio and cash flow yield have the most significant impact on expected returns. In addition, the weakest variable of all appears to be the E/P. Although, it seems that a strategy of holding stocks with high E/P would outperform a strategy of holding low E/P stocks, the variable loses it's significance when the book-to-market is added to the model. Hawawini and Keim (1999) report an average monthly return difference between the highest and the lowest CF/P portfolio of 0.89% and between the two extreme E/P portfolios of 0.72%, which is translated to an average annual difference between the two effects of about 2.0%.

Finally, the variable that has attracted most of the attention in the last years is the price-to-book value. There are many academic papers that document a significant negative relation between stock returns and P/B. Rosenberg, Reid and Lanstein (1985) formulate and test a strategy that tilts towards high book-to-price stocks, while keeping a neutral exposure on every other fundamental variable and every industry. They find that this strategy achieves highly significant and consistent results and interpret that as an evidence of market inefficiency.

The most revolutionary of all papers, however, is the work of Fama and French (1992) who find that for the 1963-1990 period, size and book-to-market equity capture the cross-sectional variation in average stock. They also find that the single factor CAPM fails to explain any of the cross sectional average return difference, once size, or book-to-market is taken into account. Furthermore, their result show that, if anything the ratio of book-to-market value plays a larger role than size in explaining equity returns. A strategy that tilts towards stocks with high B/M ratio is associated with higher abnormal returns compared to a strategy that tilts towards low B/M stocks.

Their findings confirm what for many years, scholars and investment professionals argued, that value strategies outperform in the long run. Lakonishok, Shleifer and Vishny (1994) look at value portfolio strategies based on B/M among other ratios, and focus on long horizon returns (5 years buy and hold returns). Using a sample of NYSE and AMEX firms from 1963 to 1990, they find an average annual return difference of 10.5% between high B/M (value) and low B/M (growth) stocks. They argue, however, that B/M may not be the most appropriate proxy for value stocks. B/M ratio is possible to capture factors other than the difference between value and growth stocks alone. For example a low B/M ratio may describe a company with many intangible assets (e.g. research and development) which are not reflected in the book value. It can also characterise a company whose risk is low and which has therefore future cash flows which are discounted at low rate.

Moreover the authors test two other variables that proxy for the expected growth of firms; the cash flow-to-price and earnings-to-price[6]. They find that value strategies that are based on these ratios, or on the interaction of these ratios with past performance, as expressed by the past sales growth, are more effective and produce higher returns, than more ad hoc strategies such as that based exclusively on the B/M ratio. More specifically, value strategies, in which firms are independently classified into three subgroups according to each of the two fundamental variables, produce returns on the order of 10 to 11 percent per year higher than those on similarly constructed growth strategies over the 1968 to 1990 period.

Performance differentials between value and growth stocks are not exclusive characteristics of the US market. A considerable amount of research in this area has been done for a number of developed and emerging equity markets. Levis (1989, 1995), using a variety of portfolio formation procedures, examined several stock market irregularities in the London Stock Exchange from April 1965 to March 1985. He found that, investment strategies based on P/E, dividend yield and share prices appear to be at least as profitable, if not more as strategies based on market value.

Another study that has investigated the cross-sectional predictability of UK stock returns using firm specific variables is the work of Miles and Timmermann (1996). In their paper, they analyse the predictability of annual stock returns for a large panel of non-financial companies, over the period 1977-1989. Using a number of different model specifications, they find that the coefficients on the lagged value of

[6] According to Gordon's dividend discount formula, holding discount rates and payout constant, a high cash flow-to-price firm has a low expected growth rate of cash flow and similarly for the ratio of earnings-to-price.

the logarithm of book-to-market ratio and the logarithm of the company size are highly significant, whatever estimation method was used. Confirming the US evidence, they find a positive coefficient for the book-to-market and a negative for the size variable. Extended the list of explanatory variables to include measures of debt gearing, price-earnings ratio and dividend yield they conclude that company size, book-to-market and the dividend yield contain information about future stock returns of UK companies.

Moreover they argue that, even after controlling for beta, the three company variables remain significant. In addition, they report no strong relation between the change in measured betas and changes in company characteristics. The only factor, which appears to be significantly correlated with changes in beta, is the change in company size; companies who have grown most tend to have rising betas. This result is inconsistent with the argument that earlier evidence of predictability in stock returns could be attributed to changing betas since a negative link between size and expected returns have consistently been found. Lastly they conclude that risk depends on book-to-market value, size and to lesser extent on past dividend yields.

Strong and Xu (1997) in a recent paper applied the Fama and French methodology to UK data, in order to examine whether beta, size, book-to-market, leverage and E/P ratio explain the cross section of stock returns over the period 1955-1992. The basic findings of their paper can be summarised from the following: market value dominates β in explaining average returns throughout the 1955-1992 period, but becomes insignificant when book-to-market equity or leverage are included over the 1973-1992 period. The only variables consistently significant in explaining the cross section of UK expected stock returns are book-to-market equity and leverage.

A few papers, test the performance of size and value strategies in an international context. Brouwer, Van Der Put and Veld (1995) examine the profitability of value strategies based on E/P, cash-flow-to-price, and book-to-market, for four European countries. They find an outperformance for all strategies. This outperformance is especially remarkable for the cash-flow-to-price ratio, which amounts to 20.8% per annum between the top and bottom quintiles in a univariate model. Furthermore, they demonstrate that their results cannot be explained by risk differences alone. Value strategies do not lead to an underperformance, in bad years and differences in standard deviations of the stock returns only explain a small part of the return differences.

Capaul, Rowley and Sharpe (1993), Bauman, Conover and Miller (1998), and Arshanapalli, Coggin and Dukas (1998) examine the B/P effect in a large number of countries and discover that in almost all of them an investment strategy that involves buying and holding high B/P stocks is rewarded in the long run. Capaul, Rowley and Sharpe analyse the performance of portfolios formed on the basis of book-to-market ratios in six major capital markets (France, Germany, Switzerland, UK, Japan and U.S.) from 1981 to 1992 and conclude that a substantial tilt towards value stocks (high B/M) would have been attractive, especially if implemented on a global basis.

Bauman, Conover and Miller (1998) extend the previous study in several directions; first they use a larger sample period of 10 years, from 1986 to 1996, second they encompass all of the 20 established markets represented in the MSCI, EAFE Index as well as Canada and third they use the P/E, P/CF, P/D together with P/B to classify value and growth stocks. They find that value stocks generate higher risk-adjusted returns compared to growth stocks for the majority of individual markets and for the majority of individual years examined. They also make two important observations; when growth is the dominant style the return difference is very small, whereas when value outperforms it does so by a significant amount. In addition they observe that the value-growth premium is significant in all capitalisation - size categories except the smallest.

Arshanapalli, Coggin and Dukas (1998) apply a similar methodology, but for a bigger sample (19 countries from 1975 to 1995) and reach to the same conclusion. They document that value stocks have a risk-adjusted performance superior to that of growth stocks and that performance difference increases as the investment horizon increases. They attribute the superiority of value investing across stock markets to the size and book-to-market effects as described in the multi-factor asset pricing model of Fama and French (1996).

Sinquefield (1996) tests the behaviour of size and value risk factor portfolios using a very large international sample. He finds that the international version of each three of the Fama and French premiums is larger than the US version. In addition, he shows that portfolios that hold above-market proportions of value and small stocks have above market expected returns. Besides, international value stocks and international small stocks diversify US portfolios more than EAFE. If one does not wish to concentrate in such stocks, then international diversification for US sponsors may be unnecessary.

In a recent study, Fama and French (1998) test for the existence of a value premium in an international context. After examining 13 developed and 16 emerging markets for the 1975-95 period, they conclude that value stocks tend to have higher returns than growth stocks in markets around the world. The difference for global portfolios of high and low book-to-market stocks is 7.60% per year, which is statistically significant at a 5% level. Most impressively, they report that value stocks outperform growth stocks in 12 out of 13 developed countries. Similar results were found when they test the performance of portfolios formed according to earnings/price, cash flow-to-price and dividend yield.

Finally, Chen and Zhang (1998) examine the performance of value strategies in the United States, Japan, Hong Kong, Malaysia, Taiwan and Thailand from 1970 to 1993. They find that the high average return for value (high B/M) stocks tends to persist for the well - established market of the United States; is less persistent for the growth markets of Japan, Hong Kong and Malaysia; and is almost non-existent for the high-growth markets of Taiwan and Thailand.

2.3.3 Explanations

Although there is a general agreement on the long-term outperformance of value strategies, a large debate exists concerning the explanations behind their superior returns. Three markedly different explanations have been provided for this effect. According to the first, value strategies have produced superior returns, because they are fundamentally riskier. Therefore the positive association between book-to-market, which has been the most representative value proxy, and stock returns is consistent with rational, efficient pricing in capital markets. Another school of thought relies on behavioural finance theories and market inefficiency to explain this phenomenon. Systematic errors in expectations about the future, resulted from either a series of bad or good news or naïve extrapolation of past earnings/sales growth or return performance, has been proposed to justify the observed return difference between value and growth stocks. The expectational errors cause a certain degree of miss-pricing which makes value stocks to be underpriced and growth stocks overpriced. Finally, another group of researchers attributes the impressive returns of value portfolios to a number of research design biases. In the following sections, the three different approaches in explaining the value/growth effect will be examined in a greater detail.

a. Risk-Based Explanations (Rational Pricing Theories)

The traditional explanation for the existence of this kind of anomalous price behaviour of value stocks is that the higher returns are compensation for higher systematic risk. Fama and French (1995, 1996) support this argument and claim that value stocks outperform because they are fundamentally riskier. In fact, they argue that, if stock prices are rational, book-to-market should be a direct indicator of the relative prospects of the firm. In their paper, they attempt to establish an economic rationale for their results, by examining whether the behaviour of returns in relation to size and book-to-market is consistent with the behaviour of earnings[7].

They find that both size and book-to-market are related to profitability, and that market, size and book-to-market factors explain earnings as well as returns. Specifically, firms with high B/M ratio tend to have persistent low earnings on assets relative to low B/M firms. High B/M stocks are less profitable than low B/M stocks for four years before and at least five years after ranking dates, but they tend to converge in the years after portfolio formation.

Furthermore, they perform a time series regression where changes in earnings / sales are regressed on market, size and B/M factors in yield changes. The evidence suggest that there are market, size and book-to-market factors in fundamentals (earnings / sales) that are similar to those in stock returns. Thus, they conclude that the common factors in fundamentals drive the risk factors in returns. In addition, Fama and French (1995) find that the market and size factors in fundamentals show up in returns. There is no evidence, however, that the book-to-market factor in fundamentals drives the book-to-market factor in returns.

[7] The measure of profitability that Fama and French use, is the ratio of common equity income for the fiscal year ending in year t to the book value of common equity for year t-1.

He and Ng (1994) investigate whether size and book-to-market proxy for the macroeconomic risks captured by the Chen, Roll and Ross (1986) factors. The results show that macroeconomic factors help explain the cross section of average returns on U.S stocks, over the period 1963 through 1989. However, when size and B/M are included in the regressions, the risks associated with the term and default factors lose their explanatory power. When just B/M is added, though, a smaller impact on stocks from macroeconomic risk exposures is observed. The authors, therefore, conclude that the Chen, Roll and Ross macroeconomic factors are not able to explain the B/M effect. In addition, they examine whether the relation among average returns, size and B/M indicates a relative distress effect based on dividend reductions, similar to that described in the Chan and Chen (1991) study. They show, that when they isolate relative distress risk, it has a significant effect on the cross-sectional variation in average returns. Its effect, however, decreases when they consider it jointly with either size or B/M, and it further decreases when they add both size and B/M to the regressions. This suggest that size, B/M and the distress factor are interrelated and that relative distress can explain the size effect, but only partially the effect of B/M on average stock returns. Therefore, the authors suggest that B/M and size measure different risk characteristics important for pricing stocks.

In a more recent study, which includes data from six countries (US, Japan, Hong Kong, Malaysia, Taiwan and Thailand), Chen and Zhang confirm the argument that higher returns for value stocks are compensation for higher risk. The authors examine two other risk proxies, except of the distress factor[8]: leverage which is measured by the ratio of book debt to market equity and earnings uncertainty measured by the standard deviation of earnings for fiscal year *t* over price at the December year end *t*-1. They find that the three risk variables can capture the pricing information contained in log(size) and log(B/M) for portfolios ranked by size and book-to-market. They therefore conclude that value stocks are cheap because they are usually firms under distress, have high financial leverage and face substantial uncertainty in future earnings.

[8] The distress factor is measured by the percentage of firms that cut their dividends by 25% or more in the portfolio.

All the previous studies and specially the results of Fama and French in their 1992 paper led to the development of a new asset pricing model, which according to the authors has the ability to explain all the "anomalies" left from CAPM. Using a time series regression approach, they regress monthly stock returns on returns to a market portfolio, and mimicking portfolios for size and book-to-market equity risk factors. Similarly to the cross-section regressions, the time series regressions point out that the size and book-to-market factors can explain the differences in average returns across stocks. These factors alone, however, cannot explain the large difference between the average returns of stocks and one-month bills. This job is left to the market factor. According to their three factor model, the expected excess return on portfolio *i* is:

$$E(R_i) - R_f = b_i[E(R_M) - R_f] + s_i E(SMB) + h_i E(HML),$$

where $E(R_M - R_f)$ is the excess return on a broad market portfolio, *SMB* is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, *HML* is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks. $E(R_M) - R_f$, E(SMB) and E(HML) are expected premiums while the factor sensitivities b_i, s_i, h_i are the slopes in the time series regression:

$$R_i - R_f = \alpha_i + b_i (\mathrm{R_M} - \mathrm{R_f}) + s_i \,\mathrm{SMB} + h_i \,\mathrm{HML} + \varepsilon_i$$

Fama and French (1996) test that model, by using different portfolios returns as dependent variables and observing the intercepts and the overall fit of the regression. They show that the three-factor model captures the returns to portfolios formed on E/P, cash flow-to-price, and sales growth. Growth stocks (stocks with low E/P, C/P and high sales growth) are typical of strong firms that have negative loading slopes on HML. Since the average HML return is strongly positive (about 6% annually), these negative loadings, imply lower expected returns. Conversely, value stocks (stocks with high E/P, C/F and low sales growth) tend to load positively on HML, and thus have higher returns.

Generally the model captures much of the variation in the cross section of average stock returns, and absorbs most of the anomalies that have plagued the

CAPM[9]. The empirical success of the model suggest it is an equilibrium pricing model, a three factor version of Merton's (1973) intertemporal CAPM (ICAPM) or Ross's (1976) arbitrage pricing theory.

It is known that in a two-state variable ICAPM, multifactor-minimum-variance (MMV) portfolios are generated from the risk-free security and any three linearly independent MMV portfolios. This implies a) that the expected excess returns on any three MMV portfolios describe the expected returns on all securities and portfolios and b) the realised excess returns on any three MMV portfolios perfectly describe the excess returns on other MMV portfolios. Fama and French (1996), after several tests, proved that the market portfolio (M), the small-cap (S), large-cap (B), high B/M (H) and low B/M (L) are close to multifactor-minimum-variance, and therefore R_M - R_f, SMB, HML do a good job describing average returns.

Daniel and Titman (1997) test whether the high returns of high book-to-market and small size stocks can be attributed to their factor loadings. In their analysis, they find no evidence of a separate distress factor. Contrary to Fama and French (1996), they suggest that the high returns of value and small-cap portfolios cannot be viewed as compensation for factor risk. They find that, although high book-to-market stocks do covary strongly with other book-to-market stocks, the covariances do not result from there being particular risks associated with distress, but rather reflect the fact that high book-to-market firms tend to have similar characteristics; e.g. they might be in related lines of businesses, in the same industries, or from the same regions. The authors test whether portfolios with similar characteristics, but different loadings on the Fama and French factors have different returns. After controlling for firm characteristics, expected returns do not appear to be positively related to the loadings on the market, SMB and HML factors. In short, their analysis suggest that it is the characteristics, rather than factor loadings that determine expected returns.

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[9] The three factor model is however just a model and does not explain expected returns on all securities and portfolios as Fama and French argue. The medium term continuation effect of Jegadeesh and Titman, for example, cannot be explained.

b. Behavioural Explanations (Irrational Pricing Theories)

Not all studies agree with the arguments that Fama and French and others provide to justify the existence of a value premium. Lakonishok, Shleifer and Vishny (1994) and Haugen (1995), among others, argue that the value premium, is too large to be explained by rational pricing. Lakonishok, Shleifer and Vishny (1994) argue that the value premium is irrational because periods of poor returns on value stocks are not typically periods of low GNP growth, or low overall market returns. Since, the relative value premium is not related to these obvious macroeconomic state variables, it arises because investors dislike distressed (value) stocks and so cause them to be underpriced. Finally, the authors insist that the value premium is irrational, because diversified portfolios of high and low book-to-market firms have similar return variances and therefore there is no support for the view that value strategies are fundamentally riskier from growth strategies.

A number of behavioural explanations, suggesting that value premium is a result of some sort of irrational pricing, have been proposed in the literature as alternative explanations. According to these studies there is an error in expectations which lead to the misspricing and subsequent correction in the prices of value and growth stocks. However, there is not a common agreement on the sources of expectational errors that causes overreaction among investors. Overreaction may be either due to investors' naïve extrapolation of past growth, due to analysts' earnings forecasts, due to insiders' trading, or due to various cognitive errors. A detailed review of the studies that support these explanations is provided next.

- *Extrapolation*

Extrapolation is a special case of overreaction, which implies that the future is expected to be similar to the past. The study, which strongly advocates this hypothesis is, Lakonishok, Shleifer and Vishny (1994). According to them, one possible reason for the outperformance of value strategies is that, stocks that have done very well in the past (glamour stocks) are overpriced, because some investors are too optimistic about their future prospects. The same type of investors are too pessimistic about stocks that have done vary bad in the past (value stocks). These stocks are underpriced. The authors argue that, value[10] (glamour) stocks are characterised by low (high) past growth and expected low (high) future growth in sales, earnings and cash flows. Theses past characteristics create an excessive optimism for growth stocks and pessimism for value, which is subsequently reflected in the stock prices of the two categories.

The authors test the overreaction hypothesis, by looking directly at actual future growth rates and compare them with past growth rates and expected growth rates as implied by the multiples. They observe that, although glamour stocks grew faster than value stocks during the 5 years before portfolio formation, over the 5 post-formation years the relative growth of fundamentals was much less impressive. By looking at shorter time intervals, they find that while the market correctly anticipated higher growth in the very short-term, the persistence of these higher growth rates seems to have been grossly overestimated.

The results and conclusions of Lakonishok, Shleifer and Vishny (1994) were strongly criticised by Fama and French (1995). They argue that if the market incorrectly extrapolates EPS growth, the ratio of next year's earnings to this years price should be low beginning at year i=1, when earnings stop grow as fast as extrapolation would predict. However, they find that for growth portfolios E(t+i) / P(t+i-1) is quite stable in the 11 years around portfolio formation. On the other hand, high B/M stocks have poor earnings growth. If the market incorrectly extrapolates this weak growth, then the E(t+i) / P(t+i-1) should be high at the beginning, in the year after portfolio formation, when earnings growth is better than expected. However, they find that for the two value portfolios E(t+i) / P(t+i-1) is quite stable in the 11 years around portfolio formation.

Furthermore, they argue that, if the low post-returns of growth stocks are due to incorrect extrapolation of strong earnings growth, the low returns should be a temporary phenomenon. However, returns on low B/M stocks are low and rather flat for at least five years after portfolio formation. Similarly, the high returns for the high B/M stocks persist for at last 5 years after portfolio formation. They conclude therefore that the persistent differences in average stock returns after portfolio

[10] Lakonishok, Shleifer and Vishny (1994) use earnings-to-price, cash-flow-to-price, book-to-market and 5 year average growth rate of sales to identify value and glamour stocks.

formation suggest that the higher returns of value stocks reflect equilibrium expected returns.

Two other studies that test the extrapolation hypothesis, as a candidate for explaining the higher returns of value portfolios, is LaPorta (1996) and Dechow and Sloan (1997). Both studies find no systematic evidence that stock prices reflect the naïve extrapolation of past growth in earnings and cash flows.

LaPorta (1996) tests the extrapolation hypothesis using a portfolio approach methodology. He sorts stocks primarily on forecast growth[11] and then on the basis of five-year pre-formation sales growth. If extrapolation hypothesis is valid then the returns of growth stocks, that also exhibit high past growth, will be lower than the returns on stocks that are also expected to perform well in the future, but have performed poorly in the past (temporary losers). Similarly, if naïve investors extrapolate the past, value stocks (companies with high expected growth, but low past growth) should outperform temporary winners. LaPorta find that consistent with the extrapolation hypothesis, size-adjusted returns for growth stocks are more negative than those for temporary losers. His findings, that the returns earned by value stocks are lower than that of temporary winners suggests that extrapolation is not the whole story behind the superior performance of value stocks.

Further evidence against the extrapolation hypothesis of Lakonishok, Shleifer and Vishny (1995) comes form the paper of Dechow and Sloan (1997). Using several definitions of value and growth[12], they initially examine whether there is evidence of mean reversion in sales and earnings growth as predicted by the naïve extrapolation model. Their results do not suggest that value and growth portfolios display growth characteristics that are uniformly consistent with the extrapolation hypothesis. Furthermore, analysing growth rates of portfolios formed on the basis of past sales and earnings growth they confirm the strongly mean reverting nature of growth, but the analysis of stock returns provides no clear evidence that investors naively extrapolate past growth. Specifically, contrary to the naïve extrapolation hypothesis, investors are

[11] La Porta (1996) uses the forecast five-years earnings growth as a proxy for value and growth stocks.
[12] Dechow and Sloan (1997) used book-to-market, cash-flow-to-price, earnings yield and forecast earnings growth over the next five years to define value and growth portfolios.

not deluded by past growth and appear to have anticipated the dramatic improvement in performance.

- *Analysts' Earnings Forecasts*

Investors' overreaction to growth potentials of value and growth stocks may come from analysts' earnings forecasts. Several studies examine whether the cause of misspricing between the two classes of securities and consequently the returns of contrarian strategies can be attributed to investors' naïve reliance of analysts' earnings forecasts. Analysts' projections for future EPS and EPS growth affect investors' perceptions for companies and individual stocks.

This literature is separated to the studies that look at analysts' long term earnings growth forecasts and the studies that concentrate on forecasts of next year earnings per share in order to calculate earnings surprises. According to the error-in-expectations hypothesis, analysts as well as individual investors tend to be pessimistic for value stocks and optimistic for growth stocks. The announcement of the actual earnings for both categories of stocks creates a positive surprise for value and a negative surprise for growth, which can justify their subsequent return difference. A number of studies have documented that stock returns are sensitive to earnings surprises as they react positively to good news (positive surprises) and negatively to bad news (negative surprises). Whether surprises are systematically positive for value and negative for growth in a way that can explain the value-growth premium is an issue that has concerned few researchers.

La Porta, Lakonishok, Shleifer and Vishny (1995) examine the market's reaction to earnings announcements to determine whether investors make systematic errors in pricing. They test whether earnings surprises after portfolio formation are systematically positive for value firms and negative for glamour firms. Two different definitions are used for value and growth stocks: in the first case they use the simple B/P ratio, while in the second they define value (growth) stocks as those that have had low(high) sales growth over the previous five years and currently trade for low multiples of current cash flow. They compute for each quarter the 3-day (t-1, t+1) buy and hold returns around earnings publication dates, over a period of 5 years after portfolio formation and compare them with annual buy and hold returns.

They find that event returns are substantially higher for value stocks compared to growth stocks. Return differences around earnings announcements explain approximately 25-30% of the annual return differences between value and growth stocks, in the first two to three years after portfolio formation and approximately 15-20% of return differences over years four and five[13]. Their results do not support the risk premium explanation of the superior return on value stocks. The data show that, event returns are lower than non-event returns for growth stocks, despite the higher ex-ante risk pre-imposed by the theory. This can only be explained by negative earnings surprises for growth stocks. However, they conclude that earnings surprises are not the whole story behind the outperformance of value stocks; behavioural and institutional factors may also explain the phenomenon.

The relation between value measures (E/P, CF/P, B/P) and earnings surprises has also been examined in a more recent study, by Bauman and Miller (1997). Although the authors use a different definition of surprise than La Porta, Lakonishok, Shleifer and Vishny (1995), they reach to the same conclusion. Their analysis suggest that earnings surprises are more disappointing for growth stocks than for value stocks, and this difference in surprises explain the higher on average return that value stocks earn. The interesting point in this study, however, is that this hypothesis is not confirmed when price-to-book is used as an indication of value and growth. They show that, the highest P/B portfolio (growth) tends to have the least optimistic forecast bias, with an average earnings surprise of -0.48, while the lowest P/B portfolio (value), has the most optimistic bias, with an average of -1.73. Given these puzzling results, the authors argue that earnings surprises are not correlated with price-to-book ratios. It appears that book value, per se, has only a weak direct influence on expectations.

There are some other studies whose results do not support the previous findings. Bauman and Dowen (1994) investigate the relationship between earnings forecast errors and the earnings yield anomaly. Their results indicate that analysts tend to overestimate by a larger amount the earnings of the stocks with lower earnings yield

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[13] They also test the earnings announcement reaction for the sub-sample of large stocks which are expected to be less vulnerable to miss-pricing. They indeed find a lower difference in earnings announcements returns compare to the full sample and that these differences represent a lower fraction of the annual buy and hold return differences.

than those with higher earnings yield. Nevertheless, their statistical tests failed to account for the earnings yield anomaly based on earnings surprises. Similarly, Fuller, Huberts and Levinson (1993) find that analysts' forecasts errors are approximately equal across E/P portfolios. They conclude that it is unlikely that the overly optimistic forecasts of the growth companies' earnings account for the differential performance between the E/P quintiles over the eighteen years (1973-1990) covered in their study.

Dreman and Berry (1995) define surprises as percentage over actual EPS and reach to the same conclusions. The size of earnings surprises is not remarkably different from one equity class to the other, with low P/E (value) stocks to exhibit slightly more negative surprises. Furthermore, they examine the frequency of positive and negative surprises for value and growth stocks. They find that that the size of positive surprises is greater for high P/E (growth) stocks than for low P/E (value) stocks, but the difference between value and growth for negative surprises is not significant. They also examine the number of surprises by P/E quintile and found that the positive and negative surprises were fairly equally distributed. Contrary to La Porta, Lakonishok, Shleifer and Vishny (1997) hypothesis, the authors find no evidence for the observed performance differential being attributable to analysts' tendencies systematically to miss-forecast earnings on one class of stocks versus another.

Dreman and Berry (1995), however point out that analysts' errors have an asymmetric impact on the returns of high and low P/E stocks. They distinguish between positive and negative earnings surprises and report that positive surprises for low P/E stocks result in significantly above market returns, but have a far more moderate impact on high P/E stocks. Similarly, negative surprises on high P/E stocks result in low returns, with only a minor impact on low P/E stocks. In addition, they demonstrate that stocks are not immediately priced at the appropriate level after an earnings surprise. Rather, after a prolonged period of time, stock prices revert to their mean, with low P/E stocks outperforming and the high P/E stocks under-performing the market. In other words, the price reversals of the extreme P/E stocks indicates that overreaction does not take place at the exact time of the earnings surprise announcement but turn up slowly in subsequent periods.

Another part of the literature puts forward the argument that the returns to contrarian strategies arise because prices reflect analysts' long-term earnings growth forecasts[14], despite the fact that these forecasts are systematically biased. Bauman and Dowen (1988) was one of the first studies to suggest that taking a contrarian approach to analysts' consensus expectations for long term earnings growth enables investors to earn superior security returns. Three main studies use analysts' forecast of long term growth to explain the difference in performance between value and growth stocks.

La Porta (1996) in a recent paper, using the forecast five-years earnings growth (E{g}), confirms that, it is the error-in-expectations hypothesis that is responsible for the return difference between value and growth stocks. Sorting stocks on the basis of their expected earnings growth (E{g}), he finds that low E{g} stocks produce higher subsequent returns compared to high E{g} stocks. But more interestingly, he reports a high negative relation between B/P, E/P ratios and E{g}, indicating that value stocks are associated with prior low expected earnings growth rate and subsequent average raw returns. Furthermore, he shows that in the year following portfolio formation, analysts revise their expectations sharply for both high and low expected growth stocks in the direction and magnitude predicted by the error-in-expectations hypothesis. In addition, the behaviour of excess returns around quarterly earnings announcement dates strongly supports the error-in-expectations hypothesis.

Dechow and Sloan (1997) provide further evidence in support of La Porta's (1996) argument that forecast earnings growth can explain a great deal of contrarian investment returns. They use a regression analysis to investigate the proportion of the returns to contrarian strategies that can be attributed to naïve pricing of analysts' forecast of earnings growth. Three contrarian strategies based on the book-to-market, cash-flow-to-price and earnings-to-price are examined. The one year and five year buy-and-hold returns for each contrarian strategy are regressed on the contrarian ratio and the forecast earnings growth on a univariate and a multivariate context. Their results indicate that forecast earnings growth accounts for over half of the returns to contrarian strategies and its relative importance is not surprisingly greater over the longer five year holding period.

[14] The obvious benefit from using analysts' earnings forecasts for the five year earnings growth is that they provide a relatively clean proxy for investor's expected growth rates.

On the same line is the analysis of Harris and Marston (1994), who argue that growth (measured by the mean of financial analysts' forecasts of long term in EPS) and beta are part, but not all, of the book-to-market puzzle. They report that, once growth is controlled for, beta has a significant positive link with book-to-market. Growth however plays a more significant role in explaining book-to-market than beta. Nevertheless, they show that the book-to-market effect is not easily explained by the hypothesis that growth prospects are miss-priced.

- *Cognitive errors and agency explanations*

Shefrin and Statman (1995) propose an alternative explanation related to behaviour-based approach to security valuation. They argue that asset prices in the behavioural asset pricing theory are the outcome of an interaction between two kinds of traders, information traders and noise traders. The first know the relationship between characteristics of companies and the return distributions of the stocks in these companies. Noise traders, on the other hand, make systematic errors as they assess the relationship between the characteristics of companies and the return distributions of their stocks. Shefrin and Statman analyse the Fortune magazine[15] surveys of 311 company reputations and found that survey respondents rank stocks as they believe that, good companies are large companies with low book-to-market ratios. Moreover survey respondents rank stocks as if they believe that good stocks are stocks of good companies. In other words there is a cognitive error, that leads most investors to conclude that good stocks are stocks of good companies, which is responsible for the preference for glamour stocks and the superior performance of value securities.

Lakonishok, Shleifer and Vishny (1992) and Bauman and Miller (1997) suggest an agency explanation: that analysts might be aware of the expected returns associated with value stocks, but nevertheless prefer growth stocks because they are easier to justify to their sponsors. Because most sell-side analysts are ultimately compensated on the basis of brokerage commissions generated, analysts have an incentive to sell stocks to customers. It is easier for analysts to present an enthusiastic and persuasive argument for the purchase of a stock of a company that has been performing well.

[15] Eight attributes of reputation, using the scale of zero(poor) to ten (excellent), are employed: quality of management, quality of products, innovativeness, long term investment value, financial soundness, ability to attract and keep talented people, responsibility to the community and the environment and wise use of corporate assets

Conversely, it is more difficult to justify a less popular stock of a company with poor recent performance. In this instance, the analysts need to build the case that the future for the commune will be better than the past. The fear among analysts and portfolio managers, who recommend and purchase such stock, is that if the performance of the company fails to improve, they have the awkward burden of explaining why they recommended the company at the time it had a mediocre performance.

- *Insiders Trading*

Another explanation for the out-performance of value stocks, consistent with the overreaction hypothesis, comes from the paper of Rozeff and Zaman (1997). According to their hypothesis, if value stocks are underpriced and growth stocks overpriced then corporate insiders (chairmen, officers, and directors) have incentives to take advantage of that misspricing, by buying value stocks and/or selling growth stocks more heavily. If insiders rely on their information and do not overreact then the overreaction hypothesis predicts that insiders will focus greater buying in the value stocks and greater selling in the growth stocks, hoping to profit by the eventual reversion of market prices to their fundamental values.

Defining value and growth stocks using cash flow to price and book value to price the authors document a positive relation between the proportion of buy transactions in insider trading and the previous valuation ratios. Their findings are consistent with the overreaction hypothesis, according to which outside investors overvalue growth and undervalue value stocks. Moreover the authors point out that their results are robust to other effects. Insiders buy (sell) more heavily value (growth) stocks regardless of their previous return performance. In addition, the hypothesis that there is more selling in growth stocks because insiders hold a greater fraction of these stocks can not explain changes in insider buying as growth/value deciles change.

c. Research Design Biases

Finally, another group of researchers attributes the impressive style-specific results to a number of biases. The biases that are mainly described in the literature is survivorship bias[16] and data snooping[17]. Kothari, Shanken and Sloan (1995) attribute

[16] If a database systematically excludes significant number of firms that have become individually inactive, the data can be said to suffer from survivorship bias

the superior performance of value strategies to the research design and database that is used. They argue that is possible that the Fama and French results are influenced by a combination of survivorship bias in the COMPUSTAT database, effecting the high B/M stocks' performance and period-specific performance of both low B/M, past "winner" stocks, and high B/M, past "loser" stocks. To explore the survivorship-bias problem in the COMPUSTAT data, they separately analyse data for firms on CRSP, firms on COMPUSTAT, and those on CRSP but not on COMPUSTAT. Consistent with the survivorship-bias concern, the returns of small firms on COMPUSTAT are 9 to 10 percentage points higher than those for CRSP-COMPUSTAT small firms.

Furthermore, when they use an alternative data source (the largest 500 COMPUSTAT firms) for which survivorship bias, is relatively minor, the B/M becomes marginally significant. The coefficient on B/M is reduced by 40 percent. This lead them to conclude that although not all B/M findings are attributed to selection biases, the empirical case for the particular ratio is weaker than the previous literature suggest.

Another common attack for all those studies that discover stock market anomalies and deviations from CAPM is that may be the result of data snooping [MacKinlay (1995)]. A nontrivial portion of asset pricing research is devoted to dredging for anomalies. As finance academics research through the same data, it is more likely to find patterns in average returns, like the book-to-market effect, that is inconsistent with CAPM, but can be sample specific.

It is true that the majority of empirical research in this area has been conducted for the U.S market and especially for the post-war period. Tests on international data, however, produce relations between average return and variables, like market value, B/M, E/P and CF/P much like those observed in the U.S. data., verifying that data snooping is not a convincing explanation for the existence of the value premium.

[17] Bias associated with data snooping occurs when researchers (a) examine the properties of a database or the results of other studies of a database (b) build predictive models employing promising factors based in the previous results and then (c) test the power of their models on the same database.

2.4 Interaction between size and value effects

As size and value variables have as a common factor the share price, it is obvious that they are not entirely independent phenomena. Many papers attempt to disentangle and analyse numerous variables in order to find which effects are the most predominant in explaining the cross section of stock returns.

A number of research papers have examined the interrelation between E/P and size effects. Reinganum (1981) questioned the separate existence of both size and E/P effects. He found that both effects were present in equity rates of return, if the two effects were considered separately, but not when examined together. He argues that after controlling returns for any E/P effect, a strong firm size effect still emerged. But after controlling returns for any market value effect, a separate E/P effect was not found. Basu (1983) argues that Reinganum's defective risk-adjustment of returns concealed an E/P effect that was indeed present in Reinganum's data, and that the E/P effect subsumed the size effect when both variables are jointly considered. Cook and Rozeff (1984) using different portfolio formation rules and a variety of statistical tests conclude that stock returns are being jointly related to both size and E/P ratio. Banz and Breen (1986) confirm the findings of Reinganum and found a size effect but no independent P/E effect.

Jaffe, Keim and Westerfield (1989) re-examine the two effects over a longer sample period (1951-1986) using a new methodology (Seemingly Unrelated Regression) in addition to portfolio tests and distinguishing between January and other months. They find both earnings yield and size effect to be statistically significant during the 1951-1986 period. In addition, the coefficients on both E/P and size are significant in January, while the size effect loses it's significance the other months.

The interaction between size and B/P has also attracted the academic attention. Stattman (1980) and Rosenberg, Reid & Lanstein (1985) both find a significant positive relationship between B/P and returns, even after taking account for the size effect. Stattman examines average beta-risk-adjusted portfolio returns for a wide sample of NYSE and AMEX stocks and finds positive relation between book-to-price and returns even after controlling for market value. Rosenberg, Reid and Lanstein

(1985) reach the same conclusion after examining portfolios that are constructed to be orthogonal to size.

Recent studies, including Fama and French (1992) for US, Chan, Hamao and Lakonishok (1991) for Japan, confirm the existence of two separate effects in the two markets while the studies of Levis (1989) and Strong and Xu (1997) find that size is subsumed by value ratios like P/E and P/B in the UK market.

Finally Jacobs and Levy (1988) using multivariate regression tests attempt to disentangle returns associated with 25 different anomaly measures and compare their results with earlier findings. They observe that anomalies such as low P/E and small size appear non-stationary. They also point out that controlling for tax-loss selling hypothesis and other attributes in a multivariate framework mitigate the January seasonal exhibited in the small size effect.

CHAPTER 3

THEORETICAL BACKGROUND II

"*Time Series Predictability of Stock Returns and Variances*"

3.1 Introduction

While the previous section examines mainly the cross-sectional relationship of security returns and various fundamental variables, this part describe the literature on the time-series predictability of returns and volatilities of common stocks. The question of whether the first and second moments of security returns are predictable has attracted considerable attention in the finance literature.

The issue has important application to the construction of various dynamic trading strategies that is examined in the next chapter. Whether these trading strategies involve the decision to be in, or out of the equity market (market timing), or the decision of the proportion that will be invested in equities compared to other asset classes within a strategic range (tactical asset allocation), or even the decision of the proportion that will be allocated within different equity classes (style rotation / tactical equity allocation), return and volatility modelling is crucial.

The first part of the chapter reviews the studies on stock return predictability. The literature on return predictability that is presented does not distinguish between different equity portfolios, however we believe that these studies can set the grounds for developing and expanding on *style* return predictability and building certain timing models. The problem of forecasting future price changes, using only past price changes to construct forecasts, is initially considered. Although, restricting the forecasts to be functions of past price changes may seem too restrictive to be of any interest, nevertheless this can yield surprisingly rich insides into the behaviour of asset prices. Most of the research in this area documents predictable components in security returns and emphasises that the extent of predictability is a function of the return horizon, with predictable variation in aggregate returns vary from around 3% for shorter horizons to above 25% for longer horizons.

Another part of the literature considers a number of economic and firm specific variables to construct forecasts. A number of studies suggest that fundamental variables like the dividend yield, the earnings yield or the book-to-market ratio have significant predictive ability on expected returns of equity portfolios. Moreover, an important and significant relationship between business and economic conditions and stock returns has been recognised. The main finding from these studies is that expected returns on stocks vary countercyclically: they are high around business cycle troughs, when the business conditions are weak but expected to improve, and low around business cycle peaks, when economic conditions are strong but expected to deteriorate. A number of variables (interest rates, inflation, industrial production) that can proxy the current business conditions have been found to have predictive ability on stock returns.

Potential explanations for the predictability of returns fall primarily into two areas: first some form of general or limited irrationality, such as fads, speculative bubbles or noise trading, or second some form of general equilibrium model that provides variation in real rates of return over time. The latter implies that predictability is not necessarily inconsistent with the concept of market efficiency.

The second part of the chapter concentrates on modelling and forecasting the second moment in the distribution of stock market prices. A number of different models that have been applied in financial time series are presented and compared. Particular emphasis, however, is given to the conditional heteroskedasticity class of models that have been extensively used recently to model the volatility of stock market returns.

3.2 Time Series Predictability of Stock Returns

3.2.1 Return Autocorrelations

Research on time series predictability using return autocorrelations is central to the notion of market efficiency. According to the martingale model, which is considered to be a necessary condition for an efficient market, the asset's expected price change is zero when conditioned on the asset's price history[1]. One of the most direct and intuitive tests of the random walk and martingale hypothesis for an individual time series is therefore to check for serial correlation. Under the weakest version of the random walk, the first differences of the level of the random walk must be uncorrelated at all leads and lags[2]. In this section we review the evidence on stock return autocorrelations for short and long horizons for individual securities as well as for desegregated portfolios.

a. Short horizon returns

There is substantial evidence from early academic studies that daily, weekly and monthly returns are predictable from past returns. One of the first studies that examined this issue was Fama and French (1965), who found that the first-order autocorrelation of *daily* returns is positive for 23 out of 30 Dow Jones Industrials stocks and statistically significant for 11 of 30 in the 1957-1962 period. Foerster and Keim (1992) update these results for the 1963 to 1990 period and found that 80% are significantly positive. Although the Dow 30 is a limited sample of relatively homogeneous stocks, it is an interesting sample because it represents stocks highly liquid, very actively traded with relatively tight bid-ask spreads.

Another study that investigates daily predictability, but reaches to different conclusions, is the work of French and Roll (1986). They compute autocorrelations for all NYSE and AMEX stocks and find that the daily autocorrelations are on average negative for exchange traded stocks. Interestingly, they observe that the estimated autocorrelations are inversely related to the size of the stock. Smallest stock

[1] From forecasting perspective this implies that the best forecast of tomorrow's price is simply today's price.
[2] For a complete discussion on theory and tests of martingale and random walk hypothesis see Campbell, Lo and MacKinlay (1997).

autocorrelations are the most negative, while large-cap stocks exhibit positive autocorrelations on average.

A number of other studies examine short-term autocorrelations for portfolio returns. Because of variance reduction obtained from diversification, portfolio returns provide more powerful tests of the predictive ability of past returns. However autocorrelations for returns of portfolios of small companies may be seriously biased due to infrequent trading of these securities. Reinganum (1981), Roll (1981) and Keim (1983), among others, document significant positive autocorrelations for the daily returns of small-cap portfolios. Although theoretically infrequent trading may induce these autocorrelations, according to Lo and MacKinlay (1990) this cannot explain the level of serial dependence found in the data.

Some empirical research has also been conducted for *weekly* returns. Lo and MacKinlay (1988) tested the random walk hypothesis for weekly stock returns, by comparing variance estimators derived from data samples at different frequencies for the period 1962-1985. They report positive serial correlation in weekly returns and argue that, although the effect is more profound in small size stocks, the rejection of the random walk hypothesis for weekly returns cannot be explained completely by infrequent trading or time varying volatilities. To mitigate the non-synchronous trading problem, Conrad and Kaul (1988) examine autocorrelations of Wednesday-to-Wednesday returns for size grouped portfolios of stocks that trade on both Wednesdays. Like Lo and MacKinlay (1988) they find that weekly returns are positively autocorrelated, and more so for portfolio of small stocks. The first order autocorrelation of weekly return for the portfolio of the largest decile of NYSE stocks for 1962-1985 is only 0.09. For the portfolios that include the smallest 40% of NYSE stocks, however, the first order autocorrelation of weekly returns is around 0.30, while autocorrelations of weekly returns are reliably positive out to 4 lags.

Jegadeesh (1990) finds that *monthly* returns on individual stocks exhibit significantly negative first order serial correlation and significantly positive higher order autocorrelation. He also reports that the pattern of serial correlation exhibits seasonality, with the pattern in January, significantly different from that in the other months. Using the observed systematic behaviour of stock returns, he makes one-step-ahead forecasts and forms ten portfolios. He reports a 2.49 monthly abnormal return difference between extreme decile portfolios, over the period 1934-1987. This predictability of stock returns can be attributed, according to the author, to either market inefficiency or to systematic changes in expected stock returns. The time varying expected return models, however, were not able to explain this effect.

Summers (1986) put forward the argument that prices take long temporary swings away from fundamental values, which is translated into the statistical hypothesis that prices have slowly decaying stationary components. He shows that autocorrelations of short horizon returns can give the impression that such mean reverting components of prices are no consequence, when in fact they account for a substantial fraction of the variation of returns.

Campbell, Lo and MacKinlay (1997) applied autocorrelation tests to CRSP equal and value weighted indices and individual security returns for daily, weekly and monthly frequencies. Using a recent sample, they find that weekly and monthly return autocorrelations exhibit patterns similar to those of the daily autocorrelations: positive and statistically significant at the first lag with smaller and sometimes negative higher-order autocorrelations.

There are a number of possible explanations for the patterns identified in short-term returns. They can be caused by price pressures induced by investors who are attempting to buy or sell large amounts of a particular stock quickly. Although a seller can drive the price of the stock below its fair value, the stock can be expected to return to fair value. Another possible explanation is bid-ask spreads and thin trading. The stock returns are computed using traded prices. Since the prices fluctuate between the bid and ask prices, the security returns measured over adjacent intervals will exhibit negative serial correlation. Jegadeesh (1990), however, argues that this bias is likely to be small. He reports that trading strategies that try to exploit short-term reversals are successful even when returns for the previous month do not reflect the last day of trading. On the other hand, Ball Kothari and Wasley (1995) find that bid-ask problems can be very troublesome in simulations of short-term contrarian strategies that seek to exploit short-term reversal patterns.

b. Intermediate Term Momentum Patterns in Returns

Important patterns have also been found for intermediate horizon stock market returns. Momentum or relative strength strategies, that buy winners and sell losers based on returns over the previous 6-12 months, have become very popular recently within the investment community. These strategies explore the positive autocorrelation patterns in stock returns for intermediate - term horizons. In this section, we present the evidence on the profitability of momentum strategies and on intermediate-term predictability of stock returns, while also concentrate on the explanations that have been provided for this phenomenon.

One of the recent, but very important, papers in this area comes from Jegadeesh and Titman (1993). They document that over an intermediate horizon of three to twelve months, past winners continue to outperform past losers, so that there is a momentum in stock prices. In addition, they present two simple return generating models, which allow the decomposition of excess returns, and identify the important sources of relative strength profits. The results of their tests indicate that the profits are not due to the systematic risk of the trading strategies. Moreover, the evidence indicates that the profits cannot be attributed to the lead-lag effect resulting from delayed stock price reactions to information about a common factor similar to that proposed by Lo and MacKinlay (1990). The profitability of these strategies is therefore related to market underreaction to the firm specific information.

Chopra, Lakonishok and Ritter (1992) find that when winners and losers are chosen on the basis of one-year past returns, losers continue to lose and winners continue to win during the next year after adjusting for beta and size risk; and this underperformance is entirely in the February-December period. Similar momentum patterns are also reported by DeBondt and Thaler (1985, table 1) and Ball and Kothari (1989, table 5).

Chan, Jegadeesh and Lakonishok (1996) in a recent paper relate the evidence on momentum in stock prices to the evidence on market's underreaction to earnings related information. Although, they find a strong association between price and earnings momentum, they conclude that the price momentum effect tends to be stronger and longer lived than the earnings momentum effect. One explanation that is provided is that the market responds gradually to new information, so that there are drifts in subsequent returns. Since earnings provide an ongoing source of information about firm's prospects, the focus is on market's reaction when earnings are released. Indeed, a substantial portion of the momentum effect is concentrated around subsequent earnings announcements[3]. However, the return on a stock incorporates numerous other sources of news that are not directly related to near-term earnings: stock buybacks, insider trading, and new equity issues, for example.

Another possibility for the gradual adjustment of prices is because security analysts are slow to revise their expectations about earnings, particularly when the news in earnings is unfavourable. This may be due to their reluctance to alienate management. So medium return continuation can be in part explained by underreaction to earnings information.

The existence of momentum as a result of underreaction may however be overly simplistic. A more sophisticated model of investor behaviour is needed to explain the observed patterns in returns. One interpretation that may be given is that transactions by investors who buy past winners and sell past losers move prices away from their long-run values temporarily and thereby cause prices to overreact. This interpretation is consistent with the analysis of DeLong, Shleifer, Summers and Waldman (1990) who explore the implications of what they call "positive feed back traders" on market price.

Chan, Jegadeesh and Titman (1996) also observe that there is a close association between past return performance and the portfolios' book-to-market ratios. The portfolio of past winners tends to include "growth" stocks with low book-to-market ratios. Conversely, the portfolio of past losers tends to include "value" stocks with high book-to-market ratios. Despite this association, however, when they control for beta, size and book-to-market in the context of the 3-factor model of Fama and French (1993), they find no evidence that the behaviour of returns on the different momentum portfolios can be explained by the three factors. Furthermore, Asness (1997) points out although momentum is much stronger for the most expensive firms, it is effective within all value quintiles.

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[3] The evidence from event studies shows that about 41 percent of the superior performance in the first six months of the price momentum strategy occurs around the announcement dates of earnings.

There are not many studies that provide evidence and explanations on medium return continuation for international markets. One of them is the work of Rouwenhorst (1997) that focuses on that effect within markets and across markets at the individual stock level using a sample of 2,190 stocks from 12 European countries from 1978 to 1995. He shows that an internationally diversified portfolio of medium term winners outperforms a portfolio of medium term losers[4]. He also proves that beta and size risk factor cannot explain the continuation effect. Moreover, he argues that while return continuation varies by country and size, profitability of international relative strength strategies does not require investors to take significant size or country positions.

c. Long Horizon Returns

There is a large body of academic papers demonstrating that stock returns are predictable from long-term past returns and that stock returns are mean reverting, in the sense that higher (lower) than average returns are followed by lower (higher) returns in the future. Fama and French (1987) show that long holding period returns exhibit significant negative serial correlation, and that 25%-40% of the long horizon return variation is predictable from past returns. Fama and French (1988) find that autocorrelations of returns on diversified portfolios of NYSE stocks for the 1926-1985 period are close to zero at short horizons, but they become strongly negative for three to five years. The estimates for industry portfolios suggest that predictable variation due to mean reversion is about 35% for three to five year return variances. Returns, however, were found to be more predictable for portfolios of small firms[5].

The basic motivation for using long - horizon returns is the permanent/transitory component hypothesis. According to this hypothesis, log prices are composed by two components: a random walk and a stationary process,

$$\begin{aligned} p_t &= \omega_t + y_t \\ \omega_t &= \mu + \omega_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathrm{IID}(0,\sigma^2) \\ y_t &= \text{any zero - mean stationary process} \end{aligned}$$

[4] He formed portfolios on stocks based on their returns the previous six months and tested their performance on the subsequent six months

[5] For small firm portfolios the predictable variation was estimated to be about 40% of 3-5 year return variances, while for portfolios of large firms, the percentage falls to around 25%

while ω_t and y_t are mutually exclusive. The first part ω_t is the fundamental component that reflect the efficient market price, and the second y_t is a zero-mean stationary component that reflect a short term or transitory deviation from the efficient markets price ω_t, implying the presence of fads, or other market inefficiencies. Since y_t is stationary, it is mean reverting by definition and reverts to its zero mean in the long run.

Building on this argument, Poterba and Summers (1988) using data from US and 17 other countries, show that stock returns exhibit negative autocorrelations over long intervals. They, investigate the mean reversion by looking at variances of holding period returns over different horizons. If stock returns are random, then variances of holding period returns should increase in proportion to the length of the holding period. Poterba and Summers however find that, for N from 2 to 8 years, the variance of N-year returns on diversified portfolios grows much less than in proportion to N. This evidence suggest that transitory price components account for a substantial part of the variance in returns. Finally, the authors argue that noise trading, provide a plausible explanation for the transitory components in stock returns.

Cochran and Defina (1995) in a more recent study examine whether international stock price indices contain slowly mean-reverting components using regression-based tests developed by Fama and French (1988) and variance ratio tests developed by Lo and MacKinlay (1988). The authors report that the regression-based results indicate that the indices in some countries do contain a mean reverting component. However, the set of results, which are more relevant (real prices, bias-adjusted) reveals only 2 countries out of 18 in which mean reversion is apparent. Thus, the support is quite weak, contradicting the findings of Poterba and Summers (1988). Their conclusion that stock prices generally do not mean revert is also supported by variance ratio statistics.

The economic implication of the long-term mean reversion is emphasised by the novel paper of DeBondt and Thaler (1985, 1987). In particular, using US data from 1926 to 1982, they report that stocks which experience poor performance over the past three to five years (prior losers) tend to substantially outperform prior period winners by nearly 25% over the subsequent three to five years.

The rationalisation of these findings has concerned many academics and motivated a number of studies. DeBondt and Thaler attribute their results to market overreaction to extreme good or bad news about firms. One implication of the overreaction hypothesis is a tendency for the most extreme initial winners and losers to exhibit the most extreme subsequent price reversals. According to the same authors, the winner - loser effect cannot be attributed to changes in risk as measured by the CAPM - betas. Further analysis shows that the arbitrage portfolio (W-L) has a positive beta in up markets and a negative beta in down markets, a combination that would not generally be considered particularly risky. They interpret their evidence as a manifestation of irrational behaviour by investors who tend to overreact, i.e. to overweight recent information and underweight base rate data. So with prices initially biased by either excessive optimism or pessimism, prior losers would be more attractive than prior winners.

These arguments were rigorously criticised by Chan (1988) and Ball and Kothari (1989), who argue that these return reversals are due primarily to systematic changes in equilibrium - required returns that are not captured by DeBondt and Thaler. Chan (1988) argues that the risks of the winner and loser portfolios are not constant over time. He observes, using the same sample as DeBondt and Thaler, that the estimated betas are smaller for losers and bigger for winners. Consistent with the risk explanation of the contrarian strategy, he reports large changes of betas from the rank period to test period, such that losers are riskier than winners after portfolio formation. He suggest that the contrarian beta shifts are due, at least partially, to an increase (decrease) in the loser (winner) equity beta, that results from a change in leverage associated with the accumulated losses (gains) over the formation period.

Making the same assumption, Ball and Kothari (1989) also attribute contrarian returns to leverage induced beta shifts, but they do not detect the positive covariance between beta and the risk premium. Jones (1993), on the other hand, shows that even with negatively autocorrelated index returns the simple leverage effect cannot account for the positive covariance. He argues that DeBondt and Thaler's contrarian returns can be attributed to differences in risks between extreme losers and winners, so long as the negative autocorrelation in the index represent rational time varying expected returns. However, he shows that the reversal of realisations on underlying factors from the formation to the test period bias the time varying beta estimates. Re-examining the contrarian returns with betas estimated conditional on formation-period returns, he finds that betas do not shift as much as Chan's betas, nor they shift enough to explain the DeBondt and Thaler results. He concludes therefore that, the contrarian returns result from the reversal of realisations on underlying factors that influence expected earnings, which had been reflected as biases in Chan's estimates.

A number of other explanations for the winner - loser effect have been advanced in the literature. Ball, Kothari and Shanken (1995) show that much of the reported profitability of the contrarian strategy is driven by low-priced loser stocks. The skewness in the distribution of returns due to low-priced stocks is so pronounced that, while winner and loser five-year mean returns differ by 91%, their medians differ by only 14%. Loser stock prices are so low, that their subsequent five-year returns are extreme sensitive to even a small $ change of either misspricing or microstructure bias.

The size effect has also been employed to explain DeBondt and Thaler's findings. Zarowin (1990), among others, has argued that the superior performance of losers relative to winners is not due to investors overreaction, but instead is a manifestation of the size and/or January effect, in that by the end of the ranking periods, losers tend to be smaller-sized firms than winners. He argues that when losers are compared to winners of equal size, there is little evidence of any return discrepancy, and in any periods when winners are smaller than losers, winners outperform losers. Chopra, Lakonishok and Ritter (1992), on the other hand, using a slightly different methodology[6] for identifying winners and losers, report different results. They report an economically important overreaction effect after adjusting for both time-varying betas and size. Interestingly, however, they find the overreaction effect to be much stronger among smaller firms, which are predominantly held by private investors: there is at most only weak evidence of an overreaction effect among the largest firms, that are predominantly held by institutions. Dessanaike (1993)

[6] There are some important differences in the methodology and the definition of winners and losers that may explain the contradictory research findings of various studies. DeBondt and Thaler (1985) defined winners and losers as being the best and worst 35 performing stocks over their monitoring period respectively. This number represented a relatively large proportion of stocks in 1926, but a far smaller percentage at the end of their sample period. Zarowin (1990) considers the top and bottom quintiles of stocks; and Chopra, Lakonishok and Ritter (1992) consider only the extreme 5% of performers.

rejects the hypothesis that the size effect subsumes the winner-loser effect, using a sample of large UK companies. However, his findings do not suggest that the two effects are completely independent from each other.

Finally, Lo and MacKinlay (1990) provide an alternative explanation to the winner-loser effect of DeBondt and Thaler. They argue that the fact that some contrarian strategies have positive expected profits need not imply stock market overreaction. Instead, the presence of positive cross-effects among securities provides another channel through which contrarian strategies can be profitable. In fact, for the particular contrarian strategy that Lo and MacKinlay (1990) examine, over half of the expected profits is due to cross-effects and not to negative autocorrelation in individual security returns[7].

Evidence from other national stock markets on this issue is limited. Kryzanowski and Zhang (1992) using Canadian data reject the overreaction hypothesis and report long-term continuation in stock returns. Clare and Thomas (1995) use monthly data on UK stock returns from 1955 to 1990 to examine the existence of negative serial correlation over three to five year periods. They find that losers outperform winners by a statistically significant 1.7% per annum. However, after controlling for firm size they find that this return difference can be explained by the small firm effect, confirming Zarowin's findings and concluding that long term price reversal in the UK stock market is a manifestation of the small size effect. Dissanaike (1993) also find substantial evidence in support of the overreaction hypothesis, even after controlling for size and CAPM risk using the method suggesting by Chan (1988).

Despite the different justifications that have been provided, there is a general agreement within the academic community that a strategy that buys winners and sells losers based on their past 6-12 months performance (momentum strategy) can yield superior returns. Moreover a long-term contrarian strategy (buying past losers and selling past winners) can also achieve impressive returns. Although, the empirical evidence is clear, there is not sufficient explanation to differentiate the two investment

[7] If a high return for security A today implies that security B's return will probably be high tomorrow, then a contrarian strategy will be profitable even if each security's return are unforecastable using past returns for that security alone (i.e. exhibit zero autocorrelation)

strategies and justify why in the medium term the market may be underreacting while in the long term is overreacting.

Jegadeesh and Titman (1993) argue that it is possible that the market underreacts to information about the short-term prospects of firms, but overreacts to information about their long-term prospects. This is plausible given that the nature of the information available about a firm's short-term prospects, such as earnings forecasts is different from the nature of the more ambiguous information that is used by investors to assess a firm's longer term prospects.

Chan, Jegadeesh and Lakonishok (1996) provide an alternative explanation. Stocks selected under a momentum strategy carry along a very different set of investor perception from stocks selected under a contrarian strategy. The price momentum strategy identifies low - momentum stocks, for example, on the basis of poor returns over the immediate past (the prior six months). On looking at their experience over a more extended past period, however, these stocks are on average not much different from other stocks, so investors extrapolate from the past and perceive them as "normal" stocks. Given this mindset when disappointing news arrive, investors initially discount the information. This gives rise to a subsequent downward drift in prices. In contrast, a contrarian strategy focuses on stocks that have extremely poor returns over a prolonged past period. The history of disappointments creates an investor's mindset of excessive pessimism. This may be reinforced by money managers' unwillingness to be regarded as holding an "imprudent" investment that might fall in distress. These companies, however, are not as poor investment prospects as the market perceives them to be. Rather it takes time for these stocks to shake off the unfavourable opinions that the investors have accumulated. Many times the market's learning about future earnings prospects is a long process, that may last a few years. This sets the stage for subsequent reversals in prices that may persist for several years.

Of course, this is one interpretation for the existence of momentum and reversal strategies, there are probably other explanations for these results. The distinction between these two empirical regularities is not yet clear. Clarifying the links between momentum and contrarian strategies and providing a satisfying explanation for their existence stands out as a major unresolved issue.

3.2.2 The Predictive Ability of Firm Specific Variables

Although the autocorrelation and variance ratio tests for both short and long horizon returns are suggestive of time variation in expected returns, there is a fundamental problem associated with these studies: the variation in expected returns that we try to predict represent only a small component of the total variation in returns. As Fama (1991) points out, past returns may indeed contain information about expected returns, but they are a very noisy signal. More powerful tests should exploit explanatory variables that contain more precise information on expected returns.

A number of other variables, in addition to past returns have also been found to help predict current returns. More specifically, the dividend yield, the earnings yield and the book-to-market ratio have been found to have substantial forecasting ability on stock returns. This predictability reflects deviations from fundamental value, often lasting for several years. If stock prices exhibit such irrational bubbles, the previous variables could predict returns. A high yield tends to reflect prices that are low relative to current dividends, and indicate that future prices will rise toward fundamental values. On the other hand, a low yield tends to reflect prices that are too high relative to dividends, and future prices will decline towards fundamental values.

The ability of the dividend-price ratio to predict annual returns is noted first by Shiller (1984) and Rozeff (1984). Rozeff (1984) shows that the equity risk premium can be proxied by the prospective dividend yield in the context of the Gordon growth model. The evidence on his paper indicates that returns increase continuously and monotonically as dividend yield in the prior year increases. He finds that dividend yield explains 14% of the variation in the S&P composite index over the 1926-1981 period. Rozeff claims that high returns tend to occur when the environment is perceived to be so risky that investors demand a high premium for holding stocks, while low returns tend to occur when the environment is perceived to hold such little risk that investors demand a low risk premium for holding stocks. His explanation, therefore, emphasises that the predictability of stock returns is compatible with the efficient market hypothesis. Shiller (1984) also examines the predictability of annual S&P composite returns and finds that dividend yields explain nearly 16% of the variation in the 1946-1983 period. He interprets the relationship between the dividend yield and future stock returns as evidence of noise trading. He claims that noise traders may cause stock prices to deviate temporarily from their fundamental path, and that prices eventually return to their path. According to this theory, periods with low yields are periods with overvalued stock prices and since stock prices are likely to decrease under these circumstances, a low dividend yield will be associated with lower than average future rates of return. On the other hand, periods with high dividend yields signal periods with undervalued stock prices and indicate higher future stock returns.

More recently, Fama and French (1988) examine the forecasting power of dividend yield on expected returns of value and equal weighted portfolios of NYSE stocks, over different return horizons, varying form one month to four years, during the 1927-1986 period. They find that, for monthly and quarterly frequencies, the regressions of returns on yields explain less than 5% of the variances, confirming the argument that the predictable component of returns is a small fraction of short horizon return variances. For longer horizons, on the other hand, the explanatory power increases. For example, for nominal returns over the 1941-1986 period the explanatory power for 1, 2, 3, 4 year return horizons are 12, 17, 29 and 49 percent respectively. They also perform out-of-sample forecasts for different return horizons for the 20 year period 1967-1986. Again, they confirm that the explanatory power of the regression increases with the return horizon. The authors finally argue that the increasing fraction of the variance of long horizon returns explained by dividend yield is mainly due to the slow mean reversion of expected returns. Consistent, with Fama and French's findings, Chen (1991) find that the dividend yield forecasts real and excess market returns over the next 2 years, though its forecasting power diminishes toward the end of the second year.

There are some studies that provide international evidence on that issue. Attanasio and Wadhwani (1989) examine the forecasting power of lagged dividend yield on monthly and annual returns of the FT500 index over the period 1962-1987 for UK, and of S&P500 over the period 1947-1985 for US. Consistent with others, they report a significantly positive coefficient for the lagged dividend yield and find that when they don't control for risk, lagged dividend yields are very helpful in forecasting excess returns. However, this relationship is largely due to the post war period. Furthermore, they suggest that variables, which apparently can be useful in forecasting excess returns, can be correlated with risk premia and lose their significance, when a function of the conditional variance is included in the regression. After controlling for risk using a GARCH in Mean specification, where the lagged dividend yield is incorporated in the conditional variance equation, they find no relationship between the dividend yield and returns in US, although they continue to exert a statistically significant influence in UK.

The forecasting power of price-earnings ratio has also attracted a lot of attention. Shiller (1984) is one of the first to investigate the predictive ability of the price-earnings. He reports an R^2 of 0.106 in the regression of annual stock returns and the ratio of earnings-to-price, for the 1946-1983 period. Shiller documents, however, that earnings yield has very little predictive power in the 1898-1945 period.

One of the most comprehensive studies in that direction is the paper of Campbell and Shiller (1988), who examine the predictive ability of various dividend and earnings yield ratios in the US market over the 1871-1987 period. They use the log dividend-price ratio, the lagged dividend-growth rate, the log earnings-price ratio and two log earnings-price ratios based on ten and thirty years moving average of earnings[8] as dependent variables in simple regressions on 1, 3 and 10 years real and excess returns. Their results indicate that the log dividend-price and the three E/P ratios, especially when past earnings are averaged over 10-30 years, have reliable forecasting power that also increases with the return horizon. They report that the log dividend price ratio explains 26.6% of the variance of ten-year real return, while the 30 year moving average earnings price ratio explains 56.6% of this variance. Furthermore, using a Vector Autoregressive Model (VAR), they show that long historical averages of real earnings help forecast present values of future real dividends

Another variable that has attracted attention in the literature for it's predictive power is the book-to-market ratio. Although, there is a substantial amount of research, providing evidence that book-to-market significantly explains cross-sectional variation in average returns, very little work has been done in time series applications. Kothari and Shanken (1997) evaluate the ability of an aggregate book-to-market ratio

[8]A moving average of earnings was used because annual earnings are quite noisy as measures of fundamental value.

to track time-series variation in expected market index returns, and compare its forecasting ability to that of dividend yield. Using a vector-autoregressive framework and a bootstrap simulation procedure, they find evidence that both dividend yield and book-to-market track time series variation in expected real one-year stock returns over the period 1926-1991 and the subperiod 1941-1991 in US. Their results indicate that the book-to-market relation is stronger over the full period, while the dividend yield relation is stronger in the subperiod.

3.2.3 Business Conditions and Expected Stock Returns

A lot of research has been conducted trying to relate the variation through time of expected stock returns to business conditions. The intuition behind this relationship is simple; since, business conditions affect future consumption and investment opportunities, current expected returns should be related to the recent and future health of the economy. Expected returns on stocks have been found to vary countercyclically; they are high around business cycle troughs, when business conditions are weak but expected to improve, and low around business cycle peaks, when economic conditions are strong but expected to deteriorate.

Attempts to explain predictability of stock returns within the rational asset-pricing framework rely on the notion of consumption smoothing. According to the intertemporal equilibrium model of Merton (1973), Lucas (1978) and Breeden (1979) investors maximise expected utility, which depends only on current and future consumption. Financial assets therefore are held to help smooth consumption over time and transfer purchasing power from one period to another. Thus, an asset is more desirable, if its return is expected to be high when consumption is expected to be low. Consequently, around business cycle peaks, when income is high relative to wealth, investors will attempt to smooth their consumption by saving into future periods when output and income may be lower. A higher desire to save will result in lower expected returns. Following this logic, around business cycle troughs, when economic conditions are poor and income is low, expected returns will be high.

Chen (1991) provides another explanation. He argues that variation in expected returns relates to productivity shocks that affect the demand for capital goods, and to shocks to tastes for current versus future consumption that affect the supply of savings. Specifically, in a simple economy with constant returns to scale, a higher production of capital leads to higher expected market returns. At the same time, an individual would want to smooth consumption by attempting to borrow against expected future outputs, thereby bidding up interest rates. Thus, higher expected future levels of economic activity will generally lead to higher expected stock returns. In other words, near business cycle peaks (troughs), poor (good) prospects for future real activity and investments may contribute to low (high) expected returns.

Finally, he attributes the negative relation between expected returns and the recent stage of the business cycle to changes in investors' relative risk aversion. In both single period asset pricing models, such as Sharpe (1964), Litner (1965), and multi-period models, such as Merton (1973), Rubinstein (1976), Breeden (1979) and Cox. Ingersoll and Ross (1985), the risk premium of the market is a positive function of the aggregate risk aversion parameter. He shows that relative risk aversion may increase during contractions in business cycle, so that investors will only be induced to hold securities if expected returns are high.

The stage of the business cycle and the economic conditions can be proxied by a number of variables, such as growth in industrial production, inflation, short and long interest rates, term structure, default spread, dividend yields, etc. Chen (1991) argues that the previous state variables are indeed related to changes in macroeconomy. He reports that, the current market dividend yield and a measure of the default premium (the difference between the yield on a composite corporate bond portfolio and Aaa bonds) are indicators of the current health of the economy, as measured by the recent growth rate of GNP. In addition, the current short-term interest rate, the current term structure and the lagged industrial production growth rate forecast changes in the future growth rates of GNP.

There are many papers that attempt to investigate the relation between stock returns and macroeconomic variables. One of those variables is inflation. According to the theory, changes in the expected rate of inflation would affect interest rates and nominal cash flows, therefore expected dividends and hence stock prices. There is extensive evidence in the literature, indicating a negative link between expected inflation and share prices. Fama and Schwert (1977) detect a consistent negative relation between stock returns and both expected inflation and changes in those expectations. Fama (1981) claims that the negative stock-inflation relation are induced by negative relations between inflation and real activity, which in turn are explained by a combination of money demand and the quantity theory of money. Similarly, Geske and Roll (1983) develop and test a model that explains the negative relation of stock returns and inflation to rational investors realising the adverse effect of inflation on future economic policy. Finally, in a more recent study, Attanasio and Wadhwani (1989), find that even after controlling for risk in three different ways, expected inflation is negatively correlated with excess returns in both the UK and US. However, these studies point out that the relation between excess returns and inflation is "spurious" in the sense that expected returns and inflation are both endogenous variables, simultaneously determined by exogenous state variables. That is, the relation is structural and must be modelled as such.

The most direct indicator of the past and current health of the economy, however, is the industrial production. Consistent with the theory, empirical research has shown a negative relation between expected stock returns and industrial production.

Another variable that has been extensively used in studies that examine the relation of expected returns and business conditions is interest rates. Short-term interest rates, are considered to be, to some extent, indicators of the future health of the economy. They display business a cycle behaviour with a mean reverting tendency. Since expected returns display a countercyclical behaviour, the relation between short-term interest rates and stock returns should be negative. Moreover, it has been observed that the variation in long term rates is less extreme than the variation in short term interest rates; they rise less during expansion and fall less during contradictions. As a result, the spread of long over short-term interest rates varies countercyclicaly. Therefore, if stock returns covary with the return spread, their relation should be positive. One other interest rate variable, that has been extensively used, is the default premium, or the spread between high and low quality corporate bonds. It is associated with quality differences in the corporate bond market and provides a good proxy of the current health of the economy (e.g. Fama, 1990, Schwert, 1990).

All of these variables, either alone or in a multivariate context, have been tested in academic studies. Fama and French (1989) studied the relationship of expected returns on stocks and bonds with business conditions, using three variables: the dividend yield, the term spread[9], and the default premium[10]. If bonds are priced rationally, the default spread, is a measure of business conditions, but although it shows some business cycle variation, its major swings seem to go beyond the business cycles measured by the National Bereau of Economic research (NBER). Similarly dividend yield reflect time variation in expected bond and stock returns that tend to persist beyond measured business cycles. In contrast, the term spread is more closely to the shorter term business cycles identified by the NBER and tends to be low near business cycle peaks and high near troughs.

The results from multiple time series regressions of bond and stock returns for the period 1927-1987, show that all three forecasting variables have information about expected returns on stocks and bonds. Specifically, they document that the coefficients for the term spread are positive and similar in magnitude for all the stock and bond portfolios. In contrast, the coefficients for the default spread and the dividend yield increase from high-grade to low-grade bonds and from bonds to stocks. indicating that stock predictability reflects rational variations in expected returns across asset classes. The general message of Fama and French (1989) study is that the dividend yield and the default spread are high, and consequently expected returns on stocks and bonds are high, when economic conditions are poor. In addition, the term spread and expected returns are high when economic conditions are weak, but expected to improve.

One of the most quoted papers, is the work of Chen, Roll and Ross (1986) who attempt to model equity returns as functions of macro variables and nonequity asset returns. Chen, Roll and Ross argue, based on the rational valuation formula, that systematic forces that influence returns are those that change either expected dividends or the discount factors. The variables they test are unexpected changes in risk premiums, measured by differences between returns on low grade corporate

[9] The term or maturity premium variable is defined as the difference between the Aaa yield and the one month Treasury bill.

[10] The default-premium variable is defined as the difference between the yield on a market portfolio of corporate bonds and the yield on Aaa bonds.

bonds and US government bonds, monthly and yearly growth rate in industrial production, unexpected inflation, and unexpected changes in the term premium. Their results imply that stock returns are positively correlated with the bond return spread and monthly growth in industrial production and negatively correlated with inflation and the term premium.

Moreover, Chen (1991) examines the forecasting power of four macroeconomic state variables and reports that the default spread, term structure, short term interest rate and annual industrial production growth have some degree of predictive ability over real and excess market returns. He finds that the default spread and the term structure can predict stock returns over the next one-year, although the forecasting ability of the term spread appears to fade much more quickly. The forecasting power of Treasury bill yield is limited to the next quarter, while the annual production growth, which serves as proxy for the economy, exhibits forecasting power over the next four quarters.

Keim and Stambaugh (1986), using monthly excess returns on US common stocks for the period 1930 to 1978, report that three ex ante observable variables predict ex post risk premiums on common stocks of NYSE-listed firms of various sizes, long term bonds of various default risks, and US Government bonds of various maturities. The variables that they use are: (*i*) the difference in the yield between low-grade bonds and the yield on one-month Treasury Bills, (*ii*) minus the logarithm of the ratio of the real S&P index to its previous historical average[11] (*iii*) minus the logarithm of share price, averaged across NYSE firms in the quintile of smallest market value.

As it is obvious from the previously described papers, term structure of interest rates is always considered in studies of stock return predictability. Campbell (1987) examines explicitly this variable and it's forecasting power on stock returns over the 1959-1983 period. He investigates four variables: the one- month bill rate, the spread between the two-month and one-month rate, the spread between the six-month and one-month rate, and one lag of the excess return on two-month over one-month bills.

[11] Stating the variable relative to a historical average essentially produces a detrended series without incorporating ex post information

The main conclusion from the research is that stock returns are predictable at conventional significance levels and instruments that measure the state of the term structure at the beginning of a month help to forecast excess return over the month. Campbell finds that the two spread variables are highly significant and contribute about 12% of the return variation. Interestingly, the slope coefficients for the spread between the two-month and one-month rate, and for the spread between the six-month and one-month rate were found to be negative and positive respectively.

Ferson and Harvey (1991) also study a number of proxies for the economic risks that influence security returns and find that measures of economic risks can capture predictable variations in asset returns. The group of economic variables they examine include: the monthly real per capita growth of personal consumption expenditures for non-durable goods, the difference between monthly return on Baa corporate bonds and long term government bonds, the change in difference between the average monthly yield of a 10-year Treasury bond and a 3-month T.Bill, the unexpected inflation rate, the 1-month real interest rate and the value weighted NYSE index return less 1-month T.Bill return. Much of the predicted variation of monthly excess returns of size and industry grouped common stock portfolios is associated with shifts in the assets' risk exposures and by shifts in the risk premiums. The authors prove that both betas and risk premiums change predictably over time, although changes in risk premiums are far more important than changes in betas. Moreover, the risk premium associated with a stock market index captures the largest component of the predictable variation in the stock returns, while the premiums associated with term structure shifts and default spreads are the most important for fixed-income securities.

All the previous studies that were reviewed investigate the relation of stock returns with the stage of business cycle, by looking mainly at macroeconomic variables. These studies, however, do not take into account that various sectors of the economy are effected differently by the business cycle. Moreover, output shocks in certain industrial groups tend to lead the variation in the output of other groups. It has been observed that variations in real production / consumption in the various sectors of the economy do not take place synchronously over the business cycle. Therefore, it is possible that sector output shocks, as reflected by the stock returns of constituent firms, may affect stock returns. Eleswarapu, Tiwari (1996) examine the information content of various industry based portfolios against the aggregate market index in explaining the future market returns for stocks listed in NYSE from 1926 to 1989. The authors argue that, concentrating on industry-based portfolios, the key characteristics of the business cycle is better captured. They find that lagged returns on the basic industry and textiles and trade portfolios are negatively related to future market returns, while those in the construction, consumer durables, and food and tobacco portfolios are positively related to future market returns. Their results raise some questions in models where stock return predictability is linked to aggregate output and consumption flow through changes in the intertemporal marginal rate of substitution.

3.3 Volatility Modelling and Forecasting

A lot of research has been conducted in analysing and modelling the first moment of stock returns. However, investors are not only interested in the first, but in the second or higher moments as well, when they are to decide on portfolio allocations. Volatility modelling and forecasting therefore has many practical applications, such as use in market timing or style rotation decisions, aid with portfolio selection and the provision of variance estimates for use in asset pricing models as well as pricing of derivative assets. In this section, we present some of the most commonly used stock market volatility models, with a particular emphasis in GARCH models. Although, we review the evidence on stock market volatility and the factors that affect volatility over time, this section is mainly concentrated on the methodologies that have been developed to model and forecast second moments.

3.3.1 Conditional Heteroskedastic Models

It is now considered a stylised fact that volatility of stock returns is not constant, but changes over time and large (small) changes tend to be followed by large (small) changes of either sign, Fama (1965). In other words, the volatility of equity returns seems to be serially correlated, or as it is commonly referred to the literature there is volatility clustering in stock return series. Schwert (1989) shows that the variations of volatility for monthly U.S. stock returns on the period 1857 - 1987 range from a low 2% in the early 1960s to a high of 20% in the early 1930s.

Many different explanations have been provided for this phenomenon. Lamourex and Lastrapes (1990) found that clustering in trading volume can explain this effect, while others have argued that volatility is linked to macroeconomic and business conditions. For example, Campbell (1987) and Glosten, Jagannathan and Runkle (1993) find that nominal interest rates are significant determinants of conditional volatility. The dividend yield is another variable that has been found to drive stock volatility (e.g. Attanasio, 1991 and Attanasio and Wadhwani, 1989). Engel and Rodrigues (1989) show that the variance of stock returns depends on the money supply and an oil price index, while Schwert (1989) finds a linkage to the business cycle and financial crises and points out that stock market volatility tends to be higher during recessions and reacts strongly to banking crisis.

Regardless of its origins, conditional heteroskedasticity, or volatility clustering in equity return series has been reported by many studies for a variety of markets, data frequencies and time periods (see Bollerslev, Chou and Kroner (1992) for a review study). To capture this stylised fact and in order to represent the observed autocorrelation structure in stock market return and square return series, a number of conditionally heteroskedastic time series models have been developed.

a. Standard GARCH Models

One of the most prominent tools used to model second moments is introduced by Engle (1982) with the linear ARCH model. He suggests that these unobservable second moments can be modelled by specifying a functional form for the conditional variance and estimating the first and second moments jointly. According to this, the conditional variance can be modelled as a function of the lagged residuals. In other words, the predictable volatility is dependent on past news.

$$
\begin{aligned}
R_t &= \omega + \varepsilon_t, \qquad \varepsilon_t \sim \mathrm{N}(0,\ \sigma_t^2) \\
\sigma_t^2 &= \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \cdots\cdots + \alpha_p\varepsilon_{t-p}^2
\end{aligned}
$$

where σ_t^2 is the conditional variance and ε_t are the residuals of the conditional mean equation, that represent a zero mean serially uncorrelated process, which Engle defines as an ARCH process. Engle (1982) proposes a Lagrange multiplier procedure to test for pth order ARCH process. In this test the current period's OLS residuals ε_t are squared and regressed on an intercept and past squared residuals, $\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \cdots \varepsilon_{t-p}^2$. The sample size times the R^2 of this regression is asymptotically distributed as chi-squared with p degrees of freedom if the null hypothesis ($\alpha_i = 0$ for all i) is true.

The ARCH models can be estimated using iterative, nonlinear maximum likelihood methods. The log-likelihood function for this model is given by Engle(1982):

$$
\ln L = -\frac{1}{2}\sum_{t=1}^{T}\ln(\alpha_0 + \alpha_1\varepsilon_{t-1}^2) - \frac{1}{2}\sum_{t=1}^{T}\frac{\varepsilon_t^2}{\alpha_0 + \alpha_1\varepsilon_{t-1}^2}
$$

This linear ARCH model was generalised by Bollerslev (1986) in a manner analogous to the extension from AR to ARMA models in traditional time series, by allowing past conditional variances to appear in the current conditional variance equation.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2 = \alpha_0 + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2$$

To ensure a well defined process all the parameters must be nonnegative. Furthermore, ε_t is covariance stationary, if and only if $\alpha + \beta < 1$ [Bollerslev (1986)]. The sum of α and β coefficients represent the persistence of variance to shocks. Persistence is an important characteristic of conditional variance. Poterba and Summers (1986) argue that for multiperiod assets like stocks, shocks have to persist for long time for a time-varying risk premium to be able to explain the large fluctuations observed in the stock market. If volatility changes are only transitory, no significant adjustments to the risk premium will be made by the market.

In the standard GARCH(p, q) model the effect of a return shock on current volatility declines geometrically over time. Engle and Bollerslev (1986) develop a new model, the well known IGARCH model, or Integrated GARCH, where the sum of all coefficients in the linear GARCH(p, q) model is one, in other words there is a unit root in the autoregressive polynomial. This implies that current information remains important for forecasts of the conditional variance for all future horizons, while also implies an infinite variance for the unconditional distribution of ε_t[12].

Since the early papers of Engle (1982) and Bollerslev (1986), there have been many studies that applied various standard GARCH specifications to stock market data. One of the first and most comprehensive papers of GARCH applications to daily stock market data is Akgiray (1989). The author performs a number of statistical tests and fits various ARCH and GARCH specifications and concludes that simple conditional heteroskedastic processes, which allow for autocorrelation between the first and second moments of return distributions over time, provide a very satisfactory fit to the data.

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[12] The presence of near-integrated GARCH, or $\alpha + \beta$ being close but slightly less than unity, has been found by Bollerslev (1987), Baillie and Bollerslev (1989) and French, Schwert and Stambaugh (1987) for stock market series

A number of other studies document that a small number of parameters is sufficient to model the variance dynamics over very long sample periods. Fama, French and Stambaugh (1987) use a simple GARCH (1,2) specification to model daily values of the S&P composite portfolio from January 1928 through December 1984. Other simple GARCH specifications in modelling stock market return series have been used in Chou (1988) for weekly returns of the NYSE index, Baillie and DeGennaro (1990) for the CRSP value-weighted index, Attanasio (1991) for monthly returns of NYSE and S&P500 indices, LeBaron (1992) for daily and weekly returns of the Dow Jones and S&P indices, etc. GARCH specifications have been also used to model the volatility of UK index returns. Poon and Taylor (1992) fit different GARCH models for the FT All Share Index and for different data frequencies (daily, weekly, fortnightly and monthly) from 1965 to 1989. In all cases, apart from that for monthly data, the best model was found to be the standard GARCH(1,1).

Almost all the evidence of conditional heteroskedasticity in stock returns comes from studies that use as representative index either the market or an index of large and liquid stocks. There hasn't been a lot of research towards modelling the volatility of desegregated equity portfolios. The few studies that have been published involve the modelling of conditional variance for size portfolios. Morgan and Morgan (1987), in a study of the small firm effect in the US market, find that correcting for the conditional variance in returns of portfolios long in small and short in large firms reduces the estimate of market risk and increases the estimate of abnormal return. A factor ARCH model is used by Engle, Ng and Rothschild (1989) for ten size - ranked portfolios who show that the small size effect is explained as a response to time varying covariances. Along the same lines, Schwert and Seguin (1990) find evidence of conditional heteroskedasticity and time - varying betas, when they test the capital asset pricing model (CAPM) in a multivariate framework for size - ranked portfolios. Finally, Conrad and Gultekin (1991) use a univariate and multivariate ARMA(1,1)-GARCH(1,1)-M model to describe the volatility characteristics of the 100 smallest, the 100 intermediate and the 100 largest market value stocks listed in the NYSE/AMEX stock exchanges and find that there is a distinct asymmetry in the predictability of volatilities of large versus small firms.

b. Asymmetric GARCH Models

Several authors have pointed out that the standard GARCH model may not be rich enough to capture the time series properties of high frequency stock returns. GARCH models contain several important limitations, derived mainly from the property of linearity that they display and from the quadratic form of the conditional variance. In the standard symmetric GARCH model, the impact of past values of the innovation on the current volatility is only a function of their magnitude and not of their sign. However, it has been observed that an unexpected drop in prices (bad news) increases predictable volatility more than an unexpected increase in prices (good news) of similar magnitude. Black (1976) and Cristie (1982) were the first to observe that phenomenon and they named it leverage effect. They argue that a decrease in today's stock price, changes the firms capital structure by increasing leverage. This increased leverage causes higher expected variance in the future. It is worth noting, however, that the leverage effect can only partially explain the strong negative correlation between current return and current volatility in the stock market. The asymmetric nature of the volatility response to return shocks could simply reflect the existence of time varying risk premiums (Pindyck (1984), French, Schwert and Stambaugh (1987)). If volatility is priced, an anticipated increase in volatility raises the required return on equity, leading to an immediate stock price decline. This is often referred to as the "volatility feedback effect". Campbell and Hentschel (1992) studied this phenomenon by modelling dividend process as a Quadratic GARCH and linked dividend volatility to return by assuming a linear relation between the two. Their model, in which the return is positive linear in dividend shock and negatively linear in the square of that dividend shock, is able to produce asymmetric volatility and explain the negative skewness and excess kurtosis of the data.

Another limitation of the GARCH models comes from the parameters non-negativity constrain that is required as the variance must be kept positive. In the standard GARCH model a past shock regardless of its sign, has always a positive impact on the current volatility. To deal with those limitations several different parametric specifications have been proposed in the literature. The most commonly used is the Threshold GARCH (TGARCH) introduced by Zakoian (1990) and

Glosten, Jagannathan and Runkle (1993) and the Exponential GARCH (EGARCH) developed by Nelson (1991).

According to the Threshold GARCH the quadratic form of the residuals in the standard GARCH is replaced by a piecewise linear function, allowing for different reactions to volatility to the sign of the past errors. In other words, the impact of ε_{t-1}^2 on conditional variance is different when ε_{t-1} is negative (i.e. when the dummy variable I_{t-1} in the following equation is 1), than when ε_{t-1} is positive (i.e. when the dummy variable I_{t-1} is 0).

$\sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}$, where $I_{t-1}=1$ when $\varepsilon_{t-1} < 0$ and 0 otherwise

A high and significant γ coefficient means that negative return innovations increase predictable volatility more than positive ones, which counters the objection raised to GARCH models. Another useful parameterisation is the exponential GARCH (EGARCH) introduced by Nelson (1991).

$$\log(\sigma_t^2) = \alpha_0 + \beta_1 \log(\sigma_{t-1}^2) + \alpha_1 \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

Nelson by modelling the logarithm of the variance $\log(\sigma_t^2)$ points out that it is not necessary to restrict parameter values to avoid negative variances as in the standard GARCH model. The properties of the EGARCH model are determined by the second part of the above equation. The γ parameter is essentially the parameter that allows for asymmetry. If γ is not significantly different from zero, then a positive surprise has the same effect on volatility, as a negative surprise of the same magnitude. If $-1 < \gamma < 0$, a negative surprise increases volatility more than a positive surprise. If however, $\gamma < -1$ then a positive surprise actually reduces volatility while a negative surprise increases volatility. Nelson (1991) fitted the EGARCH model to the excess daily return on the CRSP value-weighted stock market index from 1962 to 1987 and found that the γ coefficient was -0.118 and highly significant, confirming the negative correlation between return shocks and volatility.

A number of recent studies apply asymmetric volatility models in stock market data. Glosten, Jaganathan and Runkle (1993) using monthly value weighted returns on the CRSP index for the period 1951-1989 and a variety of modified TGARCH and EGARCH models, reach to the conclusion that negative residuals are associated with an increase in variance, while positive residuals are associated with a slight decrease. Other studies along these lines include the work of Engle and Ng (1993) who confirm the leverage effect using daily observations on the Japanese TOPIX stock index from January 1980 to September 1987, by utilising a number of different asymmetric GARCH models including TGARCH and EGARCH. In addition, Poon and Taylor (1991) find that the leverage coefficient γ for daily, weekly, fortnightly and monthly returns of the UK value weighted FT All share index, for the period January 1965 to December 1989 is always negative. However, they observe that the magnitude of the γ estimate increases monotonically as the frequency of the series is reduced and it is statistically significant only for returns measured at higher frequencies (i.e. daily and weekly returns).

A number of other asymmetric GARCH parameterisations, apart from TGARCH and EGARCH, have been proposed in the literature. Some of them is the logarithmic ARCH by Geweke (1986) and Pantula (1986), the Non-linear ARCH introduced by Higgins and Berra (1989), the Qualitative Threshold GARCH by Gourieroux and Monfort (1992), the sign switching ARCH model by Fornari and Mele (1997) and many others.

3.3.2 Alternative Volatility Models

Although GARCH models have attracted the attention of the academic and investment community the last decade, many other alternative specifications have been proposed to model stock market volatility.

a. Two Stages ARMA processes

One such alternative involves the construction of variance estimates by averaging the square errors obtained from models for the conditional mean estimated over finer horizons. For example, Poterba and Summers (1986), French, Schwert and Stambaugh (1987), Schwert (1989, 1990) and Schwert and Seguin (1990) construct monthly stock return variance estimates by taking the average of the square daily return within the month. French, Schwert and Stambaugh (1987) add twice the sum of the products of adjacent returns in order to account for any negative autocorrelation possibly induced by nonsynchronous trading. The variance estimator that they use is:

$$\sigma_{mt}^2 = \sum_{i=1}^{N_t} r_{it}^2 + 2\sum_{i=1}^{N_t-1} r_{it} r_{i+1,t}$$

Because σ_{mt}^2 was found non-stationary, they examine the changes in the logarithm of the standard deviation estimates. They model the first differences of $\ln\sigma_{mt}$ as a third-order moving average process, and construct conditional forecasts of S&P return variances using the following formula:

$$(1-L)\ln\sigma_{mt} = \theta_0 + (1-\theta_1 L - \theta_2 L^2 - \theta_3 L^3)u_t$$
$$\hat{\sigma}_{mt}^2 = \exp\left[2\ln\hat{\sigma}_{mt} + 2V(u_t)\right]$$

where $\ln\hat{\sigma}_{mt}$ is the fitted value from $\ln\sigma_{mt}$ and $V(u_t)$ is the variance from the prediction errors from the first equation.

Schwert (1989) estimates a 12th order autoregression for the absolute value of the errors derived from some first step estimates for the conditional mean. He also includes dummy variables to allow for different monthly standard deviations. The fitted values from the AR(12) specification for the absolute residuals represent the conditional standard deviation of returns. The specification he uses is the following

$$R_t = \sum_{j=1}^{12} \alpha_j D_{jt} + \sum_{i=1}^{12} \beta_i R_{t-i} + \varepsilon_t$$
$$|\hat{\varepsilon}_t| = \sum_{j=1}^{12} \gamma_j D_{jt} + \sum_{i=1}^{12} \rho_i |\hat{\varepsilon}_{t-i}| + u_t$$

Two-stage AR processes have also been used extensively in forecasting (e.g. Pagan and Schwert, 1990, West, Edison and Cho, 1993, West and Cho, 1995, etc.)

b. Exponential Smoothing and Moving Average Models

Simple specifications have been tested by some researchers for their ability describe and forecast volatility. Some of them is the random walk, the long term mean model, the moving average, exponential smoothing and exponentially weighted moving average model. Studies that test these models and compare them with GARCH specifications include Akgiray (1989), Dimson and Marsh (1990), Brailsford and Faff (1996), etc.

The random walk is a simple model, which assumes that volatility tomorrow will be equal to the volatility today. If volatilities fluctuate randomly then the optimal prediction is for there to be no change since the most recent observation. Another simple specification is the historical mean or Gaussian homoskedastic model. This assumes that the distribution of volatilities has a stationary mean and would be the best forecast if the time series of returns were strict white noise.

The moving average involves modelling variances as an unweighted average of previously observed variances. The choice of moving average estimation period is arbitrary and varies according to the frequency of data. A variant of the previous model is the exponential smoothing, which involves forecasting volatilities as a weighted average of previously observed volatilities. The most recent observation receives the largest weight, while earlier observations are discounted geometrically according to their age. The exponential smoothing model takes the following form:

$$\hat{\sigma}_t^2 = \phi\hat{\sigma}_{t-1}^2 + (1-\phi)\sigma_{t-1}^2$$

The smoothing parameter ϕ is constrained to lie between 0 and 1. The optimal value of this parameter is determined empirically. A similar model is the exponential weighted moving average (EWMA). It assumes that the information contained in each observation decays exponentially. The smoothing parameter is again estimating from the data by minimising the sum of squared forecast errors. EWMA models have been used by Akgiray (1990), Vasilellis and Meade (1996) among others.

c. Stochastic Volatility Model

Stochastic volatility models that are frequently used in derivatives pricing can also be used in modelling stock market volatility. An example of stochastic volatility model, used by Harvey, Ruiz and Shephard (1994) is the following:

$$\varepsilon_t = v_t \exp(\alpha_t / 2), \quad v_t \sim N(0,\ 1)$$
$$\alpha_t = \phi\alpha_{t-1} + \eta_t, \quad \eta_t \sim N(0,\ \sigma_\eta^2)$$

where v_t and η_t are serially uncorrelated and independent of each other. Here α_t measures the difference between the conditional log standard deviation of returns and its mean: it follows a zero mean AR(1) process. Thus, as opposed to standard GARCH models, the conditional variance is not deterministic, but it evolves as a first-order autoregressive process driven by a separate innovation. Moreover, the exponential specification ensures that the conditional variance remains positive.

Estimation of the model is made using Kalman filter on the measurement equation $\log(\varepsilon_t^2) = \alpha_t + \log(v_t^2)$ and the transition equation $\alpha_t = \phi\alpha_{t-1} + \eta_t$. Harvey, Ruiz and Shephard (1994) propose a quasi-maximum likelihood method, where the measurement error is rewritten as $\log(\varepsilon_t^2) = \omega + \alpha_t + \xi_t$, where $\omega = E[\log v_t^2]$ and ξ_t is assumed to be distributed N (0, $\pi^2/2$).

A variety of other methods have been proposed to estimate the above system. Melino and Turnbull (1990) and Wiggins (1987) use GMM estimators. Jacquier, Polson and Rossi (1994) have proposed a Bayesian approach, while Shephard and Kim (1994) suggest a simulation based exact maximum likelihood estimator.

d. Other Models

Since the assumption of conditional normality does not capture all the excess kurtosis observed in high frequency stock market data, *nonparametric models* can be employed in approximating the conditional variance. Pagan and Schwert (1990) and Lee (1991) use a nonparametric model with Gaussian Kernel, while Bierens and Lee (1991) propose that the best k-steps-ahead forecast can be consistently estimated by the nonparametric regression on an ARMA memory index. Nonpapametric models have also been used by West, Edison and Cho (1993) and West and Cho (1995) to model the volatility of exchange rates.

Another popular method for measuring the volatility of stock market series is based on the implied volatility from option prices. A major determinant of the option price is the volatility during the life of the option. Thus given the option price, a value for the anticipated volatility is implied via a pricing model such as the well-known Black and Scholes (1973) formula. Vasilellis and Meade (1996) model the weekly volatility for 12 companies quoted on the London Stock Exchange using implied volatilities from three different option pricing models[13] and a weighting scheme for options with different strike prices. Even though the implied volatility method can

[13] The models that were considered are 1) Black and Scholes model with Black and Merton-Roll adjustments 2) Black and Scholes model with Black and Black-Rubinstein adjustments and 3) Merton model with Black Rubinstein adjustments.

lead to estimates superior from ARCH-type and other alternatives, it is rather limited since not all assets of interest have actively traded options.

3.3.3 Volatility Forecasting

There is a debate in the literature of whether stock market volatility can be accurately forecasted and whether GARCH models can be more useful tools than simple models. There are not many papers that tests the forecasting ability of GARCH models out-of-sample and the conclusions that they reach are not very consistent.

Akgiray uses a historical average, an exponentially weighted moving average, an ARCH and a GARCH model to forecast the US stock market monthly volatility and finds that the GARCH forecasts are far better than the other three, specially in periods of high volatility (1969 - 74 and 1975 - 80).

However, Tse (1991) and Tse and Tung (1992) question the power of GARCH models to forecast volatility in the Japanese and Singaporean markets, respectively. Both studies find strong evidence that an exponential weighted moving average performs better than GARCH models. Dimson and Marsh (1990) comparing several time series models for predicting quarterly volatility in the UK stock market reach to the conclusion that the best forecasting models may well be the simplest ones. They show that more sophisticated models, incorporating a large number of estimated parameters, are more likely to underperform during a holdout period. We need to note however, that the authors didn't examine ARCH models in their study. An extension of their work towards this direction has been made by Brailsford and Faff (1996) for the Australian stock market. They compare a random walk model, a historical mean model, a moving average model, an exponential smoothing model, an exponentially weighted moving average, a simple regression, two standard GARCH models and two asymmetric TGARCH models. Although, their findings point out that the various model rankings are sensitive to the error statistic used to assess the accuracy of forecasts, they conclude that ARCH class of models and the simple regression model provide superior volatility forecasts.

Franses and Van Dijk (1996) study the performance of GARCH models and two of its non-linear specifications (the Quadratic GARCH and the Threshold GARCH) to forecast weekly variances of stock market indices in Germany, Netherlands, Spain, Italy and Sweden. Their results point out that the QGARCH model can significantly improve on the linear GARCH and the random walk, in cases when the models are calibrated on data which exclude extreme observations such as the 1987 stock market crash.

Meade (1993) compares the ability of various volatility models to provide an accurate variance estimator for equity portfolios of different sizes. Using weekly returns for 266 UK companies from 1983 to 1989, he finds that a GARCH model provides better estimates of portfolio variance than a comparable constant model. The benefits of using a GARCH model are shown to be greater over periods of greater volatility. Moreover, Investment horizons of one, two, three and six months are considered and it is noted that the superiority of GARCH tends to diminish for the six-month horizon.

Vasillelis and Meade (1996) compare various volatility models, such as weighted and unweighted averages, GARCH estimates and different option implied volatility models, for their ability to predict the variance of twelve individual UK stocks for different horizons. They agree that GARCH models may perform better in comparison with simple unweighted and exponentially weighted models, but not when compared with an option based implied volatility.

Finally, Pagan and Schwert (1990) compared a GARCH(1,2) and an EGARCH(1,2) model with a Markov switching-regime and three nonparametric models for the volatility of monthly US stock returns from 1834 to 1925 and concluded that in out-of-sample predictions, the nonparametric models are inefficient relative to parametric ones, however there are important non-linearities that can not be captured by conventional ARCH and GARCH models.

One of the most crucial factors in studies of forecasting is the evaluation of forecasts. Forecast evaluation in all the previously reviewed studies is conducted by minimising a loss function and mean square error is the most commonly used. Yet the quadratic loss function implied by MSE may not be appropriate for evaluating volatility forecasts since it penalises positive and negative forecasts symmetrically. A number of alternative methodologies to evaluate the predictive accuracy of volatility models have been recently developed which do not require symmetric loss function.

West, Edison and Cho (1993) and Engle and Hong, Kane and Noh (1993) make important contributions along these lines, proposing economic loss functions based on utility maximisation and profit maximisation using options respectively[14]. However, the economic importance of all these volatility models in terms of optimal equity portfolio selection, or dynamic market timing construction has not been adequately investigated.

[14] For a comprehensive review study on volatility forecast evaluation and a new forecast evaluation framework that subsumes a variety of economic loss functions see Lopez (1995).

CHAPTER 4

THEORETICAL BACKGROUND III

"*Market Timing, Tactical Asset Allocation and Style Rotation*"

4.1 Introduction

The evidence from the previous chapters suggests that stock returns (especially long horizon) and variances are predictable, either from past values, or from predetermined ex-ante variables. The most important issue however is, if this predictability can be implemented into profitable trading strategies resulting from active asset allocation management. Fund managers tend to utilise predictions to take positions in the stock market. The decision that involves the allocation between different *asset* classes (i.e. equities, bonds or T.bills, etc.) is referred to as *tactical asset allocation.*

Tactical Asset Allocation and specially market timing, therefore, relies on simple, or more sophisticated models to forecast equity market movements. These strategies became especially popular, both among academics and practitioners, after the market crash of October 1987. According to Phillips and Lee (1989), tactical asset allocation is:

the process of tilting the strategic asset allocation to recognise valuations embedded in the financial markets at the current time. It is the decision process that determines where the plan should be positioned within the ranges of the strategic asset allocation mix.

Tactical asset allocation decisions are thus short-term investment strategies that intend to capitalise on the cyclical nature of financial markets. Many investment professionals differentiate tactical asset allocation from market timing. Phillips and Lee define market timing as an attempt to predict equity market peaks and troughs. Thus, the critical decision, in this case, is whether to be in or out of the equity market.

Whereas tactical asset allocation or market timing is concerned with the allocation decision between different asset classes, there is a new trend that has been developed and has to do with the allocation problem within *equity* classes. Managers are not only concerned with the proportion of their funds that will be invested in equities, but also with the proportion that will be allocated within different equity classes (small-caps, large-caps, value or growth stocks). The short-term allocation decision within different equity segments is called *tactical equity allocation* or *style* *rotation*. Style rotation is gradually dominating industry rotation, and is considered today one of the most important parts of active management.

The idea behind style rotation is that the same equity factors or styles are not always rewarded. While in a certain period it would be rewarding to take a long position in small-caps, for example, this may not be the case in the next period. A portfolio manager, therefore, must recognise what styles are likely to be rewarded every time, and rotate among them accordingly. To implement a rotation strategy, however, someone needs to be able to determine the conditions under which each style is profitable and successfully forecast.

This chapter presents the literature on both tactical asset allocation and style rotation. A great emphasis is given to the literature of tactical asset allocation, as it is based on the same general principles with style rotation. Both strategies presuppose the existence of a model that can generate forecasts on stock market returns. Thus, the accuracy of forecasting and the cost of trading will determine the feasibility of the strategies. A common belief in all timing strategies is that patterns will repeat themselves, at least in the near future within a forecast horizon.

The chapter is consequently organised in two parts. In the first part, we present the literature on tactical asset allocation and market timing. A number of academic studies that have considered the potential benefits and risks associated with market timing are initially presented. We also review some papers that develop and test forecasting models and implement them into trading strategies. The second part of the chapter presents the literature on style rotation, and more precisely the tactical allocation decision between the four most popular equity classes (small-cap, large-cap, value and growth stocks). The potential rewards and risks from switching among different equity segments are first presented. Then the factors or variables that have been found important in predicting style returns in a time series context are described in the next section. Finally, we conclude by presenting a few studies that implement style forecasts into rotation strategies.

4.2 Potential Gains from Market Timing

Before attempting to implement a timing strategy, an investor needs to know what would be the likely gains and possible risks that are involved with that strategy. It is also important to find out how accurate someone needs to be in order to succeed in market timing. It is obviously, not worthwhile building a tactical allocation strategy, if after adjusting for transaction costs and commissions this strategy is not rewarding.

The literature on market timing seems not to agree on the effectiveness of these strategies. Sharpe (1975) is one of the first that examines the efficacy of market timing, looking at annual switches. He explores the potential gains from annual market timing and show how they are related to the investor's ability to make correct predictions. He is simply labelling a year as good or bad, depending on the performance of equities versus Treasury Bills and calculates, using a simple probability model[1], the expected returns net of transaction costs of a timing strategy assuming a certain level of forecasting accuracy.

After several experiments, Sharpe concludes that attempts to time the market are not likely to produce incremental returns of more than four percent per year over the long run. The evidence suggests, that a manager who attempts to time the market must be right roughly three times out of four, merely to match the overall performance of those competitors who don't.

Sharpe, however, assesses only the likely gains from annual timing and has been criticised on the grounds that investment managers actually attempt to time the market more often than annually. Droms (1989) performs two significant extensions of Sharpe's study. First, he extends the time period under investigation from 1933-1972

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[1] Assume that the hypothetical proportion of correct predictions is given by Pc . That is the probability of predicting a bull year when a bull year is actually coming, while the probability of predicting a bear year when a bull year is actually coming is (1-Pc). A comparable model is employed for bearish predictions. The actual probabilities of bull and bear markets are given by Rbull and Rbear, respectively. To estimate available return when Pc is less than one, some assumptions must be made about the probability of a bull or bear year. For all periods, Rbull and Rbear were taken from historical data. The overall expected return for any given degree of forecasting accuracy is simply a weighted average of the expected values for the four outcomes, with the probabilities of the outcomes used as weights.

to 1926-1986. Second, he examines annually, quarterly and monthly timing strategies. Nevertheless, he also turns out to be pessimistic about the advisability of market timing, concluding that successful market timing requires forecasting accuracy, beyond the abilities of most managers. More frequent forecasting increases the potential return available and reduces the level of accuracy required to outperform the market. However, the superior rewards from more frequent switching can be easily negated due to higher transaction costs.

Jeffrey (1984) looks at the risk - reward characteristics of both annual and quarterly market timing strategies between stocks and Treasury Bills, and examines the range of outcomes from worst to best, for various levels of forecasting accuracy. He argues that, because each period's return exerts different leverage on the return of the overall time frame, a high forecasting accuracy may not necessarily corresponds to high returns. Although there have been more "good" than "bad" markets, the best "good" markets have been compressed into just a few periods. If only a few of the best markets were missed, investors would have been better off following a buy and hold strategy, even if the market had been correctly timed most of the time. Examining the period 1926-1982, he calculates the worst and best timing choices, which correspond to the maximum downside risk and upside reward respectively, for a level of forecasting accuracy that range from 50% - 75%. Jeffrey finds the downside risk of being right even two-thirds of the time (67% forecasting accuracy) is nearly 50% greater than the upside reward. He concludes that the incremental rewards from market timing are vastly less than the incremental risks.

Using return data on Canadian stocks over the 1950-83 period, Chua, Woodward and To (1987) also argue that a high degree of forecasting accuracy is needed for market timing to pay off. Using a sample drawing from the probability distributions of market returns based on parameters estimated from historical returns, they find that a minimum accuracy of 80% in forecasting bear and bull markets is required. They also stress that it is more important to predict bull markets correctly than bear markets.

Some more recent studies, however, seem to be more optimistic for market timing, arguing that an attempt to time the market can be worthwhile under certain circumstances. Sy (1990), for example, shows that someone doesn't need to be right

75% of the time to succeed in market timing, as Sharpe argues. Most of the time between 1970 and 1989, about 60% predictive accuracy was sufficient to give a winning edge. In some periods, even less than 50% hit ratio could beat the market. A 50%.

He also shows that the level of predictive accuracy required to break-even decreases slightly with portfolio revision. The potential gain or loss, however, is magnified substantially by the frequency of market timing. He reports that the gains from market timing on a monthly basis are more than 24% per year above the market return. Even with 60% correct predictions on average throughout the period, the gains from monthly market timing can be nearly 5%. He also argues that market timing generally decreases the volatility of portfolio returns. The final conclusion is that for the professional investor, who can avoid large transaction costs and who can develop skills in market timing, there are considerable potential gains and someone doesn't have to be right 75% of the time.

Clarke, FitzGerald and Statman (1989), also argue that the information advantage that a market timer needs to overcome the return and transaction cost advantages of a buy and hold investor is much lower than 75% that Sharpe claims. They show that some simple rules built around GNP may offer higher returns and lower risk than a buy and hold strategy. Furthermore, Clarke, FitzGerald, Berent and Statman (1990) examine asset allocation from both the ex post and ex ante perspective and investigates how accurate an market timer needs to be to beat a buy-and-hold equity strategy. They point an investor with little information will hold stocks in more periods than a market timer with much information. Increasing the amount of information available increases the overall probability of correct market timing choice. In addition, the ex post framework shows that a market timer who is 100% accurate in predicting bear markets must still maintain some ability to predict correct bull market periods. Specifically, the authors estimate this predictive ability to be 63%.

Only few studies looked at the benefits of market timing using alternative asset classes. Kester (1990) examine the comparative benefits and required predictive accuracy of a market timing with small stocks. Three strategies are examined in his paper; a) Shifting from cash equivalents to large-firm stocks and vice versa b) shifting from cash equivalents to large-firm stocks and vice versa and c) shifting from large-firm stocks to small-firm stocks and vice versa in all equity portfolios. After examining a variety of different portfolio revision frequencies and different level of transaction costs he finds that there are benefits from market timing and that small-cap stocks offer significantly greater opportunities for market timing than large firm. Particularly, small-cap stocks, in conjunction with cash equivalents, offer more profitable opportunities for market timing in terms of both minimum required predictive accuracy and incremental return advantages, when predictive abilities exceed the minimum. He concludes that, when less restrictive and more realistic assumptions are made regarding the frequency of portfolio revision and level of transaction costs, the potential gains from market timing are significantly higher than reported by Sharpe.

There is another body of literature, which assess the efficacy of market timing using survey data. One of those studies is Wagner, Shellans and Paul (1992) who provide a survey evaluation of the performance of 25 real world market timers over the period 1985 to 1990. Using a number of different performance measures they report superior results for market timing managers compared to a buy and hold strategy. Even after accounting for management fees, a substantial majority of market timers generated risk adjusted returns in excess of those expected in accordance with the Capital Asset Pricing Model.

Brocato and Chandy (1994), being sceptical of the optimistic results of the Wagner, Shellans and Paul (1992) study, investigate the criteria used for selecting the 25 market timers. The authors argue that the selection criteria, which required each manager to have an unbroken five-year track record, were biased in favour of market timers with superior performance records and that the true size of the timer population should have been about fifty and not twenty five. In their article, they show that an ex-post properly assembled list of timers, who follow completely random decision making process give virtually identical performance as their 25 real-world counterparts.

In a recent study Benning (1997) emphasises that the risk-adjusted measure of timer effectiveness may not be an appropriate way to describe the performance of market timers. Using the Sharpe (1975) probability model and the Merton's (1981) skill level performance measures, he simulates cumulative probability plots as a function of skill level for the group of the 25 timers of Wagner, Shellans and Paul (1992) and compares it with a similar plots of no-skill, coin flipping timers and buy-and-hold investors. The author also stress the importance of management fees, taxes as well as the timer's style in assessing real world market timers

Merton's (1981) seminal work on measuring the performance of Tactical Asset Allocation, and the tests of timing skill derived from it in Henriksson and Merton (1981), Cumby and Modest (1987) and Pesaran and Timmermann (1992, 1994) allows a correct evaluation of timing strategies in survey studies.

Another study along the same lines is provided Weigel (1991), who examines the simulated and actual performance of seventeen TAA managers, that switch between stocks, long term bonds and cash equivalents (three-way market timing). Using the Merton and Henriksson (1981) methodology he finds a significant timing ability in actual as well as in manager-simulated returns. Philips, Rogers and Capaldi (1996) extended Weigel's study in several directions. Although their sample is smaller[2], they employ a more recent sample period, disallow the use of simulated returns and adjust all returns to reflect management fees. Furthermore, they use the Cumby and Modest (1987) test together with the Merton and Henriksson (1981) test to evaluate managers' performance. Their findings corroborate the conclusions of Weigel for the pre-1988 period, but not for the early period, suggesting that TAA managers display little or no timing skill.

[2] In their study Phillips, Rogers and Capaldi (1996) examine the real time performance of eleven TAA managers who collectively manage close to 95% of the domestic TAA assets in the United States.

4.3 Tactical Asset Allocation Models

Despite the arguments against market timing, the potential rewards from this type of active management can be quite attractive. Whether it is worthwhile, however, to attempt to time the equity market will mainly depend on the investors ability to correctly predict the stock market movements. Therefore, the forecasting model and consequently the trading strategy build upon that model will determine the success of market timing.

There have been a few academic studies that propose specific forecasting models and test market timing strategies. The studies that are reviewed in this section are by no means exhaustive. They are however indicative of the methods and the variables that are used in short-term timing strategies. We can separate these studies into two categories: the first includes strategies that follow simple rules or signals, like the stage of the business cycle (long in stocks during expansions, long in bonds during contradictions), the level of equity risk premium, the yield ratio, etc. The second category contains strategies that rely on more sophisticate multivariate models.

As we showed in the previous chapter, there is substantial evidence of a strong relation between the stock market and business conditions. Siegel (1991) looks at this relation and proposed several market timing trading rules. He points out that, stock returns can be significantly enhanced by successfully forecasting business cycle turning points. Comparing stock returns and economic conditions from 1802 through 1990, he observes that there is almost always a decline in the stock returns before or just after the beginning of a recession[3]. Therefore, he suggests being long in equities during economic expansions and long in short-term bonds during economic contractions. But, at which exact point in the expansion or the recession to trade will determine the profitability of the market timing strategy.

Siegel estimates the annual average returns resulting from switching between equities and bonds 1 to 6 months before and after the peak, or trough of the business cycle. He finds that when investors switch from stocks to bonds exactly at business cycle peaks and from bonds to stocks at business cycle troughs they could earn 10.5%

[3] Recessions are dated from the month NBER designated the peak of the business cycle to the month label the trough. Conversely business cycle expansions are measured from troughs to peaks.

average annual return from 1802-1990 and 11.8% during the 1946-1990 period[4]. Furthermore, he shows that an investor who leads the business cycle can earn more returns from an investor that lags the business cycle, and this gain is apparent in every subperiod. Finally, looking at all possible market timing strategies at various times around business cycles turning points, he concludes that the gains from this type of market timing are maximised (16.1% annually), by being long in stocks four months before the peak and long in bonds four months before the trough of the business cycle.

Another variable that is often used as a guiding signal in tactical asset allocation is the short-term interest rate. Breen, Glosten and Jagannathan (1989), use the one month interest rate to forecast the sign, as well as the variance of the excess returns on stocks and evaluate the forecasting ability of their model using the Cumby-Modest (1987) and Henriksson-Merton (1981) tests of market timing ability. They confirm the negative relationship between interest rates and stock returns and construct a forecasting model based on this relation using a three-year rolling regression. The basic conclusion from their paper is that Treasury bill rates can indeed forecast changes in the distribution of stock index returns, when the stock market index is the value weighted portfolio during the period 1954 to 1986. When, on the other hand, the equally weighted excess index is instead used, the forecasting model did not show statistically or economically significant forecasting ability. The authors attributed that to the leptokurtosis and January seasonal in the distribution of equally weighted index excess returns.

Lee (1997) replicates the results of Breen, Glosten and Jagannathan (1989) up to 1986 and extends the sample through the end of 1994. He observes that by regressing excess stock returns on the risk free rate, the coefficient gradually changes from highly negative and statistically significant to about zero and even positive, and statistically insignificant. Since 1987, the adjusted R^2 is consistently negative in almost periods, indicating that the relationship has virtually evaporated. Consequently, although a market timing strategy build solely on the level of the short term interest rates, is able to outperform the buy-and-hold strategy in the earlier periods, all value added is

[4] For comparison reasons note that the historical average of stocks is 9% during 1802-1990 and 12.5% during the post war period. The historical average for bonds, on the other hand, is 4.3% and 4.8% during 1802-1990 and 1946-1990 respectively.

eroded to zero by 1989. Furthermore, if such strategy is followed consistently throughout the whole sample period, it underperforms the buy-and-hold strategy by 3.65 basis points per month on average. Lee attributes the failure of the interest rates to produce a profitable timing strategy to the composite effect of the risk free rate on stock returns and volatility. When stock returns are positively related to volatility, which in turn increases with the level of short term interest rates, the overall effect of the risk free rate on stock return may be neutralised[5].

Kairys (1993) proposes a different approach to utilise short-term interest rates in the tactical asset allocation process. He argues that although the majority of studies use linear models, there is no a priori reason to believe that the relationship between short term interest rates and stock returns should be linear. Using more than 150 years of data and a simple non-linear model, he could accurately identify periods when the excess return on equities is negative. Simple trading rules based on the predicted sign of the equity risk premium were found to perform better than a passive buy-and-hold strategy, while also reducing the volatility of returns, even after allowing for 1% transaction cost per trade.

Fundamental variables are also frequently used as signals in tactical asset allocation. The basic idea behind is that an investor's equity allocation should be reduced (increased), every quarter, as the market becomes overvalued (undervalued). Thus overvaluation (undervaluation) is signalled by low (high) dividend yield, earnings yield and book-to-price ratio. Fuller and Kling (1990) examine the predictive power of dividend yield and compare it with a simple autoregressive model. Their findings suggest that a market timing strategy build on dividend yield could outperform both the buy-and-hold and a strategy based on a simple AR(1) model, for various return horizons. In addition, Sorensen and Arnott (1988) compare the dividend yield and earnings yield measures against a simplified DDM approach and find that simple measures can be more effective in market timing strategies.

Lander, Orphanides and Douvogiannis (1997) assume a linear equilibrium relationship between the expected earnings yield and bond yield. They use an error correction model that predicts the return of the S&P on the basis of deviations from a

[5] The author tested the effect of volatility using a modified GARCH in mean model. He observed that stock return volatility is much more sensitive to the level of risk free rate.

presumed equilibrium between forecasted earnings yield and bond yields. Their model provides one-month-ahead forecasts of S&P500 returns and implement simple market timing trading rules, based on the forecasted sign of the excess returns, between stocks and bonds of various maturities. The trading rule they employ, provide very satisfactory results in terms of performance enhancement and volatility reduction compared to the alternative of buying and holding the S&P over the 1984-1996 sample period.

MacBeth and Emanuel (1993), examine tactical asset allocation trading rules, following from values of three different fundamental ratios; the dividend yield, price-earnings and book-to-price. The authors suggest a trading strategy based on the following simple rule. At each point, beginning from 1945, they construct the frequency distribution of all past values of any particular fundamental ratio of interest. Then, they define the 20th and 80th percentiles of the distribution as the *critical values*, which correspond to the minimum 0% and maximum 100% equity position[6]. At subsequent dates, all past values of a fundamental ratio are used to determine the 20th and 80th percentiles. Backtesting the strategy, they find that the compound returns from the dividend yield and price/book rules are only slightly better than the returns of the 50/50 Stock/Bill passive alternative. The price/earnings rule, on the other hand, had a higher compound growth rate and a higher standard deviation, but it had lower Sharpe ratio than the benchmark. All strategies, however, failed to exceed the returns of the 100% equity benchmark.

The results of MacBeth and Emanuel, are not very supportive of tactical asset allocation following from simple valuation rules. The authors invoke two basic reasons for that: first, the variable that needs to be predicted -price- is used to calculate each one of the fundamental values. Second, virtually all the variability in dividend yield and price/book ratio, and most of the variability in price/earnings ratio, comes from the price component. Because book values and dividends have grown slowly and steadily since 1945, price changes is what drives the changes in dividend yield and price/book ratio. Moreover, overlapping return intervals creates an artificial

[6] For example the dividend yield rule calls for a 50/50 position when the dividend yield is at 3.75, provided that the critical values are 4.50 (maximum equity) and 3.00 (minimum equity).

dependence between successive returns. Spurious correlation between long-term moving average returns and intrinsic values creates a big problem in their analysis.

More sophisticated and complicated models, than simple trading rules, that described previously, often constitute the basis of market timing and tactical asset allocation. In these cases more than one variables are used to forecast excess stock returns.

One of the studies that develop and test such forecasting models and incorporate it in the tactical asset allocation process, is the paper of Nam and Branch (1994). The authors consider the allocation problem between stocks (S&P500) and Treasury Bills and propose a model to calculate the optimal allocation of funds every month, between these two asset classes. Their model, which is based on a logit regression, provides an estimate of the probabilities that the upcoming market period will be bullish or bearish[7].

They use four ex-ante indicators in their model; the growth rate in earnings, the changes in T.Bill, the T.Bill in previous month and the dividend yield. The signs of all coefficients in the regression were found to be consistent with the proposed theory. In other words, bearish market months have higher levels of earnings growth, changes in T.Bill, lagged T.Bill rates and lower levels of dividend yield than do bullish months. Using a rolling estimation procedure they find that the out-of-sample forecasting accuracy rate of their model is 73.8% for bullish periods and 43.3% for bearish periods, which gives an overall accuracy rate of 60.1%. Even with that modest predictive ability (much lower than what Sharpe suggest), they suggest that various asset allocation strategies[8], based on their model, earn higher return compared to the passive buy and hold strategy, even after taking into account transaction costs.

Along the same lines is the study of Larsen and Wozniak (1995), who use the same methodology (logit regression), but a larger set of independent variables to

[7] When the estimate of probability is greater than 0.46 a bullish month is indicated. When the probability is less than 0.46 it signals a bearish month. Note that 0.46 is associated with prior probability of bearish periods.

[8] Three different trading strategies are considered, based on the logit model. The first invests 100% in equities whenever the logit model signals a bullish month (probabilities greater than 0.46) and switch 100% to T.Bills whenever the logit model signals an upcoming bearish month (probabilities greater than 0.46). The second strategy establishes a probability range of 0.20-0.65 as neutral, which does not result to any transactions. Finally, strategy 3 is a variation of the second strategy and uses a neutral range of 0.15-0.65.

generate estimates of probabilities that the next month's stock returns will be higher or lower than yields on Treasury Bills. The authors, based on early stock return predictability studies, recognise ten market and economic variables and introduce a different trading signal. They claim that because differences in asset classes cannot be predicted with certainty on a monthly basis, a two month trend (sequential signal) in the predicted probabilities will give a better indication of the likelihood of differences in asset class returns in subsequent periods.

Fitting their model and implementing the trading rule for the 1971 to 1992 period they report an average annual return of 20.2% for the market timing strategy. This corresponds to a statistically significant 4.9% point increase in annualised average returns over the S&P500 index, as well as a reduction in portfolio risk. The market timing approach, therefore, outperforms the 100% stocks and the 50/50 fixed-weight strategies, as well as a number of other fixed-weight strategies considered. Finally, the authors defend their model by arguing that even when applying a 0.50% annual expense fee, the returns on their timing strategy is better than the passive strategies they considered.

Another study that examines whether stock market predictability can be exploited into successful investment strategies is the work of Pesaran and Timmermann (1995). The authors propose an interesting approach, where they assume that investors believe that stock returns can be predicted by means of a set of financial and macroeconomic indicators, but do not know the "true" form of the underlying specification. As time progresses and the historical observations available to investors increase, the added information is likely to lead the investor to change the forecasting equation. At each point in time, investors use only historically available information to select a model according to a predefined model selection criterion[9] and then use the chosen model to make one-period-ahead predictions of excess returns. The recursive forecasts are then employed in a portfolio switching strategy, according to which shares or bonds are held depending on whether excess returns on stocks are predicted to be positive or negative.

[9] The particular choice of regressors at each point in time is based on a number of statistical model criteria (R^2, Akaike's Information Criterion, Schwarz's Bayesian Information Criterion, and Sign Criterion).

Pesaran and Timmermann (1995) established a benchmark set of regressors, over which they search for a satisfactory prediction model, over the 1960 to 1992 period[10]. The set consists of dividend and earnings yield lagged one month, the one month Treasury Bill rate and the 12 month Treasury Bond rate, lagged one and two months, the annual growth of inflation, industrial production and money supply all lagged two months. The authors estimate a total of 202,752 models over the 1959:1 to 1992:1 period and conclude that the one month lagged value on the short-term interest rates was the most consistent and helpful forecasting variable. The usefulness of most of the other variables depends to specific economic and market regimes.

Furthermore, the authors analysed the performance of switching strategies based on recursive forecasts, given certain level of transaction costs, and different trading rules. They find that portfolios based on recursive forecasts paid a higher mean return than the buy-and-hold strategy particularly during the 1970's. Even with just 60% correct predictions most of the recursive forecasting models they test, earn above average annual returns at all of transaction cost levels.

Miles and Timmermann (1992) is another study which attempts to predict stock returns and then use these predictions to formulate an investment strategy. They develop and test a model based on three company characteristics (book-to-market, company size, dividend yield) to predict stock returns on a panel of UK companies, over the period 1978-1989. Although the emphasis of this study is more on stock picking rather on market timing or tactical asset allocation, it suggest a number of different trading strategies based on the predicted returns generated from the forecasting model and compare the performance of those strategies to a passive benchmark (equal weighted index of all shares).

The authors test eight different trading rules based on the recursive forecasts and find that five of them exceeded the equal weighted market index. A strategy that holds shares of companies for which the recursively predicted returns are positive and sells short shares of companies with a which a negative return[11], results in an average annual payoff of 20.41%, over the 1978-1989 period, which is 142 basis points higher

[10] The period 1954:1 to 1959:12 was chosen as the first parameter estimation period. The "best" model in this period was used to forecast excess returns for 1960:1.

[11] The strategy assumes that the proceeds of short sales are added to the original funds and invested equally in stocks with a positive predicted return.

than the returns of the benchmark. The most profitable strategy, however, is the one that ranks the shares according to the recursively predicted values of stock returns and holds the subset for which the predicted returns is in the top 20%. This strategy generates an average annual return of 21.6%, which is substantially (2.6% per year) higher than the average return on the market portfolio.

All the previous studies concentrate on predicting next period's equity risk premium in order to construct market-timing strategies and evaluate them using various risk-adjusted measures. However, stock market volatility must be taken very seriously into account when constructing short-term timing strategies and must be an essential part of any forecasting process. To the best of my knowledge, the only study that utilises predictions of the second together with the first moment in market timing strategies is Whitelaw (1997). In this paper, a conditional Sharpe ratio is employed to provide guidance in market timing. Predetermined financial variables[12] are used to estimate both the conditional mean and volatility of equity returns and these moments are combined to estimate the conditional Sharpe ratio. The author tests a simple strategy of estimating the conditional Sharpe ratio using a 10-year rolling regression and comparing this number to the ex-post Sharpe ratio over the prior 10 years, or to a fixed threshold Sharpe ratio. If the estimated conditional Sharpe ratio is larger (smaller) then he suggests being long (short) in equities. His strategies work much better than the buy-and-hold strategy, which confirm that there is economically significant predictable variation in stock market Sharpe ratios.

[12] The variables used to predict returns of the CRSP value weighted index is the Baa-Aaa spread, the dividend yield, the commercial paper -Treasury spread, and the one-year Treasury yield. Volatility is conditioned only upon the last two variables.

4.4 Style Rotation Strategies

In the previous sections the literature on the predictability of stock returns and tactical asset allocation is presented. The majority of the reviewed studies consider the returns on large stocks[13] as the variable of interest and as a proxy for the universe of stocks. Different equity segments (styles), however, exhibit different characteristics and their returns therefore can be sensitive to different factors.

Because style allocation is considered to be as, or even more, important than asset allocation, the identification of those driving factors behind style investing can have significant applications in timing strategies. This section is organised as follows: first some evidence on the importance of tactical style allocation will be presented. Next we present the literature on the predictability of style returns. The literature into return forecasting for style portfolios is mainly concentrated on three classes of variables: technical, economic and market indicators. Finally, we review some studies that implement forecasting models into tactical style allocation.

4.4.1 Profitability of Style Rotation

Asset allocation is one of the essential decisions in portfolio management. Recently, however, sophisticated investors, primarily in the institutional area, have discovered that style allocation among domestic equity managers may be as important as asset allocation. Furthermore, what kind of equity manager one selects (value, growth, small-cap, and so on) is actually more important than the individual manager selected within that particular style. In other words, style selection is more significant than security selection.

A study, which stresses the importance of style allocation, by comparing its potential gains to that of tactical asset allocation, is Hardy (1995). He compares the annual returns for 15 years, from 1978 to 1992, of four style indices: Large-cap growth, large-cap value, small-cap growth, and small-cap value. He observes that an investor who chose the best style would have outperformed the investor who chose the

[13] The S&P500 or the value weighted index of all stocks that are both tilted towards large capitalisation securities, were mainly used as dependent variables in time series regressions.

worst style by an average of 24% per year. For comparison, he also examines the annual returns of different asset class returns (stocks, bonds, T.Bills and real estate) over the same period. He shows that the average difference between the best and worst asset class selection is only 18.86% annually.

A number of other papers emphasise the importance of proper equity style selection in US. Case and Cusimano (1995), for example, examine the potential rewards from a tactical style allocation between three different value and growth indices (Wilshire, Salomon and BARRA/S&P). Their argument is that, a wider absolute spread between value and growth implies that there is greater potential for return enhancement from actively managing the style allocation of the equity portfolio. They find that for the 1982-1993 period all three indices produce a wide absolute spread indicating great potential reward from a style timing strategy.

Other studies simulate the performance of style rotation strategies assuming perfect foresight ability. Arnott (1989), for example, summarises the median performance of value and growth managers tracked by EAI for full decade, in the U.S. market. He observes that at some times value beat growth managers, while at other the reverse occurred. Therefore, if someone could predict which style would be rewarded, she/he would have a valuable tool for investment management. He finds that, during the 1975 to 1984 period, the average annual performance of an infallible style forecasting strategy is 20.5%, 250 basis points higher than if someone had stick with value managers in that period and 570 basis points higher if growth managers had been preferred.

Tactical style allocation can be also implemented in a more frequent basis than every year. Fan (1995) examines the potential benefits of a monthly tactical style allocation strategy between the S&P500 Value and the S&P500 Growth indices, during the period 1985-1995. He argues that, due to the mean reversion nature of equity style performance, the S&P500 index and the two style indices have more or less equal performance in the long run. However, assuming monthly rebalancing, the best style allocation would lead to 523% gross excess return relative to the S&P500, while the worst style allocation would lead to 224% gross underperformance relative to the benchmark over the 10-year period. Furthermore, even after adjusting for transaction costs[14], the best style allocation skill could generate an annual net excess return of 6.98%. The worst style-allocation skill, on the other hand, generates a gross excess return of -9.41% and net excess return of -12.59%.

Macedo (1993) looks at the benefits of tactical style allocation in the context of small capitalisation stocks[15] from 1978 to 1992. She argues that there are large differences in annual performance of small-cap value and small-cap growth stocks. Small-cap growth dominated from 1978 to 1981, while small-cap value from 1981 through 1988. However, even when one style was dominant for a long period, there were opportunities to add value through style timing. A switch from small-cap value into small-cap growth for the nine months beginning in October 1982, for example, would have added about 20% relative to staying in small-cap value. Furthermore, Macedo compares the returns on a perfect foresight portfolio (100% in best style) to a fixed allocation of 50% small value / 50% small growth. She finds a 12.27% annualised added value from the perfect forecasting strategy over the 50/50 benchmark, which is 5.6% net of transaction costs. In addition, a small reduction in the annual standard deviation is achieved.

Kao and Shumaker (1999) in a recent paper evaluates the benefits from both size and value/growth monthly and yearly timing. Assuming perfect foresight, they find that the most profitable strategy, over the 1979 to 1997 period, is the size timing within the growth segment On the other hand, a strategy that switches between large-cap value and large-cap growth offers the lowest annual returns.

All the previous studies examine the benefits of style rotation in the US market. Style management and tactical allocation between equity classes, however, has began to attract the attention of institutional investors in UK as well. Style indices have been recently introduced in UK for both performance attribution and active management. The FTSE 350 Value and Growth indices are among the most popular. The message from those indices is the same. There are significant performance differences between

[14] Fan, assumes an average five cents per share commission costs and an average $40 share price for the stocks in the S&P500 universe, the one way trading cost in terms of fund performance is about 12.5 basis points. The round- trip cost on the performance is about 25 basis points. Allowing other factors in the trading events such as price impact, a conservative 60 basis points round-trip turnover cost (or 12 cents per share one-way trading costs) is assumed in the calculation of the net excess returns.

[15] The data that were used in this study are based on the Wilshire Associates' passive style indices.

value and growth over short time periods[16]. Evidence from those indices has shown that value has outperformed growth in six of the last ten years while growth was the dominant style the rest of the decade. This simple observation obviously leads to the presumption that tactical style management can be as beneficial in UK as in US.

Even though all of these studies that have been reviewed are generally optimistic for style rotation, the evidence that they provide are not convincing enough to favour this active strategy. Obviously, perfect foresight is not a realistic assumption and transaction costs for this kind of active management would definitely be higher than for a simple market timing strategy and probably high enough to wipe out any possible profits generated with realistic forecasting skills. Sorensen, Miller and Samak (1998) examine this issue, although their paper concentrates more on the allocation decision between active and passive style management rather than on style rotation over time. They argue that active style management greatly depends on the stock picking skills of each individual style manager, the tracking error level that the overall plan sponsor is willing to accept and transaction costs. Using a number of simulation and optimisation experiments, they find that, even with a modest stock picking skill, the net performance of active style management exceeds the returns of various passive indices.

4.4.2 Determinants of Size and Value Cycles

There is no doubt that the value added from any type of active management would mainly depend on the forecasting model that is used. Forecasting models, as in the case of tactical asset allocation, will be derived from time series analysis of the separate style-index return patterns. As pointed out in the previous chapter, portfolio returns can be predictable either from past return or from predetermined market or economic variables. In this section, we review the literature on style return predictability, while cluster the evidence into three primary areas: economic, market and technical style predictors.

[16] Russell Research Commentary " UK Style Indices: Ten year historical performance ", May 1997

a. Economic Indicators

One of the distinguishing features of equity styles, mainly value / growth paired styles, is their differential industrial composition. As Fan (1995) observes, value indices tend to be dominated by banks, utilities, and basic industrial and, to a lesser extent, energy. Growth indices, on the other hand, are typically dominated by capital goods, consumer non-durables, consumer services, healthcare and retail and, to a lesser extent, technology. Similarly, Mott and Condon (1995) notice that the small-cap value index has a much heavier focus on financial services than does growth, whereas the growth index places more emphasis on technology than the value index[17]. Generally, someone could say that the value style-index is more pronounced in the mature economic sectors, while the growth style-index in the less matured or still growing sectors.

Because, the demand for each industry's output has a certain sensitivity to overall economic growth, industrial sensitivity to economic growth is an important consideration when developing style-return expectations. Thus, one intuitive explanation of the equity style trends is that they result from different economic sector compositions. Observing the characteristics of economic-sector concentration, one would expect that the style trend is related to economic cycles. Given these characteristics, the value style index is expected to do well during strong economic cycles because, the matured economic sectors tend to expand and shrink with the general economy. On the other hand, the growth-style index should do better during weaker economic cycles because, only the growing companies can resist the force of a shrinking economy.

Obviously, being able to determine the current location and future progression of the business cycle should provide useful information with respect to value/growth style return expectations. Given that the dominant characteristics of business cycles are changes in output, employment, and prices along with procyclical movements in real interest-rates, it is clear that value investing would be relatively better suited for an economy characterised by troughing or expanding output and employment, plus rising prices and real interest rates due to increased demand for goods and credits. In

[17] The authors, however, notice using regression analysis that sector bets do not fully explain the relative style performance.

contrast, growth investing is better suited in an economy where output and employment growth are peaking or contradicting, where growth characteristics are scarce in general.

Case and Cusimano (1995), using simple correlation analysis, evaluate the relationship of several measures of economic output, prices and real interest rates with value/growth cycle. They find that movements in the business cycle characteristics have tended to lead subsequent relative returns between styles, as illustrated by the higher correlation between economic activity prior to observed returns, than the correlation measured coincident and subsequent to the observed return periods. Sorensen and Lazzara (1995), using also descriptive measures, find that monthly changes in industrial production have a significant positive impact to the value/growth relative performance both in contemporaneous and in lagged terms. A positive relationship has identified between the value-growth spread and the GDP growth rate, by Kao and Shumaker (1999), indicating that value stocks are likely to outperform during expansionary periods.

Key among all economic variables are interest rates (Treasury Bill yield change - the slope of the yield curve - and the default premium). Fama and French (1993) suggest that book-to-market (a measure of value) and size are proxies for distress and that distressed firms may be more sensitive to certain business cycle factors, like changes in credit conditions, than firms that are financially less vulnerable. One would expect that growth stocks would outperform value stocks in a recessionary environment characterised by high default rates.

In addition, the duration of high growth firms' earnings should be somewhat longer than the duration of the earnings of low growth firms; therefore term structure shifts should affect the two groups of firms differently. Rising interest rates should hammer growth stocks far harder than value stocks. A growth stock can be viewed as a long duration asset that investors buy for growth in earnings; a value stock is a shorter duration asset that is bought for cyclical gains or dividend yield. Moreover, as Sorensen and Lazzara (1995) argue, since a growth stock's valuation is highly dependent on the discounted value of distant, rather than near term dividends, interest rate changes should affect growth stocks more than value. In other words, high bond yields are associated with times when value oriented portfolios outperform growth oriented portfolios.

Likewise a steeply positive yield curve is a bad sign for growth stocks; their earnings are discounted by long-term rates, whereas value stocks' earnings are discounted by short-term rates. A flat yield curve is an indicator to buy growth stocks. On the other hand, an inverting curve really favours growth stocks. Another measure can be the default premium on bonds that reflects the corporate stress. If there is worry about defaults then short duration stocks must be preferable[18].

Fisher, Toms and Blount (1995) relies on interest rates and the yield spread between short and long rates to explain the behaviour of style returns, but offer a different explanation. They argue that when interest rates rise significantly with a time lag, the result is a growth cycle. The reason behind that, is related to the overall level of debt (both short and long term) that value companies carry relative to growth companies. So it makes more sense for growth companies to raise capital by offering equity than by issuing debt. The result is that value companies tend to look to debt for additional capital, while growth companies look to equity. The impact of this difference in leverage is that when rates rise, with a time lag to work through maturity schedules, the interest costs of value companies rise faster than growth companies, negatively affecting earnings of value companies relative to growth companies. With surpressed earnings, value stocks perform more poorly than their growth counterparts. The opposite effect occurs after rates fall. Just as the yield curve affects the market as a whole, its effect on the value and growth cycles of the market can be shown even more dramatically. The key for a value / growth cycle is a narrowing or widening of the yield curve. When the spread widens or inverts, banks stop lending, whereas when it is flattening they lend aggressively. Since value firms are much more debt dependent when credit is tight, they become more defensive and do poorly; when credit is more easily available, they do well.

Jensen, Johnson and Mercer (1997, 1998) also examine the effect of interest rates changes to the value - growth return spread. They find that value stocks benefit significantly when the Fed is following an expansive monetary policy (decrease

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[18] Bensman Miriam "*Secrets of the style switchers*" *Institutional Investor*, March 1996

discount rate). On the other hand, the return premiums to value investing are generally insignificant, or negative when the Fed is in a restrictive policy stance (increase discount rate). Their findings are based on the argument that value stocks are perceived as fundamentally riskier from investors. Therefore, as monetary and economic conditions change, the risk concerns of investors shift, thereby affecting the influence of risk factors, such as book-to-price, or any other value proxy. Investors demand higher returns on risky investments as compensation for reducing consumption during economic slowdowns. Therefore, risk premiums must be relatively high on firms that have characteristics the market views as indicative of high risk in expansive policy periods.

Another study that concentrates at economic conditions to forecast style returns is the work of Arnott, Kelso, Kiscadden and Macedo (1989). This study uses the well-known BARRA factors[19] to quantify and forecast style performance. It is clear that value stocks are typically stocks with high exposure to book-to-price, earnings-to-price and dividend yield factors. They also frequently exhibit low exposure to trading activity, foreign income and market variability factors. Stocks selected by growth managers generally have the opposite exposure.

Arnott et al., examine the impact of *price inflation*, measured by the percentage change in the producer price index, to style returns. The authors find that, an increase in price inflation would be expected particularly to hurt companies with high exposures to earnings-to-price, foreign income and dividend yield. In support of this findings, Roll (1995), using also the BARRA factors, argues that accelerating inflation torpedoes the high dividend yield issues and hurt companies that dependent on foreign income. This is because rising inflation tends to push interest rates higher, which attracts foreign capital, and thereby depresses foreign currencies and foreign-denominated earnings.

Arnott and Copeland (1985) measures the correlation of the BARRA factors with two other inflation measures: the 12 month rate of change in Consumer Price index and the inflation pressure composite. The latter is designed to detect inflation

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[19] The BARRA risk factors according to the "E2" model for the US are: Market Variability, Success, Size, Trading Activity, Growth Orientation, Book-to-Price, Earnings-to-Price, earnings Variability, Financial leverage, Foreign Income, labour Intensity and Dividend Yield.

pressures as they are building, hence to anticipate acceleration in the inflation rate and is therefore forward looking, whereas the former is backward looking, based on observed history. They find that Growth oriented factors all performed better in periods of inflationary pressures and assert that, if economic conditions portend accelerating inflation, growth securities merit particular attention.

Arnott, Kelso, Kiscadden and Macedo (1989) examining the relation between the Leading economic indicator and factor returns, document a statistically significant effect of the economic health variable on market variability, earnings-to-price and financial leverage. Consistent with others, they show that an improvement in economic health could be expected to have a greater benefit for value companies, with high exposure to the earnings-to-price and financial leverage factors. Finally, the financial liquidity variable, that is also tested, demonstrates a statistically significant effect on three different factors: size, book-to-price and foreign income. The benefits from improved financial liquidity appears to flow to stock of companies with high exposure to the size factor (small-caps) and low exposure to the book-to-price factors (growth stocks), possibly in anticipation of future economic health.

A significant relationship between macroeconomic indicators and returns on small and large-cap indices has also been documented in the literature. Anderson (1997) attempts to forecast the relative annual return difference between small and large stocks[20] in the US market, using three macroeconomic predictors: the annual percent change in the consumer price index, the yield spread, defined as the difference between the average yield on 10 year Treasury bonds and the average yield on one year treasury bonds, and the 12 month in the credit spread, defined as the quotient of the division between the yields on Baa and Aaa corporate bonds. He reports that small stocks benefit from inflation, perhaps because small companies find it relatively easier to pass along price increases in inflationary times. In addition, high rates of inflation often are associated with rising economic output, which may be benefit small stocks. Furthermore, he documents that the term structure and the credit spread variable are positively associated with the relative performance of small over large stocks, confirming the results of Chan, Chen and Hsieh (1985).

[20] Anderson (1997) used the S&P500 index as a proxy for large-cap stocks and defined small stocks as stocks with capitalisation among the smallest quintile of New York Stock Exchange issues.

According to others, interest rates are what drive the relative performance of small-cap strategies. Jensen, Johnson and Mercer (1997, 1998) show that the size premium is large and significant when interest rates are reduced and the Fed is in an expansive mode, but insignificant or negative in all cases when Fed policy is restrictive, an interest rates increase.

The evidence from the previous studies suggests that there is some relationship between economic conditions and the relative performance of investment styles. However, as Mott and Condon (1995) observe, the strategy of forecasting style cycles by forecasting economic activity works better in theory than in reality. Part of the reason for this, is that shifts in the economy are notoriously difficult to predict. And even if one could correctly time a shift in the economy, style cycle shifts do not lead or lag the economic shift by a consistent amount of time, and that makes it difficult to decide when to alter the investment style.

b. Market Indicators

Except of economic variables, research on style predictability has shown that style index returns are also sensitive to various market and fundamental indicators. Arnott, Kelso, Kiscadden and Macedo (1989) examine the effects of market conditions on the 12 BARRA factor returns, using among other variables, the equity risk premium. They find that the risk premium, measured by S&P500 earnings yield minus the treasury Bill yield, is as useful in forecasting style returns as in forecasting stock market returns.

Macedo (1995b), also shows that the equity risk premium is the strongest discriminator for future style performance. She find that the equity risk premium exhibit a strong and significant negative correlation with the return spread between small-cap growth and small-cap value stocks. A high equity risk premium favours riskier portfolios. Value stocks are perceived to be more risky and so tend to do well when the equity risk premium is high. Using the same argument, she points out that equity risk premium can predict the relative performance of small and large-cap stocks.

Kao and Shumaker (1999) introduces the earnings yield gap, which is the difference between the earnings-to-price ratio of the market and the long term bond yield, as an important variable for predicting the value-growth spread. The authors find that a low earnings yield gap favours value stocks. Conversely, a high earnings yield gap that indicates a high P/E environment with low interest rates signals a growth period.

Another, market variable that has been found extremely useful is the stock market volatility. Research on domestic stock-selection has shown that historical volatility is a powerful ex ante indicator of the subsequent performance of investment styles, both for stock selection and for portfolio selection (Arnott et. al. 1989, Arnott et. all 1992, Macedo 1995a). After periods of highly volatility (measured by 6 month historical variance of market returns), value tends to outperform growth, while small-cap stocks outperform their large counterparts. The explanation for this relation comes from behavioural finance. When the market is turbulent, the prospective reward for holding assets perceived to be riskier increases as nervous investors' risk tolerance decreases and they pay a premium for comfort and oversell assets they believe to be riskier.

Shefrin and Statman (1995) provide direct evidence that investment style is linked to investors' perception of quality and risk. Their behavioural CAPM (1994) provides the theoretical foundations for explaining style return differentials. Market equilibrium and mean-variance portfolio theory prescribe that a decrease in risk tolerance results in an increase in risk premium for investment styles. Since market volatility plays a strong role in shaping market sentiment, periods of high volatility lead to investor unease, which may encourage a "flight to quality". During such times investors risk aversion increases, they bid up quality and they oversell assets perceived to be riskier. The consequence is higher premium for higher risk. Style characteristics are strongly linked with perceptions of quality. Therefore, the premium for uncomfortable or contrarian styles should be especially high after a period of high volatility. The premium for value should increase after a period of high volatility, whereas premium for relative growth should be negative.

Despite the evidence presented from the previous studies, an important caveat needs to be mentioned. Measuring volatility by six month historical variance of market returns may not necessarily be a good proxy for risk. As demonstrated in the previous chapter, stock market volatility is time-varying and a historical average is not the most appropriate risk measure. Alternative variables that could proxy the investor's sentiment might be the implied volatility derived from traded-options[21], or a conditional volatility from a GARCH specification. Whether volatility, when estimated by the above methods, can help forecasting relative style performance is an empirical research question.

Some other indicators that are often used in equity style timing as switching signals is the dividend yield, or the earnings yield differential between the two styles. In general, the growth index has a lower earnings and dividend yield than the value index. This reflects the higher growth-potential of stocks in the growth index. According to Fan (1995), the P/E spread between the growth and the value index maintains an equilibrium level in the long run. Hence, when the predicted P/E[22] narrows, the value index should do well and when the ratio widens the growth index should outperform. Based on that, the author find that the equity style predictor forecasts the right equity style 72.5% of the time from 1985 to 1995.

Ragsdale, Rao and Fochtman (1995) believe that future earnings growth is the decisive factor in predicting the future performance of small vs. large-cap stocks. They observe that small stocks clearly outperformed in the 1974-83 period and underperformed in the 1984-90 period, because investors first rewarded them for superior earnings relative to large stocks and then punished them for mediocre earnings. Therefore they suggest that the driving forces behind size style investing must be pursuit on factors that affect companies earnings growth.

One of those factors, is the foreign exposure to foreign markets. Large stocks, and to lesser extent growth stocks, are more leveraged to overseas earnings growth than small stocks. Ragsdale et al. (1995) report that the largest capitalisation group derived a great percentage (32.8% in 1992) of total sales from foreign and export sales and that foreign exposure declines with capitalisation, leaving the smallest quintile deriving only 14.3% of total sales from exports and foreign based operations. In a global environment where the local economy is trailing its foreign partners, big-cap stocks have a distinct advantage over mid-cap and small-cap stocks because of this

[21] I am grateful to Professor Elroy Dimson for suggesting this particular point.
[22] The forecast P/E is calculated based on the IBES year-one earnings forecast versus the current stock price.

foreign income. Consequently, according to Macedo (1995b), large stocks are penalised when the exchange rate is highly volatile.

c. Technical Indicators

While, the previous two sections considered predetermined variables in explaining the style cycles and forecasting their returns, this part investigate the proposition that style returns can be predicted by their own past returns. As demonstrated previously, there is substantial evidence that stock returns are predictable from past returns and generally mean reverting [Fama and French (1988), DeBondt and Thaler (1985, 1987)]. The same argument can be applied for style returns.

Variability over time in the size effect had been first highlighted in a paper by Brown, Kleidon and Marsh (1983). One of their main findings is that variability in the size effect is not entirely random. Rather over longer horizons, such as five years, the size effect exhibits predictable reversals. In other words, a five-year period in which large cap stocks outperform small caps is typically followed by a five-year period in which the relative performance is reversed, i.e., small cap issues outpace large ones.

Reinganum also (1995) investigates whether the relative performance between small and large stocks exhibits cyclical behaviour. He initially observes that the return difference between the two extreme decile portfolios (13% annually for the 1926-1989 period) has an annual standard deviation of 34%. Furthermore, he notes that although on a year-to-year basis fluctuations on the size spread appear random, interesting patterns appear on longer horizons. Over one year horizon, the autocorrelations of the size spread are somewhat positive, but not reliably different from zero. But, for a three year horizon, the autocorrelations are negative and marginally significant, indicating mean reversion. The autocorrelations remain negative and become highly significant at investment horizons of five to seven years. Thus, over longer investment horizons, a period during which large firms outperform small ones, is typically followed by a period in which the relative performance is reversed. Finally, Reinganum regresses the annual return difference between the small and large firm portfolio in year t with the annual return spread lagged one year and the annual spread lagged five years, over the period 1929-1989, using 30 year rolling windows. He reports a consistently positive and significant coefficient for the first variable and a consistently negative coefficient for the second variable, indicating short-term momentum and long-term reversals on the size effect.

Mott and Condon (1995) examine the autocorrelations of the return difference between small-cap value and small-cap growth at shorter time intervals. They report that one month relative returns between small-cap styles exhibit only a small degree of first-order autocorrelation, implying that the relative style-performance in a particular month contains little information with respect to forecasting which style will outperform in the following month. Kao and Shumaker (1999) also find very low serial correlation between different size and value-growth monthly return spreads and deduce that serial correlations may not be effective stand-alone signalling tools.

Case and Cusimano (1995) examine the time series properties of three different style index products, the Wilshire, the Salomon and BARRA/S&P values/growth style indices for monthly, quarterly and semi-annual return frequencies. They show that the relative returns between the paired styles appear to exhibit cyclical patterns through time. Moreover, a simple *runs test* is performed to investigate whether this cyclicallity is occurring by chance alone or not. They find that the runs in monthly relative style-returns are non random across all three value/growth style indices, and that a deterministic process may be at work driving the runs in relative performance.

Furthermore, they test if this deterministic process is relatively stable, or it changes through time. In other words, they test for stationarity, by comparing the cumulative-probability density functions of the relative return series for significant mean differences[23]. They find that the time series of relative style returns behave in an apparent stationary manner and conclude that it may be possible from a statistical standpoint to develop a deterministic algorithm to generate expected outcomes of relative-style performance.

A recent study by Coggin (1998) reaches to completely diferent conclusions. Using variance ratio and modified rescaled range tests he examines the random-walk and the long-term memory hypotheses for a number of different equity style indices

[23] They split their sample into two halves and calculate separately the cumulative-probability density functions for each half of the data. Then they calculated the difference between the two functions and use a Z-score, based on the mean and standard deviation of these differences. If the Z-score is significant then time series of relative style returns is not stationary.

and various truncation lags ranging from 2 to 120 months. His findings suggest that the random walk hypothesis cannot be rejected for any of the equity style indices or equity style spreads. In addition, the results from the modified rescaled range tests indicate that there is no evidence of long-term memory in equity style indices. These results imply that style index returns cannot be predicted using only the time series of returns in the information set.

Another statistical finding, which has been thoroughly researched and documented in the financial literature, is seasonality. Perhaps, the most well known seasonal effect is the January effect for small size stocks. Keim (1983), documents that the magnitude of the size effect varies by the month of the year and finds that fifty percent of the annual size premium is concentrated in the month of January. Subsequent research by Blume and Stambaugh (1983) demonstrates that, after correcting for an upward bias in average returns for small stocks, the size effect is evident only in January. Evidence on January seasonality for small-cap stocks is clear in other countries as well [see Hawawini and Keim (1999)].

Although, seasonality has been extensively researched for small-cap return series, very little work has been done for value / growth indices. Case and Cusimano (1995), find significant calendar relationships for the three value/growth style index products they examine during the 1982-1993 period. The S&P/BARRA return series exhibits significant average returns favouring the value style in the month of January. In addition, on calendar-quarter basis, the S&P/BARRA return series exhibits significant average returns favouring the value style in the first quarter and the growth style in the last quarter of the year. The other indices also exhibit seasonality, with average return being significant in other months.

Additionally, Arnott et al. (1989) find that there is significant January effect for both book-to-price and dividend yield factors, indicating that value stocks are being favoured compared to growth stocks on the first month of the year. Brensam (1996) also states that value stocks tend to beat growth in the first quarter, while growth is the winning style in the fourth. Kao and Shumaker (1999) shows that growth significantly outperforms value in the last quarter, both within small and large-cap segments. Although, these seasonal patterns in the returns of style series, can be extremely useful in statistical modelling and forecasting, someone needs to be very careful using them, as the literature doesn't provide a very clear and convincing explanation for their existence.

4.4.3 Implementing Style Return Forecasts into Rotation Strategies

Whether a style forecasting model is really successful or not, will be considered from its ability to create a profitable style rotation strategy. This section reviews and explores various techniques that have been used for equity style timing and allocation mainly in the US market. Noticeably, as style management and particularly style rotation is a relatively new area, very little research has been published. A lot of tactical style allocation is made using simple trading rules, following from the patterns and relationships described previously. However a few studies have employed econometric techniques to forecast next period's relative performance.

Jacobs and Levy (1989) model the size return spread using a constant model, an exponential smoothing, and a vector autoregressive model. They construct a monthly VAR model using three lag terms of the following set of economic variables: BAA corporate bond rate, long term Treasury bond rate, 3 month treasury bill rate, S&P500 total return, industrial production index and consumer price index. Moreover, they model the size effect using a Bayesian random walk and the same six macroeconomic variables. They find that the last model results in significantly improved forecasting performance compared to the constant specification and the unrestricted VAR.

Macedo (1995b) develops a small value versus small growth recursive forecasting model and tests it out-of-sample from January 1981 to December 1992. The variables she uses are the equity risk premium, the historical market volatility, the interest rate volatility, the leading indicator trend and the bond yield. The ex ante forecasts from the model are used to rebalance the portfolio each month, with 100% of the portfolio being put into the most attractive style. Switches are employed, whenever the expected difference in returns exceeds the transaction costs[24]. Macedo asserts that the tactical allocation model is able to add 6% annually to the 50/50 fixed benchmark, after transaction costs, and with only 19% annual turnover.

[24] 2% round trip for small-cap stocks and 0.5% for large-cap stocks was considered.

A different model is used to predict the relative future performance of small versus large securities. Almost the same variable are used except of the interest rate volatility and the bond yield, which are replaced by the exchange rate volatility and the cash yield trend variables. As before, all forecasts are made ex ante and recursively for the same period. Macedo, finds that when the S&P500 was added as a third investment option in addition to small-cap value and small-cap growth in tactical style allocation, the added value is 9.47% with a 35% turnover.

Fan (1995) utilises four style timing models to predict the future relative performance of value-growth spread. The first, the forecast GDP model, is based on the economic cycle hypothesis and on the assumption that a strong economy favours the value style investment, and vice versa. The second model is based on the predicted P/E spread, which was analysed previously. The third model is the earnings revision spread model, which is based on the stock valuation hypothesis. The earnings revision model is defined as the weighted average five month earning forecast changes. According to this theory, when the earnings revision score of the value style index is higher than that of the growth index, the value style should outperform growth and vice-versa. Finally, the last model he uses is the residual risk spread model. When a stock's residual risk increases, it means that the stock is either falling behind the general fad or is being neglected by investors. When the residual risk of value index is therefore higher than the residual risk of the growth index, the value index underperforming and vice versa.

Fan summarises the performance of the four single factor style timing models for all the sample period and for separate sub-periods. He argues that, different models work better in different periods. During extreme economic conditions, for example, the forecast GDP model would have given the most information about style trends, whereas during normal economic conditions, other models have more information. Finally, he constructs a multifactor style timing model[25] that consists of the four single

[25] The author suggests different ways to put together a multifactor model. First, he suggests a GARCH approach in order to capture the major information shocks from the market events. For example, if there is a drastic change in the real GDP, the forecast GDP model should play the central role. Another approach is to use Bayesian statistics. A third method is to use the principal component analysis to find the canonical weights for each single-factor model. Finally, he suggests to use the Markowitz mean variance optimisation to construct a multifactor style-timing model. The optimal weights are the weights that generate the maximum expected return and minimum uncertainty.

factor models with different weights. The multifactor style timing-model shows tremendous improvement over the individual single factor models. During the 1985-1994 test period, the model generated a gross annual excess return of 5.29% and an annual excess return net of transaction costs of 3.73%, which is 70% more than the best single -factor model. Among the 10-year study period, the model was able to generate positive gross excess return every year except 1990, which had a small negative excess return.

Gerber (1994) uses a logistic regression approach to forecast the probability that value will outperform growth over the next quarter. The model is based on a combination of three elements; long term trend analysis, short intermediate term runs and seasonalities. Based on the outcome probabilities the model suggests maximum value, maximum growth or a 50/50 allocation. Following the probability signals from 1987 to 1993, has resulted in an annualised return increase of 3.41%, net of an assumed 1% round-trip transaction costs relative to the 50-50 passive benchmark.

Sorensen (1995) designs a similar type of forecasting model to produce monthly categorical recommendations between value and growth styles. This model which includes not just technical, but a number of fundamental variables operates across the entire capitalisation spectrum. Three strategies[26] are tested based on the above model and compared with the returns of a passive benchmark. The results indicate that all rotation strategies generate higher returns than the benchmark and moreover exhibit a remarkable consistency across different time periods.

Kao and Shumaker (1999) apply the recursive partitioning algorithm[27], to explain the relationships between several macroeconomic variables and the value-growth spread and develop a style rotation discipline. Their technique is nonparametric and expresses the structure in the form of a binary decision tree. Applying that model to the 3 and 12 month value-growth spread, they find that it has a very high classification accuracy. Moreover, long-short portfolio strategies that

[26] The first strategy puts 100% of the portfolio into the growth or the value index, as determined by the model's prediction as the beginning of each month. Sorensen (1995) two other filtered strategies. The second, shifts from growth to value, or vice versa, only when the absolute value of the return differential is greater than 1%. The final strategy requires two consecutive monthly signals to shift from one style category to another.

[27] The recursive partitioning algorithm is a classification technique commonly used for pattern recognition.

followed the branches of the decision tree and positioned asset accordingly would have earned substantial average annual return between January 1979 and June 1997.

Finally, Satchell and Yoon (1994) implement value/growth style rotation strategies using a Markovian Switching Regime specification. Their model estimates the probability that value would outperform growth and develop trading rules on the basis of these probabilities. The trading rules were profitable, but rather sensitive to transaction costs and the frequency of switching. At 0.1% the switching strategy outperformed pure value or growth portfolios (using the Sharpe reward-to-risk as performance measure), but at 1% the switching strategy performed poorly.

The few studies that have been reviewed on style rotation are quite encouraging for this kind of active management. However, the research is not complete and there is still area for more research and further developments.

CHAPTER 5

"*Data and Methodology*"

5.1 Data Collection and Sources

Data collection is the first step and one of the most important part in every empirical research. This chapter explains the procedures that were followed to collect and organise the main dataset of the thesis and analyses the methodology that was employed to construct portfolios, or indices. A brief discussion of alternative methodologies that could be used is also provided. As some of the chapters of the thesis utilise different data samples, or variables depending on the objectives and the hypotheses tested, a separate reference on this issue will be made at the beginning of each empirical chapter.

The entire empirical analysis of this thesis is concentrated on the UK market. The decision to use UK instead of US data is based on the following arguments: First, we wish to reduce the problem of data-snooping, that refers to the process of developing a hypothesis and testing it using the same data. Since most of the hypotheses, or variations of the hypotheses that we test have been extensively investigated on US using the CRSP and COMPUSTAT databases, a serious data snooping problem could be induced, had we attempted to perform our analysis on a US data set (e.g. Banz and Breen, 1986). Second, the different institutional and regulatory structure of UK, makes the particular market a very interesting sample. Third, there is limited amount of research that has been conducted in the area for UK, which is one of the largest capital markets in the world, and further research using such a data set would, by itself, constitute a useful contribution.

The research design intention of the thesis, is to cover a wide range of companies listed in the London Stock Exchange (LSE) for a long period of time. The main reason for choosing a long sample period is to cover a large number of economic cycles and different economic conditions. A large sample period will ensure that the results will not be period specific. Given the data availability provided by UK databases, we decide to start the analysis from 1968 and carry it up to the end of 1997.

The databases that are used to collect the appropriate data for this study are DATASTREAM and London Share Price Database (LSPD). The first provides a sufficient coverage from 1965 up to date for a number of accounting and financial data, while the second starts at 1955, but does not provide as comprehensive coverage in terms of accounting information as Datastream.

The sample of companies were chosen using Datastream. Datastream is a commercial financial database and among other things gives you the ability to select and download list of companies. To ensure a wide coverage of companies we downloaded two lists; the first one (FBRIT) gives all the companies that are listed at present[1] in the London Stock Exchange. This is the most comprehensive list which includes 1953 companies for which Datastream provides research.

A common problem induced in many studies is survivorship bias (Banz and Breen (1986) and Kothari, Shanken and Sloan (1995)). In order to avoid this problem, an additional list was used (DEADUK), which contains the name of companies that have been delisted from the exchange at some point in time, either due to merger or take-over, bankruptcy, etc. Using the DEADUK list and including delisted companies, we ensure that our sample is not suffering from survivorship bias. The DEADUK list had 1915 companies at the time of the data collection. The combined lists of "alive" and "dead" companies give a total of 3868 firms.

Since we use a number of accounting variables to construct portfolios and since certain accounting variables do not have the same meaning for all firms, we decide to restrict our analysis to only non-financial firms[2]. Particularly, we exclude retail and investment banks, fund management and stockbroking companies, investment companies and other miscellaneous financial, insurance brokers, property agencies and property developers, offshore funds and investment trusts[3]. Furthermore, because of potential problems of defining accounting variables and equity capitalisation, we excluded companies with more than one class of ordinary share. A total of 537 companies were lost from the sample after the exclusions.

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[1] We must note that the data collection took place in August 1997, so the FBRIT list that is used contains all the companies that are listed in the London Stock Exchange at that date.

[2] Restricting the analysis only to non-financial firms is regarded as common practice in studies researching stock market anomalies and portfolio strategies. Some indicative studies are Fama and French (1992, 1995), Chan, Chamao and Lakonishok (1991), Lakonishok, Shleifer and Vishny (1995), Brouwer, Van Der Put and Veld (1995), Strong and Xu (1997) etc.

[3] The industrial classification of each firm was taken from Datastream.

After specifying the sample, the next step is to collect the data for each company. We collected end of month share prices, market values, dividend yields and market to book values from 1968 to 1997, using the Datastream 900B time series programme. The choice of monthly instead of daily share price data is made to reduce the problem of infrequent trading and bid-ask bias, when daily data are used (Blume and Stambaugh, 1983).

The share prices are closing prices and represent the average of bid and ask. Market to book values are defined as market value of equity divided by equity capital plus reserves minus good will and other intangibles[4]. We also collect this item on a monthly basis (end of month). In this case Datastream uses the most recently available book value of equity from the published company accounts and the market value of equity as given at the end of the month. The calculation is as follows:

$$\frac{BV}{MV} = \frac{(\text{Equity Capital} + \text{Re serves}) - (\text{Good Will \& Other In tan gibles})}{\text{Market Value of Equity}}$$

The coverage that Datastream provides for this ratio is not as comprehensive as in the case of share prices and market values, but is sufficient for the proposed research. In addition, we collected for all companies in our sample a number of accounting variables, such as earnings per share, operating profits, total loan capital, equity capital plus reserves and change in working capital using the 101X and 900C Datastream programmes. Earnings per share is defined as net profit after tax, minority interest and preference dividends divided by the year-end number of shares adjusted for subsequent rights and scrip issues. To calculate the cash flow per share item, we collected two items for all companies: net profit derived from normal activities before depreciation and operating provisions, and change in working capital. The sum of those items divided by the year end number of shares gives the cash flow per share. In addition, by dividing total loan capital to equity capital plus reserves we construct the debt to equity ratio. Dividing earnings per share and cash-flow per share with end of month share price we derive the

[4] The reason we deduct the goodwill and the other intangibles from the numerator is to make the ratio less maniputable. Some companies use to capitalise goodwill and other intangibles in their balance sheets and therefore report high book values of equity, while others exclude it and report lower book values. To ensure consistency, we deduct this term from the numerator.

earnings and cash flow yield variables. The precise definition of each variable and its source is given in table 5.1.

Market-to-book ratio, earnings yield and cash flow yield are the most important valuation variables in our study and key factors in formulating different value and growth portfolios. There are a few companies, however, which may have negative book values, earnings or cash flows. Consistent with other studies[5], we do not use stocks with negative M/B, CF/P or E/P when forming portfolios.

Another variable that is also used is the historical earnings growth. We require companies to have at least 4 years of positive past EPS figures before computing growth rates. This is necessary as growth rates cannot be computed when the base-year observation is negative, but results to a substantial amount of missing observation. We estimate annual growth rates for every company for years -1, -2, -3 prior to each year and take the simple average of the past three consecutive years to compute the historical EPS growth. Table 5.2 gives the number of companies with valid market values, market-to-book ratio, cash flow yield. earnings yield and earnings growth for each year in the sample.

We use the London Share Price Database (LSPD) instead of Datastream to collect monthly stock returns. The problem with Datastream is that it does not provide information on the exact amount of dividends paid and the ex-dividend date before 1980, which makes the calculation of returns difficult. LSPD on the other hand contains monthly return data from 1955 onwards, covering over 6,000 shares over the period. This includes every UK-listed and registered stock since 1975.

Using the *returns file* of LSPD, we collect returns for all companies listed in the UK market from 1968 to 1997. The returns are in logarithmic form (continuously compounded returns), and include dividends. The prices are adjusted for rights, splits and

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[5] Both Reinganum (1981) and Basu (1983) excluded stocks in any year in which it had negative earnings. Studies by Basu (1977), Cook and Rozeff (1984), and Dowen and Bauman (1986) have found that the effects of portfolio return rankings are essentially the same, whether stocks with negative EPS are included in or excluded from portfolio groups.

other corporate changes. The adjustments are based on the principle that the value of a share is unaltered by a change in equity structure.

Since we are interesting in portfolio returns, or in average returns for a substantial number of companies, and to be consistent with the underlying theory of portfolio models[6] we decide to use discrete monthly returns. We convert all log returns back to a discrete basis for every company using the following[7]:

$$R_t = exp(\, r_t\,) - 1$$

where R_t represents the simple return and r_t the log return for each security. We then match the returns data collected from LSPD to the financial and accounting data from Datastream using *SEDOL* numbers, which are common in the two databases. Most of the companies in LSPD database could be matched to the two Datastream lists. For the few cases that SEDOLS couldn't be matched, the name of the company was used instead of SEDOLS.

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[6] In a portfolio model with a discrete investment horizon, such as CAPM, the simple, discrete return is the appropriate variable theoretically (see Fama (1976))

[7] For a complete discussion on discrete and continuously compounded returns (log returns) see chapter 1 of Campbell, Lo and MacKinlay (1997).

TABLE 5.1: Data Description and Sources

Variable	Source	Frequency	Definition
Share Price	DS (900B)	monthly	closing prices that represent the average of bid and ask prices.
Market Value	DS (900B)	monthly	price at the end of the month multiplied by the number of shares in issue.
Market-to-Book value	DS (900B)	monthly	market value of equity divided by equity capital plus reserves minus goodwill and other intangibles
Dividend Yield	DS (900B)	monthly	it expresses the gross dividends (including tax credits) per share as a percentage of share price.
Net E.P.S Full tax	DS (900C) Item 183	annually	Net profit after tax, minority interest and preference dividends divided by the year end number of shares, adjusted for subsequent rights and script issues
Operating Profits	DS (900C) Item 137	annually	Net profit derived from normal trading activities before depreciation and operating provisions.
Change in Working Capital	DS (900C) Item 458	annually	total sources less application of funds
Total Assets Employed	DS (900C) Item 391	annually	the sum of all assets less all current liabilities
Total Loan Capital	DS (900C) Item 321	annually	all loans (including convertible, leasing finance and hire purchase) repayable in more than a year
Accounting year-end dates	DS (101X)	annually	gives the year end and month
Stock Returns	LSPD (Returns file)	monthly	logarithmic returns, inclusive of dividends. The returns are adjusted for changes in capital structure.

TABLE 5.2: Sample Characteristics

	No of firms with valid MV	No of stocks with valid M/B	No of stocks with valid E/P	No of stocks with valid CF/P	No with valid EPS growth
1968	611	544	213	205	-
1969	1214	642	687	536	-
1970	1239	658	921	602	-
1971	1274	884	933	607	217
1972	1334	1155	995	784	695
1973	1406	1217	1094	1087	942
1974	1419	1232	1146	1139	966
1975	1426	1241	1120	1128	1010
1976	1437	1252	1101	1125	1088
1977	1446	1263	1135	1161	1126
1978	1466	1288	1142	1150	1129
1979	1496	1311	1178	1193	1123
1980	1513	1328	1156	1164	1096
1981	1472	1311	989	1011	1004
1982	1473	1326	967	1013	962
1983	1485	1350	969	1027	920
1984	1532	1396	1102	1111	886
1985	1506	1368	1135	1144	868
1986	1504	1363	1107	1107	858
1987	1507	1386	1143	1152	886
1988	1535	1349	1191	1194	912
1989	1514	1290	1197	1169	911
1990	1474	1230	1127	1099	910
1991	1398	1181	1029	1011	879
1992	1323	1184	911	957	861
1993	1315	1241	858	962	852
1994	1369	1268	992	1043	864
1995	1404	1323	1101	1157	878
1996	1503	1326	1135	1173	866

5.2 Portfolio Construction

To examine the performance of equity style strategies and construct timing models, we need to have a time series of style returns. There are two basic approaches proposed in the literature. Construct portfolios, or indices using simple univariate, or multivariate methods to segregate one style from the other, and use composite style, or factor returns derived from cross sectional regressions of asset returns and factor exposures[8]. Even though, the second approach has become attractive lately, especially among academics, with the commercial success of BARRA, we will concentrate on the portfolio approach, since it is simple, has more direct applications to equity style strategies, and is used extensively in the academic literature.

There are many methods suggested in the literature for constructing size and value indices/portfolios. Obviously, each methodology serves different purposes and has different advantages and shortcomings. In this section, we provide a review of the most important portfolio construction methodologies and illustrate in detail the approach that is followed in this thesis.

5.2.1 Review of Methodologies

a. One - Way Classification Method

This is the simplest and most straightforward method and has been used in many academic studies. Examples are Reinganum (1981), Brown, Kleidon and Marsh (1983), Levis (1985), Dechow and Sloan (1997) among many others. Quartiles, quintiles, deciles or 20 portfolios can be formed after ranking stocks on the basis of a single variable, such as market value[9], book-to-market, earnings yield, etc. This is an overly simplistic method

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[8] This approach has been used by Arnott and Copeland (1985), Arnott, Kelso, Kiscadden and Macedo (1989), Michaud (1997) among others.

[9] Some small-cap indices are based on the cumulative capitalisation as a percentage of the market's capitalisation. The Hoare Govett Smaller Companies (HGSC) index covers the smallest tenth by equity capitalisation of the UK market. A companion index for small companies in UK is the HG1000 which represents the smallest 1000 companies in the market. Similarly constructed indices for US are the Russell 2000, the Wilshire Small Cap Index, the Prudential Securities Small Cap Index and many others.

that is based on a single variable and does not allow for possible interrelationships between other important variables.

b. Within - Groups Plus Randomisation Method

This method was employed by Banz (1981), Basu (1983), Cook and Rozeff (1984) and Levis (1987) among others. Initially, all stocks in the sample are ranked by a chosen variable, such as market value, and quintiles are formed. Then within each quintile, stocks are re-ranked on a second variable, such as B/M and five new portfolios are formed within each of the original size quintiles. Twenty-five portfolios are created, each one containing approximately the same number of securities.

The twenty five portfolios generated from the combination of MV and B/M portfolios are further combined to form the randomised portfolios. The value, or high B/M randomised portfolio includes securities from the first B/M quintile, but is drawn from the entire set of MV classes; thus it can be viewed as being randomised with respect to size. This implies that value (high B/M) and growth (low B/M) portfolios will have significantly different B/M ratios, but similar market values. To construct size portfolios randomised with respect to B/M a different classification procedure is required. In that case, securities must be ranked first with respect to B/M and then within each B/M group to re-rank them according to MV. The small-cap portfolio randomised with respect to B/M will include stocks from the lowest size quintile, but from all B/M classes. Small and large-cap portfolios after the randomisation will have significantly different MV, but the same by construction B/M ratios.

c. The Fama and French (1995) Independent Groups Method

One of the most interesting and appealing approaches is the method that Fama and French (1995) suggest to construct portfolios. Their method is based on the *Independent Quintile Method* originally proposed by Reinganum (1981) and used by many others. It is a simple univariate method, which uses book-to-market as proxy for value and growth and market value as proxy for size. The approach they use is the following:

In June of each year t, all stocks are ranked on market value. Then the median NYSE market value is used to allocate all stocks listed in NYSE, AMEX and NASDAQ to two groups, small and big (S and B). Stocks are also *independently* broken into three book to market equity groups, based on the breakpoints for the bottom 30% (Low), middle 40% (Middle) and top 30% (High) of the ranked values of B/M.

Six portfolios are constructed from the intersection of the two MV and the three B/M groups (S/L, S/M, S/H, B/L, B/M, B/H). For example, the S/L portfolio contains the stocks in the small market value group that are also in the low B/M group, in other words represent the small-cap growth style. Monthly value-weighted returns on the six portfolios are calculated from July of year t to June year t+1, and the portfolios are reformed in June year t+1.

The returns on the *Small-cap* portfolio is the average of the returns on the three small-stock portfolios (S/L, S/M, S/H), while the returns on the *Large-cap* portfolio is the average of the returns on the three large-stock portfolios (B/L, B/M, B/H). The two portfolios have about the same weighted average book-to-market equity. The *Value* portfolio is a simple average of the returns on the two high B/M portfolios (S/H and B/H), while the *Growth* portfolio is the average of the returns on the two low BE/ME portfolios (S/L and B/L). These portfolios are neutralised against any size effect, since they have roughly equal market value.

Finally, Fama and French construct the two style spreads, SMB and HML. Portfolio SMB meant to mimic the risk factors in returns related to size and is the monthly difference between the returns on *small* and *large-cap* portfolio. HML, on the other hand, meant to mimic the risk factor in returns related to book-to-market, and is defined as the difference in returns between the *Value* and the *Growth* portfolio. SMB is the return on a portfolio that is long in small firms and short in large firms of approximately the same book-to-market value. HML is the return on a portfolio that is long on high book-to-market firms and short in low book-to-market firms of approximately the same size.

Although, both the within groups plus randomisation and the independent groups method result in neutralising and segregating one effect from the other, they differ mainly in terms of the number of stocks per portfolio that they produce. The within groups method creates portfolios with essentially the same number of stocks per portfolio, while the independent groups method does not impose that restriction. If there are very few stocks, which are both in the lowest MV group and the lowest B/M group, then the small-cap growth portfolio will contain a limited number of securities. This will ultimately reflect the relationship between the two variables.

The method we just described is accepted and widely used by academics, after the recent Fama and French paper, but may have investment implications as well, since it results in indices that are liquid enough and viable to institutional investors.

d. Two Style Index Methodology

A number of commercial indices have been developed to describe the value and growth investment styles. Among the most well known are the S&P/BARRA and BIA International style indices that have also been used in academic studies by Sharpe (1992), Capaul, Rowley and Sharpe (1993), and Umstead (1995) among others. These indices are constructed by dividing all stocks in the market into two *mutually exclusive* groups. For each stock two pieces of information are collected: the ratio of the recent price to the most recently released book value per share and the market value of equity. Then stocks are sorted on ascending order by price to book and the capitalisation data for the individual companies are summed, starting from the top, until exactly half of the market capitalisation is accumulated[10]. The stocks are then placed accordingly into value (low price to book) and growth (high price to book) portfolios.

Although, intuitively simple and liquid enough to be attractive to institutional investors, the previous indices are not short of weaknesses. Because growth companies are those whose shares of capitalisation exceeds their share of book value, it requires fewer of them to account for half of the market capitalisation[11]. Moreover, since growth and value indices are constructed to have equal total capitalisation, and as the growth index has fewer members, the average market value of growth companies is higher than

[10] The S&P/BARRA value and growth indices use the S&P500 index as the market index. This index, however, covers approximately 75% of the market capitalisation of the traded equity securities in the U.S and therefore represent an index of large and liquid stocks.

[11] Sorensen and Lazzara (1995) reports that the S&P/BARRA growth index has typically contained between 180 to 200 companies, with the remaining 300 to 320 allocated to value index

that of value companies. This does not allow a clear distinction between the price-to-book and size effects.

A second shortcoming has to do with the concept of mutual exclusivity under which these indices are constructed. Every stock is assigned uniquely to one of two discrete categories, value or growth, based only to the value of price to book ratio. However, not in all circumstances a company can be safely categorised as either value or growth. Some companies probably don't belong in either index. As Sorensen and Lazzara (1995) point out, the stock's price to book ratio must rise above a critical threshold, in order to safely change it's classification from value to growth.

e. Frank Russell Probability Algorithm

Frank Russell Company also uses the price-to-book ratio as criterion to separate value from growth, but introduces a probability algorithm, which eliminates the mutual exclusivity problem. Given the distributions of price-to-book in the style universe, Frank Russell determines that the relationship between portfolio characteristics and the probabilities of a style membership is inherently nonlinear. The probability that a company is a value company increases as the price-to-book drops below the market level price-to-book, but it does not decline linearly. On the other hand, as the price-to-book moves away from the mean or median, the probability of value classification increases rapidly.

The Russell methodology has been applied to the FTSE style indices that have been recently introduced. The methodology involves the following steps: First, for all stocks in the market (in this case the FTSE 350) four equal capitalisation quartiles are determined, such that the 25% of stocks with the lowest price-to-book appear in the first quartile and so on. Then a non-linear probability algorithm is used to assign value/growth weights to each stock as follows: if a stock has a price-to-book ratio in the bottom 25%, it is assigned a value weight of 1.0. If the stock's price-to-book is between the first quartile break and the median, it has a weight between 1.0 and 0.5. The weight declines in a non-linear fashion from 1.0 at the first quartile break towards 0.5 depending on how close to the median the stock is. Similarly, stocks in the third quartile have a value weight between 0.5 and 0.0 and this weight also vary in a non-linear fashion. Finally, all stocks in the fourth quartile have a growth weight of 1.0.

f. Multivariate Methodologies

All the methodologies that we have described so far, suffer from the so-called simultaneity problem. Classifying stocks on the basis on a single criterion may lead to false judgements. Price-to-book ratio is the variable most commonly used to differentiate value from growth, but is not the only one. A simultaneous consideration of many factors, such as dividend yield, cash flow-to-price, price-to-book, price earnings, forecast growth, etc. could lead to better and more safe conclusions. A multifactor discriminant analysis framework is used by Sorensen and Lazzara (1995), where the independent variables are historical returns, historical P/E ratios, historical dividend yields and IBES five year projected earnings growth. The model takes the following form:

$$d_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4}$$

where d_i is the discriminant function, x_{ij} are the values of the independent variable and β_{i}, are the estimated coefficients. A panel of stocks, which can undoubtedly be characterised as value or growth by analysts and investment managers, is initially identified. Then the value/growth discrete variable (if a company is regarded as growth then the value of 1 is assigned, otherwise 0 is used) is regressed cross sectionally for all panel members upon the previously mentioned independent variables, and the β coefficients are estimated. Using these coefficients every other stock is assigned a score on a zero-to-one scale which represent the probability that the stock is a value or a growth stock.

These value/growth probabilities also facilitate the construction of *Salomon* Value and Growth indices. The large-cap growth index include the largest 50 stocks with growth probabilities equal to, or greater than 0.85. The large-cap value index, on the other hand, is composed of the largest 50 stocks with growth probabilities equal to, or lower than 0.15.

The *Russell Small-cap Style Indices* are also constructed using a multivariate method. Stocks in the Russell 2000 are sorted initially by price-to-book and secondly by the IBES long term earnings growth. Each series is standardised and then combined for a composite score; breakpoints are determined by the cumulative available market capitalisation to create three range of securities. The securities in the lower range are 100% Russell growth, while those in the upper range are 100% Russell value. Securities in the middle range are assigned proportionately to both value and growth, based on their value score relative to the median. As a result, many companies are listed in both indices, but are not weighted based on their full float-based capitalisation.

Another set of indices constructed under the utilisation of multivariate-selection criteria is the *Wilshire* value and growth indices. In the case of those indices, however, different criteria are used to classify a stock to the value index as opposed to growth. This method is based on the concept that growth is not necessarily the opposite of value. Factors like price-to-book, dividend payout, return on equity and earnings growth are considered important in the construction of the growth index. On the other hand, relative price earnings, relative dividend yield and price-to-book ratio are the crucial factors in assigning a stock in the value portfolio.

5.2.2 Methodology Used

The methodology that we use to construct style portfolios and style spreads resembles that of Fama and French (1995). We however test three other variables, in addition to the book-to-price, in the univariate classification process. These variables are the cash flow-to-price, the earnings-yo-price and the three years historical earnings growth. Although, book-to-price ratio is considered an accepted proxy for value and growth investment styles in US, there is not adequate evidence to support this proposition in UK.

Simple ratios of cash flow over price, or earnings over price are consistent with the idea behind Gordon's valuation formula. Holding discount and payout rates constant, a company with high cash flow to price has a low expected growth rate of cash flow, whereas a low cash flow to price company has a high expected cash flow growth rate. Same argument applies for high and low E/P stocks. Accounting earnings however may be misleading and biased estimate of the economic earnings, but cash flow per share is less maniputable and, therefore, possibly a less biased estimate of economically important flows accruing to the firm's shareholders. We also use three years past earnings growth as a proxy for value and growth stocks. If investors extrapolate the past, then past growth will be used to proxy for expected growth and growth companies will be companies with high historical earnings growth, while value will have much lower past growth rates. Constructing value and growth indices using E\P, CF\P and past EPS growth, in addition to B\P, will provide a more comprehensive picture to value investing in UK. The procedure that is employed is the following:

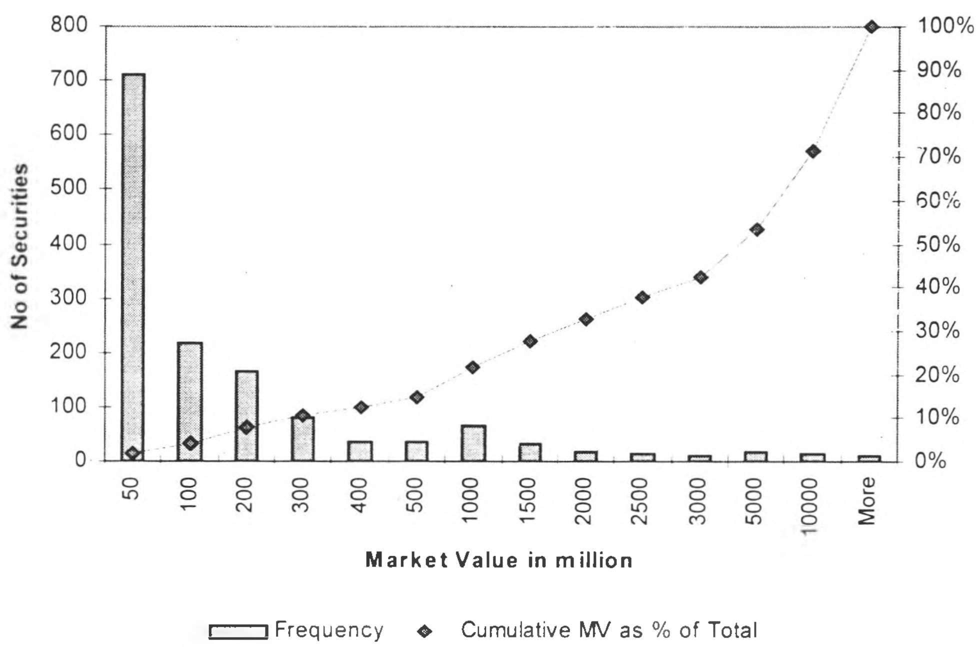
Similarly with Fama and French and consistent with other studies, we start the portfolio formation procedure at the end of June of every year. Most companies in our dataset have fiscal year that end on December 31. A small number of companies, however, have fiscal years that end on months other than December. In UK 70% of companies have a December, or March year-end and their accounts are usually published within 5 months (Lasfer and Taffler, 1995). Therefore, forming portfolios at the end of June ensures that our tests are predictive in nature, and that we do not use information that is not actually available to investors at the time of portfolio formation. Thereby, we avoid a possible look-ahead bias (Banz and Breen, 1986).

We initially sort all companies in descending order according to their end of June market value. We then cumulate the individual market values until we reach to the 80% of the total market value. These companies with the highest MV comprise the first MV segment. Companies between 80% and 90% cumulative MV are allocated to the second MV portfolio. Finally, the companies that cover the smallest 10% by equity capitalisation of the market comprise the smallest MV group.

Contrary to Fama and French, we introduce a mid-cap segment to avoid the problem of mutual exclusivity. The capitalisation breakpoints are not chosen entirely arbitrary. The small-cap capitalisation breakpoint is assigned to 10% to be consistent with

HGSC, the well-established small-cap UK benchmark. Furthermore, given the high concentration of the UK market and the distribution of market values, the particular breakpoints satisfy the liquidity and minimum number of securities requirements[12]. Figure 5.1 shows the cross-sectional distribution of market values at the end of June 1996. It is obvious that very few securities account for the largest proportion of the capitalisation of the market. Furthermore, around 1200 stocks comprise the smallest 10^{th} of the market.

Figure 5.1 Cross Sectional Distribution of Market Values



At a second stage, we independently sort all securities according to their end of June book-to-price ratio. The top 30% of the companies with the highest B/P comprise the first B/P portfolio, the middle 40% the second portfolio and the bottom 30% the third portfolio. Nine size-B/P portfolios are then created from the intersection of the three MV and the three B/P groups. Companies with low market value and high book-to-price ratio consist the small-value segment, while companies with low market value, but low B/P are

[12] We experiment with various other capitalisation breakpoints, but the 10%-10%-80% gave the most satisfactory results in terms of number of securities and total capitalisation.

allocated in the small-growth portfolio, etc. This procedure is repeated at the end of June of every year, i.e. 29 times, and the composition of the portfolios change annually. The number of securities allocated in each portfolio for every year is given at the appendix.

For each month beginning from July of each year until the end of June of the following year, discrete returns of each security within each portfolio are equally weighted[13] to form nine series of portfolio returns. *Value* stocks returns is then the simple average of small-cap value, mid-cap value and large-cap value returns, while *growth* stock returns consist of a simple average of small-cap growth, mid-cap growth and large-cap growth. Similarly, *Small-caps* returns are calculated from the simple average of small-cap value, small-cap middle and small-cap growth. Large-caps returns are derived from the return average of the large-cap value, large-cap middle and large-cap growth.

Small and Large-cap indices have by construction roughly equal market-to-book ratio but significantly different market value. Similarly value and growth indices differ dramatically with respect to market-to-book, but have nearly the same size. This is a very important property of our indices as we are interested on the effects of each style separately and not on the combined effects. Like Fama and French (1995), we construct the two style return spreads, Small - Large (S-L) and Value - Growth (V-G), to mimic the factors in returns related to size and market-to-book respectively.

Exactly the same portfolio formation procedure is followed in constructing other value and growth indices, when CF\P, E\P and past EPS growth are used as the relevant classification proxy. The appendix, at the end of the chapter, shows the distribution of market value across different portfolios constructed on the basis of each of the four variables. For the purpose of convenience we report the minimum, maximum and average market value only for the small-cap value, small-cap growth, large-cap value and large-cap growth portfolios.

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[13] Capitalisation weighted returns have also been used and are reported in the next chapters.

APPENDIX A

A1. No of stocks per portfolio (B/P is used to proxy value and growth)

	Small-cap Value	Small-cap Middle	Small-cap Growth	Mid Value	Mid-cap Middle	Mid-cap Growth	Large-cap Value	Large-cap Middle	Large-cap Growth
1968	137	153	103	16	30	30	11	36	31
1969	167	190	135	17	31	31	10	38	28
1970	172	193	127	16	33	35	10	39	37
1971	249	294	175	12	27	47	7	37	46
1972	320	370	238	21	46	60	12	54	55
1973	313	377	254	30	58	66	29	61	52
1974	325	384	281	31	66	48	20	52	47
1975	364	432	260	7	41	57	8	32	62
1976	368	412	276	6	58	46	8	40	60
1977	373	415	275	13	59	52	7	50	66
1978	350	402	284	24	67	64	30	69	56
1979	355	402	288	30	63	71	27	84	53
1980	378	428	286	20	64	64	19	64	67
1981	384	432	282	12	59	70	18	63	64
1982	391	431	306	15	63	57	15	68	59
1983	401	463	309	13	54	62	18	59	61
1984	407	461	331	21	62	61	18	72	54
1985	397	459	334	26	58	54	14	65	49
1986	402	453	329	20	61	58	15	69	50
1987	389	414	360	30	83	52	26	95	33
1988	367	434	351	41	79	50	38	81	45
1989	359	458	331	43	62	54	33	62	51
1990	379	457	314	19	47	51	18	52	52
1991	370	435	308	16	47	38	11	48	52
1992	350	415	293	20	43	36	10	50	52
1993	355	410	281	14	44	48	13	56	53
1994	358	412	312	21	57	44	21	65	45
1995	375	432	313	23	49	48	13	67	50
1996	390	444	328	21	60	57	20	71	46

A2. No of stocks per portfolio (E/P is used to proxy value and growth)

	Small-cap Value	Small-cap Middle	Small-cap Growth	Mid Value	Mid-cap Middle	Mid-cap Growth	Large-cap Value	Large-cap Middle	Large-cap Growth
1968	60	58	32	5	13	12	0	16	21
1969	199	209	144	8	39	27	3	32	39
1970	274	306	189	8	41	38	1	30	56
1971	281	332	175	5	28	50	1	22	62
1972	292	298	201	11	62	41	2	48	64
1973	296	326	233	25	56	55	15	66	48
1974	309	348	271	28	72	32	15	49	49
1975	334	386	235	7	40	49	3	33	60
1976	319	380	231	15	43	40	4	29	68
1977	329	363	253	13	53	40	6	48	55
1978	308	350	265	23	67	45	25	59	47
1979	316	371	259	30	59	59	26	67	55
1980	335	359	259	21	51	62	10	79	46
1981	265	307	239	23	47	44	27	66	32
1982	255	301	245	20	51	39	35	61	26
1983	262	317	245	26	41	36	25	60	33
1984	298	344	286	24	59	40	31	69	28
1985	300	372	299	28	57	40	37	57	26
1986	316	339	290	20	63	36	20	73	30
1987	286	360	303	35	63	43	49	68	23
1988	294	372	306	33	66	53	55	72	23
1989	323	378	300	34	59	53	29	77	33
1990	331	366	286	19	48	41	12	68	35
1991	297	327	264	18	49	28	12	60	35
1992	251	297	235	19	38	30	22	54	27
1993	227	285	219	21	31	29	26	50	26
1994	246	326	265	23	51	26	48	46	26
1995	305	367	287	24	48	34	27	60	35
1996	320	374	291	18	60	40	30	56	37

A3. No of stocks per portfolio (CF/P is used to proxy value and growth)

	Small-cap Value	Small-cap Middle	Small-cap Growth	Mid Value	Mid-cap Middle	Mid-cap Growth	Large-cap Value	Large-cap Middle	Large-cap Growth
1968	59	52	31	3	14	13	1	18	19
1969	142	154	110	11	36	23	11	29	30
1970	163	184	112	11	36	31	11	26	42
1971	169	194	102	9	32	34	8	22	50
1972	205	230	157	24	43	33	11	47	49
1973	282	334	236	30	59	45	22	53	53
1974	300	366	260	32	54	43	18	47	47
1975	325	389	241	14	40	43	6	31	58
1976	325	376	247	15	45	38	6	41	55
1977	332	368	268	13	54	38	11	53	47
1978	325	347	258	21	66	48	13	66	53
1979	338	380	241	22	60	66	17	63	69
1980	336	382	245	19	55	59	15	57	63
1981	292	317	214	13	53	51	19	62	44
1982	281	324	229	15	53	46	29	57	38
1983	303	327	251	16	50	39	14	67	38
1984	310	369	271	21	54	46	28	55	42
1985	319	388	279	21	55	49	29	49	41
1986	328	370	259	14	53	50	16	55	48
1987	321	357	287	24	66	52	29	76	35
1988	315	388	279	34	59	59	36	56	47
1989	316	380	286	35	57	51	28	68	42
1990	319	385	266	23	41	40	13	47	49
1991	300	338	249	13	45	32	13	51	33
1992	250	296	231	13	41	23	16	49	28
1993	286	302	249	10	49	32	16	65	29
1994	300	332	269	16	48	38	22	70	30
1995	347	369	301	14	58	38	14	74	37
1996	348	392	288	12	60	49	22	58	44

A4. No of stocks per portfolio (Past EPS growth is used to proxy value and growth)

	Small-cap Value	Small-cap Middle	Small-cap Growth	Mid Value	Mid-cap Middle	Mid-cap Growth	Large-cap Value	Large-cap Middle	Large-cap Growth
1968	-	-	-	-	-	-	-	-	-
1969	-	-	-	-	-	-	-	-	-
1970	-	-	-	-	-	-	-	-	-
1971	48	59	50	8	11	7	9	17	8
1972	152	191	170	24	39	22	32	48	17
1973	214	277	219	31	46	36	38	54	27
1974	241	275	240	25	56	28	24	55	22
1975	256	328	251	26	35	24	21	41	28
1976	280	341	279	17	50	25	29	44	23
1977	297	347	276	22	50	29	19	53	33
1978	285	332	263	27	63	34	27	57	41
1979	270	327	274	36	59	32	31	63	31
1980	271	324	278	31	52	30	27	62	21
1981	267	294	232	20	49	33	14	59	36
1982	258	285	203	15	48	39	16	52	46
1983	241	279	203	16	33	41	19	56	32
1984	219	248	220	25	45	24	22	61	22
1985	227	244	202	18	40	34	15	63	25
1986	219	246	198	18	42	31	20	55	29
1987	219	253	196	17	51	33	30	50	37
1988	208	245	227	18	58	30	48	62	16
1989	203	264	226	26	46	29	44	54	19
1990	238	255	237	20	46	18	15	63	18
1991	232	262	221	21	35	23	11	55	19
1992	220	267	214	23	35	20	15	42	25
1993	209	254	215	23	39	18	24	48	22
1994	217	243	214	17	41	26	25	62	19
1995	217	253	226	19	38	20	27	60	18
1996	208	255	217	24	41	18	28	50	25

APPENDIX B

B1. Distribution of Market Values for Small - Cap Value portfolios

	Market to Book			*Cash Flow-to-Price*			*Earnings-to-price*			*Past EPS growth*		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1968	0.13	4.27	16.55	0.54	3.40	11.04	0.45	3.13	9.81	-	-	-
1969	0.13	3.32	15.87	0.05	2.44	16.33	0.13	3.83	17.87	-	-	-
1970	0.12	2.74	11.57	0.02	1.51	10.83	0.12	3.00	14.44	-	-	-
1971	0.02	2.32	17.81	0.02	1.77	17.47	0.20	3.97	19.11	0.37	4.16	14.25
1972	0.02	2.37	14.80	0.02	2.77	16.43	0.02	4.39	18.27	0.02	4.96	20.68
1973	0.02	2.53	12.45	0.02	2.92	13.50	0.02	2.97	13.42	0.02	3.71	14.70
1974	0.02	1.74	6.83	0.02	1.78	6.83	0.02	1.73	7.40	0.02	2.18	8.77
1975	0.02	1.57	12.42	0.02	1.70	13.43	0.05	1.74	12.98	0.02	2.41	15.35
1976	0.02	1.83	14.95	0.08	2.17	16.38	0.06	2.24	16.09	0.02	2.88	17.52
1977	0.02	2.26	16.06	0.02	2.56	19.06	0.02	2.71	19.24	0.02	3.51	19.24
1978	0.02	3.39	17.39	0.02	3.54	18.51	0.02	3.33	18.66	0.02	3.86	19.27
1979	0.02	4.18	21.41	0.09	4.20	23.30	0.02	4.28	23.30	0.02	5.66	23.54
1980	0.02	3.25	22.03	0.11	4.77	28.51	0.11	4.46	27.25	0.02	5.87	29.09
1981	0.03	4.20	34.21	0.10	7.03	38.86	0.03	6.14	38.24	0.12	6.70	38.24
1982	0.06	4.10	35.58	0.15	7.99	42.42	0.13	6.83	40.28	0.06	6.92	42.95
1983	0.08	6.16	52.62	0.12	9.55	62.56	0.08	7.79	62.01	0.12	10.20	70.72
1984	0.08	7.46	50.00	0.19	11.43	60.67	0.08	8.97	60.67	0.34	13.00	74.57
1985	0.08	10.68	73.16	0.55	13.53	78.98	0.08	11.49	82.09	0.60	15.71	84.60
1986	0.25	15.27	97.98	0.45	19.23	110.36	0.20	14.01	99.02	0.44	22.31	124.98
1987	0.23	25.30	132.26	0.84	30.91	150.92	0.44	26.89	150.92	0.48	37.54	183.70
1988	0.29	23.57	115.30	1.44	26.92	126.65	0.28	22.46	124.60	0.48	33.28	169.01
1989	0.27	27.52	131.67	0.27	35.05	148.66	0.27	31.26	147.41	1.95	46.20	195.61
1990	0.13	23.91	188.87	0.23	31.38	204.32	0.23	27.52	207.45	1.05	41.24	226.58
1991	0.12	20.27	234.59	0.12	31.75	247.16	0.44	30.20	247.16	0.44	39.98	259.99
1992	0.24	20.61	225.05	0.84	32.52	247.01	0.29	32.94	313.65	0.16	44.42	299.14
1993	0.13	25.03	251.78	0.11	41.19	340.50	0.32	29.44	300.77	0.13	53.66	331.16
1994	0.21	32.71	264.94	1.22	48.57	332.02	0.42	43.08	320.46	0.21	65.94	346.15
1995	0.15	34.32	261.08	0.15	38.07	293.89	0.15	35.66	266.01	0.42	71.46	437.74
1996	0.18	35.98	286.49	0.33	47.23	355.18	0.18	44.85	347.07	1.49	87.76	471.71
All years	0.11	12.17	90.89	0.28	16.13	105.23	0.17	14.53	104.33	0.35	24.45	136.13

Note: The minimum, maximum, and average market value (in million of sterling pounds) is reported for different small-cap value portfolios formed on the basis of book-to-price, cash flow-to-price, earnings-to-price and three years historical EPS growth.

B2. Distribution of Market Values for Small - Cap Growth portfolios

	Market to Book			*Cash Flow-to-Price*			*Earnings-to-price*			*Past EPS growth*		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1968	0.68	6.83	16.58	0.68	4.99	12.32	1.51	5.34	10.33	-	-	-
1969	0.08	5.88	16.99	0.08	5.44	18.23	0.78	6.29	18.23	-	-	-
1970	0.07	5.31	14.23	0.08	3.43	13.95	0.61	5.26	14.53	-	-	-
1971	0.10	5.32	18.12	0.08	4.63	18.14	0.84	6.18	18.66	0.98	6.12	17.47
1972	0.09	5.09	15.39	0.15	4.82	16.38	0.40	6.55	18.26	0.07	6.40	21.71
1973	0.16	4.11	12.63	0.14	3.69	13.69	0.16	4.10	13.74	0.06	4.51	14.96
1974	0.09	2.16	6.75	0.08	2.12	7.43	0.16	2.29	7.61	0.06	2.29	8.83
1975	0.05	3.06	12.00	0.04	3.47	13.35	0.12	3.28	13.35	0.05	2.56	15.65
1976	0.06	4.08	15.40	0.06	3.84	15.84	0.05	3.39	15.42	0.05	3.54	16.38
1977	0.07	5.04	17.20	0.08	4.63	19.42	0.07	4.68	19.33	0.09	4.33	20.33
1978	0.16	5.66	18.00	0.12	5.14	18.39	0.07	5.62	18.60	0.05	4.90	19.07
1979	0.16	7.15	21.51	0.02	7.57	23.40	0.16	7.28	23.40	0.13	5.96	23.83
1980	0.16	7.84	25.58	0.02	7.19	27.82	0.15	7.92	28.50	0.14	6.38	29.23
1981	0.16	9.73	33.11	0.12	9.44	38.30	0.10	10.96	38.30	0.10	10.67	39.57
1982	0.21	9.57	35.52	0.06	9.31	42.56	0.11	11.36	42.29	0.11	12.45	44.35
1983	0.36	13.29	53.30	0.14	14.77	64.48	0.42	16.88	64.48	0.14	18.48	71.90
1984	0.13	13.45	54.72	0.31	13.33	59.71	0.20	18.67	65.90	0.41	17.44	75.01
1985	0.61	18.28	74.06	0.32	17.64	80.58	0.32	22.54	80.58	0.22	21.66	86.28
1986	0.50	24.95	97.51	0.20	26.02	111.66	0.45	32.57	113.36	0.75	33.00	135.00
1987	0.95	34.92	132.96	0.44	37.71	153.93	0.95	43.46	149.47	2.85	55.59	193.57
1988	1.66	30.32	113.93	0.28	31.59	125.45	1.35	39.49	128.70	0.90	44.32	169.89
1989	1.50	36.50	138.18	0.44	36.37	139.89	1.33	41.10	147.70	0.27	49.38	194.40
1990	1.20	43.33	191.77	0.53	46.93	207.45	1.10	48.79	211.05	0.23	45.66	250.88
1991	0.82	54.61	228.75	0.44	49.14	247.49	0.72	53.57	253.04	0.12	51.75	248.26
1992	0.40	64.37	239.27	0.39	57.52	303.07	0.51	61.12	310.98	0.85	67.78	265.86
1993	0.73	78.22	293.93	0.32	71.97	355.11	0.96	79.53	321.08	0.92	73.58	323.40
1994	0.71	65.39	261.45	0.42	63.65	328.00	1.25	71.19	317.41	1.22	77.67	368.63
1995	0.83	71.92	268.71	0.42	69.89	304.17	1.25	73.40	299.70	1.47	79.62	416.75
1996	0.27	79.01	286.62	0.64	85.57	369.76	0.88	92.25	357.82	0.64	90.07	468.35
All years	0.45	24.67	93.59	0.24	24.20	108.62	0.59	27.07	107.65	0.50	30.62	136.14

Note: The minimum, maximum, and average market value (in million of sterling pounds) is reported for different small-cap growth portfolios formed on the basis of book-to-price, cash flow-to-price, earnings-to-price and three years historical EPS growth.

B3. Distribution of Market Value for Large - Value portfolios

	Market to Book			*Cash Flow-to-Price*			*Earnings-to-price*			*Past EPS growth*		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1968	55	243	1360	-	-	-	-	-	-	-	-	-
1969	54	77	122	59	73	82	53	120	508	-	-	-
1970	43	104	353	102	102	102	43	115	396	-	-	-
1971	63	74	86	85	85	85	63	184	568	50	111	297
1972	52	164	618	133	451	770	66	509	2147	64	297	1834
1973	38	290	2116	41	199	661	44	275	2116	45	286	2116
1974	26	114	1000	27	147	1000	34	221	1475	31	124	465
1975	45	73	134	115	1279	1969	49	722	1969	50	145	498
1976	63	95	150	79	133	206	63	98	153	62	177	643
1977	65	113	205	65	90	122	65	227	886	96	349	3595
1978	52	137	394	58	312	3022	61	157	519	64	338	3208
1979	59	154	393	67	244	1007	67	198	1007	75	396	4176
1980	69	170	347	80	1264	5632	77	634	5632	92	334	2225
1981	91	249	1651	105	697	5697	105	775	5697	117	390	1651
1982	113	198	357	115	590	5087	126	723	5087	143	241	716
1983	148	326	1098	179	779	6563	193	1106	6563	193	1307	7914
1984	160	761	6938	179	1055	8442	179	1226	8442	238	867	8442
1985	211	614	1449	251	1273	9616	251	1463	9616	280	961	4467
1986	307	1326	8761	350	2991	13320	346	2067	10785	394	1330	5866
1987	406	1705	15667	423	2089	16800	423	1837	16800	500	2903	21292
1988	353	1475	11435	361	2108	15570	361	1603	15570	447	1848	11435
1989	465	1653	14056	494	2469	15120	494	1769	15120	553	2822	15906
1990	595	1294	2880	654	1186	2880	673	1211	2880	739	2428	9500
1991	981	1575	2500	730	2052	10418	855	3069	17686	885	2768	10644
1992	834	1265	2025	844	2220	20513	940	4585	20513	913	2160	8459
1993	919	1621	2990	1005	3581	26367	985	4139	26367	1079	2155	7014
1994	843	1746	4425	940	3998	22963	940	4329	22963	1055	2696	12442
1995	1029	1835	3552	1004	2910	24449	1037	2423	10298	1247	4228	24449
1996	874	2094	7961	1077	4364	21595	1067	4663	21595	1338	4675	21595
All years	310	743	3276	332	1336	8278	337	1398	8050	413	1398	7340

Note: The minimum, maximum, and average market value (in million of sterling pounds) is reported for different large - cap value portfolios formed on the basis of book-to-price, cash flow-to-price, earnings-to-price and three years historical EPS growth.

B4. Distribution of Market Value for Large - Growth portfolios

	Market to Book			*Cash Flow-to-Price*			*Earnings-to-price*			*Past EPS growth*		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1968	51	146	604	40	150	604	40	136	604	-	-	-
1969	51	237	2649	52	236	2649	51	247	2355	-	-	-
1970	41	129	630	41	166	1262	43	149	630	-	-	-
1971	53	169	941	53	254	2243	58	211	1350	45	168	443
1972	48	166	895	50	197	895	56	194	895	66	144	454
1973	39	121	847	44	230	2116	43	160	847	45	119	467
1974	26	111	467	28	111	465	28	125	467	30	107	491
1975	45	183	1278	47	163	696	47	168	804	47	298	1969
1976	53	260	2409	55	244	2359	55	222	2007	62	416	2409
1977	58	329	3595	64	264	3595	71	218	1097	67	285	2267
1978	52	224	1465	58	282	3208	58	243	1465	61	234	1465
1979	67	258	1981	70	365	4812	66	295	1989	74	470	4812
1980	65	370	5632	76	304	1175	75	327	2173	94	721	5632
1981	91	435	4049	106	571	4049	106	514	4049	118	625	5697
1982	100	472	5410	115	696	5410	113	607	5410	120	692	5410
1983	145	725	6145	167	692	3239	168	883	6145	179	1003	6145
1984	161	790	5213	169	689	3184	178	725	3184	211	978	3486
1985	212	1148	12540	242	1096	4589	260	1072	4589	269	1256	4785
1986	304	1451	7513	320	1570	7513	331	1491	7513	382	1829	10785
1987	405	1996	12213	468	2875	21292	433	2000	12213	509	1664	12213
1988	352	1402	7343	369	1449	4391	386	1837	15330	457	1147	7343
1989	482	2132	10242	482	1769	10242	482	2136	10242	581	1268	2358
1990	595	2812	12452	713	2844	12452	713	2990	12452	727	2789	17073
1991	759	3162	18812	759	3310	18812	813	2988	18812	855	3239	9428
1992	778	3504	19806	843	4987	19806	903	4185	19806	924	5176	20513
1993	864	3908	16761	1079	3092	16592	962	3843	16761	1063	5741	16761
1994	841	5273	16617	980	2680	8831	901	3429	12442	1021	3650	12264
1995	976	4090	26877	1068	3930	24826	1064	4694	26877	1304	4439	24733
1996	877	4195	30615	1098	3905	19023	1071	4341	19023	1369	4356	31984
All years	296	1317	8138	333	1349	7253	330	1394	7294	411	1647	8130

Note: The minimum, maximum, and average market value (in million of sterling pounds) is reported for different large - cap growth portfolios formed on the basis of book-to-price, cash flow-to-price, earnings-to-price and three years historical EPS growth.

CHAPTER 6

"Performance and Risk Characteristics of Size and Value Portfolios"

6.1 Introduction and Hypotheses Tested

There is a growing body of academic research demonstrating economic and statistically significant returns for size and value investment strategies. More specifically, small-cap stocks and stocks with high ratios of fundamentals to price (value) are found to outperform in the long term in many developed and emerging capital markets (Hawawini and Keim (1999), Capaul, Rowley and Sharpe (1993), Fama and French (1997), Bauman, Conover and Miller (1998), etc.). Recent evidence, however, shows a disappearing or even reversal of the size effect (see Ragsdale, Rao and Fochtman (1993) for US, and Dimson and Marsh (1999) for UK evidence) and a weakening of traditional value measures.

This chapter re-examines the size and value effect in UK using a recent sample and a portfolio construction methodology, which allows to control for the interrelationship between size and value measures. Furthermore, we present the fundamental characteristics and unconditional performance of various size and value investment strategies, using not just book-to-price to identify undervalue/overvalue securities, but earnings-to-price, cash flow-to-price and historical EPS growth.

Although there is significant evidence, specially from early studies, that small-caps and value stocks outperform in the long run, the issue of whether portfolio returns and style premiums remain after adjusting for various risk factors is not yet clear. This chapter investigates the fundamental risks underlying style investing in the UK market and contributes to the debate of whether return differentials among style portfolios consist risk premiums and compensation for higher risk exposures.

Asset pricing theories suggest that one possible explanation of why the observed average returns are different for different equity classes is their risk characteristics and consequently their response to risk factors. The simplest adjustment that can be made is to control for a market risk factor in the context of CAPM. Studies that investigate the performance of portfolios after adjusting for market risk includes Jegadeesh (1992) and Berk (1995) for size portfolios and Fama and French (1995, 1996) and Daniel and Titman (1997) for value/growth portfolios. Most of the evidence provided from these US studies points out that difference in market betas alone are not sufficient to explain the size and value effects. We re-examine this hypothesis for different UK style portfolios and for a recent sample period.

Another source of dependence among portfolios may come from their differential industrial composition and consequent sensitivity to industry risk factors. Using industry risk factors to explain the perfromance of equity portfolios has not attracted particular attention in the literature. Two main reasons lead us to relate size and value performance with the performance of certain industries. First, since the demand of each industry's output has certain sensitivity to overall economic growth, using industry-based portfolios is another way to capture the characteristics of the business cycle. Therefore, the different industrial composition and sensitivity between equity portfolios may indicate different response to economic conditions. Second, as style investment is considered by many as an enhancement of industry investment, it would be interesting to see to what extent a bet on smaller companies or value stocks is also a bet on relative industry perfromance.

Finally, we utilise a number of macroeconomic variables to explain differences in returns across investment styles. The sensitivity of size and value portfolios to common macroeconomic factors in the context of APT, has been examined by Chan, Chen and Hsieh (1985), He and Ng (1994), Roll (1995) for US and Levis (1995) for UK among others. In addition, the explanatory power of individual macroeconomic variables, such as interest rates, exchange rates, economic growth, etc. for the returns of desegregated equity portfolios, has been documented in numerous studies. In this chapter, we investigate whether there are significant differences in betas of several macroeconomic factors and whether these differences can explain the size and value premiums.

The objectives of this chapter can be summarised as follows:

1. To examine the fundamental characteristics and return performance of various size and value investment strategies in UK using a recent sample, four different definitions of value and growth and a methodology which allows to disentangle one effect from the other.
2. To investigate whether difference in returns between size and value portfolios can be explained by correcting for differences in market risk across portfolios.

3. To test whether the difference in performance of various size and value portfolios can be linked to the performance of certain industries.
4. To examine the sensitivity of different style portfolios to various macroeconomic variables and assess the importance of these variables in explaining the size and value premium.

The rest of the chapter is organised as follows. The next section shows the fundamental characteristics and raw (unadjusted) performance of all style portfolios and style spreads that we consider. Section 6.3 presents market adjusted returns for all size and value portfolios and investigates whether CAPM betas can explain the size and value premiums. Sections 6.4 and 6.5 demonstrate the effect of industry and macroeconomic risks to style returns and premiums. Section 6.6 summarises the findings and concludes.

6.2 Fundamental Characteristics and Performance of Style Portfolios

At the end of July of each year from 1968 to 1997 nine portfolios are constructed using a variant of the Fama and French (1995) independent groups method, described in the previous chapter. Four different definitions of value/growth style are used which result to 4×9=36 size-value portfolios. More specifically, the ratios of book-to-price, earnings-to-price, cash flow-to-price and 3 years past earnings growth are used to proxy value and growth.

For each one of the nine portfolios and for every year in the sample, we calculate the average market value, and median market-to-book ratio, dividend yield, price earnings, cash flow yield and total debt to equity ratio. We also estimate the values of these ratios for the aggregate small-cap, large-cap, value and growth portfolios.

Table 6.1, presents the average fundamental characteristics for each style portfolio. Panel A shows the results of portfolios formed on the basis of market value and book-to-price ratio. Panels B and C present statistics on portfolios constructed using earnings yield and cash flow yield respectively to represent value and growth. Lastly, panel D exhibits the fundamental characteristics of portfolios formed on the basis of size and historical EPS growth. The first two columns of the first panel in table 6.1, show the average market value and market-to-book ratio for every style portfolio. Given the portfolio formation procedure, small and large-cap portfolios have substantially different market value, but almost the same on average market-to-book ratios, while value and growth portfolios differ significantly on market-to-book, but not so much on their market value.

Value portfolios have higher dividend and cash flow yields and lower price earnings ratios than growth portfolios. Size portfolios show no clear differences on any of these measures. Large-value stocks appear to have the highest dividend yield (5.99), while middle-Growth the lowest (3.62). Large-growth is the portfolio with the highest P/E ratio (21.01) and small-value the portfolio with the highest cash flow yield (0.38). The last column shows the average debt to equity ratio. We observe a substantial difference in leverage between size portfolios of the same B/P category. It is also worth noting that, value stocks appear to be more leveraged than their growth counterparts. The average debt to equity ratio for all value stocks is 0.24, slightly higher than that of growth stocks.

TABLE 6.1 Fundamental Characteristics of Style Portfolios

Panel A: B/P is used to proxy value and growth

	Market Value (million £)	Market to Book	Dividend Yield	Price Earnings	Cash Flow Yield	Debt / Equity
Small-cap Value	12.17	0.63	5.55	15.11	0.38	0.10
Small-cap Medium	20.24	1.32	5.44	14.69	0.31	0.07
Small-cap Growth	24.67	4.41	4.14	18.40	0.21	0.07
Mid-cap Value	168.95	0.68	5.71	18.83	0.32	0.27
Mid-cap Medium	164.79	1.36	5.37	14.12	0.28	0.20
Mid-cap Growth	163.84	4.30	3.62	18.25	0.19	0.16
Large-cap Value	1142.92	0.70	5.99	16.88	0.29	0.35
Large-cap Medium	1346.31	1.36	5.37	14.66	0.28	0.32
Large-cap Growth	1317.13	4.21	5.71	21.01	0.18	0.30
SMALL-cap	19.03	2.12	5.04	16.07	0.30	0.08
LARGE-cap	1268.78	2.09	5.09	15.73	0.25	0.32
VALUE	441.34	0.67	5.75	15.60	0.33	0.24
GROWTH	501.88	4.31	3.89	19.22	0.19	0.18

Panel B: E/P is used to proxy value and growth

	Market Value (million £)	Market to Book	Dividend Yield	Price Earnings	Cash Flow Yield	Debt / Equity
Small-cap Value	8.11	0.94	6.68	8.52	0.47	0.06
Small-cap Medium	17.83	1.36	5.49	13.21	0.29	0.08
Small-cap Growth	13.89	1.44	3.86	24.01	0.18	0.09
Mid-cap Value	193.92	1.10	6.17	8.83	0.42	0.21
Mid-cap Medium	169.10	1.57	5.01	13.64	0.26	0.21
Mid-cap Growth	166.83	2.19	3.24	22.54	0.16	0.20
Large-cap Value	724.24	1.10	6.27	8.85	0.43	0.33
Large-cap Medium	783.91	1.62	5.08	13.55	0.27	0.33
Large-cap Growth	779.54	2.08	3.47	21.24	0.16	0.25
SMALL-cap	13.27	1.25	5.34	15.25	0.31	0.08
LARGE-cap	762.56	1.60	4.94	14.55	0.28	0.30
VALUE	308.76	1.05	6.37	8.73	0.44	0.20
GROWTH	320.09	1.90	3.52	22.59	0.17	0.18

Panel C: CF/P is used to proxy value and growth

	Market Value (million £)	Market to Book	Dividend Yield	Price Earnings	Cash Flow Yield	Debt / Equity
Small-cap Value	6.93	0.92	5.85	9.90	0.62	0.12
Small-cap Medium	15.71	1.36	5.54	12.54	0.30	0.08
Small-cap Growth	17.18	1.56	4.31	18.11	0.14	0.06
Mid-cap Value	644.51	1.19	6.04	10.62	0.52	0.33
Mid-cap Medium	727.39	1.56	5.06	13.32	0.29	0.22
Mid-cap Growth	828.83	2.12	3.54	19.24	0.14	0.15
Large-cap Value	175.35	1.27	5.88	11.31	0.54	0.49
Large-cap Medium	180.01	1.48	5.22	13.28	0.28	0.32
Large-cap Growth	165.79	2.17	3.87	18.07	0.14	0.22
SMALL-cap	13.27	1.28	5.23	13.52	0.35	0.08
LARGE-cap	733.58	1.64	4.99	14.22	0.32	0.34
VALUE	275.59	1.12	5.92	10.61	0.56	0.31
GROWTH	337.27	1.95	3.91	18.47	0.14	0.14

Panel D: Historical EPS growth is used to proxy value and growth

	Market Value (million £)	Market to Book	Dividend Yield	Price Earnings	Cash Flow Yield	Debt / Equity
Small-cap Value	26.11	0.95	6.39	14.98	0.31	0.07
Small-cap Medium	35.82	1.22	5.69	11.70	0.33	0.07
Small-cap Growth	32.65	1.30	4.98	10.95	0.37	0.07
Mid-cap Value	263.41	1.38	6.43	14.32	0.27	0.29
Mid-cap Medium	256.13	1.60	4.86	13.04	0.27	0.21
Mid-cap Growth	246.81	1.85	4.03	13.64	0.25	0.17
Large-cap Value	1497.01	1.30	6.28	14.59	0.25	0.34
Large-cap Medium	1763.29	1.60	4.93	12.93	0.25	0.32
Large-cap Growth	1771.01	1.85	4.29	13.27	0.24	0.28
SMALL-cap	31.53	1.16	5.69	12.54	0.34	0.07
LARGE-cap	1677.10	1.58	5.17	13.60	0.25	0.31
VALUE	595.51	1.21	6.37	14.63	0.28	0.23
GROWTH	683.48	1.67	4.43	12.62	0.28	0.17

Note: Nine size-value portfolios are constructed using a variant of Fama and French (1995) independent groups method, for the period 1968 to 1997. The ratios of book-to-price, earnings-to-price, cash flow-to-price and three years past earnings growth are employed to proxy for value and growth. The average market value and median book-to-price, dividend yield, price earnings, cash flow-to-price and debt-to-equity ratio are reported for each one of the nine portfolios and for the four composite indices.

Similar patterns can be identified when other variables are used to proxy value and growth. Generally, value stocks are stocks with low price-to-book and price earnings ratio, and high cash flow-to-price and dividend yield compared to growth. With the exception of high and low CF/P (Panel C), not significant differences in debt-to-equity ratio are identified between value and growth stocks. On the other hand, small and large-cap stocks have nearly the same ratios of price to fundamentals, but substantially different debt-to-equity ratio. In all classification procedures large-caps appear to be almost four times more leveraged than small-caps.

Table 6.2, reports average annual equal and value weighted returns for the whole sample period (July 1968-June 1997) and for three sub-sample periods (July 1968-June 1978, July 1978-June 1988, July 1988-June 1997). We use value weighted in addition to equal weighted returns, as the capitalisation weighting tends to correct for some of the tendency for single stocks to have fat-tailed distributions. The equal weighted returns represent simple arithmetic mean returns. Geometric mean returns, which assume reinvestment of capital gains, have also been calculated and are reported in the appendix

We also examine the performance of style portfolios in different periods to measure the consistency of the return difference over time between size and value investment strategies. Panels A, B, C and D shows average returns for portfolios formed on the basis of MV and B/P, E/P, CF/P and historical EPS growth respectively. Annual returns for aggregate size and value portfolios, as well as for the two style spreads are also presented at the end of each panel.

Value stocks, classified according to book-to-price significantly outperform their counterparts. The average annual return of the value index is 23.583% (22.317% on a value weighted basis), almost 11.5% higher than the returns of the growth index. What is even more striking, however, is that this difference seems to persist in all three sub-periods and across different size categories. The average annual value-growth spread is 12.465% (15.294%) for the first decade, 12.366% (10.395%) for the second and 9.802% (7.121%) for the third, indicating a high persistence in performance for value stocks. It is also interesting that, this difference in performance is apparent whether we focus on the small-cap, mid-cap or large-cap segment. These results confirm the findings of previous studies, which document a positive relation between book-to-price ratio and stock returns.

The relation, however, between stock returns and other indicia of value, like E/P, CF/P and EPS growth is not as strong. High E/P stocks outperform low E/P stocks of the same size by an average of 3.713% over the last 30 years. It is interesting to note that, the value-growth premium, when proxied by the difference between high E/P and low E/P stocks, is weakening over the last years and becomes just under 2% over the last decade. Even lower is the return difference between value and growth stocks, when CF/P is used to proxy value and growth (panel C). In this case, the value portfolio actually underperforms the growth portfolio over the last decade. Low CF/P stocks earn 0.345% (2.193%) more than the high CF/P stocks. This overperformance of growth stocks is especially apparent for small and mid-cap stocks.

The same conclusion can be drawn, by looking at portfolios formed on the basis of past EPS growth. Low earnings growth (value) portfolios earn an average annual return of 2.235% (0.932%) more than high growth portfolios. In this case however, and in contrast with the previous cases, the last period (1988-1997) is the most rewarding period for value investment strategies.

The summary results for value and growth portfolios based on all four criteria indicate that value portfolios outperform growth portfolios in most of the period under study and regardless of whether we concentrate on a small or large size of the market. B/M however, appears to produce the highest return spread between value and growth stocks compared to CF/P, E/P and 3 years past EPS growth.

Table 6.2 also presents the evidence for size portfolios. It is obvious that small-caps perform slightly better than large-cap stocks over the whole sample period. The difference in performance ranges from just 0.834%, when size portfolios are neutralised against B/M effects, to 3.468%, when we control for EPS growth. However, the size premium appears to be period specific for all classifications procedures. Panel A shows that the average annual return on an equally weighted basis for the small-cap index is 17.516%[1] for the whole sample period, that is just

[1] Our results coincide with the average annual returns of Hoare Govett, the well established UK small-cap index, over the same period. The total returns of HGSC (Hoare Govett Smaller Companies) index from 1968 to 1997 was 17.9%.

0.834% higher than the return of the large-cap index. Although, this result may appear surprising at first, given the size effect that has been observed in the UK market, it can be explained by looking at the last sub-period. From July 1988 to June 1997 the large-cap portfolio earned an average equal weighted return of 13.283%, while the small-cap index had an average annual performance of 8.984%. The same reversal of size effect is documented in all the other portfolio formation processes.

The size spread is not even consistent among different sub-portfolios. Comparing the performance of small-cap and large-cap indices of the same B/P category, it is worth noting that small-caps with low B/P ratio perform better than large-caps with low B/P ratio. Conversely, we observe a monotonic increasing pattern in performance as we move from small-cap growth to large-cap growth.

TABLE 6.2: Average Annual Portfolio Returns

Panel A: B/M is used to proxy value and growth

	1968-1997		1968-1977		1978-1987		1988-1997	
	E.W.	V.W.	E.W.	V.W.	E.W.	V.W.	E.W.	V.W.
Small-cap Value	25.752	21.831	24.440	22.902	35.911	29.585	15.921	12.037
Small-cap Medium	16.514	14.981	14.592	13.763	25.635	22.858	8.526	7.593
Small-cap Growth	10.251	10.070	9.689	8.296	17.783	16.846	2.526	4.535
Mid-cap Value	24.415	23.680	25.588	24.692	30.319	29.951	16.575	15.597
Mid-cap Medium	15.945	15.954	12.593	13.645	23.164	22.241	11.659	11.533
Mid-cap Growth	12.153	11.743	10.487	9.873	19.500	18.445	5.852	6.373
Large-cap Value	20.583	21.419	18.377	22.455	26.030	24.287	16.994	17.060
Large-cap Medium	15.920	15.907	13.201	11.975	22.964	21.902	11.113	13.583
Large-cap Growth	13.542	11.902	10.834	5.989	17.879	17.386	11.743	12.401
SMALL-cap	17.516	15.637	16.247	14.983	26.443	23.090	8.984	8.051
LARGE-cap	16.682	16.402	14.134	13.479	22.298	21.185	13.283	14.358
VALUE	23.583	22.317	22.795	23.350	30.750	27.948	16.506	14.891
GROWTH	11.982	11.248	10.330	8.056	18.384	17.553	6.704	7.770
S - L	0.834	-0.765	2.113	1.504	4.145	1.905	-4.299	-6.307
V - G	11.601	11.069	12.465	15.294	12.366	10.395	9.802	7.121

Panel B: E/P is used to proxy value and growth

	1968-1997		1968-1977		1978-1987		1988-1997	
	E.W.	V.W.	E.W.	V.W.	E.W.	V.W.	E.W.	V.W.
Small-cap Value	19.775	16.795	20.767	19.052	30.313	25.117	6.965	5.040
Small-cap Medium	16.284	14.139	14.287	13.230	25.003	21.839	8.815	6.595
Small-cap Growth	15.200	12.951	11.045	9.179	24.642	20.845	9.326	8.372
Mid-cap Value	18.896	14.004	17.560	9.766	24.991	18.860	13.610	13.316
Mid-cap Medium	15.857	15.852	15.280	17.662	22.534	19.272	9.080	10.040
Mid-cap Growth	13.923	15.133	10.981	12.314	20.214	22.015	10.201	10.619
Large-cap Value	16.706	16.397	11.538	14.238	22.934	20.890	14.954	13.565
Large-cap Medium	14.338	14.842	12.134	11.300	19.769	19.055	10.751	14.097
Large-cap Growth	14.698	13.818	10.993	6.147	21.946	22.212	10.759	13.015
SMALL-cap	17.086	14.629	15.366	13.820	26.653	22.601	8.368	6.669
LARGE-cap	14.980	14.792	10.952	9.975	21.550	20.719	12.155	13.559
VALUE	18.320	15.682	16.391	14.278	26.079	21.622	11.843	10.640
GROWTH	14.607	13.967	11.006	9.213	22.268	21.691	10.095	10.669
S - L	2.106	-0.163	4.414	3.845	5.103	1.882	-3.787	-6.890
V - G	3.713	1.715	5.385	5.065	3.811	-0.069	1.748	-0.029

Panel C: CF/P is used to proxy value and growth

	1968-1997		1968-1977		1978-1987		1988-1997	
	E.W.	V.W.	E.W.	V W.	E.W.	V.W.	E.W.	V.W.
Small-cap Value	20.053	15.193	19.402	16.086	30.311	23.772	9.379	4.670
Small-cap Medium	16.971	14.916	16.112	14.664	25.801	22.382	8.113	6.900
Small-cap Growth	16.171	14.163	13.019	11.100	24.860	22.010	10.019	8.849
Mid-cap Value	15.642	15.804	14.856	16.042	23.190	21.365	8.129	9.362
Mid-cap Medium	17.046	16.956	15.113	15.862	23.149	22.134	12.411	12.419
Mid-cap Growth	14.589	14.999	12.255	13.648	20.692	20.785	10.400	10.071
Large-cap Value	17.517	16.068	13.560	13.550	23.540	22.455	15.221	11.769
Large-cap Medium	14.923	13.649	12.370	8.035	21.292	19.037	10.684	13.899
Large-cap Growth	14.781	13.533	10.260	7.755	20.593	19.377	13.345	13.459
SMALL-cap	17.732	14.758	16.178	13.950	26.991	22.722	9.170	6.806
LARGE-cap	15.740	14.417	12.063	9.780	21.808	20.290	13.083	13.042
VALUE	17.737	15.689	15.939	15.226	25.680	22.531	10.910	8.600
GROWTH	15.180	14.232	11.844	10.834	22.048	20.724	11.255	10.793
S - L	1.992	0.341	4.115	4.170	5.183	2.432	-3.913	-6.236
V - G	2.557	1.457	4.095	4.392	3.632	1.807	-0.345	-2.193

Panel D: Historical EPS growth is used to proxy value and growth

	1968-1997		1968-1977		1978-1987		1988-1997	
	E.W.	V.W.	E.W.	V.W.	E.W.	V.W.	E.W.	V.W.
Small-cap Value	20.987	18.523	22.818	21.261	28.967	25.019	10.695	9.176
Small-cap Medium	18.956	17.118	20.351	19.239	25.501	23.496	10.599	8.380
Small-cap Growth	18.884	17.633	22.008	19.084	27.715	22.799	6.641	10.764
Mid-cap Value	19.414	18.868	22.565	22.364	22.781	22.001	13.222	12.669
Mid-cap Medium	16.705	16.744	16.044	17.037	22.914	22.233	10.320	10.416
Mid-cap Growth	16.327	16.426	19.151	20.105	22.939	22.014	6.783	7.356
Large-cap Value	16.858	14.419	15.575	10.989	23.374	19.300	10.616	11.665
Large-cap Medium	16.223	15.736	14.942	13.331	20.894	20.632	12.028	12.167
Large-cap Growth	15.341	14.955	15.271	14.122	18.988	19.593	11.343	10.448
SMALL-cap	19.609	17.758	21.726	19.862	27.394	23.771	9.311	9.440
LARGE-cap	16.141	15.037	15.263	12.814	21.085	19.842	11.329	11.427
VALUE	19.086	17.270	20.319	18.205	25.041	22.107	11.511	11.170
GROWTH	16.851	16.338	18.810	17.770	23.214	21.469	8.256	9.523
S - L	3.468	2.721	6.463	7.048	6.309	3.929	-2.018	-1.987
V - G	2.235	0.932	1.509	0.435	1.827	0.638	3.255	1.647

Note: E.W. denotes equal weighted returns and V.W. value weighted returns. The first sub-sample covers the period July 1968 (July 1971 for EPS growth portfolios) to June 1978. The second from July 1978 to June 1988 and the third from July 1988 to June 1997.

6.3 The Effect of Market Risk to Style Returns

The previous section provides descriptive evidence on the characteristics and unconditional performance of different size and value portfolios. In this section, we use a regression methodology to estimate the statistical significance of that performance and examine whether differences in style return spreads remain after adjusting for differences in market, or systematic risk between portfolios.

We employ a pooled time series - cross-section regression methodology with dummy variables that are used to classify returns along style dimensions[2]. A dummy variable takes the value of one or zero depending on the class to which the dependent variable belongs. The monthly excess returns of each style portfolio are regressed on a constant and two dummy variables.

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{BP} D_{BP} + \varepsilon_{p,t}$$

The two dummy variables represent the MV and B/P classification groups. We restrict this analysis to the portfolio with the highest and lowest MV and B/P, i.e. to small-value (SV), small-growth (SG), large-value (LV) and large-growth (LG). The first dummy D_{size} takes the value of one if the observed return is from a small-cap portfolio, either SV or SG. The second dummy variable, D_{BP} takes the value of 1 if the observed return is from a high B/P portfolio, either SV or LV. The regression pools the monthly excess returns (for 348 month) on the four style portfolios, for a total of 1392 observations. Exactly the same process is followed for the other classification procedures[3]. The three-month treasury bill yield is used as the risk free rate.

Table 6.3 reports the regression results for each different classification procedure. The t-statistics are adjusted for cross - sectional heteroskedasticity using the method of White (1980) and are reported under each estimated coefficient. The coefficients show the marginal contribution of each style after adjusting for the other. A bet on small rather than large companies of the same book-to-market during the period 1968-1997 would have resulted in profit of 7.8 basis point every month or an

[2] This technique was first used by Roll (1995) to test the significance of the performance of various style portfolios in US.

[3] In the case of historical EPS growth, the sample covers 1248 observations as the first three years are excluded.

annual return of 0.938% more in favour of small-caps. On the other hand, investing on high B/P stocks (value) would have generated 94 basis points more every month than investing on low B/P stocks (growth) of the same size. Furthermore, the incremental return from buying value stocks is statistically significant (t-stat 3.02). The intercept in the previous regression shows the monthly excess return of the large-growth portfolio (D_{size}=0 and D_{Value} = 0). The adjusted R^2, the F-statistic and the probability that all coefficients are jointly 0 are also reported at the end of the table.

The results from the other variables show that there is not statistically significant difference between the returns of value and growth stocks. Only when B/P is used as a classification variable, value stocks significantly outperform growth.

TABLE 6.3: Marginal Contribution of Each Style to Excess Return

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{Value} D_{Value} + \varepsilon_{p,t}$$

	Book To Price	Earnings To Price	Cash Flow To Price	Historical Earnings Growth
Intercept	0.1631 (0.5759)	0.3810 (1.3080)	0.4187 (1.4744)	0.4542 (1.4125)
D_{size}	0.0782 (0.2507)	0.1512 (0.4836)	0.1636 (0.5380)	0.3196 (0.9494)
D_{value}	0.9392** (3.0119)	0.2719 (0.3836)	0.2757 (0.9068)	0.1508 (0.4480)
R^2 - adjusted	0.0065	0.0007	0.0008	0.0008
F - statistic	4.5674	0.5010	0.5559	0.5510
Prob(F-stat)	0.0105	0.6060	0.5736	0.5764

Note: Excess returns of different size and value portfolios are regressed in time series - cross sectional basis against two dummies which are used to classify style dimensions. D_{size} takes the value of 1, when the observed return is from a small-cap portfolio, either SV or SG, whereas D_{value} takes the value of 1, if the observed return is from a value portfolio, either SV or LV. Value is proxied using B/P, E/P, CF/P and EPS growth and the results of each regression are reported in a different column. T - statistics adjusted for cross sectional heteroskedasticity are reported in parenthesis.

The results in table 6.3 are based on unconditional excess returns; they are not risk adjusted. To adjust for market risk, we include the market excess returns along with the dummy variables in the pooled cross sectional - time series regressions. Moreover, we add a set of cross-product terms between the dummy variables and the market excess return. We use the FTALL Share as the UK market index. The regression takes the following form:

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{Value} D_{Value} + \beta_{LG}(R_{M,t} - R_{f,t}) + \\ + \beta_{size} D_{size}(R_{M,t} - R_{f,t}) + \beta_{Value} D_{Value}(R_{M,t} - R_{f,t})$$

The alphas (α_{size}, α_{Value}) are now showing the incremental effects of each style after adjusting for market risk. The market risk of each style portfolio can be identified, by looking at the relevant beta coefficients. The β's from the cross product terms shows the differences in market risk between size or value portfolios. Table 6.4 presents the estimated coefficients, together with the associated corrected t-statistics in parenthesis.

The results from all classification procedures indicate that market risk cannot explain the return difference between style portfolios. High B/P stocks continue to generate higher returns compared to low B/P stocks even after controlling for market risk. After that adjustment a bet on value stocks would still generate 0.94% more every month, while a bet on small-caps 0.07%. Looking at the betas of the cross product terms (β_{size} and β_{BP}), we can conclude that neither value and growth, nor small and large-cap stocks have significantly different market betas. With the exception of CF/P portfolios, all of the value incremental betas are negative, although not statistically significant.

Value portfolios classified on the basis of E/P and EPS growth, also don't perform significantly better compared to growth after removing systematic risk. The only exception is the case of CF/P portfolios, where alpha is 0.27 and marginally significant. The size effect remains non-existent, even after removing market risk. Only when we control for earnings growth and market risk (last column), then small-caps performance is significantly higher than large-caps, but only at a marginal level (t-stat: 1.8741)

TABLE 6.4: The Effect of Market Risk to Style Returns

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{Value} D_{Value} + \beta_{LG}(R_{M,t} - R_{f,t}) +$$
$$+ \beta_{size} D_{size}(R_{M,t} - R_{f,t}) + \beta_{Value} D_{Value}(R_{M,t} - R_{f,t})$$

	Book To Price	**Earnings To Price**	**Cash Flow To Price**	**Historical Earnings Growth**
Intercept	0.2437 (1.5309)	0.4539** (2.6415)	0.4972** (3.0624)	0.4952 (2.6464)
D_{size}	0.0744 (0.4664)	0.1608 (0.9487)	0.1617 (1.0973)	0.3170* (1.8741)
D_{value}	0.9389** (5.8859)	0.2584 (1.5324)	0.2762* (1.8747)	0.1495 (0.8837)
$D_{LG}(R_M-R_f)$	1.0731** (17.1602)	1.0443** (15.1189)	1.0467** (15.8197)	1.0911** (14.4206)
$D_{size}(R_M-R_f)$	-0.0506 (-0.8355)	-0.0179 (-0.3114)	-0.0252 (-0.4708)	-0.0676 (-1.0798)
$D_{value}(R_M-R_f)$	-0.0039 (-0.0656)	-0.0336 (-0.5587)	0.0066 (0.1237)	-0.0351 (-0.5611)
R^2 - adjusted	0.7441	0.7139	0.7690	0.7505
F - statistic	810.1817	685.9069	922.9196	747.2821
Prob(F-stat)	0.0000	0.0000	0.0000	0.0000

Note: Excess returns of different size and value portfolios are regressed in time series - cross sectional basis against two dummies, which are used to classify style dimensions, the market excess return and the cross product terms between the dummies and the market excess return. D_{size} takes the value of 1, when the observed return is from a small-cap portfolio, either SV or SG, whereas D_{value} takes the value of 1, if the observed return is from a value portfolio, either SV or LV. Value is proxied using B/P, E/P, CF/P and EPS growth and the results of each regression are reported in a different column. T - statistics adjusted for cross sectional heteroskedasticity are reported in parenthesis.

6.4 The Effect of Industry Risk to Style Returns

One possible reason for the difference in performance across style portfolios might be their different exposure to industries. A number of papers point out that the industrial composition of style indices is an important parameter to understand differences in performance (see Dimson and Marsh (1999) for size indices and Fan (1995) and Mott and Condon (1995) for value/growth indices). However, none of these studies focus on the question of whether size or value effect dissipates when we adjust for industry differences.

In this section, we identify the industrial distribution for each style portfolio and examine the sensitivity of relative style returns to industry factors using the same time series - cross section regression methodology. Every stock in our sample is allocated into 11 industrial groups using the Datastream industrial classification codes. The precise industrial grouping is reported in the appendix at the end of the chapter. Each year and for each one of the four style portfolios we calculate the number of stocks that belong to each industrial group. Table 6.5 presents the average industrial distribution (1968-1997) for the SV, SG, LV, LG style portfolios. As before, panels A to D report results for each different value classification procedure

Panel A indicates that, compared to the whole sample, small companies with high B/P are overweight in consumer-non-durables and underweight in basic industries and retailers. Small-cap growth stocks (low B/P) have relatively more weight in consumer services (that include technology stocks) and leisure and less in basic industries, consumer non-durables and transportation. Large-value stocks are heavily weighted in capital goods, mineral extraction, transportation and utilities and they have substantially less weight compared to the market in consumer durables, consumer services, retailers and other industries. Finally, large-growth stocks are largely overweighted in retailers and basic industries. Although each different classification scheme results to different industrial weighting for the style portfolios, some trends can be easily identified. The more distinct differences appear to be between small and large-cap stocks. Large-cap stocks seem to be on average dominated by basic industries, mineral extraction and utilities, while small-caps are severely over-represented in leisure and media, consumer services and consumer durables compared to large-caps.

TABLE 6.5: Average Industry Distribution Within Style Portfolios

	SV	SG	LV	LG	All Sample
Panel A: B/P is used to proxy value and growth					
Basic Industries	12.86%	12.90%	13.91%	26.04%	15.33%
Capital Goods	26.20%	24.02%	35.73%	22.40%	26.19%
Consumer Durables	4.10%	3.67%	0.00%	2.40%	3.55%
Consumer Non-Durables	15.03%	9.00%	12.84%	13.58%	12.86%
Consumer Services	14.44%	18.02%	0.00%	7.86%	13.55%
Leisure and Media	6.45%	8.34%	5.09%	2.67%	6.66%
Mineral Extraction	1.00%	2.40%	5.39%	4.91%	2.17%
Retailers	7.82%	10.55%	2.17%	16.09%	9.34%
Transportation	3.65%	1.24%	9.96%	1.82%	2.52%
Utilities	0.43%	1.18%	12.60%	1.93%	1.26%
Others	8.02%	8.68%	2.32%	0.29%	6.59%
Panel B: E/P is used to proxy value and growth					
Basic Industries	14.67%	11.42%	10.09%	22.32%	15.62%
Capital Goods	26.37%	23.61%	25.96%	22.06%	26.15%
Consumer Durables	5.25%	3.08%	0.20%	1.09%	3.63%
Consumer Non-Durables	14.66%	12.16%	24.71%	10.28%	13.02%
Consumer Services	16.85%	14.56%	2.31%	6.76%	14.13%
Leisure and Media	5.91%	9.24%	1.87%	5.02%	6.79%
Mineral Extraction	0.74%	2.96%	9.08%	7.08%	1.93%
Retailers	6.33%	12.86%	2.33%	17.87%	9.92%
Transportation	2.00%	2.14%	10.44%	3.06%	2.15%
Utilities	0.81%	1.10%	12.75%	3.65%	1.33%
Others	6.41%	6.88%	0.26%	0.80%	5.33%
Panel C: CF/P is used to proxy value and growth					
Basic Industries	14.34%	13.89%	21.66%	19.79%	15.64%
Capital Goods	25.39%	22.66%	21.13%	22.55%	26.36%
Consumer Durables	5.18%	3.61%	0.27%	1.63%	3.73%
Consumer Non-Durables	12.53%	12.38%	21.17%	9.18%	12.95%
Consumer Services	15.80%	15.25%	6.00%	5.52%	13.92%
Leisure and Media	5.80%	10.70%	1.39%	6.93%	6.65%
Mineral Extraction	0.97%	2.32%	15.18%	4.50%	2.00%
Retailers	9.65%	10.62%	2.12%	20.07%	9.99%
Transportation	2.71%	1.87%	3.94%	3.38%	2.25%
Utilities	1.23%	0.16%	5.56%	5.41%	1.26%
Others	6.40%	6.54%	1.58%	1.03%	5.25%
Panel D: Past EPS growth is used to proxy value and growth					
Basic Industries	13.86%	15.03%	25.64%	18.10%	15.93%
Capital Goods	26.96%	26.44%	37.29%	26.58%	26.57%
Consumer Durables	4.30%	3.99%	0.58%	2.40%	3.73%
Consumer Non-Durables	14.73%	13.11%	10.18%	16.45%	13.63%
Consumer Services	15.57%	17.24%	6.69%	10.01%	14.07%
Leisure and Media	5.91%	6.25%	4.12%	4.26%	6.60%
Mineral Extraction	1.54%	0.94%	1.96%	5.78%	1.83%
Retailers	8.24%	10.03%	9.22%	10.96%	10.20%
Transportation	2.06%	2.07%	2.34%	1.86%	2.08%
Utilities	0.28%	0.52%	1.34%	2.87%	1.10%
Others	6.55%	4.40%	0.64%	0.75%	4.25%

No clear and consistent evidence however appears for value and growth portfolios. Consistent with most classification procedures, growth index has a much heavier focus on retailers, leisure and media (with the exception of B/P portfolios) and consumer services (exception are portfolios formed on the basis of E/P and CF/P). Value, on the other hand, is dominated by capital goods and consumer non-durables. However, these trends tend to be weaker than the trends identified between small and large-cap portfolios.

The question of whether these differences in industrial distribution among portfolios can explain the observed return differentials can not be answered without calculating the sensitivity of the style returns to each one of the previous industry factors. Each year starting from 1968 we form 11 portfolios based on the industry classifications and calculate their returns using equal weights. Descriptive statistics for the 11 industry portfolios are presented in table 6.6. The table shows the average number of firms, market value, book-to-price, earnings-to-price cash flow-to-price and past EPS growth for each industry.

TABLE 6.6: Descriptive Statistics for the 11 Industry Portfolios (1968-1997)

	No of Firms	MV (£ millions)	B/P	E/P	CF/P	EPS growth	Annual Return
Basic Industrials	158	222.07	0.720	0.078	0.307	0.159	19.470%
Capital Goods	275	109.61	0.786	0.079	0.311	0.150	16.951%
Consumer Durables	37	40.42	0.764	0.086	0.375	0.154	17.277%
Consumer Non Durables	133	199.59	0.844	0.082	0.310	0.149	17.578%
Consumer Services	149	41.20	0.703	0.080	0.318	0.164	18.794%
Leisure & Media	72	85.43	0.787	0.070	0.225	0.162	20.183%
Mineral Extraction	23	899.66	0.664	0.056	0.263	0.142	14.929%
Retailers	97	201.05	0.667	0.066	0.262	0.180	19.351%
Transport	26	163.32	0.996	0.076	0.329	0.162	18.295%
Utilities	14	1091.69	0.426	0.047	0.456	0.188	19.008%
Others	66	15.99	0.876	0.086	0.340	0.152	6.735%

Note: At the end of June of every year, eleven industry portfolios are constructed. The table presents the average number of firms that are allocated in each portfolio, as well as the average market value, book-to-price, earnings-to-price, cash flow-to-price and earnings growth. Moreover, average annual equally weighted returns are presented for each industry portfolio.

Using the same time series - cross sectional regression methodology we estimate the effect of each one of these industry portfolios to relative style returns. We again regress the excess returns of style portfolios against the two style dummies, the eleven industry portfolio returns and the cross product between the dummies and the industry returns. The pooled time series - cross sectional regression will now have a total of 36 parameters to estimate: the intercept, 2 intercept dummy variables, 11 industry factors and 22 slope dummy variable coefficients (2 of each of the 11 industry factors). The regression takes the following form:

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{BP} D_{BP} + \sum_{I=1}^{11} (\beta_{LG} F_{I,t} + \beta_{size} D_{size} F_{I,t} + \beta_{BP} D_{BP} F_{I,t}) + \varepsilon_{p,t}$$

where $F_{I,t}$ is the observed excess return on industry portfolio I in month t. The results from four different set of regressions, for each different value/growth classification, are reported in table 6.7. White heteroskedasticity adjusted t-statistics are in parenthesis.

The alphas for the size dummy denotes the rewards from betting in small against large stocks, after taking into account the differences in value and industry effects. Similarly, the alphas for the value/growth dummy shows the returns of an investment that holds a long position in the value and a short position in the growth portfolio, while being neutral to size and every industry bet. The betas for the cross product terms indicate the difference in industry risks between different style portfolios.

The most striking result is that the intercept dummy variable coefficient for size is now higher and statistically significant in all classification procedures. Controlling for industry risk strengthens the size effect and makes the small-large arbitrage portfolio more profitable. That implies that small-caps were more sensitive to certain underperforming industries, than large-caps over the last thirty years.

After adjusting for differences in industry risks, small-caps outperform large-caps by nearly 35 basis points (57 basis points when we control for EPS growth - panel D), which is both economically and statistically significant. Small-caps have significantly lower betas than large-caps in basic industries, capital goods, mineral extraction, retailers and utilities. They are on the other hand, more sensitive to movements in consumer non-durables, consumer services and other industries compared to large-cap securities.

Industry risk has a smaller, but still remarkable, impact to the value/growth effect. The alpha for B/P portfolios (panel A) is higher and more significant, after adjusting for industry risk. The alphas for the rest of value measures have also increased and become statistically significant. An investment in high E/P portfolios, for example, produce 44 basis points per month higher returns than low E/P portfolios, after controlling for size and industry risks. Similar alphas are generated for the other value/growth arbitrage portfolios (48 and 34 basis points per month for CF/P and EPS growth portfolios respectively). These results confirm the general message from Sorensen and Thum (1992) paper that value works better when employed with controlled risk factors than without.

Significant industry risk differences between high and low B/P stocks appear in capital goods and utilities. Value (high B/P) stocks have significantly higher sensitivity to movements in capital goods industry than growth (low B/P) stocks. When, however, utility stocks rise growth companies are affected more relative to value. Constructing value/growth portfolios using other variables other than B/P, leads to different results. Consumer durables, retail and other industries seem to affect significantly different the return of high and low E/P stocks. High CF/P stocks, on the other hand, have significantly higher betas on consumer non durables and other industries and lower betas on leisure and utility industry risk factors compared to low CF/P stocks. The utility industry has also different sensitivity to the returns of low and high past earnings growth firms.

Overall, we observe that there are significant differences both in the distribution of stocks within style indices and in the way industry risk factors affect size and value portfolios. Controlling for industry risk factors strengthens the size and value/growth effect and lead to significant style arbitrage profits.

TABLE 6.7: The Effect of Industry Risk to Style Returns

Panel A: B/P is used to proxy value and growth

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{BP} D_{BP} + \sum_{I=1}^{11} (\beta_{LG} F_{I,t} + \beta_{size} D_{size} F_{I,t} + \beta_{BP} D_{BP} F_{I,t}) + \varepsilon_{p,t}$$

	LG	Size	B/P
alphas	-1.6184**	0.3481**	1.0885**
	(-10.8174)	(2.2725)	(7.1052)
Industry betas			
Basic Industries	0.4797**	-0.4059**	0.0157
	(4.8409)	(-3.7991)	(0.1476)
Capital Goods	0.9151**	-0.8758**	0.2018*
	(7.5837)	(-7.1584)	(1.6499)
Consumer Durables	-0.3449**	0.2395**	0.0865
	(-5.9106)	(2.2724)	(0.8214)
Consumer non Durables	-0.0954	0.4358**	-0.0008
	(-0.9961)	(7.0926)	(-0.0144)
Consumer Services	-0.5623**	0.8757**	-0.0788
	(-6.6814)	(9.3647)	(-0.8429)
Leisure & Media	0.1176	0.0456	-0.1190
	(1.5098)	(0.5571)	(-1.4530)
Mineral Extraction	0.0897**	-0.0844**	0.0002
	(3.2161)	(-2.8110)	(0.0083)
Retailers	0.4822**	-0.4017**	-0.1074
	(6.4130)	(-5.2195)	(-1.3965)
Transport	0.0092	0.0037	0.0023
	(0.1749)	(0.0646)	(0.0396)
Utilities	0.1589**	-0.1506**	-0.0735**
	(5.4466)	(-5.1948)	(-2.5355)
Others	-0.2235**	0.3293**	0.0435
	(-4.9633)	(6.4595)	(0.8533)

Note: Excess returns on four style portfolios formed on the basis of market value and book-to-price are regressed, in a time series - cross sectional basis, against two dummies that represent the size and value/growth style, eleven industry portfolio returns and the cross products between the dummies and industry returns. The first column shows the intercept and the coefficient of the industry portfolios. The second column shows the alpha coefficient on the size dummy and the beta coefficients on the cross product between the size dummy and each one of the industry portfolios. The third column presents the alpha coefficient on the book-to-price dummy and the beta coefficients on the cross product between the book-to-price dummy and each one of the industry portfolios. T-statistics adjusted for cross sectional heteroskedasticity using the method of White (1980) are reported in parenthesis under each coefficient.

Panel B: E/P is used to proxy value and growth

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{EP} D_{EP} + \sum_{I=1}^{11} (\beta_{LG} F_{I,t} + \beta_{size} D_{size} F_{I,t} + \beta_{EP} D_{EP} F_{I,t}) + \varepsilon_{p,t}$$

	LG	Size	E/P
alphas	-1.3630**	0.3775**	0.4372**
	(-7.8190)	(1.9940)	(2.3190)
Industry betas			
Basic Industries	0.4150**	-0.4532**	0.0910
	(3.4428)	(-3.5812)	(0.7212)
Capital Goods	0.7953**	-0.6465**	-0.0316
	(5.4154)	(-3.7899)	(-0.1856)
Consumer Durables	-0.3256**	0.1215	0.1761*
	(-4.6655)	(1.1268)	(1.6471)
Consumer non Durables	-0.0006	0.4183**	0.0252
	(-0.0063)	(6.0033)	(0.3643)
Consumer Services	-0.4904**	0.7808**	-0.0157
	(-4.1333)	(6.5527)	(-0.1332)
Leisure & Media	0.0238	0.1265	-0.0889
	(0.2805)	(1.3510)	(-0.9568)
Mineral Extraction	0.1597**	-0.1349**	-0.0575*
	(5.0523)	(-4.3660)	(-1.8702)
Retailers	0.4845**	-0.3100**	-0.2173**
	(6.4151)	(-4.0222)	(-2.8308)
Transport	0.0077	0.0101	0.0041
	(0.1302)	(0.1462)	(0.0589)
Utilities	0.1714**	-0.1734**	-0.0418
	(5.7004)	(-5.3641)	(-1.2971)
Others	-0.2289**	0.2730**	0.1315**
	(-4.9247)	(5.3333)	(2.5746)

Note: Excess returns on four style portfolios formed on the basis of market value and earnings-to-price are regressed, in a time series - cross sectional basis, against two dummies that represent the size and value/growth style, eleven industry portfolio returns and the cross products between the dummies and industry returns. The first column shows the intercept and the coefficient of the industry portfolios. The second column shows the alpha coefficient on the size dummy and the beta coefficients on the cross product between the size dummy and each one of the industry portfolios. The third column presents the alpha coefficient on the earnings-to-price dummy and the beta coefficients on the cross product between the earnings-to-price dummy and each one of the industry portfolios. T-statistics adjusted for cross sectional heteroskedasticity using the method of White (1980) are reported in parenthesis under each coefficient.

Panel C: CF/P is used to proxy value and growth

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{CFP} D_{CFP} + \sum_{I=1}^{11} (\beta_{LG} F_{I,t} + \beta_{size} D_{size} F_{I,t} + \beta_{CFP} D_{CFP} F_{I,t}) + \varepsilon_{p,t}$$

	LG	Size	CF/P
alphas	-1.3279**	0.3526**	0.4789**
	(-8.3793)	(2.3284)	(3.1622)
Industry betas			
Basic Industries	0.4153**	-0.2697**	-0.1627
	(3.9161)	(-2.5508)	(-1.5387)
Capital Goods	0.8450**	-0.6961**	0.0273
	(6.7068)	(-6.0319)	(0.2369)
Consumer Durables	-0.2955**	0.1089	0.0776
	(-4.7326)	(1.1189)	(0.7970)
Consumer non Durables	0.0060	0.3123**	0.1180**
	(0.0643)	(5.4549)	(2.0616)
Consumer Services	-0.5976**	0.8253**	0.1692*
	(-6.8455)	(9.4167)	(1.9307)
Leisure & Media	0.0892	0.0822	-0.1531**
	(1.2243)	(1.1171)	(-2.0801)
Mineral Extraction	0.1224**	-0.1211**	0.0021
	(4.2831)	(-4.2682)	(0.0754)
Retailers	0.5025**	-0.3675**	-0.1158
	(6.4739)	(-4.9104)	(-1.5478)
Transport	0.0071	0.0031	-0.0182
	(0.1393)	(0.0633)	(-0.3712)
Utilities	0.1521**	-0.1464**	-0.0730**
	(5.4876)	(-5.3907)	(-2.6892)
Others	-0.2368**	0.2892**	0.1047**
	(-5.2498)	(6.5221)	(2.3632)

Note: Excess returns on four style portfolios formed on the basis of market value and cash flow-to-price are regressed, in a time series - cross sectional basis, against two dummies that represent the size and value growth style, eleven industry portfolio returns and the cross products between the dummies and industry returns. The first column shows the intercept and the coefficient of the industry portfolios. The second column shows the alpha coefficient on the size dummy and the beta coefficients on the cross product between the size dummy and each one of the industry portfolios. The third column presents the alpha coefficient on the cash flow-to-price dummy and the beta coefficients on the cross product between the cash flow-to-price dummy and each one of the industry portfolios. T-statistics adjusted for cross sectional heteroskedasticity using the method of White (1980) are reported in parenthesis under each coefficient.

Panel D: EPS growth is used to proxy value and growth

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{EG} D_{EG} + \sum_{I=1}^{11} (\beta_{LG} F_{I,t} + \beta_{size} D_{size} F_{I,t} + \beta_{EG} D_{EG} F_{I,t}) + \varepsilon_{p,t}$$

	LG	Size	EPS growth
alphas	-1.4450**	0.5684**	0.3434**
	(-8.5166)	(3.5228)	(2.1286)
Industry betas			
Basic Industries	0.4160**	-0.3317**	0.0728
	(3.5528)	(-2.9874)	(0.6557)
Capital Goods	1.0411**	-0.7968**	0.0215
	(7.2181)	(-6.2892)	(0.1702)
Consumer Durables	-0.3123**	0.0913	-0.0470
	(-4.1658)	(0.8937)	(-0.4602)
Consumer non Durables	0.0716	0.3251**	0.0941
	(0.6264)	(5.1168)	(1.4812)
Consumer Services	-0.7144**	0.9768**	0.0130
	(-6.4239)	(9.6624)	(0.1295)
Leisure & Media	0.0339	0.0364	-0.0542
	(0.3884)	(0.4427)	(-0.6599)
Mineral Extraction	0.1188**	-0.1411**	0.0189
	(3.7428)	(-4.4590)	(0.5977)
Retailers	0.4746**	-0.3617**	-0.1270
	(5.5674)	(-4.5402)	(-1.5940)
Transport	-0.0220	0.0451	-0.0190
	(-0.4080)	(0.8455)	(-0.3560)
Utilities	0.1785**	-0.1449**	-0.1125**
	(5.1496)	(-4.6363)	(-3.6013)
Others	-0.2346**	0.2701**	0.0824*
	(-4.6198)	(5.5316)	(1.6885)

Note: Excess returns on four style portfolios formed on the basis of market value and EPS growth are regressed, in a time series - cross sectional basis, against two dummies that represent the size and value growth style, eleven industry portfolio returns and the cross products between the dummies and industry returns. The first column shows the intercept and the coefficient of the industry portfolios. The second column shows the alpha coefficient on the size dummy and the beta coefficients on the cross product between the size dummy and each one of the industry portfolios. The third column presents the alpha coefficient on the EPS growth dummy and the beta coefficients on the cross product between the EPS growth dummy and each one of the industry portfolios. T-statistics adjusted for cross sectional heteroskedasticity using the method of White (1980) are reported in parenthesis under each coefficient.

6.5 The Effect of Macroeconomic Risk to Style Returns

U.S. evidence has shown that there are some important differences is structural characteristics (earnings, leverage, dividend reduction) between stocks with different market value, or valuation ratios (see Chan and Chen (1991), Fama and French (1995), Chen and Zhang (1998)). If size and value spreads constitute risk premia as Fama and French (1995, 1996) claim and if there are differences in structural characteristics between stocks with different market value and valuation ratios, then that would induce difference in return sensitivities (betas) to common economic variables.

The purpose of this section is to test whether there are important differences in the return sensitivities of size and value portfolios to a number of macroeconomic variables, and re-examine the size and value effects after adjusting for these differences. We initially employ the same pooled time series - cross sectional regression methodology and use the following five variables together with the size and value dummies:

Variable	Definition
1. Equity risk premium	Monthly difference between the returns on the FTALL Share index and the 3 month Treasury Bill.
2. Term Structure	Monthly difference between the yield of 20 year Gilts and 3 month Treasury Bills
3. Economic Growth	Yearly change in UK industrial production
4. Exchange Rate	Monthly change in the £ / $ exchange rate
5. Change in Short Term Interest Rate	Monthly change in the 3 month Treasury bill yield

All the previous variables are collected from Datastream database and cover the same period as the return data, that is July 1968 to June 1997. Including these variables in the pooled time series - cross sectional regression gives us a total of 18 parameters to estimate (the intercept, 2 dummy intercepts, 5 factors and 5×2 slope dummy variable). The regression equation takes the following form:

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{value} D_{value} + \sum_{K=1}^{5} (\beta_{LG} F_{K,t} + \beta_{size} D_{size} F_{K,t} + \beta_{value} D_{value} F_{K,t}) + \varepsilon_{p,t}$$

Table 6.9 shows the size and value premiums after controlling for all these factors. As before, the four columns correspond to the four different classification procedures that are used to proxy the value and growth style. White - adjusted t-statistics are reported in parenthesis under each estimated coefficient.

Concentrating first to the size intercept dummy, D_{size}, we observe that the size premium becomes negative, although not statistically significant in any case, except the first where it is marginally significant. The negative sign implies that after controlling for macroeconomic risks and various value measures small-caps actually underperform large-caps. However, this is not done at such a high significant level to allow us to draw safe conclusions.

There are some important differences in the sensitivities of small and large-cap returns to macro factors, but these differences are not apparent for all factors and in all cases. Market betas as shown previously (section 6.3) are not significantly different between size portfolios. However, the term structure variable shows a t-statistic above three for all D_{size} cases. That shows that small-caps are significantly more sensitive to yield curve movements than large-caps. The economic growth variable appears to be positive and marginally significant in two out of four cases. When we control for B/P and CF/P effects, not significant differences in the sensitivity of size portfolios to economic growth are observed. Exchange rate movements also affect significantly different the two security classes. The sign of the variable is negative, implying that large-caps carry more exchange rate risk than small-caps. Change in the short term interest rates are not found to be important in any case, except the third when we control for CF/P. In that case small-caps are more sensitive to changes in interest rates than large caps with the same CF/P ratio. Summarising the results, we could say that the evidence on the macroeconomic risks is mixed for size portfolios. Small-cap stocks are more susceptible to some risk sources and less susceptible to others. Nevertheless, there are some important macroeconomic risk differences between size portfolios that should be taken into account.

The picture is much different for the value/growth portfolios. There is consistent evidence that value stocks are not riskier than growth. In none of the definitions that we employ did we find any significant macroeconomic risk difference between the two equity classes. It seems that the return differentials between high and low B/P stocks do not reflect compensation for market or macroeconomic risks. The parameter for the $D_{B/P}$ variable remains positive and highly significant after adjusting for differences in macroeconomic risks. The other value/growth premiums ($D_{E/P}$, $D_{CF/P}$, $D_{EPS\ growth}$) have also not been affected from the risk adjustment. They remain positive but not significant as they were in table 6.3.

The R^2's and F-statistics from the regressions indicate a relative good fit of the model. The proportion of variation explained by the variables range from 71.75% to 78.13%. We need to note however that most of the R^2 is due to the market factor. Nevertheless, there is some increase in the explanatory power over the single-factor market model regression of table 6.4.

The previous analysis shows the differences in risk characteristics between size (value) portfolios after controlling for value (size) effects. It doesn't however denote the risk and return profiles of each different style portfolio. To assess the importance of macroeconomic factors to each individual style portfolio and correct for cross-sectional dependence in the residuals we employ Zellner's (1962) Seemingly Unrelated Regression (SUR). The SUR estimation is simply the application of generalised least squares estimation to a group of seemingly unrelated equations. The equations are related through the non-zero covariances associated with error terms across different equations at a given point in time. The residuals are uncorrelated over time but correlated across equations[4]. That is

$$\begin{aligned} \operatorname{cov}(u_{it}, u_{js}) &= \sigma_{ij} \quad \text{if } t = s \\ &= 0 \quad \text{if } t \neq s \end{aligned}$$

In the SUR model, we first estimate each equation separately by ordinary least squares. We then obtain the estimated residuals $\hat{u}_{it}$. From these estimated residuals we compute the estimates of the covariances σ_{ij} $\hat{\sigma}_{ij} = [1/(T-k)]\sum \hat{u}_{ij}\hat{u}_{jt}$, where k is the number of regression parameters estimated. After we estimate σ_{ij}, we re-estimate all the N cross - sectional equations jointly, using generalised least squares. With the GLS procedure based on a consistent estimate of the covariance matrix the estimators are consistent and are asymptotically as efficient as the GLS estimator based on the true covariance matrix.

[4] This type of correlation would arise if there are some omitted variables that are common to all equations.

TABLE 6.8: The Effect of Macroeconomic Risk to Style Returns

$$R_{p,t} - R_{f,t} = \alpha_{LG} + \alpha_{size} D_{size} + \alpha_{value} D_{value} + \sum_{K=1}^{5} (\beta_{LG} F_{K,t} + \beta_{size} D_{size} F_{K,t} + \beta_{value} D_{value} F_{K,t}) + \varepsilon_{p,t}$$

	Book To Price	Earnings To Price	Cash Flow To Price	Historical EPS Growth
Intercept	0.6436**	0.8944**	0.9379**	0.8246**
	(3.6588)	(4.7061)	(5.1860)	(4.1053)
D_{size}	-0.2929*	-0.2597	-0.1935	-0.0657
	(-1.6770)	(-1.3900)	(-1.1748)	(-0.3452)
D_{value}	0.7858**	0.1375	0.0879	0.1558
	(4.4990)	(0.7360)	(0.5340)	(0.8180)
$F_{equity\ risk\ premium}$	1.0984**	1.0715**	1.0711**	1.1160**
	(17.5317)	(15.5538)	(16.2160)	(15.0562)
$F_{term\ structure}$	-0.1998**	-0.2352**	-0.2124**	-0.1818**
	(-2.6157)	(-2.9288)	(-2.7280)	(-2.3243)
$F_{ind\ production\ growth}$	-9.0067**	-7.0392*	-7.3070*	-6.4200
	(-2.4520)	(-1.7758)	(-1.9567)	(-1.5333)
$F_{change\ in\ £\ \$}$	8.6854	11.4243**	9.8308*	11.2696*
	(1.6341)	(2.0916)	(1.8784)	(1.8853)
$F_{change\ in\ 3M\ T.Bill}$	-2.4902	-2.7449*	-3.8783**	-2.2317
	(-1.5027)	(-1.6550)	(-2.3373)	(-1.2342)
$D_{size} \times F_{equity\ risk\ premium}$	-0.0812	-0.0529	-0.0533	-0.0978
	(-1.3363)	(-0.9209)	(-0.9949)	(-1.5854)
$D_{size} \times F_{term\ structure}$	0.2340**	0.2624**	0.2247**	0.2277**
	(3.0407)	(3.4761)	(3.2697)	(3.1021)
$D_{size} \times F_{ind\ production\ growth}$	5.9526	7.2752*	4.0534	6.8310*
	(1.5448)	(1.7574)	(1.1599)	(1.7011)
$D_{size} \times F_{change\ in\ £\ \$}$	-12.5257**	-10.3804**	-7.6733	-13.3810**
	(-2.3831)	(-2.0201)	(-1.5814)	(-2.4229)
$D_{size} \times F_{change\ in\ 3M\ T.Bill}$	1.6906	3.0018	4.4547**	1.3431
	(1.0054)	(1.5202)	(2.7890)	(0.8584)
$D_{value} \times F_{equity\ risk\ premiumt}$	-0.0097	-0.0353	-0.0009	-0.0341
	(-0.1599)	(-0.6146)	(-0.0179)	(-0.5523)
$D_{value} \times F_{term\ structure}$	0.0483	0.0504	0.0730	-0.0049
	(0.6276)	(0.6688)	(1.0632)	(-0.0667)
$D_{value} \times F_{ind\ production\ growth}$	6.0416	1.1997	6.1197*	-0.0441
	(1.5680)	(0.2898)	(1.7513)	(-0.0109)
$D_{value} \times F_{change\ in\ £\ \$}$	4.0324	-4.5880	-3.9206	0.9037
	(0.7672)	(-0.8928)	(-0.8080)	(0.1636)
$D_{value} \times F_{change\ in\ 3M\ T.Bill}$	-0.3813	-1.1391	-2.4246	-0.3457
	(-0.2267)	(-0.5769)	(-1.5180)	(-0.2209)
R^2 - adjusted	0.7478	0.7175	0.7813	0.7571
F - statistic	234.5930	201.0685	277.9569	224.8536
Prob(F-stat)	0.0000	0.0000	0.0000	0.0000

Note: Excess returns on four style portfolios formed on the basis of market value and one of B/P, E/P, CF/P and EPS growth are regressed, in a time series - cross sectional basis, against two dummies that represent the size and value/growth style, five macroeconomic variables and the cross products between the dummies and the macroeconomic variables. The regression results that correspond to each different value/growth classification procedure are presented in a different column in table 6.8.

The same five variables are used as before and a separate regression model with distinct coefficients is estimated for each different style portfolio (SV, SG, LV, LG). The system of equations takes the following form:

$$R_{SV,t} - R_{f,t} = \alpha_{SV} + \sum_{k=1}^{5}(\beta_{k,t}F_{k,t}) + \varepsilon_{SV,t}$$
$$R_{SG,t} - R_{f,t} = \alpha_{SG} + \sum_{k=1}^{5}(\beta_{k,t}F_{k,t}) + \varepsilon_{SG,t}$$
$$R_{LV,t} - R_{f,t} = \alpha_{LV} + \sum_{k=1}^{5}(\beta_{k,t}F_{k,t}) + \varepsilon_{LV,t}$$
$$R_{LG,t} - R_{f,t} = \alpha_{LG} + \sum_{k=1}^{5}(\beta_{k,t}F_{k,t}) + \varepsilon_{LG,t}$$

Table 6.9 shows the results form the SUR estimation for each different classification procedure. The results of a Wald test for the equality of coefficients across the four different style portfolios is also reported. The probability of accepting the null hypothesis of equal coefficients is reported in parenthesis.

Panel A reports results from portfolios formed on the basis of market value and book-to-price ratio. The four size-value portfolios generate significantly different excess returns after adjusting for macroeconomic risks. The best performing portfolio is the small-cap - high B/P portfolio, whereas the worst performing is the small-cap - low B/P. Large-cap portfolios have higher market betas than small-caps, although the Wald test can not reject the null hypothesis of equal market betas across the four style portfolios. Term structure affects positively the returns of small-caps, although the relation is marginally significant, and negatively the performance of large-caps (the relation is statistically significant only in the case of large-cap growth stocks). Moreover, the Wald test indicates that the term structure coefficients are not equal across the four equity classes. Economic growth affects negatively the returns of low book-to-price securities and the relation is significant at a 5% level for small-caps and at 10% level for large-caps. Finally, exchange rate and short term interest rate changes do not affect significantly different style portfolios as the Wald test indicates.

The adjusted R-squared indicates a very good fit of the model, with most of the explanatory power attributed to the market factor. The goodness of fit is better small – cap portfolios as by construction tend to be more diversified.

The macroeconomic risk profiles of size and value portfolios formed using E/P, CF/P and historical earnings growth can be seen in panels B, C and D. Term structure appears to be the most consistent variable in the way it affects style portfolios. Regardless of the classification variable that is used, term structure coefficients are significantly different across portfolios. Market betas, however, do not seem to be different with only exception portfolios formed on the basis oh past EPS growth.

None of the other three macroeconomic variables (industrial production growth, change in exchange rate, change in short term interest rate) affect significantly portfolios formed on the basis of earnings-to-price (panel B) and past EPS growth (panel D). When cash flow-to-price is used to classify stock as value and growth, there are some important relationships identified between style portfolio returns and economic growth or movements in interest rates.

TABLE 6.9: Macroeconomic Risk Characteristics of Style Returns (SUR Estimation)

Panel A: B/P is used to proxy value and growth

	SV	SG	LV	LG	Wald Test
Intercept	1.3496**	0.1315*	1.2504**	0.8892**	127.4796**
	(14.7801)	(1.8061)	(4.4677)	(3.8351)	(0.0000)
Equity Risk Premium	1.0008**	1.0261**	1.0817**	1.0739**	2.9905
	(61.1830)	(78.6520)	(21.5769)	(25.8557)	(0.3930)
Term Structure	0.0628*	0.0480*	-0.1631	-0.2460**	9.4771**
	(1.8375)	(1.7599)	(-1.5552)	(-2.8319)	(0.0235)
Industrial Production Growth	2.3657	-2.8060**	-1.8387	-8.4864*	7.1041*
	(1.3426)	(-1.9968)	(-0.3404)	(-1.8968)	(0.0686)
Change in £/S exchange rate	-2.2188	-0.7546	13.134	2.7202	3.6231
	(-0.7886)	(-0.3363)	(1.5232)	(0.3807)	(0.3051)
Change in 3M T.Bill	0.5027	-0.3899	-5.3835*	-5.6540**	4.0680
	(0.5075)	(-0.4936)	(-1.7734)	(-2.2482)	(0.2542)
R^2 - adjusted	0.9242	0.9525	0.6027	0.6822	

Panel B: E/P is used to proxy value and growth

	SV	SG	LV	LG	Wald Test
Intercept	0.8143**	0.5897**	1.0228**	0.9660**	5.8382
	(9.7283)	(7.9568)	(3.4992)	(3.8358)	(0.1197)
Equity Risk Premium	1.0194**	0.9832**	0.9950**	1.0920**	10.2746**
	(67.9890)	(74.0476)	(19.0016)	(24.2067)	(0.0163)
Term Structure	0.0882**	0.0145	-0.2169**	-0.2506**	11.4640**
	(2.8145)	(0.5222)	(-1.9807)	(-2.6555)	(0.0094)
Industrial Production Growth	1.7003	-0.1384	-6.3306	-5.8605	2.5197
	(1.0527)	(-0.0968)	(-1.1224)	(-1.2060)	(0.4717)
Change in £/S exchange rate	-0.1764	-2.1572	3.7963	11.8250	2.9932
	(-0.0684)	(-0.9446)	(0.4215)	(1.5239)	(0.3926)
Change in 3M T.Bill	0.0276	-0.0763	-1.4427	-5.4545**	3.7143
	(0.0304)	(-0.0949)	(-0.4550)	(-1.9968)	(0.2940)
R^2 - adjusted	0.9381	0.9464	0.5300	0.6534	

Panel C: CF/P is used to proxy value and growth

	SV	SG	LV	LG	Wald Test
Intercept	0.8851**	0.6889**	1.0373**	1.0224**	34.0976**
	(9.9601)	(10.2546)	(4.6549)	(4.1949)	(0.0000)
Equity Risk Premium	1.0307**	1.0036**	1.0366**	1.0691**	5.2126
	(64.7513)	(83.3968)	(25.9660)	(24.4875)	(0.1568)
Term Structure	0.0681**	0.0233	-0.1742	-0.2563**	8.8174**
	(2.0477)	(0.9280)	(-2.0862)	(-2.8071)	(0.0318)
Industrial Production Growth	1.7989	-2.2938*	0.3159	-7.4618	7.9882**
	(1.0491)	(-1.7695)	(0.0734)	(-1.5866)	(0.0462)
Change in £/$ exchange rate	-0.8908	1.2895	2.9291	7.7483	1.2004
	(-0.3253)	(0.6229)	(0.4265)	(1.0317)	(0.7529)
Change in 3M T.Bill	-0.2772	-0.3435	-6.4556**	-5.7981**	5.4965
	(-0.2876)	(-0.4714)	(-2.6707)	(-2.1932)	(0.1388)
R^2 - adjusted	0.9320	0.9573	0.6882	0.6586	

Panel D: EPS growth is used to proxy value and growth

	SV	SG	LG	LV	Wald Test
Intercept	0.9298**	0.7393**	0.9902**	0.8675**	13.0219**
	(10.1941)	(9.6210)	(3.9113)	(3.1939)	(0.0045)
Equity Risk Premium	0.9963**	1.0086**	1.0605**	1.1138**	4.9867
	(61.2369)	(73.5805)	(23.4844)	(22.9877)	(0.1727)
Term Structure	0.0364	0.0450	-0.2067**	-0.2069**	8.3388**
	(1.0764)	(1.5774)	(-2.1991)	(-2.0513)	(0.0395)
Industrial Production Growth	-0.1171	0.4639	-5.7680	-5.9714	2.1595
	(-0.0674)	(0.3168)	(-1.1957)	(-1.1537)	(0.5399)
Change in £/$ exchange rate	-2.5154	0.1918	12.4928	7.0772	3.2013
	(-0.9111)	(0.0824)	(1.6304)	(0.8608)	(0.3616)
Change in 3M T.Bill	0.5247	0.1215	-3.6710	-4.4547	2.7120
	(0.5367)	(0.1476)	(-1.3528)	(-1.5300)	(0.4381)
R^2 - adjusted	0.9277	0.9490	0.6490	0.6396	

6.6 Summary and Conclusion

Using UK data over the past thirty years, from 1968 to 1997, stocks are classified into value/growth and small/large segments, by employing a portfolio construction methodology, which allows disentangling one effect from the other. Four different variables are used to define value and growth stocks; namely the book-to-price, the earnings-to-price, the cash flow yield and the historical earnings growth. We show that value stocks have consistently high book-to-price ratios, high dividend and cash flow-to-prices and low price earnings ratio.

In terms of performance, value stocks significantly outperform their counterparts, only when book-to-price is used to form portfolios. After adjusting for differences in market value, high E\P, CF\P and low EPS growth stocks do not seem to exhibit significantly different excess returns compared with growth stocks. In addition, small-caps outperform large caps, but this outperformance is not statistically or economically significant, mainly due to the poor performance of smaller companies during the last decade.

We next ask whether style performance can be attributed to various sources of risk. Using a pooled time series -cross sectional regression methodology, suggested by Roll (1995), we test whether the single factor CAPM, or two different multi-factor models can explain the style premiums. Our results indicate that betas of different size and value portfolios are not significantly different, and market risk alone can not explain the long-term return differences between style portfolios. Size and value portfolios, however, exhibit different sensitivity to industry portfolio returns. Using 11 industry portfolios and employing the same time series - cross sectional methodology, we find that the impact of industry risk is much higher between small and large companies than between value and growth. Nevertheless, adjusting for these differences strengthens the size and value effects for all different proxies used and leads to statistically significant excess returns of the size and value arbitrage portfolios.

We, finally, test the sensitivity of different size and value stocks to common macroeconomic factors. We find that term structure and exchange rate movements affect differently size portfolios, while the are no significant differences in the sensitivity of these portfolios to economic growth, interest rates and equity risk premium. On the other hand, no significant difference in macroeconomic risk of any source is evident between value and growth portfolios. Therefore, return differentials between value and growth portfolios, do not reflect compensation for market or macroeconomc risks.

In short our results suggest that, although industry or macroeconomic based factor models might be able to explain some part of the size premium, the difference in returns between high and low book-to-market can not be attributed to differences in sensitivities to market, industry or economic factors. Alternative explanations, such as the overreaction hypothesis, might be more relevant.

APPENDIX A: Geometric Annual Portfolio Returns

Panel A: B/M is used to proxy value and growth

	1968-1997	1968-1977	1978-1987	1988-1997
Small-cap Value	24.286	22.781	34.484	14.713
Small-cap Medium	15.107	12.944	24.247	7.421
Small-cap Growth	8.721	7.991	16.259	1.207
Mid-cap Value	18.012	14.171	24.061	15.586
Mid-cap Medium	13.601	9.754	20.868	9.838
Mid-cap Growth	11.264	7.472	15.719	10.545
Large-cap Value	21.794	22.004	27.759	14.970
Large-cap Medium	13.498	9.117	21.212	9.838
Large-cap Growth	9.977	7.322	17.447	4.667
SMALL-cap	16.079	14.605	25.049	7.816
LARGE-cap	14.441	10.665	20.342	12.105
VALUE	21.685	20.161	28.997	15.296
GROWTH	10.172	7.841	16.607	5.642
S - L	1.638	3.940	4.706	-4.289
V - G	11.513	12.320	12.390	9.654

Panel B: E/P is used to proxy value and growth

	1968-1997	1968-1977	1978-1987	1988-1997
Small-cap Value	18.257	19.085	29.033	5.483
Small-cap Medium	14.912	12.599	23.732	7.741
Small-cap Growth	13.780	9.390	23.129	8.330
Mid-cap Value	13.703	6.755	20.986	13.378
Mid-cap Medium	11.961	8.360	17.750	9.553
Mid-cap Growth	12.253	7.421	19.575	9.525
Large-cap Value	15.978	13.473	22.551	11.489
Large-cap Medium	13.399	11.573	20.585	7.485
Large-cap Growth	11.657	7.648	18.043	9.046
SMALL-cap	15.691	13.733	25.333	7.227
LARGE-cap	12.896	8.023	19.551	10.946
VALUE	16.401	13.887	24.384	10.370
GROWTH	12.806	8.513	20.436	9.138
S - L	2.795	5.710	5.781	-3.720
V - G	3.595	5.374	3.948	1.232

Panel C: CF/P is used to proxy value and growth

	1968-1997	1968-1977	1978-1987	1988-1997
Small-cap Value	18.496	17.684	28.887	7.949
Small-cap Medium	15.531	14.318	24.472	7.012
Small-cap Growth	14.718	11.327	23.370	8.926
Mid-cap Value	15.329	10.474	21.533	13.861
Mid-cap Medium	12.507	8.561	19.229	9.454
Mid-cap Growth	12.451	6.792	18.425	12.132
Large-cap Value	12.747	11.074	20.672	5.849
Large-cap Medium	14.646	11.553	21.089	10.954
Large-cap Growth	12.292	8.688	18.733	9.168
SMALL-cap	16.283	14.475	25.612	7.997
LARGE-cap	13.580	8.860	19.841	11.899
VALUE	15.832	13.478	23.926	9.504
GROWTH	13.363	9.241	20.326	10.241
S - L	2.703	5.615	5.771	-3.901
V - G	2.469	4.237	3.600	-0.736

Panel D: Historical EPS growth is used to proxy value and growth

	1968-1997	1968-1977	1978-1987	1988-1997
Small-cap Value	19.459	20.866	27.594	9.398
Small-cap Medium	17.568	18.212	24.340	9.591
Small-cap Growth	17.328	19.804	26.333	5.493
Mid-cap Value	16.765	18.062	20.739	11.359
Mid-cap Medium	14.204	11.625	20.871	8.836
Mid-cap Growth	13.476	14.064	20.664	5.084
Large-cap Value	14.431	11.498	21.156	9.275
Large-cap Medium	13.828	10.451	18.948	10.785
Large-cap Growth	12.653	10.416	16.749	9.855
SMALL-cap	18.158	19.673	26.126	8.198
LARGE-cap	14.974	14.774	20.906	8.571
VALUE	17.166	17.257	23.385	10.224
GROWTH	14.718	15.121	21.419	7.005
S - L	3.185	4.900	5.220	-0.373
V - G	2.448	2.136	1.966	3.219

APPENDIX B: Industry Classification

1. Basic Industries	Health Care Pharmaceuticals Plantations Chemicals Steel Metallurgy Diversified Industrials Paper, Packaging and Printing Publishing
2. Capital Goods	Building and Construction Building Materials and Merchants Electronic and Electrical Equipment Vehicle Assemblers Vehicle Components Engineering
3. Consumer Durables	Floor Coverings Furnishment Household Reqs. Security and Alarms
4. Consumer Non Durables	Food Producers Tobacco Clothing Footwear and Leather Stationary Producers Textiles
5. Consumer Services	Engineering Contractors Engineering Fabricators Business Support Computer Software and Services Education and Training Home Entertainment Laundries and Cleaners Hotels
6. Leisure and Media	Breweries, Pubs and Restaurants Broadcasting Leisure Facilities Media Agencies
7. Mineral Extraction	Gold Mining Oil Exploration and Production Oil Integrated Other Mining

8. Retailers	Food Retailers Retailers Multi Departments Retailers General
9. Transportation	Airlines Bus and Coach Railways Shipping Other Transport
10. Utilities	Electric Electricity Gas Distribution Water
11. Other	Other Businesses

CHAPTER 7

"*Investors' Expectations and the Performance of Value and Growth Portfolios*"

7.1 Introduction and Hypotheses Tested

The previous chapter shows that value stocks, when proxied by book-to-price, outperform growth stocks in UK over the last thirty years, and this outperformance is consistent across different sub-periods and size portfolios. Value stocks' superior relative performance can not, however, be attributed to market, industry or macroeconomic risk factors. Controlling for risk differences between the two equity classes does not eliminate the value effect.

These results indicate that book-to-price is not a proxy for common risk factors and the positive association between the particular ratio and stock returns may be inconsistent with rational, efficient pricing in capital markets. In this chapter, we investigate whether certain behavioural finance theories and market inefficiency can provide a more plausible explanation.

Systematic errors in expectations about the future, resulted from either a series of bad or good news, or naïve extrapolation of past earnings or sales growth, has been proposed to justify the observed return difference between value and growth stocks. Expectational errors cause a certain degree of misspricing, which makes value stocks to be underpriced and growth stocks overpriced. However, although many academics support the errors-in-expectations hypothesis, they do not necessarily agree on the sources of these errors.

If indeed investors expectations are too extreme (very optimistic about growth stocks and very pessimistic about value), the next question is where do these expectations come from. The two basic sources of expectational errors that causes overreaction proposed in the literature are firms' past sales and earnings growth (e.g. Lakonishok, Shleifer and Vishny, 1995) and analysts' forecasts of long term growth (e.g. La Porta, 1996). According to Lakonishok, Shleifer and Vishny (hereafter LSV), the expectations embedded in stock prices are consistent with investors naively extrapolating past earnings and sales growth, despite the fact that growth is mean reverting. They argue that, value (growth) stocks are characterised by low (high) past growth and expected low (high) future growth in sales, earnings and cash flows. These past characteristics create an excessive optimism for growth and pessimism for value, which is subsequently reflected in the stock prices of the two stock categories.

Extrapolation, however, is a special case of overreaction, which implies that the future is expected to be similar to the past. A number of researchers were doubtful of whether the market incorrectly extrapolates past earnings or sales growth. La Porta (1996) and Dechow and Sloan (1997) find no systematic evidence that stock prices reflect the naïve extrapolation of past growth in earnings and cash flows. However, their results suggest that stock prices naively incorporate analysts' forecasts of long term growth. Following this excessive optimism (pessimism) of analysts for value (growth) stocks, the realisation of actual EPS figures in the future creates a positive surprise for value which pushes their prices up and a negative surprise for growth which pushes their prices down.

The purpose of this chapter is to examine two different versions of overreaction hypothesis as potential explanations for the value-growth premium in UK. The first is the extrapolation hypothesis that can be summarised as follows:

HYPOTHESIS 1: ***Investor's extrapolation of past performance and earnings growth cause a misspricing in value and growth stocks which can justify the difference in their subsequent returns.***

Using, as before, different definitions of value and growth, we look at how profitability and price performance is evolving around portfolio formation for all the different value and growth portfolios and investigate whether the earnings and returns of all those portfolios display the pattern of mean reversion predicted by the naïve extrapolation model.

We next ask whether this past earnings and return characteristics of value and growth stocks cause investors to extrapolate the past and overprice growth, while underprice value stocks. We use a direct test where portfolios are formed independently, on the basis of B/P (CF/P, E/P) and 3 years past EPS growth, as well as 3 year pre-formation cumulative rate of return. A testable implication of the extrapolation hypothesis is that the return of low B/P and high past growth securities will be lower than the returns on stocks that are also expected to perform well in the future (low B/P), but have performed poorly in the past (temporary losers). Similarly, if naïve investors extrapolate the past, then value stocks (High B/P, low past growth) should outperform temporary winners (high B/P, high past growth).

A second alternative is to concentrate on EPS forecasts made by analysts as a major source of investor's expectational errors. As opposed to La Porta (1996) and Dechow and Sloan (1997), we do not attempt to investigate whether stock prices incorporate analysts' forecasts of long term earnings growth. Instead, we concentrate on analysts' errors for value and growth stocks immediately after portfolio formation as candidates for explaining their post-formation return difference. The second hypothesis we examine can be summarised as follows:

HYPOTHESIS 2: ***Positive and negative surprises have an asymmetric effect on the returns of value and growth portfolios, in favour of the former, in a fashion that is consistent with the error - in - expectations hypothesis.***

If investors make systematically errors in their expectations, they expect growth companies to do well in the future, while perceive value stocks as "bad" investments and are bearish about their future prospects. That implies that a positive surprise may be regarded as good news for value stocks and will have a significant more positive impact on their returns compared to growth stocks. On the other hand, a negative surprise is regarded as bad news for growth stocks and has a significantly more negative impact on the returns of growth stocks, with only a minor effect on the returns of value.

The rest of the chapter is organised as follows. The next section presents descriptive statistics on the performance and earnings growth patterns of various value and growth portfolios and investigates whether these patterns are similar to those predicted by the naïve extrapolation model. Section 7.3 examines whether investors' extrapolation of past earnings growth and price performance can explain the return difference between value and growth. Section 7.4 assess the impact of earnings surprises to the returns of value and growth portfolios and section 7.5 concludes.

7.2 Portfolio Returns and Earnings Growth Characteristics

If the naïve extrapolation model of LSV holds, then value stocks should be stocks with disappointing historical earnings growth and poor past performance compared to growth. These characteristics however do not persist. Value stocks' earnings tend to grow faster than growth. Because investors do not understand the temporary nature of returns and earnings growth, they extrapolate the past characteristics to the future, so they overprice growth and underprice value stocks.

Tables 7.1 to 7.4 examines the previous hypothesis by presenting returns, and standardised EPS figures for five years before and after portfolio formation for a number of different value and growth portfolios. Table 7.1, gives the returns and characteristics of value and growth portfolios, constructed on the basis of book-to-price ratio. Panel A presents average annual returns for years 1 through 5, as well as holding period returns (HPR) for 1, 3 and 5 year before and after the portfolio formation date. Simple returns assume the simple accumulation of returns, under monthly rebalancing, whereas the calculation of holding period returns is compounded, thus reflecting a more realistic buy-and-hold strategy. Multiyear cumulative or holding period returns are calculated as follows:

$$HPR_t(k) = \left[\prod_{j=0}^{k} (1 + R_{tj}) \right] - 1$$

where k is 12, 36 and 60 for 1, 3 and 5 years cumulative returns respectively. The numbers presented are the averages across all formation periods in the sample. T-statistics, which test the equality of mean returns between value and growth portfolios are also reported in a separate column. We denote significance at 5% level with ** and at 10% level with *.

We observe that value portfolios formed on the basis of book-to-price ratio significantly outperform growth portfolios in the year immediately after the formation. High B/P stocks outperform low B/P stocks about 11.5% per year, which is both economically and statistically significant. The outperformance of value stocks continues in the next 5 years, although the gap between them and low B/P stocks is closing and the difference is not statistically significant any longer. However, an investor who is long in high B/P stocks and has an investment horizon of 5 years would had earned 211.911% at the end of the period, while a growth oriented investor, that is long in low B/P stocks would had realised an average cumulative return of just 118.417%, over the same period.

It is interesting to note that high B/P stocks exhibit poor relative performance in the years before portfolio formation in comparison to low B/P stocks. We find a significant return difference of about 16% in favour of growth portfolio in the year before the formation. This return differential between the low and high B/P portfolio persists and is economically and statistically significant, even 4 years before the event year. The data, therefore, suggest that high B/P stocks were prior "losers" that became "winners" on the years after portfolio formation. Low B/P stocks display the same price reversals, but on the opposite direction, which points out to the fact that the B/P effect might be a manifestation of the winner-loser effect documented by DeBondt and Thaler (1985, 1987). Section 7.3 explores the issue of overreaction to previous price performance as an explanation for the higher future returns of value compared to growth stocks.

Panel B, reports standardised EPS 11 years around the portfolio formation year, using the same procedure as Fama and French (1995). Median EPS[1] are estimated for every B/P portfolio, at exactly the year of formation as well as 5 years before and after that year. The median EPS are next averaged, separately, across portfolio formation years t =1968 to 1997. The average EPS figures are then standardised so that the ratios are 1.0 in the portfolio formation year.

We observe that average EPS growth exhibit the same relative reversal patterns as returns for high and low B/P portfolios. The EPS growth of low B/P stocks is much stronger than that of high B/P stocks before the portfolio formation year, but this growth stops and becomes insignificant after the formation. Value stocks' earnings, on the other hand, grow with the same pace before and after the event year. This result consists a clear evidence that EPS growth exhibit a reverting pattern for both classes of stocks. Past growth tends to be higher for the low B/P portfolio, whereas future growth higher for the high B/P portfolio. Whether the market incorrectly extrapolate this past earnings growth, or correctly forecasts it's reversion and fairly price value and growth stocks, is the main subject of LSV and Fama and French debate and a question we address in the next section.

[1] We use the median instead of cross sectional-average EPS to reduce the problem of outliers in the earnings data.

We replicate the analysis for all the other value/growth portfolios, constructed using E/P, CF/P and past EPS growth, and report the relevant results in tables 7.2 and 7.3 and 7.4 respectively. We find that the high E/P portfolio earn higher returns (18.320%) than the low E/P portfolio (14.607%), although this difference is not statistically significant even at 10% level. The difference between the returns of value and growth portfolios proxied by E/P remains positive for all five post-formation years, but never pass our significance test. Similarly to B/P portfolios, high E/P stocks used to be previous "losers", whereas low E/P stocks previous "winners" at the year before the portfolio formation. A statistically significant return difference of almost 16% in favour of low yield securities confirms the previous proposition. In contrast to B/P portfolios, this is evident only for the year immediate before the formation year, and not for the other years, where the two class of securities reveal almost identical average annual returns.

The pattern of EPS growth is by no means similar to the one of B/P portfolios. Low E/P stocks exhibit higher EPS growth compared to high E/P stocks after portfolio formation, and higher pre-formation growth only one year before. These patterns in the EPS growth rates of earnings yield portfolios do not seem to be consistent with the naïve extrapolation model of LSV.

Cash flow-to-price portfolios exhibit an average annual return difference of about 2.5% to 4% for the post-formation years, but not statistically significant at any conventional significance level. Furthermore, high cash flow-to-price stocks, like the rest of value portfolios, earn significantly lower returns compared to their counterparts, for couple of years before portfolio formation. Looking at their growth characteristics, we observe that the EPS of low CF/P stocks grow at a higher rate compared to high CF/P stocks, both before and after the formation year and do not display the patterns expected by naïve extrapolation model.

Table 7.4 display returns and growth characteristics for portfolios formed on the basis of 3 years past EPS growth[2]. Similarly with CF/P and E/P portfolios, stocks with low past EPS growth (value) outperform stocks with high EPS growth, for 1 to 5 years after the formation year, but this difference in performance is not found to be statistically significant. The low EPS growth portfolio exhibits significantly lower

[2] We have also constructed portfolios based on 5 years previous earnings growth, but the results were qualitatively similar and are not reported.

average return compared to the high EPS growth portfolio in all three most recent pre-formation years. Panel B, shows the mean reverting pattern of EPS predicted by the naïve extrapolation model. Low EPS growth stocks exhibit a strong growth in the five post-formation years, while exactly the opposite is evident for high EPS growth stocks.

Summarising this preliminary evidence, we can say that high B/P stocks significantly outperform low B/P stocks in the year following portfolio formation None of the other proxies generate significant value-growth return spreads. We find that value stocks, based on either one of the four proxies, are prior losers, while growth stocks are prior winners for at least 3 years before portfolio formation. Finally, when B/P or past EPS growth is used to form value and growth portfolios, a clear reversal pattern in earnings growth appears between the two equity classes, which is consistent with the extrapolation hypothesis. The picture is rather confusing when E/P and CF/P are employed.

TABLE 7.1: Return and EPS growth patterns for Value and Growth Portfolios formed on the basis of Book-to-Price ratio

	High B/P (Value)	Middle	Low B/P (Growth)	T-test (V=G)
Panel A: Average Annual and Buy and Hold Portfolio Returns				
R - 5	15.588%	19.861%	24.133%	-1.4722
R - 4	15.361%	20.091%	25.231%	-1.7230*
R - 3	13.999%	19.902%	27.066%	-2.3531**
R - 2	11.856%	19.193%	27.359%	-2.8387**
R - 1	11.186%	19.244%	26.939%	-2.9893**
R + 1	23.583%	16.126%	11.982%	2.2770**
R + 2	23.431%	19.449%	13.536%	1.9150*
R + 3	20.393%	19.137%	15.565%	0.8977
R + 4	21.052%	18.019%	16.904%	0.7380
R + 5	19.448%	17.884%	16.035%	0.5775
HPR_{t-5-t}	90.049%	155.751%	260.934%	
HPR_{t-3-t}	49.759%	83.059%	132.249%	
HPR_{t-1-t}	14.016%	23.202%	33.825%	
HPR_{t-t+1}	26.725%	17.662%	12.966%	
HPR_{t-t+3}	95.677%	70.571%	50.004%	
HPR_{t-t+5}	211.911%	157.327%	118.417%	
Panel B: Standardised EPS 11 Years Around Portfolio Formation				
EPS (-5)	0.8157	0.7573	0.6329	
EPS (-4)	0.8723	0.7994	0.6887	
EPS (-3)	0.9127	0.8480	0.7438	
EPS (-2)	0.9256	0.8826	0.8149	
EPS (-1)	0.9660	0.9500	0.9289	
EPS (0)	1.0000	1.0000	1.0000	
EPS (+1)	1.0521	1.0285	1.0227	
EPS (+2)	1.0670	1.0521	1.0074	
EPS (+3)	1.1218	1.0823	1.0117	
EPS (+4)	1.1647	1.1043	1.0207	
EPS (+5)	1.1714	1.1262	1.0349	

Note: Average annual returns and standardised median EPS for high, middle and low B/P portfolios for five years before and after the portfolio formation date are reported. HPR represent holding period returns for 1, 3 and 5 years before and after the formation. The last column test presents the results of a t-test for the equality of mean returns between high and low B/P stocks.

TABLE 7.2: Return and EPS growth patterns for Value and Growth Portfolios formed on the basis of Earnings-to-Price ratio

	High E/P (Value)	Middle	Low E/P (Growth)	T-test (V=G)
Panel A: Average Annual and Buy and Hold Portfolio Returns				
R - 5	20.097%	20.562%	22.037%	-0.3293
R - 4	19.877%	21.017%	22.427%	-0.4396
R - 3	21.755%	21.301%	22.921%	-0.2070
R - 2	20.860%	21.429%	23.854%	-0.5565
R - 1	11.712%	20.051%	27.700%	-2.9978**
R +1	18.320%	15.493%	14.607%	0.7335
R + 2	20.315%	16.770%	13.879%	1.2362
R + 3	21.294%	18.331%	15.240%	1.1367
R + 4	21.864%	18.044%	16.026%	1.0599
R +5	18.912%	17.518%	15.899%	0.5274
HPR $_{t-5-t}$	140.819%	170.457%	225.605%	
HPR $_{t-3-t}$	74.437%	90.937%	118.308%	
HPR $_{t-1-t}$	13.842%	24.425%	34.627%	
HPR $_{t-t+1}$	20.570%	16.831%	15.751%	
HPR $_{t-t+3}$	83.365%	65.701%	55.302%	
HPR $_{t-t+5}$	186.639%	148.551%	122.272%	
Panel B: Standardised EPS 11 Years Around Portfolio Formation				
EPS (-5)	0.6807	0.6952	0.7487	
EPS (-4)	0.7459	0.7360	0.7521	
EPS (-3)	0.8431	0.7850	0.7567	
EPS (-2)	0.9456	0.8460	0.7806	
EPS (-1)	1.0939	0.9362	0.7634	
EPS (0)	1.0000	1.0000	1.0000	
EPS (+1)	0.9646	1.0341	1.0918	
EPS (+2)	0.9927	1.0432	1.1212	
EPS (+3)	1.0244	1.0498	1.1779	
EPS (+4)	1.0591	1.0751	1.2004	
EPS (+5)	1.0620	1.1015	1.2289	

Note: Average annual returns and standardised median EPS for high, middle and low E/P portfolios for five years before and after the portfolio formation date are reported. HPR represent holding period returns for 1, 3 and 5 years before and after the formation. The last column test presents the results of a t-test for the equality of mean returns between high and low E/P stocks.

TABLE 7.3: Return and EPS growth patterns for Value and Growth Portfolios formed on the basis of Cash Flow-to-Price ratio

	High CF/P (Value)	Middle	Low CF/P (Growth)	T-test (V=G)
Panel A: Average Annual and Buy and Hold Portfolio Returns				
R - 5	18.648%	20.287%	22.171%	-0.6039
R - 4	16.434%	20.638%	24.144%	-1.3604
R - 3	17.137%	20.809%	24.671%	-1.3430
R - 2	16.249%	20.797%	25.302%	-1.6850*
R - 1	12.799%	20.513%	25.529%	-2.4547**
R + 1	17.737%	16.313%	15.180%	0.5022
R + 2	18.549%	16.445%	15.009%	0.6765
R + 3	20.226%	18.543%	15.885%	0.7988
R + 4	20.878%	18.240%	16.850%	0.7098
R + 5	18.973%	17.597%	16.280%	0.4558
HPR_{t-5-t}	118.409%	165.170%	228.398%	
HPR_{t-3-t}	63.503%	88.750%	119.737%	
HPR_{t-1-t}	15.609%	24.885%	31.841%	
HPR_{t-t+1}	19.848%	17.812%	16.476%	
HPR_{t-t+3}	78.421%	67.893%	58.823%	
HPR_{t-t+5}	176.998%	152.149%	129.076%	
Panel B: Standardised EPS 11 Years Around Portfolio Formation				
EPS (-5)	0.7360	0.7212	0.6616	
EPS (-4)	0.7958	0.7586	0.7089	
EPS (-3)	0.8173	0.8081	0.7568	
EPS (-2)	0.8733	0.8586	0.8113	
EPS (-1)	0.9557	0.9420	0.8728	
EPS (0)	1.0000	1.0000	1.0000	
EPS (+1)	0.9477	1.0284	1.0456	
EPS (+2)	1.0062	1.0478	1.0647	
EPS (+3)	1.0130	1.0719	1.0934	
EPS (+4)	1.0393	1.0826	1.1107	
EPS (+5)	1.0967	1.0869	1.1448	

Note: Average annual returns and standardised median EPS for high, middle and low CF/P portfolios for five years before and after the portfolio formation date are reported. HPR represent holding period returns for 1, 3 and 5 years before and after the formation. The last column test presents the results of a t-test for the equality of mean returns between high and low CF/P stocks.

TABLE 7.4: Return and EPS growth patterns for Value and Growth Portfolios formed on the basis of past EPS growth

	Low EPS growth (Value)	Middle	High EPS growth (Growth)	T-test (V=G)
Panel A: Average Annual and Buy and Hold Portfolio Returns				
R - 5	22.367%	21.662%	20.935%	0.2365
R - 4	17.099%	21.234%	26.220%	-1.5686
R - 3	8.229%	19.982%	33.923%	-4.4533**
R - 2	8.438%	20.699%	34.510%	-4.5100**
R - 1	14.701%	21.418%	29.874%	-2.6447**
R +1	19.086%	17.295%	16.851%	0.3973
R + 2	19.084%	15.555%	14.514%	0.7758
R + 3	19.062%	17.765%	15.316%	0.6154
R + 4	22.139%	19.985%	19.866%	0.3636
R +5	20.594%	19.761%	18.703%	0.3430
HPR_{t-5-t}	99.140%	182.020%	337.647%	
HPR_{t-3-t}	35.375%	84.046%	165.404%	
HPR_{t-1-t}	15.533%	23.594%	34.669%	
HPR_{t-t+1}	20.757%	18.766%	18.185%	
HPR_{t-t+3}	78.940%	66.793%	58.824%	
HPR_{t-t+5}	178.684%	149.659%	129.006%	
Panel B: Standardised EPS 11 Years Around Portfolio Formation				
EPS (-5)	1.0758	0.6106	0.3933	
EPS (-4)	1.2145	0.6638	0.3815	
EPS (-3)	1.3472	0.7398	0.4173	
EPS (-2)	1.2767	0.8185	0.5626	
EPS (-1)	1.1741	0.9058	0.7608	
EPS (0)	1.0000	1.0000	1.0000	
EPS (+1)	1.1465	1.0531	1.0238	
EPS (+2)	1.2188	1.0596	0.9496	
EPS (+3)	1.2827	1.0809	0.8879	
EPS (+4)	1.3993	1.0997	0.8446	
EPS (+5)	1.4621	1.1066	0.7859	

Note: Average annual returns and standardised median EPS for high, middle and low EPS growth portfolios for five years before and after the portfolio formation date are reported. HPR represent holding period returns for 1, 3 and 5 years before and after the formation. The last column test presents the results of a t-test for the equality of mean returns between high and low EPS growth stocks.

7.3 Test of the Extrapolation Hypothesis

Following La Porta's approach we test whether investors extrapolate past earnings growth and past price performance and whether this extrapolation can justify the return differential between value and growth stocks. If investor's extrapolate the past then they would overestimate previously successful companies, while underestimate the stocks of companies that have done bad in the past. If this is the case and if earnings growth and performance is not persistent, but reverting, then past losers would outperform past winners.

In other words, if the extrapolation hypothesis is valid then the returns of low book-to-price stocks, that also have a good record of past performance will be lower than the returns of growth stocks that have performed poorly in the past (temporary losers). Similarly, if naïve investors extrapolate the past, then value stocks (companies with high book-to-price ratio, but disappointing previous performance) should outperform temporary winners. We use two different variables to proxy for previous performance: the three years past earnings growth and the previous cumulative rate of return over the last three years. In addition, we use the ratios of book-to-price, earnings-to-price and cash flow-to-price to define value and growth portfolios.

Table 7.5 presents the results of portfolios formed using any of the previous fundamental ratios, B/P, E/P, CF/P and three years past earnings growth. The procedure we use is the following: every year we sort companies in descending order on the basis of either B/P, E/P or CF/P and create three portfolios based on the top 30%, mid 40% and bottom 30% of ranked values. We then sort independently firms according to past earnings growth and create three groups using the same procedure. Nine portfolios are considered from the intersection of B/P (E/P, CF/P) and past EPS growth groups.

We report the results from portfolios resulted from the intersection of past EPS growth with only the high and low B/P (E/P, CF/P), and not the middle, for the purpose of convenience. Panel A, presents average annual returns and standard deviations of portfolios formed on the basis of B/M and past growth over the 1971 to 1997 period. The t-stats test the equality of mean returns between the high and low past EPS growth portfolios. P-values are reported in parenthesis.

Low past growth stocks earn slightly higher returns than high past growth, within the high B/P segment, but this difference is not statistically significant. Even more disappointing for the extrapolation hypothesis are the results of Growth portfolios. Growth stocks (low B/P) with disappointing past EPS growth slightly underperfom stocks with low B/P and good previous earnings growth, although this is not statistically significant. Panels B and C, report similar results for portfolios formed on the basis of E/P and CF/P respectively. In no case, does the low previous EPS growth outperform the high EPS growth portfolio at a statistically significant basis.

Our results suggest that if misspricing and subsequent price correction is the reason for the outperformance of value compared to growth stocks, this is not made because investors are fooled by the previous earnings growth patterns of these stocks. If the market extrapolates the past and overreact to previous earnings growth, then the returns of low EPS growth stocks would had been significantly higher than the results of high EPS growth stocks, both for the value and growth portfolios. Our analysis, however, indicate that this is not the case, so the source of overreaction, and expectational errors is not the past earnings growth of value and growth stocks.

We next ask whether it is the previous long-term performance of value and growth that cause investors' overreaction. A number of papers have attributed the well known winner - loser effect to market overreaction. DeBondt and Thaler (1985, 1987) and Chopra, Lakonishok and Ritter (1992) are two of the most important papers that favour the overreaction hypothesis as an explanation of long term price reversals. Although their work has been criticised by many others (e.g. Chan, 1988, Ball and Kothari, 1989, Zarowin, 1990, Ball, Kothari and Shanken, 1995, etc.), who provide alternative explanations, market overreaction still remains a testable hypothesis.

Given the higher return performance of growth relative to value stocks over the pre-formation period that was documented in the previous section, we ask whether investors overprice the former and underprice the later believing that this performance will continue in the future. If this is the case then value stocks with low previous returns will outperform value stocks with high past returns. The same would be true for growth portfolios. We follow exactly the same procedure as with past earnings growth, but this time we rank stocks on the basis of their past three years cumulative rate of return. We use the three years past returns to be consistent with the DeBondt and Thaler. Five years cumulative rates of returns were also tested with no significant differences in the results. Table 7.6 presents one year annual average returns and standard deviation for portfolios formed on the basis of any of the fundamental variables (B/M, E/P, CF/P) and previous price performance.

In five out of six cases, past winners underperform past losers. Exception is the case of low B/P stocks, when previously successful stocks continue to outperform but by a marginal amount. The results of the t-tests, however, point out that the difference in the performance between prior losers and winners is by no mean significant at any conventional significant level. Therefore, contrary to overreaction hypothesis, past winners (losers) do not become losers (winner) in the year after portfolio formation. The difference on the post-formation returns between winners and losers in any of the value and growth portfolio is not sufficient to explain the value and growth premium over the subsequent year.

In short, the evidence in this section points out that the market does not extrapolate either the past earnings growth, or previous price performance. The results indicate that the sources of overreaction that are suggested by Lakonishok, Shleifer and Vishny (1995) and DeBondt and Thaler (1985, 1987) can not explain the return difference between value and growth portfolios in UK.

TABLE 7.5: Test of Extrapolation I (Portfolios Formed on the Basis of Fundamental Ratios and Three Years Past Earnings Growth)

Panel A: Book-to-Price is used to proxy Value and Growth

B/P	High B/P (Value)			T-test	Low B/P (Growth)			T-test
EPS growth	High	Mid	Low	(H=L)	High	Mid	Low	(H=L)
Annual Return	24.47%	24.63%	27.23%	-0.5403	13.62%	13.37%	10.61%	0.5800
St. Deviation	18.22%	17.79%	18.56%	(0.5891)	19.50%	17.92%	17.81%	(0.5621)
B/P	1.5375	1.5272	1.5931		0.3822	0.4078	0.4332	
EPS growth	0.3621	0.1396	-0.0701		0.3593	0.1532	-0.0213	

Panel B: Earnings - to - Price is used to proxy for Value and Growth

E/P	High E/P (Value)			T-test	Low E/P (Growth)			T-test
EPS growth	High	Mid	Low	(H=L)	High	Mid	Low	(H=L)
Annual Return	16.06%	15.43%	18.57%	-0.5043	20.37%	20.85%	25.16%	-0.8943
St. Deviation	18.36%	17.43%	17.56%	(0.6142)	18.90%	17.96%	19.74%	(0.3715)
E/P	0.1284	0.1234	0.1261		0.0315	0.0312	0.0304	
EPS growth	0.3943	0.1502	-0.1221		0.4145	0.1556	-0.0319	

Panel C: Cash Flow - to - Price is used to proxy for Value and Growth

CF/P	High CF/P (Value)			T-test	Low CF/P (Growth)			T-test
EPS growth	High	Mid	Low	(H=L)	High	Mid	Low	(H=L)
Annual Return	20.70%	20.45%	22.75%	-0.3988	17.11%	16.02%	19.32%	-0.4306
St. Deviation	18.57%	17.96%	18.59%	(0.6902)	19.21%	17.52%	17.80%	(0.6669)
CF/P	0.6028	0.5980	0.6224		0.1517	0.1561	0.1413	
EPS growth	0.4185	0.1551	-0.0716		0.3956	0.1531	-0.0768	

Note: Portfolios are constructed on the basis of either book-to-price (panel A), earnings-to-price (panel B), or cash flow-to-price (panel C) and 3 year past earnings growth. Average annual returns and standard deviations for the year after the formation are reported. The t-stats test the equality of mean returns between the high and low past EPS growth portfolios. P-value are reported in parenthesis

TABLE 7.6: Test of Extrapolation II (Portfolios Formed on the Basis of Fundamental Ratios and Past Three Years Cumulative Rate of Return)

Panel A: Book-to-Market is used to proxy for Value and Growth

B/P	High B/P (Value)			T-test	Low B/P (Growth)			T-test
Prior - R	High	Mid	Low	(H=L)	High	Mid	Low	(H=L)
Annual Return	21.99%	24.03%	29.29%	-1.3699	12.43%	11.13%	11.53%	0.1647
St. Deviation	17.32%	17.32%	20.95%	(0.1712)	17.32%	18.39%	20.95%	(0.8692)
B/P	1.5412	1.5975	1.8188		0.3520	0.3699	0.3422	
Prior - R	1.0582	0.1919	-0.5159		1.3526	0.2623	-0.4721	

Panel B: Earnings - to - Price is used to proxy for Value and Growth

E/P	High E/P (Value)			T-test	Low E/P (Growth)			T-test
Prior - R	High	Mid	Low	(H=L)	High	Mid	Low	(H=L)
Annual Return	18.08%	21.44%	23.06%	-0.9285	15.68%	15.54%	19.37%	-0.7220
St. Deviation	17.99%	17.84%	20.57%	(0.3534)	17.29%	17.15%	19.44%	(0.4705)
E/P	0.1221	0.1219	0.1518		0.0457	0.0450	0.0383	
Prior - R	1.4813	0.3302	-0.4118		1.8932	0.3426	-0.4192	

Panel C: Cash Flow - to - Price is used to proxy for Value and Growth

CF/P	High CF/P (Value)			T-test	Low CF/P (Growth)			T-test
Prior - R	High	Mid	Low	(H=L)	High	Mid	Low	(H=L)
Annual Return	17.40%	21.31%	23.04%	-1.0763	16.04%	17.41%	18.83%	-0.5370
St. Deviation	17.20%	20.48%	17.49%	(0.2822)	17.79%	19.68%	17.72%	(0.5914)
CF/P	0.9812	0.9521	1.1803		0.1368	0.1371	0.1261	
Prior - R	1.4659	0.3081	-0.4515		1.8487	0.3444	-0.4345	

Note: Portfolios are constructed on the basis of either book-to-price (panel A), earnings-to-price (panel B), or cash flow-to-price (panel C) and 3 year past cumulative rate of return. Average annual returns and standard deviations for the year after the formation are reported. The t-stats test the equality of mean returns between the high and low past price performance portfolios. P-value are reported in parenthesis

7.4 The Impact of Earnings Surprises to the Returns of Contrarian Strategies

Extrapolation is not the only source of overreaction. Investors' overreaction to the growth potential of value and growth stocks may be reflected in analysts' earnings forecasts. Analysts' projections for future EPS affect investors' perceptions for companies and individual stocks. According to the error-in-expectations hypothesis, analysts tend to be pessimistic about value stocks and optimistic about growth. The announcement of the actual earnings for both categories of stocks creates a positive surprise for value and a negative surprise for growth stocks, which can justify their subsequent return difference.

Although the previous hypothesis has been researched by some academics, their conclusions are not consistent. LaPorta, Lakonishok, Shleifer and Vishny (1997) and Bauman and Miller (1997), although they use different approaches, agree that earnings surprises are disappointing for growth stocks and positive for value and this might be an explanation for their difference in returns. Fuller, Huberts and Levinson (1993), Bauman and Dowen (1994) and Dreman and Berry (1995), on the other hand, did not find the same relationship between the sign of surprises and the value/growth classification.

In this section, we examine the distribution of earnings surprises between value and growth portfolios in UK, using various different definitions of surprises, and a number of different proxies to classify stocks as value and growth. Furthermore, we investigate the impact of analyst's positive and negative errors to the returns of value and growth stocks.

7.4.1 Data Sample and Methodology

To test the role of earnings surprises in explaining the return difference between value and growth stocks we collect analysts' earnings forecasts for a wide range of UK companies for the period 1987 until 1997, using the I/B/E/S database. The sample is restricted to the period when UK analysts' EPS forecast data are available on the Institutional Brokers Estimates System (I/B/E/S). I/B/E/S provides a global database of analysts' forecasts of earnings per share, cash flow per share, dividends per share and net profits per share for publicly traded companies world-wide. It covers estimates for around 17,000 companies for 47 countries and uses 6,500 analysts from

750 research firms. The forecasts cover a variety of horizons ranging from 1 to 36 months before the announcement of actual data. Moreover it includes estimates of 5 year long term earnings growth, although these data are available for a limited amount of companies.

For the purposes of our research we have collected consensus (mean) earnings per share forecasts for 1 to 12 months prior to the announcement for all companies that were available in the UK I/B/E/S database. A total of 10,749 forecast estimates correspond to 1,774 UK companies from 1987 to 1997. In addition, the median and standard deviation of analysts' forecasts as well as the number of analysts following each stock are collected. Finally, we use the announcement dates in the I/B/E/S tapes to match the EPS forecasts with the accounting and returns data of individual stocks.

Analysts' forecast errors, or earnings surprises are defined using four different methods. We define earnings surprise as the difference between the actual value of firm's earnings per share and the median forecast value, scaled by the absolute value of the actual outcome. We use the same numerator, but scale the error by the absolute forecast value.

The EPS of some stocks are more difficult to forecast. as reflected by a wide range of forecasts among analysts. In such instances, we would expect a greater divergence in forecasts to be associated with a correspondingly larger difference between reported EPS and the mean consensus forecast. To adjust for differences in the uncertainty of expectations among stocks, the normalisation factor of standard deviation of the individual analyst forecast is applied as the denominator to the forecast error. We require a company to have an EPS consensus produced by at least three analysts reported in July of year t[3]. Finally, because the forecast-error variance is larger for firms with higher share value, we normalise the forecast error by the share price at exactly the month the forecast is made. The four definitions that are employed are the following:

[3] A number of studies that use this definition for EPS surprises require at least five analysts to produce forecasts for the firms' EPS. We found however that we are loosing to many observations especially from small companies when we impose the previous restriction, so we don't exclude a forecast from our sample unless is made by less than three analysts.

$$SUR1\ (\%ACT) = \frac{Actual\ EPS - Median\ Forecast\ EPS}{|Actual\ EPS|}$$

$$SUR2\ (\%FOR) = \frac{Actual\ EPS - Median\ Forecast\ EPS}{|Median\ Forecast\ EPS|}$$

$$SUR3\ (\%STDEV) = \frac{Actual\ EPS - Median\ Forecast\ EPS}{|St.Deviation\ of\ Analysts\ Forecasts|}$$

$$SUR4\ (\%ACT) = \frac{Actual\ EPS - Mean\ Forecast\ EPS}{|Share\ \mathrm{Pr}ice|}$$

Since our purpose is to link the earnings surprises with the rates of returns for different portfolios measured in July of every year, we use EPS forecasts made exactly on that month to estimate surprises, provided that the announcement of the actual EPS is made within the following 12 months. Finally, the data are trimmed to eliminate suspect data and outliers. All errors are standardised and each observation above 3 or below -3 standard deviations is removed from the sample. Matching the forecasts earnings data with the accounting variables we observe that I/B/E/S does not provide data for a significant proportion of small companies. We could find earnings forecasts only for 25% approximately of the companies allocated in the small-cap portfolio. The coverage is sufficiently wider for large and mid-cap stocks. The appendix at the end of the chapter shows the number of companies that have valid earnings surprises for every style portfolio.

7.4.2 Empirical Results

Table 7.7 presents average earnings surprises using all the above definitions, for different value and growth portfolios using one of B/P, E/P, CF/P and past EPS growth variables. We have also calculated average earnings surprises using forecasts made by analysts for 1 to 12 months prior to announcement and report these results for different value and growth portfolios in the appendix. The results suggest, using any definition that value stocks exhibit more negative surprises than growth stocks, since analysts are too optimistic for their earnings. This is rather surprising and initially contradicts the naive expectation hypothesis and the findings of Bauman and Miller (1997).

TABLE 7.7: Earnings Surprises for Different Value and Growth Portfolios

Portfolio	Surprise (% ACT)	Surprise (% FOR)	Surprise (A-F/SD)	Surprise (A-F/P) *100
High B/P (Value)	-22.88%	-12.78%	-0.651	-1.724
Mid B/P	-22.87%	-7.51%	-0.594	-0.862
Low B/P (Growth)	-10.41%	-3.28%	-0.427	-0.522
High E/P (Value)	-24.85%	-13.14%	-0.958	-1.803
Mid E/P	-11.55%	-0.66%	-0.362	-0.269
Low E/P (Growth)	-15.09%	-6.14%	0.057	-0.635
High CF/P (Value)	-28.84%	-11.21%	-0.944	-1.569
Mid CF/P	-14.10%	-3.08%	-0.388	-0.579
Low CF/P (Growth)	-7.14%	-6.49%	-0.022	-0.365
Low EPS growth (Value)	-34.78%	-17.49%	-1.042	-1.604
Mid EPS growth	-12.18%	-4.59%	-0.679	-0.679
High EPS growth (Growth)	-10.53%	-3.18%	-0.031	-0.476

Note: Average earnings surprises, from 1987 to 1997, are reported for value and growth portfolios, using one of either book-to-price, earnings-to-price, cash flow-to-price and past EPS growth to proxy for value and growth. EPS forecasts made in July of every year are used to estimate surprises.

Looking at the distribution of surprises and concentrating on just the errors defined as percentage over actual, we find that although surprises are on average more negative for value companies, there is still a significant number of positive surprises within value portfolios. Table 7.8, gives the number of positive and negative surprises, as well as the percentage over total, for every value and growth portfolio[4]. Interestingly, for high B/P companies, even if investors are on average optimistic (surprise is -22.88%), value companies exhibit as many positive as negative surprises. Furthermore, high B/P companies have roughly the same percentage of positive and negative surprises compared to low B/P. The picture is quite similar when value and growth portfolios are formed on the basis of historical earnings growth. Value stocks exhibit slightly lower percentage of positive surprises (44.35%) than growth does (49.90%). Likewise, negative surprises are 5% more for low growth, than for high growth companies.

[4] The percentage of positive and negative surprises do not sum up to 100%, as there are few occasions where analysts predict correct the EPS of companies and the surprise is exactly 0.

TABLE 7.8: Distribution of Earnings Surprises and Number of Analysts for Different Value and Growth Portfolios

Portfolio	Surprise (% ACT)	No of Positive Surprises	No of Negative Surprises	No of Analysts
High B/P (Value)	-22.88%	66.9 (47.96%)	66.4 (47.60%)	8.870
Mid B/P	-22.87%	131.3 (46.89%)	137.3 (49.04%)	9.912
Low B/P (Growth)	-10.41%	101.6 (49.13%)	95.8 (46.32%)	9.342
High E/P (Value)	-24.85%	58.8 (37.57%)	89.5 (57.19%)	10.197
Mid E/P	-11.55%	136.4 (49.91%)	127.0 (46.47%)	9.973
Low E/P (Growth)	-15.09%	92.2 (54.88%)	67.7 (40.30%)	9.342
High CF/P (Value)	-28.84%	57.8 (39.94%)	80.8 (55.84%)	10.170
Mid CF/ P	-14.10%	128.7 (47.79%)	129.4 (48.05%)	9.950
Low CF/P (Growth)	-7.14%	101.2 (55.67%)	72.4 (39.82%)	9.498
Low EPS growth (Value)	-34.78%	61.6 (44.35%)	71.9 (51.76%)	9.021
Mid EPS growth	-12.18%	104.7 (48.34%)	102.2 (47.18%)	9.245
High EPS growth (Growth)	-10.53%	72.0 (49.90%)	67.0 (46.43%)	9.756

Note: The number of positive and negative surprises, as well as the percentage over total, for every value and growth portfolio are reported. The average number of analysts that are following each category of stock is also presented.

The difference in the proportion of positive and negative surprises between value and growth is more pronounced, when E/P and CF/P are used as criterion for forming portfolios. It seems that about 55% of analysts' projections were on average proven to be pessimistic for low CF/P and E/P companies, that is about 16% - 17% more than the amount of pessimistic forecasts made for high CF/P and E/P companies. Even if earnings surprises are on average more negative for value than for growth portfolios, table 7.8 indicates that the sign of surprises are not very differently distributed among portfolios, with the exception of CF/P and E/P portfolios. There is still a substantial amount of EPS forecasts that were lower than the realised values for both value and growth portfolios.

Table 7.8 also presents the average number of analysts that are following value and growth stocks. As opposed to size portfolios, no significant differences on analysts' coverage between value and growth can be identified. No evidence on institutional neglect between the two equity classes similar to that between size portfolios can be identified.

The next question we address is how does positive and negative surprises affect the performance of value and growth stocks. If the error in expectations is correct, value stocks would be perceived by investors and analysts as "bad" stocks and a positive surprise will be received as good news for the particular companies and consequently cause an increase in their share price. A negative surprise, on the other hand, is not an unexpected event for value stocks and will only have a moderate impact on their share prices. Growth companies should also be affected differently by surprises. A company with low values of fundamentals to price, is expected to do well in the future, so a positive surprise may not be considered as good news and certainly won't change investors expectations, thus having less effect on price. Conversely, a negative surprise for growth companies is certainly an unexpected event that will have a damaging effect on their share price.

We extend the analysis of Dreman and Berry (1995) by testing many different value and growth portfolios for the UK market and using two different approaches to assess the impact of positive and negative surprises on the returns of value and growth portfolios.

Table 7.9 presents one-year buy-and-hold returns for value and growth portfolios that exhibit positive and negative earnings surprises. Stocks are categorised according to the sign of analysts' forecast errors and one of B/P, E/P, CF/P, or EPS growth. The table also reports the average returns for all surprises in each value/growth category for comparisons. The sample period that is covered in this analysis is from 1987 to 1997, so the returns that are reported are not directly comparable with the returns of the previous sections.

The evidence clearly suggests that value stocks, which experience positive surprises, outperform growth stocks, which also had positive surprises. In addition, this analysis indicates that consistently with the error in expectations hypothesis, negative surprises have a more dramatic effect on the returns of low B/P stocks, than on the returns of high B/P securities. Companies with high B/P ratio which experience negative earnings surprises earn 11.15% over the current year, while low B/P stocks with negative surprises realise an average return of -5.65%. The same pattern is observed for past earnings growth, but not for E/P and CF/P portfolios.

TABLE 7.9: One Year Buy and Hold Returns for Value and Growth Portfolios that Exhibit Positive and Negative Earnings Surprises

Panel A: B/P is used to proxy value and growth

	Positive SUR	Negative SUR	All Surprises
High B/P (Value)	21.68%	11.15%	16.05%
Mid B/P	19.42%	-0.70%	8.38%
Low B/P (Growth)	16.90%	-5.65%	5.87%
Average	19.13%	0.36%	

Panel B: E/P is used to proxy value and growth

	Positive SUR	Negative SUR	All Surprises
High E/P (Value)	21.61%	0.51%	7.64%
Mid E/P	17.45%	-0.98%	8.20%
Low E/P (Growth)	19.16%	-0.26%	10.56%
Average	18.87%	-0.30%	

Panel C: CF/P is used to proxy value and growth

	Positive SUR	Negative SUR	All Surprises
High CF/P (Value)	20.34%	0.60%	7.75%
Mid CF/P	18.69%	-2.11%	7.66%
Low CF/P (Growth)	18.43%	1.19%	11.27%
Average	19.09%	-0.46%	

Panel D: Historical EPS growth is used to proxy value and growth

	Positive SUR	Negative SUR	All Surprises
Low E PS growth (Value)	20.91%	2.11%	10.21%
Mid EPS growth	18.55%	0.89%	9.48%
High EPS growth (Growth)	15.87%	-3.00%	6.15%
Average	18.43%	0.14%	

Note: Portfolios are constructed on the basis of one of either B/P, E/P, CF/P, or historical EPS growth and the sign of analysts' forecasts errors (earnings surprises). One-year holding period returns are estimated from July of year t to June of year t+1. The sample period is from 1987 to 1997. Average equal weighted returns for all surprises (including 0) are reported for each portfolio in the last column. Finally, average returns for all stocks that experience positive surprises and for all stocks that had negative surprises are presented in the last row of every panel.

A multivariate regression analysis approach is employed to evaluate the impact of surprises to value and growth portfolio returns. The returns of different B/P (CF/P, E/P, and past EPS growth) portfolios are regressed against earnings surprises on a time series - cross sectional basis. We run two different set of regressions; one for positive and one for negative surprises, after controlling for size, using the logarithm of market value of equity. We use a system of regressions for every value / growth classification and estimate this multivariate system using Generalised Method of Moments (Hansen (1982)), where surprises and size are used as instrumental variables to the model. The GMM approach assumes that the disturbances in the equations are uncorrelated with the instruments. The method of White (1980) is used to correct standard errors for cross - sectional heteroskedasticity. The positive surprises' system of equations that is used is the following

$$\begin{aligned} R_{value} &= \alpha_1 + \beta_1 SUR(+) + \gamma_1 \ln(MV) \\ R_{middle} &= \alpha_2 + \beta_2 SUR(+) + \gamma_2 \ln(MV) \\ R_{growth} &= \alpha_3 + \beta_3 SUR(+) + \gamma_3 \ln(MV) \end{aligned}$$

If the errors-in-expectation hypothesis is valid then the surprise coefficient would be positive and significant for value and insignificant for growth. In addition, we expect to find a monotonic decline in the magnitude of the coefficients as we move from value to growth stocks ($\beta_1 < \beta_2 < \beta_3$). Similarly, the following system is used for negative surprises:

$$\begin{aligned} R_{value} &= \alpha_1 + \beta_1 SUR(-) + \gamma_1 \ln(MV) \\ R_{middle} &= \alpha_2 + \beta_2 SUR(-) + \gamma_2 \ln(MV) \\ R_{growth} &= \alpha_3 + \beta_3 SUR(-) + \gamma_3 \ln(MV) \end{aligned}$$

We expect to find a positive and significant coefficient for growth stocks and a smaller and probably insignificant response coefficient for value. Since the SUR(-) variable takes only negative values, a positive coefficient would indicate that a large negative surprise will cause a *decrease* in the portfolio returns.

Table 7.10 presents results from estimating the positive surprises system for different value and growth portfolios proxied by one of B/P, E/P, CF/P or past EPS growth variables. We report adjusted R^2 coefficients, as well as Wald χ^2 statistics to test the null hypothesis that the coefficient of positive surprises for all three portfolios are the same ((β_1 = β_2 = β_3). The results indicate that for all, but past EPS growth portfolios, positive surprises have a bigger and significant impact on the returns of value stocks, while only a small and insignificant effect on the performance of growth. The Wald test rejects the null hypothesis of equality among positive surprises' responses for B/P and E/P but not for CF/P portfolios.

Table 7.11 presents the relevant results for negative surprises. The evidence here is also consistent with the hypothesis. Negative surprises have a smaller coefficient to the returns of value compared to growth and in three out of four cases (with the exception of high B/P stocks) this coefficient is not statistically significant. Quite remarkably, in almost all cases, we observe a monotonic decline in the magnitude of the coefficients as we move from value to growth portfolios. Furthermore, the null hypothesis of equal response coefficients to negative surprises is accepted only for E/P portfolios. This evidence confirms the hypothesis that a negative surprise is not considered a bad unexpected event for value stocks as these are perceived by investors to be stocks with low potentials. On the other hand, an earnings disappointment would affect negatively the returns of growth companies as this would contradict investors' expectations.

TABLE 7.10: The Impact of Positive Earnings Surprises on the Returns of Value and Growth Portfolios

$$R_{value} = \alpha_1 + \beta_1 SUR(+) + \gamma_1 \ln(MV)$$
$$R_{middle} = \alpha_2 + \beta_2 SUR(+) + \gamma_2 \ln(MV)$$
$$R_{growth} = \alpha_3 + \beta_3 SUR(+) + \gamma_3 \ln(MV)$$

		Intercept	SUR (+)	ln (MV)	adj - R^2	Wald χ^2 Test (β_1=β_2=β_3)
B/P	Value	0.1566 **	**0.1055** **	-0.0112	0.0216	6.6488
		(4.0767)	(2.5628)	(-1.4927)		(0.0359)
	Middle	0.1794 **	**0.1309** **	-0.0189 **	0.0379	
		(5.0533)	(3.6174)	(-3.1387)		
	Growth	0.1491 **	**0.0672**	-0.0062	0.0048	
		(3.4666)	(1.4233)	(-0.8848)		
E/P	Value	0.1031 **	**0.3069** **	-0.0031	0.0236	10.3351
		(2.2375)	(2.0699)	(-0.3930)		(0.0057)
	Middle	0.1726 **	**0.2977** **	-0.0169 **	0.0245	
		(5.4325)	(4.0248)	(-3.1986)		
	Growth	0.2333 **	**0.0572**	-0.0185 **	0.0118	
		(5.0400)	(1.5876)	(-2.3739)		
CF/P	Value	0.1577 **	**0.1162** **	-0.0120	0.0181	0.6025
		(3.4785)	(2.2131)	(-1.4543)		(0.7398)
	Middle	0.1640 **	**0.1589** **	-0.0109 **	0.0140	
		(5.1343)	(2.0651)	(-2.1033)		
	Growth	0.2750 **	**0.0834**	-0.0281 **	0.0214	
		(5.5017)	(1.3904)	(-3.4181)		
EPS growth	Value	0.2251 **	**0.0608**	-0.0175 **	0.0163	5.2461
		(4.4928)	(1.6354)	(-2.1170)		(0.0725)
	Middle	0.1793 **	**0.2309** **	-0.0124 **	0.0181	
		(5.1637)	(2.9185)	(-2.2497)		
	Growth	0.1620 **	**0.3478** *	-0.0187 **	0.0461	
		(2.9254)	(1.6618)	(-2.1159)		

Note: The impact of positive surprises to the one year holding period returns of different value and growth portfolios is evaluated using a multivariate GMM time series - cross sectional regression. SUR is defined as (Actual EPS - Forecast EPS) / Actual EPS. Only positive values of the ratio are included in the regression. MV is the market value of equity at the start of the portfolio formation, i.e. July of each year t. The sample period is from 1987 to 1997. T-stats are corrected for cross sectional heteroskedasticity using the method of White (1980) and are reported under each coefficient. The Wald χ^2 statistic tests the equality of the positive surprise response coefficients. P-values are reported in parenthesis.

TABLE 7.11 : The Impact of Negative Earnings Surprises on the Returns of Value and Growth portfolios

$$R_{value} = \alpha_1 + \beta_1 SUR(-) + \gamma_1 \ln(MV)$$
$$R_{middle} = \alpha_2 + \beta_2 SUR(-) + \gamma_2 \ln(MV)$$
$$R_{growth} = \alpha_3 + \beta_3 SUR(-) + \gamma_3 \ln(MV)$$

		Intercept	SUR (-)	ln (MV)	adj - R^2	Wald χ^2 Test ($\beta_1=\beta_2=\beta_3$)
B/P	Value	0.1080 (1.6150)	**0.0256** ** (2.5993)	-0.0179 (-1.2732)	0.0133	5.6356 (0.0597)
	Middle	-0.1102 ** (-3.7795)	**0.0294** ** (2.3102)	0.0115 ** (2.3102)	0.0163	
	Growth	-0.1976 ** (-5.1516)	**0.0578** ** (4.5014)	0.0240 ** (3.7313)	0.0507	
E/P	Value	-0.1011 ** (-2.4973)	**0.0136** (0.8125)	0.0099 (1.3591)	0.0073	1.7317 (0.4260)
	Middle	-0.0845 ** (-2.8718)	**0.0350** ** (3.1287)	0.0090 * (1.8047)	0.0174	
	Growth	0.0123 (0.2655)	**0.0378** ** (5.0050)	-0.0081 (-0.9460)	0.0357	
CF/P	Value	-0.0789 * (-1.9321)	**0.0104** (0.8189)	0.0033 (0.4199)	0.0034	6.0025 (0.0497)
	Middle	-0.1014 (-3.6071)	**0.0389** ** (4.2085)	0.0113 ** (2.3317)	0.0315	
	Growth	-0.0163 (-0.3376)	**0.0545** ** (4.0826)	0.0005 (0.0607)	0.0275	
EPS growth	Value	-0.0671 * (-1.6563)	**0.0066** (0.7913)	0.0056 (0.7537)	0.0181	11.5137 (0.0031)
	Middle	-0.0483 (-1.3962)	**0.0394** ** (2.6799)	0.0055 (0.9025)	0.0153	
	Growth	-0.0004 (-0.0107)	**0.0604** ** (4.1205)	-0.0103 (-1.4580)	0.0412	

Note: The impact of negative surprises to the one year holding period returns of different value and growth portfolios is evaluated using a multivariate GMM time series - cross sectional regression. SUR is defined as (Actual EPS - Forecast EPS) / Actual EPS. Only negative values of the ratio are included in the regression. MV is the market value of equity at the start of the portfolio formation, i.e. July of each year t. The sample period is from 1987 to 1997. T-stats are corrected for cross sectional heteroskedasticity using the method of White (1980) and are reported under each coefficient. The Wald χ^2 statistic tests the equality of the negative surprise response coefficients. P-values are reported in parenthesis.

7.5 Summary and Conclusion

This chapter investigates whether the difference in the returns between value and growth stocks, proxied by a number of different variables (B/P, E/P, CF/P and three years past earnings growth) can be explained by expectation errors made by investors and analysts. Investors' expectations are extreme maybe because they look at past earnings growth and performance of firms and naively extrapolate the past. Using data from companies listed in UK the last 30 years, we reject the extrapolation hypothesis of Lakonishok, Shleifer and Vishny (1995). We find that, although value (growth) stocks are stocks with low (high) past EPS growth and bad price performance, the market does not incorrectly extrapolate the past and stock prices of value and growth do not reflect the naive extrapolation of past earnings growth or returns.

Extreme expectations however may be reflected on analysts' earnings forecasts. Using I/B/E/S earnings forecast data from 1987 to 1997, we find that, although analysts are on average more optimistic for value stocks, there is a substantial amount of positive surprises characterising these stocks. Furthermore, we study the effect of positive and negative earnings surprises on the returns of value and growth portfolios by employing a simple portfolio approach and a multivariate GMM framework. We find that positive and negative surprises have an asymmetric effect on the returns of value and growth, in favour of the former, in a fashion that is consistent with the error - in - expectations hypothesis. A positive surprise is regarded as good news for value stocks and has a significantly more positive impact on their returns compared to growth stocks. On the other hand, a negative surprise is regarded as bad news for growth stocks and has a significantly more negative impact on their performance, with only a minor impact on the returns of value stocks.

APPENDIX A: Number of Stocks with Valid Analysts Earnings Forecasts Data

Panel A: B/P is used to proxy value and growth

	SV	SM	SG	MV	MM	MG	LV	LM	LG
1987	96	119	84	19	48	32	17	77	25
1988	99	154	97	22	54	30	28	65	35
1989	96	146	105	30	44	38	20	51	37
1990	100	168	106	14	38	43	15	43	44
1991	91	194	146	14	39	29	8	37	44
1992	107	191	155	14	34	32	7	41	45
1993	104	183	147	8	32	36	6	42	44
1994	121	227	156	16	46	34	15	56	41
1995	128	230	164	17	38	39	5	54	42
1996	145	233	145	16	55	51	17	61	42

Panel B: E/P is used to proxy value and growth

	SV	SM	SG	MV	MM	MG	LV	LM	LG
1987	92	151	76	21	47	26	38	59	18
1988	131	187	94	22	50	34	45	62	18
1989	141	163	108	26	53	38	27	68	28
1990	140	181	126	17	44	34	11	61	34
1991	135	196	136	15	41	25	10	55	33
1992	118	185	141	11	34	27	20	48	24
1993	121	220	141	15	31	28	24	50	24
1994	116	232	156	14	45	23	40	43	23
1995	160	272	167	18	46	32	23	58	33
1996	179	273	195	16	58	39	30	53	35

Panel C: CF/P is used to proxy value and growth

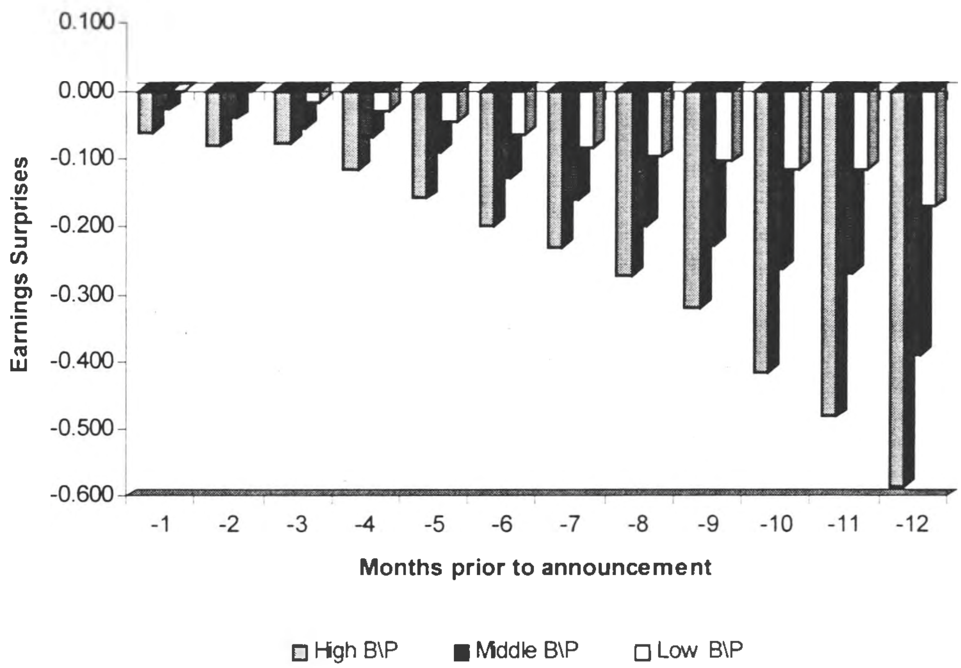
	SV	SM	SG	MV	MM	MG	LV	LM	LG
1987	98	135	90	21	66	29	10	51	34
1988	115	186	107	28	57	39	25	41	41
1989	121	164	109	22	63	37	28	49	40
1990	124	196	113	13	41	47	20	38	35
1991	123	196	131	12	44	36	10	40	30
1992	111	184	132	15	40	26	10	39	23
1993	137	218	163	15	63	27	8	42	30
1994	136	223	153	19	61	27	14	40	29
1995	168	262	182	13	68	35	9	56	34
1996	191	273	191	21	55	43	12	56	47

Panel D: Historical EPS growth is used to proxy value and growth

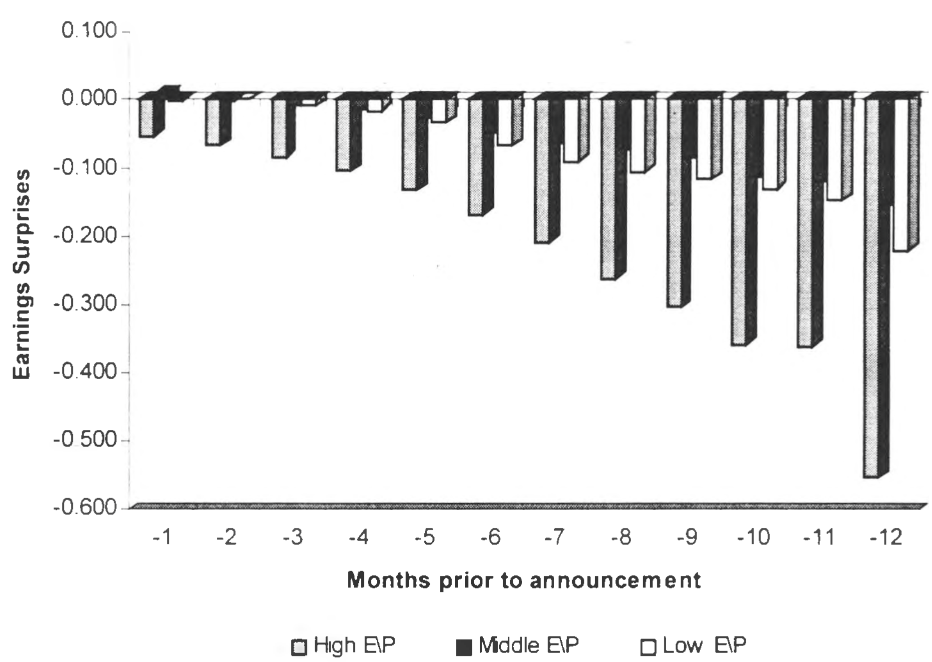
	SV	SM	SG	MV	MM	MG	LV	LM	LG
1987	56	106	79	13	37	20	22	43	30
1988	83	124	100	15	48	21	38	53	11
1989	93	123	91	22	41	24	39	47	18
1990	114	141	114	19	42	16	14	56	18
1991	121	153	126	21	31	20	9	50	16
1992	121	156	124	22	29	18	11	37	23
1993	131	182	159	22	35	17	22	48	20
1994	138	164	138	14	33	22	23	56	17
1995	136	186	152	18	31	19	26	57	17
1996	134	198	149	22	39	18	26	49	24

APPENDIX B: Average EPS Surprises for 1 to 12 Months Before the Announcement Date (1987 - 1997)

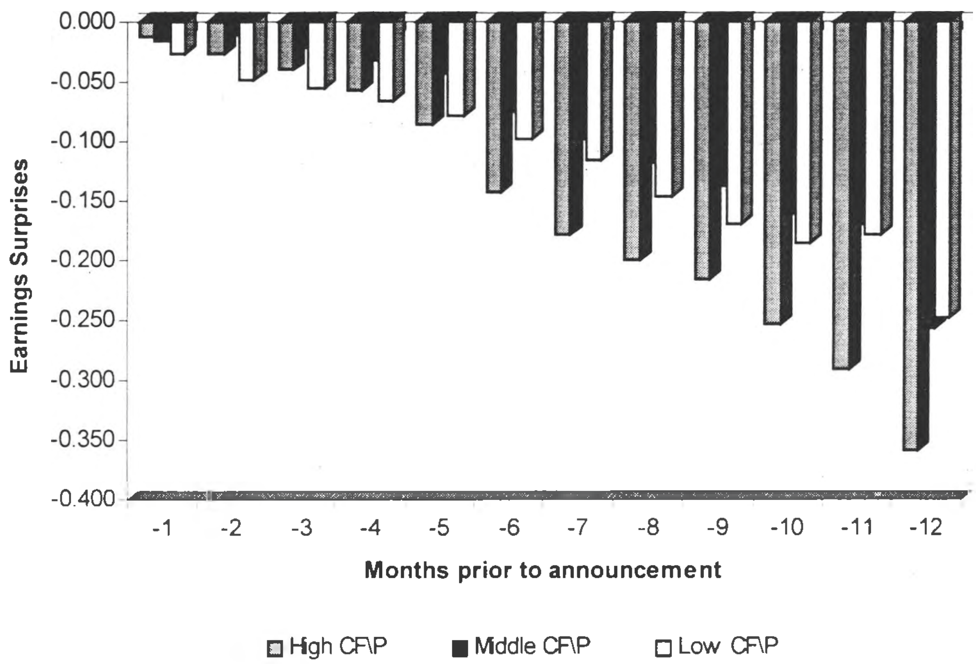
Panel A: B/P is used to proxy value and growth



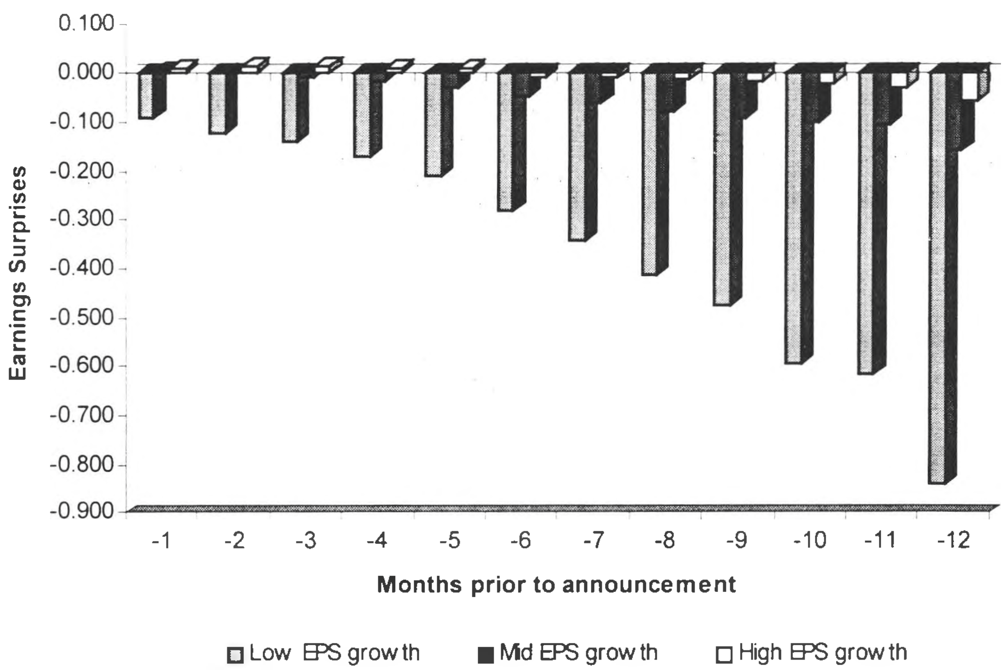
Panel B: E/P is used to proxy value and growth



Panel C: CF/P is used to proxy value and growth



Panel D: Historical EPS growth is used to proxy value and growth



CHAPTER 8

"*The Profitability of Style Rotation Strategies*"

8.1 Introduction

The previous chapters provide evidence on the long term performance and characteristics of various size and value investment strategies in the UK market. These strategies assume that the investor has a consistent investment policy and always search for stocks that satisfy his or her selection criteria. Every year, portfolios are reformed and the constituents of the size or value indices change to meet the style managers' objectives. We find that, over the last thirty years, a consistent investment in small companies would generate slightly higher returns than a similar investment in large-caps, while a continuous search for high B/P stocks would result to a significant outperformance.

Style consistency, however, is not necessarily an optimal strategy. As the volatility of the equity risk premium creates a need for active asset allocation, the variability in the equity style premium creates a need for style rotation strategies. For the active-portfolio manager, rotation among different equity (style) segments, may provide opportunities for portfolio performance enhancement. Kahn (1996), for example, reports that most funds do not systematically follow a value or growth stock orientation, but instead are prone to either shift between one or the other, or adopt a blend. In addition, although half of the equity funds studied stayed within their target size category, a few moved across portfolios of small and large stocks. At the same time, however, Indro, Jiang, Hu and Lee (1998) report that funds that instituted both a change in their value-growth as well as small-large capitalization stock allocation strategy were the worst performing group of actively managed funds.

This chapter studies the variability in the returns of style spreads over time and assess the potential profitability of style rotation strategies based on the small / large-cap and value / growth segments of the market. We use the B/P ratio as the most relevant proxy to construct the value-growth spread. There is considerable US and UK evidence that the previous variable is priced[1] and it is the most accepted proxy for constructing value and growth indices both among academics (Sharpe, 1992) and practitioners (BARRA/S&P, Frank Russell).

[1] A number of papers document that B\P can explain the cross section of stock returns (see Fama and French (1992) for US and Strong and Xu (1997) for UK evidence) and mimicking portfolios constructed on the basis of B\P ratio are priced in time series asset pricing models (see Fama and French (1995)).

The chapter has two objectives:

1. To explore the profit potential of style rotation strategies in UK during the period 1968-1997, assuming both perfect and a range of intermediate levels of forecasting ability as well as different amount of transaction costs.
2. To develop and test a style rotation model based on a set of economic and market factors selected for their ability to predict the direction of the style spread at a given month.

A substantial amount of work has been done in evaluating the potential rewards from market timing. Sharpe (1975) was the first to examine the efficacy of market timing between cash and equities and highlight the potential benefits of such strategies. Jeffrey (1984), using the same framework, casts some doubt on the benefits of market timing. He argues that the incremental rewards from such strategies do not necessarily match the incremental risks. A number of other studies draw more optimistic conclusions (e.g. Sy, 1990, Clarke et al., 1989, Wagner et al., 1992). Almost all agree, however, that the benefits of market timing directly depend on a number of factors such as the transaction costs, the frequency of portfolio rebalancing, and the managers' forecasting skill.

Very little work has been done on this issue for style rotation, or tactical equity allocation. Kester (1990) expand the scope of market timing strategies by including small firms, while Case and Cusimano (1995) apply the same principles on value and growth indices. Kao and Shumaker (1998) compare style (value vs. growth), size and market timing strategies in US. All these studies report some profit enhancement depending on transaction costs and the frequency of portfolio revision. Unfortunately, however, they offer very limited guidance in terms of the level of forecasting ability required and the potential of achieving this level.

Coggin (1998) tested the random walk and the long-term memory hypothesis for a number of US equity style indices and style spreads and found evidence in support of the former. He conclude that style indices cannot be predicted using only the time series of returns as information variables, instead forecasts should be conditioned on outside information, such as the business cycle and interest rates.

A number of studies have indeed attempted to link the performance of style portfolios to various macroeconomic factors. Fama and French (1993) suggest that book-to-market and size are proxies for distress and that distressed firms may be more sensitive to certain business cycle factors.

Jensen, Johnson and Mercer (1998), for example, find that size and book-to-market effect depend on the monetary environment. Sorensen and Lazzara (1995) find a positive relationship between the growth in industrial production and interest rates and the value - growth return spread. Anderson (1997) reports that small stocks benefit from inflation, perhaps because small companies find it relatively easier to pass along price increases in inflationary times. He also shows that the yield curve is positively related to relative performance of small over large stocks. Ragsdale, Rao and Fochtman (1995) argue that future earnings growth is the decisive factor in predicting the performance of small vs. large-cap stocks; one of the factors, that is likely to affect earnings is exposure to foreign markets. Thus, large stocks are penalised when the exchange rate is highly volatile.

At a more general level, Macedo (1995) maintains that the equity risk premium is the strongest discriminator for future style performance. A high equity risk premium favours riskier portfolios. Value stocks are perceived to be more risky and so tend to do well when the equity risk premium is high. In short, there are good reasons and considerable empirical evidence to suggest that both the size and value spreads are associated with economic fundamentals.

The results of this chapter contribute to the debate of whether investors should pursue a dynamic style rotation strategy, or be dedicated to a certain investment philosophy for a long period of time. The sensitivity of this decision to transaction costs and forecasting skills will be emphasised. Furthermore, the identification of factors that can be used to forecast the direction of style spread and build style rotation trading rules is another contribution.

The rest of the chapter is organised as follows: The next section shows the time variability of size and value monthly, quarterly and semi-annual return spreads and introduces the need for style rotation. Section 8.3 shows the likely gains and risks from style rotation and presents some simulation results for assessing the average gross and net profits from rotation for certain levels of forecasting skills. Section 8.4

examines the variables and the model we use to forecast style spreads and section 8.5 presents the results from various trading rules build upon the forecasting model. Finally section 8.6 summarises the findings and concludes.

8.2 The Need for Style Rotation

A number of studies compare investment styles historically to find which produces the highest returns and lowest standard deviation. Such analysis is very sensitive to the time period chosen and, in any case, past results offer no guarantee of future performance. There is, however, a lot of certainty (supported by evidence) regarding the outperformance of small-cap and value investment strategies in the long run for the majority of capital markets. This, nevertheless, does not imply that value, or small stocks outperform in all time periods and economic conditions. Even the most successful styles and strategies sometimes experience underperformance. There have been many subperiods in which the returns of growth and large-cap securities were higher than the returns of value and small-cap issues. So, market rewards styles at different times for different reasons. This variability of the style spread makes style rotation a necessity. In other words, as value or small-cap stocks do not outperform every time period, a discipline that forecasts when styles will go in or out of favour could add value to investors.

Figure 8.1 shows the 12-month moving average of the return spread (on an equally weighted basis) between the small and large-cap index and between value and growth portfolios. It is clear that different times favour different types of stocks. The small-cap investment strategy, for example, had two good cycles in the first half of our sample, each one lasting about 2.5 to 3 years (1971-1973 and 1977-1980). Large-caps, on the other hand, were more profitable from 1988 to 1992. The value-growth spread exhibits less variability, but some cyclical movements are still apparent. Although the sign variation in the case of value-growth spread is not as obvious as in the case of size spread, there are still some periods when growth stocks give better returns than value.

Tables 8.1 and 8.2 present the sign and magnitude variation of the size and value-growth spreads respectively. The tables show the number of periods when one index performs better than the other by a specified amount. We examine the variability of style spreads using monthly, quarterly and semi-annual non-overlapping returns. Quarterly and semi-annual returns assume simple accumulation of returns under monthly rebalancing and are measured by adding the respective monthly returns. Our sample from July 1968 to June 1997 contains 348 monthly, 116 quarterly and 58 semi-annual returns.

FIGURE 8.1: 12 Month Moving Average of Style Spreads

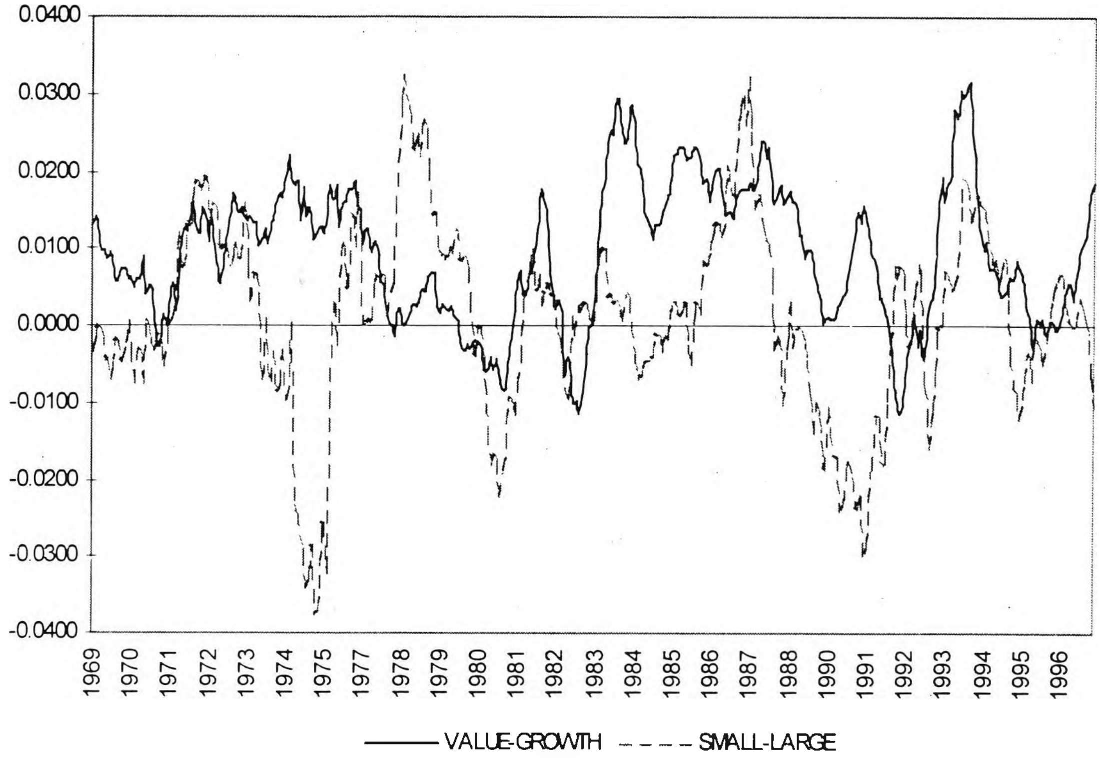


Table 8.1 shows that small-caps outperformed large-caps 183 months out of 348, or 52.59% of the time. The table also presents the amount and percentage of months that small-caps' relative outperformance exceeds a specified threshold, ranging from 50 to 300 basis points. The results indicate that in 137 months, or in 39.37% of the time, small-caps outperform their counterparts by more than 100 basis points. Furthermore, for 95 out of 348 months (27.30%) the returns of small-cap index were higher than the returns of large-cap index by more than 200 basis points, while in 64 months the outperformance exceeded 3%. Table 8.1 shows that there is a significant number of months (165) where the size return spread becomes negative and large companies earn higher returns than small. What is even more interesting is that, most of the times when large-caps outperform small-caps they do so by a substantial amount. In 120, 83, and 52 months the large-small return spread exceeds 1%, 2% and 3% respectively.

The same conclusion can be drawn by looking at quarterly and semi-annual returns. Whatever the investment horizon, the size style spread appears to be extremely volatile. It seems that, although small-caps perform better than large-caps most of the times, there are plenty of periods when large-caps produce higher returns. Therefore, a model that provides signals to switch from one equity class to the other, and attempts to capture the sign variation of the size spread is definitely worth considered.

Table 8.2 shows the relevant results for the monthly, quarterly and semi-annual value-growth return spread. Value stocks outperform growth in 232 or 66.67% of the months. A high percentage of outperformance is also recorded for lower frequency returns, such as quarterly (65.52%) and semi-annual (81.03%) returns. Although, the value-growth return spread appears to be more consistent than the small-large spread, still some benefits from equity style timing may arise. The returns of growth stocks exceeds the returns of value by more than 100 basis points in 58 months, or 16.67% of the time. More apparent return differentials in favour of low B/P stocks that exceed 2% and 3% have been manifested in 30 and 14 months respectively. Growth significantly outperforms value relatively more frequent, when we look at quarterly and semi-annual returns. The growth-value quarterly return spread is higher than 2% and 3% for 31 and 28 out of 118 quarters respectively.

If an investor can recognise the periods when growth outperforms value by a critical amount and decide to rotate from one equity class to another, it is possible that he or she would outperform the market. We need however to point out that the lower variation of value-growth spread compared to small-large spread might result in less obvious benefits from style rotation. The next section presents the risks and benefits of these two types of equity style rotation and the efficacy of achieving these benefits with realistic level of forecasting skills.

TABLE 8.1: Consistency of Small - Large Return Spread

	Monthly Returns	Quarterly Returns	Semi - Annual Returns
S - L > 0	183 (52.59%)	64 (55.17%)	32 (55.17%)
S - L > 50 bp	159 (45.69%)	57 (49.14%)	30 (51.72%)
S - L > 100 bp	137 (39.37%)	52 (44.83%)	29 (50.00%)
S - L > 150 bp	120 (34.48%)	49 (42.24%)	28 (48.28%)
S - L > 200 bp	95 (27.30%)	45 (38.79%)	27 (46.55%)
S - L > 250 bp	76 (21.84%)	39 (33.62%)	24 (41.38%)
S - L > 300 bp	64 (18.39%)	35 (30.17%)	23 (39.66%)
L - S > 0	165 (47.41%)	52 (44.83%)	26 (44.83%)
L - S > 50 bp	137 (39.37%)	47 (40.52%)	22 (37.93%)
L - S > 100 bp	120 (34.48%)	44 (37.93%)	22 (37.93%)
L - S > 150 bp	101 (29.02%)	40 (34.48%)	21 (36.21%)
L - S > 200 bp	83 (23.85%)	35 (30.17%)	21 (36.21%)
L - S > 250 bp	68 (19.54%)	30 (25.86%)	20 (34.48%)
L - S > 300 bp	52 (14.94%)	25 (21.55%)	18 (31.03%)

TABLE 8.2: Consistency of Value - Growth Return Spread

	Monthly Returns	Quarterly Returns	Semi - Annual Returns
V - G > 0	232 (66.67%)	76 (65.52%)	47 (81.03%)
V - G > 50 bp	199 (57.18%)	74 (63.79%)	45 (77.59%)
V - G > 100 bp	164 (47.13%)	70 (60.34%)	40 (68.97%)
V - G > 150 bp	135 (38.79%)	67 (57.76%)	38 (65.52%)
V - G > 200 bp	103 (29.60%)	65 (56.03%)	37 (63.79%)
V - G > 250 bp	86 (27.71%)	65 (56.03%)	36 (62.07%)
V - G > 300 bp	61 (17.53%)	61 (52.59%)	33 (56.90%)
G - V > 0	116 (33.33%)	40 (34.48%)	11 (18.97%)
G - V > 50 bp	85 (24.43%)	40 (34.48%)	10 (17.24%)
G - V > 100 bp	58 (16.67%)	37 (31.90%)	8 (13.79%)
G - V > 150 bp	42 (12.07%)	33 (28.45%)	8 (13.79%)
G - V > 200 bp	30 (8.62%)	31 (26.72%)	8 (13.79%)
G - V > 250 bp	20 (5.75%)	30 (25.86%)	5 (8.62%)
G - V > 300 bp	14 (4.02%)	28 (24.14%)	5 (8.62%)

Note: The tables present the number of periods when one index outperforms the other by a pre-specified threshold ranging from 0 to 300 basis points. S represents the small-cap index, L the large-cap index, V the value index and G the growth index. Results with regard to monthly and non-overlapping quarterly and semi-annual returns are presented.

8.3 Likely Gains from Style Rotation

Effective implementation of style rotation strategies requires a realistic assessment of the manager's degree of forecasting ability. Figure 8.2 shows the maximum and minimum possible profit for investors, with different levels of forecasting skills, rotating between small and large stocks. Forecasting skill in this case is synonymous to *hit ratio*, or the percentage of months that the investor predicts correct which equity style will outperform. The allocation decision is assumed to occur at monthly intervals on the basis of the corresponding index performance. A month is assumed that is predicted correctly when the hypothetical investor has chosen to allocate all of her/his funds in the best performing index.

The graph first illustrates the two extreme paths of style rotation results that connect the ultimate points of being totally right (at the top left) and totally wrong (at the lower right). There are 348 months in our sample, from July 1968 to June 1997. Someone who is able to predict every single of the 348 months correctly and chose the right style to invest in, could have earned a 33.81% average annual return, or 17.47% above the average total return of FT All Share during the past 29 years. Assuming 100 basis points transaction costs for every switch, the perfect foresight strategy results in 160 switches that reduces the average returns to 28.29%. At the other extreme, an investor who is consistently wrong on the direction of the spread would generate an average gross annual return of 0.38% or -5.14% after deducting transaction costs.

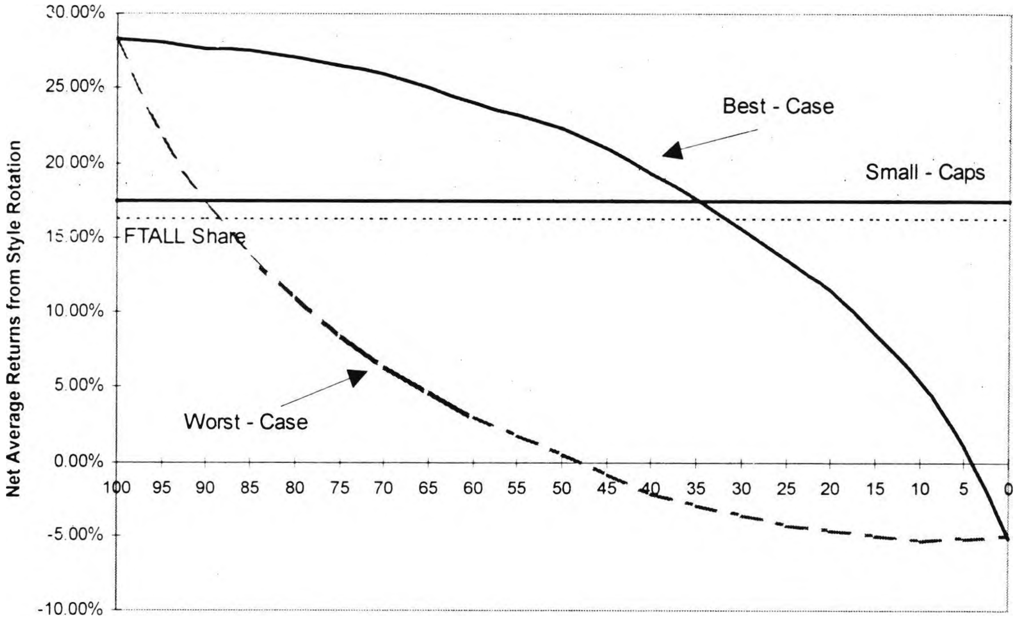
Making the case more realistic, we assume that an investor can succeed in forecasting only a given percentage of these 348 months. To assess the robustness of style rotation, we calculate the highest and lowest possible profits under different forecasting accuracy levels, starting from 5% to 95%. The best-case scenario for 60% accuracy rate, for example, corresponds to the case when an investor manages to capture the best 209 (60%) months with the highest absolute return spread. The worst-case scenario, on the other hand, is when an investor misses the 139 best months (40%). In this case of course, the transaction costs exceeds the potential benefits from rotation.

Figure 8.2 shows the impact of forecasting accuracy rates to the net average annual returns. The upper curve corresponds to the best-case scenario, while the lower curve to the worst case-scenario for the same accuracy level. The slope of the upper best-case curve falls gradually at the top, but becomes steeper as the timing accuracy rate diminishes. Exactly the reverse applies to the lower worst-case curve, where the downward slope is steepest at the beginning and flattens at the end. It is interesting to note that, even with a modest 35% forecasting ability the highest possible profits conditional on a 100% hit ratio exceed the profits of the FT All share index and break even with the performance of the small-cap index. However, if an investor picks the wrong months (worst-case scenario), she/he needs more than 90% accuracy rate to have an advantage over passive strategies.

We have also experiment with transaction costs of 200 basis points for every switch. The higher costs obviously had a negative effect on the rotation profits. The net average annual return for a perfect foresight strategy are now reduced to 22.77%. In addition, at least 55% accuracy rate is required to outperform the small-cap passive benchmark.

FIGURE 8.2: Impact of Style Timing Accuracy Rates on Net Annual Returns

(The Case of Small vs. Large Rotation)

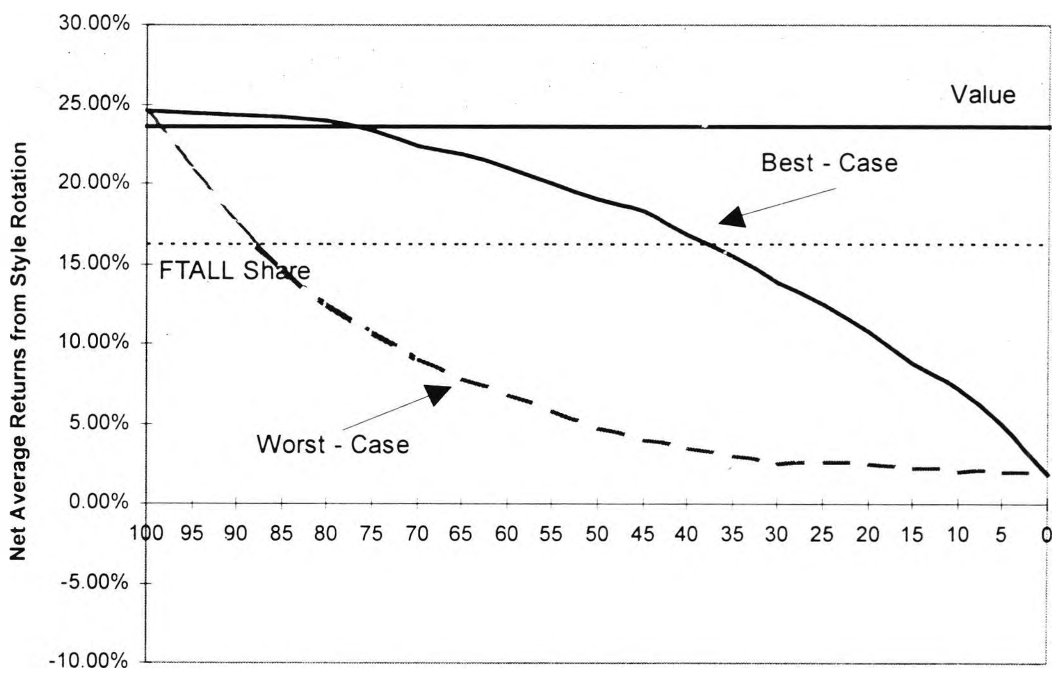


The same type of analysis is applied to a different framework, in the case of value - growth rotation. A perfect foresight rotation strategy earns a 29.10% gross average annual return or 24.51% net of 100bp transaction costs; this is just 0.93% more than the return of a value buy-and-hold strategy. The downside risk, however, is also less than in the case of small - large rotation. The gross returns of a rotation strategy that has been totally wrong in forecasting the sign of the value-growth spread is 6.47% or 1.88%, after adjusting for transaction costs. It is obvious that, the smaller variation of the value spread makes rotation less profitable, but less risky as well.

Figure 8.3 shows the minimum and maximum possible gains for value-growth rotation that correspond to different levels of forecasting accuracy. The shape of the curves look the same with the previous graph, but the distance between them is now narrower, indicating the lower risk that is involved with value-growth rotation. We need to point out, however, that even if an investor picks always the right months, she/he needs a minimum of 75% accuracy to exceed the value buy-and-hold strategy. The results for the value - growth rotation strategy are even more disappointing when applying 200 basis points transaction costs. Even if someone could forecast the sign of the style spread in all months correctly, he/she wouldn't be able to outperform the value buy-and-hold strategy.

FIGURE 8.3: Impact of Style Timing Accuracy Rates on Net Annual Returns

(The Case of Value vs. Growth Rotation)



The previous analysis points out that being generally accurate in style rotation is important, but not as important as being accurate at certain periods in time. Jeffrey (1984) shows that high forecasting accuracy may not necessarily correspond to high returns if some of the few months, when the absolute spread is very wide, are missed. A skilful market timer therefore is the one that not only manages to forecast with high accuracy rate, but also has the ability to be right on the months that count most.

So far, we have assumed that an investor makes either the best or the worst possible choice for a given level of forecasting accuracy. For each accuracy rate, however, there is a whole distribution of profits. To assess the *average* profitability of a style rotation strategy one has to estimate the entire distribution of the profit/loss function at different levels of forecasting skill. Thus, we conduct a simulation experiment, where each iteration corresponds to a different combination of months assumed to be correctly predicted for a certain probability rate, and consequently produces a different gross average annual profit and loss schedule. We run a simulation with 10,000 iterations and estimate the distribution of the resulted profits for four different forecasting accuracy levels - 50%, 60%, 70% and 80%.

Figure 8.4 shows the simulated cumulative distributions of the net annual returns that result from a monthly rotation strategy with small and large-cap stocks. Each curve corresponds to a different level of forecasting accuracy. The straight line denotes the average annual return performance of the small-cap index, which is the target threshold. The impact of accuracy rates on the distribution of rotation profits is clear from the graph. The whole distribution is shifted to the right as the rate of forecasting accuracy increases. Figure 8.4 presents rotation profits after adjusting for 100 basis points round -trip transaction costs for every switch. We have also calculated the rotation profits net of 200 basis points and present the relevant simulated distribution in the appendix. Considering 100 to 200 basis points round trip transaction costs seems a realistic assumption for style rotation, as these strategies require high turnover rates and may involve trading of highly illiquid stocks[2].

The simulated mean annual return after adjusting for 100 basis points transaction costs is 12.15% with 50% accuracy rate, 15.51% with 60%, 18.90% with

[2] We are grateful to Maurizio Murzia and an anonymous referee from Journal of Portfolio Management for stressing that point.

70% and 22.34% with 80%. Applying 200 basis points every time a switch is made reduces the net annual returns about 4% to 5%. Even a 70% hit ratio this time is not likely to outperform the small-cap index. The average net return for 70% accuracy rate is 14.03%, when transaction costs of 200 basis points are employed.

We apply the same simulation exercise to the value-growth rotation scheme. Figure 8.5 gives the distributions of annual net returns from rotation for different accuracy rates. The mean of the simulated distributions after the deduction of 100 basis points transaction costs are 12.85%, 15.17% 17.61% and 20.14% for each of the four accuracy rates respectively. The results point out that a rotation scheme with even a 80% accuracy rate is almost impossible to beat the value buy-and-hold strategy. The figures are significantly reduced when we repeat the simulations with 200 basis points transaction costs.

In short, our results suggest that a successful value-growth rotation strategy requires considerable levels of forecasting skill. More specifically, after controlling for transaction costs, one needs to be correct more than 80% of the time to exceed the performance of a buy-and-hold value strategy. Thus, the long-term consistency of value stocks makes any attempt to take advantage of its monthly variations rather risky with anything less than really superior forecasting skills. The results, on the other hand, are more promising for size style rotation. The evidence in the following section suggests that a 65% to 70% accuracy rate is not beyond the scope of a relatively simple forecasting model based on economic fundamentals.

FIGURE 8.4: Simulated Net Annual Return Distributions

(Small vs. Large Rotation)

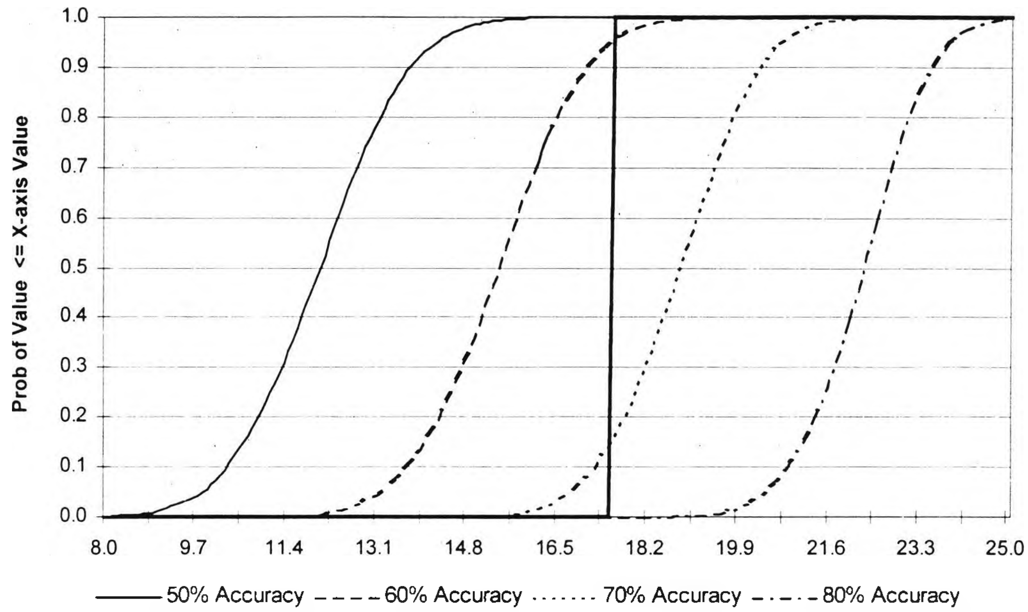
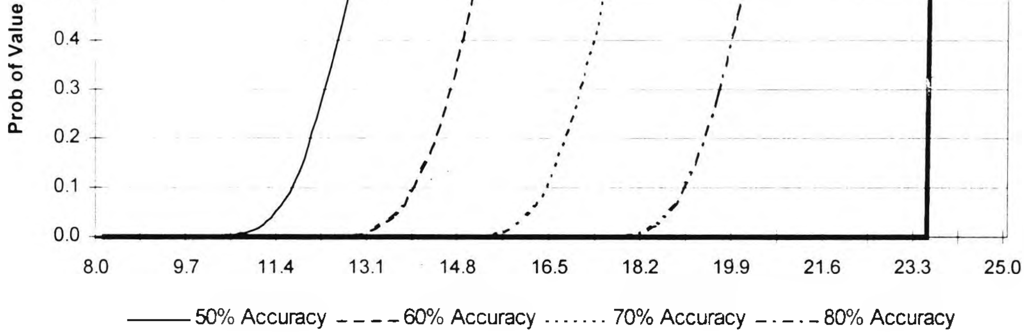


FIGURE 8.5: Simulated Net Annual Return Distributions

(Value vs. Growth Rotation)



Note: The figures shows the probability of the net annual returns from monthly rotation between small (value) and large (growth) stocks being lower or equal than the values specified in the X -axis. 100 basis points round-trip transaction costs are deducted every time a switch is made. The straight line is the average annual return of the small-cap (value) buy-and-hold strategy, which is the target threshold.

8.4 Forecasting the Size and Value Spreads

A number of studies examine the return predictability of desegregate security portfolios formed on the basis of market value and various fundamental variables. Most of the studies document that style portfolio returns are predictable, either from past returns of from predetermined market and economic variables. This section investigates the predictability of size and value monthly return spreads as opposed to individual style portfolios.

The relation between economic activity and relative style performance has attracted considerable attention among academics and practitioners[3]. This relation is examined by looking at certain economic indicators. We use the annual change in coincident aggregate economic indicator as a proxy for economic activity. The Coincident indicator is currently comprised of six component series; GDP at factor cost, an index of production, CBI quarterly surveys of below capacity utilisation and the change in stocks of raw materials and the monetary aggregate (M0) divided by the GDP deflator.

We also test the sensitivity of size and value spreads to the following set of variables: The monthly change in the 3 month treasury bill yield, a term structure variable defined as the monthly yield difference between 20 year government gilt and 3 month treasury bill, and an inflation variable derived from the monthly logarithmic change in the consumer price index.

We have also tested the monthly equity risk premium (difference between the returns of FTALL Share index and the monthly yield of 3 month Treasury Bills) and the monthly change in the £/$ exchange rate. Finally, we use a relative valuation ratio which corresponds to the average dividend yield of one index over the average dividend yield of the other. All the variables that are used are lagged one month to ensure that our tests are predictive in nature[4]. There is no severe multicollinearity problem in using all these variables in the regression. The highest correlation is 0.31 between the term structure and the dividend yield ratio.

[3] For an extensive review of the relevant literature see chapter 4.

[4] The reader should note that the results in this section are not directly comparable with the results in chapter 6 (section 6.5) as all the variables we use are lagged and not contemporaneous and the methodology used is different.

Tables 8.3 and 8.4 report results from univariate, multiple OLS and Logit estimation on the small - large and value - growth spread for the sample period July 1969 to June 1997. The first 12 observations are lost due to the calculation of the annual change of Coincident Indicator. The first column shows the results from univariate OLS regression and the second from multiple OLS[5]. All OLS regressions have been corrected for heteroskedasticity using the method suggested by White (1980). The last column in tables 8.3 and 8.4 gives coefficients and t-statistics from a logit regression estimation, which uses in the dependent side a binary variable that takes the value of 1, if the spread is positive and the value of 0, if the spread is negative.

The logit estimation is based on the logistic distribution; this is the cumulative distribution of the hyperbolic-secant-square distribution, whose density function is given by:

$$\Pr(y_t = 1|x_t, \beta) = \frac{e^{x'\beta}}{(1+e^{x'\beta})}$$

The logistic and the cumulative normal distributions differ very little, and only at the tails. Hence, unless the sample size is very large, the empirical results obtained from the two will be very close[6]. The parameters are estimated using the method of maximum likelihood. The logistic function has been used frequently in cases in which the dependent variable is binary (logit analysis). Another approach is to use discriminant analysis, by employing ordinary least square procedures. The general rule is that if the independent variables are normally distributed, the discriminant analysis estimator is the true maximum likelihood estimator and therefore is asymptotically more efficient than the logit maximum - likelihood estimator. Since our independent variables are not normal the discriminant analysis estimator is not even consistent, whereas the logit maximum likelihood estimation is consistent and therefore more robust.

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[5] We also used a GMM (Generalised Method of Moments) estimation that yields results that are robust to both heteroskedasticity and serial correlation, but the results were not different and are not reported.

[6] For a complete discussion of logit and other limited dependent variable models see Maddala (1983), and Hosmer and Lemeshow (1989).

The t-statistics in the logit regression have been calculated from standard errors using the method of quasi-maximum likelihood, or pseudo maximum likelihood (Huber/White). These standard errors are not robust to heteroskedasticity in binary dependent variable models. They are however robust to certain misspecifications of the underlying distribution of the dependent variable. Tables 8.3 and 8.4 present the number of observation, where the dependent variable is 1 and 0 and the mean of the dependent variable. They also show the maximised value of the log likelihood function, as well as the maximised log likelihood, when all slope coefficients are restricted to zero (Restricted Log Likelihood). The Likelihood Ratio (LR) statistic tests the joint null hypothesis that all slope coefficients, except the constant, are zero and is computed as -2(LL - Restricted LL). The number in parentheses is the degrees of freedom, which corresponds to the number of restrictions under test. The probability (LR stat.) is the p-value of the LR test statistic. Under the null hypothesis, the LR test statistic is asymptotically distributed as a χ^2 variable, with degrees of freedom equal to the number of restrictions under test. Finally, the McFadden R-squared is the likelihood ratio index computed as 1-LL/(Restricted LL).

Table 8.3 presents results for the small-large monthly return spread. In the univariate regression, the inflation and the equity risk premium are highly significant, while the term structure and the dividend yield ratio only marginally pass the significance test. All the variables retain their sign in OLS and logit estimation and some of them become more significant. The McFadden R^2 in the logit regression is 9.16% and the value of the Likelihood ratio test 42.56, which is significant at all conventional significance levels.

The results of the regressions point out that small-caps relatively benefit from rising interest rates and equity risk premium, widening of the yield curve and lower rates of inflation. Providing a plausible explanation for all our results is certainly not straightforward. The style indices we use cover a wide range of companies from a variety of economic sectors with different structures. Therefore, a great degree of speculation is required to provide a clear interpretation of the coefficient signs for all the variables we examine.

The sign of the interest rate variable can be explained by looking at the relative level of debt of small and large companies. In chapter 6 (section 6.2) we show that the total debt to equity ratio of large companies is almost four times higher than that of small firms. Large companies are relatively more credible and it's easier for them to raise capital by issuing debt. When interest rates go up then large-caps face much higher interest costs than small-caps, which has a direct affect in their earnings. A number of large firms, however, are not directly exposed to interest rate risks as they can hedge against undesirable interest rate movements using a number of derivative instruments. This may explain why, although we find a positive relation between interest rates and size spread, this relation is not very strong. A stronger relation can be identified between the term structure and the sign of the small-large monthly return spread. The yield curve affects the rate at which the stream of cash flows of various companies are discounted (see Chen, Roll and Ross, 1985). Moreover, the term structure of interest rates is related to the expected growth rate of GNP and consumption. Chen (1991) points out that if future output is expected to be high, individuals desire to smooth consumption by attempting to borrow against the expected future consumption, thereby bidding up interest rates.

The strong relationship between equity risk premium and next month's size spread confirms the findings of Macedo (1995). A high equity risk premium favours riskier portfolios and as small-caps are perceived to be more risky they tend to do well when equity risk premium is high. The sign of the inflation variable is rather puzzling and in contrary with the results of Anderson (1997), who find that small caps benefit from inflation because they find relatively easier to pass along price increases in inflationary times.

Table 8.4 shows the coefficients and the t-statistics from the regressions on the value-growth spread. In contrast to the size spread regressions, the term structure, the equity risk premium and the dividend yield ratio, are now insignificant in the univariate OLS regressions and are not included in the other estimation procedures. Instead, the one month lagged value-growth spread together with the inflation variable seems to be the most important explanatory factors. The McFadden R^2 of the logit model is lower than in the case of the small-large spread, but the likelihood ratio test can not easily rejects the null hypothesis of joint equality of slope coefficients.

The inflation sign is consistent with the US findings and indicates that rising inflation hurts more value than growth stocks, causing the next month return spread to be negative. The change in the short term interest rate and the annual change in the coincident indicator that seem to be marginally significant in the univariate case, become insignificant when they are regressed together with other variables. The monthly change in the £/$ exchange rate pass the 95% significance level in all estimation cases. The sign of the variable indicates that a rise in the monthly £/$ exchange rate benefits more growth than value securities. An appreciation of sterling may hurt exporting companies as it makes their products less competitive. It can also have an adverse effect for firms that have debts in foreign denominated currencies. A thorough examination of the earnings and an analysis of the factors that affect the earnings of value and growth companies may provide a justification of the exchange rate coefficient.

TABLE 8.3: Predictors of Small - Large Spread

	Univariate OLS	OLS	Logit
Constant		-0.0140	-0.5839
		(-1.3578)	(0.8993)
Inflation	-1.1769**	-1.4503**	-51.4201**
	(-2.6860)	(-2.9284)	(-2.3330)
Term structure	0.0021*	0.0008	0.1290**
	(1.7828)	(0.7403)	(2.1570)
Annual Change in Coincident Indicator	0.0548	0.0461	2.2591
	(1.5102)	(1.2543)	(0.9720)
Change in 3 month T.BILL yield	0.0294	0.0411**	2.3729
	(1.2440)	(2.1989)	(1.5426)
Small/Large Dividend Yield Ratio	0.0283*	0.0238*	0.9051
	(1.6927)	(1.9067)	(1.2059)
Equity risk premium	0.1996**	0.0411**	11.9202**
	(2.9033)	(2.1989)	(3.7066)
Obs. with Dependent Variable = 1			178
Obs. with Dependent Variable = 0			158
Mean of Dependent Variable			0.5297
Log Likelihood			-211.0210
Restricted Log Likelihood			-232.3019
LR Statistic (6 d.f.)			42.5617
Probability (LR stat.)			0.0000
McFadden R-squared			0.0916

Note: The table reports results from univariate, multiple OLS, and Logit estimation on the Small - Large spread from July 1969 to June 1997. The Small - Large spread is the monthly difference between the returns of the low market value index and the returns of the high market value index. Both indices are equally weighted and have approximately the same book-to-price ratio. The inflation variable is the monthly logarithmic change of the consumer price index, the term structure is the monthly difference between the yield on 20 year government gilt and 3 month Treasury bill. The equity risk premium is the monthly return difference between FT All Share index and 3 month Treasury Bills. The yield ratio is the average dividend yield of the small-cap index over the average dividend yield of the large-cap index. All variables are lagged one month. T-statistics are reported in parenthesis. Standard errors have been corrected for heteroskedasticity using the method of White (1980) in OLS regressions. Huber/White quasi-maximum likelihood (or pseudo ML) standard errors robust to misspecifications of the underlying distribution of the dependent variable are used in the logit regressions. ** denotes significance at 5% level and * significance at 10% level.

TABLE 8.4: Predictors of Value - Growth Spread

	Univariate OLS	OLS	Logit
Constant		0.0111**	0.8363**
		(6.6317)	(4.9181)
[Value-Growth] (-1)	0.2140**	0.2059**	18.0020**
	(3.7413)	(3.6142)	(3.1944)
Annual Change in Coincident Indicator	0.0404*	0.0218	1.7330
	(1.9410)	(1.0520)	(0.7789)
Inflation	-0.5777**	-0.5355**	-42.6208**
	(-3.3918)	(-3.1417)	(-2.5598)
Change in 3 month T.BILL yield	-0.0131*	-0.0071	-0.7569
	(-1.9596)	(-0.5158)	(-0.5141)
Term Structure	0.0004		
	(0.9204)		
Monthly Change in £/$ ex rate	-0.0850**	-0.0926**	-4.8142**
	(-2.1185)	(-2.4233)	(-2.4177)
Equity risk premium	0.0298		
	(1.0776)		
Value/Growth Dividend Yield Ratio	-0.0001		
	(-0.0298)		
Obs. with Dependent Variable = 1			223
Obs. with Dependent Variable = 0			113
Mean of Dependent Variable			0.6636
Log Likelihood			-204.2522
Restricted Log Likelihood			-214.5522
LR Statistic (5 d.f.)			20..6060
Probability (LR stat.)			0.0009
McFadden R-squared			0.0480

Note: The table reports results from univariate, multiple OLS, and Logit estimation on the Value - Growth spread from July 1969 to June 1997. The Value - Growth spread is the monthly difference between the returns of the high book-to-price index and the returns of the low book-to-price index. Both indices are equally weighted and have approximately the same market value. The inflation variable is the monthly logarithmic change of the consumer price index, the term structure is the monthly difference between the yield on 20 year government gilt and 3 month Treasury bill. The equity risk premium is the monthly return difference between FT All Share index and 3 month Treasury Bills. The yield ratio is the average dividend yield of the value index over the average dividend yield of the growth index. All variables are lagged one month. T-statistics are reported in parenthesis. Standard errors have been corrected for heteroskedasticity using the method of White (1980) in OLS regressions. Huber/White quasi-maximum likelihood (or pseudo ML) standard errors robust to misspecifications of the underlying distribution of the dependent variable are used in the logit regressions. ** denotes significance at 5% level and * significance at 10% level.

8.5 Style Rotation Strategies Based on the Logit Regression Forecasting Model

The logit regressions in the previous section suggest that the sign of the style spreads is related to a number of economic and market characteristics. Forecasting the sign of the style spread may be sufficient for a successful style rotation strategy. Logit regression is mainly used in models of qualitative choice and is applied to situations in which the dependent variable represents discrete events or choices. This methodology, however, is also found in time series applications where the variable to be explained is originally in a continuous form and is transformed in a discrete.

Applications of logit regression in market and equity timing studies include the work of Nam and Branch (1994), Larsen and Woznak (1995) and Gerber (1994). The model methodology relies on the notion that style allocation, and more generally investment timing may depend more on a proper forecast of the direction of the risk environment than on the magnitude. The model provides estimates of the probabilities that the upcoming market period will be a value (growth) or small-cap (large-cap) period. These outcome probabilities will provide guidance in the tactical style allocation process.

The procedure we use is the following: we classify each month as 1 or 0 based on the sign of the style spread. If in a particular month small-caps (value stocks) perform better than large-caps (growth stocks) we classify this month as 1, otherwise we set 0. We use the variables described previously as predictors.

Following the analysis of the previous section, we fit a model that uses a constant, the inflation, the term structure, the annual change in Coincident indicator, the change in 3 month Treasury Bill yield, the relative dividend yield ratio between small and large-cap stocks and the equity risk premium to forecast the sign of the monthly size return spread. In addition, we fit a model that uses the constant, the previous month spread, the annual change in coincident indicator, the inflation, the monthly change in 3 month Treasury Bill yield and the monthly change in £/$ exchange rate, to predict the sign of the value-growth return spread. Fitting the previous logit models we get the following form:

$$\log \frac{\hat{P}_t}{1-\hat{P}_t} = \hat{\alpha} + \hat{\beta} X_t$$

The conditional probability $\hat{P}_t$ give the likelihood that the next month will be a value (growth) or a small-cap (large-cap) month and is clearly the focus of this exercise. The forecasting probabilities are generated under a rigorous ex-ante framework, where the only information used for each forecast is that available prior to the period being forecast. In our analysis, all the variables that are used are lagged one month.

We use a recursive forecasting technique and a holdout sample of 276 months where the out-of-sample evaluation is taking place. An initial estimation period of 72 months from July 1968 to June 1974 is used to generate probabilities for the next twelve months starting from July 1974 to June 1975. Then the previous twelve months are added to the estimation period and the model is re-estimated. Using the new coefficients we generate probability estimates for the following twelve months, starting from July 1975 to June 1976. The procedure is repeated 23 times and a time series of logit probabilities for both spreads is generated.

A probability value above 0.5 indicates that a month that favours small-caps is likely to occur, while a probability value below 0.5 indicates preference for large-cap stocks. To evaluate our model, we assume that if in a particular month the spread is positive and the probability is above 0.5 or if the spread is negative and the probability is below 0.5, then the forecast has been successful, otherwise the forecast has failed. Based on that criterion, we found that the first model results in 60.14% of correct predictions. The model for the small-large spread gives 175 months (63.41%) when the logit probability is higher than 0.5 and 101 months (36.59%) when the estimated probability is lower than 0.5.

The second model for the value-growth spread gives a 68.84% accuracy rate, when employing the 50% cut-off point criterion. According to the estimated probabilities there are 228 months (82.61%) when the logit probability is higher than 0.5 and just 48 months (17.39%) when the probabilities signal a growth month ($\hat{P}_t$ < 0.5).

Table 8.5 provides the results from different trading strategies that can be developed based on the estimated logit probabilities and evaluates those strategies by comparing their performance with the performance of various passive strategies.

Strategy I, is a strategy that invests 100% in small-cap securities, whenever the logit model signals a small-cap month (probability greater than 0.5) and moves to 100% large stocks, whenever the logit model signals an upcoming large-cap month (probability less than 0.5). The problem with the previous strategy is that it classifies each month as either small-cap or large-cap favourite, regardless of the magnitude of the probability. A probability outcome of 0.51 and another one of 0.99, both result in a 100% allocation of funds in small-cap issues. To minimize this limitation and make the allocation strategy more relative, we test two other trading rules.

Strategy II, defines the probability range of 0.45 - 0.55 as neutral and in this case simply allocates 100% of the funds in the same equity class as in the previous month. *Strategy III* assumes that a two-month trend (sequential signal) in the predicted probabilities will give a better indication of the likelihood of differences in equity class returns in subsequent time periods. Therefore, it requires the predicted probabilities to be higher (lower) than 0.5 not just for the current month but for the previous month as well, before it signals a 100% allocation of funds to small-caps (large-caps). If the previous condition is not met then a 50/50 fixed allocation is preferred. Both previous strategies result in reducing the amount of monthly switches and therefore the transaction cost expenses.

Table 8.5 shows the average annual returns and the end of period wealth that corresponds to an initial investment of £100 for every one of the previous three timing strategies, assuming different levels of transaction costs. It also reports the annualised standard deviation and the Sharpe ratio as well as the number of recommended switches that corresponds to each strategy. For comparison purposes, we also give the relevant figures for the perfect foresight strategy and three passive buy-and-hold strategies involving the following indices; FT All Share, small-cap and large-cap.

It is clear that all three timing strategies perform much better than the buy-and-hold strategies, even after adjusting for transaction costs. Strategy I seems to be the most profitable when no transaction costs are taken into account. When 100, 150 or 200 basis points are deducted every time a switch is made, the second strategy appears to be more preferable.

It is interesting to note that, although the three rotation strategies perform much better than the buy-and-hold strategies, they do not carry higher risk. The standard deviation is about 18% for all three rotation strategies, which results to a Sharpe ratio before transaction costs of 1.386, 1.394 and 1.374 for each timing strategy respectively. Not surprisingly, the third rotation strategy is the one with the lowest historical volatility, 17.931%.

For each timing strategy, we have also calculated the level of transaction costs that gives the same end of period wealth with the small-cap buy-and-hold strategy. Rotation strategy I can be advantageous with transaction costs up to 217 basis points, while the second strategy gives a winning edge with transaction costs less than 379 basis points. Institutional investors that can switch from one equity class to another and pay less than 301 basis points every time, can also make profits by following the last rotation strategy.

Although, the model can predict with an accuracy rate of nearly 60%, the trading strategies developed from the model outperform easily the passive indices. This may indicate the ability of the probability model to capture the "good" months in our sample period. However, the potential gains from a perfect foresight strategy are still far away, implying that there is room for further improvement.

The results from the value-growth spread model confirms the message of our simulation experiment and are in line with the concept that the value buy-and-hold strategy is superior to value-growth rotation. We evaluate three strategies based on the same principles as in the previous case and present the relevant results in table 6. Ignoring transaction costs, all three strategies perform slightly better than the passive value buy-and-hold index. When transaction costs are taken into account, then the profits from the rotation strategies are significantly reduced. Increasing the level of transaction costs and calculating the end of period wealth net of 100, 150 and 200 basis points, we can not find any rotation strategy that is superior from the value buy-and-hold.

The volatilities and the Sharpe ratios, indicate that almost all strategies have the same volatility, but all of the rotation strategies that we tested correspond to slightly better Sharpe ratios compared to the value index. The Sharpe ratio is 1.363, 1.347 and 1.338 for the three trading strategies respectively and 1.312 for the passive value buy-and-hold strategy.

The solution from the linear programming problem, that we have set to calculate the amount of transaction costs that break even, leads to the same conclusion. The first trading rule can be advantageous for institutional investors that can make trades without loosing more than 61 basis points, while the two neutral strategies can make profits relative to the value index with transaction costs up to 54 and 29 basis points respectively. The actual transaction costs of the rotation strategies however is very unlikely to be that low as the specific trades (move from 100% value to 100% growth) impose very high turnover rates.

The previous results suggest that our model for the value-growth rotation only marginally can outperform the passive index alternative. When transaction costs are assumed no real benefits can be gained by following the previous trading rules. Even though, the model that we developed can predict with higher accuracy rate the monthly style trend, compared to the previous model for the size spread, the relative advantage that it offers is much smaller. As was demonstrated in the previous sections, a very high accuracy rate and precision is needed for a market timer, to outperform the value buy-and-hold strategy.

TABLE 8.5: Evaluation of the Logit Forecasting Model for the Small-Large Spread (1974-1997)

	Strategy 1	Strategy 2	Strategy 3	Perfect Foresight	Small Caps	Large Caps	FTALL
Average Annual Returns (%)	**25.20**	**25.02**	**24.634**	**37.46**	**20.58**	**20.21**	**20.07**
net of trans costs (100bp)	(23.24)	(23.93)	(23.40)	(32.11)			
net of trans costs (150bp)	(22.26)	(23.39)	(22.79)	(29.44)			
net of trans costs (200bp)	(21.28)	(22.85)	(22.18)	(26.76)			
End of Period Wealth	**£ 21,405**	**£ 20,724**	**£ 18,698**	**£ 310,429**	**£ 7,795**	**£ 5,864**	**£ 5,848**
net of trans costs (100bp)	(£ 13,479)	(£ 16,068)	(£ 13,998)	(£ 93,311)			
net of trans costs (150bp)	(£ 10,677)	(£ 14,135)	(£ 12,105)	(£ 50,932)			
net of trans costs (200bp)	(£ 8,448)	(£ 12,426)	(£ 10,465)	(£ 27,716)			
Break even transaction costs (benchmark: Small-cap index)	*217 bp*	*379 bp*	*301 bp*				
St. Deviation	**18.18**	**17.95**	**17.93**	**20.59**	**17.18**	**22.13**	**21.86**
Sharpe Ratio	**1.39**	**1.39**	**1.37**	**1.82**	**1.20**	**0.91**	**0.92**
No of Recommended Switches	47	26	59	123			
% of correct predictions	60.14%	60.87%					
% of Small-cap predictions	63.41%	62.68%	54.71%	51.09%			
% of Large-cap predictions	36.59%	37.32%	27.90%	48.91%			
% of neutral positions			17.39%				

Note: Strategy 1, is a strategy that invests 100% in small-cap (large-cap) stocks, whenever the estimated logit probability is higher (lower) than 0.5. According to Strategy 2 if the estimated probability lies within the range of 0.45-0.55 no switch is made. Strategy 3 requires two sequential signals (probability higher or lower than 0.5) to switch equity class, otherwise a 50/50 neutral position is suggested. Break-even transaction costs for each strategy are the transaction costs that give the same end of period wealth as the small-cap passive index.

TABLE 8.6: Evaluation of the Logit Forecasting Model for the Value-Growth Spread (1974-1997)

	Strategy 1	Strategy 2	Strategy 3	Perfect Foresight	Value	Growth	FTALL
Average Annual Returns (%)	**27.47**	**27.12**	**26.84**	**32.28**	**26.67**	**15.27**	**20.07**
net of trans costs (100bp)	(26.18)	(26.29)	(25.47)	(27.84)			
net of trans costs (150bp)	(25.53)	(25.87)	(24.84)	(25.63)			
net of trans costs (200bp)	(24.89)	(25.454)	(24.18)	(23.41)			
End of Period Wealth	**£ 33,128**	**£ 30,651**	**£ 28,859**	**£ 98,271**	**£ 27,506**	**£ 2,122**	**£ 5,848**
net of trans costs (100bp)	(£ 24,411)	(£ 25,085)	(£ 24,494)	(£ 36,330)			
net of trans costs (150bp)	(£ 20,931)	(£ 22,676)	(£ 22,750)	(£ 22,008)			
net of trans costs (200bp)	(£ 17,933)	(£ 20,487)	(£ 21,007)	(£ 13,299)			
Break even transaction costs (benchmark: Value index)	*61 bp*	*54 bp*	*29 bp*				
St. Deviation	**20.15**	**20.13**	**20.07**	**20.04**	**20.32**	**19.66**	**21.86**
Sharpe Ratio	**1.36**	**1.35**	**1.34**	**1.61**	**1.31**	**0.78**	**0.92**
No of Recommended Switches	31	20	33	102			
% of correct predictions	68.84%	67.39%					
% of Value predictions	82.61%	85.28%	83.33%				
% of Growth predictions	17.39%	14.72%	5.43%				
% of neutral positions			11.23%				

Note: Strategy 1, is a strategy that invests 100% in Value (Growth) stocks, whenever the estimated logit probability is higher (lower) than 0.5. According to Strategy 2 if the estimated probability lies within the range of 0.45-0.55 no switch is made. Strategy 3 requires two sequential signals (probability higher or lower than 0.5) to switch equity class, otherwise a 50/50 neutral position is suggested. Break-even transaction costs for each strategy are the transaction costs that give the same end of period wealth as the value passive index.

8.6 Summary and Conclusion

The chapter examines the return behaviour of different style indices (small-cap, large-cap, value and growth) in the UK market the last 30 years and investigates the possibility to add value over a buy-and-hold strategy by making tactical style shifts. Although, we find that value stocks, defined as stocks with high B/P, and small - cap issues performed better the last 30 years, we show that there were a large number of periods, where the opposite equity styles were in favour.

Distinguishing two different rotation schemes (small-caps vs. large-caps and value vs. growth) we have calculated the maximum potential gains and risks for each case separately. We found that an investor with perfect forecasting accuracy could had made 28.29% average annual returns net of 100 basis points round-trip transaction costs by switching between different size portfolios, and 24.51% net average annual returns by rotating between value and growth securities on a monthly basis.

The previous figures, however, assume perfect foresight, which clearly is not a very realistic scenario. We relax the assumption of 100% accuracy rate and calculate the maximum and minimum profits from rotation for each different accuracy level, from 5% to 95%. We point out that there is a wide range of profits that corresponds to every different accuracy rate and this range is wider in the case of small-large rotation than in the case of value-growth. We also show that the minimum accuracy rate that is required to succeed in style timing is 35% in the case of small vs. large -cap and around 75% in the case of value vs. growth. This requires that an investor predicts correct the months where the absolute difference between the styles is high and fails in months where the absolute return spread is low, which is also not a very realistic scenario.

We relax the previous assumption, by conducting a simulation experiment in order to find the entire distribution of rotation profits that corresponds to four different accuracy rates (50%, 60%, 70%, and 80%). The simulated means are then compared to the average annual returns of passive buy-and-hold strategies. We find that, even though a modest accuracy rate is sufficient to give a winning edge for the small-large rotation, more than 80% forecasting ability is required for a timing strategy in the case of value-growth to outperform the benchmark.

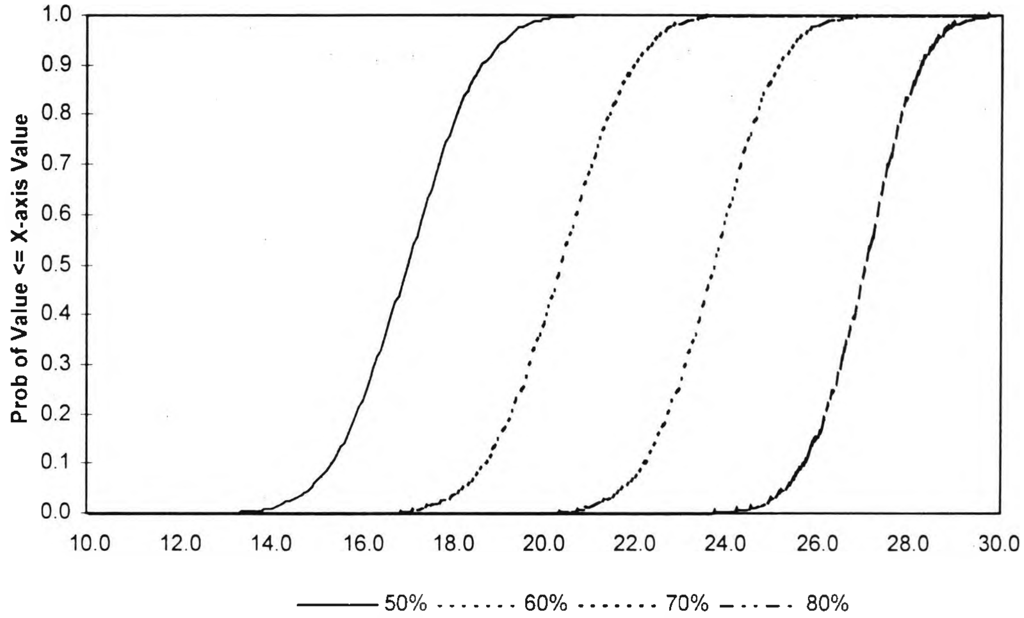
We identify a number of macroeconomic and market factors that appear to predict the direction of the next month's style spread. More specifically, our logit regressions suggest a significant relation between economic activity, or more generally the stage of the business cycle, and the sign of the equity style spread dummy. Using the fitted logit probabilities, we develop and test out-of-sample, three trading rules. Our results suggest that style rotation strategies based on small and large stocks can be highly rewarding, but only marginally successful in the case of value and growth stocks. The strong persistence in the performance of value stocks the last thirty years, makes it almost impossible to make excess profits from rotation, specially after adjusting for transaction costs.

The fundamental implication of our findings is that the profitability of style rotation strategies depends entirely on the temporal volatility of the underlying return spread between the styles that the manager is following. Thus, the on-going debate, among professional fund managers, about style consistency and market performance is fundamentally an empirical question. Style consistency is a prudent strategy for investors with very long investment horizons and strong views on the performance of the targeted style. In all other cases, controlled style rotation strategies based on the underlying fundamental characteristics of the relevant style indices can be value enhancing.

APPENDIX

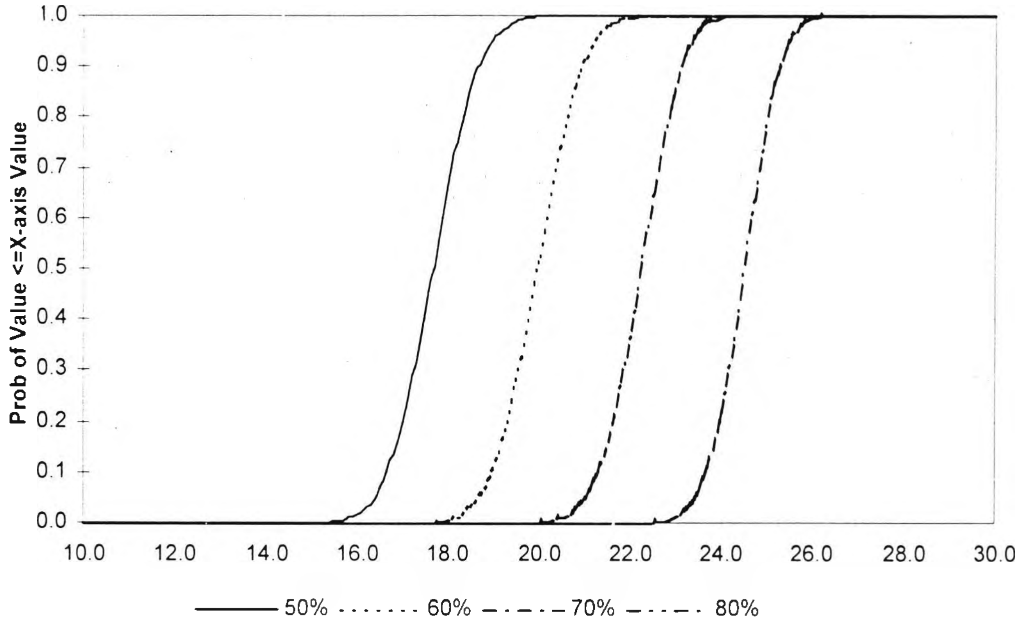
A: Simulated Gross Annual Return Distributions

(Small vs. Large Rotation)



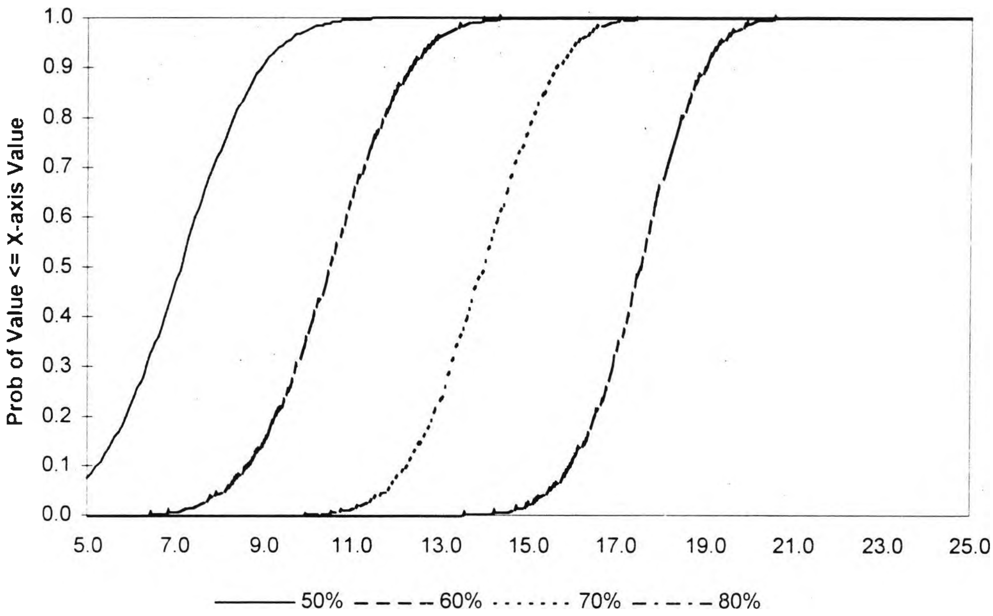
B: Simulated Gross Annual Return Distributions

(Value vs. Growth Rotation)



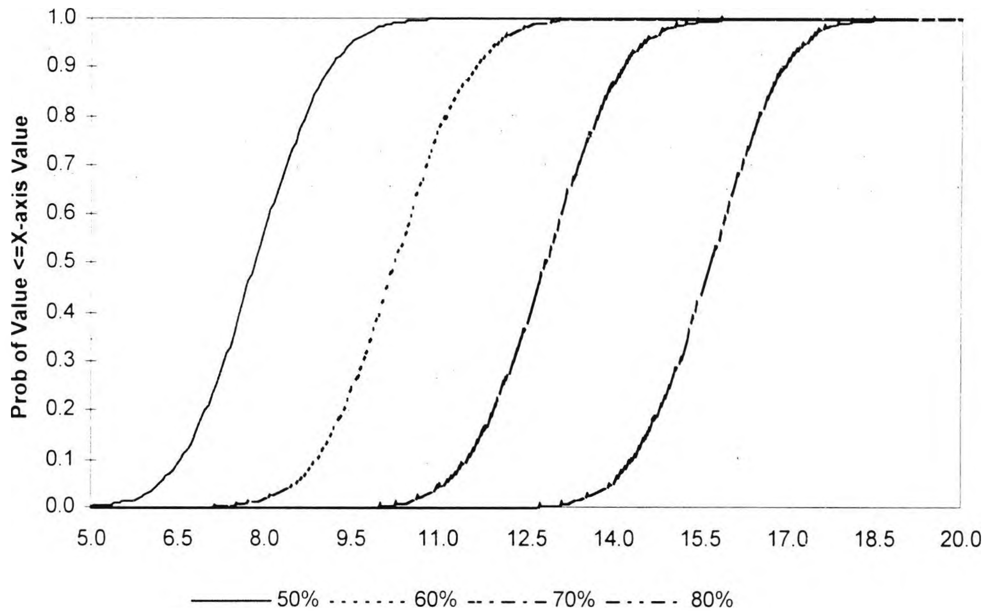
C: Simulated Annual Return Distributions (Net of 200 bp)

(Small vs. Large Rotation)



D: Simulated Annual Return Distributions (Net of 200 bp)

(Value vs. Growth Rotation)



CHAPTER 9

"Modelling and Forecasting the Volatility of UK Style Index Returns"

9.1 Introduction

Although the focus of attention in style investment strategies is the modelling and forecasting of portfolio returns, very little research has been conducted towards measuring and analysing the variance of those returns. Modelling and comparing the volatility of style portfolios is, however, equally important since it can lead in better understanding of asset pricing and more efficient construction of dynamic rotation strategies.

Conventional measures such as standard deviations, betas and performance in up and down markets have been extensively used to compare the risk of small against large-cap stocks and value against growth (e.g. Berk, 1995, Lakonishok, Shleifer and Vishny, 1995, LaPorta, 1996, Arshanapalli, Coggin and Dukas, 1997, etc.). Risk can also be measured from the exposure of portfolios to fundamental (e.g. Chan and Chen, 1991, Fama and French, 1995, Chan and Zhang 1998, etc.) or macroeconomic risk factors (e.g. Chan, Chen and Hsieh, 1985, Roll, 1995 etc.).

Almost all of these studies however use unconditional standard deviations or betas, assuming that risk is constant through time[1]. Volatility of stock returns however is not constant, but change over time and large (small) changes tend to be followed by large (small) changes of either sign. In this chapter, we relax the assumption of constant variances and examine whether volatility of style index returns is time-varying and whether style portfolios exhibit the same volatility characteristics over time.

We employ the well-known autoregressive conditional heteroskedasticity models (ARCH) to capture the phenomenon of volatility clustering in time series of stock returns. Since the development of ARCH model by Engle (1982), a significant volume of papers, applying variations of this model to stock market return series, have been published[2]. Almost all the evidence of conditional heteroskedasticity in stock returns, however, comes from studies that uses as representative index either the market or an index of large and liquid stocks.

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[1] Conditional risk measures for different equity portfolios in the context of asset pricing models have been employed by Schwert and Seguin (1990), Ferson and Harvey (1991), Levis (1995), Jagannathan and Wang (1996), among others.

[2] For a comprehensive review of these studies see Bollersev, Chou and Kroner (1992)

The few studies that have been published involve the modelling of conditional variance and covariances for size portfolios. Some indicative papers is Morgan and Morgan (1987), Engle, Ng and Rothschild (1989), Schwert and Seguin (1990) and Conrad and Gultekin (1991). To the best of our knowledge, there is no paper that models and compares the conditional volatility of value and growth portfolios.

In this chapter, we investigate whether the volatility of weekly style index return series in the UK market is time-varying, by concentrating on portfolios of stocks with high market value of equity (large-caps), low market value of equity (small-caps), high book-to-price (value) and low book-to-price book ratio (growth). We model the conditional volatility of these style indices using GARCH class of models and compare the persistence of volatility for the four series. Standard GARCH models have been often used as a tool to describe the conditional volatility of stock index returns. These models however, assume that only the magnitude and not the sign of past shocks, or unanticipated returns determines the conditional variance. We adjust for this limitation by estimating a TGARCH (Threshold GARCH) as well as an EGARCH (Exponential GARCH) model, in which the variance responds asymmetrically to positive and negative residuals, and test whether this asymmetry is revealed in all style indices. The news impact curve is also estimated and compared for all stock indices, in order to understand how past period's surprises affect conditional volatility.

Modelling the conditional variance of small, large, value and growth stock indices, using a variety of symmetric and asymmetric GARCH models, is not the only objective of this chapter. There is a debate among academics of whether ARCH -class of models can outperform simple volatility models (random walk or historical mean) in out-of-sample forecasts. We shed some light to this issue by evaluating the predictive ability of a GARCH(1,1), TGARCH(1,1) and an EGARCH(1,1) for horizons of 1, 4 and 13 weeks for all equity portfolios. Out of sample evaluation of different forecasting models is made by comparing the error statistics (mean error, mean absolute error, root mean square error) and by conducting a standard forecasting efficiency test. However, all the above error statistics assume quadratic loss functions, which is not appropriate for evaluating volatility forecasts. Therefore, we test whether there is economic value added using GARCH volatility forecasts, by implementing them into specific style rotation strategies.

The rest of the chapter is organised as follows. In section 9.2, we describe the data we use and analyse the time series properties of our style indices. Section 9.3 presents results from estimating different symmetric and asymmetric GARCH models. A discussion of the different volatility characteristics of the four style indices is also provided. The next section focuses on forecasting the second moment of small, large, value and growth portfolio returns, using different models and compares the out-of-sample performance of those models. Section 9.5 utilises quarterly volatility forecasts of value and growth indices into specific rotation strategies. Section 9.6 summarises the findings and concludes.

9.2 Time Series Properties of Style Indices

For each company in our sample we collect weekly (Wednesday close to Wednesday close) share prices from Datastream database for the period staring from July 1968 to the end of June 1997. Using the same portfolio formation procedure as in the previous chapters, time series of weekly equal weighted returns are generated for an index of small-caps, large-caps, value (high B/P) and growth (low B/P) stocks. The choice of a weekly sampling interval is largely a compromise between the relatively few monthly observations and the potential biases associated with infrequent trading, the bid-ask spread effect, etc. in daily data. The weekly returns series are not adjusted for dividends. Ignoring dividend distributions does not create a serious problem in volatility studies with high frequency data (Poon and Taylor, 1992).

The period between 1968 and 1997 consists of 1,513 weekly observations. In table 9.1, a number of descriptive statistics for the four style index return series are reported. These include the following distribution parameters: mean, median, standard deviation, skewness, kurtosis, minimum, maximum, Jarque Berra and Kolomogorov-Smirnov D statistic for the null hypothesis of normality.

The sample statistics indicate that value stocks produce on average the highest capital gains the last 30 years, while growth stocks the lowest. All indices with the exception of small-caps exhibit positive, although not very significant skewness. All the kurtosis values are very much larger than 3, with the growth index having the largest coefficient, which shows that for all series the distribution of returns has heavy tails and sharp peaks at the centre compared to the normal distribution. The Jarque Berra and the Kolomogorov-Smirnov test leads to the rejection of normality for all style indices confirming what is now known as a stylised fact, that weekly stock returns are not normally distributed. Table 9.1 also presents the correlation matrix between the returns of the four style indices. The correlations among the indices are very high, with highest being the correlation between large and value stocks and lowest the correlation between small and large-cap stocks. Furthermore, the large and growth style indices display relatively higher correlation with the FTALL Share index.

TABLE 9.1: Descriptive Statistics for Small, Large, Value, and Growth Weekly Return Series [July 1968 : June 1997]

Panel A: Distribution Characteristics

	Small	Large	Value	Growth
Mean ($\times 10^2$)	0.2649	0.2257	0.3678	0.1514
Median ($\times 10^2$)	0.3421	0.2502	0.3792	0.2536
Max	0.1681	0.2654	0.2153	0.2361
Min	-0.1460	-0.1790	-0.1522	-0.1802
Std. Deviation	0.0178	0.0263	0.0230	0.0220
Skewness	-0.2146	0.6470	0.5367	0.3074
Kurtosis	13.986	15.238	12.9007	17.6533
Jarque Berra	7620.721	9548.487	6252.233	13560.140
	[0.000]	[0.000]	[0.000]	[0.000]
K-S D statistic	0.0941	0.0641	0.0668	0.0814
Sample Size	1513			

Panel B: Correlation Matrix

	Small	Large	Value	Growth	FTALL Share
Small	1.0000				
Large	0.7946	1.0000			
Value	0.8768	0.9462	1.0000		
Growth	0.9181	0.9389	0.9243	1.0000	
FTALL Share	0.7931	0.9676	0.9041	0.9385	1.0000

Table 9.2, provides autocorrelation coefficients up to six lags, together with Ljung-Box tests for 6 and 12 lags, for the corresponding returns, squared returns and absolute returns for each one of the four aggregate style indices. All four return series display high first - lag autocorrelations, with the returns of small-caps to be much more dependent than the returns of large-caps, largely due to thin trading that is apparent in small companies' stocks. Value and growth securities display the same degree of linear dependence as can be seen from the autocorrelation functions. Moreover, it is obvious that the magnitude and persistence of the autocorrelations decline monotonically as we move to higher order lags. Furthermore, the Box - Pierce Q statistic with 6 and 12 lags has a value ranging from 67.958 to 511.880 and from 79.097 to 524.910 respectively for the four weekly style return series, which is significant at all the conventional significance levels.

TABLE 9.2: Autocorrelation Coefficients of Realised, Squared and Absolute Weekly Returns for Small, Large, Value and Growth Style Indices

	$\hat{\rho}_1$	$\hat{\rho}_2$	$\hat{\rho}_3$	$\hat{\rho}_4$	$\hat{\rho}_5$	$\hat{\rho}_6$	Q (6)	Q (12)
R_{SMALL}	0.430	0.290	0.190	0.125	0.095	0.091	511.88 [0.000]	524.91 [0.000]
R_{LARGE}	0.111	0.171	0.023	0.048	0.001	0.014	67.958 [0.000]	79.097 [0.000]
R_{VALUE}	0.227	0.209	0.087	0.082	0.044	0.054	173.66 [0.000]	179.64 [0.000]
R_{GROWTH}	0.267	0.205	0.082	0.080	0.038	0.049	197.58 [0.000]	205.20 [0.000]
$(R_{SMALL})^2$	0.346	0.246	0.108	0.053	0.085	0.065	313.33 [0.000]	344.54 [0.000]
$(R_{LARGE})^2$	0.163	0.349	0.073	0.068	0.071	0.086	259.04 [0.000]	310.82 [0.000]
$(R_{VALUE})^2$	0.185	0.333	0.120	0.062	0.103	0.056	268.89 [0.000]	337.00 [0.000]
$(R_{GROWTH})^2$	0.217	0.242	0.075	0.047	0.096	0.038	188.65 [0.000]	228.57 [0.000]
$\lvert R_{SMALL} \rvert$	0.395	0.309	0.183	0.150	0.106	0.116	504.94 [0.000]	607.04 [0.000]
$\lvert R_{LARGE} \rvert$	0.204	0.226	0.119	0.171	0.119	0.175	274.85 [0.000]	427.54 [0.000]
$\lvert R_{VALUE} \rvert$	0.239	0.235	0.144	0.155	0.129	0.116	284.23 [0.000]	445.37 [0.000]
$\lvert R_{GROWTH} \rvert$	0.268	0.244	0.152	0.157	0.123	0.126	318.85 [0.000]	442.40 [0.000]

Note: R_{SMALL}, R_{LARGE}, R_{VALUE} and R_{GROWTH} are weekly portfolio returns of the Small, Large, Value and Growth indices respectively. The table reports estimated autocorrelations up to 6 lags for the weekly realised returns, squared returns and absolute returns from July 1968 to June 1997. Under the null hypothesis that the true autocorrelations are zero, the standard error of the estimated autocorrelation is 0.02571. The Q-statistics (with p values in brackets) test the hypothesis that all autocorrelations up to 6 lags and up to 12 lags are jointly zero.

Figures 9.1 to 9.4 show the autocorrelation coefficients of realised, squared and absolute returns for the four style indices. The autocorrelations of the absolute and squared return series are statistically significant and much higher than those of the realised return series, however they decay relatively slowly at longer lags. In addition, the autocorrelation in absolute returns is generally higher than that in squared returns. This evidence confirms the findings of Mandelbrot (1963), Fama (1965) and Granger, Ding and Spear (1997) that large (small) price changes are followed by large (small) changes, of either sign.

Figure 9.1: Autocorrelation Coefficients for *Small-cap* weekly Return Series

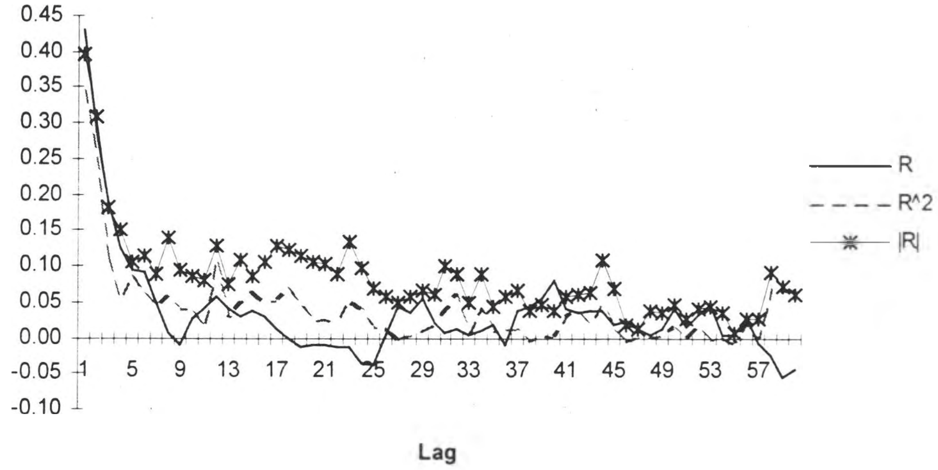


Figure 9.2: Autocorrelation Coefficients for *Large-cap* weekly Return Series

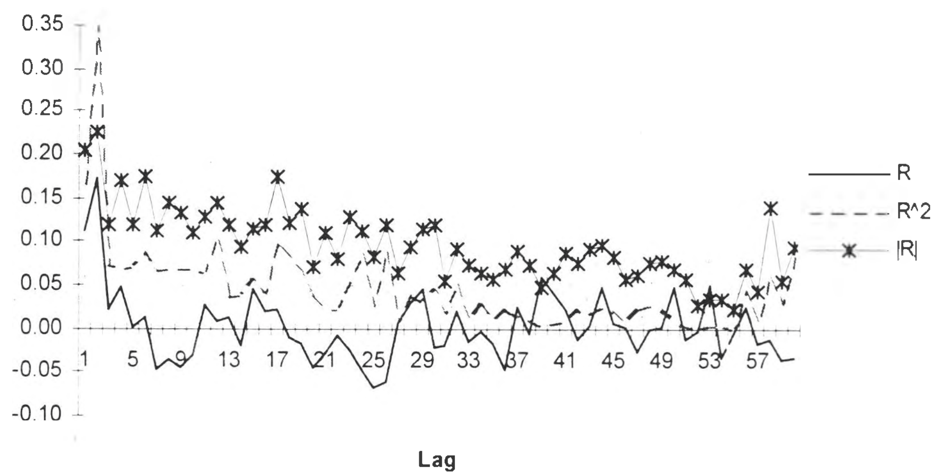


Figure 9.3: Autocorrelation Coefficients for *Value* Index weekly Return Series

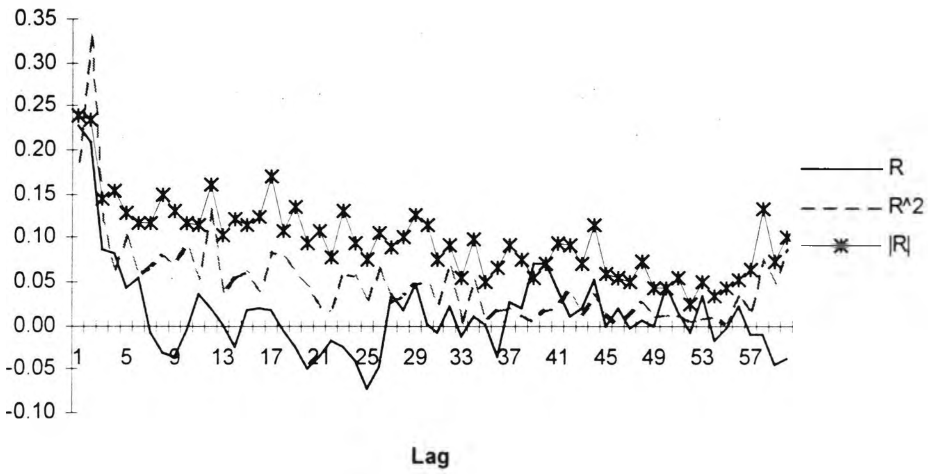
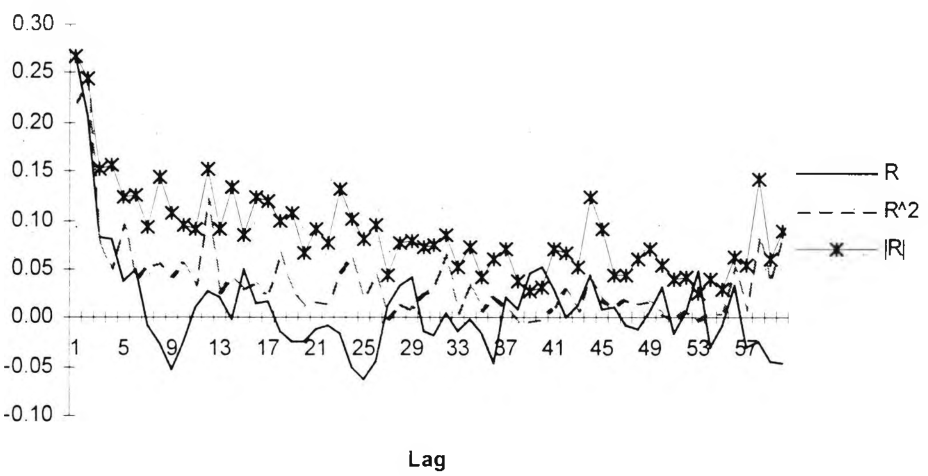


Figure 9.4: Autocorrelation Coefficients for *Growth* Index weekly Return Series



The structure that appears in the absolute and squared returns for all our series is an indication of non linear dependence, which may be explained by the fact that variances are not constant, but change over time. Changing variance can also explain the high level of kurtosis in return distributions. We therefore need a model that can capture these stylised facts of linear dependence, changing variance and excess kurtosis in the return distribution.

Table 9.3 presents autocorrelations of the residuals, squared and absolute residuals of an AR(2) model[3], with an additional term (dummy variable) to capture the first week of January effect, for all style portfolios.

$$R_{Index,\,t} = \phi_0 + \phi_1 R_{Index,\,t-1} + \phi_2 R_{Index,\,t-2} + \delta\, DJ + \varepsilon_t$$

where DJ = 1, for the first week of January (ending on a Wednesday), and DJ = 0, for all other weeks. Many studies have shown that returns are higher at the beginning of January, especially for small companies' stocks (e.g. Keim, 1983, Roll, 1983, Reinganum, 1983, etc.). January is a very important month for firms, since most of them use the calendar year as their fiscal year and a number of relevant information arrive at that time[4].

The residuals of the model exhibit no significant autocorrelation as indicated by the estimated autocorrelations and the Q-statistics for all our return series. However, the correlograms of the absolute and squared residuals display very similar pattern to their counterparts in the return series as shown in table 9.3. The Q stats for 6 and 12 lags are much higher than the critical values, which shows clearly that the residuals exhibit high level of linear dependence and suggests the need to model the implied persistence in conditional variance.

A non-linear process that includes functions of past value of squared residuals, would explicitly allow the probability distribution of returns to depend on past realisations. A model that closely approximates second - order non-linear processes is the well known ARCH (Autoregressive Conditional Heteroskedasticity) model

[3] An AR(2) specification was judged as the best specification for all return series, compared to an AR(1) or higher order, since was able to remove all serial correlation from the residuals and give significant coefficients for all the parameters.

[4] Conrad, Gultekin and Kaul (1991) used a dummy for the first week of January to take into account of the turn-of-the-year effect in returns and volatilities of size portfolios for the US market.

developed by Engle (1982), where both the first and second moments of R_{index} are allowed to depend on its past values.

A more formal test for the presence of autoregressive conditional heteroskedasticity is a Lagrange Multiplier (LM) test for the null hypothesis that there is no ARCH effect. It can be calculated as TR^2 from the regression of ε_t^2 on $\varepsilon_{t-1}^2, \ldots, \varepsilon_{t-q}^2$, where T denotes the sample size, and residuals are simply estimated from the AR(2) model. LM tests for 12 lags has been applied to all our four style return series. The values of TR^2 are 259.32 for the Small-cap index, 181.13 for the Large-cap index, 184.17 and 164.86 for the Value and Growth indices respectively, which are much higher that the critical value χ^2 (12) at all significance levels.

TABLE 9.3: Autocorrelation Coefficients of Realised, Squared and Absolute Weekly Residuals from an AR(2) Model

$$R_{Index,\,t} = \phi_0 + \phi_1 R_{Index,\,t-1} + \phi_2 R_{Index,\,t-2} + \delta\, DJ + \varepsilon_t$$

	$\hat{\rho}$	$\hat{\rho}_2$	$\hat{\rho}_3$	$\hat{\rho}_4$	$\hat{\rho}_5$	$\hat{\rho}_6$	Q (6)	Q (12)
ε_{SMALL}	-0.006	-0.022	0.023	0.001	0.016	0.053	6.286 [0.392]	15.075 [0.237]
ε_{LARGE}	0.002	-0.005	-0.011	0.017	0.001	0.017	1.0979 [0.982]	11.463 [0.490]
ε_{VALUE}	-0.002	-0.012	0.002	0.022	0.015	0.047	4.637 [0.591]	13.961 [0.303]
ε_{GROWTH}	0.001	-0.009	-0.011	0.026	0.007	0.045	4.4485 [0.616]	12.836 [0.381]
$(\varepsilon_{SMALL})^2$	0.279	0.122	0.116	0.111	0.093	0.043	194.91 [0.000]	223.63 [0.000]
$(\varepsilon_{LARGE})^2$	0.210	0.265	0.071	0.070	0.088	0.126	224.09 [0.000]	276.15 [0.000]
$(\varepsilon_{VALUE})^2$	0.233	0.248	0.121	0.084	0.120	0.082	240.01 [0.000]	308.71 [0.000]
$(\varepsilon_{GROWTH})^2$	0.251	0.173	0.086	0.066	0.110	0.058	182.69 [0.000]	218.19 [0.000]
$\lvert\varepsilon_{SMALL}\rvert$	0.346	0.251	0.208	0.206	0.164	0.118	468.74 [0.000]	600.54 [0.000]
$\lvert\varepsilon_{LARGE}\rvert$	0.234	0.203	0.134	0.170	0.140	0.184	297.91 [0.000]	448.42 [0.000]
$\lvert\varepsilon_{VALUE}\rvert$	0.265	0.215	0.181	0.184	0.173	0.137	351.78 [0.000]	552.07 [0.000]
$\lvert\varepsilon_{GROWTH}\rvert$	0.283	0.227	0.178	0.188	0.157	0.134	365.44 [0.000]	500.88 [0.000]

9.3 Conditional Heteroskedastic Models

9.3.1 Univariate AR(2) - GARCH(1,1) Model

In this section, we test whether there is conditional heteroskedasticity in time series of UK style index returns by fitting a number of different GARCH models. The simplest specification is the GARCH model developed by Bollersev (1986), which is considered an extension of the ARCH model, analogous to the extension from AR to ARMA models in traditional time series. In the GARCH(p,q) model not just past residuals, but past conditional variances may affect the current conditional variance.

We estimate a GARCH(1,1) model for all four weekly style return series, taking as a mean equation the AR(2) specification described in the previous section. The model is of the following form:

$$R_{Index,\,t} = \phi_0 + \phi_1 R_{Index,\,t-1} + \phi_2 R_{Index,\,t-2} + \delta DJ + \varepsilon_t \qquad \varepsilon_t \sim N(0,\ \sigma_t^2)$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

We use the same mean and variance specification for all four series for comparison purposes, although it seems that the above model is describing well enough the properties of all our indices. Different values of p and q are tried from 0,1 to 3,3 by applying likelihood ratio tests successively until the improvement in the likelihood function becomes insignificant. The GARCH (1,1) model was found to be an adequate model in all four cases, confirming the findings of other researchers that small number of parameters seems sufficient to model the variance dynamics over very long sample periods. The GARCH (1,1) model has also been advocated for stock returns in some U.S. studies (e.g. Chou, 1988, and Ballie and DeGenarro, 1990).

Non-linear optimisation techniques are used to calculate the maximum likelihood estimates based on the BHHH [Berndt, Hall, Hall and Hausman (1974)] algorithm. The resulting maximum log-likelihood values for all different return series are reported in table 9.4. The GARCH (1,1) model gives estimates under the assumption of conditional normality. Robust t-statistics are also calculated using the procedure in Bollersev and Wooldridge (1992). Table 9.4 shows the model estimates and a number of diagnostic tests.

TABLE 9.4: GARCH (1,1) Model Estimates for Style Index Weekly Return Series

$$R_{Index,t} = \phi_0 + \phi_1 R_{Index,t-1} + \phi_2 R_{Index,t-2} + \delta DJ$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Parameters & Diagnostics	Small -Caps	Large - Caps	High B/P (Value)	Low B/P (Growth)
$\phi_0 \times 10^2$	0.1313	0.2372	0.3008	0.1313
	(3.3165)	(3.2818)	(3.9930)	(2.3586)
ϕ_1	0.3908	0.0777	0.1792	0.2107
	(11.4564)	(2.5161)	(5.2451)	(6.4241)
ϕ_2	0.1105	0.0502	0.0999	0.0840
	(3.1962)	(1.4554)	(2.6601)	(2.4274)
$\delta \times 10^2$	0.9617	0.6950	0.5633	0.9533
	(3.4389)	(2.1041)	(2.1062)	(2.8783)
$\alpha_0 \times 10^3$	0.0108	0.0203	0.0160	0.0167
	(2.2785)	(2.5811)	(1.7688)	(2.3826)
α_1	0.1543	0.0957	0.1072	0.1326
	(3.9228)	(3.3467)	(2.6688)	(3.3571)
β_1	0.8117	0.8754	0.8627	0.8354
	(15.8473)	(26.0724)	(16.1055)	(17.2194)
$\alpha_1 + \beta_1$	0.9660	0.9711	0.9699	0.9680
half life	20 weeks	24 weeks	22 weeks	21 weeks
Adjust R^2	0.1993	0.0231	0.0709	0.0861
Log - Likelihood	4317.082	3544.712	3773.868	3882.790
Skewness	-0.6091	-0.1554	-0.0134	-0.3842
Kurtosis	7.8057	7.8473	8.1911	8.2160
Jarque - Berra	1547.501	1485.379	1696.623	1750.137
Q(6)	8.6877	7.9942	8.6336	9.8111
	[0.192]	[0.239]	[0.195]	[0.133]
Q(12)	10.1060	16.600	10.223	13.460
	[0.607]	[0.165]	[0.596]	[0.337]
LM ARCH test	9.7947	7.5018	6.1678	8.0540
(12 lags)	[0.633]	[0.8227]	[0.9073]	[0.7808]
$Q^2(6)$	6.2343	5.4736	4.0205	5.3061
	[0.397]	[0.485]	[0.674]	[0.505]
$Q^2(12)$	10.160	7.5227	6.2899	8.2368
	[0.602]	[0.821]	[0.901]	[0.766]
σ_e	0.1285	0.1911	0.1663	0.1647

Note: R_{Index} are the weekly returns of small, large, value and growth indices, and DJ is a dummy variable that takes the value of 1 on the first week of January and 0 otherwise. The GARCH (1,1) model gives estimates under the assumption of conditional normality. Robust t-statistics (in parenthesis) are calculated using the procedure in Bollersev and Wooldridge (1992). The sample period is from July 3, 1968, until June 25, 1997, for a total of 1513 observations. Q(6), Q(12) and $Q^2(6)$, $Q^2(12)$ are the Box Pierce portmanteau test statistics, with 6 and 12 lags, applied to the standardised and squared standardised residuals, respectively. They provide a test for the presence of autocorrelation and ARCH effects, respectively. P-values for each test statistic are in brackets. The skewness, kurtosis and Jarque Berra statistic test for normality on the standardised residuals. The LM statistic test the presence of remaining significant ARCH effects. The p-values are reported in brackets below the LM test statistic. Finally, σ_e gives the annualised unconditional standard deviation of the residual series.

The autoregressive coefficients in the mean equation are all significant at 5% level, with the exception of ϕ_2 for large-cap stocks, indicating the presence of serial correlation in the return series. It is also worth noting that, the first week of January dummy is positive and highly significant, although the relation is markedly stronger in the case of small-caps and growth stocks[5]. Estimates of GARCH (1,1) models provide strong evidence of changing conditional variance for all style indices[6]. The estimates of α_1 and β_1 are always statistically significant. The sum of the coefficient is less than unity, which suggest that the conditional variance follow a stationary process. The sum $\alpha_1 + \beta_1$ in the conditional variance equation provides a measure for the persistence of volatility, since expected future volatility decays towards the unconditional variance σ_e^2 according to the equation:

$$\sigma_e^2 = \frac{\alpha_0}{1-(\alpha_1 + \beta_1)}$$

The persistence in volatility is 0.9660, 0.9711, 0.9699 and 0.9680 for the small, large, value and growth return series respectively. Large-caps are the category of stocks that display the highest degree of persistence in volatility, while small-caps exhibit the lowest. Our maximum likelihood estimates of $\alpha_1 + \beta_1$ is consistent with the estimates of 0.9610 in Poon and Taylor (1992) for UK weekly data using the FT index from January 1985 to December 1989 and considerably lower than the estimate of 0.986 for US weekly data reported in Chou (1988). Another way to view the volatility persistence is by calculating the half life of volatility shocks, which is $\ln(0.5)$ divided by $\ln(\alpha_1 + \beta_1)$. The half-life of volatility shocks range from 20 weeks for small-cap stocks to 24 weeks for large companies' stocks. Value and growth stocks do not appear to have significant differences in volatility persistence. The annualised unconditional standard deviation is also given at the end of table 9.4.

No indications of serious linear model misspecification are observed, since the Ljung-Box statistics for all four indices show a lack of serial correlation in both the standardised residuals and squared standardised residuals. The LM ARCH test, at 12

[5] We tested whether the January Dummy affects the conditional variance as well, by including the term in the variance equation, but the coefficient was found not significant in all cases, contradicting the findings of Conrad, Gultekin and Kaul (1991)

[6] We reestimated the model after excluding the extreme observations during October 1987, but the results were very similar.

lags, rejects the presence of remaining significant ARCH effects for all series. Properly specified GARCH models should be able to significantly reduce the excess skewness and kurtosis evident in nominal style returns (Table 9.1). We notice that although, with the exception of Small-caps, the normalised residuals for the rest of the style indices exhibit no skewness there is strong evidence of kurtosis for all cases. Nevertheless, the level of kurtosis is significantly lower than that observed in raw returns. The Jarque Berra statistic leads to rejection of normality for the standardised residuals of all style indices.

To obtain a better picture of how volatility of UK style indices change over time, we estimate the conditional variance from the weekly *abnormal* returns of the four style indices. We use the following GARCH specification:

$$R_{I,t} - R_{M,t} = \phi_0 + \varepsilon_t \qquad \varepsilon_t \sim N(0,\ \sigma_t^2)$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Subtracting the returns of the FTALL Share from style returns allow us to segregate the style effects and see how net style volatility is changing through time. Figures 9.5 and 9.6, plot the conditional variance as estimated from the previous GARCH (1,1) model for the small-cap and large-cap and for the value and growth weekly abnormal return series respectively. The correlation between the conditional variance series is higher in the case of small and large stocks (0.6820), than in the case of value and growth (0.5202). The volatility of small stock's abnormal returns is higher than of any other index. The average conditional variance is about 5 times higher than of large -caps. Value stocks, on the other hand, appear to be much riskier than growth securities, although there are some periods when growth volatility is slightly higher than value volatility.

Figure 9.5: Estimated Weekly Volatility of the Small and Large-cap Index Abnormal Returns from GARCH (1,1) Model

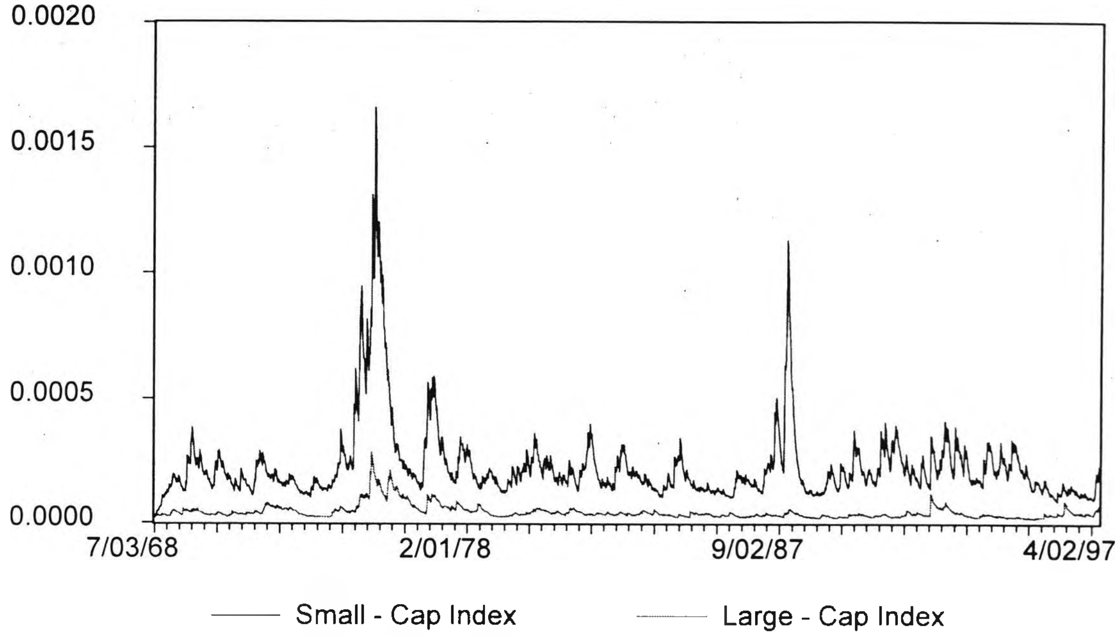
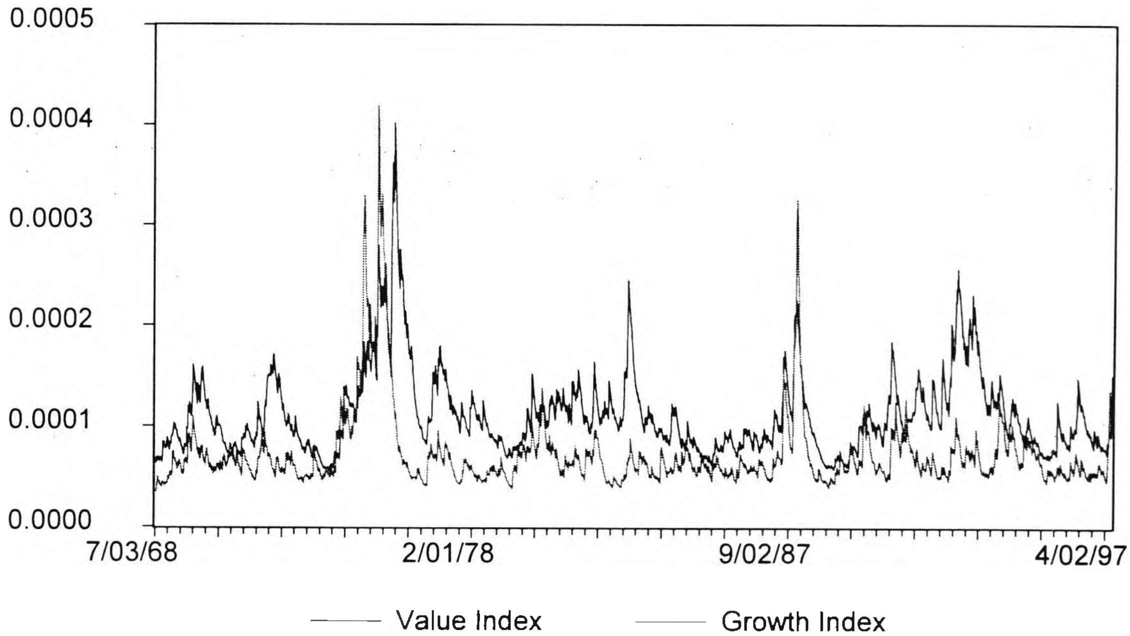


Figure 9.6: Estimated Weekly Volatility of the Value and Growth Index Abnormal Returns from GARCH (1,1) Model



9.3.2 Modified AR(2) - GARCH(1,1) Model

So far we have showed that volatility is time varying for all UK style indices and a GARCH (1,1) model is able to capture this time variability observed in weekly returns. Another interesting question is what causes volatility to change over time. One of the reasons excess volatility has been observed in stock returns is interest rates. Short-term interest rates carry expectations about inflation, which results to higher uncertainty and higher consequently stock market volatility. Fama and Schwert (1977), Campbell (1987) and Glosten, Jagannathan and Runkle (1993) show that nominal interest rates can explain the volatility movements in US stock returns. However not all categories of stocks exhibit the same sensitivity to interest rate and inflation rises. Arnott and Copeland (1985) for example assert, that growth oriented factors are affected more that value factors in periods of inflationary and interest rate pressures. Jensen, Johnson and Mercer (1998) find that the unconditional volatility in the monthly returns of value and small - cap portfolios is not affected as we move from an expansive to a restrictive monetary environment. On the other hand, the standard deviation of growth and large-cap portfolio returns' increases significantly when discount rates are rising (restrictive monetary environment).

We test whether the yield on 3-month UK Treasury bill can significantly affect the conditional volatility of the four style indices, by including the interest rate variable in the variance equation of the GARCH model. We restrict our sample from 1975, due to the lack of available interest rate data in weekly frequency from Datastream database. The new sample includes 1173 observations and the results of the modified GARCH (1,1) estimation are reported in table 9.5.

The coefficient on the interest rate variable appears to be positive for all indices, but significant only in the case of large and growth securities confirming in a way the results of Jensen, Johnson and Mercer (1998). The t-statistic on the c parameter in the variance equation is lower than the critical value at 5% significance level for the other two indices, small-cap and value. Table 9.5 also shows the coefficients and the t-stats for the other parameters and a number of diagnostics. We must note that the results of the modified GARCH are not directly comparable with the results of other GARCH specifications due to the different sample period.

TABLE 9.5: Modified GARCH (1,1) Estimates for Style Weekly Return Series

$$R_{Index,\,t} = \phi_0 + \phi_1 R_{Index,\,t-1} + \phi_2 R_{Index,\,t-2} + \delta\, DJ$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + c r_{ft}$$

Parameters & Diagnostics	Small -Caps	Large - Caps	High B/P (Value)	Low B/P (Growth)
$\phi_0 \times 10^2$	0.1421	0.2450	0.3288	0.1507
	(3.3080)	(3.2715)	(3.9172)	(2.5248)
ϕ_1	0.3938	0.0786	0.1765	0.2011
	(10.1459)	(2.2790)	(4.3862)	(5.4999)
ϕ_2	0.1188	0.0612	0.0884	0.0858
	(3.0661)	(1.7008)	(2.0955)	(2.2721)
$\delta \times 10^2$	0.6958	0.5200	0.4163	0.7341
	(4.6208)	(1.4731)	(1.2594)	(3.3026)
$\alpha_0 \times 10^3$	-0.0027	-0.0072	-0.0023	-0.0041
	(-0.7871)	(-0.9422)	(-0.3471)	(-0.7241)
α_1	0.1294	0.0730	0.0871	0.0985
	(3.4415)	(2.4156)	(2.2986)	(3.0592)
β_1	0.8166	0.8616	0.8639	0.8416
	(13.2149)	(20.3593)	(15.9992)	(16.5280)
c	0.0014	0.0041	0.0022	0.0024
	(1.5695)	(2.6294)	(1.6359)	(2.2147)
Adjust R^2	0.1945	0.0249	0.0718	0.0834
Log - Likelihood	3435.192	2815.208	2981.989	3090.277
Skewness	-0.4962	-0.2059	0.0837	-0.3825
Kurtosis	8.0420	8.6148	9.4079	8.9117
Jarque - Berra	1290.646	1549.162	2008.247	1736.754
Q(6)	3.6214	2.5104	4.0737	4.8456
	[0.728]	[0.867]	[0.667]	[0.564]
Q(12)	6.4696	7.6844	4.5161	7.0886
	[0.891]	[0.809]	[0.972]	[0.852]
LM ARCH test (12 lags)	11.6326	7.3750	5.4423	8.5587
	[0.475]	[0.831]	[0.9415]	[0.740]
$Q^2(6)$	8.3661	6.6549	4.5483	7.2450
	[0.212]	[0.354]	[0.603]	[0.299]
$Q^2(12)$	12.083	7.1982	5.3314	8.5460
	[0.439]	[0.844]	[0.946]	[0.741]

Note: R_{index} are the weekly returns of small, large, value and growth indices, and DJ is a dummy variable that takes the value of 1 on the first week of January and 0 otherwise. r_{ft} is the yield in the 3 month UK treasury Bill. The modified GARCH (1,1) model gives estimates under the assumption of conditional normality. Robust t-statistics (in parenthesis) are calculated using the procedure in Bollersev and Wooldridge (1992). The sample period is from January 8, 1975, until June 25, 1997, for a total of 1173 observations. Q(6), Q(12) and $Q^2(6)$, $Q^2(12)$ are the Box Pierce portmanteau test statistics, with 6 and 12 lags, applied to the standardised and squared standardised residuals, respectively. They provide a test for the presence of autocorrelation and ARCH effects, respectively. P values for each test statistic are in brackets. The skewness, kurtosis and Jarque Berra statistic test for normality on the standardised residuals. The LM statistic test the presence of remaining significant ARCH effects. The p values are reported in brackets below the LM test statistic.

9.3.3 Asymmetric Volatility Models

One of the most important characteristics of stock market volatility is the fact that it is asymmetric in the way it responds to positive and negative past unexpected events, news. It has been observed that an unexpected drop in prices (bad news) increases volatility more than an unexpected increase in prices (bad news) of similar magnitude. This asymmetric nature of volatility response to return shocks reflects either a leverage effect (e.g. Black, 1976 and Cristie, 1982), or the existence of time varying risk premiums (e.g. Pindyck, 1984, French, Schwert and Stambaugh, 1987).

There is a considerable amount of evidence suggesting that stock market volatility is asymmetric and that the standard GARCH model is not adequate to capture this phenomenon. Nelson (1990), Glosten, Jagannathan and Runkle (1993), Engle and Ng (1993), Poon and Taylor (1991), among others, show that the sign of past residuals must be taken into account when modelling the conditional variance. All of these studies, however, model the volatility of a value weighted stock market index, that is basically dominated by large capitalisation stocks. In this section, we examine whether conditional volatility is indeed asymmetric for all different equity classes, or whether this is a phenomenon apparent only in large and liquid securities.

To test whether asymmetry is present in the weekly style index conditional variances and whether the standard GARCH model provide an adequate description of volatility dynamics, we utilise a number of tests. The test we employ is the *Sign Bias Test*, the *Negative Size Bias Test* and the *Positive Size Bias Test*, as well as a *joint test* of all three, proposed by Engle and Ng (1993), to examine whether the squared standardised residuals obtained from the standard symmetric GARCH are independent and identically distributed. These tests examine whether the squared normalised residuals can be predicted by some variables observed in the past, which are not included in the model being used. If this is the case, then the variance model is misspecified.

The Sign Bias test examines whether positive and negative innovations affect future volatility differently from the prediction of the model. In this test the squared normalised residuals are regressed on a constant and a dummy variable that takes the value of 1 if ε_{t-1} is negative and 0 otherwise. The Sign Bias test statistic is simply the t-statistic on the coefficient of the dummy variable.

The Negative and the Positive Size Bias test are also very important. If large past return shocks, either negative or positive, cause more volatility than a quadratic function allows, then the standard GARCH model underestimates volatility after a large return shock and overestimates volatility after a small return shock. The Negative Size Bias test examines whether larger *negative* past residuals are correlated with larger biases in estimated volatility, while Positive Size Bias test shows if larger *positive* past shocks are correlated with larger biases in volatility. In the Negative Size Bias test, the squared standardised residuals are regressed on a constant and the product of a dummy that takes the value of 1 if ε_{t-1} is negative and 0 otherwise and ε_{t-1}. The Negative Sign Bias is the t-statistic on this coefficient. In the Positive Size Bias test we regress the squared standardised residuals on a constant and the product of a dummy that takes the value of 1 if ε_{t-1} is positive and 0 otherwise and ε_{t-1}. The following equations represent the sign bias, the negative size bias and the positive size bias test respectively.

$$(\varepsilon_t / \sigma_t)^2 = \alpha + b_1 S_{t-1}^{-} + e$$
$$(\varepsilon_t / \sigma_t)^2 = \alpha + b_2 S_{t-1}^{-} \varepsilon_{t-1} + e$$
$$(\varepsilon_t / \sigma_t)^2 = \alpha + b_3 S_{t-1}^{+} \varepsilon_{t-1} + e$$

Table 9.6 gives the coefficient and t-statistics on b_1, b_2, b_3, that represent the sign bias, positive size bias and negative size bias tests respectively. We also report a joint test of all three, which is an LM test for adding all three previous variables together. The test statistic is equal to T times R^2 from a regression of the standardised squared residuals on the three above variables, that follows a chi-square distribution with three degrees of freedom.

Table 9.6 shows the asymmetry diagnostic tests for the normalised squared residuals obtained from the GARCH(1,1) specification for small, large, value and growth indices respectively. The sign bias test is significant at the 5% level for large-caps and growth stocks, indicating that negative ε_{t-1} influence current volatility more than positive ε_{t-1}. The negative size bias test is also significant in all cases, except in growth stocks, where it is marginally significant, indicating that large negative shocks cause more volatility than small ones. Conversely, positive size bias is rejected, denoting that there is not significant difference for small and large positive shocks in any of the style indices we examine. The joint test for asymmetry indicate that in all cases the AR(2) - GARCH (1,1) seems to have a problem in capturing the correct impact of innovations on volatility. The LM test is significant at 5% level for large stocks and at 10% level for small, value and growth securities.

TABLE 9.6: Diagnostic Tests for Asymmetry in GARCH(1,1) Model

	Small - Caps	Large - Caps	Value	Growth
Sign Bias	0.1794	0.3369**	0.1473	0.3296**
	(1.3287)	(2.5117)	(1.0673)	(2.3794)
Negative Size Bias	-13.8732**	-8.7867**	-11.5058**	-9.2084*
	(-2.0623)	(-2.0338)	(-2.1859)	(-1.7297)
Positive Size Bias	-0.8229	-3.4087	-4.3303	-3.5020
	(-0.1207)	(-0.8343)	(-0.8845)	(-0.6599)
Joint Test	8.8334*	12.1492**	7.9938*	9.5038*

Note: In the Sign bias test the squared normalised residuals are regressed on a constant and a dummy variable that takes the value of 1 if ε_{t-1} is negative and 0 otherwise. In the Negative (Positive) Size Bias test, the squared standardised residuals are regressed on a constant and the product of a dummy that takes the value of 1 if ε_{t-1} is negative (positive) and 0 otherwise and ε_{t-1}. The joint test of all three, is an LM test for adding all three previous variables together. Two asterisks (**) denote significance at 5% level, while one asterisk (*) denotes significance at 10% level.

The previous results indicate that the symmetric GARCH(1,1) model that we have used is not rich enough to capture the properties of conditional volatility. A number of different asymmetric volatility specifications have been proposed in the literature. To adjust for asymmetries we estimate the threshold GARCH (TGARCH) model introduced by Zakoian (1990) and Glosten, Jagannathan and Runkle (1993) and the exponential GARCH (EGARCH) model of Nelson (1990). The TGARCH specification is the simplest way to control for the asymmetric respond of unexpected events to conditional variance. This is done by allowing the impact of past squared innovations to be different depending on whether these innovations are negative or, positive. The TGARCH is represented by the following equation:

$\sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}$, where I_{t-1}=1 when $\varepsilon_{t-1} < 0$ and 0 otherwise

TABLE 9.7: TGARCH (1,1) Model Estimates for Style Index Weekly Returns

$$R_{Index,t} = \phi_0 + \phi_1 R_{Index,t-1} + \phi_2 R_{Index,t-2} + \delta DJ$$

$$\sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 e_{t-1}^2 + \gamma e_{t-1}^2 I_{t-1}$$

Parameters & Diagnostics	Small -Caps	Large - Caps	High B/P (Value)	Low B/P (Growth)
$\phi_0 \times 10^2$	0.0928	0.1583	0.2433	0.0853
	(2.5489)	(2.4472)	(4.0389)	(1.6538)
ϕ_1	0.4014	0.0766	0.1806	0.2129
	(12.2095)	(2.5551)	(5.7538)	(6.5689)
ϕ_2	0.1281	0.0772	0.1159	0.0944
	(3.7879)	(2.3237)	(3.3491)	(2.7398)
δ	0.0108	0.7151	0.0072	0.0103
	(3.3629)	(2.2005)	(2.3738)	(2.8715)
$\alpha_0 \times 10^3$	0.00914	0.0143	0.0150	0.0143
	(2.2976)	(2.8328)	(2.2805)	(2.7121)
α_1	0.0967	0.0358	0.0565	0.0750
	(2.8608)	(1.9633)	(2.6881)	(2.2975)
γ	**0.1025**	**0.0986**	**0.1023**	**0.1064**
	(1.5077)	**(2.6746)**	**(1.7508)**	**(1.8988)**
β_1	0.8261	0.8965	0.8662	0.8462
	(18.4799)	(45.3771)	(20.9616)	(22.1001)
Adjust R^2	0.1982	0.0280	0.0728	0.0872
Log - Likelihood	4323.518	3556.743	3783.296	3891.276
Skewness	-0.5757	-0.1215	-0.0577	-0.3612
Kurtosis	7.7807	7.5504	7.7671	8.3504
Jarque - Berra	1522.401	1307.371	1431.623	1835.165
Q(6)	5.5039	4.8665	6.6177	8.7851
	[0.481]	[0.561]	[0.358]	[0.186]
Q(12)	7.3692	13.425	8.5414	12.378
	[0.832]	[0.339]	[0.742]	[0.416]
LM ARCH test	8.6268	5.7011	4.9595	6.4489
(12 lags)	[0.7344]	[0.9303]	[0.9593]	[0.8917]
$Q^2(6)$	5.1809	3.8153	3.0828	3.9469
	[0.521]	[0.702]	[0.798]	[0.684]
$Q^2(12)$	8.8064	5.7431	4.9317	6.5363
	[0.719]	[0.928]	[0.960]	[0.887]

Note: R_{Index} are the weekly returns of small, large, value and growth indices, and DJ is a dummy variable that takes the value of 1 on the first week of January and 0 otherwise. I_{t-1} is a dummy that takes the value of 1 when e_{t-1} is negative and 0 otherwise. The TGARCH (1,1) model gives estimates under the assumption of conditional normality. Robust t-statistics (in parenthesis) are calculated using the procedure in Bollersev and Wooldridge (1992). The sample period is from July 3, 1968, until June 25, 1997, for a total of 1513 observations. Q(6), Q(12) and $Q^2(6)$, $Q^2(12)$ are the Box Pierce portmanteau test statistics, with 6 and 12 lags, applied to the standardised and squared standardised residuals, respectively. They provide a test for the presence of autocorrelation and ARCH effects, respectively. P values for each test statistic are in brackets. The skewness, kurtosis and Jarque Berra statistic test for normality on the standardised residuals. The LM statistic test the presence of remaining significant ARCH effects. The p values are reported in brackets below the LM test statistic.

Table 9.7 shows the coefficients and t-statistics (in parenthesis), as well as a number of diagnostic tests, from estimating a TGARCH (1, 1) model for the small, large, value and growth stock indices. The results show that the autoregressive coefficients, as well as the January dummy coefficient, are all significantly different from zero for all stock indices in the mean equation. But, what is more important to note is that the γ coefficient that allows for asymmetry in the variance equation is highly significant for large-cap stocks, but only marginal significant for value and growth indices. The volatility seems to react symmetrically to "bad" and "good" news for the small-cap index.

There is a slight improvement in the log-likelihood function compared to standard GARCH (1,1) model for all four style indices, with the biggest improvement in the case of large stocks. No linear dependence is detected in the standardised residuals, since the Ljung-Box Q statistics for 6 and 12 lags are both below the critical values. Nevertheless, there is still some degree of skewness and kurtosis, although less severe than in the case of GARCH(1,1) model. Growth stocks seem to have the most leptokurtic distribution (coefficient of kurtosis in the standardised residuals of 8.3504) among all the stock indices. Finally, no significant linear structure appears in the squared standardised residuals, indicating no ARCH effect left.

A final diagnostic test is to examine whether there is some sign bias or positive/negative size bias left after the TGARCH specification. Table 9.8 shows the results of the asymmetry diagnostic tests for the standardised squared residuals obtained from the previous GARCH(1,1) specification. It is obvious, that that in all equity indices the coefficients on all three tests (sign bias, negative size bias and positive size bias) are not significantly different from zero and the LM joint test is not significant even at 10% level. This confirms that the TGARCH model is able to capture the asymmetry dynamics of conditional variance for all equity style indices.

To understand the differences in the impact of news on conditional volatility for the different stock indices, we plot the news impact curve from TGARCH for each one of the four series. The news impact curve relates past return shocks (news) to current volatility and measures how new information is incorporated into volatility estimates. The news impact curve has important implications for portfolio selection and rotation strategies. It is important to know how a major unexpected change in the share prices will affect the predictable volatility of the stock indices, and if the volatility of all indices will react in the same manner after a bad, or good unexpected event.

TABLE 9.8: Diagnostic Tests for Asymmetry in TGARCH(1,1) Model

	Small - Caps	Large - Caps	Value	Growth
Sign Bias	0.1085	0.1925	0.0336	0.2096
	(0.8083)	(1.4609)	(0.2512)	(1.5006)
Negative Size Bias	-7.4865	-3.9569	-5.3549	-3.5229
	(-1.1080)	(-0.9165)	(-1.0337)	(-0.6496)
Positive Size Bias	5.1689	0.2419	-0.1791	1.1504
	(0.7698)	(0.0608)	(-0.0379)	(0.2170)
Joint Test	3.2866	4.4162	1.2921	3.7210

Note: In the Sign bias test the squared normalised residuals are regressed on a constant and a dummy variable that takes the value of 1 if ε_{t-1} is negative and 0 otherwise. In the Negative (Positive) Size Bias test, the squared standardised residuals are regressed on a constant and the product of a dummy that takes the value of 1 if ε_{t-1} is negative (positive) and 0 otherwise and ε_{t-1}. The joint test of all three, is an LM test for adding all three previous variables together. Two asterisks (**) denote significance at 5% level, while one asterisk (*) denotes significance at 10% level.

The news impact curve for the TGARCH (1,1) model is given by the following equations:

$$\sigma_t^2 = A + \alpha_1 \cdot \varepsilon_{t-1}^2 \text{ , for } \varepsilon_{t-1} > 0$$
$$\sigma_t^2 = A + (\alpha_1 + \gamma) \cdot \varepsilon_{t-1}^2 \text{ , for } \varepsilon_{t-1} < 0 \quad \text{where}$$
$$A = \alpha_0 + \beta_1 \cdot \sigma_{Un}^2$$

where σ_{Un}^2 is the unconditional variance. Figure 9.7 shows the news impact curve calculated from the following equations for the small and large-cap stocks. It is interesting to note that, for small stocks the biggest part of the two sides of the news impact curve is steeper than the large-caps news impact curve. This indicates that extreme good and bad news are causing more volatility in the case of small stocks than in the case of large securities. On the other hand, small past shocks (either negative or positive) cause relatively more volatility to large-caps. Figure 9.7 also reveals the asymmetric behaviour of volatility in the two different equity classes. The news impact curve is centred at ε_{t-1}, but has different slopes for the positive and negative sides. Nevertheless, negative shocks cause relatively more volatility than positive ones in the case of large companies, whereas the impact is rather more symmetric for smaller companies' stocks.

Two main reasons may exist for that phenomenon. Bad news cause relatively more volatility to large-cap stocks, because large companies are much more leveraged. In chapter 6, we showed that the debt to equity ratio of UK large stocks is almost four times higher than that of smaller stocks. Bad news result in a significant drop in the share price and therefore a lower stock price reduces the value of equity relative to corporate debt. This causes an increase in corporate leverage which also results to an increase in the risk of holding stocks. Increasing the debt to equity ratio of the already leveraged large stocks have a significant positive impact in volatility. Smaller stocks, on the other hand, are less leveraged so an increase in their gearing does not have the same negative impact. Another reason why the asymmetric behaviour in volatility is not observed in small stocks has to do with the liquidity and the thin trading problem of these stocks. It is possible that bad news may not be discounted immediately, in the case of small-caps due to the thin trading problem that is evident.

Figure 9.8 shows the relevant news impact curve for value and growth stock indices. In this case, there are no significant differences in the impact of past shocks in conditional volatility. For a wide range of small shocks (either positive or negative) the two curves are almost identical and only for very large shocks the conditional variance of growth stocks appears to be slightly higher. Moreover, the volatility of both indices seems to have a nearly symmetric shape around zero indicating the absence of leverage effect.

The results from the TGARCH model indicate an asymmetric volatility behaviour, or the presence of leverage effect only for large and liquid stocks, while for the other equity categories the picture is not yet clear. Even if asymmetry is captured (looking at the sign and size bias tests and the news impact curves) with the TGARCH model, there is still excess skewness and kurtosis displayed in the normalised residuals. Furthermore, the threshold GARCH is considered a very simplistic parameterisation[7], which may not be adequate enough to capture the volatility dynamics.

[7] For a review of the properties and characteristics of different threshold GARCH models see Rabemananjara and Zakoian (1993).

FIGURE 9.7: TGARCH(1,1) News Impact Curve for Small and Large-cap Style Indices

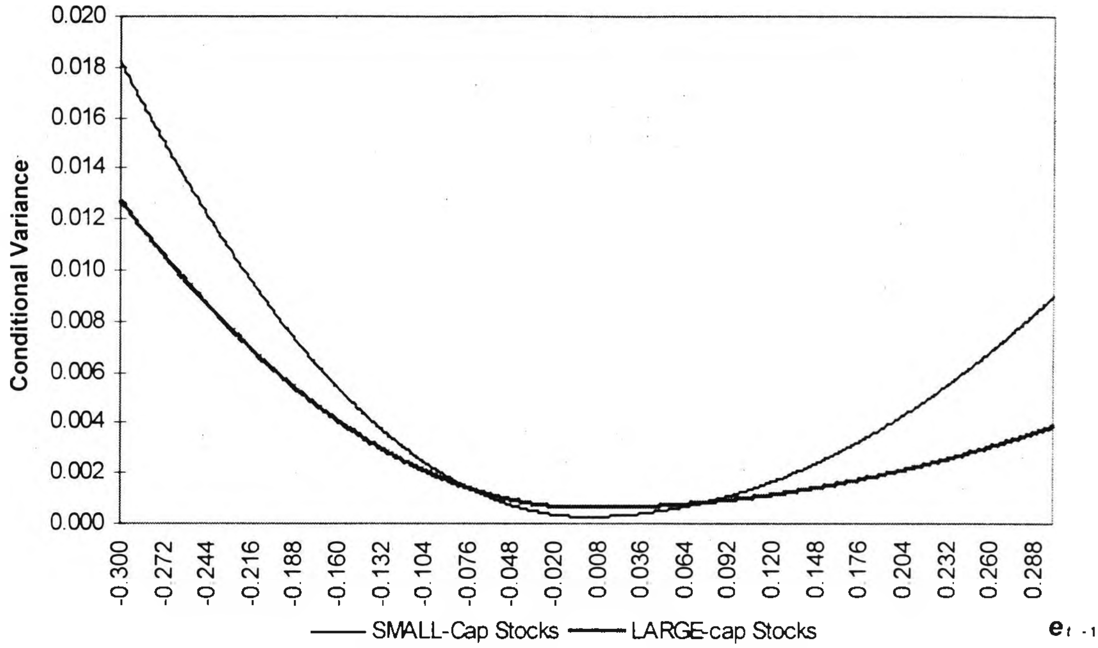
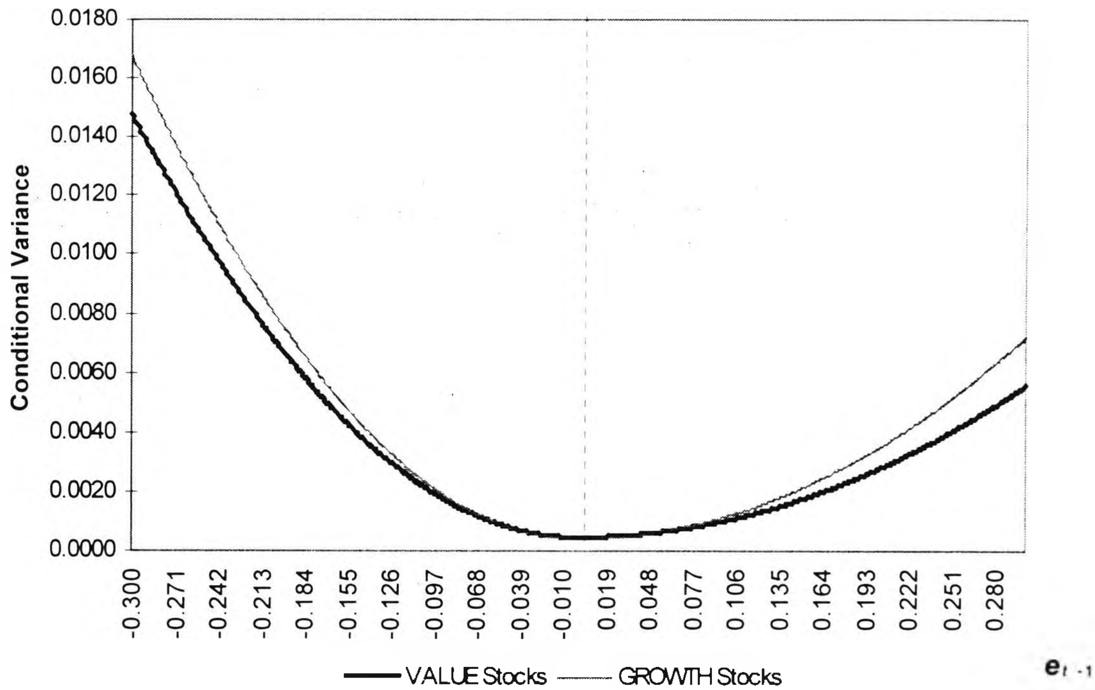


FIGURE 9.8: TGARCH(1,1) News Impact Curve for Value and Growth Style Indices



A more useful specification, which has been used extensively in the literature is the exponential GARCH model of Nelson (1990). In the EGARCH (p,q) model the conditional variance is a function of past innovations as defined by the following equation:

$$\log(\sigma_t^2) = \alpha_0 + \beta_1 \log(\sigma_{t-1}^2) + \alpha_1 \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

Unlike the previous GARCH specifications we have used, there are no restrictions on the parameters α_i and β_i to ensure non-negativity of the conditional variance. The properties of the EGARCH model are determined by the second part of the above equation. The γ parameter is essentially the parameter that allows for asymmetry. If γ is not significantly different from zero, then a positive surprise has the same effect on volatility as a negative surprise of the same magnitude. If $-1 < \gamma < 0$, a negative surprise increases volatility more than a positive surprise. When, however, $\gamma < -1$ then a positive surprise actually reduces volatility, while a negative surprise increases volatility.

To test the consistency of our results, we estimate an EGARCH (1,1) model for all our style indices and present the findings and relevant diagnostic tests in table 9.9. The results are similar to the previous model. The coefficient of asymmetry γ, in the conditional variance equation, is negative but above -1 for all stock indices, denoting that volatility increases more after a negative surprise (bad news), than after a positive one (good news). Nevertheless, only in large stocks is this coefficient significant at 5% level. The log - likelihood function has been slightly increased in all cases but growth stocks, compared to the TGARCH model. The diagnostics for the residuals look good, except for skewness and kurtosis, which remain high. Finally, as table 9.10 indicates, in none of the series there is significant sign and size bias left from EGARCH.

The results from both the TGARCH and the EGARCH model provide convincing evidence that stock market volatility is asymmetric, but not for all categories of stocks. The conditional variance of large and liquid securities reacts differently to positive and negative past return shocks, or unexpected events. This is not the case however for other equity classes, where volatility appears to be more symmetric in the way it responds to news.

TABLE 9.9: EGARCH (1,1) Model Estimates for Style Index Weekly Returns

$$R_{Index,t} = \phi_0 + \phi_1 R_{Index,t-1} + \phi_2 R_{Index,t-2} + \delta\, DJ$$

$$\log(\sigma_t^2) = \alpha_0 + \beta_1 \log(\sigma_{t-1}^2) + \alpha_1\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}^2}\right| - \sqrt{\frac{2}{\pi}}\right) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}^2}$$

Parameters & Diagnostics	Small -Caps	Large - Caps	High B/P (Value)	Low B/P (Growth)
$\phi_0 \times 10^2$	0.1047	0.1389	0.2144	0.0855
	(2.7315)	(2.0022)	(3.4803)	(1.6598)
ϕ_1	0.4031	0.0770	0.1698	0.2127
	(12.5896)	(2.5914)	(5.1916)	(6.5633)
ϕ_2	0.1236	0.0763	0.1210	0.0945
	(4.1088)	(2.4278)	(3.5401)	(2.7435)
δ	0.0105	0.0059	0.0100	0.0103
	(4.1971)	(1.7851)	(3.1280)	(2.8720)
α_0	-0.3205	-0.1309	-0.2704	-0.2380
	(-2.8609)	(-3.2823)	(-2.4158)	(2.7138)
α_1	0.2484	0.1554	0.2100	0.22226
	(5.1538)	(4.3071)	(3.8039)	(2.2887)
γ	-0.08697	-0.2013	-0.1049	-0.1089
	(-1.7002)	(-2.5390)	(-1.6577)	(-1.9005)
β_1	0.9602	0.9816	0.9642	0.9685
	(45.2084)	(103.5250)	(51.4015)	(21.8776)
Adjusted R^2	0.1983	0.0275	0.0725	0.0872
Log - Likelihood	4332.047	3562.786	3788.246	3891.276
Skewness	-0.5216	-0.1211	-0.0564	-0.3622
Kurtosis	7.5711	7.2127	7.6494	8.3583
Jarque - Berra	1384.037	1121.015	1361.804	1840.687
Q(6)	5.4957	4.8928	7.0494	8.7888
	[0.482]	[0.558]	[0.347]	[0.186]
Q(12)	7.5510	12.835	9.2611	12.380
	[0.819]	[0.381]	[0.680]	[0.416]
LM ARCH test	10.3707	10.0238	6.1784	6.4208
(12 lags)	[0.5834]	[0.6138]	[0.9068]	[0.8934]
$Q^2(6)$	6.9068	8.8751	4.8444	3.9265
	[0.330]	[0.181]	[0.564]	[0.687]
$Q^2(12)$	10.901	10.298	6.3071	6.5043
	[0.537]	[0.590]	[0.900]	[0.889]

Note: R_{index} are the weekly returns of small, large, value and growth indices, and DJ is a dummy variable that takes the value of 1 on the first week of January and 0 otherwise. The EGARCH (1,1) model gives estimates under the assumption of conditional normality. Robust t-statistics (in parenthesis) are calculated using the procedure in Bollersev and Wooldridge (1992). The sample period is from July 3, 1968, until June 25, 1997, for a total of 1513 observations. Q(6), Q(12) and $Q^2(6)$, $Q^2(12)$ are the Box Pierce portmanteau test statistics, with 6 and 12 lags, applied to the standardised and squared standardised residuals, respectively. They provide a test for the presence of autocorrelation and ARCH effects, respectively. The skewness, kurtosis and Jarque Berra statistic test for normality on the standardised residuals. The LM statistic test the presence of remaining significant ARCH effects. The p values are reported in brackets below the LM test statistic.

TABLE 9.10: Diagnostic Tests for Asymmetry in EGARCH(1,1) Model

	Small - Caps	Large - Caps	Value	Growth
Sign Bias	0.0578	0.1665	0.0091	0.2089
	(0.4369)	(1.2970)	(0.0686)	(1.4948)
Negative Size Bias	-7.9392	-5.6216	-6.1338	-3.4692
	(-1.1962)	(-1.3320)	(-1.1890)	(-0.6394)
Positive Size Bias	9.2471	0.9172	0.5897	1.1685
	(1.3944)	(0.2376)	(0.1268)	(0.2203)
Joint Test	5.1474	3.4720	2.1238	3.7104

Note: In the Sign bias test the squared normalised residuals are regressed on a constant and a dummy variable that takes the value of 1 if ε_{t-1} is negative and 0 otherwise. In the Negative (Positive) Size Bias test, the squared standardised residuals are regressed on a constant and the product of a dummy that takes the value of 1 if ε_{t-1} is negative (positive) and 0 otherwise and ε_{t-1}. The joint test of all three, is an LM test for adding all three previous variables together. Two asterisks (**) denote significance at 5% level, while one asterisk (*) denotes significance at 10% level.

9.4 Using GARCH Models to Forecast Volatility

In the previous section we showed that volatility is time varying for all UK equity index portfolios, and two asymmetric GARCH models (TGARCH and EGARCH) can be very helpful in capturing the volatility dynamics of certain style indices. This part investigates the ability of different GARCH specifications to forecast volatility out-of-sample. GARCH models have been extensively used recently for forecasting purposes, but their ability to accurately predict stock market volatility has been questioned. In this section, we test the power of various GARCH models to forecast the variance of each one of our style indices for different horizons.

We empirically test the out-of-sample forecasting ability of three different GARCH models; the standard GARCH(1,1), the Glosten, Jagannathan and Runkle's threshold GARCH (1,1) and Nelson's exponential GARCH (1,1) model. These models are compared with the random walk model, which sets this period's variance equal to past period's variance, and a historical mean model, which is simply the long term average of past observed volatilities. If variance is constant (homoskedastic) the historical mean model should give the most accurate forecasts. The random walk and the historical mean model consist our benchmark forecasts.

The various models' parameters are estimated using an initial set of data and these parameters are then applied to later data, thus forming out-of-sample forecasts for horizons of 1 week, 4 weeks and 13 weeks (quarter). The time series of weekly returns for each of the four series is divided into two parts. The first part, which covers the first 755 weeks, is used to estimate the models, while the second is used to generate forecasts for the variance of returns. Thus, the first week for which out-of-sample forecasts are obtained is the first week of January 1983[8].

We use rolling samples, in which the sample size used for estimation was fixed at 755 observations. Hence, for each subsequent forecast, the estimation sample is shifted forward by one week. In other words, we fit the models that we test to a sample of nearly 15 years (755 weeks), generate a one-step-ahead forecast, delete the first observation from the sample and add the next one, and generate again a one-step-

[8] The decision to split the sample into two halves and begin the forecasting at the midpoint of the sample is rather arbitrarily, but we don't believe that a smaller or larger out-of-sample period would had influenced the results.

ahead forecast. We have also experiment with expanding samples, in which the sample size grew as additional observations were added, but there were not significant differences in the results so we report only the results with rolling samples.

To evaluate the ability of all these models to adequately forecast volatility and construct various error statistics, we need a measure of the "true volatility". Since we don't have higher than weekly frequency data we need to make some assumptions for the estimate of the real weekly volatility. We can either define volatility by

$$\sigma_t = (r - \bar{r})^2$$

where $\bar{r}$ is the average return over the last 5 years (260 weeks), or we can simply set weekly variance to be equal to the square return over the particular week. We used both measures and we didn't find significant differences in the estimates of the error statistics. We report the results that correspond to the second method.

One-step-ahead (weekly) forecasts are obtained simply by estimating and fitting the various models according to their respective formulae. Consequently, the number of forecasts that are generated and evaluated are 756 for weekly, 189 for 4 weeks and 58 for quarterly horizon.

Forecasting performance is initially evaluated using the mean forecast error (ME), the mean absolute error (MAE) and the root mean square error (RMSE). The previous error statistics are calculated as follows:

$$ME = \frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t^2 - \sigma_t^2)$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{\sigma}_t^2 - \sigma_t^2\right|$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t^2 - \sigma_t^2)^2}$$

where $\hat{\sigma}_t^2$ and σ_t^2 is the estimated and realised variance and T = 756, 189 and 58 for weekly, monthly and quarterly horizons respectively. The ME, which is the simple average of forecast errors, does not allow for the offsetting effect of errors of different signs and as such little credence should be placed upon it. However, it can be used as a general guide as to whether the particular model over or underpredicts volatility. The MAE which is the simple average of the absolute value of forecast errors, avoids this problem. The MAE is an appropriate criterion if the cost of erring is proportionate to the size of forecast error. RMSE is the square root of a simple average of square forecast errors. The RMSE is larger than the MAE, unless all errors are of the same size, in which case the two measure are identical. All the above statistics imply a quadratic loss function, which penalises positive and negative forecasts symmetrically.

Table 9.11 gives results from the out-of-sample forecast evaluation using the previous three measures for all five models that we test. Results for each style index, and for forecasts of 1, 4 and 13 weeks ahead, are reported in panels A, B and C respectively. In each panel, there are also two additional columns that indicate the model's rank according to MAE or RMSE, with 1 denoting the best and 5 the worst model.

For weekly forecasts we observe that with the exception of small-caps, all GARCH class of models that we test, overpredict volatility. The MAE statistic indicates that the EGARCH(1,1) model provides the most accurate forecasts for all four stock categories. The Random walk could marginally beat GARCH and TGARCH only for small stock's volatility prediction. In all other cases GARCH(1,1) was ranked second and TGARCH(1,1) third. The RMSE's also confirm the superiority of EGARCH in forecasting the volatility of style indices, although again in small-caps it is beaten by the random walk.

TABLE 9.11: Out-of-Sample Forecasting Performance of Volatility Models

Panel A. Forecast Horizon: 1 Week

Index	Model	ME	MAE	Rank	RMSE	Rank
SMALL	Random Walk	-0.00064	0.29125	2	1.03210	1
	Hist. Mean	0.12729	0.41979	5	1.12410	5
	GARCH(1,1)	-0.01298	0.30184	4	1.10270	3
	TGARCH(1,1)	-0.01970	0.29979	3	1.10380	4
	EGARCH(1,1)	-0.04253	0.28262	1	1.09290	2
LARGE	Random Walk	-0.00030	0.56412	4	1.97460	5
	Hist. Mean	0.45946	0.80717	5	1.82930	3
	GARCH(1,1)	0.09362	0.54509	2	1.80800	2
	TGARCH(1,1)	0.10217	0.56052	3	1.83580	4
	EGARCH(1,1)	0.04226	0.52251	1	1.79730	1
VALUE	Random Walk	-0.00036	0.45156	4	1.57000	5
	Hist. Mean	0.32383	0.63758	5	1.45030	4
	GARCH(1,1)	0.03156	0.42781	2	1.43360	2
	TGARCH(1,1)	0.03736	0.43698	3	1.44870	3
	EGARCH(1,1)	0.00728	0.41227	1	1.41990	1
GROWTH	Random Walk	-0.00050	0.42039	4	1.62870	5
	Hist. Mean	0.29959	0.61734	5	1.55950	3
	GARCH(1,1)	0.03423	0.40500	2	1.55030	2
	TGARCH(1,1)	0.04595	0.41481	3	1.56220	4
	EGARCH(1,1)	0.01064	0.38958	1	1.53720	1

Panel B. Forecast Horizon: 4 Weeks

Index	Model	ME	MAE	Rank	RMSE	Rank
SMALL	Random Walk	-0.00195	1.11930	4	3.24440	5
	Hist. Mean	0.39572	1.35860	5	2.85800	4
	GARCH(1,1)	-0.08091	0.94490	3	2.74690	2
	TGARCH(1,1)	-0.10776	0.94330	2	2.75620	3
	EGARCH(1,1)	-0.19910	0.89207	1	2.69650	1
LARGE	Random Walk	0.00165	1.88360	4	6.22130	5
	Hist. Mean	1.46200	2.43990	5	4.65510	3
	GARCH(1,1)	0.33649	1.58320	2	4.60530	2
	TGARCH(1,1)	0.37068	1.66320	3	4.78890	4
	EGARCH(1,1)	0.13104	1.54970	1	4.56320	1
VALUE	Random Walk	0.00387	1.55830	4	4.57940	5
	Hist. Mean	1.00830	1.96600	5	3.52750	3
	GARCH(1,1)	0.05870	1.25990	2	3.40400	2
	TGARCH(1,1)	0.08191	1.33580	3	3.55840	4
	EGARCH(1,1)	-0.03844	1.23990	1	3.39710	1
GROWTH	Random Walk	-0.00102	1.43680	4	5.06640	5
	Hist. Mean	0.97198	1.94530	5	3.96730	3
	GARCH(1,1)	0.12058	1.22770	2	3.92190	2
	TGARCH(1,1)	0.16744	1.27670	3	4.00080	4
	EGARCH(1,1)	0.02621	1.18580	1	3.86160	1

Panel C. Forecast Horizon: 13 Weeks (3 months)

Index	**Model**	**ME**	**MAE**	**Rank**	**RMSE**	**Rank**
SMALL	Random Walk	0.01510	3.19090	4	8.70710	5
	Hist. Mean	1.28270	3.81220	5	6.90560	4
	GARCH(1,1)	-0.26142	2.02850	3	4.35880	2
	TGARCH(1,1)	-0.34711	2.02000	1	4.34720	1
	EGARCH(1,1)	-0.64491	2.02500	2	4.63460	3
LARGE	Random Walk	0.06176	4.74870	4	12.32300	5
	Hist. Mean	4.73400	7.10410	5	9.93660	4
	GARCH(1,1)	1.09180	3.32080	1	5.98750	2
	TGARCH(1,1)	1.19890	3.34550	2	5.76790	1
	EGARCH(1,1)	0.41676	3.47550	3	6.56610	3
VALUE	Random Walk	0.06651	4.06690	4	9.46720	5
	Hist. Mean	3.25920	5.47620	5	7.73500	4
	GARCH(1,1)	0.19042	2.69480	1	4.98640	2
	TGARCH(1,1)	0.26576	2.88200	2	4.95380	1
	EGARCH(1,1)	-0.12691	2.91300	3	5.48780	3
GROWTH	Random Walk	0.02789	4.10380	4	11.37100	5
	Hist. Mean	3.14560	5.46750	5	8.80970	4
	GARCH(1,1)	0.39323	2.48640	1	5.13250	2
	TGARCH(1,1)	0.54547	2.59360	2	4.86880	1
	EGARCH(1,1)	0.08435	2.59130	3	5.64590	3

Note: ME is the mean error statistic defined by expression (1) below. MAE is the mean absolute error statistic determined by the expression (2). RMSE is the root mean square error defined by the expression (3). The errors are calculated from forecasts obtained for the period 5/151983 - 25/6/97. The errors that are reported have been multiplied by $\times 10^{-3}$.

$$ME = \frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t^2 - \sigma_t^2) \qquad (1)$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{\sigma}_t^2 - \sigma_t^2\right| \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t^2 - \sigma_t^2)^2} \qquad (3)$$

where T = 756, 189 and 58 for weekly, monthly and quarterly forecasting horizons respectively

A closer look at the actual values of the error statistics indicate that, although there is a clear advantage of random walk and GARCH models over the historical mean, all previous four models are not producing substantially different forecasting accuracy. For small-stocks' volatility EGARCH is slightly more accurate (2.9%) than random walk, but still 32% more accurate than the historical mean, as indicating by the values of the MAE's. Furthermore, EGARCH produces 7.4%, 8.7% and 7.3% more accurate predictions than the random walk for large, value and growth stocks respectively. Finally, it is interesting to note that forecasts are generally more precise for small stocks' and less precise for large stocks' volatility.

A useful robustness test is to investigate whether our results are period specific. We have calculated RMSE's for every 3 years in the out-of-sample period for all forecasting models and for each one of the equity style indices. The results, which are reported in table 9.12, indicate that the EGARCH is preferred in 9 out of 20 cases, while the random walk in only 4 cases. GARCH and TGARCH models give the smallest RMSE only in 2 and 3 occasions respectively. Furthermore, the variance forecasts are much more accurate in the first and the last period of our sample, while in the 1986 - 88 period no GARCH model in any of the indices was able to beat the random walk.

TABLE 9.12: Root Mean Square Errors from Volatility Forecasts of Style Indices [Forecast Horizon : 1 Week]

		Forecast Period				
Index	**Model**	**1983 - 85**	**1986 - 88**	**1989 - 91**	**1992 - 94**	**1995 - 97**
SMALL	Random Walk	0.32279	**1.99870**	0.75523	0.66948	0.13968
	Hist. Mean	0.37189	2.26230	0.68750	0.52760	0.31079
	GARCH(1,1)	0.25873	2.24260	0.68418	0.52806	0.13315
	TGARCH(1,1)	0.26043	2.24490	0.68505	0.52887	**0.12769**
	EGARCH(1,1)	**0.25347**	2.23060	**0.66752**	**0.50452**	0.13305
LARGE	Random Walk	0.74378	**3.40880**	0.97125	2.37100	**0.23790**
	Hist. Mean	0.88956	3.38300	0.83865	1.68170	0.65512
	GARCH(1,1)	0.58308	3.48490	**0.69030**	1.64610	0.30235
	TGARCH(1,1)	0.57055	3.55800	0.69228	**1.63860**	0.31949
	EGARCH(1,1)	**0.54721**	3.46110	0.69253	1.64760	0.32459
VALUE	Random Walk	0.56858	**2.44830**	0.77630	2.22030	**0.17505**
	Hist. Mean	0.67683	2.54590	0.70253	1.57680	0.50642
	GARCH(1,1)	0.45908	2.60530	0.61477	1.57760	0.20396
	TGARCH(1,1)	0.45669	2.64440	0.61575	1.57420	0.24851
	EGARCH(1,1)	**0.44265**	2.57690	**0.61367**	**1.56650**	0.23134
GROWTH	Random Walk	0.60619	3.09880	0.80396	1.45800	0.21539
	Hist. Mean	0.65296	**3.07750**	0.72800	1.05020	0.47233
	GARCH(1,1)	0.47120	3.14210	0.64005	1.02180	**0.18824**
	TGARCH(1,1)	0.47022	3.17250	0.63995	**1.01310**	0.19980
	EGARCH(1,1)	**0.46162**	3.11400	**0.63946**	1.01600	0.19187

Looking at the results for monthly and quarterly variance forecasts in table 9.11, we can see that, not surprisingly, there is a tendency of the MAE's and RMSE's to increase at longer horizons. The accuracy of the forecasts therefore is deteriorated as we move to lower frequency forecasts. Nevertheless, GARCH models perform much better than the random walk and the historical mean and the advantage that we gain by using GARCH models is now more apparent. For forecast horizon of 4 weeks, the EGARCH is clearly the most consistent model, being best in all four equity indices that we examine. EGARCH can forecast squared returns about 17% more accurate than random walk in the case of small-caps and about 25% more accurate than the benchmark for the rest of the indices.

The ranking of volatility models is somewhat different for 13 weeks horizon. The GARCH (1,1) is the model that produces the smallest MAE, while the TGARCH (1,1) is consistently preferable according to RMSE. Although the ranking among the GARCH class of models is different there is clear evidence that all these models easily beat the random walk and produce relatively more precise quarterly volatility forecasts. The advantage that we gain by using some sort of GARCH specification instead of a "naive" model to forecast the variance at a quarterly horizon is over 40% in all four cases.

The previous results point out that GARCH models give relatively more accurate forecasts compared to the random walk and the historical mean model for all forecasting horizons and equity portfolios. All the statistics we employ, however, assume a quadratic loss function, which may not be appropriate for evaluating volatility forecasts, since it penalises positive and negative forecasts symmetrically. In the next section, we evaluate various volatility forecasting models in terms of the economic value they add. We also assess the forecasts, using a standard efficiency test suggested by Pagan and Schwert (1990), where the true variance is regressed to a constant and the forecasted variance obtained from the various models that we examine. The results from the efficiency tests are presented in the appendix at the end of the chapter.

9.5 Implications for Style Rotation Strategies

It is widely accepted that a correct estimate of next period's volatility is extremely helpful in market timing, strategic and tactical asset allocation, financial planning and rotation between equity styles. Money managers are interested in predicting not only next period's return, but next period's volatility as well, when they decide on the allocation of funds between different asset, or equity classes. Specially, pension fund managers and investment managers with high risk averse clients place a lot of emphasis in controlling and managing the risk of their portfolios.

The total risk of an equity portfolio is determined by the volatility of the equity classes and the correlation between them. Different volatility models for equity style indices will consequently result to different style allocations across time. Therefore, the more precise is the estimate of future volatility, the best fund allocation can be achieved. In this section we evaluate the models we use to forecast volatility by comparing their ability to suggest optimal minimum variance allocations between value and growth stocks across time.

We use the quarterly variance predictions for value and growth style indices, derived from 5 different volatility models (GARCH, TGARCH, EGARCH, Random Walk and Historical Average) into a quadratic optimisation procedure to find the optimal weights every quarter between the two equity classes, that minimise the portfolio's risk. The next quarter's correlation between the two indices is obtained by the previous five year quarterly return data. For each quarter, staring from 1983 to 1997, we performed five different minimum variance optimisations.

Table 9.13 shows the effect of different volatility inputs, derived from each one of the previous forecasting models, to the minimum variance portfolio. From the weights obtained from the optimisation, we calculate the average quarterly standard deviation and reward to variability ratio for each model. The GARCH specification results to the lowest standard deviation (0.0544), compared to the other models. Not very far behind are the other two GARCH models, the EGARCH (0.0549) and the TGARCH (0.0554). In terms of reward-to-variability, the EGARCH outperforms all the other models with second best being the Random Walk. Panel A also gives the average allocation between value and growth proposed from each one of the five models we test. The GARCH and EGARCH models results in very similar allocations

(26% value - 74% growth), while the TGARCH slightly overweights value (32%) compared to the other models

Table 9.13, panel B compares the average reward-to-variability of different models. The table presents the average difference for that ratio between all different combination of models, and tests whether this difference is statistically significant. It is evident that the GARCH models have substantially different reward-to-variability ratios compared to other models. However, the variation over time of these differences are quite large compared to their means, resulted in statistically insignificant t-statistics. Only the EGARCH gives significantly on average higher ratios when compared to the standard GARCH and TGARCH models.

TABLE 9.13: The Effect of Different Volatility Forecasts to the Minimum Variance Portfolio (The Case of Allocation Between Value and Growth)

Panel A: Characteristics of Minimum Variance Portfolio

Models	Mean Quarterly St Deviation	Mean Reward to Variability Ratio	Average Value Weight	Average Growth Weight
Random Walk	0.0572	0.6883	0.3276	0.6724
Historical Mean	0.0561	0.6478	0.2465	0.7535
GARCH (1,1)	0.0544	0.6697	0.2610	0.7390
TGARCH (1,1)	0.0554	0.6628	0.3267	0.6733
EGARCH (1,1)	0.0549	0.7018	0.2607	0.7393

Panel B: Differences in Average Reward - to - Variability Ratio Between Models

Models	Mean	T-test ($H_0 : \mu = 0$)	p - value
GARCH - Hist. Mean	0.0218	0.5756	0.5672
GARCH - RW	-0.0187	-0.2598	0.7960
GARCH - TGARCH	0.0069	0.3830	0.7031
GARCH - EGARCH	-0.0321	-2.0704	0.0430
TGARCH - Hist. Mean	0.0150	0.3761	0.7083
TGARCH - RW	-0.0255	-0.3612	0.7193
TGARCH - EGARCH	-0.0390	-2.0903	0.0411
EGARCH - Hist. Mean	0.0540	1.3476	0.1831
EGARCH - RW	0.0135	0.1931	0.8476

9.6 Summary and Conclusion

The time series properties of weekly returns on four style indices (small-caps, large-caps, value and growth stocks) for the last 30 years, illustrates that their variance is not constant over time and that small (large) price changes tend to be followed by small (large) changes of either sign. Therefore, long term sample or unconditional variances should not be used to compare the riskiness of equity portfolios. Instead, autoregressive conditional heteroskedasticity models seems to capture the dynamics of stock market volatility.

In this chapter, we show that the volatility of UK style indices is time-varying and an AR(2)-GARCH(1,1) provides an adequate specification. Using that parameterisation, we find that all indices exhibit almost the same volatility characteristics, with large-caps to display the higher persistence in variance. Value stocks have slightly higher average conditional variance compared to growth, but there are still many periods where growth volatility exceeds value.

The volatility of style indices also differs in the way it responds to interest rate movements. In the previous chapters, we demonstrate that changes in short term interest rates affect the first moment of different equity portfolios. Since, interest rates carry expectations about inflation, they may also influence the conditional volatility of equity portfolios. Short-term interest rates are found to affect large and growth stocks' volatility, while the impact on the other two indices is not significant. Furthermore, the chapter investigates whether volatility is asymmetric in the way it responds to positive and negative past unexpected events. Using a number of diagnostic tests and fitting two different asymmetric GARCH models (TGARCH and EGARCH), we show that the leverage effect, or the asymmetry in stock market volatility is a phenomenon that is evident only in large and liquid securities.

The second part of the chapter concentrates on forecasting the volatility movements of equity style indices. Using a large out-of-sample period and a rolling sample methodology, we compare the ability of various GARCH specifications against two simple models (Random Walk, Homoskedastic) to forecast future variance at different horizons. Our findings suggest that ARCH class of models, particularly EGARCH (1,1), dominate the random walk and the homoskedastic model in out-of-sample forecasting of volatility for all equity style indices, and this superiority is more clear at longer horizon forecasts (4 weeks and 13 weeks).

The results have important implications in dynamic style rotation strategies. We emphasise that, by implementing value and growth volatility forecasts from different models into a quarterly minimum variance optimisation. We find that GARCH volatility forecasts lead to an improved value/growth allocation across time and consequently lower portfolio variance. Therefore, any portfolio manager who is interested in style rotation should model the variance of the individual equity classes using some sort of GARCH specification.

APPENDIX

Regression Tests of Efficiency for the Volatility Forecasts

Panel A. Forecast Horizon: 1 Week

Index	Model	α	β	$\chi^2(2)$	$Q(12)$	R^2
SMALL	Random Walk	0.0001	0.5513	28.0247	5.1624	0.3040
		(4.7512)	(4.8136)	[0.0000]	(0.9521)	
	Hist. Mean	-0.0003	1.6739	3.2682**	322.0005	0.0008
		(-0.5738)	(0.9951)	[0.1951]	(0.0000)	
	GARCH(1,1)	0.0001	0.6084	7.2296	250.0864	0.0386
		(2.6812)	(2.3952)	[0.0269]	(0.0000)	
	TGARCH(1,1)	0.0001	0.5919	8.9738	249.5706	0.0378
		(2.9780)	(2.3797)	[0.0112]	(0.0000)	
	EGARCH(1,1)	0.0001	0.8279	3.9426**	249.5881	0.0465
		(1.7595)	(2.4437)	[0.1392]	(0.0000)	
LARGE	Random Walk	0.0002	0.3612	25.8138	19.0536	0.1305
		(4.9609)	(2.2946)	[0.0000]	(0.087)	
	Hist. Mean	-0.0006	1.3393	26.8555	102.7918	0.0022
		(-1.5518)	(2.5061)	[0.0000]	(0.0000)	
	GARCH(1,1)	0.0003	0.1715	219.3127	98.7090	0.0017
		(3.1531)	(2.0488)	[0.0000]	(0.0000)	
	TGARCH(1,1)	0.0003	0.1351	367.2327	98.7321	0.0018
		(3.6528)	(2.1697)	[0.0000]	(0.0000)	
	EGARCH(1,1)	0.0003	0.1860	148.0189	98.9271	0.0016
		(3.4870)	(2.3391)	[0.0000]	(0.0000)	
VALUE	Random Walk	0.0002	0.3421	21.5605	8.7461	0.1170
		(4.4797)	(2.0949)	[0.0000]	(0.7244)	
	Hist. Mean	-0.0005	1.3972	17.2302	96.0864	0.0019
		(-1.1197)	(1.9272)	[0.0001]	(0.0000)	
	GARCH(1,1)	0.0002	0.2704	168.9798	86.4530	0.0045
		(3.8587)	(4.6702)	[0.0000]	(0.0000)	
	TGARCH(1,1)	0.0002	0.1926	355.5095	87.7670	0.0032
		(4.1998)	(4.1082)	[0.0000]	(0.0000)	
	EGARCH(1,1)	0.0002	0.3678	78.22324	86.0936	0.0050
		(3.5730)	(5.1449)	[0.0000]	(0.0000)	
GROWTH	Random Walk	0.0001	0.4230	29.5482	20.8545	0.1790
		(4.8319)	(3.0281)	[0.0000]	(0.0525)	
	Hist. Mean	-0.0005	1.4830	16.4739	144.8193	0.0015
		(-1.6103)	(2.4303)	[0.0002]	(0.0000)	
	GARCH(1,1)	0.0002	0.3235	194.8377	125.3084	0.0079
		(3.1817)	(6.3168)	[0.0000]	(0.0000)	
	TGARCH(1,1)	0.0002	0.2798	308.0079	125.3528	0.0076
		(3.2681)	(6.6424)	[0.0000]	(0.0000)	
	EGARCH(1,1)	0.0002	0.4146	100.0295	122.6432	0.0091
		(2.9617)	(6.3868)	[0.0000]	(0.0000)	

Panel B. Forecast Horizon: 4 Weeks

Index	Model	α	β	$\chi^2(2)$	$Q(12)$	R^2
SMALL	Random Walk	0.0006	0.3479	422.8986	7.4740	0.1211
		(3.6732)	(10.1646)	[0.0000]	(0.8247)	
	Hist. Mean	-0.0083	6.5076	18.2286	38.4567	0.0259
		(-1.3381)	(1.4547)	[0.0001]	(0.0000)	
	GARCH(1,1)	0.0004	0.6600	5.8343*	10.8575	0.0897
		(2.0404)	(3.8004)	[0.0540]	(0.5411)	
	TGARCH(1,1)	0.0004	0.6408	7.4726	10.8862	0.0877
		(2.2630)	(3.8483)	[0.0238]	(0.5386)	
	EGARCH(1,1)	0.0002	0.8834	1.9113**	12.0014	0.1058
		(1.3639)	(3.9710)	[0.3845]	(0.4455)	
LARGE	Random Walk	0.0017	0.0202	13352.2200	4.0705	0.0004
		(4.6485)	(1.1675)	[0.0000]	(0.9821)	
	Hist. Mean	-0.0058	2.3608	98.4994	3.8822	0.0167
		(-1.5068)	(1.8271)	[0.0000]	(0.9854)	
	GARCH(1,1)	0.0012	0.2487	142.0230	2.7112	0.0083
		(2.7145)	(2.8288)	[0.0000]	(0.9972)	
	TGARCH(1,1)	0.0014	0.1601	463.1417	2.6418	0.0058
		(3.5924)	(3.2111)	[0.0000]	(0.9975)	
	EGARCH(1,1)	0.0013	0.2478	154.2966	2.6665	0.0064
		(3.3034)	(3.7068)	[0.0000]	(0.9974)	
VALUE	Random Walk	0.0013	0.0917	2131.0570	6.4046	0.0084
		(4.6667)	(3.8654)	[0.0000]	(0.8943)	
	Hist. Mean	-0.0050	2.6378	44.0786	9.2575	0.0170
		(-1.5150)	(1.8438)	[0.0000]	(0.6807)	
	GARCH(1,1)	0.0007	0.4895	7.0196	2.4789	0.0353
		(1.8601)	(2.5200)	[0.0299]	(0.9982)	
	TGARCH(1,1)	0.0010	0.2649	21.0261	3.8918	0.0143
		(3.0394)	(1.6485)	[0.0000]	(0.9853)	
	EGARCH(1,1)	0.0007	0.5044	4.1460**	2.9338	0.0223
		(1.7572)	(2.0667)	[0.1258]	(0.9959)	
GROWTH	Random Walk	-0.0063	3.3596	119.9482	7.1053	0.0185
		(-1.4205)	(1.6022)	[0.0000]	(0.8505)	
	Hist. Mean	0.0011	0.1407	10618.2400	2.7432	0.0198
		(3.6480)	(12.0783)	[0.0000]	(0.9971)	
	GARCH(1,1)	0.0007	0.4137	11.2541	1.2431	0.0286
		(2.2579)	(5.9790)	[0.0035]	(1.000)	
	TGARCH(1,1)	0.0008	0.3399	18.5942	1.2705	0.0252
		(2.5704)	(6.7710)	[0.0000]	(1.000)	
	EGARCH(1,1)	0.0006	0.5069	5.5123**	1.3083	0.0301
		(1.5894)	(6.5475)	[0.0635]	(1.000)	

Panel C. Forecast Horizon: 13 Weeks

Index	Model	α	β	$\chi^2(2)$	$Q(12)$	R^2
SMALL	Random Walk	0.0027	0.191648	44.1330	1.9981	0.03667
		(3.1492)	(1.4790)	[0.0000]	(0.9994)	
	Hist. Mean	-0.0382	8.864010	21.9457	7.2000	0.08781
		(-1.5075)	(1.5874)	[0.0000]	(0.8441)	
	GARCH(1,1)	-0.0020	1.722422	10.2020	10.6561	0.72386
		(-3.1887)	(6.6368)	[0.0060]	(0.5585)	
	TGARCH(1,1)	-0.0017	1.687609	8.4407	9.5766	0.71917
		(-2.8952)	(6.5421)	[0.0146]	(0.6530)	
	EGARCH(1,1)	-0.0027	2.210739	27.8045	10.4022	0.78715
		(-5.1108)	(9.2405)	[0.0000]	(0.5807)	
LARGE	Random Walk	0.0056	0.0338	498.5273	1.4772	0.0011
		(4.0852)	(0.6891)	[0.0000]	(1.0000)	
	Hist. Mean	-0.0200	2.4506	87.8585	2.1152	0.0472
		(-1.3380)	(1.6176)	[0.0000]	(0.9992)	
	GARCH(1,1)	-0.0060	1.7130	18.3977	9.7165	0.6772
		(-3.4296)	(6.1013)	[0.0001]	(0.6408)	
	TGARCH(1,1)	-0.0029	1.2522	9.4301	8.2690	0.6209
		(-1.9410)	(5.0272)	[0.0089]	(0.7637)	
	EGARCH(1,1)	-0.0046	1.6754	11.0827	5.3081	0.5429
		(-3.0640)	(8.1562)	[0.0039]	(0.9468)	
VALUE	Random Walk	0.0042	0.1122	135.6592	4.1077	0.0125
		(3.9919)	(1.4697)	[0.0000]	(0.9814)	
	Hist. Mean	-0.0183	2.8551	37.0863	6.1605	0.0476
		(-1.3650)	(1.6331)	[0.0000]	(0.9077)	
	GARCH(1,1)	-0.0028	1.5310	6.2977	8.5051	0.5789
		(-2.1614)	(4.7438)	[0.0429]	(0.7445)	
	TGARCH(1,1)	-0.0017	1.2871	1.9001**	7.5479	0.5434
		(-1.3572)	(4.8628)	[0.3867]	(0.8193)	
	EGARCH(1,1)	-0.0038	1.8487	4.4733**	8.6537	0.5133
		(-2.1146)	(4.4069)	[0.1068]	(0.7321)	
GROWTH	Random Walk	0.0039	0.0681	233.5038	1.1615	0.0046
		(3.3420)	(1.1151)	[0.0000]	(1.0000)	
	Hist. Mean	-0.0237	3.8059	119.6914	2.1677	0.0538
		(-1.2942)	(1.4394)	[0.0000]	(0.9991)	
	GARCH(1,1)	-0.0039	1.7810	20.5127	9.8167	0.7710
		(-4.3419)	(7.7553)	[0.0000]	(0.6320)	
	TGARCH(1,1)	-0.0032	1.5581	17.5454	10.2637	0.7603
		(-3.9385)	(7.7949)	[0.0001]	(0.5928)	
	EGARCH(1,1)	-0.0046	2.0637	15.9092	10.5558	0.7366
		(-3.9740)	(6.8890)	[0.0003]	(0.5673)	

Note: The table reports results of the regression $\sigma^2_{Index} = \alpha + \beta\hat{\sigma}^2_{m,j} + u$, where dependent variable is the variance of index returns and independent variable is the forecasted variance from model m at horizons j = 1, 4, 13 weeks. T-statistics using Newey - West heteroskedasticity and autocorrelation correction are in parenthesis under the coefficient estimates. The $\chi^2(2)$ column gives the point estimate and asymptotic p-values in brackets for H_0: $\alpha = 0$, $\beta = 1$. R^2 is the coefficient of determination and Q(12) is the Box - Pierce Q statistic that test the hypothesis that all autocorrelations up to 12 lags are jointly zero, with it's p value in parenthesis below it

CHAPTER 10

"*Conclusions, Implications and Suggestions for Further Research*"

10.1 Main Findings and Conclusions from the Thesis

This thesis examines the performance and risk characteristics of various style portfolios in UK over the last thirty years (1968-1997) and sheds some light on the debate of whether it is risk differences, or market overreaction that can justify the difference in performance between value and growth stocks. Moreover, the short-term variation in return spreads and volatility is investigated and the opportunities for profit enhancement and volatility reduction through style rotation are evaluated. The main findings and fundamental conclusions from the research are summarised as follows:

Various size and value portfolios are constructed by classifying a large range of stocks based on market value, book-to-price, earnings-to-price, cash flow-to-price and historical EPS growth, using a variant of the Fama and French (1995) independent groups method. Our results indicate an economically and statistically significant positive relation between book-to-price and stock returns, confirming the findings of U.S studies. High book-to-price (value) stocks outperform low book-to-price (growth) stocks, by more than 10% per annum, and this difference persists in all subperiods and after adjusting for market value. When, however, earnings, cash flow yield, or past EPS growth is used to proxy value and growth, no significant difference is observed between the two equity classes. Furthermore, small-caps outperform large-caps, but this outperformance is not statistically or economically significant, mainly due to the poor performance of smaller companies over the last decade.

A challenging research question is why return differences between equity classes are observed and what can explain the value-growth premium in UK. We investigate two competing hypotheses; risk differences against market overreaction. According to the first, style premiums can be attributed to differences in various risk factors. Using a pooled time series - cross sectional methodology suggested by Roll (1995), we test whether market, industry, or macroeconomic risk factors can explain the size and value style premiums. Our results indicate that CAPM betas of several size and value portfolios are not significantly different and market risk alone can not explain the long-term return differences between style portfolios.

Size and value portfolios exhibit different sensitivity to industry portfolio returns. We find that the impact of industry risk is much higher between small and large companies than between value and growth. Nevertheless, adjusting for these differences strengthens the size and value effects and leads to statistically significant excess returns of the size and value arbitrage portfolios.

We also employ a multi-factor macroeconomic model to test whether there are important differences in the sensitivities of style portfolios to common macroeconomic factors. Although, we identify some important differences in economic risks between size portfolios, no significant difference in macroeconomic risk of any source is evident between value and growth portfolios. High book-to-price securities continue to earn significantly higher returns compared to their counterparts, even after adjusting for market, industry or macroeconomic risk differences.

This leads us to examine an alternative hypothesis consistent with market inefficiency and irrational pricing. According to that, investors make systematic errors in their expectations about the future prospects of value and growth stocks, by looking either at their past performance and profitability (extrapolation), or at analysts EPS forecasts. These errors cause an overreaction, which results to a certain misspricing of these equity classes that may explain the difference in their returns.

We find that, although the relative reversal patterns in price performance (for all value and growth portfolios) and earnings growth (for B/P and EPS growth portfolios) are consistent with the naïve extrapolation hypothesis, investor's extrapolation of past performance and earnings growth cannot justify the difference in the performance between value and growth portfolios. We document, however, that extreme expectations are reflected on analysts' earnings forecasts. We show that positive and negative earnings surprises have an asymmetric effect on the returns of value and growth, in favour of the former, in a fashion that is consistent with the error in expectations hypothesis. A positive surprise is regarded as good news for value stocks and has a significantly more positive impact on their returns compared to growth stocks. On the other hand, a negative surprise is regarded as bad news for growth stocks and has a significantly more negative impact on their performance, with only a minor impact on the returns of value stocks.

Although, the average size and value return spreads are positive in the long term, we observe that there are a significant number of periods when the spreads are negative and large-cap and growth become the dominant styles. This implies that significant profits can be realised by forecasting the sign of the style spread and switching on a monthly basis from one equity class to another. The profits from style rotation, however, directly depends on the variability of the underlying spread, the amount of transaction costs, and most importantly the level of forecasting skill. We show that even after assuming 200 basis points round-trip transaction costs, rotating between small and large-cap securities can be advantageous compared to a passive buy-and-hold strategy with less than 70% forecasting accuracy. On the other hand, more than 80% forecasting skill is required on average, in the case of value/growth timing strategy, to outperform the benchmark. The required forecasting skill drops significantly when we adjust for lower level of transaction costs

Forecasting the style spreads however is not straightforward. We find that a logit regression model that uses various market and macroeconomic factors can only explain a small percentage of the two spreads' variances. Nevertheless, trading rules developed based on estimated logit probabilities can be highly rewarding in the case of small / large rotation, but only marginally successful in the case of value and growth stocks, after adjusting for realistic levels of transaction costs. Our results suggest that, given the variability in the sign of the size and value premiums, an active style rotation between size portfolios is more likely to be successful, than a similar rotation strategy between value and growth stocks.

Style rotation may also require a proper modelling and accurate forecasting of the volatility of style returns. We find that volatility of weekly style index returns is not constant over time, but time varying and the sample or unconditional variance shouldn't be used to describe the risk of style portfolios. We suggest various GARCH parameterisations to characterise the volatility properties of different style indices. We find that large-caps display the higher persistence in variance and the higher on average conditional volatility. In addition, high B/P (value) stocks have slightly higher average conditional variance compared to growth, but there are still many periods where low B/P (growth) volatility exceeds value. We also find that only the variance of large and growth stocks is affected by movements in short-term interest rates, whereas the relation is very week in the case of the other two indices. Finally, we detect an asymmetry in the way volatility responds to bad and good past unexpected events just for large and liquid securities and not for the other equity classes.

A standard GARCH and two asymmetric GARCH models are then compared with two simple models (random walk, long-term mean) for their ability to forecast future variances at different horizons. Our results indicate that GARCH class of models, particularly EGARCH (1,1), dominate the random walk and the homoskedastic model in out-of-sample forecasting of volatility for all equity style indices, and this superiority is more clear at longer horizon forecasts (4 weeks and 13 weeks).

These results have important implications in dynamic style rotation strategies. We emphasise that, by implementing value and growth volatility forecasts from different models into a quarterly minimum variance optimisation. We find that GARCH volatility forecasts lead to an improved value/growth allocation across time and consequently lower portfolio variance. Therefore, any portfolio manager which is interested in style rotation, should model the variance of the individual equity classes using some sort of GARCH specification.

10.2 Limitations of the Thesis and Suggestions for Further Research

Since the main conclusions of this thesis rely on empirical findings, there are some important limitations in the research design and methodology that need to be emphasised. Furthermore, the thesis has identified as many research questions and areas for further research as it has sought to address.

First of all, since there is not accepted definition of value and growth. We experiment with different variables, using a variant of the Fama and French (1995) independent groups method. It would be useful to replicate the results of this study, using alternative methodologies for creating value and growth style indices, and test whether our findings are sensitive to the method we choose to construct portfolios. A more sophisticated approach that utilises multiple criteria to classify stocks into value and growth categories could give a more precise definition.

The study emphasises the positive and significant relationship between book-to-price and stock returns and points out that value strategies work only when that particular ratio is employed to construct portfolios. An interesting research question is what differentiates book-to-price ratio from the other two fundamental ratios (earnings-to-price and cash flow-to-price) and what makes book-to-price be more positively related to stock returns than earnings and cash flow yield.

Chapter 6, examines whether differences in market, industry or macroeconomic factor betas can explain the size and value effects. The analysis that is provided, however, uses unconditional betas and risk premiums, assuming that risk is constant through time. Conditional asset pricing models, which allow betas and risk premiums to vary over time, might be more useful in describing differences in risk characteristics between style portfolios. Time varying betas may be able to explain the variability of size and value-growth return spreads and creates the framework for a successful style rotation model.

Another important issue is related to the impact of earnings surprises to the returns of value and growth portfolios that is investigated in chapter 7. In this chapter, we examine the relationship between earnings surprises and one-year holding period returns. The short-term effect to returns immediately after the realisation of the surprise is also of great interest. An event study, which allows the calculation of abnormal returns for few days around the announcement of the earnings, would provide a useful insight towards assessing the reaction of different style portfolio returns to positive and negative earnings surprises.

A number of different directions for research can be suggested on the issue of style rotation. This thesis examines the rotation between two distinct equity classes. Style timing is implemented either switching between aggregate small and large-cap stocks, or by independently switching between high and low book-to-price securities. Another useful extension is to study the opportunities and the feasibility of a style rotation that involves more than two equity classes. Rotating, for example, among small-cap value, small-cap growth, large-cap value and large-cap growth. The identification of the required forecasting ability and the potential gains and risks involved from this type of active equity management, are some of the issues that could be researched.

Furthermore, the logit model that we propose for style rotation is rather limited as it enables the forecast of the direction and not of the magnitude of the style spreads over next month. In addition, the returns and variances of style indices are modelled and forecasted separately and the covariance of the returns is assumed to be constant. A multivariate GARCH model, which allows both the variances and the covariances to be time varying and enables a joint estimation of all the parameters that are needed for an optimisation process, can be extremely useful and may lead to more precise forecasts. A joint estimation of the first and the second moments of the return distribution of style indices also allows a proper estimation of conditional Sharpe ratios, which can be used as indicators for active style rotation strategies.

The research of whether GARCH is the most appropriate model to forecast style return variances is far from complete. Chapter 9 of this thesis proves that volatility is time varying and GARCH models should be preferred from constant variance models. Alternative specifications, however, may give more precise estimates of next period's volatility for style indices. Non-parametric, stochastic volatility and exponential weighted moving average models are some other approaches that can be used and compared with GARCH models. All the above issues constitute important directions for further research and may certainly help us to gain an insight into some aspects of asset pricing and active equity management.

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