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STYLE ANOMALIES ON THE LONDON STOCK EXCHANGE:

AN ANALYSIS OF UNIVARIATE, MULTIVARIATE AND TIMING STRATEGIES

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Prepared under the supervision of Professor Paul van Rensburg and presented to the School of Management Studies in fulfilment of the requirements for the degree of

MASTER OF COMMERCE

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February 2005

Abstract

According to Dimson (1998), modern financial theory is founded on the assumption that markets are highly efficient. The presence of anomalous stock market behaviour has therefore attracted a great amount of research internationally. This thesis investigates the presence and exploitability of style anomalies on the London Stock Exchange (LSE) and is divided into three main branches of research.

Firstly, a methodology similar to Fama and Macbeth (1973) is used to empirically investigate cross-sectional relationships between a wide range of firm-specific attributes and monthly returns on the FTSE All share index. The results show that interest cover before tax, three-month, six-month, one-year and eighteen-month momentum, crossover3_12, beta, and return on equity are found to be significantly positively related to future returns while log of price, the payout ratio, and price variance are found to be significantly negatively related to future returns. These so called 'anomalies' persist after a CAPM risk adjustment, with only return on equity becoming insignificant. The anomalies also persist after a three factor APT risk adjustment with only the payout ratio and return on equity becoming insignificant. Most relationships are found to hold out-of-sample, although a few changes occur to the list of significant attributes, suggesting a need for style timing.

Secondly, useful univariate attributes are used to develop multivariate expected return models. The optimal method of selecting attributes for multifactor models is investigated by constructing models using stepwise procedures based on different selection criteria and comparing the out-of-sample performance of these models. The information coefficient (IC) is found to be the best selection criteria outperforming all other criteria as well as the all attribute model. Multifactor models show robust performance achieving an IC of over 0.1 out-of-sample. Results indicate that out-of-sample performance is largely dependent on the number of factors included in a model. Including too many factors lowers forecast accuracy and including too few raises the likelihood of missing a performing factor.

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Thirdly, the predictability of style payoffs is investigated. Robust relationships are discovered within the time-series of payoffs. There is strong low order autocorrelation, most powerful at one lag for the majority of styles. Trailing moving averages are found to have strong forecasting power with six-month and one-year moving averages dominating eighteen-month and two-year moving averages. Style payoffs are found to have an element of seasonality with a few styles paying off more strongly in April – the tax year end for individuals in the UK. A number of Granger dynamic relationships are discovered between payoffs and stationary macroeconomic variables, mostly related to the business cycle. As a broad generalisation, styles perceived to be riskier, such as size, risk, and momentum, perform better when the economy is strong and styles perceived to be 'safer', such as value, perform better when the economy is weak. Eight style payoff forecasting models are tested: three regression based models, one based on the past twelve month trailing mean payoff (12M Reg), one based on the first twelve lags (AR12) and one based on a selection of time-series variables and lagged macroeconomic variables (Consolidated), and five trailing mean models, forecasting based on the entire historic trailing mean (Mean), the eighteen-month trailing mean (18M), the twelve-month trailing mean (12M), the six-month trailing mean (6M) and the trailing observation (1M).

Over all styles individually, the 1M model performs best out-of-sample, followed by the 6M model. The mean model is found to be the worst model tested in- and out-of-sample providing strong evidence that style payoffs are time varying. The Consolidated model is beaten out-of-sample by the more simple trailing mean models that forecast based on the mean payoff over a trailing period. The most important source of forecasting power is therefore located in the time-series of payoffs itself. This conclusion is confirmed in multivariate tests, where the 6M model is found to perform best, achieving an out-of-sample IC of 0.14. Out-of-sample results show strong evidence that timing strategies, particularly the use of a six-month trailing mean, can enhance the explanatory power of multifactor expected return models.

Declaration

I, Steve Bradshaw, hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other University. I empower the University to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

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Acknowledgements

The author would like to acknowledge the supervision and guidance of Professor Paul van Rensburg of the University of Cape Town.

The author would also like to acknowledge his use of the newly extended Finance Research Laboratory at the University of Cape Town, Management Studies Department.

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Introduction

"There is mounting evidence that relative stock returns can be predicted by factors that are inconsistent with the accepted paradigms of modern finance."

Haugen and Baker (1996)

1.1. Introduction

For a number of years the Capital Asset Pricing Model (CAPM) credited to Sharpe (1964), Lintner (1965), and Black (1972) and Ross's (1976) Arbitrage Pricing Theory (APT) were held as complete accounts of risk and return in capital markets and the assumptions regarding investor rationality and efficient markets were widely accepted. Over time however, an enormous body of empirical research has shown that there are firm-specific variables other than CAPM and APT variables that explain the cross-section of expected returns. These variables, termed style[1] anomalies, either draw their explanatory power from rational sources such as liquidity and risk or from irrational sources such as over-reaction and neglect. In either case, the exploitation of these anomalies has led to abnormally high returns after adjusting for conventional measures of risk. Furthermore, the same anomalies have consistently appeared in empirical studies on developed and developing markets, implying that the anomalies represent systematically priced variables. Unfortunately, the joint hypothesis problem prevents the outright rejection of both market efficiency and the CAPM and APT models as the two ideas are inseparable. However, it has been demonstrated in most markets that firm-specific variables (the so-called anomalies) have more explanatory power than conventional risk variables over the cross-section of expected returns.

The concept of equity styles has been around for decades. An equity style is simply an equity class, a portfolio of shares that share a common characteristic. Style portfolios may comprise small shares, growth shares, value shares or shares with the same technical price history. Kao and Shumaker (1999) agree with this general definition of styles, proposing risk, size, value, growth, quality, momentum, leverage and even market sectors as examples of styles.

[1] The terms style, style anomaly, attribute and firm-specific attribute are used interchangeably

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Haugen and Baker (1996) demonstrate that it is possible to combine styles into a multivariate framework that is better able to exploit anomalous behaviour. They construct expected return models based on medium term relationships between styles and expected returns in five developed markets. The models all show robust performance out-of-sample.

Despite consistency across markets, evidence has revealed that important styles may change direction for extended periods of time. For instance, large firms outperformed small firms in the United Kingdom (UK) over the period 1985 – 1993. It is held that the reason for such reversals is that style payoffs are conditional on underlying conditions in the macroeconomy. Expected return models therefore need to take into account patterns in style payoffs if they are to fully exploit anomalies.

"The ongoing 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 indexes can be value-enhancing."

Levis and Liodakis (1999)

A schematic representation of the branches of research covered in this thesis, based on the market efficiency framework described by Fama (1991) is displayed in *Figure 1.3.1.*

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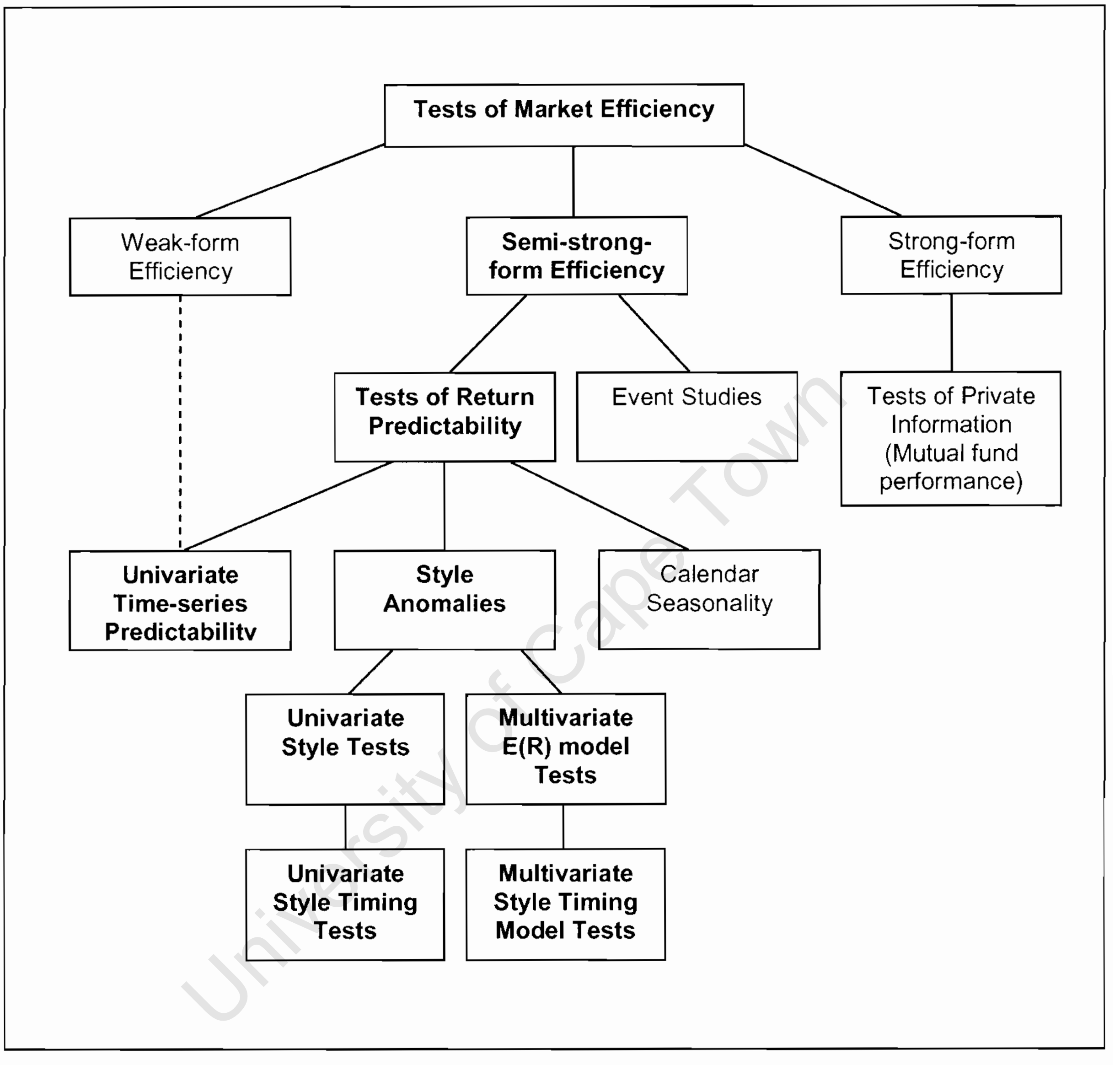
Figure 1.3.1. Schematic Representation of the Area of Research

Represents the main branches of research related to market efficiency showing the decomposition of work relating to style anomalies in this thesis. The schema is adapted from the overview provided in Fama (1991) Areas of research covered in this thesis are bolded



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1.2. Contribution

This thesis contributes to the body of research investigating style anomalies in the UK. This thesis aims to find the best combination of important attributes to construct an optimal expected return model in the UK. As mentioned, a vast number of studies have been performed around the world on attributes and combinations of attributes that are related with outperformance (anomalies), however the area of how best to combine these attributes into a multivariate framework has received little attention. Haugen and Baker (1996) assume that a model incorporating as many influential factors as possible will produce the optimal result. This study aims to test the validity of this assumption.

More evidence is provided on the predictability of style payoffs in the UK. Style momentum, calendar seasonality, and economic relationships are investigated.

This thesis provides one of the first documented attempts to extend a regression based methodology to include aspects of style timing. Whilst other authors have looked at strategies involving rotation between style portfolios, it appears that none have integrated timing with multivariate regression based methodologies. Forecasting models are initially evaluated on their ability to predict future style payoffs for each style individually. The different forecasting models are then used to construct multifactor expected return models. A comparison of these models reveals which forecasting methodology is most appropriate in a multivariate environment.

The division of the data set into in-sample and out-of-sample data sets allows for robust conclusions to be drawn from all tests performed.

1.3. Thesis Organisation

Chapter two provides an overview of the theory relevant to research conducted in this thesis. The chapter discusses concepts related to market efficiency, the random walk model, and the development of two major asset pricing models, the CAPM and the APT. This is followed by a brief synopsis of the main explanations provided in the literature for style anomalies. The chapter provides a theoretical background to expected return modelling within a multivariate framework, introducing some of the performance measures used to evaluate a model's explanatory power. The chapter concludes with an introduction to style timing, discussing the two main areas of research, style momentum and economic relationships.

Chapter three outlines international research relating to style anomalies, expected return modelling and style timing.

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Chapter four provides an extensive summary of style research in the UK. The chapter reviews studies on the topic of market efficiency in the UK highlighting studies that investigate style anomalies. Since most research has focussed on the areas of value, momentum and size, these anomalies receive much of the attention. A brief overview of calendar seasonality in the UK is provided. The chapter concludes with a review of Levis and Liodakis (1999) who are responsible for the most notable work on style timing in the UK.

The research objective of this thesis forms Chapter five.

Chapters five, six and seven pertain to the three main areas of empirical research conducted. The data and methodology used in each chapter is discussed at the start of the chapter. Chapter six contains both univariate and multivariate testing. The share return and attribute data sets are introduced and several adjustments to the data set are discussed and implemented. All analysis is performed first on the in-sample period 1 March 1990 – 1 February 2000, leaving the out-of-sample period, 1 March 2000 – 1 February 2004, to confirm in-sample results. The univariate section adopts the cross-sectional technique of Fama and Macbeth (1973) to investigate which individual attributes are significantly able to forecast the variation in realised returns. The same univariate tests are run after risk adjusting the returns data set using first the CAPM and then a three factor APT model. A cluster analysis is performed on the monthly payoffs produced by each anomaly. The multivariate section applies a similar methodology to that of Haugen and Baker (1996) to construct multifactor expected return models using in-sample data. A step-wise model construction procedure is tested using different criteria for the inclusion of factors into the model. The models are then evaluated out-of-sample.

Chapter seven contains the primary tests on style timing. Style momentum, style seasonality, and the existence of relationships between style payoffs and economic variables are investigated in-sample. These results are used to develop the forecasting models in Chapter eight.

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Chapter eight develops eight style forecasting models. In the first section the forecasting models are evaluated individually for each style. The second section applies the eight forecasting models to the Haugen and Baker (1996) multivariate framework and the overall ability of each forecasting method is evaluated.

Chapter nine reviews the implications of results from univariate, multivariate and style timing tests and concludes the thesis.

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2

Theoretical Overview

2.1. Introduction

The degree to which asset returns are predictable attracts a great deal of interest from both academics and practitioners. Academics wish to develop an understanding of the return generating process and evaluate the extent of informational efficiency in stock markets while practitioners wish to exploit empirical results to achieve improved rates of return. In this chapter, some of the more influential theory relating to market efficiency, asset price modelling, style anomalies, expected return modelling and style timing is reviewed.

The remainder of this chapter is set out as follows. *Section 2.2.* discusses theory relating to market efficiency, *Section 2.3.* discusses explanations provided for stock market anomalies, *Section 2.4.*discusses theory relating to the construction and evaluation of multifactor expected return models, *Section 2.5.* discusses theory relating to style timing, and *Section 2.6.* summarises the key theory and concludes.

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2.2. Market Efficiency

According to Dimson (1998), modern financial theory is founded on three central assumptions, that markets are highly efficient, that investors exploit potential arbitrage opportunities, and that investors are always rational. Fama (1970) develops the idea of an efficient market in which all relevant information is impounded into the price of financial assets. Market efficiency was originally described by Bachelier (1900) who postulated that

"past, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes".

The random walk theory of share prices implies that successive returns are serially independent implying that the last share price is the best prediction of all future share prices. Karl Pearson (1905) likens the theory to the search procedure for finding a drunk left in a middle of a field. If the drunk can be expected to stagger in a totally unpredictable and random fashion, he is likely to end up closer to where he had been left than to any other point! Kendall examined 22 UK stock and commodity price series, concluding that the random changes from one period to the next swamp any systematic effect which may be present. These empirical observations came to be labelled the random walk theory.

Fama (1970) outlines three forms of this market efficiency: weak form, semi-strong form and strong form. The weak form of the efficient market hypothesis claims that prices fully reflect the sequence of past prices. The semi-strong form asserts that prices reflect all publicly available relevant information, while the strong form of market efficiency asserts prices reflect information known to any participant. Fama (1970) finds markets in the United States of America (US) to be weak-form efficient.

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Markowitz (1952) presented a theory of portfolio risk and return, showing how investors could optimise their portfolios. Markowitz's (1952) model generates the efficient frontier of portfolios. Each investor is expected to select an efficient portfolio according to his own level of risk aversion. Sharpe (1964) Lintner (1965) and Black (1972) extended Markowitz's (1952) model to develop a single index model known as the capital asset pricing model (CAPM) where the return on each individual security is related to the return on the market index. Based on a number of assumptions about market efficiency, the CAPM derives beta as the only priced risk factor. All non-systematic (asset specific) risk is diversified away by investors, leaving the market risk factor as the only priced explanatory variable. The return generating process is represented by

$$R_{it} = r_f + \beta_i (r_m - r_f) + \varepsilon_{it}, \tag{1}$$

where R_{it} is the realised returns earned by share i in time period t, r_f is realised return on a risk-free asset, r_m is the realised return on the market portfolio, ε_{it} is the error term, and β_i is the beta coefficient for share i measuring the share's systematic risk or sensitivity to the market factor, derived as:

$$\beta_i = \frac{\text{cov}(R_i, R_m)}{\sigma_m^2}. \tag{2}$$

CAPM and market efficiency became the dominant paradigm in finance during the 1970s. A large body of empirical research demonstrated the difficulty of beating the market by analysing publicly available information or by employing professional investment advisors (Dimson, 1998).

A turning point occurred with Roll's (1977) CAPM critique. Previously the CAPM was tested using a broad equity market index such as the S&P500 as the market portfolio. Roll (1977) demonstrates that the market, as defined in the CAPM is an index of all wealth including bonds, property, foreign assets, human capital, etc. Roll argues that unless this market portfolio is known with certainty, the CAPM can never be tested. Many subsequent tests of the CAPM have interpreted their results in terms of the mean-variance efficiency of the portfolio used to proxy the market portfolio. In addition, Roll (1976) and many others find the positive beta return relationship insignificant. Fama and French 1992 show that many other explanatory variables are better able to explain returns than beta.

Unlike previous studies, Pettengill, Sundaram & Mathur (1995) find support for a significant beta-return relationship in the US data between 1926 and 1990. Pettengill *et al.* (1995) contend that the CAPM models *expected* and not *realised* returns. They predict a positive beta-return relationships in months where the excess return on the market is positive (*up market months*) and an inverse relationship in months where the excess return on the market is negative (*down market months*). They argue the beta-return relationship should be inverted in down market months as shareholders are not rewarded for holding shares with low betas or diversifying away non-systematic risk. Adjusting for expectations of negative market returns, Pettengill *et al.* (1995) find a consistent and significant relationship between beta and returns over their entire sample period. This result does not directly support the CAPM model, but implies that beta is a useful measure of risk.

The arbitrage pricing theory (APT), proposed by Ross (1976) integrates a multiple factor return generating process with arbitrage principles. The result is a multi-risk-

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factor pricing model that is not reliant on the CAPM market portfolio, indeed the factors are not explicitly identified. APT is represented by the following linear k-factor model,

$$R_{it} = E(R_{ft}) + \sum_{k=1}^{K} \beta_{ik} f_{kt} + \varepsilon_{it} \tag{3}$$

where,

R_{it} = realised returns earned by asset i in time period t, where i = 1,2… N and t = 1,2… T

R_{ft} = realised returns earned by a risk-free asset in time period t, where i = 1,2… N and t = 1,2… T

$E(R_{it})$ = expected rate of return of asset i for period t at the beginning of period t

f_{kt} = the k^{th} risk factor that impacts on asset i's returns at time t, where k = 1,2… K.

β_{ik} = an OLS regression estimated coefficient that measures the sensitivity of R_{it} to movements in f_{kt}

ε_{it} = a normally distributed random error term t which measures the unexplained residual return of asset i in period t, where $E(\varepsilon_{it}) = 0$.

All risk factors represent unexpected movements in pervasive economic forces and have expected value of zero (i.e. $E(f_{kt}) = 0$). The risk factors can be obtained through factor analysis or selected from a universe of macroeconomic factors. The former has the drawback that factors usually have no economic interpretation. Chen, Roll and Ross (1986), who pioneered the economic factor approach, argue that there exists a fundamental valuation model that determines asset prices. They contend that the choice of factors should include any systematic influences that impact future dividends, the way traders and investors form expectations, and the rate at which investors discount future cash flows. It is widely held that the APT model gives a more accurate account of risk, particularly in markets where there is more than one systematic risk factor.

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A central difficulty in interpreting studies that test market efficiency is the joint hypothesis problem. In any test, the magnitude of over-performance depends critically on the choice of benchmark (Dimson and Marsh, 1986), making it difficult to interpret results. Anomalies may be an indication of market inefficiency or alternatively an indication of shortcomings in the asset pricing model being used. Even if there is no misestimation or bias in computed abnormal returns, the underlying asset pricing model may be misspecified. Therefore, an evaluation of market efficiency is inescapably an evaluation of an asset pricing model.

2.3. Style Anomalies

A multitude of studies (most notably Fama and French, 1992) have shown sets of shares with a common firm-specific attribute (style) outperforming or underperforming the market on a risk adjusted basis. The anomalous styles represent risk, value, growth, profitability, liquidity, size, and technical (momentum) factors. There are a number of competing explanations for the existence of these style anomalies. Some view the anomalies as general violations of market efficiency, while others such as Ball (1978) and Fama and French (1992) believe the anomalies represent risk-premia unaccounted for in conventional asset pricing models. Van Rensburg (2001) groups the explanations into three categories of arguments, (i) methodological bias, (ii) Investor irrationality, and (iii) Investor rationality.

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2.3.1 Arguments of Methodological bias

Kandel and Stambaugh (1995) demonstrate that CAPM mispricings can arise when betas are calculated using a market portfolio that lies inside the minimum variance portfolio. This could explain systematic deviations from CAPM predictions. Roll and Ross (1994) concur that empirical studies have failed to produce the hypothesised relation between betas and returns suggesting that the cause is the mean-variance inefficiency of the market proxy.

Berk (2000) shows that the portfolio sorting and testing procedure used by, among others, Fama and French (1995) is statistically flawed. Berk shows that portfolio return predictions obtained using an asset pricing model will be less extreme than the true predictions of the model. This is because the overall variance of predictions is downwardly biased. According to ANOVA theory the overall variance of returns can be separated into variance within portfolios and variance between portfolio's. Berk demonstrates that the latter is not captured by the testing procedure. As the procedure forms portfolios using a variable known to be related to return, the result of the bias is that portfolio means do not have to be as extreme to be significant. This results in an increase of significant CAPM anomalies. This problem with portfolio sorts is the main reason that this thesis adopts a regression approach rather than a portfolio approach.

These arguments contend that anomalies are either spurious (sample specific) or a result of flaws in the data set or methodology. Lo and MacKinlay (1990) show that the effects of data-snooping can have a considerable effect on results. They argue that researchers aware of the properties of a data set, through their own work or through previously published work, can easily report spurious relationships. Kothari, Shanken and Sloan (1995) investigate the problem of survivorship bias arising when a data set completely excludes shares delisting during the period analysed. They postulate that the cause of delisting is usually due to financial distress and conclude that the returns of surviving shares may overstate reality. Banz and Breen (1986) highlight another problem known as look-ahead bias. Look-ahead bias occurs when data reflects information not yet available to market participants.

There is now a considerable body of research documenting the anomalies across different markets and time periods. For an example of an international study, see Haugen and Baker (1996). The argument that anomalies are spurious is therefore becoming increasingly unconvincing. Survivorship bias has been shown to be less problematic than initially suggested (See Chan, Jegadeesh and Lakonishok, 1995) and look-ahead bias is only a problem in certain data sets.

A review of the data and methodological biases encountered along with the treatment of each is presented in *Section 6.2.3.* and *Section 6.3.3.* respectively.

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2.3.2. Arguments of Investor Irrationality

These arguments fall into the category of research branded behavioural finance. The central idea is that anomalies persist because of investor behavioural patterns inconsistent with rational theory. De Bondt and Thaler (1985) find that shares that performed poorly over the previous three to five year period *(losers)* outperform *winners* in the next three to five years. The mean reversion of returns is explained by the so-called *overreaction hypothesis* that investors over- (under-) value shares that have performed well (poorly) in the past. This explanation is supported by Lakonishok, Shleifer, and Vishny (1994), Jegadeesh and Titman (1993), and Haugen (1995) who employ contrarian value strategies to exploit the irrational behaviour. De Bondt and Thaler (1985) and Lakonishok, Shleifer, and Vishny (1994) also observe irrational investor behaviour relating to the price-earnings multiple (P/E) of a share. They find that *glamour* shares with high P/E ratios have done well in the past and are temporarily overvalued. They reason that investors extrapolate past earnings too far into the future, not accounting for the effects of competition. *Value* Shares with low P/E ratios are thought to be temporarily undervalued because investors are overly pessimistic.

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Behavioural explanations have been around for many years, De Bondt and Thaler first published their findings in the US in 1985, yet increased competition among investment managers has not resulted in increased market efficiency and the reduction of reported anomalies (Haugen, 1995). Lakonishok, Shleifer and Vishny (1994) provide a reason for this. They suggest that large institutional investors are also attracted to *glamour* shares due to a phenomenon he terms 'window dressing'. Managers include shares that have provided good returns in the past and are unlikely to go bankrupt in the future as these shares are favourably perceived by *naïve* investors who consequently invest in their funds. This agency problem is widespread as many institutional investors are remunerated based on the funds under their control. Haugen (1995) also reasons that institutional fund managers may ignore value strategies that take longer to payoff as they are forced to focus on short-term returns due to performance evaluation and compensation structures.

2.2.3. Arguments of Investor Rationality

Fama and French (1992, 1993, 1995, 1996a, 1996b, 1998) and Ball (1978) propose that the so called 'anomalies' are consistent with market efficiency. They argue that anomalies result from misspecified asset pricing models that do not give a full account of the risk-profile of each share. They interpret size and book-to-market (B/M) as proxies for 'unobserved' risk factors, arguing that firms with similar attributes are sensitive to the same macroeconomic factors like growth surprises and interest rate risk. Ball (1978) agrees that empirical contradictions of the CAPM are more likely caused by a fault in the pricing model than by market inefficiency. Ball (1978) proposes that the P/E ratio acts as a 'catch-all' accounting for all risk factors omitted by asset pricing tests. He argues that riskier firms have higher expected returns and therefore lower prices. The market consensus of a firm's overall risk profile is represented by the firm's P/E ratio. Lakonishok, Shleifer and Vishny (1994) raise the point that it is impossible to reject a risk based explanation that relies on an unspecified multifactor model. Any attribute that explains returns is simply proposed as a proxy for some unobservable risk factor. Lakonishok, Shleifer and Vishny (1994) report that the weight of evidence contradicts the notion that *value* strategies are fundamentally riskier. Fama and French (1996a) acknowledge this weakness suggesting that a strong economic framework for risk needs to be constructed to support their empirical findings.

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Another argument regarding liquidity is proposed by Amihud and Mendelson (1986.) They show that a relationship between liquidity and returns remains after adjusting for CAPM risk. Brennan and Subrahmanyan (1996) find a liquidity premium on shares with lower trading volumes that persists after adjusting for risk using the Fama and French (1992) 3 factor model. Brennan, Chordia and Subrahmanyan (1998) show that the relationship persists after an APT risk adjustment. The argument proposes that any value strategies that rely on investing in less liquid shares may achieve abnormal returns due to the liquidity premium. Roll (1981) argues that the CAPM size anomaly is a result of misspecification of CAPM risk due to autocorrelation caused by thin-trading. He shows that the bias has a significant effect on daily data, and less so on monthly data. Dimson and Marsh (2001) however show that the UK size effect persists when portfolios are rebalanced annually and annual returns are compared. It is very unlikely therefore that the size effect is a result of thin trading.

2.4. Expected Return Models

Expected return models attempt to explain the cross-section of future returns. They use quantitative methods on historically price-sensitive information to develop predictions for individual share returns. To do this, they cross-sectionally estimate the tendency for shares with differing exposures to different style attributes to earn differing returns using either a portfolio sorting or regression analysis approach. Models can then be used to place long and short bets on shares expected to finish in the top and bottom return fractiles respectively.

2.4.1. Portfolio Sorting versus Regression Analysis

Two approaches, portfolio sorting and regression analysis, are commonly used to investigate style anomalies and create expected return models. The portfolio sorting approach involves the monthly sorting of shares into fractiles according to a firm-specific attribute or combination of attributes and comparing the average returns earned by each fractile. In more developed markets this approach is simplified by the public availability of style indexes. The regression approach involves simultaneously estimating the cross-sectional regression coefficients (monthly payoffs) to a selection of firm-specific attributes, regressed against future returns using an ordinary least squares (OLS), cross-sectional, multiple regression analysis. In this way a time-series of monthly payoffs is constructed for each style to represent how well the style is able to explain the cross-section of returns in each month.

Achour, Harvey, Hopkins, and Lang (1998) argue that the regression approach imposes a overly rigid structure on the data if style coefficients are estimated on the entire sample of returns. Problems arise when style coefficients are time varying. In addition, Achour *et al.* (1998) argue that cross-sectional regression methods fall short in emerging markets where there are only a small number of actively traded shares. Instead, Achour, Campbell, Hopkins, and Lang (1999) use a sorting procedure,

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forming portfolios according to style relationships estimated using a short sample to investigate anomalies in emerging markets. Another problem associated with the regression approach raised by Serra (2002) is that factor loadings are used by forecasting models as independent variables to estimate cross-sectional regressions however these variables have to be estimated in the first place. Standard errors are therefore understated because they include the additional error caused by the estimation of the factor loadings. This is known as the error-in-variables bias. However, Serra (2002) and Maddala (1998) argue that the portfolio approach also suffers from this bias. Additionally, the portfolio sorting approach may conceal the significance of return relevant attributes within portfolio averages Roll (1977). This makes it difficult to reject the null hypothesis that a criterion has no effect on security returns.. Berk (2000) points out an error in sorting into fractiles and then comparing to risk adjusted returns. He argues that CAPM/APT predictions will be less extreme, having a lower variance, as part of the total variance occurs between fractiles and this is not captured by the procedure. The result of the bias is that fractile means don't have to be as extreme to be significant, so more anomalies are discovered

Both approaches suffer from the data-snooping bias (see *Section 6.2.3.*) if the criteria in portfolio formation or attributes in regression analysis are the same as in prior research (Lo and MacKinlay, 1990).

On balance, it appears that the regression analysis approach has fewer statistical biases than the portfolio sorting approach. This thesis uses the regression analysis approach in most analysis.

2.4.2. Theory Behind Active Management and Expected Return Modelling

Clarke, de Silva and Thorley (2002) define the value added through active portfolio management (R_A) as the difference between returns on an actively managed portfolios and returns on a benchmark portfolio. They define the active weight for share i (Δw_i) as the amount by which it is held relative to the benchmark portfolio and r_i as the return generated by each share. Value added (R_A) is then derived as,

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$$R_A = \sum_{i=1}^{N} \Delta w_i . r_i \quad (1)$$

Value is added when over-weighted shares achieve positive returns and when under-weighted shares achieve negative returns. Clarke, de Silva and Thorley (2002) propose that R_A is related to the manager's ability to predict returns (signal quality) and the manager's ability to construct a portfolio that exploits his forecasting ability (portfolio construction). The former, signal quality, is measured as the correlation between return forecasts and realised returns, known as the information coefficient (IC). A number of firms use IC as a relative performance measure to evaluate their analysts. The latter, portfolio construction, is measured as the correlation between active weights and forecast returns, known as the transfer coefficient (TC). TC is equal to one when there are no constraints on the manager's portfolio.

Grinold's (1989) fundamental law of active management relates the expected performance of a manager's portfolio to the expected IC of the manager's forecasting process and the breadth of shares that the manager provides forecasts for. Expected performance is measured by the information ratio, IR, defined as the active portfolio's expected return adjusted for the active portfolio's level of risk,

$$IR = \frac{E(R_A)}{\sigma_A} \quad (2)$$

The *fundamental law* derived by Grinold (1989) is expressed as,

$$IR = E(IC)\sqrt{N} \quad (3)$$

where N is the number of forecasts used to create the actively managed portfolio. In terms of expected return,

$$E(R_A) = IC\sqrt{N}\sigma_A \quad (4)$$

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Grinold (1989) shows that managers can add more value by covering (and forecasting) more share returns. A manager's performance can be improved by either improving the accuracy of forecasts or increasing the number of forecasts.

Grinold and Kahn (1995) argue that the objective of active management is portfolio optimisation based on selecting optimal active weights to maximise the (mean-variance) utility function given by

$$U = E(R_A) - \lambda\sigma_A^2 \tag{5}$$

where λ measures risk aversion and $E(R_A)$ is given by

$$E(R_A) = \sum_{i=1}^{N} \Delta w_i . E(r_i) \tag{6}$$

and the active portfolio variance is given by the weighted average of the variance of each share held,

$$\sigma_A^2 = \sum_{i=1}^{N} \Delta w_i^2 \sigma_i^2 \tag{7}$$

By substituting (2) into (5) we obtain

$$U = IR.\sigma_A - \lambda\sigma_A^2 \tag{8}$$

When U is maximised, the optimal level of risk is,

$$\sigma_A^* = \frac{IR}{2\lambda} \tag{9}$$

σ_A^* is therefore positively related to the managers forecasting ability and inversely related to the manager's risk aversion

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Alternatively, by substituting (6) and (7) into (5) and then solving for Δw_i, the unconstrained optimal weights formula is obtained

$$\Delta w_i^* = \frac{E(R_i)}{\sigma_i^2}\frac{1}{2\lambda} \tag{10}$$

The full informational content of the return forecasts is transferred into the optimal active weights. The IR therefore determines a manager's potential to add value through the active weights he adopts, where Δw_i^* represents the optimal weight for each share.

If portfolio construction limitations are introduced, the manager's information ratio will be lowered. Grinold (1989) acknowledges this stating that IR gives an upper bound of the value a manager can add. Goodwin (1998) also finds that the original fundamental law provides an upper bound on potential information ratios. According to Clarke, de Silva and Thorley (2002) in practice a common rule of thumb is to cut the information ratio given by the fundamental law in half.

Clarke, de Silva and Thorley (2002) extend Grinold's (1989) fundamental law to incorporate a transfer coefficient measuring the effect of portfolio constraints on value added. They define Δw_i as the actual weights after considering portfolio limitations. The transfer coefficient (TC) is the cross-sectional correlation coefficient between risk-adjusted active weights (Δw_i) and forecast returns ($E(R_i)$) for all N shares in the active portfolio. They show that,

$$IR = TC.IC.\sqrt{N} \tag{11}$$

and in terms of expected return

$$E(R_A) = TC.IC.\sqrt{N}.\sigma_A \tag{12}$$

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In a world with no constraints *TC* is approximately 1.0. Note that, by not subscripting IC, we have assumed that IC is equal across all shares. In practise this is unlikely as portfolio managers and researchers usually have more skill at forecasting returns in some sectors than others.

Clarke, de Silva and Thorley (2002) measure manager performance without taking into account the effect of breadth using the performance coefficient (PC). PC is defined as the correlation between risk-adjusted active weights and realized residual returns. They prove that PC is equal to IR divided by $\sqrt{N}$. By substitution into *Equation 11*, we can express the generalized fundamental law in correlation coefficient form as

$$PC \simeq TC.IC \tag{13}$$

Sorensen, Qian, Schoen, and Hua (2004) extend the ideas of Grinold (1989), and Clarke, de Silva and Thorley (2002). They show that when combining two attributes with independent IC's to build a two-factor model there is an inverse relationship between the combined model IC and the correlation between the payoffs to each attribute. They also show that model standard deviation is inversely related to correlations between attributes. The net effect, assuming independent IC's is that IR is unaffected by the correlation between attribute payoffs. When dependence between attribute IC's is allowed (as is usually the case in practice) there is a strong inverse relationship between IR and the correlation between attribute payoffs. This result can be extended to multifactor expected return models. The message is simple: when building linear multifactor models, combining attributes with low (or negative) correlations will lead to higher IC's.

2.4.3. Performance Measures for Expected Return Models

The most common performance measure is the monthly IC, the monthly cross-sectional correlation between forecast and realised returns. IC measures the overall ability of a model to rank shares. Grinold (1989) introduces the information ratio (IR) *(see Section 2.4.2.)* to measure performance, approximated as,

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$$IR \approx IC\sqrt{N} \tag{14}$$

where N is the number of shares forecasted in the month being measured. The IR takes into account the breadth over which skill (IC) is exercised. Qian and Hua's (2003) information ratio adjusts the mean IC by the variation in IC.

$$IR \approx \frac{\overline{IC_t}}{stdev(IC_t)} \tag{15}$$

where $\overline{IC_t}$ is the mean monthly IC and $stdev(IC_t)$ is the standard deviation of IC. The Qian and Hua (2003) IR approximation provides a measure of the statistical significance of the final mean IC, by taking into account the volatility in IC across observations.

Achour *et al.* (1999) design a number of portfolio performance measures, including the percentage of periods in which the portfolio outperformed the market portfolio, the longest string of market outperforming periods, the number of periods with positive return divided by the number of periods with negative returns, the number of periods with negative returns and both the longest strings of positive and negative periods. The final ratio designed is the success ratio, defined as the mean of the percentage of shares in the top portfolio that outperform the benchmark portfolio and the percentage that underperform in the bottom portfolio in a single period. The success ratio indicates the robustness of portfolio performance. These methods are most useful to evaluate performance when a portfolio sorting approach is adopted.

2.5. Style Timing

Lucas, van Dijk and Kloek (2001) contend that style payoff time-variation occurs because style payoffs are conditional on certain, possibly unobservable, economic variables. If we accept this, two alternative approaches exist to forecast the variability in style payoffs.

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2.5.1. Style Momentum

The second approach also assumes that style payoffs vary over time due to unobservable economic influences. However, instead of trying to find proxies for these influences, the history of style payoffs is used to explain future payoffs. This approach can be thought of as style momentum. The term 'style momentum' is used by Wang (2003) to describe both positive and negative autocorrelation. Wang (2003) suggests a number of explanations for style momentum profits. Risk adjusted momentum profits may be due to shortcomings in the Fama-French pricing model used to adjust returns for risk. Alternatively, he suggests that profits could be due to the time-varying risk of the style portfolios. If this is the case, the style betas with respect to the Fama-French three factors would change significantly over the course of time resulting in the static Fama-French model being inadequate to explain returns. Finally, he suggests profits may be generated by a risk-based model with non-stationary time-varying parameters.

Wang (2003) argues that style momentum occurs due to the fact that style returns are non-stationary. He argues that momentum profits are related to macro-economic variables such as market cycles. Style persistence occurs as macro-economic influences tend to change slowly and in a predictable manner. If the macro-economic variables supporting a size premium are in place today, it is likely that they will still be in place in one months time. Barberis and Shleifer (2001) investigating behavioural anomalies, suggest that irrational trend-chasing investors can create cyclical investment style returns.

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2.5.2. Macroeconomic Relationships

The first approach involves testing relationships between style payoffs and a range of economic variables. Variables identified with significant explanatory power can then be combined to build a factor-model to predict the style payoff one month ahead. This approach has the advantage that the specific economic relationships used to predict the future style payoff can be assessed directly. It may be intuitively apparent that an economic relationship that worked in the past will no longer work in the future. The disadvantages of only using a factor model to forecast payoffs are threefold. The factor model may be incomplete, it may include spurious factors and it may suffer from attribute specification error[2]. Multifactor models are quite likely to be incomplete as it is impossible to test the entire universe of economic factors, indeed an important economic factor may not have an observable proxy at all. For example, confidence in corporate governance may be a factor influencing the size premium, yet no such time-series index exists. Much research has been conducted in this area, perhaps in response to Fama's (1991) challenge,

"We should deepen the search for links between time-varying expected returns and business conditions, as well as for tests of whether the links conform to common sense and the predictions of asset pricing models"

2.6. Summary and Conclusion

CAPM and APT models are used in this thesis as benchmark pricing models against which the explanatory power of firm-specific attributes is assessed. Due to the joint hypothesis problem, any conclusions regarding market efficiency are dependent on these underlying models of asset prices. There exist three schools of thought regarding the existence of stock market anomalies. Some argue that anomalies are purely the result of biases in the data and methodology of past studies, while others argue that they approximate unobservable risk factors. The dominant theory, however, is that anomalies represent irrational investor behaviour and can be exploited to achieve abnormally high returns. Expected return models attempt to exploit discovered anomalies within a multivariate framework and can be evaluated on their ability to forecast returns. Time-variation in style payoffs has been attributed to the theory that style payoffs are conditional on economic factors. If this is accepted, univariate time-series modelling of style payoffs and economic relationships can be used to forecast the variability in style payoffs.

The topics discussed in this chapter outline the most important theoretical considerations relevant to the empirical work conducted in this thesis. Research

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[2] Definitions are provided in *Chapter 7*

supporting and contradicting the theory explained in this chapter is presented in *Chapters 3 and 4*.

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3

International Research

3.1. Introduction

An overwhelming amount of evidence of anomalous stock market behaviour has been produced over the last thirty years. In this chapter a brief overview will be provided of the more renowned international research into style anomalies. Initially, most asset pricing research was produced in the US, however there is now a growing body of research aimed at extending results to virtually all markets around the world.

Although a great deal of research has focussed on the univariate testing of style anomalies, far less research has aimed at the multivariate exploitation of these anomalies. The second section of this chapter highlights some of the more influential research in the area of multivariate expected return modelling.

The remainder of this chapter is set out as follows. *Section 3.2.* discusses research relating to anomalies, *Section 3.3.* discusses research relating to multivariate modelling, *Section 3.4.*discusses research relating to style timing, and *Section 3.5.* summarises the key findings and concludes.

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3.2. Style Anomalies

Ball and Brown (1968) find evidence of post-earnings announcement drift in the same direction as the earnings surprise. Ball (1978) summarises 20 studies on earnings and dividends related anomalies, concluding that the collective evidence of anomalous behaviour is strong. Basu (1977) is one of the first to investigate the use of price/earnings ratios to forecast share returns. Studying 1400 shares over the period 1956 - 1971, he observes that low p/e securities outperform high p/e shares by more than 7% per year. Though Dimson (1998) notes that his results could be interpreted as a challenge to the CAPM benchmark, Basu argues that his results indicate market inefficiency. Banz's (1981) reports that smaller companies outperform larger companies. Over the period 1931 - 1975 the 50 smallest shares outperformed the 50 largest by an average of 1% per month after adjusting for risk. Many studies have confirmed the size effect in different companies. For a comprehensive overview, see Dimson and Marsh (1989).

Fama and French (1992) provide evidence of a number of style anomalies in the US. They find that market capitalisation and book-to-market equity subsume the influences of price/earnings ratios and leverage. Fama and French (1992) claim that results are consistent with market efficiency, arguing that firm-specific attributes proxy for unobservable risk factors. For example small firms are said to be more vulnerable to economic downturns. Their model can be regarded as an empirical model similar to arbitrage pricing theory. Fama and French (1992) and Chan and Chen (1991) consequently believe that value shares are inherently more risky arguing that the premium to these shares is expected and required. This argument has been opposed by most authors. Chopra, Lakonishok, and Ritter (1992), Lakonishok, Shleifer, and Vishny (1994), and Haugen (1995) believe that the premium returns to value shares are unexpected and systematically surprise investors. They argue that investors overreact to past successes and failures. (see *Section 2.3.2.*)

Haugen and Baker (1996) identify five classes of style anomalies: risk, liquidity, price level (value), growth potential, and price history (technical factors). They find attributes in each of these classes significantly able to explain the cross-section of returns.

There is a growing body of research assessing whether the same style anomalies are globally relevant. Serra (2002) finds that the most significant factors are common across a sample of 21 emerging markets. Fama and French (1998) and Rouwenhorst (1999) show that roughly the same style anomalies, representing size, book-to-market, earnings-price and momentum that have been found in developed markets are present in emerging markets. Haugen and Baker (1996) confirm that there is a great deal of similarity in the important factors across markets. Serra (2002) shows the payoffs to significant factors across emerging markets are not highly correlated. The implication is that while anomalies exist in each market for similar reasons, the pricing of each style is localised, i.e. style anomalies are not integrated across markets.

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In addition to the style anomalies discussed above, there is considerable literature on stock market seasonality, including month-of-the-year, week-of-the-month, day-of-the-week, and hour-of-the-day effects. Some of these patterns are integrated with style anomalies, notably the January size effect, whilst others are unrelated. This thesis will touch on the subject briefly with regards to style timing. A brief review of UK seasonality research is provided in *Section 4.6*.

3.3. Expected Return Models

Achour, Harvey, Hopkins, and Lang (1998) adopt the portfolio sorting approach in three developing markets, sorting shares into portfolios according to a selection of style attributes. The constructed portfolios easily outperform benchmarks also absorbing transaction costs. Achour, Harvey, Hopkins, and Lang (1999) construct similar models in the South African market. The models outperform standard benchmarks out-of-sample with the buy portfolio outperforming the sell portfolio by a significant 24% per annum.

Haugen and Baker (1996) construct multivariate expected return models in the US and four other developed markets. They report that the expected return models are significantly able to outperform the market after adjusting for risk. Furthermore, models comprising only factors related to momentum and models comprising only factors related to value produce spreads significantly lower than the complete multivariate models. Haugen and Baker (1996) conclude that the collective power of many of the factors accounts for the strong forecasting ability of the expected return models. Avramov and Chordia (2004) study return predictability at the firm level in the US constructing efficient portfolios from individual shares. Similar to Haugen and Baker (1996), a multivariate regression of excess returns on various firm-specific attributes is used to generate expected returns and variance for each share. Investment strategies based on these regressions outperform passive benchmarks. The superior performance is robust to the inclusion of portfolio constraints, and estimation risk

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3.4. Style Timing

Lucas, van Dijk, and Kloek (2001) provide US evidence that the relationship between future returns and certain firm-specific attributes varies over time. They show that relationships can depart from the long-term patterns documented in the literature for extended periods. Chan and Karceski (2000) confirm this, showing that in the US the size and value effects, for which there is much documented support, are inverse over the period 1990 through 1998. This can be a major worry for professional investment managers employing certain investment styles. Although a style may payoff in the long term, professional money managers are often judged by short term returns relative to a prespecified benchmark. Both annual outperformance and intra-year variability of the outperformance are important (Roll, 1992). Levis and Liodakis (1999) show that style consistency, that is investing based on one style, is not necessarily an optimal strategy. In the same way that asset class trends create a need for active asset allocation, style trends create a need for style rotation. Kahn (1996) reports that US funds that move between style classes, such as Fidelity Magellan, are frequently able to generate superior returns, however she advises investors wanting to themselves control and diversify between asset and style classes not to invest with such a fund. She reports that most funds do not systematically follow a value or growth stock orientation, but instead tend to either shift between one and the other, or adopt a blend. On the other hand, half of the equity funds studied stayed within their target size category. Kahn (1996) suggests that style consistent funds are more likely to be volatile than those that diversify as styles go in and out of favour. Indro, Jiang, Hu, and Lee (1998) however report that US funds that changed both their value versus growth and small firm versus large firm strategies were the worst-performing group of actively managed funds. Brown and Harlow (2002) find that style consistent funds produce higher returns after controlling for past performance and portfolio turnover.

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Many researchers have looked at the possibility of directly timing the market. Sharpe (1975) examines the possible gains from timing bull and bear markets by switching between cash and equities. He reports that the gains from directly timing the market are modest at best. Unless a manager can correctly predict whether the market will be good or bad 7 times out of 10, he should avoid trying to predict the market at all. Kester (1990) shows that market timing strategies, specifically strategies involving switching between cash and equities, are more effective on portfolios of small firms. With more realistic assumptions, he shows that the predictive power needed to exploit market swings is lower than previously shown by researchers such as Sharpe (1975). Kester (1990) concludes that at transaction cost levels lower than 1%, a reasonably accurate market timing strategy is able to outperform a fixed-asset-mix portfolio. Case and Cusimano (1995) apply the same principles on value and growth portfolios. They report that timing can be profitable depending on transaction costs and the frequency of portfolio revision. Jeffrey (1984) however, finds market timing to be both difficult and dangerous arguing that the risks outweigh the potential benefits. Because periods of great market appreciation (and depreciation) are few and appear to be unpredictable, it only takes a few wrong decisions to seriously tarnish the long term returns produced by market timers. Sharpe (1975) makes the comment that the military is usually very well prepared to fight the previous war. Unfortunately, the next war is always very different from the last. For most investors therefore, the timing of overall market returns is an ill-conceived business. Fortunately, the evidence regarding style timing has been more encouraging.

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3.3.1. Style Momentum and Economic relationships

This section contains empirical evidence for both approaches to style timing, style momentum and economic relationships, as discussed in *Section 2.5*. The evidence is not subdivided as a significant number of the studies reviewed investigate both approaches.

Coggin (1998) finds evidence that markets are weak-form efficient with regards to the relative performance of equity style indexes in the US between 1984 to 1989. He finds that the spread between small versus large and value versus growth style indexes cannot be predicted using only the time-series of style spreads. He suggests that forecasts should be conditioned on outside information, such as the business cycle and interest rates.

Bauman (1995) looks at the measurement of fund performance taking stock market cycles into account. He finds that the mean returns for a selection of style funds vary considerably over short time horizons yet converge when returns are measured over several stock market cycles.[3] This suggests that the business cycle may be an important influence on style returns.

Lucas, van Dijk and Kloek (2001), using a portfolio approach on US data from 1984 to 1999, show the time variation of the forecasting power of a firm's attributes is partially predictable. Adjusting for risk, they find significant and robust excess returns to style rotation strategies. Economic factors, in particular the term spread of interest rates and the annual growth rate of a composite index of business cycle indicators, exhibit the best overall performance. Rotation based on purely statistical time-series modelling and fixed investment styles are less robust. Techniques, such as pooling, averaging and autoregressive modelling are not found to be useful in predicting the future sign and magnitude of style payoffs. Economic business cycle variables are found to have a robust relationship with variation in the coefficients.

A number of studies have successfully linked the performance of style portfolios to macroeconomic factors. Anderson (1997) finds that small shares benefit from inflation. He suggests that small companies find it easier to pass along price increases in inflationary times. Anderson (1997) shows that the yield curve is positively related to the size premium. I.e. small shares perform better when there is a large premium on long term interest rates. Fama and French (1993) reason that book-to-market and size are proxies for financial distress. They suggest that distressed firms are more sensitive to business cycle factors. Sorensen and Lazzara (1995) find a significant positive relationship between both growth in industrial production and interest rates and the value/growth return spread.

Jensen, Johnson, and Mercer (1998) find that size and book-to-market payoffs in the US are dependent on the monetary environment. They argue that Federal Reserve policy and trends in interest rates are the dominant factors determining the stock market's major direction. In the 32-year study period, they classify all 384 months as either an expansive or restrictive monetary environment. They use a dummy variable representing the monetary environment that changes when the discount rate is adjusted in an opposite direction from the previous rate change. Their sample consists of 164 expansive months and 201 restrictive months. Returns to the general stock

[3] The value style, however, is found to be considerably less risky than other styles.

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market are nearly six times higher during expansive environments than during restrictive environments. Furthermore, risk is lower in expansive periods. Therefore the performance of long-term investments has been markedly superior during expansive monetary periods. The T-bill portfolio is the only portfolio that exhibits higher returns during restrictive monetary periods. In restrictive policy environments, T-bills have a higher return than the growth portfolios and the large-firm portfolio. Remarkably, investors following a growth strategy could have increased their return and reduced their risk to approximately one-twenty-fifth of its previous level by investing in T-bills whenever the discount rate was increased.

Jensen, Johnson, and Mercer (1998) find the value premium to be statistically significant and fairly stable across 4 decades. The value premium is further found to be significant under both monetary environments but considerably larger during periods of expansive policy. The small-firm premium is found to be much less consistent over time. The premium is statistically significant in expansive periods and insignificant in restrictive periods. They conclude that changes in the monetary environment, and not time, play the prominent role in determining the magnitude of the value and small-firm premiums.

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Gertler and Gilchrist (1994) also find that small firms in the US are disproportionately affected by a tightening in monetary policy. Kiyotaki and Moore (1997) show that credit constraints have a strong *transmission* effect on the business cycle. Bernanke and Gertler (1989) explain why the ease at which money can be borrowed (specifically the collective condition of the balance sheets of an economies lenders) is an important macro-economic variable affecting the business cycle and share returns. Perez-Quiros and Timmermann (2000) find empirical support for these theories in the US, showing that small firms are more sensitive than large firms to changes in variables that measure credit conditions.

Using a portfolio approach, Macedo (1995) demonstrates that both style based strategies and style timing pay off at a country level. He tests a *relative value* strategy that invests in international markets with low price/ book, price/ earnings, price/ cash flow and high dividend yield and a *relative strength* strategy that invests in markets with high momentum. Both strategies earn significant returns, however both become insignificant after transaction costs are taken into account. Macedo (1995) rejects a risk-based explanation, putting forward a behavioural argument for why the style strategies work at a country level. He argues that investors are just as irrational investing between countries as between assets within a country.

Macedo (1995) finds that recent style performance is a poor predictor of future style performance. Differences between relative strength[4] (momentum) and relative value portfolios over the trailing 1, 3, 6 and 12 month periods did not forecast subsequent style performance. Macedo (1995) finds market volatility to be a good forecasting variable for the relative value - relative strength spread. He theorises that investors perception of quality and risk influence the return to each style. Mean-variance portfolio theory asserts that a decrease in risk tolerance causes an increase in the premium demanded on risky assets, i.e. an increase in the market risk premium. Similarly, the premium on styles perceived as riskier will increase as risk tolerance decreases. Macedo (1995) argues that risk tolerance is lower after periods of volatility, causing investors to oversell value shares that are perceived as more risky than their glamour counterparts. On the other hand, the premium for relative strength investing is proposed to be stronger after periods of confidence and market stability. The result is that periods of volatility are followed by large relative value - relative strength spreads. Unfortunately style risk premiums and the level of risk aversion cannot be measured directly, however they can be approximated. Return differentials between portfolios formed along style lines are used to proxy style risk premiums and global volatility is used to proxy risk aversion. Global volatility is calculated each month as the aggregated standard deviation of monthly returns to all countries over the previous six months. Macedo (1995) tests a strategy that shifts between countries, favouring markets with *relative value* after periods of global volatility and markets with *relative strength* otherwise. He finds that this variable strategy outperforms either fixed-style strategy and is significant after transaction costs.

Chordia and Shivakumar (2002) find that expected returns vary over time, depending on the state of the economy. They show that momentum profits can be explained by the following set of lagged macroeconomic variables: the value weighted market

[4] The term relative strength used by Macedo (1995) is synonymous with momentum in this thesis

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dividend yield, the default spread, the term spread of interest rates and the 3 month T-bill yield. They argue that the T-bill yield is a proxy for expectations of future economic activity. Dividend yield is associated with slow mean reversion in share returns over several economic cycles. It is included as a proxy for unobservable risk factors since a high dividend yield must indicate that dividends are being discounted at a higher rate. The default spread is the difference between the average yield on BAA Moodys rated bonds and AAA Moodys rated bonds. It is included to capture the effect of the default premium which tracks long-term business cycles. I.e. the default premium is higher during recessions and lower during expansionary periods. The term spread is given by the difference in yield between 10 year bonds and three month T-bills. The term spread tracks short-term business cycles.

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Sensitivities to each macro-economic factor are obtained via a multifactor regression and used to calculate a one-month ahead forecast. The model explains a significant portion of the variation in the time-series of payoffs to a momentum strategy. Chordia and Shivakumar (2002) then subdivide their sample into expansionary periods and recessionary periods. Momentum strategy payoffs are positive (and significant) during expansionary periods and negative during recessionary periods. The difference between the return over each sub-sample is highly significant. This may be because recessionary periods are of shorter duration than expansionary periods, although this is unlikely to significantly affect the result. They conclude that the profitability of momentum payoffs are time-varying and can be partly forecast using business-cycle variables.

Asness, Friedman, Krial and Liew. (2000) build a model to time the relative payoffs to value and growth portfolios using a measure of the market's overall value spread (the spread in valuation multiples between the value portfolio and the growth portfolio) and the earnings growth spread (the spread in expected earnings growth between the growth portfolio and the value portfolio). The justification to use value and growth spreads comes from the Gordon growth model. For both the value and growth portfolios,

$$E(R_{value}) = E/P_{value} + g_{value} \tag{1}$$

$$E(R_{growth}) = E/P_{growth} + g_{growth} \tag{2}$$

Taking the difference between these two equations, they arrive at a fairly simple style timing model:

$$E(R_{value} - R_{growth}) = (E/P_{value} - E/P_{growth}) - (g_{growth} - g_{value}) \tag{3}$$

The spread in returns between the growth and value portfolios (payoff to value) is composed of two terms, $(E/P_{value} - E/P_{growth})$ represents the value spread and $(g_{growth} - g_{value})$ represents the growth spread. Note that the sign of the growth spread has been reversed. Since growth shares tend to be strong earners, and value shares tend to be relatively distressed, $(g_{growth} - g_{value})$ should be positive. Equation (3) therefore shows that both the value spread and the growth spread are important determinants of the expected return difference between the value and growth styles. Therefore, a low E/P (value multiple) can be justified if a stock's expected earnings growth is strong.

Rather than using only E/P to approximate value, Asness *et al.* (2000) use a composite measure incorporating earnings-to-price (E/P), book-to-price (B/P), and sales-to-price (S/P) ratios. They calculate industry-adjusted versions of each of the three value measures, comparing each stock's accounting ratio to its industry average, and form a value composite measure as follows:

$$\text{Value Composite} = \text{Average [Rank (E/P), Rank (B/P), Rank (S/P)]} \tag{4}$$

They then rank shares based on this composite measure to form value deciles. Similarly growth deciles are constructed using analysts' long-term earnings growth estimates from the Institutional Broker's Estimate System (IBES) historical database. Both sets of portfolios are rebalanced quarterly over the period 1982 – 1999.

Asness *et al.* (2000) find that the combination of the value spread and the earnings growth spread is best able to forecast (with statistical significance) the difference in

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future returns between the top value decile and the top growth decile. Additionally, the correlation between the two spreads is 0.62. When value spreads are wider than normal, growth spreads tend to be wider than normal. This confirms that the value spread alone is not a sufficient indicator of the attractiveness of value strategies. In general, when value shares are priced more cheaply than average compared to growth shares, they are also giving up more expected earnings growth than normal. According to the Gordon model, if value spreads are driven only by the expected earnings spread, then there could be no abnormal expected return advantage to value versus growth. Because the correlation is different to one, both spreads are important to predict the relative success of a value strategy versus a growth strategy

Berk, Green and Naik (1999) develop a similar theoretical framework to explain share returns. The value of a firm is given by the sum of the value of its assets and the value of its growth options (future projects). Expected returns are therefore determined by the current interest rate and the systematic risk of the firm's current assets. Because growth firms have more growth options than value firms, they are more sensitive to changes in interest rates. The model explains momentum in share returns, since returns are dependent on interest rates and systematic risk, both of which are persistent.

Wang (2003) finds that style momentum and style rotation strategies based on LOGIT models generate abnormally high returns in the US, even after controlling for the Fama-French 3 factor risk model[5] (1993). Wang (2003) considers a set of nine size and book-to-market sorted portfolios representing well-known investment styles (displayed in *Figure 3.3.1.1.*). Exchange-traded funds (ETFs) are available on all nine style indexes.

5 The three Fama-French factors are: return on the market, size and book-to-market.

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Figure 3.3.1.1. Nine Style portfolios analysed by Wang (2003).

Figure is taken from Wang (2003)

Small Cap Growth	Small Cap Neutral	Small Cap Value
Mid Cap Growth	Mid Cap Neutral	Mid Cap Value
Large Cap Growth	Large Cap Neutral	Large Cap Value

Wang (2003) investigates style momentum by ranking the style portfolios in each month according to their returns over the previous month. His style momentum strategy buys the winner style and short-sells the loser style. Over the period 1960 - 2001, this strategy generates significant profits; the average annualised return of the past winner is more than 16 percent higher than that of the loser. This return difference is significantly larger than the difference between the average returns of any two style portfolios. Risk adjustment using the Fama and French (1993) three factor model actually strengthens, rather than explains, the style momentum profits.

Wang (2003) investigates the last explanation by constructing a three factor LOGIT model based on the three Fama-French factors. The LOGIT model is used to predict relative style performance. These predictions are used to rotate between the different styles.

Both the lagged market factor and the lagged size factor are statistically significant predictors of the relative performance between small-cap and large-cap shares. Positive coefficients indicate that small-cap shares perform better when small-cap shares and the market have done relatively well in the previous month. In the LOGIT regression for the relative performance between value and growth shares, both the lagged value factor and the intercept are statistically significant.

Wang (2003) concludes that style momentum is at least as profitable as individual share momentum and with the growth of ETF's, it is much easier to deal with a small number of style indexes than with thousands of individual shares.

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Kao and Shumaker (1999) look at the profitability of style timing strategies in the US. They find that timing strategies based on asset class and size historically provide more outperformance *opportunities* than timing strategies based on value and growth. That is, with perfect foresight, timing asset class and size trends is more profitable than timing value and growth trends. Kao and Shumaker (1999) find calendar seasonality in the payoff to the value-growth style. They find that value significantly outperforms growth in the first calendar quarter while growth outperforms value in the fourth quarter.

Kao and Shumaker (1999) test seven macro-economic relationships against the *ex ante* 12 month value-growth return spread (value portfolio return – growth portfolio return.) The macro-economic variables tested are,

1. the yield curve spread (10 year bond yields / 3 month T-bill yields),
2. real (30-year) bond yield,
3. corporate credit spread (AA bond yields - BBB bond yields),
4. high-yield spread (High yield bonds / comparable treasuries),
5. estimated GDP growth rate,
6. earnings-yield gap ($E/P_{S\&P\ 500}$ – Long term bond yield) and
7. historical (12 month) CPI inflation index.

Earnings-yield gap is found to best explain the style spread (greatest R^2). When interest rates are high and earnings-yields are low value shares are favoured by investors seeking good yields. Conversely, when interest rates are low and earnings-yields are high, growth shares are preferred.

Yield-curve spreads and real bond yields are found to be positively correlated with style spreads. They argue that valuations of growth shares rely on expected earnings growth some distance into the future, whereas valuations of value shares rely more on currently available information. Growth shares can therefore be thought to have longer *duration* than value shares. Increases to long term interest rates and future interest rates will harm the discounted value of future earnings and therefore disproportionately affect growth shares. This explains why growth shares

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underperform value shares when the yield curve is steep (I.e. long term or expected future interest rates are particularly high.

It is proposed that credit spreads and high-yield spreads may be important as growth shares are less cyclical and therefore outperform value shares in a recessionary environment characterised by high default rates and large risk-premiums. Neither univariate relationship is found to be significant, however, both variables are found to be useful in a multivariate environment. It is argued that GDP growth reflects corporate profit cycles. When corporate profit growth is high, operating leverage contributes disproportionately to value shares profitability. Value shares are therefore likely to outperform when GDP growth is high. GDP is found to be positively correlated with the style spread.

Kao and Shumaker (1999) develop a multivariate framework for explaining the expected style spread. Instead of regression analysis, a nonparametric technique, the recursive partitioning algorithm (RPA), is used to integrate relationships. The multivariate model correctly classified whether value would outperform growth 69 percent of the time in the learning sample and 58 percent of the time overall. The model was substantially more accurate for the three month horizon, than the 12 month horizon.

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3.3.2. Timing in Practice

According to Kao and Shumaker (1999), there are two types of equity style timing practitioners: active style switchers and factor forecasters. Style switchers analyse and model the drivers of their defined styles. They then invest in style indexes or alternatively sell the style forecasts to other asset managers. Some investment banks offer style switching models as part of the quantitative research they provide to clients. In the US, this form of investing is fairly new and few assets are under the management of style switchers. Factor forecasters use quantitative methods to forecast share returns via an econometric model and/ or a multivariate pricing model. The factor forecaster is usually not focussed on value or growth style timing, however the timing is built into the asset pricing models. According to Kao and Shumaker

(1999), these managers have a longer performance history and a larger asset base than style switchers.

3.5. Summary and Conclusion

The most frequent criticism of anomaly related literature is that results are simply a result of data-mining and are unlikely to hold out-of-sample. According to Black (1993), *"most of the so-called anomalies that have plagued the literature on investments seems (sic) likely to be the result of data-mining."* This argument grows weaker and weaker as the international body of research on style anomalies expands and the same attributes continue to be found, functioning in the same direction across markets.

This chapter presents evidence on univariate style anomalies, multivariate expected return modelling and style timing. While anomalies are widely accepted few researchers have attempted to combine attributes to form multivariate expected return models. Those that have, most notably Haugen and Baker (1996), have been able to earn a substantial premium on the market. Likewise, style timing is receiving growing attention as researchers become aware of studies (such as Wang, 2003) where abnormal returns accrue to strategies involving timing style performance.

There are good fundamental reasons and considerable empirical evidence to suggest that style payoffs, particularly relating to size and value, are associated with economic fundamentals relating to exchange rates, interest rates, inflation, the business cycle, market volatility, market yields, the yield curve and spreads in important attributes. On the other hand, the evidence for style momentum has been mixed with some studies showing that the time-series of style payoffs has significant forecasting power and others showing that it does not.

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4.

UK Specific Research

4.1. Introduction

In contrast to the US, there is less published research in the UK investigating style factors and testing the relationship between expected returns and beta. (This is confirmed by Strong and Xu (1997) and Beenstock & Chan (1986)). For example, on style timing, a subject that has received a considerable amount of attention in the US, only one significant UK contribution (Levis and Liodakis, 1999) is discovered. In this chapter an overview is provided of UK research pertaining to market efficiency, market anomalies, seasonality of returns and style timing

The remainder of this chapter is set out as follows. *Section 4.2.* discusses tests of market efficiency, *Section 4.3.* *Section 4.4.*, and *Section 4.5.* discuss research on anomalies relating to value, momentum and size respectively. *Section 4.6.* discusses research on seasonality, *Section 4.7.* discusses research relating to style timing, and *Section 4.8.* summarises the key findings and concludes.

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4.2. Tests of Market Efficiency

Dimson and March (2001) construct a comprehensive data set of the returns generated by each asset class in the UK from 1955 to 1999. Using the definition for the equity risk premium provided by Ibbotson (2000) as the amount by which the annual return on high-cap equities exceeds the annual return on treasury bills, they report the UK equity risk premium to be 6.2% over the 44 year period. Over the same period the US equity risk premium is reported to be 6.2%.

Due to the joint-hypothesis problem, empirical tests of market efficiency are by nature tests of the ability of asset-pricing models to explain the cross-section of returns. Empirical tests in the UK have focussed either on providing empirical anomalies that are unexplained by the model in question, such as seasonality, momentum and value strategies, or on contradicting model assumptions, such as the positive beta, return relationship assumed by CAPM. The second category of tests will be dealt with first, as these will determine whether the pricing models have validity in the UK. Thereafter it will be investigated whether there are certain situations where the pricing models are systematically unable to explain the entire cross-section of returns.

Over the period 1960-1992, Strong and Xu (1997) find evidence of a positive beta risk premium using OLS regressions of UK share returns against market beta, however the relationship becomes insignificant when controlling for either market value or a selection of accounting-based variables. Corhay, Hawawini and Michel (1988) find no evidence of a positive beta risk premium in the UK over the period 1955-1983.

Fletcher (1997) reports an insignificant unconditional relationship between beta and returns. However, consistent with US studies (See Pettengill *et al.*, 1995), he finds that the relationship is conditional on the sign of the excess returns on the market index. He reports a significant positive beta-return relationship holds in *up market months* and a significant negative relationship holds in *down market months*. Unlike Pettengill *et al.* (1995), the relationship is not symmetrical in *down* and *up market* months. The negative *down market* relationship is significantly stronger than the positive *up market* relationship. He concludes that beta may still have a useful role in the UK if conditioned on the sign of the market premium .

Hung, Shackelton and Xu (2004) examine determinants of the cross-section of portfolio returns with respect to CAPM beta, value and size. They use the CAPM test developed by Pettengill et.al. (1995) which controls for the sign of the market premium. Similar to Pettengill *et al.* (1995) they find that testing the CAPM by separating up and down market months yields a high significance for beta in explaining the cross-section of stock returns. This beta effect is robust with respect to the Fama and French (1992) size and value factors. The Fama and French risk factors on the other hand, also remain significant after adjusting for CAPM using the Pettengill *et al.* (1995) methodology. The value effect reacts fairly symmetrically across up and down markets while the size effect yields higher returns for smaller shares in down markets

Additionally Hung *et al.* (2004) test higher order asset pricing models including systematic risks beyond the traditional CAPM beta covariance. These models test

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relationships between excess share returns and powers of the market premium. They find limited evidence for the existence of higher order pricing factors.

Fletcher (1997) confirms that the Pettengill *et al.* (1995) US results regarding the relationship between beta and returns hold in the UK over the period 1975 – 1994. Fletcher (1997) finds a strong positive relationship between beta and returns in upmarket months, and a strong negative relationship in downmarket months. The upmarket/ downmarket results remain intact after excluding January months (see *seasonality*) and the market crash of October 1987. In general he is unable to find a positive beta-return relationship.

Beenstock & Chan (1986) construct and test an APT model on UK data using a factor analytic technique on monthly data from 1961-1981. They report that their APT models explain a high level of variation similar to results from US tests. A 20 factor model explains significantly more variation than a four factor model. They conclude that although there are likely a number of idiosyncratic factors, the total number of priced factors is unlikely to be small. Beenstock & Chan (1986) reject the CAPM in favour of APT as the best model to explain the cross-section in UK returns. They fail to find a significant positive relationship between return and beta, and find a negative, though insignificant, relationship for some samples and periods. Beenstock & Chan (1988) test APT in the UK using the alternative approach described by Chen, Roll & Ross (1986) of identifying economic variables to proxy for risk factors. Using monthly returns over the period 1977- 1983 a four factor model was suggested by the data. The four risk factors, interest rate, cost of fuel and materials, the money supply and inflation significantly explained future returns with a typical R^2 of about 0.33.

Poon & Taylor (1991) investigate whether the economic factors identified by Chen, Roll & Ross (1986) in the US apply to the UK. They report a significant rank correlation between size and mean returns over the period 1965–1984. The performance of the Chen, Roll & Ross model is, in the words of Poon & Taylor (1991), “not particularly convincing.” Only one of the three sub-periods analysed (1968 – 1977) produced significant t-statistics at the 5% level. They report that the multivariate results are unstable under construction. A factor can be significant in one multivariate model but insignificant in another model comprised of a different

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combination of factors. In regressions including macroeconomic risk factors, they are unable to find any contemporaneous relationship between beta and return, contradicting the CAPM assumption. Pesaran and Timmermann (2000) investigate whether macroeconomic state variables can be used by UK investors to improve the risk-return trade-off offered by a passive investment in the market portfolio. They find evidence that business-cycle variables do have *ex ante* explanatory power over share returns.

Miles and Timmermann (1996) investigate asset-pricing anomalies in the UK using, company accounting data from 1975 to 1990. They search for relationships between returns and a number of firm-specific predictor variables, including book-to-market-value, earnings-to-price, leverage, dividend yield and size. Similar to Fama and MacBeth (1973) in the US, they analyse the slope coefficients of monthly cross-sectional regressions. Miles and Timmermann (1996) report that both beta and size do not play significant (linear) roles in explaining UK returns. Likewise, dividend yield, earnings-to-price and financial leverage are not found to be significant predictors. Miles and Timmermann (1996) do however find that book-to-market-value, and to a lesser extent liquidity and size, contain information about the cross-section of returns. Firms with high book-to-market-value ratios outperform shares with lower ratios. Although there is no linear relationship between size and future returns, firms in the smallest decile earned substantially higher returns than other firms. They also find evidence that shares with particularly low liquidity earn abnormally high returns.

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Na, Green and Maggioni (1995) confirm that CAPM cannot explain UK monthly returns over the period 1972-1985. They show that violations of the CAPM assumptions lead to variables other than the market portfolio that can explain returns. They argue that the problems with CAPM are mainly due to what they term market imperfections, including transaction costs, taxes and regulatory restrictions. They attempt to model the optimisation of transaction costs and other constraints. Although they are unable to model the optimisation process successfully, they show that transaction cost variables have a significant impact on asset returns. Dimson (1983), using UK data, shows that thin-trading, a source of transaction costs, causes conventional risk measures to be biased. Specifically, CAPM beta is shown to be downwardly biased. Thin-trading is therefore presented as one reason for the empirical failure of CAPM in the UK.

Strong and Xu (1997) argue that the weakness of asset pricing models to explain the cross-section of UK returns is partly due to extremely high expected inflation rates (indicated by high short term interest rates) experienced in the UK. Boudoukh, Richardson & Smith (1993) provide evidence that the ex ante market risk premium can be negative during periods of high expected inflation, especially if the term structure of interest rates is downwardly sloping. Strong and Xu (1997) report that the UK experienced high and variable rates of inflation throughout the first half of their sample period. Inflation peaked at over 24% in 1975 and was in double figures for 7 of the first 9 years of the period 1973–1991. They conclude that pricing methodologies may be strained when applied across a period of such economic turbulence.

4.3. Anomalies Representing Value

Levis (1985) reports the presence of a number of pricing anomalies on the LSE. Levis (1985) finds dividend yield, PE, price and size significantly related to future returns. He reports a large degree of interdependency between the four effects, although dividend yield and PE ratios appear to subsume the size and price effects.

Strong and Xu (1997) test for a relationship between future returns and market value, book to market equity, leverage, earnings to price and beta adopting the methodology of Fama and French (1992). They find a positive beta risk premium from a simple regression of return on market beta, however this relationship becomes insignificant when including market value or accounting variables in a multiple regression. Market value dominates beta in explaining average returns throughout the 1955–1992 period, but becomes insignificant when book to market equity or leverage variables are included over the 1973–1992 period (for which they have accounting data.) The only variables found to consistently explain the cross-section of UK returns are book-to-market equity and leverage. Interestingly, they find the explanatory power of combinations of accounting and market variables low.

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According to the rational valuations formula, share prices should reflect the discounted present value of all expected dividends. Price movements should therefore either reflect changes in expected dividends or changes in the discount rate. Cuthbertson, Hayes and Nitzche (1999) investigate these relationships in the UK and confirm that UK share returns are affected by expected returns and changes in expected dividends. Persistence of expected return and less so respectability of expected returns explain the movement of share prices. Campbell (1991) finds that even if the degree of predictability of returns is low, news on future dividends and returns can have a large effect if the returns are persistent. Cuthbertson *et al.* (1999) use a multivariate framework to calculate variation in stock returns. They use a log-linear version of the rational valuation formula separating unexpected changes in real returns into news about expected discount rates and news about future dividends noting any covariance between them. They use a data set that aggregates the UK stock market index from 1918-1993. They record one period changes in the price returns and unconstrained dividends. They then perform multivariate variable regressions using the quantitatively drawn factors dividend to price, yield spread, default spread, gilt to equity yield and a volatility measure to obtain expected returns.

Cuthbertson *et al.* (1999) calculate unexpected returns from the discount rates and expected dividends of each respective stock price according to the news made available during the respective periods. They claim that any news that affects the dividends or discount rates and possibly both must affect unexpected returns. Cuthbertson *et al.* (1999) conclude that a significant portion of the variance in unexpected share returns is due to news about future expected returns. Cuthbertson, Hayes and Nitzsche (1997) find that the UK stock market is inefficient according to the rational valuations formula under both CAPM and value-at-risk metrics. Value-at-risk is a risk measure that estimates the probability of portfolio losses based on statistical analysis of historical price trends and volatility. Cuthbertson *et al.* (1997) find that agents are guilty of *short-termism,* i.e. they give too little weight to future dividends and returns.

Levis and Liodakis (1999) investigate value-based market timing strategies in the UK, using book-to market as a measure of value. They show that value strategies have

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consistently delivered higher annual returns. They examine the sources of errors in investors' expectation about future growth. They find that errors in investors' expectations are more likely to be due to biases in analysts' earning forecasts than to naive extrapolation of past growth in earnings and sales.

Gregory, Harris and Michou (2001) investigate the profitability of value strategies in the UK based on the variables, book-to-market ratio (BM), earning-to-price ratio (EP), cash flow-to-price ratio (CP), and past sales growth (SG). over the period 1975-1998. Following the methodology of Lakonishok, Shleifer, and Vishny (1994) , Gregory *et al.* (2001) partition shares into ranked decile portfolios based on their BM, EP, CP and SG which are rebalanced annually. They report each attribute significantly explains the cross-section of returns and differences between glamour and value portfolio's are not due to market risk. Gregory *et al.* (2001) then perform a two-variable classification of value and glamour shares based on past growth, proxied by SG, and expected future growth, proxied by BM, EP, or CP. Shares are sorted independently by SG and by BM, EP, or CP, and nine intersection portfolios are formed. The utmost value portfolio consists of the shares with both low past growth (low SG) and low expected future growth (high BM, EP, or CP), while the utmost glamour portfolio consists of shares with both high past growth (high SG) and high expected future growth (low BM, EP or CP). The two-variable analysis confirms the results of the one-variable analysis; value shares significantly outperform glamour shares. When SG and BM are used as the classification variables, the difference in the average first year return between the utmost value portfolio and the utmost glamour portfolio is 24.62% annually.

Gregory *et al.* (2001) examine the sources of superior returns of value strategies. The three-factor *risk* model of Fama and French (1993) is applied to test whether excess returns of value strategies can be explained. The model fails to fully explain the superior return of value strategies using the two-variable classifications: SG & BM and SG & EP.

Xu (2001) points out that the extremely strong empirical evidence generated by Gregory *et al.* (2001) may be a result of selection bias. Following Lakonishok *et al.* (1994), Gregory *et al.* (2001) exclude companies with negative book values, earnings,

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or cash flows. This could explain the conspicuously high returns in the first year of the holding period. Xu (2001) however argues that on balance, the relative number of shares with negative earnings is unlikely to significantly affect the high returns reported.

Gregory, Harris and Michou (2003) construct a multifactor asset pricing model employing macroeconomic state variables to represent systematic risk. They then investigate the relationship between returns on value investments and risk as represented by their macroeconomic model. They report that there is no evidence to support the view that value investments are fundamentally more risky. Analysing the performance of value strategies in different market conditions, they find that value strategies do not perform worse in adverse states of the world. Furthermore, value portfolio's do not have higher risk as measured by their volatility and Sharpe ratios.

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4.4. Anomalies Representing Momentum

Momentum strategies seek to exploit the predictability of returns. Hon and Tonks (2003) separate momentum strategies into reversal (contrarian) and persistence (momentum[6]) strategies. Persistence strategies expect returns to be positively auto-correlated while reversal strategies expect returns to be negatively autocorrelated. The time horizon on reversal strategies is usually longer than on momentum strategies.

Clare and Thomas (1995) report significant evidence of reversal (over-reaction) at the 24-month and the 36-month horizons in the UK over the period 1955-1990. They are unable to show significance at the 12-month horizon. Dissanaike (1997) uses a sample of larger shares (constituents of the FT500 Index) over the period 1975-1991. By using larger shares and a buy-and-hold strategy he is able to reduce the problem of thin trading as well as reducing the probability that the momentum effect is merely a proxy for the small firm effect. Dissanaike (1997) reports evidence of reversal at the 12-month horizon. The past-loser portfolio earns 5.8% annually while the past winner

[6] Hon and Tonks (2003) use the term momentum to describe positively autocorrelated share returns. Throughout this thesis, however, the term persistence is used to describe positively autocorrelated returns while momentum is used to describe both positively and negatively autocorrelated returns.

portfolio earns - 5.76% annually over the sample period. A risk-adjustment confirms that this anomaly is not a proxy for CAPM risk. Dissanaike (2002) tests whether the reversal effect is subsumed by the size effect. He reports a weak size effect within the FT500 sample, significant at the 5% level. The loser-winner effect is significant at the 5% significance level. Dissanaike (2002) concludes that the size and momentum effects are not completely independent of each other but the size effect does not subsume the momentum effect.

Liu, Strong and Xu (1999) identify the presence of momentum profits in UK stock returns over the period 1977 - 1996. After controlling for systematic risk, size, price, book-to-market ratio, and cash earnings-to-price ratio they are still able to show a significant momentum effect. By dividing their data set into sub-samples they show that momentum effects are robust in the UK.

One possible explanation of the momentum anomaly is that thin trading accounts for much of the *apparent* predictability. Morgan (2000) however, reports that infrequent trading only explains only a small proportion of the serial correlation observed in monthly UK stock returns. The implication is that there must exist other more pertinent reasons for the momentum anomaly.

Hon & Tonks (2003) report the presence of momentum in the UK for the period 1977 to 1996. Unlike Liu *et al.* (1999) however, the momentum anomaly is not found to be robust over all sub-periods. Momentum is not significant over the sub-period 1955 – 1976 and most of the entire-period anomaly results from momentum in the latter half of the sample.

4.5. The Size Anomaly

Much UK research has been focused specifically on the size effect. The UK size effect became prominent in 1987, with the launch of the propriety smaller-companies index. The index covers firms that comprise the bottom tenth by capitalisation of the LSE. According to Dimson and Marsh (1987) the back history of the index (1955 – 1986) reveals that smaller companies outperform the overall index by 6% annually.

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This generated a great deal of interest in small firms. Dimson and Marsh (2001) report that during 1987 and 1988 there were over 200 follow up size articles in the UK press, at least 30 initial public offerings of funds that reproduced extracts of the back history in their prospectus's and numerous institutions that developed low-cap investment strategies. After the 1987 - 1988 period however, the premium reversed and over the next decade the small cap index underperformed the overall index by 6% (Dimson and Marsh, 2001). This reversal is similar to the reversal that happened in the US. After Banz (1981) and Reinganum (1981) published research on the US size premium, there was a flurry of new fund activity to take advantage of the anomaly. However, the premium went from + 5.5% between 1955 – 1983 to – 8.1% between 1984 – 1999 (Dimson and Marsh, 2001). This evidence of cyclicality of the size anomaly supports further research into style timing.

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Levis (1985) tests the relationship between mean return and firm size for UK firms over the period 1958–1982. Levis (1985) reports the smallest decile in terms of size outperforms the largest decile by 6·5% annually. Unfortunately the size effect is found to be unstable over time. Additionally, Levis (1985) finds evidence for the UK that smaller firms have lower betas than larger firms. This is supported by Dimson and Marsh (1983) contradicting the CAPM assumption that there is a positive linear relationship between expected return and beta (as a proxy for risk.) Levis (1988), using quarterly returns, again reports that the smallest portfolio outperforms the largest (by 6% annually) over the period 1966-1982. Small companies are shown to be less risky than larger companies in terms of systematic and overall risk. This result is unlikely due to thin-trading as quarterly returns data are used. An interesting observation is that while the performance of large firms in the UK is similar to that of large firms in the US, small UK firms earn only half the return of small US firms (Using US results produced by Reinganum (1983)). The implication is that the size effect is not as pervasive in the UK as it is in the US.

Levis (1988) examines the implications of institutional trading on share prices of size-sorted portfolios. Given the preference of institutional investors for larger firms due to portfolio constraints and window-dressing (see Haugen and Baker, 1996) and the support for what he terms the market impact hypothesis, whereby large transactions and buying/selling imbalances have a significant effect on returns, Levis (1988) proposes that the size premium observed in most international markets should be associated with the pattern of institutional trading. He is however, unable to find evidence to support the association and is forced to reject the market impact hypothesis along with the implication that the size premium is related to institutional trading patterns. Levis (1988) also investigates whether institutional activity stabilizes or destabilizes the UK market. He assumes that if a major quarterly share price movement coincides with institutional activity over the quarter, the evidence points to market impact, whereas, if the institutional activity happens in the quarter following a major price movement, the evidence is assumed not to support the market impact hypothesis as institutions are potentially reacting to the price change, certainly not causing it. Levis (1988) reports institutions tending to "follow the market" (Levis, 1988 p173) rather than influence it. He argues that the institutions do not destabilize the UK market. No evidence of feedback is uncovered by the transfer model constructed, another sign that institutions add stability to the market.

Vermaelen (1988) questions the results of Levis (1988) on the basis that quarterly returns are too long to show correlations between market returns and institutional activity. Institutions, he argues, react within one quarter and multiple price movements are possible per quarter. He argues that the methodology of Levis (1988) is unable to separate contemporaneous price movements due to market impact from independent price movements. The situation is more complicated when institutions react to independent price movements and this causes further movement. Unfortunately, only quarterly data is available for institutional activity, so the relationships cannot be subjected to greater scrutiny.

Fletcher (1997) presents a subsidiary result[7] that provides little support for the size effect in UK returns for the period 1975 to 1994. He acknowledges that this may be a result of a possible non-linear relationship between portfolio average return and the proxy for portfolio size.

Dimson and March (2001) investigate the UK size effect over the period 1955 – 1999. They divide shares into the categories: *large-cap*, *small-cap* and *micro-cap*

[7] The focus of Fletcher (1997) is the relationship between beta and returns

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rebalancing on an annual basis to minimise problems associated with thin trading. Over the 44 year period micro-cap shares yielded an annual (geometric) mean return of 14% whereas high-cap shares yielded an annual (geometric) mean return of 8.1%. Dimson and March (2001) however, find that the size effect is not stable over all sub-periods. By analysing dividend histories they are able to show that smaller firms performed fundamentally better than larger firms. In 1955 the dividend yield for UK micro-caps was 4.6% higher than for high-caps and over the period 1955 – 1988 the micro-cap dividends grew at an annualized rate that was 4.5% greater than high-cap dividends. At the same time the price-to-dividend ratio increased by 3.4%. They report that the reversal in the size effect in 1988 corresponds to poor small-cap dividend yields (1.6% below large-cap yields) amplified by the high dividend growth expectations underpinning small-cap prices. They show that the same relationships hold in the US over the same period. Dimson and March (2001) conclude that the premium earned on micro-cap shares is related to:

a) dividend income,
b) dividend growth rates,
c) market determined dividend yields.

In the US seasonality has significantly affected tests of the size anomaly (Keim, 1983). Corhay, Hawawini and Michel (1988) find a May-size effect on the LSE over the period 1957-1963, while the size effect on its own is found to be insignificant. Dimson and Marsh (2001) find that seasonality plays an insignificant role in the UK size anomaly.

4.6. Seasonality

The calendar effect and the day-of-the-week effect. have both been identified in the UK, however the evidence is mixed.

Theobald and Price (1984) investigate daily seasonality in UK returns over the period 1975-1981. They find that Monday returns are significantly lower than the average daily return. This result is confirmed by Condoyanni, O'Hanlon and Ward (1988)

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who find the weekend effect pervades all major international stock markets. Theobald and Price (1984) and Condoyanni *et al.* (1988) find that the weekend effect is weakened by a characteristic of the LSE to do with the settlement of dividends. Shares in both samples typically go ex-div on a Monday and are settled 21 days later (also on a Monday.) The discounting of the dividend in the returns calculations causes a positive price effect on the ex-div Monday and on the settlement Monday. (See Theobald and Price (1984) for an extensive discussion of the account/settlement date effect.) By separating ex-div and settlement Mondays from the sample, Condoyanni *et al.* (1988) confirm the effect.

There has been strong evidence of a January effect in the US (for example Rozeff and Kinney, 1976). Keim (1983) attributes around half of the US size effect to abnormal returns in January. The US effect is concentrated on the last trading day of December and the first few trading days of January. Three prominent explanations for stock market calendar seasonality have been given: risk seasonality (Rogalski and Tinnic, 1976), tax loss selling around the year-end (Roll, 1983) and portfolio-rebalancing *(window-dressing)* (Haugen and Lakonishok, 1988) Dimson and Marsh (2001) present a convincing argument that international evidence does not support risk seasonality as an explanation.

There has been mixed support for the second two explanations. Reinganum and Shapiro (1987) argue that tax trading only translates into a seasonal pattern of prices if investors are either irrational or ignorant of the price seasonality. In an efficient market, trading volume will increase as a result of tax-loss selling, however arbitrage trading will hold prices at their *true* levels. The UK tax year end for individuals is 5 April and differs for companies depending on their reporting year end which is usually around end-March or end-December (Dimson and Marsh, 2001). Reinganum and Shapiro (1987) investigate the effects of tax legislation and tax-loss selling on prices of firms listed on the LSE between 1955 and 1980. Capital gains tax was introduced in the UK on 6 April 1965 at an effective rate of 30% on corporations. By separating their data into pre-1965 and post-1965 sub-samples, they are able to show that both January and April effects only become significant after the introduction of capital gains taxes in 1965.

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Controlling for size, Levis (1985) finds a May effect, but no January or April effects. Dimson and Marsh (2001) report that between 1955 – 1999, UK shares perform significantly better in January (yielding a premium of 2.8%) and in April (2.7%) however they find no evidence of the combined "turn-of-year-size-effect" reported in the US literature.

Clare, Psaradakis and Thomas (1995) find strong evidence of both January and April effects in the UK FTSE All share data for the period 1955-1990. Share returns are abnormally high in January and April and decline over the remaining months, increasing marginally in December. This evidence is robust across size sorted portfolios and is unaffected by a risk adjustment process. Clare *et al.* (1995) propose four explanations for the seasonal variation. They suggest a surplus of funds for investment by pension funds may develop at the end of the year as individuals "load their pension funds" to avoid tax. The January effect may be caused by the US 'turn of year' tax-loss-selling effect as the UK capital market is highly integrated with the US market. Alternatively variation may be due to window-dressing by fund managers and institutional tax-loss selling in the UK.

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4.7. Style Timing

Levis and Liodakis (1999) provide the most significant analysis of style rotation in the UK. they test rotation strategies between value and growth and small and large cap portfolios over the period 1968-1997. They test the profit potential assuming perfect and intermediate levels of forecasting ability and assess the average gains from rotation using a Monte Carlo simulation.

Portfolios are formed each month using market value as a measure of size and the market-to-book ratio as a measure of value/ growth. The sorting procedure ensures that small- and large-cap portfolios have roughly the same average market-to-book ratios and value and growth portfolios have roughly the same average market value. Levis and Liodakis (1999) note that large-cap shares are substantially more leveraged than small- cap shares. Similarly value shares are more leveraged than their growth counterparts.

The difference in performance between growth and value portfolios is significant, even after controlling for size, over the entire period The difference is also significant over all four sub-periods. The difference in performance between size portfolios is significant over each sub-period, but not over the entire period. Levis and Liodakis (1999) argue that different times favour different types of shares. For example, small-cap firms have two good cycles, each lasting 2.5 to 3 years (1971-1973 and 1977-1980). Large-caps, on the other hand, are more profitable from 1988 to 1992. This is consistent with other UK research on the size anomaly.

Apart from the longer-term cyclical movements of the size spread, higher frequency variations provide further justification for style rotation strategies. Out of 348 months in the sample, small-caps perform better in 183 months (53%), while large-caps are better off in 165 months (47%). Although the sign variation in the value/growth spread is not as dominant, there are still periods when growth shares outperform value shares. The value/growth spread is positive In 232 months (67%), and negative in 116 months (33%). It is clear then that there are potential gains for a style investor who can predict the future style spread. An investor able to predict the sign of the size spread correctly in every single month and then invest fully in the predicted index would have earned 33.81% annual return, (17% above the FTSE All Share index return). Even with only 35% forecasting accuracy, the profits from rotation exceed the profits of the FT All Share index and break even with the performance of the small-cap index. In the case of value/growth rotation, a perfect foresight rotation strategy earns 29.10% annual return. A minimum of 75% accuracy is needed to exceed the value buy-and-hold strategy.

Levis and Liodakis (1999) construct multifactor macroeconomic models to predict the size and value spreads. The following one-month-lagged economic variables are considered:

1. The annual percentage change in the coincident (business cycle) indicator;
2. The monthly change in the three-month Treasury bill yield,
3. The yield curve, defined as the monthly yield difference between the twenty-year government gilt and the three-month Treasury bill;

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4. inflation, derived from percentage change in the CPI.
5. the monthly equity risk premium,
6. the monthly change in the pound/dollar exchange rate,
7. a dividend yield ratio variable that corresponds to the average dividend yield of one index over the average dividend yield of the other.

They regress each lagged macroeconomic variable separately against the size spread and the value/ growth spread. Spreads are calculated as the monthly difference between the return on the top style portfolio and the return on the bottom style portfolio, both equal-weighted. Multivariate regressions are then performed on each spread using all the factors as independent variables. Multicollinearity is not a problem as the highest correlation between dependent variables is 0.31 between the term structure variable and the dividend yield ratio. Multifactor logit regressions are constructed to predict the sign of the spread.

In the univariate regressions with the size spread as dependent variable, inflation and the equity risk premium are found to be highly significant, while the term structure and dividend yield are marginally significant. All the variables retain their sign in OLS and logit estimations, and some of them even become more significant. The adjusted R^2 in the multiple OLS regressions is 12.33%. Regression coefficients indicate that small-cap returns benefit from rising interest rates, a large equity risk premium, a widening
the yield curve and lower inflation.

In the value/ growth univariate regressions, the one-month lagged value/ growth spread, £/$ exchange rate and inflation are found to be highly significant while changes in the short-term interest rate and the coincident indicator are marginally significant. The latter two variables become insignificant when they are included in multivariate regressions. The term structure, equity risk premium and dividend yield are found to be insignificant. Regression coefficients indicate that inflation, a rise in the monthly £/$ exchange rate and a rise in short term interest rates all benefit growth shares more than value shares. The significance of the lagged spread variable indicates momentum in the value/growth styles. The multivariate value/growth model has an adjusted R^2 of 9.56% which is lower than that of the size spread.

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The macroeconomic logit regressions allow for models to be constructed to predict the sign of the style spread one month ahead. Three investing strategies are constructed to predict the style spread for size and value/ growth. Strategy 1 invests 100% in small-cap (value) shares whenever the logit model signals a small-cap (value) month (logit probability greater than 0.5), and moves to 100% large (growth) shares, whenever the logit model signals an upcoming large-cap (growth) month (probability less than 0.5). The drawback of this strategy is that it classifies each month as either small-cap or large-cap, regardless of the magnitude of the probability. Strategy 2 defines the probability range of 0.45–0.55 as neutral, and in this case simply allocates 100% of the funds to the same equity class as in the previous month. Strategy 3 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. If this condition is not met, then a 50/50 fixed allocation is preferred. Strategies 2 and 3 both result in reducing the amount of monthly switches and therefore the transaction costs.

For the size spread, all three rotation strategies perform much better than the buy and-hold small-cap strategy, even after adjusting for high transaction costs. In addition, they do not involve higher risk. Strategy 1 is most profitable when no transaction costs are taken into account. When 100 basis points are deducted for each trade, the second strategy becomes preferable. The third rotation strategy has the lowest volatility at 17.93%. The three strategies are less successful at predicting the value/growth spread. All three perform slightly better than the passive value buy and hold strategy, if transaction costs are ignored. When transaction costs are taken into account no rotation strategy is superior to the value buy-and-hold strategy. Even though the model can predict the monthly style trend more accurately than the size spread, the relative trading advantage that it offers is much lower.

Levis and Liodakis (1999) argue that the profitability of style rotation strategies depends on the volatility of the return spread between styles. Rotation between size portfolios works because of the volatility of the size premium over time. They conclude that style consistency is a prudent strategy for investors with very long investment horizons and strong confidence in the performance of their chosen style.

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Otherwise, style rotation strategies based on the underlying fundamental characteristics of the relevant style indexes can add value.

4.8. Summary and Conclusion

Market efficiency has received mixed support in the UK. Most researchers have failed to show that CAPM beta is positively related to returns, except Fletcher (1997) who argues the relationship is inverted when the market premium is negative. Beenstock & Chan (1986, 1988) test APT in the UK using both a factor analytic technique and the technique of identifying economic variables to proxy for risk factors. Both are found to successfully explain UK returns. Poon and Taylor (1991) on the other hand develop an economic factor APT model that they feel is unable to explain returns consistently. A host of studies show anomalies relating to value, momentum and size that persist after risk adjustment via traditional asset pricing risk models. The attributes are similar in nature to anomalies documented in the US. Strong and Xu (1997) argue that the weakness of asset pricing models to explain the cross-section of UK returns is partly due to extremely high expected inflation rates in the UK.

The calendar effect and the day-of-the-week effect have both been identified in the UK, however the evidence is mixed. There appears to be a turn-of-the-year effect in April, the tax year-end for individuals. Levis and Liodakis (1999) find that style payoffs are predictable using time-series methods and economic relationships. They report that style rotation strategies are more profitable than style consistency strategies.

The UK evidence is therefore in favour of the existence of exploitable anomalies.

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5.

Research Objective

This thesis investigates whether a selection of attributes belonging to firms listed on the LSE represent style anomalies and remain significant after adjusting for CAPM and APT risk.

This thesis tests which of the three criteria, t-statistic of slope, IC, or Grinold's IR (1989) is most appropriate to select combinations of factors in a stepwise procedure. The resulting models are tested out-of-sample. The models are also compared to an all attribute model to test whether models built using selection methods produce better results than a model that incorporates all attributes.

This thesis then establishes which styles show predictability using time-series methods, economic relationships and calendar seasonality. The results are used to build style forecasting models which are evaluated for each style. The style forecasting models are then incorporated into the multivariate framework to evaluate which forecasting model is most appropriate for use in the construction of expected return models. Once again all evaluation will be performed using out-of-sample performance.

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6.

Univariate and Multivariate Tests of Style Anomalies

6.1. Introduction

This chapter empirically investigates the cross-sectional relationships between firm-specific attributes and share returns on the LSE following the methodology of Fama and MacBeth (1973). Following Robertson (2002) CAPM and APT models are used to adjust share returns and test whether anomalies persist. The attribute payoffs are further cluster analysed. Out-of-sample tests are used to determine whether the relationships are sample specific or not.

Once individual attributes have been tested, the chapter engages in multivariate expected return modelling, following the methodology of Haugen and Baker (1996). Four multivariate models are constructed using a stepwise attribute selection procedure. The performance of these models is compared in- and out-of-sample. The results will reveal whether anomalies can be exploited within a multivariate context.

The remainder of this chapter is set out as follows. *Section 6.2.* describes the data employed, *Section 6.3.* discusses the methodology followed, *Section 6.4.* reports the univariate results, *Section 6.5.* reports the multivariate results and *Section 6.6.* summarises the key findings and concludes.

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6.2. Data

The primary data source of this thesis is DataStream. The sample of monthly share data covers the period March 1990 to February 2004. The period March 1990 to February 2000 is used for in-sample testing and the period March 2000 to February 2004 is reserved for out-of-sample testing. Constituents are drawn from the FTSE UK series All Share Index as it appeared on 1 January 2000. This implies that the in-sample period suffers from the problem of survivorship bias while the out-of-sample period is completely free of survivorship bias. The FTSE All Share Index has fairly strict liquidity requirements reducing the problem of thin trading. The FTSE index ground rules pertaining to liquidity requirements are displayed in *Appendix A.1.*

6.2.1. Returns

Returns at time t are calculated using the Return Index (RI) supplied by DataStream that incorporates price and dividend information and controls for capital events such as capitalisation issues and stock splits. Share returns for the month ending at time t are calculated as: $(RI_t - RI_{t-1}) / RI_{t-1}$. The absolute value of monthly returns are limited to 200% due to concern that these outliers represent errors. In addition, returns more than three standard deviations away from the mean, are crimped to three standard deviations from the mean to reduce the large effect of returns outliers. This winsorisation process ensures that results are robust and not heavily influenced by one or two outliers. Shares that de-list during the analysis period are given a return of -100% in the month of delisting. Shares not yet in existence for a given month are excluded from the analysis in that month. Haugen and Baker (1996) assign to missing share attribute values the mean attribute value for the month however, it is held that this approach may introduce statistical bias. Instead, where attribute values are missing for a share month, the entire share month is excluded.

6.2.2. Attributes

A list of firm-specific attributes, shortened to attribute*s*, tested in this thesis is provided in *Table 6.2.1.* Detailed descriptions of the attributes are displayed in *Appendix A.2.* and financial ratios underlying the attributes are displayed in *Appendix A.3.* They relate to the size, value, growth, profitability, liquidity, risk and returns momentum of each share. The groups of attributes in *Table 6.2.1.* are formed with reference to the cluster analysis (*Table 6.4.1.1.*) The availability of each attribute over the in- and out-of-sample periods is shown in *Appendix A.4.* and graphically presented in *Appendix A.5.*

As with returns, the attributes for each share in each month are subjected to a winsorisation process whereby outliers more than three standard deviations away from the mean are set equal to three standard deviations from the mean. The monthly

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cross-section of each attribute is then standardized by subtracting the cross-sectional mean and dividing by the cross-sectional standard deviation of each attribute. The result is that in each month, each attribute has a mean of zero and a standard deviation of one. Direct comparisons can then be made between the cross-sectional regression coefficients of each attribute. Van Rensburg and Robertson (2003) show that standardization does not have a significant effect on the t-statistics of the monthly regression slope coefficients. This confirmatory test is repeated using Students t-test to compare standardised regression coefficients against non-standardized coefficients. While the test shows that the t-statistic is somewhat influenced by the standardisation procedure, the differences are not significant. *Appendix A.6.* shows the full results of the test.

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Table 6.2.2.1. List of firm-specific attributes.

Names of the firm characteristics used in this study. Attributes are grouped according to their general proximity in the cluster analysis combined with *a priori* reasoning. Comprehensive descriptions and formulas for calculating ratios are detailed in *Appendix A.2. and A.3.*

Code	Name
Size	
LMV	Log of market value
LPrice	Log of price
Value	
BVTP	Book value to price ratio
CEY	Cash flow to price ratio (Cash earnings yield)
DY	Dividend yield
EY	Earnings yield
Sales_to_MV	Sales to market value ratio
Growth	
CEYG1	One-month growth of the cash flow to price ratio
CEYG12	Twelve-month growth of the cash flow to price ratio
DPSG12	Twelve-month growth of the dividend per share ratio
DPSG24	Two-year growth of the dividend per share ratio
EG12_P	(Twelve-month growth in earnings) divided by price
EG24_P	(Two-year growth in earnings) divided by price
ExpectedGrowth	Expected earnings growth rate (ROE * (1 - POUT))
Gearing	Financial gearing ratio
POUT	Dividend payout ratio
ROE	Return on book value of equity
SG12	Twelve-month growth in sales
SG24	Two-year growth in sales
Liquidity	
Current	Current ratio
ICBT	Interest cover before tax
NCA_to_MV	Net current assets to market value
Risk	
Beta	Beta
PVar12	Twelve-month price variance
RetVar12	Twelve month returns variance
Momentum	
Crossover3_12	Three-month returns momentum crossover twelve-month returns momentum
Mom1	One-month returns momentum
Mom3	Three-month returns momentum
Mom6	Six month returns momentum
Mom12	Twelve-month returns momentum
Mom18	Eighteen-month returns momentum

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6.2.3 Potential Data Related Limitations

Survivorship Bias

The theory of survivorship bias proposes that if firms delisting during the sample period are not included in the sample, average returns will be overstated, as firms surviving the sample period must be those that perform consistently well. This argument is presented by Kothari, Shanken and Sloan (1995) who show that US firms that de-listed from the COMPUSTAT data set showed on average a lower annual return, after controlling for CAPM beta, than shares that remained listed.

Using a data set completely devoid of survivorship and look-ahead bias, Davis (1994) finds that over the 1940 – 1963 period in the US, book-to-market value (B/M), earnings-to-price (E/P) and cash-flow to price (CF/P) all have explanatory power over the cross-section of returns. CAPM beta, on the other hand, is found to have no explanatory power. Davis concludes that the style attributes under study have been related to share returns for over 50 years and are "*not artefacts of data snooping or survivorship bias*." (1994)

Chan, Jegadeesh and Lakonishok (1995) investigate the effects of selection bias. Contrary to expectation, they find the reasons for a share being removed from a data set seldom involve financial distress. Most removals occurred due to mergers and acquisitions and companies failing to comply with exchange regulations *(Table 6.2.3.1.)*..

They report 9.6 percent of the eligible CRSP company-years are missing Compustat data for the 1968 - 1992 period. Of these missing observations, they conservatively estimate that only 3.1 percent can be classified as financially distressed cases. After comparing annual returns and the book-to-market effect on both the set of *surviving* firms and the set of all firms, they conclude that "*it is highly unlikely that the anomalous relations based on accounting variables are due to selection bias*"

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Table 6.2.3.1. Reasons for missing US data

Number of CRSP NYSE-Amex domestic primary companies missing data on Compustat, 1963-1992
Source: Chan, Jegadeesh and Lakonishok (1995:286)

Description	1963-67	1968-92
Issue still trading on NYSE-Amex	319	179
Merger or acquisition	1,083	533
Issue stopped trading as result of company liquidation	55	23
Issue stopped trading on exchange - reason unavailable	431	299
Issue moved from NYSE-Amex to other exchange	19	18
Delisted by current exchange (gone private, bankruptcy, insolvency, did not meet exchange listing guidelines)	21	70
Delisted by SEC	2	4
Total	**1,990**	**1,099**

The in-sample results of this thesis are subject to the effects of survivorship bias. The time-series of cross-sectional data analysed is obtained using a register of shares listed in 2000 (as far back as available). Shares that delist during the in-sample period (1 Mar 1990 – 1 Feb 2000) are consequently excluded from all analysis as they are not present on the 2000 register of shares. However, the out-of-sample period (1 Mar 2000 – 1 Feb 2004) is notably free from survivorship bias. Shares that delist during the out-of-sample period are given a return of -100% in the month of delisting. Appendix A.5. shows graphically that the number of firms decreases over the out-of-sample period as firms delist.

Data Snooping

Data-snooping has received much attention in financial literature. Using UN data, Leinweber, Managing Director of First Quadrant, Pasadena California, made the revealing discovery that the best predictor of the S&P500 index was butter production in Bangladesh. (Sullivan, Timmerman, and White, 1999).

Lo and MacKinlay (1995) expose the problem endemic to statistically motivated studies: They argue that when an extremely large set of initial variables are used to

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search for predictors of returns, it is inevitable that spurious (sample specific) predictors will be identified. Spurious predictors will fail on new data and be of no practical benefit. The problem is exacerbated in the US where many studies have used the same CRSP and COMPUSTAT data sets. If a researcher learns about a model that appears to work, he or she confirms its performance using similar historical data.

Kennedy (2003) suggests *"...if economic theory cannot defend the use of a variable as an explanatory variable, it should not be included in the set of potential independent variables. Such theorizing should take place before any empirical testing of the appropriateness of potential independent variables"*. Grinold and Kahn (1995) agree that factors should be selected intuitively without reference to the data Ferson, Sarkisson and Simin (2003) recommend that an adjustment be made to lower individual t-statistics as more attributes are tested.

The fact that so many attributes are able to explain future returns in historical data sets clashes with the inability of mutual funds to consistently beat the market. (Both Carhart (1997) and Wermers (2000) find that on average mutual funds are not able to beat the market after considering transaction costs and expenses). Lakonishok, Shleifer, and Vishny (1994) argue that many individual investors and institutional fund managers fail to beat the market because they choose *"glamour"* shares over the perceived riskier *"value"* shares. They present a number of convincing explanations, arguing that anomalies persist because of investor irrationality and are not simply the product of naïve data-mining.

Certain evidence in the US is suggestive of spurious data mining. Dividend yield, for example, became popular in the 1980s, but fails to work for post 1990 data [Goyal and Welch, 2003]. Lucas, van Dijk and Kloek (2001), show, using US data from 1984 to 1999, that payoff's to firm-specific attributes vary appreciably over time.

However, there is an overwhelming body of international research developing that supports the same anomalies across independent samples. Haugen and Baker (1996)

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for example, find similar results over five world equity markets. They report the magnitude and sign of the payoffs to their 12 most significant factors to be similar across markets. They also find low correlations between the payoffs across markets. (See *Section 3.2.* for a review of the international findings on anomalies).

It must also be noted that non-spurious attributes may stop (or start) performing for a number of economic reasons. If the payoff to a style changes over time in a predictable fashion, then models will be able to predict the future predictive power of attributes. In this case the attribute has a time-varying payoff and is not spurious. Lucas, van Dijk and Kloek (2001) are able to partially predict payoff changes using business cycle indicators.

Sullivan, Timmerman, and White (1999) propose that opportunities disappear out-of-sample because of greater market efficiency. They suggest that this may be due to lower transaction costs, increased liquidity and learning by market participants over time. They examine 26 trading rules applied to the Dow Jones Industrial Average over a period of 100 years. They report that a number of these rules have statistically significant predictive abilities in-sample, however none of the rules still work out-of-sample.

It is clear that cross-sample and out-of-sample testing play vital roles in determining which factors are non-spurious and have future predictive power. It is reassuring then that international research provides strong support for the continued existence of the same anomalies. In- and out-of-sample comparisons in this thesis will establish that anomalies uncovered are not spurious. However, the final *caveat* to researchers remains:

Attributes that continue to perform out-of-sample may eventually fail on new data.

Look-ahead Bias

Banz and Breen (1986) point out the existence of look-ahead bias in a number of data sets. Look-ahead bias exists when predictor variables are backfilled beyond the date

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that the information became available to market participants. Earnings figures, in particular, can be backfilled to the financial year end date. This can result in spectacular predictive power, as the following example illustrates. Suppose Earnings yield (E/Y) is used to predict subsequent returns. If a firm is about to announce a positive earnings surprise and E/Y already incorporates the new earnings, E/Y will be too high. When the announcement is made, the share price will react positively seemingly predicted by E/Y. Negative announcements will also exaggerate E/Y's predictive ability.

This thesis is not affected by look-ahead bias as all data is obtained from Datastream. Datastream only records information when it is available to market participants.

Thin trading

The returns on a share that trades infrequently may not encompass changes in the market value of the share and may contain measurement errors. In addition, any anomalies found that rely on infrequently traded shares will not be easily exploitable, especially within a short term investment horizon..

There are two forms of infrequent trading: non-synchronous trading and non-trading. non-synchronous trading implies that trading takes place in every time interval but not necessarily at the close of the interval of measurement of the returns data (see Dimson, 1979), while, non-trading occurs when securities do not trade in every consecutive time interval (see Stoll and Whaley, 1990). Morgan (2000) explains that non-synchronous trading becomes non-trading as the interval of measurement shrinks. If returns are calculated on a monthly basis then most LSE shares will have traded at least once in the month, however, not all shares will have traded precisely at the close of trading on the last day of the month (non-synchronous trading). If the interval of measurement is shortened to ten minutes, many shares will not have traded in the period of measurement (non-trading).

Non-synchronous and non- trading results in a measurement error in observed returns on individual shares, portfolios and market indexes. This measurement error generates serial correlation in the returns data. Morgan (2000) however, reports that although

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thin trading is more prevalent in the UK than in the US, it is proportionally less important in explaining the degree of serial correlation in share returns in the UK than in the US. He shows that infrequent trading only explains a small proportion of the serial correlation observed in monthly UK stock returns.

Haugen and Baker (1996) describe the problem of *bid ask bounce*. The problem arises in extremely thinly traded shares as trades happen at either the bid or ask price yet returns are measured close-to-close. To illustrate the problem, assume that the bid-ask spread of a share remains constant. If the share trades at the bid price at the end of month t, there is an even chance that it will trade at the ask price at the end of months t-1 and t+1. The return for the share at time t will therefore be zero or negative and at t+1 will be either zero or positive. The result is that returns appear negatively autocorrelated. This phenomenon however, cannot be exploited, and represents a bias in the way returns are calculated.

Problems of thin trading in this thesis are overcome by selecting shares that belong to the FTSE Allshare index. The misleadingly named index has a liquidity requirement, only including companies with a turnover of at least 0.5% of shares in issue (See Appendix A.1.). Additionally, by using monthly returns, problems of thin trading are substantially reduced.

Outliers

Outliers in the data may represent abnormal events or erroneous information in the data set. Whether reliable or not, outliers have a dominating influence on statistical testing, limiting the usefulness of results. For this reason the influence of outlying attributes is reduced by crimping the outlying values to three standard deviations away from the cross-sectional mean. The data-points crimped represent 0.48% of the total data set.

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6.3. Methodology

6.3.1. Univariate Methodology

Unadjusted Tests

Cross-sectional regressions are performed on each factor against *ex post* returns similar to van Rensburg and Robertson (2003). Before running any regressions, the data for each factor in each month are winsorised and standardized. See *Section 6.2.* for details of this process. Each attribute is tested individually using a cross-sectional ordinary least squares (OLS) regression comparable to that of Fama and MacBeth (1973) and Ferson and Harvey (1991, 1998).

$$r_{i,t+1} = \gamma_{0,t+1} + \gamma_{1,t+1} A_{it} + \varepsilon_{i,t+1} \tag{1}$$

Where the dependent variable, $r_{i,t+1}$, is the return on share *i* for month *t+1*, The dependent variable, A_{it}, is the standardized value of the attribute being tested for share *i* at the end of month *t*. $\gamma_{0,t+1}$, the intercept term, and $\gamma_{1,t+1}$, the slope coefficient are estimates produced by the regression. $\varepsilon_{i,t+1}$ represents the residual error.

For each attribute, this regression is repeated each month from 1 March 1990 to 1 February 2000 (in-sample) and 1 March 2000 to 1 February 2004 (out-of-sample) creating a time-series of slopes representing the payoff to the attribute in each month. Student's t-test is used to test whether the mean slope coefficient is significantly different to zero in-sample and out-of-sample.

In-sample and out-of-sample attribute payoffs are compared using a comparative t-statistic defined as:

$$t_{calculated} = \frac{(\overline{X}_1 - \overline{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{T_1} + \frac{s_2^2}{T_2}}} \tag{2}$$

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where $\overline{X}_1$ and $\overline{X}_2$ are the in-sample and out-of-sample means, $\mu_1 - \mu_2$ is the hypothesised difference in population means (zero in our case), T_1 and T_2 are the sample sizes (number of months) and s is the pooled sample standard deviation calculated as:

$$s^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{T_1 + T_2 - 2}. \tag{3}$$

Cluster Analysis

The payoffs of each attribute are cluster analysed to identify which styles perform similarly over time. The analysis uses an agglomerative hierarchical clustering algorithm (Statsoft Inc. Electronic Textbook, 2003) to compute Euclidean distances between clusters. Complete linkage is used to join neighbouring clusters. The complete linkage algorithm calculates distances between clusters as the greatest distance between any two objects from each cluster. (Statsoft Inc. Electronic Textbook, 2003). In the first step of the analysis, each attribute forms a cluster. Thereafter, in each step, clusters nearest each other (with the least distance) are grouped together to form a new cluster. A vertical tree diagram is used to present the results of the cluster analysis. It identifies the relational structure between attribute payoffs.

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Risk adjusted tests

Once it has been established that there exists a relationship between an attribute and *ex post* returns, it then needs to be tested that this attribute is not simply a proxy for systematic risk. In order to test this, two models of risk adjusted return are employed, the single factor CAPM model and a two factor APT model.

Using the CAPM model, share returns are adjusted for their level of systematic risk. CAPM separates share returns into a risk free (constant) factor, a risk factor representing the reward for taking on systematic risk and an error term representing return unexplained by the first two factors. Non-systematic risk is excluded from the model on the basis that it can be eliminated by holding a diversified portfolio.

$$r_{i,t} = r_{f,t} + \beta_i(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \qquad (4)$$

$r_{i,t}$ and $r_{m,t}$ represent realized returns for month *t* on share *i* and the market *(m)*. $r_{f,t}$ denotes the return on a risk-free asset and β_i is a measure of the exposure of share i to the market (formally defined as the covariance between r_i and r_m divided by the variance of r_m). $\varepsilon_{i,t}$ denotes the portion of $r_{i,t}$ left unexplained by the model. According to CAPM, $\varepsilon_{i,t}$ should be randomly distributed around zero.

Employing an OLS regression across the entire sample, excess share returns are regressed on excess market returns. The regression equation is obtained by rearranging the CAPM formula (4) so that $r_{f,t}$ is on the left-hand side.

$$(r_{i,t} - r_{f,t}) = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \acute{\varepsilon}_{i,t} \qquad (5)$$

The random error term $\varepsilon_{i,t}$ from equation (4) is separated in equation (5) into a constant term, α_i, and a random error term, $\acute{\varepsilon}_{i,t}$. Clearly if the CAPM assumptions hold then the constant term α_i will be zero. The composite term (α_i + $\varepsilon_{i,t}$) represents abnormal realised return (AR_{it}) over and above that predicted by the CAPM model. Rearranging,

$$AR_{it} = (\alpha_i + \varepsilon_{i,t}) = (r_{i,t} - r_{f,t}) - \beta_i(r_{m,t} - r_{f,t}) \qquad (6)$$

The FTSE UK series All Share Index and the UK three-month T-bill rate are used as proxies for $r_{m,t}$ and $r_{f,t}$ respectively.

The same univariate OLS procedure is used to regress AR_{it+1} on each attribute each month:

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$$AR_{it+1} = \gamma_{0,t+1} + \gamma_{1,t+1}A_t + e_{i,t+1} \quad (7)$$

For each attribute, a time-series of CAPM adjusted payoff's is created. The mean of this time-series is tested using Student's t-test to establish which attributes remain significantly related to returns after adjusting for risk.

There may be more than one risk factor in the economy, in which case an improved measure of each share's systematic risk can be obtained using a multifactor APT model, in place of the CAPM model. Principal (maximum likelihood) factor analysis is performed on a dataset of FTSE UK level 6 indexes over the period 1 Mar 1990 - 1 Feb 2000 to identify sources of common variation in share returns. The eigenvalues for each factor are cumulatively plotted on a graph and a scree test determines the number of factors extracted. The scree test ensures that a parsimonious number of factors are extracted that are still able to explain most of the variation in the data. Van Rensburg and Slaney (1997) refer to two possible cut-off points: the factor at which the scree plot first starts to flatten out, or the factor before the scree plot flattens out. They point out that the factor extraction decision is essentially a trade-off between the increased parsimony offered by a smaller number of factors and the increased explanatory power that results as more factors are extracted. A third cut-off point often used extracts all factors with eigenvalues greater than 1.00.

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The correlation between an individual factor and a variable is known as a factor loading. Normalized varimax rotation is performed to ensure that variables are assigned to one factor. Each factor thus represents a group of shares that behave similarly. For each source of common variation (factor), a proxy is obtained as the share index with the highest correlation to that factor.

The results of the factor analysis indicate that a three factor APT model should be used. The APT model separates share returns into a risk free (constant) factor and three factors relating to two distinct sources of risk.

$$r_{i,t} = r_{f,t} + \beta_{f1,i}(r_{f1,t} - r_{f,t}) + \beta_{f2,i}(r_{f2,t} - r_{f,t}) + \beta_{f3,i}(r_{f3,t} - r_{f,t}) + \varepsilon_{i,t} \tag{8}$$

Rearranging,

$$(r_{i,t} - r_{f,t}) = \alpha_i + \beta_{f1,i}(r_{f1,t} - r_{f,t}) + \beta_{f2,i}(r_{f2,t} - r_{f,t}) + \beta_{f3,i}(r_{f3,t} - r_{f,t}) + \acute{\varepsilon}_{i,t} \tag{9}$$

$r_{f,t}$ and $r_{i,t}$ once again represent the realized return for a risk-free asset and for share *i* respectively. $r_{f1,t}$, $r_{f2,t}$ and $r_{f3,t}$ represent the return for Factors 1, 2 and 3 over the period *t*. As in the CAPM test, the composite term ($\alpha_i + \acute{\varepsilon}_{i,t}$) represents abnormal realised return (AR_{it}) and can be expressed as,

$$\begin{aligned} AR_{it} &= (\alpha_i + \acute{\varepsilon}_{i,t}) \\ &= (r_{i,t} - r_{f,t}) - \beta_{f1,i}(r_{f1,t} - r_{f,t}) - \beta_{f2,i}(r_{f2,t} - r_{f,t}) - \beta_{f,3i}(r_{f3,t} - r_{f,t}) \end{aligned} \tag{10}$$

Similarly, for each month, AR_{it} is regressed against each attribute to create a time-series of payoffs.

$$AR_{it} = \gamma_{0,t+1} + \gamma_{1,t+1} A_t + e_{i,t+1} \tag{11}$$

The mean slope coefficient is tested for each attribute using Student's t-test. As the CAPM and APT betas are derived from the data set that the style tests are performed on, the CAPM and APT models are likely to perform better than they would out-of-sample. This results in the risk-adjusted tests being biased against identifying significant characteristics and thus strengthens the importance of any significant characteristics found.

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Attributes that are found to be significant in the CAPM and APT tests are related to risk-adjusted *ex post* share returns. That is, they are more than just proxies for risk, as given by the CAPM and APT models.

6.3.2. Multivariate Methodology

Individual attributes with an in-sample univariate t-statistic with absolute value greater than one are used to construct a multifactor model. Attributes that perform strongly over sub-periods but change sign midway during the sample period may be missed by this screening procedure. However, a scan of the payoff graphs (*Appendix A7 - A14*) reveals that none of the attributes with absolute value of t-statistic less than one, appears to perform strongly over sub-periods. Correlations between attribute payoffs are observed. Fairly high correlations are permitted as the stepwise multivariate procedure takes the multicollinearity into account when it accepts an attribute into the model.

Multifactor expected returns models are constructed using a similar methodology to that of Haugen and Baker (1996) In each month a cross-sectional OLS multiple regression is performed with the one-month forward return as dependent variable and all attributes included in the model as independent variables. In this fashion monthly payoffs (slope coefficients) are simultaneously estimated for each attribute in the model:

$$r_{i,t+1} = \alpha_{t+1} + \sum_{k} \beta_{k,t+1} F_{i,k,t} + u_{i,t+1} \qquad (12)$$

where:

$r_{i,t+1}$ = return to stock i in month $t+1$,

$\beta_{k,t+1}$ = estimated regression coefficient of factor k in month $t+1$,

$F_{i,k,t}$ = exposure to factor k for stock i at the end of month t.

In accordance with Haugen and Baker (1996) the twelve-month trailing mean of each attribute payoff is used to estimate the following month's payoff and thereby construct an equation to forecast returns one month ahead. Using the twelve month

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trailing mean as opposed to the historical mean implies that a degree of style timing is built into the forecasting process. Given the attribute values for share i at the end of the month t and the estimated attribute payoffs for month $t + 1$, a relative expected return (forecast) can be calculated,

$$E(r_{i,t+1}) = \alpha_{t+1} + \sum_{k} E(\beta_{k,t+1}) F_{i,k,t} \tag{13}$$

where:

$E(r_{i,t})$ = expected return to share i in month t,

$E(\beta_{k,t})$ = expected payoff to factor k in month t

Monthly expected returns for each share are then compared to the realised returns to assess model performance.

Four multi-factor models are constructed and tested. The first model includes all attributes with an in-sample absolute value of univariate mean greater than one The other three models all employ a stepwise inclusion procedure to *optimise* the attributes included in the model. Each of these optimised models relies on a measurement criterion to select attributes. Model 2 uses the slope of t-statistic, Model 3 uses the information coefficient (IC) and Model 4 uses Grinold's (1989) information ratio approximation (IR). Definitions of each criterion are provided in *Table 6.3.2.* Attributes are first ranked according to their univariate in-sample performance. At each step a new attribute is included in the model and the performance of the model is measured according to a performance criterion over the in-sample period. The new attribute is included in the model if and only if an improvement in the criterion score occurs. Certain attributes may only exert explanatory power in conjunction with a combination of other factors. Therefore, the entire stepwise process is repeated with attributes selected in the previous run-through included up-front and previously unselected attributes retested. This stepwise procedure is repeated until no new attributes are included in an entire stepwise run-through.

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Table 6.3.2. Summary of Stepwise Performance Criteria

Descriptions of performance measurement criteria used in stepwise procedures

Criterion	Description	Underlying Formula
T-Statistic of Slope	T-statistic of the time-series of slope coefficients obtained in regressions between expected and actual returns in each month.	$t = \frac{\beta_{R,E(R)}\sqrt{T}}{\sigma_{\beta_{R,E(R)}}}$ where T represents the number of months tested
Information Coefficient (IC)	Mean correlation between expected and realised returns in each month.	$IC = \rho\ (E(R_{it}), R_{it})$
Grinold's (1989) Information Ratio approximation (IR)	Mean information ratio (IR). IR is an adaptation of the information coefficient that takes into account the number of shares forecast each month	$IR \approx IC\sqrt{N}$ Where n is the number of shares forecast in the month.

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The construction methodology and a brief justification is now provided for each performance criterion for each performance criterion. The first criterion listed in *Table 6.3.2*, the t-statistic of slope, is important as it provides a measure of the difference in performance between high ranked shares and low ranked shares. In constructing a model to take advantage of mispricings, the t-statistic is extremely important as it is strongly influenced by returns from shares in the top and bottom fractiles. In particular the models constructed in this thesis invest (long and short) only in the highest and lowest forecast return deciles, therefore the ability of the model to rank shares with returns around the median is less important. The t-statistic of slope is obtained by calculating the mean and standard deviation of the monthly slope coefficient estimated in the monthly regression of expected returns against realised returns and applying the following formula,

$$t_{\beta_{R_t,E(R)_t}} = \frac{\overline{\beta}_{R_t,E(R)_t}}{\sigma_{\beta_{R_t,E(R)_t}}}\sqrt{T}\,, \qquad (14)$$

where:

$$\beta_{R_t, E(R)_t} = \frac{Cov(R_t, E(R)_t)}{\sigma^2_{E(R)_t}}, \quad (15)$$

and

$\overline{\beta}$ = the mean monthly slope coefficient,

σ_β = the standard deviation of the monthly slope coefficients and

T = the number of monthly observations.

The second criterion, the information coefficient (IC), is very commonly used as a performance diagnostic to assess a portfolio manager's ability. IC measures the overall ability of a model to rank shares. IC is calculated using the Pearson correlation coefficient to estimate the correlation between expected and realised returns.

$$IC = \rho\,(E(R_{it}), R_{it}) \quad (16)$$

The third criterion, Grinold's (1989) Information Ratio (IR) adapts the IC coefficient by taking the breadth of shares over which forecasts are made into account.

$$IR \approx IC\sqrt{N} \quad (17)$$

where IC is as before and N denotes the number of shares forecast.

The four models are then tested out-of-sample. Testing is done using the same performance criteria defined above with four additions, namely Qian and Hua's (2003) Information Ratio and the decile spread, decile spread standard deviation and decile spread t-statistic.

Qian and Hua's (2003) Information Ratio adjusts the Information Coefficient for the volatility in performance,

$$IR \approx \frac{\overline{IC_t}}{stdev(IC_t)} \quad (18)$$

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where $\overline{IC_t}$ is the mean monthly IC and $stdev(IC_t)$ is the standard deviation of IC. This IR approximation provides a measure of the statistical significance of the final mean IC.

The decile spread criteria are fractile performance measures. There are many fractile performance measures available. Achour, Harvey, Hopkins, and Lang (1999), for example, use over thirty different fractile performance measures to assess model performance. While this thesis has focused on a regression based approach to model construction and testing, the decile spread is included in model evaluation as it is very intuitive and the most commonly used fractile performance measure. The decile spread measures the difference between the average return earned by shares in the top decile of forecast returns and the average return earned by shares in the lowest decile. The standard deviation of the decile spread gives an indication of how consistently the model performs. The t-statistic of the mean decile spread incorporates both the magnitude and consistency of the decile spread to give a robust measure of model performance. Decile performance is displayed graphically for in-sample and out-of-sample periods.

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6.3.3 Potential Methodology Related Limitations

Attribute Specification Error

Two forms of misspecification bias may be present in the selection of attributes for the univariate and multivariate regressions. Firstly, an irrelevant attribute may be included in a regression. This would result in the regression estimates for the included attributes being less accurate (yet unbiased). Secondly, a relevant attribute may be excluded from the regression. In this case the estimates for the attributes included will be more accurate (yet biased). This bias comes from the fact that part of the underlying explanatory power is due to the excluded attribute.

Durham (2000) argues that a large amount of research is flawed as researchers do not control for attributes shown to influence share return. Fama and French (1992) identify six factors related to returns however they omit other variables that previous studies indicate affect stock returns. For example, they do not consider, any price-history factors (DeBont and Thaler, 1985). In another influential study, Jegadeesh and Titman (1993) test for size, calendar phenomena and earnings announcement effects, but do not consider accounting-based variables such as BE/ME, which Fama and French (1992) find to be significant. Durham (2000) points out that neither Fama and French (1992) nor Jegadeesh and Titman (1993) control for economic variables in the APT literature (Chen *et al.*, 1986).

Durham propounds using a technique called extreme bound analysis (EBA) by which he regresses each attribute against forward returns controlling for the other (*doubtful*) attributes being tested and a set of (*free*) variables representing macro-factors such as CAPM market beta and the Chen *et al.* (1986) APT factors. Using this more strict testing procedure, he finds extremely few attributes are robust. This suggests that prior studies have suffered from specification bias. In emerging markets he finds only price momentum and volatility factors to be robust. In developed markets he finds only long-term momentum to be robust.

Trading Costs

The fact that anomalies persist may be the result of trading costs that prevent prices reaching their equilibrium level. Trading costs will naturally constrain real-world applications where it is preferable to keep trading costs down by limiting the turnover of shares. González-Rivera, Lee and Mishra (2003) rank shares based on forecast return from a number of different trading rules observing changes in rank over time. They report that shares with especially high (low) forecast returns tend to experience greater shifts in rank. However they are partly able to predict movements in rank. Haugen and Baker (1996) find that share returns have a tendency to mean revert. They also find this tendency strongest in shares in the top and bottom fractiles This is regrettable, as real-world models will require taking positions in shares with extreme forecast returns.

The models developed in this thesis are rebalanced on a monthly basis. This rebalancing will no longer be optimal when trading costs are introduced. An optimised model incorporating trading costs will only hold shares that are forecast to remain in the top fractile. This optimisation problem is highlighted for future inquiry.

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Research in the US, conducted by Haugen and Baker (1996) indicates that trading considerations do not significantly erode abnormal returns generated.

Haugen and Baker (1996) build a *"real-world"* model using only the largest 1000 shares from their sample of 3000, rebalancing quarterly as opposed to monthly and only investing up to 5% in any single share. They assume a 2% cost to cover both buying and selling and limit portfolio turnover to 20%. Given these constraints they are still able to generate returns significantly higher than the Russell 1000 index. In addition, the volatility of returns is significantly lower than that of the index.

6.4. Univariate Results

6.4.1. Cluster Analysis

Attribute correlations are shown in Table 6.4.1.1. Attributes are already grouped according to the cluster analysis to make patterns more visible. High correlations are permitted as the stepwise multivariate procedure takes the multicollinearity into account when it accepts an attribute into the model. Table 6.4.1.1. reveals that the momentum attributes are highly correlated with each other. The yield attributes in the value group are highly correlated with each other and with the momentum attributes. This is likely due to the common influence of the variable, price, used in the construction of each of these attributes. There are no other patterns of strong correlation between attributes.

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Table 6.4.1.1. Correlations Between Attribute Payoffs

Pearson correlation matrix of all attributes. To conserve space Expectedgrowth and Sales_to_MV are shortened to Exp_G and S_to_MV. Correlations exceeding 0.80 are shown in bold

		Size		Value					Growth											
		LMV	LPRICE	BVTP	CEY	DY	EY	S_to_MV	CEYG1	CEYG12	DPSG12	DPSG24	EG12_P	EG24_P	EXP_G	Gearing	POUT	ROE	SG12	SG24
Size	LMV																			
	LPRICE	0.7																		
Value	BVTP	0.3	-0.2																	
	CEY	0.4	-0.1	0.6																
	DY	0.3	-0.3	0.6	**0.8**															
	EY	0.3	-0.3	0.5	**0.9**	**0.9**														
	S_to_MV	-0.2	-0.7	0.4	0.5	0.7	0.7													
Growth	CEYG1	0.2	-0.3	0.5	0.6	0.7	0.7	0.6												
	CEYG12	0.3	0.0	0.3	0.5	0.3	0.3	0.2	0.3											
	DPSG12	0.3	0.4	-0.1	0.1	-0.2	0.0	-0.4	-0.1	0.2										
	DPSG24	0.2	0.4	0.0	0.0	-0.1	0.0	-0.4	-0.1	0.0	0.5									
	EG12_P	0.0	0.0	0.0	-0.1	0.0	-0.1	0.1	0.1	0.0	-0.2	-0.1								
	EG24_P	0.1	0.0	0.0	0.0	0.1	0.0	0.1	0.2	0.2	0.0	-0.1	0.7							
	EXP_G	-0.5	-0.5	0.0	-0.1	0.1	0.0	0.4	0.0	-0.2	-0.4	-0.2	0.1	-0.1						
	Gearing	-0.3	-0.1	-0.4	-0.3	-0.3	-0.2	0.1	-0.2	-0.3	-0.3	-0.2	0.2	0.1	0.2					
	POUT	0.7	0.1	0.7	0.8	0.8	0.7	0.4	0.6	0.4	0.2	0.1	-0.1	0.0	-0.2	-0.4				
	ROE	0.4	0.3	0.0	0.3	0.2	0.2	-0.1	0.1	0.1	0.3	0.0	-0.3	-0.1	-0.5	-0.2	0.3			
	SG12	-0.3	0.2	-0.6	-0.6	-0.7	-0.7	-0.6	-0.6	-0.3	0.2	0.1	0.0	0.0	-0.1	0.2	-0.7	-0.1		
	SG24	-0.3	0.0	-0.3	-0.5	-0.5	-0.5	-0.3	-0.3	-0.2	0.0	0.1	-0.1	-0.1	0.0	0.2	-0.5	-0.2	0.6	
Lqdty	Current	-0.2	0.2	-0.3	-0.6	-0.6	-0.6	-0.5	-0.5	-0.2	-0.1	0.0	0.1	0.0	0.0	0.0	-0.5	-0.2	0.4	0.4
	ICBT	0.0	-0.1	0.1	0.2	0.1	0.2	0.0	0.1	0.0	0.3	0.1	-0.2	-0.2	-0.2	-0.2	0.2	0.2	0.0	0.0
	NCA_to_MV	-0.2	-0.5	0.4	0.2	0.4	0.4	0.5	0.1	0.1	-0.2	-0.1	-0.2	-0.2	0.2	-0.1	0.2	-0.2	-0.3	-0.1
Risk	Beta	-0.3	0.1	-0.5	-0.7	-0.8	-0.8	-0.5	-0.6	-0.3	-0.2	-0.1	0.1	0.0	0.0	0.3	-0.8	-0.2	0.7	0.5
	PVar12	-0.3	0.1	-0.5	-0.5	-0.5	-0.6	-0.4	-0.4	-0.5	-0.2	0.1	0.0	-0.2	0.2	0.3	-0.7	-0.2	0.5	0.4
	RetVar12	-0.6	-0.2	-0.5	-0.7	-0.6	-0.6	-0.2	-0.5	-0.5	-0.4	-0.2	0.1	-0.1	0.3	0.4	**-0.8**	-0.3	0.5	0.4
Momentum	Crossover3_12	-0.3	0.3	-0.6	-0.7	-0.7	-0.7	-0.6	-0.6	-0.3	-0.1	0.0	0.1	-0.1	0.0	0.2	-0.7	-0.2	0.7	0.5
	MOM1	-0.2	0.4	-0.6	-0.7	-0.8	-0.8	-0.7	-0.7	-0.2	0.1	0.1	0.0	-0.1	0.0	0.3	-0.7	-0.1	0.7	0.5
	MOM3	-0.2	0.5	-0.7	-0.7	**-0.8**	-0.8	-0.8	-0.7	-0.2	0.2	0.2	0.0	-0.1	-0.1	0.2	-0.7	-0.1	0.7	0.5
	MOM6	-0.2	0.5	-0.7	-0.7	**-0.8**	-0.8	-0.8	-0.7	-0.3	0.2	0.2	0.0	-0.1	-0.1	0.2	-0.7	-0.1	0.7	0.5
	MOM12	-0.3	0.4	-0.7	-0.7	**-0.8**	**-0.8**	-0.7	-0.7	-0.3	0.2	0.2	0.0	0.0	-0.1	0.2	-0.7	-0.1	0.7	0.4
	MOM18	0.0	0.5	-0.6	-0.6	**-0.8**	-0.8	**-0.8**	-0.7	-0.2	0.5	0.3	-0.1	-0.1	-0.3	0.1	-0.5	0.1	0.7	0.4

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Table 6.4.1.1. Correlations Between Attribute Payoffs (Continued)

		Liquidity			Risk			Momentum				
		Current	ICBT	NCA_to_MV	Beta	PVar12	RetVar12	Crossover3_12	MOM1	MOM3	MOM6	MOM12
Liquidity	Current											
	ICBT	-0.2										
	NCA_to_MV	0.1	0.1									
Risk	Beta	0.6	-0.3	-0.2								
	PVar12	0.4	-0.2	-0.3	0.5							
	RetVar12	0.5	-0.2	0.1	0.7	0.6						
Momentum	Crossover3_12	0.6	-0.1	-0.3	0.8	0.7	0.7					
	MOM1	0.5	-0.1	-0.3	0.7	0.7	0.6	**0.8**				
	MOM3	0.5	-0.1	-0.4	0.7	0.6	0.6	**0.8**	**0.9**			
	MOM6	0.5	-0.1	-0.4	0.7	0.6	0.5	**0.8**	**0.9**	**0.9**		
	MOM12	0.5	-0.2	-0.4	0.8	0.5	0.6	0.8	**0.9**	**0.9**	**0.9**	
	MOM18	0.5	0.0	-0.5	0.6	0.4	0.3	0.6	0.7	**0.8**	**0.8**	**0.8**

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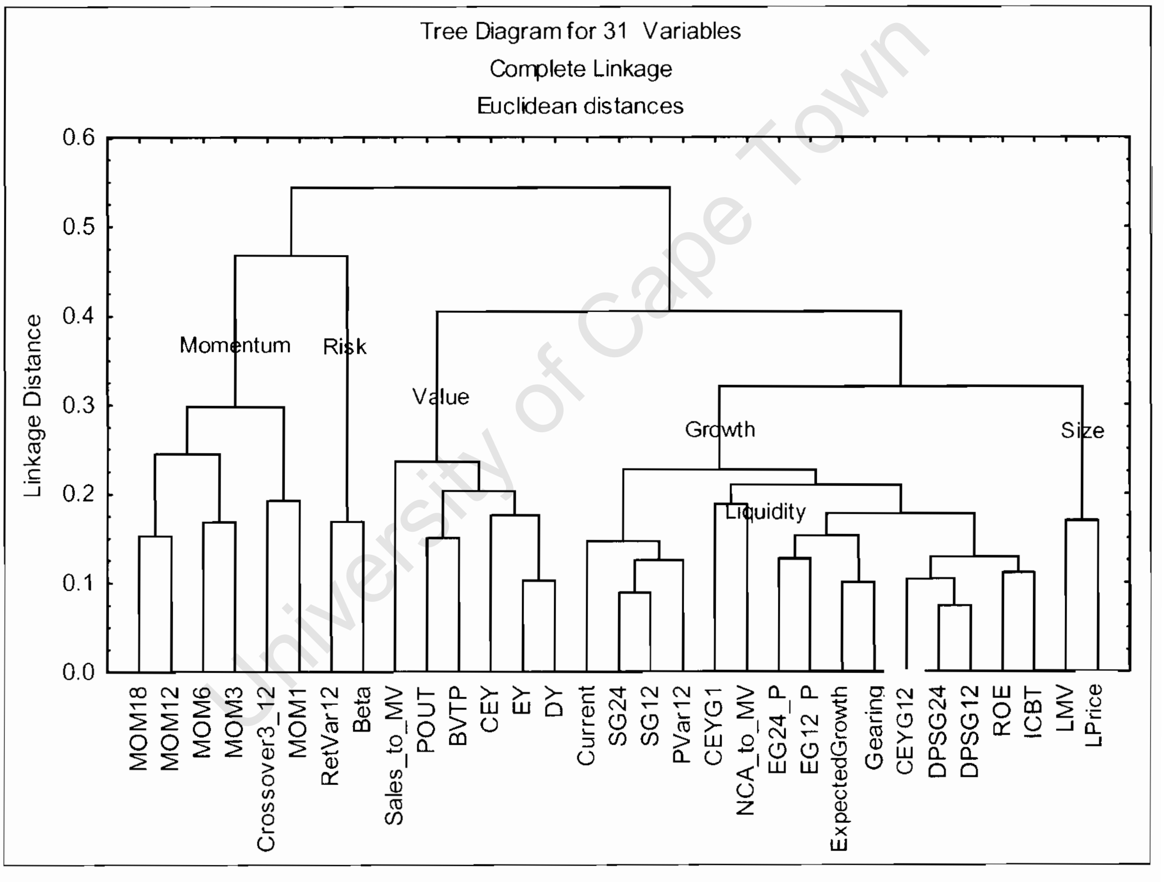
Monthly univariate regression slopes over the in-sample and out-sample periods are cluster analysed to identify the relational structure between attribute payoffs. A vertical tree diagram of the analysis is presented in *Figure 6.4.1.1.*

Figure 6.4.1.1. Cluster Analysis of Attribute payoffs.

Vertical tree diagram showing the stepwise hierarchical cluster analysis of monthly attribute payoffs (univariate slope coefficients) over the period 1 Mar 1990 – 1 Feb 2004. The analysis uses Euclidean distances between clusters and the complete linkage rule to join neighbouring clusters. The complete linkage rule calculates distances between clusters as the greatest distance between any two objects from each cluster. (Statsoft Inc. Electronic Textbook, 2003). In the first step of the analysis, each attribute forms a cluster. In each step thereafter clusters nearest each other (with least distance) are grouped together to form a new cluster until there is only one cluster.



The cluster analysis reveals that there are five main sources of variation (clusters) in the style payoffs analysed. The main clusters represent momentum, risk, value, growth and size. The growth cluster includes an element of liquidity. Constituents of each cluster, with a few exceptions made to conform to generally accepted opinion, are listed in *Table 6.2.2.1.*

6.4.2. In-sample Univariate Results

Table 6.4.2.1. shows the individual factor payoffs over the in-sample period. 11 attributes are shown to be significant at the 95% confidence level. Interest cover before tax, three-month, six-month, one-year and eighteen-month momentum, crossover3_12, beta and return on equity are found to be significantly positively related to future returns while log of price, the payout ratio and price variance are found to be significantly negatively related to future returns. For an attribute to be significant it needs to perform consistently over the sample period. For example, if the payoff to an attribute is highly significant over all sub-periods, but changes sign midway through the sample period, the overall mean t-statistic may become insignificant. Size (as measured by log of market value) pays off in the opposite direction during the early nineties. Subsequently, however it changes sign and becomes a strongly performing negative attribute returning to the more intuitive direction where small firms earn higher returns. This is consistent with other UK research on the size anomaly. Levis and Liodakis (1999) for example show that large-caps are more profitable from 1988 to 1992.

A market (CAPM) model and a three-factor APT model are constructed to risk-adjust returns. The factor analytic construction of the three-factor APT model is presented in *Appendix A.15*.

The risk adjusted payoffs indicate that neither CAPM nor APT risk factors can explain away style returns. Most style t-statistics are slightly less significant after risk adjustment although some styles such as log of market value and one-year dividend per share growth only become significant after risk adjustment. The reason for this may be that stripping returns of the CAPM and APT risk factors reduces outside noise and allows style relationships to be shown more clearly. It is possible to conclude that style returns are independent of CAPM and APT risk factors.

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Table 6.4.2.1. In-sample Monthly Cross-sectional Regressions

The mean monthly cross-sectional coefficients are reported for each attribute for the in-sample period from 1 Mar 1990 – 1 Feb 2000 (120 monthly observations). Attribute definitions are presented in Table 6.2.2.1. The coefficients are estimated using univariate cross-sectional regressions of stock returns. Factors are ranked according to the absolute value of the t-statistic of the mean regression coefficient. Factors showing an absolute value of t-statistic less than one are separated. T-statistics significant at the 5% level are bolded. Results of the same test run after both a CAPM and three factor APT risk adjustment process are displayed.

Attribute	Before Risk Adjustment			After CAPM Risk Adjustment			After APT Risk Adjustment		
	T-statistic	Mean	Std. deviation	T-statistic	Mean	Std. deviation	T-statistic	Mean	Std. deviation
ICBT	**5.43**	0.002	0.005	**4.73**	0.002	0.006	**5.95**	0.003	0.006
LPrice	**-4.51**	-0.005	0.012	**-4.31**	-0.005	0.014	**-3.86**	-0.005	0.013
MOM18	**4.22**	0.006	0.017	**3.63**	0.006	0.018	**2.91**	0.004	0.014
MOM12	**3.25**	0.005	0.017	**2.92**	0.005	0.021	**2.76**	0.004	0.014
POUT	**-3.06**	-0.004	0.012	**-2.68**	-0.004	0.015	-1.04	-0.001	0.012
Crossover3_12	**2.93**	0.004	0.015	**2.92**	0.005	0.018	**2.94**	0.003	0.012
PVar12	**-2.88**	-0.003	0.009	**-2.42**	-0.002	0.011	**-3.62**	-0.003	0.010
MOM6	**2.84**	0.005	0.018	**2.76**	0.005	0.021	**2.59**	0.003	0.014
Beta	**2.70**	0.004	0.018	-	-	-	-	-	-
ROE	**2.28**	0.002	0.007	0.69	0.001	0.010	1.02	0.001	0.011
MOM3	**2.13**	0.004	0.018	**2.06**	0.004	0.022	1.56	0.002	0.015
RetVar12	1.94	0.003	0.017	1.66	0.003	0.019	0.25	0.000	0.016
DY	-1.92	-0.003	0.017	-1.72	-0.003	0.019	0.04	0.000	0.015
Gearing	-1.88	-0.001	0.006	-0.84	-0.001	0.009	-0.87	-0.001	0.009
SG12	1.77	0.001	0.008	**1.76**	0.001	0.009	0.74	0.000	0.007
BVTP	1.61	0.002	0.010	0.98	0.001	0.013	**2.87**	0.003	0.011
LMV	-1.61	-0.002	0.015	**-2.26**	-0.004	0.018	-1.23	-0.002	0.017
EG24_P	1.54	0.001	0.010	0.35	0.000	0.013	0.01	0.000	0.013
DPSG12	1.52	0.001	0.006	0.40	0.000	0.007	0.17	0.000	0.007
Sales_to_MV	-1.51	-0.002	0.015	-0.39	-0.001	0.018	0.89	0.001	0.015
Current	1.37	0.001	0.007	0.52	0.000	0.008	-0.76	-0.001	0.008
EG12_P	1.35	0.001	0.010	0.87	0.001	0.014	0.95	0.001	0.014
DPSG24	-1.28	-0.001	0.006	**-2.05**	-0.001	0.006	**-2.17**	-0.001	0.006
SG24	1.24	0.001	0.006	0.46	0.000	0.006	-0.59	0.000	0.006
CEYG1	-1.21	-0.001	0.010	-0.93	-0.001	0.011	-0.48	0.000	0.008
MOM1	1.18	0.002	0.015	1.26	0.002	0.018	0.65	0.001	0.012
EY	-1.04	-0.002	0.016	-0.74	-0.001	0.018	1.08	0.001	0.014
CEY	-0.96	-0.001	0.015	-0.91	-0.002	0.021	0.56	0.001	0.017
CEYG12	0.50	0.000	0.005	0.82	0.000	0.007	1.12	0.001	0.006
NCA_to_MV	0.21	0.000	0.009	0.05	0.000	0.013	0.56	0.001	0.012
Expectedgrowth	0.06	0.000	0.005	0.30	0.000	0.006	0.19	0.000	0.006

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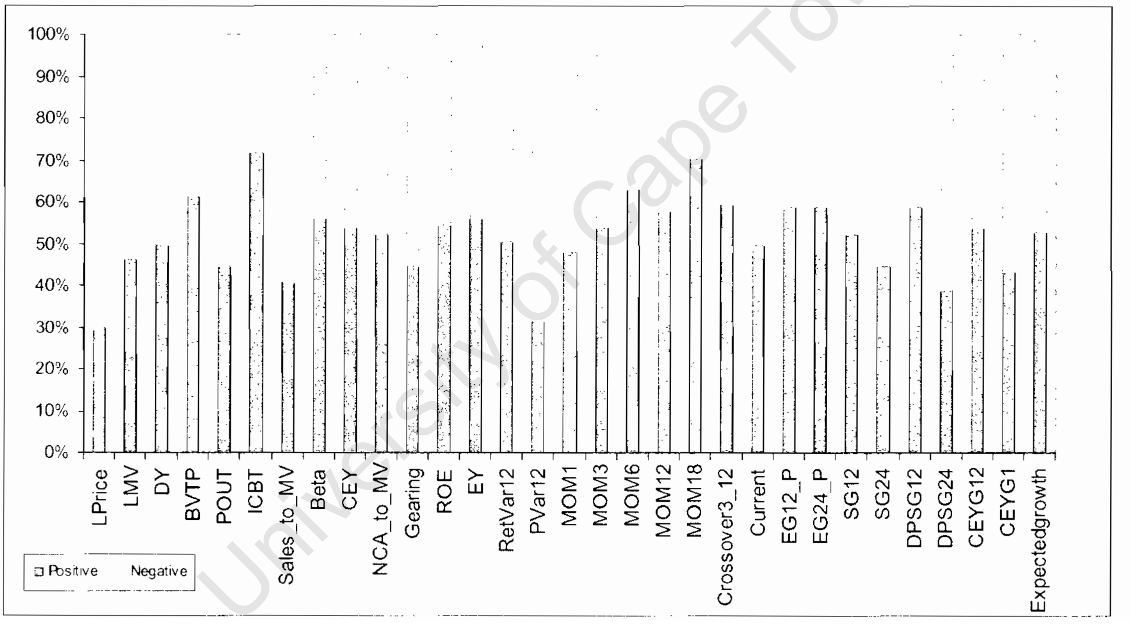
Figure 6.4.2.1. displays the styles that perform consistently over the in-sample period. Log of price and twelve month price variance both show a high proportion of negative months while interest cover before tax, eighteen-month momentum and book value to price both show a high proportion of positive months. Even styles that perform well appear to have a fair ratio of months where the sign of the payoff is opposite to the sign of the mean payoff. This supports research into style timing, to take advantage of these months where styles perform in the opposite direction.

Figure 6.4.2.1. Style consistency graphic

Displays proportion of months with positive and negative slope coefficients from the unadjusted univariate regressions performed on each style over the in-sample period 1 Mar 1990 – 1 Feb 2000.



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6.4.3. Out-of-Sample Univariate Results

Table 6.4.3.1. shows the individual factor payoffs over the out-of-sample period, 1 March 2000 – 1 February 2004. 11 attributes are shown to be significant at the 95% confidence level. Interest cover before tax is no longer found to be the best performing attribute, although it is found to be significant at the 95% level. Book value to price and sales to market value, both measures of value, are found to be most significant in the out-of-sample period. Once again, both risk adjustments do not affect results. There is strong evidence that anomalies are not related to either CAPM or APT risk.

Table 6.4.3.1. Out-of-sample Monthly Cross-sectional Regressions

The mean monthly cross-sectional coefficients are reported for each attribute over the out-sample period from 1 Mar 2000 – 1 Feb 2004 (48 monthly observations). The coefficients are estimated using univariate cross-sectional regressions of stock returns. Factors are ranked according to the absolute value of the t-statistic of the mean regression coefficient. Factors showing an absolute value of t-statistic less than one are separated. T-statistics significant at the 5% level are bolded. Results of the same test run after both a CAPM and APT risk adjustment process are displayed.

Attribute	Unadjusted			After CAPM Risk Adjustment			After APT Risk Adjustment		
	T-statistic	Mean	Std. deviation	T-statistic	Mean	Std. deviation	T-statistic	Mean	Std. deviation
BVTP	**4.27**	0.008	0.014	**3.28**	0.008	0.017	**3.16**	0.007	0.016
Sales_to_MV	**3.92**	0.012	0.021	**5.76**	0.015	0.018	**4.96**	0.011	0.015
Current	**-3.61**	-0.008	0.015	**-3.73**	-0.007	0.013	-1.77	-0.004	0.014
EY	**3.52**	0.011	0.021	**3.72**	0.011	0.020	**2.56**	0.007	0.018
PVar12	**-3.33**	-0.005	0.011	**-3.45**	-0.006	0.011	-1.74	-0.003	0.011
ICBT	**3.08**	0.005	0.011	**3.14**	0.004	0.009	1.93	0.003	0.009
DY	**2.58**	0.009	0.023	**2.85**	0.011	0.026	**2.71**	0.009	0.023
SG12	**-2.52**	-0.004	0.012	**-2.44**	-0.004	0.013	-0.20	0.000	0.012
POUT	**2.32**	0.007	0.020	**2.33**	0.006	0.018	1.49	0.003	0.016
SG24	**-2.08**	-0.002	0.008	**-2.84**	-0.003	0.008	-0.47	-0.001	0.009
EG12_P	**2.05**	0.002	0.008	-0.55	-0.005	0.058	-0.57	-0.005	0.058
CEY	1.85	0.007	0.027	1.33	0.006	0.028	0.62	0.002	0.024
RetVar12	-1.77	-0.008	0.032	-1.46	-0.006	0.030	-0.53	-0.002	0.022
EG24_P	1.64	0.003	0.011	-0.78	-0.003	0.029	-1.15	-0.005	0.030
Beta	-1.61	-0.009	0.037	-	-	-	-	-	-
CEYG1	-1.55	-0.004	0.017	-0.85	-0.002	0.017	0.83	0.002	0.014
NCA_to_MV	1.36	0.003	0.013	**2.91**	0.005	0.011	**2.88**	0.005	0.011
MOM6	1.28	0.007	0.036	0.14	0.001	0.029	-0.57	-0.002	0.019
LPrice	-1.10	-0.004	0.024	**-2.77**	-0.008	0.020	**-2.30**	-0.006	0.018
CEYG12	-1.06	-0.001	0.007	-0.77	-0.001	0.008	0.22	0.000	0.010
Crossover3_12	1.00	0.002	0.015	1.37	0.001	0.005	1.54	0.002	0.008
DPSG24	-0.88	-0.001	0.009	-1.68	-0.002	0.009	-1.62	-0.002	0.007
MOM1	0.81	0.003	0.025	-0.20	-0.001	0.023	-1.77	-0.005	0.019
ROE	0.80	0.001	0.011	0.28	0.000	0.012	-0.90	-0.002	0.012
MOM12	0.64	0.003	0.034	-0.20	-0.001	0.030	-0.79	-0.002	0.021
MOM18	-0.62	-0.003	0.032	-1.37	-0.006	0.029	-1.53	-0.005	0.022
DPSG12	0.22	0.000	0.009	-1.03	-0.001	0.008	-0.34	0.000	0.009
MOM3	0.22	0.001	0.029	-0.21	-0.001	0.025	-1.02	-0.003	0.018
Gearing	-0.22	0.000	0.006	-0.09	0.000	0.007	-0.22	0.000	0.007
Expectedgrowth	-0.06	0.000	0.005	0.50	0.000	0.005	0.82	0.001	0.005
LMV	-0.06	0.000	0.017	-1.43	-0.004	0.018	-1.69	-0.004	0.016

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Appendix A.17. presents the market beta of each style over the combined in- and out-of-sample periods. The low betas, all well below the value 1.0, help to explain why the CAPM and APT adjustments have such minor effects on style anomalies. As expected the (Datastream maintained) beta is the only style with a beta over 0.05. Indeed, most style payoffs are negatively related to excess market returns. I.e. they perform better when the market is down. *Figure 6.4.3.1* shows the consistency of style payoffs during the out-of-sample period. Sales growth, current ratio and all risk styles show consistently negative payoffs while book value to price and sales to market value show consistently positive performance. Even though log of price is overall a negative attribute it performs positively in the greater proportion of months. This indicates a lack of consistency and therefore a lack of exploitability.

Figure 6.4.3.1. Style consistency graphic

Displays proportion of months with positive and negative slope coefficients from the unadjusted univariate regressions performed on each style over the out-of-sample period 1 Mar 2000 – 1 Feb 2004.

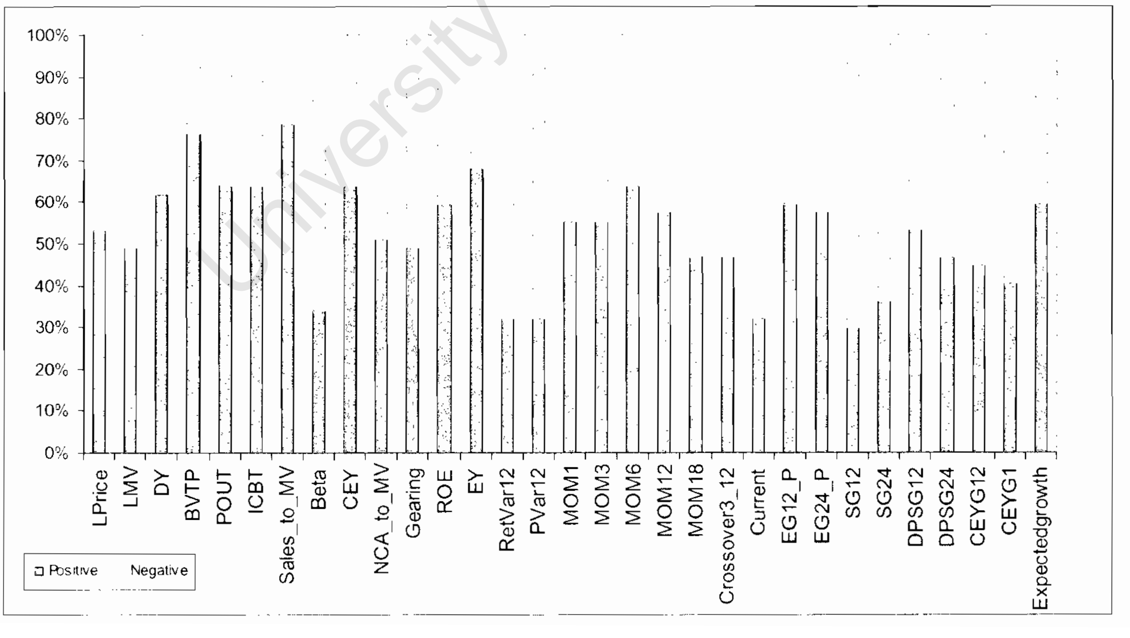

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Table 6.4.3.2. compares in-sample and out-of-sample attribute performance. A number of in-sample-significant attributes, such as log of price and one-year and eighteen-month momentum loose significance in the out-of-sample period and a number of new attributes become significant. However for all attributes the difference between in-sample and out-of-sample means is not significant at the 5% level. The change in attributes that are significant at the 5% level suggest that anomalies are not all time-invariant and that there is benefit to be gained from timing anomalies.

Table 6.4.3.2. Comparison of In- and Out-of-sample Univariate Results

The mean monthly cross-sectional coefficients are reported for each factor for the in-sample period from 1 Mar 1990 – 1 Feb 2000 and the out-sample period 1 Mar 2000 – 1 Jan 2004. The coefficients are estimated using univariate cross-sectional regressions of stock returns. Factors are ranked according to the absolute value of the t-statistic of the mean regression coefficient. Factors showing an absolute value of t-statistic less than one in-sample are separated and significant t-statistics are displayed in bold.

Attribute	Insample		Outsample		Comparison of Means T-statistic
	T-statistic	Mean	T-statistic	Mean	(assuming unequal variance)
ICBT	**5.43**	0.0024	**3.08**	0.0051	0.03
LPrice	**-4.51**	-0.0049	-1.10	-0.0039	0.33
MOM18	**4.22**	0.0064	-0.62	-0.0029	0.50
MOM12	**3.25**	0.0050	0.64	0.0031	0.50
POUT	**-3.06**	-0.0035	**2.32**	0.0066	0.00
Crossover3_12	**2.93**	0.0041	1.00	0.0022	0.51
PVar12	**-2.88**	-0.0025	**-3.33**	-0.0052	1.00
MOM6	**2.84**	0.0046	1.28	0.0067	0.00
Beta	**2.70**	0.0044	-1.61	-0.0086	0.31
ROE	**2.28**	0.0015	0.80	0.0013	0.67
MOM3	**2.13**	0.0035	0.22	0.0009	0.27
RetVar12	1.94	0.0029	-1.77	-0.0082	0.01
DY	-1.92	-0.0030	**2.58**	0.0087	0.01
Gearing	-1.88	-0.0011	-0.22	-0.0002	0.00
SG12	1.77	0.0012	**-2.52**	-0.0044	0.00
BVTP	1.61	0.0015	4.27	0.0085	0.21
LMV	-1.61	-0.0022	-0.06	-0.0001	0.19
EG24_P	1.54	0.0013	1.64	0.0026	0.46
DPSG12	1.52	0.0008	0.22	0.0003	0.29
Sales_to_MV	-1.51	-0.0021	**3.92**	0.0120	0.09
Sales_to_MV	1.37	0.0009	**3.92**	0.0120	0.01
EG12_P	1.35	0.0012	**2.05**	0.0024	0.68
DPSG24	-1.28	-0.0007	-0.88	-0.0011	0.02
SG24	1.24	0.0008	**-2.08**	-0.0024	0.12
CEYG1	-1.21	-0.0011	-1.55	-0.0038	0.68
MOM1	1.18	0.0016	0.81	0.0029	0.40
EY	-1.04	-0.0015	**3.52**	0.0107	0.00
CEY	-0.96	-0.0013	1.85	0.0072	0.04
CEYG12	0.50	0.0002	-1.06	-0.0011	0.82
NCA_to_MV	0.21	0.0002	1.36	0.0025	0.05
Expectedgrowth	0.06	0.0000	-0.06	0.0000	0.82

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The time-series of univariate slope coefficients is displayed graphically in *Appendices A7 - A14*. Attributes are grouped into clusters formed on the basis of the cluster analysis performed in *Section 6.4.1*.

6.5. Multivariate Results

6.5.1. Model Construction

The composition of the four multifactor models constructed is outlined in *Table 6.5.1.1* The all factor model consists of all attributes showing an individual absolute value of t-statistic greater than one. The other three models are constructed using the stepwise procedure described in *Section 6.3.2*. The stepwise selection procedure for each model is displayed in *Appendices A.18 – A.20*.

The T-statistic of Slope model (TSM) and the Information Ratio model (IRM) both retain far fewer attributes than the Information Coefficient model (ICM). This could well be the cause of any differences in model performance that arise. It is understandable that both Grinold's (1989) Information Ratio and T-statistic of Slope select fewer attributes than IC as both criteria include the number of shares being forecast. They are therefore more strict on the inclusion of attributes with missing data points. Indeed the composition of the TSM and IRM models are extremely similar (They only differ by one attribute, beta, that appears in the IRM model.) This is due to the both criteria being very similar in construction. Also noteworthy is that virtually all the attributes selected using either Grinold's (1989) Information Ratio or T-statistic of Slope criteria are picked up by the Information coefficient criterion. This suggests that possible differences in outperformance between ICM on the one hand and IRM and TSM on the other hand may not be due to the individual attributes selected by the IRM and TSM models but rather the number of attributes selected by the IRM and TSM models.

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Table 6.5.1.1. Model Composition

Lists the attributes included in each model using the stepwise procedure outlined above. Results of the stepwise selection procedure are displayed in *Appendices E.1. – E.3.*.

Model	Attributes	Constituent attributes
All Attribute Model (AAM)	27	ICBT, LPrice, MOM18, MOM12, POUT, Crossover3_12, PVar12, MOM6, Beta, ROE, MOM3, RetVar12, DY, Gearing, SG12, BVTP, LMV, EG24_P, DPSG12, Sales_to_MV, Current, EG12_P, DPSG24, SG24, CEYG1, MOM1, EY
T-statistic of Slope Model (TSM)	6	ICBT, LPrice, MOM18, DY, BVTP, POUT
IC Model (ICM)	11	ICBT, LPrice, MOM18, MOM12, Crossover3_12, Beta, ROE, DY, SG12, BVTP, SG24
Grinold's (1989) Information Ratio Model (IRM)	7	ICBT, LPrice, MOM18, Beta, BVTP, POUT, DY

6.5.2. In-sample Performance

The in-sample performance of each model is presented in *Table 6.5.2.1.* For each criterion above the line, the greatest (or in the case of standard deviation, the least) value is bolded. All of the models, except the all attribute model, perform impressively well over the in-sample period with IC values greater than 0.1. This is noteworthy as Grinold and Kahn (1995) suggest an IC greater than 0.1 shows sufficient signal quality to make the model profitable in practice. The ICM, IRM and TSM models all achieve a monthly decile spread of 4%.

Weighing up all the performance criteria, the T-statistic of Slope Model appears to perform the best in-sample. It is ahead on t-statistic of slope, Qian and Hua's (2003) IR and t-statistic of the decile spread. It is also not far off the top values for IC and Grinold's (1989) IR. It must be noted that part of the reason for the TSM model's in-sample outperformance may be because attributes that become less populated toward the

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Table 6.5.2.1. In-sample and Out-of-sample Evaluation of Multifactor Models

Displays the performance of each multifactor model during the in-sample (1 Mar 1990 – 1 Feb 2000) and out-of-sample (1 Mar 2000 – 1 Feb 2004) periods. Mean slope is obtained by running monthly regressions of expected returns against realised returns over the sample period and taking the mean value of the monthly slope coefficient. T-statistic of slope is obtained by dividing the mean slope by its standard deviation over the sample period and multiplying by the number of observations in each month. IC is obtained by applying Pearson's correlation coefficient to expected and realised returns. Qian and Hua's (2003) Information Ratio is obtained by dividing IC by the standard deviation of IC and Grinold's (1989) Information Ratio is obtained by multiplying IC by the square root of the number of forecasts each month. Mean monthly values are displayed for both information ratio's The decile spread measures the difference between the average return earned by shares in the top decile of forecast returns and the average return earned by shares in the lowest decile. The standard deviation of the decile spread is displayed along with the T-statistic of spread which takes into account the mean and standard deviation of the spread along with the number of shares forecast each month. Earliest (latest) number of shares relates to the number of observations at the start (end) of the period. For each criterion the greatest (or in the case of standard deviations, the least) value is bolded for both the in-sample and out-of-sample periods.

	All Attribute Model (AAM)		T-statistic of Slope Model (TSM)		IC Model (ICM)		IR Model (IRM)	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Mean Slope	0.19	0.31	**0.87**	0.47	0.72	**0.60**	0.86	0.52
Standard Deviation of Slope	**0.48**	**0.85**	0.89	1.25	0.87	1.08	0.95	1.57
T-statistic of Slope	4.28	2.52	**10.69**	2.53	9.04	**3.74**	9.95	2.27
IC	0.003	0.070	0.115	0.047	**0.122**	**0.110**	0.117	0.060
Standard Deviation of IC	0.206	0.210	**0.109**	0.214	0.139	**0.194**	0.119	0.265
Mean IR (Qian and Hua)	0.01	0.33	**1.05**	0.22	0.88	**0.56**	0.99	0.23
Mean IR (Grinold)	0.33	1.63	2.66	1.27	2.34	**2.67**	**2.74**	1.63
Decile Spread	0.02	0.02	0.04	-0.04	**0.05**	**0.04**	0.04	-0.04
T-statistic of Spread	2.30	0.51	**8.10**	-0.90	7.28	**1.19**	7.43	-0.81
Standard Deviation of Spread	0.09	0.15	**0.05**	0.16	0.07	**0.13**	0.06	0.16
Earliest Number of Shares	132	448	402	655	132	559	402	655
Earliest Number of Shares	301	523	530	721	381	581	530	721
Latest Number of Shares	505	309	687	734	576	338	687	734

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starting-point of the sample are rejected by the TSM model. *Appendix A.5.* shows the number of observations for each attribute every six months throughout the in-sample and out-of-sample periods) The result is that the TSM model has more data-points to draw from allowing the forecast anomalies to show through more clearly.

The All Attribute Model performs poorly over the in-sample period. This may be because the inclusion of too many attributes results in a loss of model forecasting power or, once again, a result of less data for some attributes over the initial years of the sample period.

In-sample significance may be spurious as only attributes significant over the in-sample period were used as candidate factors for the multi-factor models. The out-of-sample results are therefore important to establish whether the models are a true account of the data generating process or merely the result of over-enthusiastic data-mining. The latter seems highly unlikely due to the simplicity of the attributes tested and the growing international research that shows these same attributes performing over different markets.

6.5.3. Out-of-sample Performance

Out-of-sample results are displayed in *Table 6.5.2.1.* and confirm that model performance is not spurious. The ICM model performs best over the out-of-sample period in terms of all performance criteria, achieving a monthly decile spread of 4%, a significant t-statistic of slope, and an IC greater than 0,1. None of the other models match the performance of the IC model. The performance evaluations are confirmed by the performance graphs *(Appendices A.21. – A.24.).* All models are able to generate a significant spread between deciles 1 and 10 over the out-of-sample period. The superior out-of-sample performance of the ICM model is displayed strikingly with the ICM model generating the best spread between deciles 1, 5 and 10. The graphs reveal that all the models perform poorly during the "IT bubble collapse" and its aftermath (1999 – 2001) as structural changes took place in the data generating process. This is evidenced by attributes, such as beta and momentum, changing sign. The models need time to adapt to these changes as model forecasts are based on a 12 month estimation period. ICM copes the best during the post-IT bubble period, possibly because of its reliance on more attributes compared to the IRM and TSM models. Some of these "extra" attributes perform much better out-of-sample than in-sample, for example two-year earnings growth and cash earnings yield. This could be due to structural changes that occurred after the IT bubble period. The AAM model does not cope well during this period, although it recovers very well between 2002 and 2004 resulting in a considerably improved out-of-sample performance, outperforming both the IRM and TSM models based on IC.

It is important therefore that selection procedures are not too strict in determining which attributes are accepted into each model. By applying strict criteria it may be possible to tweak in-sample performance by eliminating under-performing attributes, but the end result is a decrease in the robustness of the model out-of-sample. This finding supports the temping practice of including one or two attributes believed to be important but not yet found to be significant in historical tests. It also supports the need for style timing models that provide better forecasts of attribute payoffs.

Model selection procedures must not accept too many or too few attributes. In both cases the result is a decrease in out-of-sample model performance, although the latter appears to be a more serious problem.

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6.6. Summary and Conclusion

In the univariate tests, eleven attributes are found to be significant at the 5% level over the in-sample period: Interest cover before tax, log of price, eighteen-month momentum, one-year momentum, the payout ratio, crossover3_12, price variance, six month momentum, beta, return on equity and three-month momentum. For all attributes, the difference between in-sample and out-of-sample means is not significant at the 5% level. Despite this, only three of the in-sample attributes remain significant at the 5% level out-of-sample: interest cover before tax, the payout ratio and price variance. Additionally, a number of new attributes become significant: dividend yield, one-year and two year sales growth, one-year earnings growth, book value to price, sales to market value, the current ratio and earnings yield. This indicates that research into style timing is critically important. Both APT and CAPM risk adjustments do not remove the anomalies. The adjustments decrease the significance of most attributes while increasing the significance of others. In confirmation with the literature, size (as measured by log of market value) pays off in the opposite direction during the early nineties. Subsequently it changes sign and becomes a strongly performing negative attribute. Unexpectedly, the same effect is not observed with log of price.

The multivariate tests show that by blending styles it is possible to generate strong performance, confirming the results of Haugen and Baker (1996) in the US. The ICM model performs best overall by a fair distance, achieving an IC over 0.1 and a monthly decile spread over 4% during both in- and out-of-sample periods. The reason that the ICM model outperforms the other models is likely to be due to the greater number of attributes retained by the IC selection criteria. The IRM and TSM models both have more stringent selection criteria that take into account the number of monthly observations of potential factors.

It also appears that including too many factors has a negative impact on performance. The All Attribute model comprising 27 factors performs well below the ICM model, particularly during the in-sample period. The AAM model does improve out-of sample to beat both the IRM and TSM models. It is clear therefore that model robustness hinges on the number of attributes included. Placing too many bets increases statistical interference within the forecast process lowering forecast accuracy and placing too few bets increases reliance on potentially spurious factors and raises the likelihood of missing a late performing factor. Out-of-sample results show that the latter is a far more serious problem.

It is clear that anomalies on the LSE exist and persist out-of-sample. These anomalies are not proxies for CAPM or APT risk and can be successfully exploited in a multivariate environment.

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7.

Style Timing Explanatory Analysis (In-sample)

7.1. Introduction

Throughout the univariate and multivariate tests there has been evidence that it would be of significant benefit if expected return models could improve forecasts of style payoffs to take into account changes in the sign and magnitude of the payoff. Some styles perform strongly in one direction for a number of years and then change sign to perform strongly in the opposite direction for a number of years. Beta is a good example – it pays off positively over the period 1 March 1998 – 1 March 2000 and then negatively over the period 1 March 2000 to 1 March 2003 (See *Appendix A.13.)*. There are other styles, such as expected growth, that swing between a positive to negative payoff more frequently. Time-variation may be an indication that a style is spurious and not an exploitable stock market anomaly, however if sign changes are predictable, styles that vary over time become exploitable. For this reason it is decided to analyse the payoff predictability of all styles and not just styles that have a significant consistent (single direction) mean. Hopefully styles not found to be significant consistent performers, may show an element of predictability thereby becoming exploitable. On the other end of the spectrum, it may also be possible to improve styles that do perform consistently in one direction.

Appendix B.1. compares the consistent performance of each style against the performance possible if payoff signs can be perfectly forecast. Attributes that do not show consistent performance, such as expected growth and net current assets, show high "potential" performance. This backs the decision taken to look for predictability in all style payoffs. If these inconsistent styles are found to be unpredictable, the conclusion can be drawn that they do not represent stock market anomalies. *Appendix B.1.* demonstrates that all t-statistics can be significantly improved if the style can be timed, even the t-statistics of consistent styles such as log of price and interest cover before tax. The question of style predictability is therefore crucial to determine whether expected return models should take timing into account. The multifactor models in *Section 6.5.* already include an element of timing as they only use twelve months to forecast style payoffs. If results indicate predictability, in *Chapter 8* more

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appropriate timing models will be incorporated into attribute selection and payoff forecasting in future expected return-models.

In this section two approaches are adopted to test style predictability. The first approach involves univariate time-series forecasting and is referred to as style momentum, while the second involves the identification of economic relationships. The term style momentum is adopted from Wang (2003) to describe both positive and negative autocorrelation. The results show that the term is not misleading as all significant autocorrelation is found to be positive. Results from both approaches are incorporated in the construction of multi-factor payoff forecasting models in *Chapter 8*.

The remainder of this chapter is set out as follows. *Section 7.2.* describes the data and methodology, *Section 7.3.* reports the style momentum results, *Section 7.4.* reports the seasonality results, *Section 7.5.* reports the macroeconomic relationship results and *Section 7.6.* summarises the key findings and concludes.

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7.2. Data and Methodology

This section is divided into three sections: style momentum, style seasonality and economic relationships. The dataset comprises the time-series of monthly slope coefficients for the twenty-seven attributes regressed on future returns in *Chapter 6* and the monthly values of fifteen macroeconomic variables over the in- and out-of-sample periods. The macroeconomic variables are selected based on past research in the UK and US markets and are displayed in *Table 7.5.1.*

7.2.1. Style Momentum Methodology

Relationships between style payoffs and their own lagged values and lagged moving averages are tested. The lags that are meaningfully related to each style payoff should fall within the first twelve lags, since the data is monthly. For each style payoff, a twelve lag correlogram is produced showing the autocorrelations and partial-autocorrelations between each style payoff and its first twelve lags. Autocorrelations for each lag k are measured by the Pearson's product-moment correlation coefficient between values of the series k lags apart,

$$\rho_k = \frac{\sum_{t-k+1}^{T}(Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{T}(Y_t - \bar{Y})^2}, \tag{19}$$

where Y_t is the series of style payoffs and $\bar{Y}$ is the sample mean of Y_t. If τ_1 is found to be non-zero, there exists first order correlation in Y. For lags k = 1 to 12, the test statistic,

$$\rho_{obs} = \rho_k \cdot \sqrt{\frac{T-2}{1-\rho_k^2}}, \tag{20}$$

is tested for significance using Student's t-test and *T-2* degrees of freedom, where *T* is the number of comparisons being made (months).

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The Ljung-Box Q-Statistic is used to test for autocorrelation up to a prespecified number of lags. (H_0: There is no autocorrelation up to order *k*.)

$$Q_{obs} = T(T+2)\sum_{j=1}^{k}\frac{\rho_j^2}{T-J} \tag{21}$$

where τ_j is the *j*-th autocorrelation and *T* is the number of months and *k* is the maximum number of lags included in the test. Under the null hypothesis, Q_{obs} is asymptotically distributed as a chi-squared (χ^2) distribution with *k* degrees of freedom. Q_{obs} is calculated and tested for *k* = 1 to 12.

Partial autocorrelations are calculated for lags $k = 1$ to 12 as the regression coefficient on Y_{t-k} when Y_t is regressed on a constant, $Y_{t-1}, \ldots, Y_{t-k}$. The partial correlation therefore measures the correlation between values of the series k lags apart after controlling for the influence of the intervening lags. The partial-correlation observed is tested using the same t-statistic described in the test for autocorrelation. If only autocorrelation of order less than k is present, the partial autocorrelation of order k will be close to zero.

The explanatory power of trailing moving averages of style payoffs are tested for significance. Six-month, one-year, eighteen-month and two-year trailing moving averages are individually regressed on the style payoff one period ahead of the moving average. The constant and slope coefficients are then tested against the null hypotheses that state they are each equal to zero. A combined t-statistic is calculated to measure the usefulness of the regression for forecasting purposes. The combined measure is calculated by adding the absolute value of the t-statistic of the slope coefficient to the absolute value of the t-statistic of constant coefficient.

An autoregressive model is constructed to further test which styles exhibit forecastable components. For each attribute, a 12 lag autoregression equation (labelled AR12), is estimated as follows,

$$y_{it} = \alpha_i + \sum_{k=1}^{12} \beta_{ik} y_{it-k} + \varepsilon_{it} \qquad (22)$$

The AR12 models are evaluated for each style using the usual regression diagnostics.

7.2.2. Seasonality Methodology

A scan for the presence of seasonality in style payoffs is conducted using the twelve month correlograms. Twelfth order autocorrelations and partial autocorrelations are tested for significance to establish whether a pattern of seasonality is present in style payoffs. A comparison t-test using pooled variance and assuming unequal variance

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between samples is used to compare the mean payoff in each calendar month with the overall mean payoff.

7.2.3. Macroeconomic Relationships Methodology

All candidate macroeconomic variables are tested for the presence of a unit root using the Augmented Dickey-Fuller (ADF) test. The presence of a unit root implies that a series is non-stationary. The unit root test is performed to avoid the problem of spurious correlation that arises between two non-stationary series (Yule (1926) and Granger and Newbold (1974)). ADF tests the null hypothesis that the data generating process consists of a stochastic component only against the alternate of a unit root and non-stationarity. For each macroeconomic variable (y_{it}), ADF tests that the β coefficients in the equation below are not significantly different from zero,

$$\Delta y_{it} = \alpha_{i0} + \beta_{i0} y_{it-1} + \sum_{v=1}^{V} b_{iv} \Delta y_{it-v} + \varepsilon_{it} \quad \text{where } \varepsilon_{it} \sim \mathrm{IID}(0,\sigma^2) \qquad (22)$$

The inclusion of a constant term (α_{i0}) allows for a random walk where the mean is not zero, and is appropriate for all macroeconomic variables being tested. No time trend is included in the ADF test equation. The Dickey-Fuller test rejects non-stationarity if the value of the t-statistic for each β coefficients lies to the left of the Mackinnon critical value, ($H_0 : \beta_0 = 0$). The Augmented Dickey-Fuller test uses a stepwise process whereby lagged difference terms are included until the residual of the equation is white noise. The maximum number of lags is set to four. If a series is found to be non-stationary, a new series is formed by taking the log of values of the old series and then first differencing the new series. In the case of returns data, logs are not taken, only first differencing is performed. Once this adjustment has been made, the new series is retested. Variables that are still non-stationary after differencing and variables held to lose economic meaning in the process of differencing are excluded from further analysis. A scan for the presence of seasonality in the macroeconomic data is conducted using the twelve month correlograms.

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A preliminary test for the presence of economic relationships is conducted by testing the Pearson's product-moment correlations between macroeconomic variables at the start of each month and the style payoffs for the month following. The same t-statistic used to test for significant correlations, described in *Equation 20* of *Section 7.2.1.*, is used. The correlations give an idea of potential economic relationships, however, significance does not necessarily imply causality. Predictability in the time-series of style payoffs, or the influence of an outside variable (such as inflation) may be the cause of a spurious economic relationship.

The Granger causality test proposed by Granger (1969) and Sims (1972) is used to test for dynamic relationships between macroeconomic variables and style payoffs. The Granger test measures the influence of past values of an exogenous variable, x, on the value of y controlling for the time-series predictability in y. If a significant influence is discovered then it is said that x "Granger causes" y. Unrestricted (23a) and restricted (23b) equations are estimated as follows,

$$y_t = \sum_{k=1}^{K} \alpha_k y_{t-k} + \varepsilon \tag{23a}$$

$$y_t = \sum_{k=1}^{K} \alpha_k y_{t-k} + \sum_{k=1}^{K} \beta_k x_{t-k} + \varepsilon \tag{23b}$$

The Granger test is conducted on equation 23b. The null hypothesis that the coefficients, β_1, β_2, …, β_k are all equal to zero is tested using an F statistic ~F(K,N-K) where N is the number of time-series observations. It must be noted that the statement "x Granger causes y" does not necessarily imply that y is the effect or the result of x. Granger causality measures precedence and information content but does not by itself indicate causality as defined in any dictionary. For this reason out-of-sample testing and the *a priori* screening of relationships that appear spurious or dependent on another variable are important in the construction and evaluation of forecasting models.

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7.3. Style Momentum Results

Univariate time-series methods are applied to style payoffs to test whether there is an element of predictability in the payoff to each style over time. Autocorrelations, partial autocorrelations and autoregressions with lagged moving averages as independent variable are tested for significance.

Autocorrelations are shown in *Table 7.3.1.* Most styles show strong evidence of autocorrelation at early lags. As expected, all first order correlations are positive. Crossover3_12 shows a first order autocorrelation of 0.7. Most of the momentum's, beta, returns variance, earnings yield, cash earnings yield, dividend yield, payout ratio, sales to market value, and two-year sales growth all show first-order autocorrelations greater than 0.5. The Ljung-Box Q-Statistic is used to test for autocorrelation up to a prespecified number of lags. The results *(Appendix B.2.)* show that virtually all styles exhibit autocorrelation. Only net current assets to market value, one- and two-year earnings growth, one-year cash earnings growth and one-year dividend per share growth are free of autocorrelation. Most styles already show significant Q-statistics at one lag.

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Table 7.3.1. Autocorrelations Of Slope Coefficients

Displays Pearson's correlation coefficients between attribute payoffs and lags one to twelve Correlations are calculated over the in-sample period (1 Mar 1990 – 1 Feb 2000). Coefficients significant at the 5% level are displayed in bold.

	1	2	3	4	5	6	7	8	9	10	11	12
Size												
LMV	**0.3**	0.2	0.1	0.1	0.0	0.1	0.1	0.3	0.1	-0.1	0.0	0.1
LPrice	**0.3**	0.2	0.1	0.1	0.0	-0.1	0.0	0.0	-0.1	-0.3	-0.1	0.0
Value												
BVTP	**0.3**	**0.3**	0.2	0.0	0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.2
CEY	**0.5**	**0.4**	**0.3**	0.2	0.1	0.0	0.0	0.0	-0.1	-0.1	0.0	0.1
DY	**0.6**	**0.4**	**0.3**	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0
EY	**0.6**	**0.5**	**0.3**	0.1	0.1	0.0	-0.1	-0.1	-0.1	-0.1	0.0	0.0
Sales_to_MV	**0.5**	**0.3**	0.3	0.1	0.0	-0.1	-0.2	-0.1	-0.1	-0.1	0.1	0.1
Growth												
CEYG1	0.2	0.1	**0.4**	0.2	0.0	0.0	0.0	0.0	-0.1	-0.1	0.0	-0.2
CEYG12	0.0	0.1	0.0	0.0	0.1	-0.2	0.1	-0.1	0.1	0.0	-0.1	0.0
DPSG12	0.1	0.1	0.1	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1
DPSG24	0.1	0.2	0.1	0.1	0.1	0.1	-0.2	-0.2	-0.1	-0.2	-0.2	0.0
EG12_P	0.1	-0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0
EG24_P	0.1	-0.1	-0.2	-0.1	-0.1	0.0	0.0	-0.1	0.0	0.2	0.2	0.0
Expectedgrowth	0.2	0.1	0.1	0.2	0.0	0.1	0.2	0.0	0.0	-0.1	0.2	0.0
Gearing	0.2	0.2	0.2	0.1	0.2	0.0	0.0	0.1	0.1	0.2	0.1	0.0
POUT	**0.5**	**0.4**	**0.3**	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.2	0.2
ROE	0.2	0.2	**0.3**	**0.4**	0.1	0.2	0.2	0.2	0.1	0.1	0.1	0.1
SG12	**0.5**	**0.4**	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1
SG24	**0.4**	**0.3**	0.1	0.2	0.2	0.2	0.1	0.2	0.1	0.2	0.1	0.1
Liquidity												
Current	**0.4**	0.3	0.2	0.1	0.1	0.1	0.0	0.1	0.1	0.0	0.0	0.1
ICBT	0.2	0.0	**0.3**	0.1	-0.1	0.1	0.1	0.0	-0.1	0.0	0.0	-0.1
NCA_to_MV	0.1	0.0	-0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	0.0	0.0
Risk												
Beta	**0.5**	**0.4**	**0.3**	0.1	0.1	0.0	0.0	0.2	0.1	0.2	0.2	0.1
PVar12	**0.4**	**0.4**	**0.4**	0.2	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.0
RetVar12	**0.5**	**0.3**	**0.3**	0.1	0.1	0.1	0.1	0.0	0.1	0.0	0.1	0.1
Momentum												
Crossover3_12	**0.7**	**0.5**	**0.4**	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
MOM1	**0.6**	**0.4**	**0.3**	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1
MOM3	**0.6**	**0.5**	**0.4**	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0
MOM6	**0.6**	**0.5**	**0.4**	0.2	0.1	0.1	0.1	0.0	-0.1	-0.1	0.0	0.0
MOM12	**0.6**	**0.5**	**0.3**	0.2	0.1	0.1	0.0	0.0	-0.1	0.0	0.1	0.1
MOM18	**0.5**	**0.3**	**0.3**	0.2	0.0	-0.1	-0.1	-0.1	-0.1	-0.1	0.0	0.0

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Partial autocorrelations reveal the explanatory power of each lag controlling for the other eleven lags. The partial autocorrelation tests shown in *Table 7.3.2.* present the correlations of each style with each lag after controlling for all earlier lags. The first column of partial autocorrelations in *Table 7.3.2.* is identical to the first column of autocorrelations in *Table 7.3.1.* Results confirm that most of the explanatory power exposed in the Q-statistic test originates from the first lag. The momentum attributes in particular show strong first order correlation.

Table 7.3.2. Partial Autocorrelations Of Slope Coefficients

Displays the style payoff partial autocorrelation coefficients for lags one to twelve. The partial autocorrelation at each lag shows the correlation between the slope coefficient and that lag while controlling for the influence of all earlier lags. Partial correlations are calculated over the in-sample period (1 Mar 1990 – 1 Feb 2000). Coefficients significant at the 5% level are displayed in bold.

	1	2	3	4	5	6	7	8	9	10	11	12
Size												
LMV	**0.3**	0.2	0.0	0.1	0.0	0.1	0.1	0.2	-0.1	-0.2	0.1	0.1
LPrice	**0.3**	0.1	0.0	0.1	-0.1	-0.2	0.1	0.0	-0.1	-0.2	0.0	0.1
Value												
BVTP	**0.3**	0.2	0.1	-0.1	0.1	-0.1	0.1	-0.1	0.1	0.0	0.0	0.1
CEY	**0.5**	0.2	0.2	-0.1	-0.1	-0.1	0.0	0.1	0.0	-0.1	0.1	0.1
DY	**0.6**	0.1	0.0	-0.1	-0.1	0.0	0.0	0.1	-0.1	0.0	0.1	0.0
EY	**0.6**	0.2	0.0	-0.2	0.0	0.0	-0.1	0.0	0.0	0.0	0.1	0.0
Sales_to_MV	**0.5**	0.1	0.1	-0.2	-0.1	-0.2	0.0	0.1	0.0	0.0	0.2	0.1
Growth												
CEYG1	0.2	0.1	**0.4**	0.0	-0.1	-0.1	0.0	0.0	-0.1	0.0	0.1	-0.1
CEYG12	0.0	0.1	0.0	0.0	0.0	-0.2	0.1	0.0	0.1	0.0	-0.1	0.0
DPSG12	0.1	0.1	0.0	0.0	0.1	0.0	0.1	-0.1	0.0	0.0	0.0	0.0
DPSG24	0.1	0.2	0.1	0.1	0.0	0.0	-0.3	-0.2	0.0	0.0	-0.1	0.1
EG12_P	0.1	-0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0
EG24_P	0.1	-0.1	-0.2	-0.1	-0.1	0.0	0.0	-0.1	0.0	0.2	0.1	0.0
Expectedgrowth	0.2	0.1	0.1	0.2	0.0	0.0	0.2	-0.1	0.0	-0.1	0.1	0.0
Gearing	0.2	0.2	0.1	0.0	0.1	-0.1	0.0	0.1	0.1	0.1	0.1	-0.1
POUT	**0.5**	0.3	0.1	-0.1	0.0	0.1	0.1	0.1	-0.1	0.0	0.1	0.1
ROE	0.2	0.1	**0.3**	**0.3**	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0
SG12	**0.5**	0.2	0.0	0.1	-0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0
SG24	**0.4**	0.2	-0.1	0.1	0.1	0.1	-0.1	0.2	-0.1	0.1	0.0	-0.2
Liquidity												
Current	**0.4**	0.1	0.1	-0.1	0.0	0.0	-0.1	0.2	0.0	-0.1	0.1	0.1
ICBT	0.2	0.0	**0.3**	0.0	-0.1	0.0	0.1	0.0	-0.1	0.0	0.0	0.0
NCA_to_MV	0.1	-0.1	-0.1	0.1	0.1	-0.1	0.1	0.0	0.0	-0.1	0.0	0.0
Risk												
Beta	**0.5**	0.2	0.1	-0.2	0.0	-0.1	0.1	0.2	0.0	0.1	0.0	0.0
PVar12	**0.4**	0.3	0.2	-0.1	-0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1
RetVar12	**0.5**	0.1	0.1	-0.1	0.0	0.0	0.1	-0.1	0.1	-0.1	0.1	0.1
Momentum												
Crossover3_12	**0.7**	0.1	0.1	-0.2	0.0	0.1	0.2	0.0	-0.1	0.1	-0.1	0.1
MOM1	**0.6**	0.2	0.0	-0.2	-0.1	0.1	0.1	0.0	-0.2	0.0	0.0	0.0
MOM3	**0.6**	0.2	0.1	-0.2	-0.1	0.1	0.2	0.0	-0.2	0.0	0.1	0.0
MOM6	**0.6**	0.2	0.1	-0.1	-0.1	0.0	0.1	0.0	-0.2	0.0	0.2	0.1
MOM12	**0.6**	0.1	0.0	-0.1	-0.1	0.1	0.0	0.0	-0.1	0.1	0.2	0.0
MOM18	**0.5**	0.0	0.1	0.0	-0.2	0.0	0.0	0.0	0.0	0.0	0.1	0.0

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A twelve month autoregressive model (labelled AR12) is constructed for each style and the in-sample results are displayed in *Appendix C.3*. Over the in-sample period, the AR12 models have significant F-statistics for all styles except for net current assets to market value, both earnings growth attributes and twelve month growth in cash earnings. It must be noted that there is element of look-ahead bias as the model parameters were estimated over the same period. Out-of-sample performance is presented in *Appendix C.11*. (The diagnostics in- and out-of-sample are different as the coefficients in the in-sample equation are statically estimated while the coefficients in the out-of-sample equation are re-estimated at each point using an expanding window.) The AR12 models do not continue their extremely strong in-sample performance out-of-sample, however a number of styles do still show significant predictability out-of-sample.

Since it is clear that over the in-sample period most autocorrelation occurs at early lags, it is worth comparing the AR12 model against a model that uses only one lag to forecast the style payoff, the 1M model. The complete out-of-sample comparison is made in *Section 8.3.3.* which discusses relative model performance for each style in- and out-of-sample. It is worth noting here that while in-sample the AR12 model performs much better than the 1M model, out-of-sample the 1M model performs much better than the AR12 model for most styles. It appears therefore that the first order autocorrelation is more robust than the higher order autocorrelation. This difference in relative model performance can be seen in *Figure 8.3.2.1.* and *Figure 8.3.3.1.* in *Chapter 8.*

Results from autoregressions, where style payoffs are regressed against their trailing moving averages, are shown in *Table 7.3.3.* The results show many regression coefficients significant. A combined t-statistic is calculated to measure the usefulness of the regression for forecasting purposes. The combined measure is calculated by adding the absolute value of the t-statistic of the slope coefficient to the absolute value of the t-statistic of constant coefficient. According to the combined measure the six-month regressions perform best by a fair margin, followed by the one-year, and then the two-year and eighteen-month regressions. This confirms the idea that most of the predictability in payoffs comes from earlier lags. This is evidenced particularly in the momentum, growth and liquidity clusters where the six-month mean significantly outperforms the other means.

Generally, the slope coefficient is found to be significant more frequently than the constant coefficient for all moving averages. However, log of price and interest cover before tax have stronger constant elements than slope elements. They perform consistently, regardless of the economic environment. Some styles display strong timing and consistent elements. One-month momentum, cash earnings yield and sales growth are good examples. The longer horizon momentum attributes all show strong

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slope coefficients and weak constant coefficients. This confirms US research (E.g. Wang, 2003) that shows momentum profits are time varying.

Table 7.3.3. (Auto) Regressions Between Payoffs And Their Moving Averages

Displays the coefficients and related t-statistics from regressions performed with the slope coefficient (payoff) to each attribute (style) as dependent variable and the moving average of the slope coefficient as independent variable. The regressions are performed over the in-sample period (1 Mar 1990 – 1 Feb 2000). Coefficients significant at the 5% level are displayed in bold.

	6M Mean		12M Mean		18M Mean		24M Mean	
Size	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*
LMV	0.0	**0.5**	0.0	**0.6**	**0.0**	0.4	**0.0**	0.5
(T-stat)	-(1.4)	**(2.8)**	-(1.7)	**(2.7)**	**-(2.3)**	(1.2)	**-(2.2)**	(1.2)
Combined Abs(t)	*4.1*		*4.3*		*3.5*		*3.4*	
LPrice	**0.0**	0.3	**0.0**	-0.1	**0.0**	-0.4	**0.0**	-0.8
(T-stat)	**-(2.2)**	(1.6)	**-(2.9)**	-(0.2)	**-(3.2)**	-(1.0)	**-(3.1)**	-(1.5)
Combined Abs(t)	*3.8*		*3.1*		*4.2*		*4.6*	
Value	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*
BVTP	0.0	**0.8**	0.0	**0.9**	**0.0**	0.8	**0.0**	1.1
(T-stat)	-(0.6)	**(4.3)**	-(1.2)	**(3.6)**	-(1.0)	**(2.6)**	-(1.6)	**(3.0)**
Combined Abs(t)	*4.8*		*4.9*		*3.6*		*4.6*	
CEY	0.0	**1.5**	0.0	**2.6**	**0.0**	2.7	**0.0**	3.6
(T-stat)	-(1.9)	**(8.1)**	**-(2.7)**	**(6.9)**	**-(2.9)**	**(5.0)**	**-(3.2)**	**(4.7)**
Combined Abs(t)	*10.0*		*9.5*		*7.9*		*7.9*	
DY	0.0	**1.4**	0.0	**2.4**	**0.0**	3.2	**0.0**	4.9
(T-stat)	-(1.3)	**(7.7)**	-(1.7)	**(7.2)**	-(1.5)	**(6.3)**	-(0.7)	**(7.3)**
Combined Abs(t)	*9.0*		*8.9*		*7.8*		*8.1*	
EY	0.0	**1.5**	0.0	**2.7**	**0.0**	3.7	**0.0**	5.3
(T-stat)	-(1.8)	**(8.6)**	**-(3.1)**	**(7.1)**	**-(3.8)**	**(6.8)**	**-(4.8)**	**(7.5)**
Combined Abs(t)	*10.5*		*10.2*		*10.6*		*12.3*	
Sales_to_MV	0.0	**0.7**	0.0	**1.0**	**0.0**	0.8	**0.0**	1.1
(T-stat)	-(1.2)	**(3.7)**	-(1.3)	**(2.7)**	-(1.4)	(1.8)	-(1.2)	(1.8)
Combined Abs(t)	*4.8*		*4.0*		*3.2*		*3.0*	
Growth	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*
CEYG1	0.0	**1.0**	0.0	**1.0**	**0.0**	0.2	**0.0**	0.4
(T-stat)	-(1.1)	**(4.7)**	-(1.6)	**(2.4)**	-(1.7)	(0.3)	-(1.6)	(0.4)
Combined Abs(t)	*5.7*		*4.0*		*2.0*		*2.1*	
CEYG12	0.0	**0.1**	0.0	**0.4**	**0.0**	-0.1	**0.0**	-0.7
(T-stat)	(0.2)	(0.5)	-(0.1)	(0.9)	-(0.1)	-(0.2)	(0.3)	-(1.0)
Combined Abs(t)	*0.7*		*1.0*		*0.3*		*1.3*	
DPSG12	0.0	**0.4**	0.0	**0.5**	**0.0**	0.3	**0.0**	0.0
(T-stat)	(0.8)	**(2.1)**	(0.7)	**(2.2)**	(0.4)	(1.2)	(0.5)	(0.0)
Combined Abs(t)	*2.9*		*2.9*		*1.6*		*0.5*	
DPSG24	0.0	**0.4**	0.0	**-0.1**	**0.0**	0.2	**0.0**	0.4
(T-stat)	-(1.0)	**(2.6)**	-(2.0)	-(0.2)	-(1.1)	(0.5)	-(0.5)	(1.1)
Combined Abs(t)	*3.6*		*2.2*		*1.6*		*1.6*	
EG12_P	0.0	**-0.1**	0.0	**0.2**	**0.0**	-0.2	**0.0**	-1.0
(T-stat)	(1.1)	-(0.5)	(1.0)	(0.7)	(1.5)	-(0.4)	**(2.8)**	-(2.0)
Combined Abs(t)	*1.7*		*1.7*		*1.9*		*4.7*	
EG24_P	0.0	**-0.4**	0.0	**0.3**	**0.0**	-0.1	**0.0**	0.2
(T-stat)	(1.8)	-(1.6)	(0.9)	(0.7)	(1.0)	-(0.2)	(0.7)	(0.4)
Combined Abs(t)	*3.4*		*1.6*		*1.2*		*1.1*	
Expectedgrowth	0.0	**0.4**	0.0	**0.4**	**0.0**	0.3	**0.0**	-0.2
(T-stat)	(0.2)	**(2.5)**	(0.6)	**(2.0)**	(1.3)	(1.1)	(2.0)	-(0.7)
Combined Abs(t)	*2.8*		*2.6*		*2.3*		*2.6*	

Table 7.3.3. (Auto) Regressions (continued)

	6M Mean		12M Mean		18M Mean		24M Mean	
Growth (cont.)	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*
Gearing	0.0	**0.4**	0.0	**0.5**	**0.0**	0.1	**0.0**	-0.2
(T-stat)	-(0.6)	**(2.6)**	(0.1)	**(2.4)**	(0.0)	(0.4)	-(0.4)	-(0.7)
Combined Abs(t)	*3.2*		*2.5*		*0.4*		*1.1*	
POUT	0.0	**1.2**	0.0	**1.6**	**0.0**	1.7	**0.0**	2.1
(T-stat)	-(1.0)	**(7.0)**	-(1.0)	**(7.0)**	-(1.2)	**(5.7)**	-(0.7)	**(5.7)**
Combined Abs(t)	*8.0*		*8.0*		*6.9*		*6.4*	
ROE	0.0	**0.7**	0.0	**0.7**	**0.0**	0.2	**0.0**	-0.2
(T-stat)	(0.4)	**(4.7)**	-(0.1)	**(3.9)**	-(0.3)	(1.2)	(0.2)	-(0.7)
Combined Abs(t)	*5.2*		*4.0*		*1.5*		*1.0*	
SG12	0.0	**1.2**	0.0	**1.8**	**0.0**	2.5	**0.0**	3.3
(T-stat)	(1.2)	**(6.9)**	(1.8)	**(7.7)**	(2.0)	**(7.7)**	**(2.6)**	**(7.9)**
Combined Abs(t)	*8.2*		*9.5*		*9.7*		*10.5*	
SG24	0.0	**0.9**	0.0	**1.2**	**0.0**	1.6	**0.0**	2.1
(T-stat)	(1.0)	**(5.8)**	(1.6)	**(5.6)**	**(2.2)**	**(5.1)**	**(2.8)**	**(4.7)**
Combined Abs(t)	*6.9*		*7.2*		*7.3*		*7.5*	
Liquidity	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*
Current	0.0	**0.9**	0.0	**1.1**	**0.0**	1.2	**0.0**	0.9
(T-stat)	(1.1)	**(4.7)**	(1.1)	**(4.0)**	(1.5)	**(3.5)**	(1.2)	(2.0)
Combined Abs(t)	*5.8*		*5.1*		*5.0*		*3.2*	
ICBT	0.0	**0.3**	0.0	**0.3**	**0.0**	0.2	**0.0**	-0.1
(T-stat)	**(2.4)**	(1.9)	**(2.1)**	(1.4)	(1.8)	(0.9)	**(2.0)**	-(0.2)
Combined Abs(t)	*4.2*		*3.4*		*2.7*		*2.2*	
NCA_to_MV	0.0	**0.2**	0.0	**0.2**	**0.0**	0.4	**0.0**	0.4
(T-stat)	(0.2)	(0.9)	-(0.3)	(0.6)	-(0.2)	(1.1)	-(0.6)	(1.0)
Combined Abs(t)	*1.2*		*0.9*		*1.3*		*1.6*	
Risk	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*
Beta	0.0	**1.1**	0.0	**2.0**	**0.0**	2.4	**0.0**	3.2
(T-stat)	(1.2)	**(6.2)**	(0.6)	**(7.6)**	(0.3)	**(6.2)**	-(0.2)	**(6.4)**
Combined Abs(t)	*7.4*		*8.1*		*6.5*		*6.6*	
PVar12	0.0	**1.0**	0.0	**1.2**	**0.0**	1.2	**0.0**	0.9
(T-stat)	(1.0)	**(6.3)**	(1.9)	**(5.3)**	**(2.2)**	**(4.6)**	(1.6)	**(2.7)**
Combined Abs(t)	*7.2*		*7.2*		*6.8*		*4.3*	
RetVar12	0.0	**1.0**	0.0	**1.5**	**0.0**	1.4	**0.0**	1.7
(T-stat)	(1.3)	**(5.6)**	(1.3)	**(5.6)**	**(2.0)**	**(3.9)**	(1.9)	**(3.4)**
Combined Abs(t)	*6.9*		*6.9*		*5.9*		*5.3*	

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Table 7.3.3. (Auto) Regressions (continued)

	6M Mean		12M Mean		18M Mean		24M Mean	
Momentum	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*	*c*	*Slope*
Crossover3_12	0.0	2.0	0.0	3.3	0.0	4.5	0.0	5.9
(T-stat)	-(0.1)	(14.9)	-(0.8)	(15.6)	-(1.4)	(15.7)	-(2.3)	(16.3)
Combined Abs(t)	*15.0*		*16.3*		*17.1*		*18.6*	
MOM1	0.0	1.5	0.0	2.2	0.0	2.4	0.0	3.0
(T-stat)	(1.7)	(8.1)	(2.6)	(6.4)	(2.6)	(4.7)	(2.8)	(5.2)
Combined Abs(t)	*9.8*		*8.9*		*7.3*		*7.9*	
MOM3	0.0	1.7	0.0	2.2	0.0	2.6	0.0	3.2
(T-stat)	(1.4)	(11.1)	(1.7)	(8.0)	(1.6)	(6.2)	(1.4)	(7.2)
Combined Abs(t)	*12.4*		*9.7*		*7.8*		*8.6*	
MOM6	0.0	1.6	0.0	2.0	0.0	2.1	0.0	2.5
(T-stat)	(0.6)	(10.6)	(0.9)	(7.2)	(0.9)	(5.4)	(0.8)	(5.8)
Combined Abs(t)	*11.2*		*8.1*		*6.3*		*6.6*	
MOM12	0.0	1.5	0.0	1.9	0.0	1.9	0.0	2.1
(T-stat)	(0.6)	(9.0)	(0.3)	(6.3)	(0.6)	(4.8)	(0.4)	(5.2)
Combined Abs(t)	*9.5*		*6.6*		*5.4*		*5.6*	
MOM18	0.0	1.0	0.0	1.3	0.0	1.2	0.0	1.5
(T-stat)	(0.9)	(5.5)	(0.7)	(3.6)	(0.5)	(2.7)	(0.0)	(2.8)
Combined Abs(t)	*6.4*		*4.3*		*3.2*		*2.9*	

The evidence contradicts the US findings of Lucas, van Dijk and Kloek (2001) who find that statistical techniques such as averaging and autoregressive modelling are not useful in predicting the future sign and magnitude of style payoffs.

The t-statistics of the constant and slope coefficients from the twelve-month moving average regression are graphically presented in *Figure 7.3.1.* They allow for comparisons across styles and between constant and slope coefficients. Crossover3_12 shows the most significant slope coefficient. Interestingly, a number of styles have significant positive slope coefficients, even styles such as earnings yield and cash earnings yield that have negative constant coefficients. This indicates persistence, or momentum, in style payoffs.

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Figure 7.3.1. Summary of 12 Month Moving Average Autoregressions In-sample

Shows t-statistics of the constant and slope coefficients estimated during the ordinary least squares regression of each attribute payoff against its own trailing twelve-month moving average over the in-sample period, 1 Mar 1990 – 1 Feb 2000

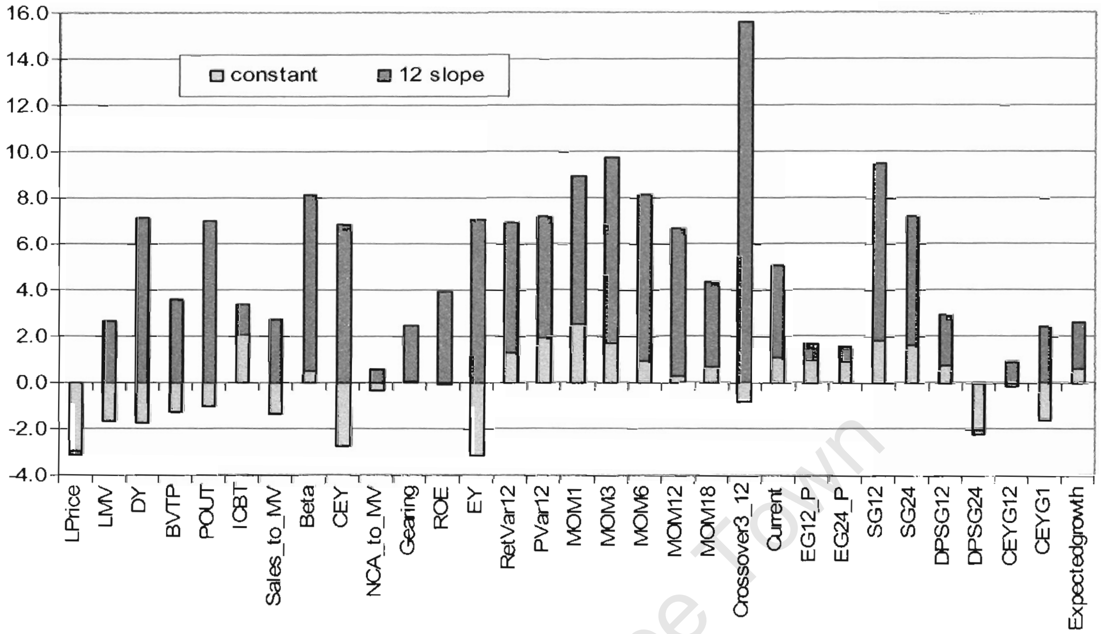

Table 7.3.4. summarises the results from the autocorrelations and autoregressions, showing the associated p-value of each test. It highlights that some styles show more predictability than others. For example, net current assets to market value has no significant forecasters while the momentum attributes have strongly significant lags and moving averages. Importantly however, all style clusters show evidence of predictability with the size, value, risk and momentum clusters showing the most consistent predictability across styles. The growth and liquidity comprise both predictable and non-predictable styles. In general *Table 7.3.4.* shows that early lags are most powerful and that the six-month and one-year trailing means are the most significant moving average forecasting techniques. The evidence is therefore strongly in favour of style momentum. This confirms the US findings of Wang (2003) who concludes that style momentum is at least as profitable as individual share momentum.

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Table 7.3.4. Summary of lag and moving average forecasting ability

Shows probabilities associated with autocorrelation t-statistics and autoregression coefficient t-statistics over the in-sample period, 1 Mar 1990 – 1 Feb 2000. The slope and coefficients for each moving average regression are presented in columns 14 to 21 grouped by slope and coefficient. I.e. 6 constant and 6 slope refer to coefficients estimated by the trailing six-month mean regression. The underlying autocorrelation and autoregression values can be found in *Table 7.3.2* and *Table 7.3.3*

	Lags (p-values)												6M Mean		12M Mean		18M Mean		24M Mean	
	1	2	3	4	5	6	7	8	9	10	11	12	c	Slope	c	Slope	c	Slope	c	Slope
Size																				
LMV	**0.00**	**0.01**	0.51	0.24	0.92	0.29	0.12	**0.01**	0.55	0.27	0.66	0.43	0.17	**0.01**	0.10	**0.01**	**0.02**	0.23	**0.03**	0.23
LPrice	**0.00**	**0.05**	0.51	0.17	0.69	0.13	0.99	0.81	0.18	**0.01**	0.35	0.86	**0.03**	0.11	**0.00**	0.81	**0.00**	0.30	**0.00**	0.15
Value																				
BVTP	**0.00**	**0.00**	**0.01**	0.62	0.23	0.71	0.44	0.83	0.52	0.47	0.74	0.12	0.56	**0.00**	0.22	**0.00**	0.32	**0.01**	0.10	**0.00**
CEY	**0.00**	**0.00**	**0.00**	0.05	0.31	0.84	0.76	0.94	0.55	0.38	0.69	0.51	0.06	**0.00**	**0.01**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
DY	**0.00**	**0.00**	**0.00**	0.18	0.81	0.92	0.68	0.67	0.78	0.85	0.50	0.65	0.20	**0.00**	0.09	**0.00**	0.14	**0.00**	0.48	**0.00**
EY	**0.00**	**0.00**	**0.00**	0.15	0.45	0.91	0.42	0.54	0.35	0.45	0.88	0.64	0.07	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Sales_to_MV	**0.00**	**0.00**	**0.01**	0.56	0.76	0.13	0.10	0.46	0.23	0.31	0.22	0.13	0.24	**0.00**	0.19	**0.01**	0.16	0.08	0.25	0.07
Growth																				
CEYG1	**0.01**	0.20	**0.00**	0.07	0.84	0.82	0.93	0.67	0.22	0.49	0.91	0.08	0.29	**0.00**	0.11	**0.02**	0.09	0.78	0.10	0.66
CEYG12	0.91	0.33	0.74	0.60	0.56	0.10	0.19	0.55	0.36	0.91	0.48	0.82	0.83	0.63	0.91	0.36	0.92	0.82	0.78	0.33
DPSG12	0.13	0.12	0.40	0.93	0.11	0.52	0.14	0.72	0.77	0.61	0.59	0.40	0.40	**0.04**	0.46	**0.03**	0.68	0.23	0.59	0.99
DPSG24	0.16	**0.01**	0.11	0.18	0.32	0.60	**0.04**	0.08	0.30	0.12	**0.03**	0.85	0.33	**0.01**	0.05	0.84	0.29	0.61	0.59	0.28
EG12_P	0.25	**0.02**	0.60	0.87	0.86	0.86	0.86	0.76	0.99	0.70	0.27	0.98	0.25	0.60	0.32	0.47	0.13	0.71	**0.01**	0.05
EG24_P	0.16	0.33	**0.04**	0.22	0.35	0.78	0.86	0.60	0.65	0.07	0.11	0.91	0.08	0.11	0.35	0.49	0.33	0.83	0.50	0.68
Expectedgrowth	0.09	0.12	0.19	**0.01**	0.66	0.59	**0.02**	0.92	0.99	0.45	0.09	0.76	0.81	**0.01**	0.56	**0.05**	0.20	0.29	0.05	0.52
Gearing	**0.05**	**0.03**	0.10	0.47	0.08	0.70	0.61	0.20	0.42	0.09	0.22	0.87	0.55	**0.01**	0.92	**0.02**	0.97	0.69	0.70	0.49
POUT	**0.00**	**0.00**	**0.00**	0.16	0.17	0.26	0.17	0.07	0.33	0.19	0.10	0.09	0.31	**0.00**	0.33	**0.00**	0.25	**0.00**	0.48	**0.00**
ROE	**0.01**	0.08	**0.00**	**0.00**	0.18	0.07	0.08	**0.02**	0.47	0.50	0.16	0.26	0.66	**0.00**	0.95	**0.00**	0.77	0.23	0.80	0.47
SG12	**0.00**	**0.00**	**0.01**	**0.02**	0.36	0.22	0.25	0.16	0.17	0.12	0.21	0.23	0.22	**0.00**	0.08	**0.00**	0.05	**0.00**	**0.01**	**0.00**
SG24	**0.00**	**0.00**	0.26	**0.05**	**0.04**	**0.01**	0.51	**0.02**	0.44	**0.02**	0.14	0.59	0.31	**0.00**	0.10	**0.00**	**0.03**	**0.00**	**0.01**	**0.00**
Liquidity																				
Current	**0.00**	**0.01**	**0.03**	0.40	0.42	0.55	0.87	0.22	0.41	0.67	0.75	0.29	0.27	**0.00**	0.29	**0.00**	0.14	**0.00**	0.22	0.05
ICBT	0.10	0.98	**0.00**	0.20	0.33	0.51	0.22	0.85	0.48	0.80	0.75	0.39	**0.02**	0.06	**0.04**	0.18	0.07	0.39	**0.05**	0.86
NCA_to_MV	0.12	0.62	0.44	0.30	0.14	0.64	0.62	0.79	0.76	0.31	0.70	0.97	0.81	0.37	0.75	0.54	0.86	0.28	0.57	0.33
Risk																				
Beta	**0.00**	**0.00**	**0.00**	0.23	0.53	0.96	0.82	0.10	0.35	**0.03**	**0.04**	0.20	0.21	**0.00**	0.57	**0.00**	0.73	**0.00**	0.80	**0.00**
PVar12	**0.00**	**0.00**	**0.00**	0.06	0.45	0.09	0.23	0.36	0.30	0.21	0.48	0.85	0.33	**0.00**	0.05	**0.00**	**0.03**	**0.00**	0.12	**0.01**
RetVar12	**0.00**	**0.00**	**0.00**	0.20	0.49	0.47	0.12	0.70	0.41	0.66	0.40	0.19	0.18	**0.00**	0.20	**0.00**	**0.04**	**0.00**	0.06	**0.00**
Momentum																				
Crossover3_12	**0.00**	**0.00**	**0.00**	0.06	0.25	0.35	0.17	0.19	0.37	0.19	0.69	0.81	0.89	**0.00**	0.45	**0.00**	0.15	**0.00**	**0.03**	**0.00**
MOM1	**0.00**	**0.00**	**0.00**	0.20	0.98	0.97	0.71	0.61	0.78	0.75	0.84	0.59	0.09	**0.00**	**0.01**	**0.00**	**0.01**	**0.00**	**0.01**	**0.00**
MOM3	**0.00**	**0.00**	**0.00**	**0.02**	0.40	0.57	0.35	0.55	0.98	0.83	0.90	0.74	0.18	**0.00**	0.09	**0.00**	0.11	**0.00**	0.16	**0.00**
MOM6	**0.00**	**0.00**	**0.00**	**0.02**	0.25	0.51	0.35	0.74	0.50	0.56	0.93	0.81	0.54	**0.00**	0.35	**0.00**	0.35	**0.00**	0.45	**0.00**
MOM12	**0.00**	**0.00**	**0.00**	0.07	0.47	0.51	0.96	0.88	0.54	0.69	0.55	0.49	0.56	**0.00**	0.77	**0.00**	0.58	**0.00**	0.70	**0.00**
MOM18	**0.00**	**0.00**	**0.00**	**0.05**	0.97	0.55	0.58	0.33	0.34	0.39	0.86	0.78	0.36	**0.00**	0.50	**0.00**	0.61	**0.01**	0.97	**0.01**

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7.4. Style Seasonality Results

The twelfth lag autocorrelation and partial autocorrelation are tested for significance to discover whether a pattern of seasonality exists. The results are displayed in *Appendix B.3.*. No styles are found to display a pattern of annual seasonality. The mean payoff for each month is then compared to the mean payoff over all months. The results, shown in *Table 7.4.1.*, indicate that a number of styles perform significantly better over April than over other months. Sales to market value is most affected during April, with log of price (but not log of market value) six-month and one-year momentum, one-year sales growth and two year dividend growth all significant at the 5% level. April style seasonality is noteworthy given that the tax year-end for individuals is on the 5 April. A number of past UK studies (Dimson and Marsh, 2001 and Clare, Psaradakis and Thomas, 1995) have found April stock market returns to be significantly higher than average returns. These past studies have suggested that tax-loss selling, and subsequent repurchasing, is the cause of the April effect. Turn-of-the-year investor behaviour may cause styles to stand out more strongly or alternatively, styles may perform better in the buoyant April market.

A similar January turn-of-the-year effect has been documented in the US by Rozeff and Kinney (1976). Keim (1983) finds the US size anomaly is strongly related to the turn-of-the-year effect. Dimson and Marsh (2001) however find no turn-of-year size relationship in the UK. The evidence presented in this thesis indicates that there may indeed be a turn-of-the-year size effect in the UK. A few other style-months are found significant, however no explanation is suggested for these anomalies. With the number of style months tested it is likely that a few spurious results emerge. Due to the nature of multifactor time-series forecasting models, seasonality is not incorporated in any of the timing models constructed in *Chapter 8*. Future research however could look at enhancing model performance by controlling for the April effect.

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Table 7.4.1. Results: Calendar Seasonality In Style Payoffs in each month

Probability values associated with the null that the mean style payoff in a month is not significantly different to the overall mean payoff in all months. The test performs a comparison t-test using pooled variance and assuming unequal variance between samples, over the in-sample period (1 Mar 1990 – 1 Feb 2000). P-values significant at the 5% level are bolded.

	January	February	March	April	May	June	July	August	September	October	November	December
Size												
LMV	0.05	0.98	0.81	0.38	0.55	0.75	**0.05**	0.74	0.62	0.57	0.55	0.17
LPrice	0.11	0.38	0.56	**0.02**	0.30	0.49	0.05	0.55	0.30	0.39	0.37	**0.01**
Value												
BVTP	0.27	0.94	0.89	0.97	0.22	0.29	0.39	0.13	0.18	0.79	0.66	0.60
CEY	0.12	0.60	**0.02**	0.28	0.55	0.18	0.67	0.55	0.84	0.46	0.76	0.96
DY	0.12	0.83	0.07	0.06	0.22	0.88	0.67	0.88	0.80	0.35	0.69	0.59
EY	0.30	0.97	0.05	0.27	0.42	0.72	0.51	0.86	0.84	0.50	0.66	0.55
Sales_to_MV	0.30	0.82	**0.05**	**0.00**	0.30	0.74	0.16	0.55	0.09	0.08	0.63	**0.02**
Growth												
CEYG1	**0.05**	0.37	0.55	0.34	0.68	0.55	0.60	0.34	0.39	0.39	0.64	0.08
CEYG12	0.49	0.42	0.07	0.50	0.44	0.58	0.46	0.69	0.71	0.90	0.12	0.83
DPSG12	0.57	0.59	0.90	0.06	0.99	0.39	0.42	0.96	0.29	0.38	0.19	**0.03**
DPSG24	0.50	0.39	0.90	**0.04**	0.62	0.44	0.84	0.91	0.32	0.41	0.83	0.43
EG12_P	0.97	0.38	0.73	0.59	0.42	0.28	0.73	0.94	0.81	0.83	0.67	0.59
EG24_P	0.66	0.21	0.18	0.08	0.30	0.07	0.17	0.71	0.85	0.54	0.46	0.33
Expectedgrowth	0.73	0.30	0.49	0.15	0.64	0.38	0.86	0.91	0.36	0.45	0.54	0.37
Gearing	0.12	0.30	0.44	0.63	0.43	0.64	0.70	0.28	0.12	0.70	0.30	0.44
POUT	0.10	0.63	0.38	0.90	0.37	0.50	0.16	0.74	0.64	0.26	0.60	0.58
ROE	0.82	0.52	0.14	0.78	0.69	0.13	0.49	0.68	0.92	0.26	0.88	0.34
SG12	0.83	0.32	0.52	**0.04**	0.46	1.00	0.21	0.63	0.42	0.17	0.67	0.60
SG24	0.36	0.44	0.29	0.75	0.96	0.69	0.80	0.31	0.74	0.49	0.95	0.73
Liquidity												
Current	0.30	0.83	0.23	0.34	0.42	0.41	0.38	0.78	0.92	**0.04**	0.57	0.78
ICBT	0.86	0.54	0.97	0.72	0.47	0.62	0.72	0.92	0.08	0.41	0.81	0.78
NCA_to_MV	0.84	0.99	0.30	0.59	0.85	0.36	0.48	0.54	0.59	0.30	0.35	0.31
Risk												
Beta	0.35	0.94	0.36	0.77	0.52	0.30	0.76	1.00	0.06	0.11	0.33	0.77
PVar12	0.21	0.98	0.50	0.51	0.50	0.21	0.95	0.97	0.90	0.74	0.38	0.85
RetVar12	0.17	0.72	0.13	0.64	0.62	0.09	0.31	0.54	0.22	0.23	0.35	0.82
Momentum												
Crossover3_12	0.94	0.32	0.35	0.61	0.42	0.82	0.14	**0.01**	0.18	0.75	0.48	0.91
MOM1	0.50	0.37	0.69	0.13	0.63	0.77	0.20	0.33	0.97	0.24	0.42	0.33
MOM3	0.51	0.32	0.53	0.08	0.64	0.95	0.07	0.65	0.37	0.40	0.81	0.25
MOM6	0.70	0.21	0.44	**0.03**	0.32	0.70	0.28	0.66	0.32	0.31	0.95	0.20
MOM12	0.72	0.18	0.36	**0.03**	0.39	0.27	0.74	0.73	0.43	0.34	0.68	0.10
MOM18	1.00	0.74	0.10	0.09	0.44	0.09	0.26	0.28	0.20	0.45	0.58	0.06

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7.5. Macroeconomic Relationship Results

Based on prior research a list of nineteen candidate macroeconomic variables is constructed (displayed in *Table 7.5.1.*). The variables cover interest rates, exchange rates, inflation, the monetary environment, the cross-sectional dispersions of key firm-specific attributes, a market index, the market's aggregated earnings, earnings yield, dividend yield and standard deviation, and measures of business confidence. A detailed description of each variable is provided in *Appendix B.4.*

Table 7.5.1. Macroeconomic Factors

Displays the codes and names of preliminary macroeconomic factors used in analysis. Complete definitions are provided in *Appendix B.4.*

Code	Description
Interest Rates, Exchange Rates, Inflation and the Money Supply	
Tbill_3Month	Three months treasury bills yield
Bond_20y	Gross redemption yield on 20 year gilts
Term_Structure	Difference between the gross redemption yield on 20 year gilts and the three months treasury bills yield
Inflation	Annual inflation rate
Moneysupply	UK money supply (M4) at current prices
Exrate	Dollar value of one Pound (US $ TO £1)
Cross-sectional Dispersions of Attributes	
DY_Dsp	Monthly standard deviation of dividend yield (as defined in Appendix A.2.)
EG12P_ Dsp	Monthly standard deviation of the attribute EG12P (as defined in Appendix A.2.)
EG24P_ Dsp	Monthly standard deviation of the attribute EG24P (as defined in Appendix A.2.)
EY_ Dsp	Monthly standard deviation of Earnings yield (as defined in Appendix A.2.)
Market Variables	
Mkt_DY	Aggregate dividend yield of the market
Mkt_Earnings	Aggregate earnings of the market
Mkt_EY	Aggregate earnings yield of the market
EY_Gap	Difference between the aggregate earnings yield of the market and the gross redemption yield on 20 year gilts
DS_Index	Value of the Datastream maintained LSE overall index
Mkt_RP	Difference between monthly return on the market and the three months treasury bills yield
Mkt_stdDev6m	Standard deviation of the Datastream index (DS_Index) over the past six months.
Business Cycle Indicators	
Composite	UK Composite Leading Indicator
Optimism	Business optimism

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Before any meaningful analysis of the macroeconomic data can take place, the stationarity of each variable needs to be tested and existing unit roots removed. *Table 7.5.2.* shows the results of the Augmented Dickey-Fuller test.

Table 7.5.2. Results of unit roots tests

Displays results from the augmented Dickey Fuller test. The maximum number of lags is set to four. A series is found to be non-stationary if the p-value associated with the ADF test is greater than 0.05, the variable is then either first differenced (in the case of returns data) or log first differenced and retested. The prefix D indicates first differencing and the prefix DL indicates first differencing of the log of values. Variables that are still non-stationary after differencing and variables held to lose economic meaning in the process of differencing are excluded from further analysis. EY_GAP is included at the first step for reasons provided in the text.

	Levels		First Differences		
Variable	ADF Test Statistic	P-Value	Adj Variable	ADF Test Statistic	P-Value
Bond_20y	-1.77	0.08	DBond_20y	-5.17	0.00
Composite	-1.39	0.17	DLComposite	-5.40	0.00
DY_Dsp	-0.53	0.60	**Excluded**	-4.69	0.00
EG12P_Dsp	-3.16	0.00	-	-	-
EG24P_Dsp	-2.37	0.02	-	-	-
ExRate	-2.53	0.01	-	-	-
EY_Gap	-1.36	0.17	-	-	-
EY_Dsp	-2.34	0.02	-	-	-
Inflation	-4.06	0.00	-	-	-
Mkt_DY	-1.60	0.11	**Excluded**	-	-
Mkt_Earnings	-0.87	0.39	DLMkt_Earnin	-4.13	0.00
Mkt_EY	-2.24	0.03	-	-	-
Mkt_RP	-5.78	0.00	-	-	-
Mkt_StdDev6m	-3.01	0.00	-	-	-
DS_Index	-1.40	0.16	DLDS_Index	-5.75	0.00
Moneysupply	3.39	0.00	DLMoneysuppl	-4.84	0.00
Optimism	-3.34	0.00	-	-	-
Tbill_3Month	-3.50	0.00	-	-	-
Term_Structure	-2.98	0.00	-	-	-

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Seven variables are found to be non-stationary. The other non-stationary variables are either log differenced or, in the case of yields, differenced. It is felt that first differencing the dividend yield spread, the market dividend yield and the earnings yield gap will remove the economic meaning behind such factors. Dividend yield spread and market dividend yield are therefore excluded from further analysis. In the case of earnings yield gap, because there is no *a priori* reason to believe that it should be non-stationary and because other studies have found it to be stationary, it is left in the pool of factors. Once these adjustments have been made, all remaining variables are found to be non-stationary.

Table 7.5.3. shows the correlations between macroeconomic variables.

Table 7.5.3. Correlations Between Macroeconomic Factors

Pearson product-moment correlation matrix between macroeconomic factors. Correlations are calculated over the period 1 Mar 1990 – 1 Feb 2004. Correlations exceeding 0.50 are shown in bold.

	Interest Rates, Exchange Rates, Inflation and the Money Supply						Cross-sectional Dispersions of Attributes		
	TBILL_3MONTH	DBOND_20Y	TERM_STRUCTURE	INFLATION	DLMONEYSUPPLY	EXRATE	EG12P_DSP	EG24P_DSP	EY_DSP
DBOND_20Y	-0.1								
TERM_STRUCTURE	-0.6	0.2							
INFLATION	**0.9**	-0.1	-0.6						
DLMONEYSUPPLY	0.1	-0.1	-0.1	0.1					
EXRATE	**0.7**	-0.1	-0.5	**0.7**	0.1				
EG12P_DSP	-0.2	0.1	0.2	0.0	0.0	0.1			
EG24P_DSP	-0.1	0.0	0.2	0.0	-0.1	0.2	**0.6**		
EY_DSP	-0.3	0.1	0.0	0.0	0.1	0.1	**0.7**	**0.5**	
DLMKT_EARNINGS	-0.1	0.1	0.2	-0.1	0.1	-0.1	-0.1	0.1	0.0
MKT_EY	**0.6**	-0.1	-0.1	**0.7**	0.1	**0.6**	0.3	0.3	0.2
EY_GAP	**0.6**	0.0	0.1	0.3	-0.1	0.2	-0.4	-0.2	-0.6
DLDS_Index	0.0	-0.3	0.1	0.0	0.0	0.1	0.0	0.1	0.0
MKT_RP	0.0	-0.3	0.1	0.0	0.0	0.0	0.0	0.1	0.1
MKT_STDDEV6M	-0.3	0.0	-0.2	-0.2	-0.1	-0.1	0.1	0.1	0.4
DLCOMPOSITE	-0.2	0.0	0.2	-0.2	-0.2	-0.2	-0.1	0.0	-0.1
OPTIMISM	-0.3	0.1	**0.6**	-0.4	0.0	-0.3	-0.1	0.0	-0.2

	Market Variables						Business Cycle Indicators	
	DLMKT_EARNINGS	MKT_EY	EY_GAP	DLDS_Index	MKT_RP	MKT_STDDEV6M	DLCOMPOSITE	OPTIMISM
DBOND_20Y								
TERM_STRUCTURE								
INFLATION								
DLMONEYSUPPLY								
EXRATE								
EG12P_DSP								
EG24P_DSP								
EY_DSP								
DLMKT_EARNINGS								
MKT_EY	0.0							
EY_GAP	0.0	0.3						
DLDS_Index	0.0	0.1	0.0					
MKT_RP	0.0	0.1	-0.1	1.0				
MKT_STDDEV6M	-0.1	-0.3	-0.6	-0.1	0.0			
DLCOMPOSITE	-0.1	-0.2	0.1	0.4	0.4	-0.1		
OPTIMISM	0.2	-0.2	0.3	-0.1	-0.1	-0.4	0.0	

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At this point, the market risk premium (MKT_RP) is removed from analysis as it is extremely strongly positively correlated with market returns (DLDS_Index).

The key macroeconomic variables appear to be inter-related. Market earnings yield, interest rates, exchange rates and inflation are all highly correlated with each other. The direction of the causality is unclear, however the variables are clearly related through the state of the economy. In particular inflation is strongly linked to short term interest rates. The business optimism indicator is also strongly correlated with inflation, earnings yield, earnings yield spread and the term structure of interest rates, although this is likely due to these variables featuring in the construction of the business optimism indicator. It is clear therefore that the key macroeconomic variables contain a number of links. This should show up in the combinations of variables that work together to explain each style payoff time-series.

Pearson's product-moment correlations are calculated between one-month-lagged macroeconomic variables and style payoffs. The correlations suggest potential economic relationships, however, significance does not necessarily imply causality. The correlation matrix is displayed in *Table 7.5.4.* It shows a number of variables are significantly correlated. Due to the high number of relationships tested, a few of these significant relationships may well be spurious. Predictability in the time-series of style payoffs (which we confirmed in *Section 7.3.*) or the influence of an outside variable (such as inflation) may also be the cause of a spurious economic relationship. The Granger test will reduce this problem by controlling for predictability in the time-series of style payoffs.

Table 7.5.4. shows the most frequently significant macroeconomic variables appear to be short term interest rates, the composite index, the exchange rate, the earnings yield on the market, and the earnings yield gap.

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Table 7.5.4. Correlations Between Style Payoffs And Lagged Macroeconomic Variables

Pearson product-moment correlation matrix between style slope coefficients (payoffs) and one-month-lagged macroeconomic factors. Correlations are calculated over the period 1 Mar 1990 – 1 Feb 2004. Correlation t-statistics are shown and bolded if significant at the 5% level using a two sided test. The critical t-value is 1.98.

	Size		Value					Growth					
	LMV	LPrice	BVTP	CEY	DY	EY	Sales_to_MV	CEYG1	CEYG12	DPSG12	DPSG24	EG12_P	EG24_P
Interest Rates, Exchange Rates, Inflation and the Money Supply													
TBILL_3MONTH	**(0.4)**	**(0.2)**	**(0.2)**	(0.1)	(0.2)	(0.2)	(0.0)	(0.2)	(0.2)	(0.2)	(0.1)	-(0.1)	(0.0)
(t-statistic)	**(4.4)**	**(2.3)**	**(2.3)**	(1.4)	(1.8)	(1.7)	-(0.5)	(1.8)	(1.8)	(2.4)	(1.1)	-(1.4)	(0.4)
DBOND_20Y	-(0.1)	(0.0)	-(0.1)	(0.1)	(0.0)	(0.1)	(0.1)	(0.1)	(0.1)	(0.0)	(0.0)	(0.0)	(0.2)
(t-statistic)	-(1.2)	(0.2)	-(1.6)	(1.1)	-(0.1)	(0.8)	(1.0)	(1.4)	(1.3)	-(0.1)	-(0.1)	(0.4)	(1.7)
TERM_STRUCTURE	(0.0)	(0.1)	**-(0.2)**	**-(0.2)**	**-(0.3)**	**-(0.3)**	-(0.1)	(0.1)	**-(0.2)**	-(0.1)	(0.1)	(0.1)	(0.0)
(t-statistic)	(0.1)	(1.3)	**-(2.7)**	**-(2.8)**	**-(3.3)**	**-(3.1)**	-(1.4)	(0.8)	**-(2.2)**	-(0.5)	(1.0)	(0.6)	(0.5)
INFLATION	**(0.4)**	(0.2)	(0.2)	(0.2)	**(0.2)**	**(0.2)**	(0.0)	**(0.2)**	(0.2)	(0.2)	(0.1)	-(0.1)	(0.0)
(t-statistic)	**(4.1)**	(2.0)	(1.9)	(1.9)	**(2.5)**	**(2.1)**	(0.2)	**(2.4)**	(1.9)	(1.8)	(1.3)	-(0.9)	(0.4)
DLMONEYSUPPLY	(0.1)	(0.0)	-(0.1)	(0.0)	(0.0)	(0.0)	-(0.1)	(0.0)	(0.0)	(0.1)	**(0.2)**	(0.0)	(0.0)
(t-statistic)	(0.6)	(0.5)	-(0.6)	-(0.3)	-(0.4)	-(0.3)	-(0.8)	(0.3)	-(0.3)	(1.3)	**(2.1)**	-(0.4)	(0.0)
EXRATE	**(0.3)**	**(0.2)**	**(0.2)**	(0.0)	(0.0)	(0.1)	-(0.1)	(0.1)	(0.1)	(0.3)	**(0.2)**	-(0.1)	(0.0)
(t-statistic)	**(3.3)**	**(2.3)**	**(2.1)**	(0.2)	(0.5)	(0.8)	-(1.5)	(1.1)	(1.0)	(3.0)	**(2.1)**	-(1.4)	-(0.3)
Cross-sectional Dispersions of Attributes													
EG12P_DSP	**(0.3)**	(0.2)	**(0.2)**	(0.1)	(0.1)	(0.1)	(0.0)	(0.1)	(0.2)	(0.1)	(0.0)	-(0.1)	(0.1)
(t-statistic)	**(3.0)**	(1.8)	**(2.4)**	(1.6)	(1.1)	(1.5)	(0.0)	(1.1)	(2.2)	(0.6)	-(0.2)	-(1.0)	(1.4)
EG24P_DSP	(0.1)	(0.0)	(0.1)	(0.0)	(0.1)	(0.1)	(0.1)	(0.0)	(0.0)	-(0.2)	-(0.1)	(0.2)	(0.2)
(t-statistic)	(1.5)	(0.0)	(1.2)	(0.1)	(1.1)	(1.1)	(1.1)	(0.4)	-(0.2)	-(1.8)	-(1.6)	(2.0)	(2.2)
EY_DSP	**(0.2)**	(0.1)	(0.1)	-(0.1)	(0.0)	(0.0)	-(0.1)	(0.1)	(0.1)	(0.1)	(0.0)	-(0.1)	(0.0)
(t-statistic)	**(2.4)**	(1.3)	(1.4)	-(0.8)	(0.3)	(0.1)	-(0.8)	(1.6)	(0.6)	(0.9)	-(0.3)	-(0.7)	(0.2)
Market Variables													
DLMKT_EARNINGS	(0.0)	(0.0)	-(0.1)	(0.0)	(0.1)	(0.0)	(0.1)	(0.1)	**-(0.2)**	-(0.2)	(0.0)	(0.1)	(0.0)
(t-statistic)	-(0.2)	-(0.1)	-(0.6)	(0.2)	(1.0)	(0.3)	(1.6)	(1.0)	**-(2.0)**	-(1.8)	-(0.1)	(1.1)	-(0.5)
MKT_EY	**(0.5)**	(0.2)	**(0.4)**	**(0.3)**	**(0.4)**	**(0.3)**	(0.1)	**(0.3)**	(0.2)	(0.1)	(0.1)	-(0.1)	(0.0)
(t-statistic)	**(6.1)**	(1.8)	**(4.1)**	**(3.6)**	**(4.5)**	**(4.0)**	(1.4)	**(3.5)**	(1.8)	(1.0)	(0.9)	-(1.4)	(0.4)
EY_GAP	(0.2)	(0.0)	**(0.2)**	**(0.2)**	**(0.2)**	**(0.3)**	(0.2)	(0.1)	(0.1)	(0.0)	-(0.1)	(0.0)	**(0.2)**
(t-statistic)	(1.8)	(0.1)	**(2.6)**	**(2.3)**	**(2.4)**	**(2.9)**	(1.7)	(0.7)	(1.5)	-(0.2)	-(0.8)	-(0.5)	**(2.0)**
DLDS_INDEX	(0.2)	-(0.1)	(0.1)	(0.0)	(0.1)	(0.0)	(0.1)	(0.1)	-(0.1)	**-(0.2)**	**-(0.2)**	(0.0)	(0.0)
(t-statistic)	(1.7)	-(0.9)	(1.3)	(0.1)	(1.2)	-(0.4)	(1.2)	(0.8)	-(1.4)	**-(2.5)**	**-(2.6)**	(0.4)	(0.5)
MKT_STDDEV6M	**-(0.2)**	-(0.1)	**-(0.2)**	-(0.1)	-(0.2)	-(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	-(0.1)	(0.1)	-(0.1)
(t-statistic)	**-(2.5)**	-(1.3)	**-(2.3)**	-(1.3)	-(1.7)	-(1.4)	-(0.2)	-(0.1)	-(0.2)	-(0.4)	-(1.1)	(0.9)	-(0.7)
Business Cycle Indicators													
DLCOMPOSITE	**-(0.3)**	**-(0.4)**	(0.0)	(0.0)	(0.1)	(0.1)	**(0.3)**	(0.1)	(0.0)	**-(0.3)**	**-(0.4)**	(0.0)	(0.1)
(t-statistic)	**-(3.3)**	**-(4.5)**	(0.1)	(0.5)	(1.1)	(0.6)	**(3.0)**	(1.4)	(0.1)	**-(3.9)**	**-(4.6)**	(0.5)	(1.4)
OPTIMISM	**-(0.2)**	-(0.1)	-(0.2)	-(0.1)	-(0.2)	-(0.1)	(0.0)	**-(0.3)**	-(0.1)	**-(0.2)**	-(0.1)	(0.0)	(0.0)
(t-statistic)	**-(2.7)**	-(0.6)	-(1.7)	-(1.4)	-(1.8)	-(1.6)	-(0.2)	**-(3.8)**	-(1.6)	**-(2.1)**	-(1.2)	(0.1)	-(0.3)

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Table 7.5.4. Correlations Between Style Payoffs And Lagged Macroeconomic Variables (continued)

	Growth (continued)						Liquidity		
	Expectedgrowth	Gearing	POUT	ROE	SG12	SG24	Current	ICBT	NCA_to_MV
Interest Rates, Exchange Rates, Inflation and the Money Supply									
TBILL_3MONTH	**-(0.4)**	**-(0.4)**	**(0.3)**	**(0.4)**	**-(0.2)**	**-(0.2)**	(0.0)	**(0.3)**	(0.0)
(t-statistic)	**-(4.5)**	**-(4.3)**	**(4.1)**	**(4.8)**	**-(2.0)**	**-(2.0)**	-(0.5)	**(3.0)**	(0.4)
DBOND_20Y	(0.0)	(0.1)	-(0.1)	-(0.1)	(0.0)	(0.1)	(0.0)	(0.1)	(0.0)
(t-statistic)	-(0.1)	(0.8)	-(0.6)	-(1.6)	(0.5)	(0.7)	-(0.5)	(0.9)	-(0.4)
TERM_STRUCTURE	**(0.3)**	-(0.1)	-(0.2)	**-(0.2)**	(0.1)	(0.2)	(0.2)	(0.0)	(0.0)
(t-statistic)	**(3.5)**	-(0.6)	-(1.8)	**-(2.4)**	(0.6)	**(2.7)**	(2.0)	-(0.1)	-(0.2)
INFLATION	**-(0.3)**	**-(0.4)**	**(0.3)**	**(0.4)**	**-(0.2)**	**-(0.2)**	-(0.1)	**(0.2)**	(0.0)
(t-statistic)	**-(3.5)**	**-(4.2)**	**(3.8)**	**(4.6)**	**-(2.4)**	**-(2.2)**	-(0.6)	**(2.1)**	(0.4)
DLMONEYSUPPLY	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	-(0.2)	(0.0)	-(0.1)	(0.0)
(t-statistic)	-(0.1)	(0.0)	-(0.2)	(0.1)	-(0.1)	-(1.8)	-(0.1)	-(1.0)	-(0.5)
EXRATE	**-(0.3)**	**-(0.3)**	**(0.2)**	**(0.2)**	-(0.1)	-(0.1)	(0.0)	**(0.3)**	(0.1)
(t-statistic)	**-(4.0)**	**-(3.2)**	**(2.5)**	**(2.7)**	-(0.9)	-(0.7)	(0.5)	**(3.8)**	(0.6)
Cross-sectional Dispersions of Attributes									
EG12P_DSP	-(0.2)	**-(0.2)**	**(0.3)**	(0.1)	**-(0.2)**	-(0.2)	(0.0)	(0.1)	(0.1)
(t-statistic)	-(1.8)	**-(2.0)**	**(3.1)**	(0.8)	**-(2.7)**	-(2.0)	(0.5)	(0.7)	(1.1)
EG24P_DSP	(0.1)	(0.0)	(0.1)	-(0.1)	-(0.2)	-(0.1)	(0.0)	(0.0)	(0.1)
(t-statistic)	(1.2)	(0.4)	(1.4)	-(1.5)	-(2.0)	-(1.6)	(0.0)	-(0.5)	(0.6)
EY_DSP	**-(0.3)**	**-(0.3)**	(0.1)	**(0.3)**	(0.0)	(0.1)	**(0.2)**	(0.2)	(0.1)
(t-statistic)	**-(3.9)**	**-(3.4)**	(1.5)	**(3.6)**	(0.5)	(0.9)	**(2.3)**	(1.8)	(1.2)
Market Variables									
DLMKT_EARNINGS	**(0.2)**	(0.1)	-(0.1)	-(0.1)	-(0.1)	-(0.1)	-(0.1)	**-(0.3)**	(0.0)
(t-statistic)	**(2.3)**	(1.6)	-(0.6)	-(1.2)	-(1.5)	-(1.5)	-(0.8)	**-(3.1)**	-(0.5)
MKT_EY	**-(0.2)**	**-(0.4)**	**(0.5)**	**(0.4)**	**-(0.4)**	**-(0.3)**	-(0.1)	**(0.2)**	(0.1)
(t-statistic)	**-(2.3)**	**-(4.1)**	**(6.3)**	**(4.7)**	**-(5.1)**	**-(3.8)**	-(1.4)	**(2.1)**	(1.6)
EY_GAP	-(0.1)	-(0.1)	**(0.3)**	(0.2)	**-(0.3)**	**-(0.3)**	-(0.2)	(0.2)	(0.1)
(t-statistic)	-(0.9)	-(1.5)	**(4.0)**	(1.8)	**-(3.0)**	**-(3.8)**	-(1.8)	(1.7)	(1.2)
DLDS_INDEX	(0.1)	-(0.1)	(0.0)	(0.0)	-(0.1)	(0.0)	(0.1)	**-(0.3)**	(0.1)
(t-statistic)	(0.7)	-(0.6)	(0.1)	(0.1)	-(0.9)	(0.5)	(1.2)	**-(2.9)**	(0.6)
MKT_STDDEV6M	(0.0)	(0.0)	**-(0.3)**	-(0.1)	**(0.2)**	**(0.3)**	(0.1)	-(0.2)	(0.0)
(t-statistic)	(0.4)	(0.5)	**-(3.2)**	-(1.6)	**(2.8)**	**(3.6)**	(1.3)	-(1.9)	-(0.2)
Business Cycle Indicators									
DLCOMPOSITE	(0.1)	(0.0)	-(0.1)	(0.0)	(0.1)	(0.1)	(0.0)	(0.0)	(0.1)
(t-statistic)	(1.3)	-(0.1)	-(1.3)	(0.4)	(1.0)	(1.4)	(0.3)	-(0.3)	(1.0)
OPTIMISM	**(0.2)**	**(0.3)**	**-(0.2)**	**-(0.2)**	(0.0)	-(0.1)	(0.0)	-(0.1)	-(0.1)
(t-statistic)	**(2.8)**	**(2.9)**	**-(2.1)**	**-(2.5)**	(0.4)	-(0.7)	-(0.5)	-(0.6)	-(1.1)

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Table 7.5.4. Correlations Between Style Payoffs And Lagged Macroeconomic Variables (continued)

	Risk			Momentum					
	Beta	**PVar12**	**RetVar12**	**Crossover3_12**	**MOM1**	**MOM3**	**MOM6**	**MOM12**	**MOM18**
Interest Rates, Exchange Rates, Inflation and the Money Supply									
TBILL_3MONTH	**-(0.3)**	**-(0.3)**	**-(0.3)**	-(0.2)	-(0.2)	-(0.2)	-(0.1)	**-(0.2)**	(0.0)
(t-statistic)	**-(3.2)**	**-(3.5)**	**-(3.7)**	-(1.9)	-(1.9)	-(1.9)	-(1.1)	**-(2.2)**	(0.5)
DBOND_20Y	-(0.1)	(0.0)	(0.0)	(0.0)	-(0.1)	(0.0)	(0.0)	-(0.1)	-(0.1)
(t-statistic)	-(1.0)	(0.4)	-(0.5)	(0.1)	-(0.7)	-(0.3)	-(0.4)	-(0.9)	-(1.0)
TERM_STRUCTURE	(0.2)	-(0.1)	**(0.2)**	**-(0.3)**	-(0.1)	(0.0)	(0.0)	(0.1)	**(0.2)**
(t-statistic)	(1.7)	-(0.8)	**(2.5)**	**-(2.9)**	-(1.5)	(0.0)	(0.2)	(0.9)	**(2.3)**
INFLATION	**-(0.3)**	**-(0.3)**	**-(0.3)**	**-(0.2)**	**-(0.2)**	**-(0.2)**	-(0.1)	**-(0.2)**	(0.0)
(t-statistic)	**-(3.5)**	**-(3.0)**	**-(3.3)**	**-(2.2)**	**-(2.2)**	**-(2.2)**	-(1.3)	**-(2.2)**	-(0.4)
DLMONEYSUPPLY	(0.0)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.1)	(0.1)
(t-statistic)	-(0.2)	(0.7)	(0.0)	-(0.3)	(0.5)	(0.0)	(0.3)	(0.7)	(0.8)
EXRATE	-(0.1)	**-(0.2)**	**-(0.2)**	(0.0)	(0.0)	(0.0)	(0.0)	-(0.1)	(0.1)
(t-statistic)	-(1.6)	**-(2.1)**	**-(2.3)**	-(0.3)	-(0.5)	-(0.4)	-(0.1)	-(0.8)	(1.0)
Cross-sectional Dispersions of Attributes									
EG12P_DSP	-(0.2)	**-(0.3)**	**-(0.3)**	**-(0.2)**	-(0.2)	-(0.1)	-(0.2)	**-(0.2)**	-(0.1)
(t-statistic)	-(1.8)	**-(3.2)**	**-(3.1)**	**-(2.2)**	-(2.0)	-(1.6)	-(1.8)	**-(2.1)**	-(0.7)
EG24P_DSP	-(0.1)	-(0.1)	-(0.1)	-(0.1)	-(0.1)	**-(0.2)**	-(0.2)	**-(0.2)**	**-(0.2)**
(t-statistic)	-(0.9)	-(1.0)	-(1.0)	-(1.4)	-(1.0)	**-(2.1)**	-(1.9)	**-(2.0)**	**-(2.2)**
EY_DSP	(0.0)	-(0.1)	(0.0)	(0.0)	-(0.1)	(0.0)	(0.0)	-(0.1)	(0.1)
(t-statistic)	-(0.2)	-(1.5)	-(0.4)	(0.4)	-(0.7)	-(0.4)	(0.0)	-(0.7)	(0.8)
Market Variables									
DLMKT_EARNINGS	-(0.1)	(0.1)	(0.0)	-(0.1)	-(0.1)	-(0.1)	-(0.1)	-(0.1)	**-(0.2)**
(t-statistic)	-(0.6)	(1.1)	(0.1)	-(1.0)	-(0.7)	-(1.3)	-(1.3)	-(0.8)	**-(2.0)**
MKT_EY	**-(0.4)**	**-(0.4)**	**-(0.4)**	**-(0.4)**	**-(0.4)**	**-(0.4)**	**-(0.3)**	**-(0.4)**	**-(0.2)**
(t-statistic)	**-(5.4)**	**-(4.3)**	**-(4.7)**	**-(5.2)**	**-(4.3)**	**-(4.8)**	**-(3.8)**	**-(4.3)**	**-(2.3)**
EY_GAP	**-(0.3)**	**-(0.3)**	**-(0.3)**	**-(0.3)**	**-(0.3)**	**-(0.3)**	**-(0.3)**	**-(0.3)**	**-(0.1)**
(t-statistic)	**-(4.0)**	**-(3.8)**	**-(3.6)**	**-(3.3)**	**-(3.0)**	**-(3.4)**	**-(2.8)**	**-(3.7)**	-(1.4)
DLDS_INDEX	**(0.3)**	(0.1)	**(0.2)**	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	-(0.1)
(t-statistic)	**(3.4)**	(0.7)	**(2.1)**	(0.2)	(0.2)	-(0.3)	(0.0)	(0.5)	-(1.4)
MKT_STDDEV6M	**(0.3)**	(0.1)	**(0.2)**	**(0.3)**	(0.2)	**(0.2)**	**(0.2)**	(0.2)	(0.0)
(t-statistic)	**(3.1)**	(1.3)	**(2.5)**	**(3.3)**	(1.7)	**(2.3)**	**(2.0)**	(1.8)	(0.2)
Business Cycle Indicators									
DLCOMPOSITE	**(0.2)**	(0.0)	**(0.2)**	(0.0)	-(0.1)	-(0.1)	-(0.1)	-(0.1)	-(0.2)
(t-statistic)	**(2.0)**	(0.3)	**(2.3)**	(0.3)	-(1.2)	-(1.3)	-(1.6)	-(0.7)	-(2.0)
OPTIMISM	(0.1)	**(0.2)**	**(0.2)**	(0.2)	**(0.2)**	(0.2)	(0.1)	(0.2)	(0.1)
(t-statistic)	(1.3)	**(2.2)**	**(2.0)**	(1.7)	**(2.2)**	(1.8)	(1.5)	(1.9)	(0.6)

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The main trends in *Table 7.5.4.* are now discussed.

Size

A number of economic variables are found to be related to the size anomaly. Because the size anomaly has a negative payoff, i.e. small firms outperform large firms, positive correlations in *Table 7.5.4.* indicate that when the economic variable concerned is high, large firms are advantaged. As expected, the log of market value and the log of price correlation signs are identical, although the log of market value correlations are generally more significant. Both log of market value and log of price are negatively correlated with the composite and optimism indexes, i.e. small firms perform well when the economy is gaining in strength. Small firms are also significantly benefited by low exchange rates, low inflation and low short term interest rates. This supports the UK findings of Levis and Liodakis (1999), who find inflation to be a significant determinant of the size spread, and the US findings of Jensen, Johnson, and Mercer (1998), Gertler and Gilchrist (1994), and Anderson (1997), who report that small shares benefit from inflation and a greater spread in long and short term interest rates (In this thesis, however, size is not found to be related to the term structure of interest rates.) Anderson (1997) suggests that small companies find it easier to pass along price increases in inflationary times. Small firms are also found to benefit from a high market earnings yield. High yields reflect low share prices and therefore uncertainty about the future.

These relationships show that small firms are more sensitive to changes in the business environment. When investors lose confidence they are less willing to invest in small firms which are perceived to be riskier than large firms. The resulting 'flight to quality' lowers the returns on small firms. Similarly, small firms benefit from upturns, as the lower risk of bankruptcy has a greater effect on small firm prices than large firm prices. Perez-Quiros and Timmermann (2000) also suggest that small firms are more sensitive than large firms to changes in variables that measure credit conditions. It is argued that small firms are better able to take advantage of growth opportunities that arise in a booming economy. Whether this is true or not, market sentiment appears to reflect the statement by placing a premium on small firm prices during economic expansion.

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Value

It is surprising that earnings yield is not correlated with the dispersion in earnings yield. Rather the spread in earnings yield is significantly correlated with log of market value, gearing and ROE. Results therefore do not confirm Asness *et al.* (2000) who find that higher value spreads are associated with stronger payoffs to value attributes. Value shares (with high yields) are found to perform well when the earnings yield of the market is high. This is explained by the 'flight to quality' argument. Conventional wisdom asserts that these shares are safer than other investments as they offer high yields (particularly dividend yields). Therefore, when yields are high and confidence is low, value shares perform well. This supports Kao and Shumaker (1999), who find that the earnings-yield gap best explains the value/ growth spread in the US. The optimism index is negatively correlated with all value attributes. As expected, value shares do not perform as well when the economy is strong. Value shares also perform poorly when the term structure is wide, indicating that interest rates are expected to fall.

Growth and Liquidity

Growth companies are strongly affected by inflation and short term interest rates. This supports the UK findings of Levis and Liodakis (1999) who find that inflation is one of the main determinants of the growth/ value spread. The reason is that growth companies, and investors, project earnings further into the future than value investors, and interest and inflation rates have a greater affect on discounted cash flows that occur further into the future. The earnings growth spread also affects growth companies. Wider spreads likely make the top growth companies appear more attractive. The composite and optimism indexes are negatively correlated with a number of growth attributes, particularly dividend per share growth. It appears that dividends become less important when the economy is strong. Consistent with the 'flight to quality', during economic downturns investors leave riskier growth investments for safer value investments that offer good yields.

As expected, when interest rates are high, highly geared companies perform worse, as do companies with low interest cover before tax ratios (high debt burdens). Interestingly, these companies are far more affected by short term rate increases than 20 year band increases.

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Risk

The risk attributes are strongly affected by interest rates, inflation and the market yield. These variables all have an effect on investor risk preferences.

It is important that the return on the market (DLDS_Index) does not have a strong effect on many of the styles (in all clusters). This shows that the styles behave independently to the market and confirms that styles do not approximate conventional CAPM risk.

Momentum

The momentum styles are affected by the earnings yield on the market, the standard deviation of the market and inflation. The finding that momentum is positively linked to market volatility contradicts the US findings presented by Macedo (1995) who shows market volatility to be a good forecasting variable for the relative value - momentum spread, but in the other direction. Momentum also performs well when the earnings yield on the market is low implying high confidence levels. Momentum therefore appears to work well when the market is at very high levels, possibly because during these 'market boom' times there is an increase in new untrained market participants resulting in less emphasis being placed on underlying fundamentals. Even experienced investors may act irrationally when returns are unreasonably good. Inflation appears to be an important constraint on momentum. When inflation is high, momentum does not work as well. This contradicts the US findings of Chordia and Shivakumar (2002) who report that momentum strategy payoffs are positive and significant during expansionary periods, characterised by high inflation, and negative during recessionary periods.

The Granger causality test is performed on twelve lags to uncover dynamic relationships between lagged macroeconomic variables and style payoffs. The p-values associated with the null hypothesis of no Granger causality are displayed in *Appendix B.5*. A number of significant dynamic relationships are discovered. Once again, due to the high number of relationships tested, a few of these significant relationships may be spurious. A summary of the important macroeconomic factors for each style is provided in *Table 7.5.5* . The granger results are particularly

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important for differenced variables, such as market returns, as the last difference is more heavily influenced by noise than is the case for state variables. Using twelve months of differences should give a more accurate reflection of the economic situation.

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Table 7.5.5. Macroeconomic Variables that Granger Cause Attribute Slopes

Displays summarised results from the Granger test performed with twelve lags. The Granger test reveals the macroeconomic variables that Granger cause slope coefficients after controlling for the effect of the time-series of slope coefficients. Appendix I.5. displays probability values associated with each Granger test.

Slopes	Macro variables								
Size									
LMV	DLComposite	EG12P_Dsp	DLDS_ Index						
LPrice	DLComposite	Tbill_3Month	DLDS_ Index						
Value									
BVTP	Mkt_StdDev6m								
CEY		EY_Gap							
DY	Mkt_stdDev6m		DLComposite	Optimism				DLMkt_Earnings	
EY									
Sales_to_MV		EY_Gap	DLComposite						
Growth									
CEYG1			EY_Gap	Optimism	Mkt_EY		ExRate	DLMkt_Earnings	
CEYG12			EY_Gap	Optimism		Term_Structure			
DPSG12	EG24P_Dsp	EG12P_Dsp				Term_Structure	ExRate		Tbill_3Month
DPSG24	EG24P_Dsp								
EG12_P	EG24P_Dsp		EY_Gap	Optimism	Mkt_EY				EY_Dsp
EG24_P	EG24P_Dsp								
Expectedgrowth	EG24P_Dsp	EG12P_Dsp							
Gearing	EG24P_Dsp								
POUT								DLMkt_Earnings	
ROE									
SG12	Inflation								
SG24		EY_Gap	Mkt_StdDev6m						
Liquidity									
Current	DLComposite								
ICBT	Mkt_EY	Mkt_stdDev6m							
NCA_to_MV	EG24P_Dsp	ExRate							
Risk									
Beta		Optimism	Mkt_StdDev6m						
PVar12	EY_Dsp								
RetVar12	EY_Dsp	Optimism	DLDS_ Index						
Momentum									
Crossover3_12	Mkt_StdDev6m	Optimism							
MOM1		Optimism							
MOM3	Mkt_StdDev6m	Optimism	DLComposite						
MOM6	Mkt_StdDev6m								
MOM12	Mkt_StdDev6m								
MOM18	Mkt_StdDev6m								

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The Granger results largely confirm the lagged correlation results. Size is found to be related to the composite index of leading indicators, short term interest rates, market returns, the spread in earnings growth and short term interest rates confirming the findings of Levis and Liodakis (1999). The relationships show that small firms are benefited by upturns in the economy more than large firms.

During economic downturns, markets are less worried about growth opportunities, and more worried about value attributes such as dividend yield and earnings yield. This finding is strongly supported by evidence on value and growth styles. Payout ratio and dividend yield are both affected by growth in market earnings. When earnings are increasing, investors are not too concerned about dividends and growth shares perform well, however, when earnings suffer investors place a premium on value attributes such as dividend yields. The same business cycle argument applies to the attributes, interest cover before tax, sales to market value, beta, cash earnings yield, returns variance, price variance.

Book value to price and dividend yield are found to be dependent on the past volatility of the overall market. This may also be due to the "flight to value" described above, that follows periods of high volatility in share prices. The momentum attributes are also found to be positively related to the past volatility of the overall market. This contradicts the finding of Macedo (1995) that momentum suffers after periods of volatility.

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Earnings growth, expected growth and dividend per share growth are all affected by the spread in earnings growth. This confirms Asness *et al.* (2000) who find that the spread in earnings growth is able to forecast the difference in future returns between the top value decile and the top growth decile. A larger growth spread appears to improve the performance of growth styles. This is likely because growth outliers are easier to detect and show better returns when there is a large variance in the earnings growth attribute. Sales growth is linked to inflation, a sign that growth may be better rewarded in inflationary environments.

Dividend per share growth and cash earnings yield growth are both Granger caused by exchange rates and the term structure of interest rates. The former shows that growth performs better when the pound is at a low level to the dollar, possibly a sign that growth companies are either already exporting, or thinking of expanding into export markets. The latter shows that growth performs better when the term structure is narrow. This is confirmation of the credit argument presented by Perez-Quiros and Timmermann (2000) for small firms. Growth companies, like small firms, are more likely to expand than value companies. The term structure is therefore more important to them.

The Granger results therefore confirm the lagged correlations. A number of macroeconomic relationships related to the business cycle and changes in investor risk preferences appear to be important in explaining the time-variation of style payoffs.

7.6. Summary and Conclusion

In this section, the explanatory power of both elements from within the time-series of style payoffs and selected lagged macroeconomic variables was tested for significance. Virtually every style showed strong autocorrelation at early lags. Of the trailing moving averages, the six-month moving average performed best, closely followed by the one-year moving average. In general the slope coefficients of the moving averages show a high level of significance, indicating strong evidence of predictable variation in style payoffs.

Confirming past research, the April turn-of-the-year effect has a significant effect on a few of the styles.

A number of stationary macroeconomic variables are found to influence style payoffs. Useful macroeconomic factors relate to interest rates, exchange rates, inflation, the cross-sectional dispersions of key firm-specific attributes, a market index, the aggregated earnings, earnings yield, dividend yield and standard deviation of the market, and measures of business confidence. It is found that styles held to be perceived as riskier by the market, such as size, risk, and momentum, perform better when the economy is strong and styles held to be perceived by the market as 'safer', such as value, perform better when the economy is weak.

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The results from all the univariate time-series tests and macroeconomic tests are combined to produce multifactor forecasting models for each style in Chapter 8.

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8.

Style Forecasting Models

8.1. Introduction

In *Chapter 7.* time-series methods were used to investigate the predictability of style payoffs in-sample. In this chapter, eight style payoff forecasting models are constructed to take advantage of the predictability highlighted in *Chapter 7.* The forecasting models are on each style over the in-sample period and over the, until now untouched, out-of-sample period.

The eight forecasting models are applied to the multivariate framework developed in *Chapter 6.5.* to see if the best multivariate expected return model in *Chapter 6* (ICM) can be improved upon by incorporating the eight style forecasting models. The results will give an indication of which forecasting method is most appropriate in a multivariate environment. The forecasting models are not used to select attributes, only to improve payoff forecasts. The eleven ICM attributes are used for all models. Fixing the attributes allows for the best comparison of relative forecasting ability as results are not obscured by differences in attribute performance.

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The remainder of this chapter is set out as follows. *Section 8.2.* describes the data and methodology, *Section 8.3.* reports the forecasting model results for individual styles, *Section 8.4.* reports the forecasting model results in a multivariate context, and *Section 8.5.* summarises the key findings and concludes.

8.2. Data and Methodology

The dataset for this chapter comprises the time-series of monthly slope coefficients for the twenty-seven attributes regressed on future returns in Chapter 6 and the monthly values of the fifteen stationary macroeconomic variables introduced in Chapter 7 over the in- and out-of-sample periods.

8.2.1. Methodology of Forecasting Models for Individual Styles

Eight style payoff forecasting models are constructed, the 1M, 6M, 12M, 18M, 12M Reg, Mean, AR12 and Consolidated models. A summary of each model is provided in *Table 8.2.1.1.* The 1M, 6M, 12M, and 18M models forecast payoffs based on the mean payoff over the trailing one-month, six-months, twelve-months and eighteen-months respectively. The 12M model was used in *Section 6.5.* to forecast payoffs used in the construction of multifactor models. This was done to capture some element of style timing. The Mean model forecasts payoffs based on the entire historical trailing mean payoff. The one-month model is not a conventional AR1 model as it does not include a constant term or provide estimates of the slope coefficient. Rather it forecasts the previous payoff value one month ahead. This model will perform best if the payoffs follow a random walk, as the best estimate of a random walk is the last value available.

The AR12, Consolidated and 12M Reg models are all based on regression equations constructed using data over the in-sample period. The AR12 model is constructed using the 12 lag autoregression equation displayed as *Equation 22* in *Section 7.2.1* The 12M Reg model is based on the equation estimated when the trailing twelve month moving average is regressed on the style payoff one month ahead including a constant term.

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Table 8.2.1.1. Summary of Forecasting Models

Where definitions refer to in-sample period they relate to the period 1 Mar 1990 – 1 Feb 2000

Code	Name and description
1M Model	One-month Moving Average Model Forecast is equal to the payoff in previous month
6M Model	Six-month Moving Average Model Forecast is equal to the six month trailing moving average
12M Model	Twelve-month Moving Average Model Forecast is equal to the twelve month trailing moving average
18M Model	Eighteen-month Moving Average Model Forecast is equal to the twelve month trailing moving average
12M Reg Model	Twelve-month Moving Average Regression Model Forecast is made using the regression equation with a constant term and the trailing 12 month moving average payoff as the independant variable. In-sample, coefficients of the model are estimated over the entire in-sample period. Out-of-sample, coefficients of the model are estimated retrospectively using an expanding window.
Mean Model	Historic Mean Model Forecast is equal to the trailing historic mean estimated retrospectively using an expanding window
AR12 Model	Twelve lag Autoregressive model Forecast is made using the regression equation consisting of a constant term and the first 12 lagged style payoffs. In-sample, coefficients of the model are estimated over the entire in-sample period. Out-of-sample, coefficients of the model are estimated retrospectively using an expanding window.
Consolidated Model	Consolidated Model Forecast is made using the consolidated regression equation which incorporates a constant term and macroeconomic and style payoff time-series factors. The independent variables for the consolidated model of each style are shown in *Appendix C.1*. In-sample, coefficients of the model are estimated over the entire in-sample period. Out-of-sample, coefficients of the model are estimated retrospectively using an expanding window.

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The Consolidated model combines the meaningful factors that emerge from the research performed on style momentum and economic relationships to form multifactor forecasting models. Candidate factors for the Consolidated model are: the twelve individual payoff lags significantly correlated to the style payoff, the trailing six, twelve, eighteen and twenty four month moving averages found to have a significant relationship with the style payoff and lastly the lags of macroeconomic variables found to Granger cause style payoffs that are significantly correlated to style payoffs. Only significant lags of important macroeconomic variables are included in order to keep the models manageable and meaningful. If all twelve lags that together granger cause style payoffs were included, some styles would have factor models of up to seventy factors. A screen is therefore applied to the factors listed above to eliminate "double counting" factors that explain the same variation. The goal is to develop a parsimonious model that captures the main explanatory influences on each style. In each case a maximum of one auto-moving average is selected. If the model uses initial lags, the twelve month moving average is preferred to the six month moving average, if it is significant. Since virtually all style payoff series are highly auto-correlated, the first payoff lag is included in all Consolidated models. A constant term is included in each regression to capture the consistent effect of each style.

The three regression models are estimated differently in- and out-of-sample. In-sample the equation coefficients are estimated using data from the entire in-sample period. This, combined with the fact that models are constructed using knowledge gained from the (in-sample) primary style timing results in Chapter 7 implies that there is an element of look-ahead bias in the in-sample model results. Out-of-sample however, an expanding window is used to estimate regression coefficients. At each point in time, each regression model re-estimates regression coefficients based on the dataset beginning March 1990 and ending one month before the point. Each of the regression based models is evaluated using standard regression diagnostics over the in-sample period. Static regression forecasting is used to evaluate the models on their ability to forecast one month ahead.

The forecasting ability of all eight models is evaluated in- and out-of sample using three main criteria, Theil's inequality coefficient, ratio sign forecast correctly and the correlation between forecast and realised payoffs. Although a number of forecasting error statistics are calculated (such as mean absolute percentage error), Theil's coefficient is used as the main error comparison statistic. The reason is that Theil's coefficient is scale invariant and always lies between zero and one, where zero indicates a perfect fit with no error, making comparisons more meaningful. The lower Theil's coefficient, the lower the error and the better the forecasting ability of the model. Theil's inequality coefficient is defined as

$$U = \frac{\sqrt{\sum_{t=1}^{h}(\hat{y}_t - y_t)^2 / h}}{\sqrt{\sum_{t=1}^{h}\hat{y}_t^2 / h} + \sqrt{\sum_{t=1}^{h}y_t^2 / h}}, \tag{24}$$

where $\hat{y}$ and y represent forecast and realised payoffs at time t and h represents the number of forecasts made.

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The models are also evaluated on their ability to forecast the payoff sign correctly. Sign forecasting is important as it can have a large effect on the performance of expected return models. The probability associated with the number of signs correctly forecast is calculated using the non-parametric Sign test where the null hypothesis states that the model is able to forecast correctly less than 50% of the time. If h forecasts are made and f of the forecasts are correct (in terms of sign), then the probability associated with f is calculated as,

$$\text{P(Number of correct forecasts} = f) = \binom{h}{f} 0.5^{f} 0.5^{h-f} \tag{25}$$

where,

$$\binom{h}{f} = \frac{h!}{f!(h-f)!} \tag{26}$$

This gives the binomial probability mass function. If the cumulative probability associated with the number of correct forecasts is greater than 0.95 we may reject the null at the 5% level (i.e. f has a P-value of 0.05). Note that a one-sided test is used as we expect the model to forecast better than a random process.

Correlation between forecast and realised payoffs is compared between models. This is the equivalent of the IC measure used to evaluate expected return models and gives an easily interpreted and comparable statistic.

The error from each model is further broken down into three components, bias, variance and co-variance. Each of these lies between zero and one and together they sum to one. The bias proportion measures how far the mean of the forecast is from the mean of the actual series. The variance proportion measures how far the variation of the forecast is from the variation of the actual series. The covariance proportion measures the remaining unsystematic forecasting errors. If a forecast is good, the bias and variance proportions will be close to zero and the covariance proportion will be close to one. Definitions of each are provided,

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$$\text{Bias Proportion} = \frac{\left(\left(\sum_{t=1}^{h} \hat{y}_t / h\right) - \overline{y}\right)^2}{\sqrt{\sum_{t=1}^{h} (\hat{y}_t - y_t)^2 / h}}, \quad (25)$$

$$\text{Variance Proportion} = \frac{(s_{\hat{y}} - s_y)^2}{\sqrt{\sum_{t=1}^{h} (\hat{y}_t - y_t)^2 / h}}, \quad (26)$$

$$\text{Covariance Proportion} = \frac{2(1-r) s_{\hat{y}} s_y}{\sqrt{\sum_{t=1}^{h} (\hat{y}_t - y_t)^2 / h}}, \quad (27)$$

where $(\sum_{t=1}^{h} \hat{y}_t / h)$, $\overline{y}$, $s_{\hat{y}}$, s_y are the means and standard deviations of $\hat{y}$ and y, and r is the correlation between $\hat{y}$ and y.

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8.2.2. Methodology of Forecasting Models in a Multivariate Framework

The eight style payoff forecasting models described in *Table 8.2.11.* are applied to the multivariate framework developed in *Section 6.5.* to investigate whether an improvement in the performance of expected return models can be achieved. The attributes from the best performing expected return model in *Section 6.5.*, the ICM model, are fixed and the forecasting procedure is allowed to vary based on the six criteria (models) developed in *Section 8.2.1.* The first step involves estimating the monthly payoffs to each attribute controlling for the other attributes. This is done using the OLS multiple regression analysis described in *Section 6.3.2.* developed by Haugen and Baker (1996). The controlled monthly payoffs are then used to estimate the payoff one month ahead based on the forecasting model being tested. For instance, the AR12 model forecasts ahead using the regression equation estimated on the previous twelve lags of controlled payoffs. Each forecasting model can then be evaluated using the familiar IC diagnostics.

8.3. Results of Forecasting Models for Individual Styles

8.3.1. Model Construction

Eight style payoff forecasting models are constructed, the 1M, 6M, 12M, 18M, 12M Reg, Mean, AR12 and Consolidated models, according to the methodology described in *Section 8.2.1.* Definitions of the eight models appear in *Table 8.2.1.1.* Briefly explained, the 1M, 6M, 12M, and 18M models forecasts payoffs based on the one-, six-, twelve- and eighteen-month trailing moving averages, the Mean model forecasts based on the historical mean and the AR12 model is based on the autoregression of the first twelve payoff lags. The 12MA Reg model is based on the regression of the twelve month trailing mean against payoffs and the Consolidated model is constructed as described in *Section 8.2.1.* to include a parsimonious set of macroeconomic and style time-series factors. A summary of the final Consolidated model factors selected for each style is presented in *Table 8.3.1.*

Note that over the in-sample period the regression based models use coefficients estimated over the whole period while over the out-of-sample period the regression based models use an expanding window to estimate coefficients. See *Section 8.2.1.* for a more detailed explanation of the expanding window.

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Table 8.3.1.1. Consolidated Model Construction

Displays the Consolidated model constituents for each style. Consolidated models combine the meaningful factors that emerge from the research performed on style momentum and economic relationships to form multifactor forecasting models. Candidate factors for these Consolidated models are: the twelve individual payoff lags significantly correlated to the style payoff, the trailing six-, twelve-, eighteen- and twenty-four-month moving averages found to have a significant relationship with the style payoff and lastly the significant lags of macroeconomic variables found to Granger cause style payoffs that are significantly correlated to style payoffs. A full description of the construction process can be obtained in *Section 8.2.1.*

Slopes	lags	MA	Factor1	Lags	MA6	MA12	Factor2	Lags	MA6	MA12
Size										
LMV	1 2	MA12	DLComposite	01,02,03,04	y		EG12P_Dsp	01,02,03,04		y
LPrice	1 2	MA12	DLComposite	01,02,03	y		DS_Index	2		
Value										
BVTP	1 2 3	MA12	Mkt_stdDev6m			y				
CEY	1 2 3	MA12	EY_Gap	1		y				
DY	1 2 3	MA12	DLComposite			y	DLMkt_Earnings	07,08		
EY	1 2 3	MA12								
Sales_to_MV	1 2 3	MA12	DLComposite	01,08,09,10		y	EY_Gap	08,09,10,11,12		y
Growth										
CEYG1	1 2 3	MA12	ExRate				EY_Gap			
CEYG12	1		EY_Gap				Optimism			
DPSG12	1	MA12	EG12P_Dsp				EG24P_Dsp		y	y
DPSG24	1 2		EG24P_Dsp	04,05,06,07,08,09	y	y				
EG12_P	1 2		EG24P_Dsp	2	y		EY_Gap			
EG24_P	1 2 3		EG24P_Dsp	01,02,03	y					
Expectedgrowth	1 2 3 4	MA12	EG12P_Dsp				EG24P_Dsp		y	y
Gearing	1 2	MA12	EG24P_Dsp	3		y				
POUT	1 2 3	MA12	DLMkt_Earnings							
ROE	1 2 3 4	MA12								
SG12	1 2 3 4	MA12	Inflation	01,02,03,04,05	y					
SG24	1 2 3 4 5 6	MA12	EY_Gap	01,02,03,04,05	y	y	Mkt_StdDev6m	01,02,03,04	y	y
Liquidity										
Current	1 2 3	MA12	DLComposite			y				
ICBT	1 2 3		Mkt_EY			y	Mkt_StdDev6m	02,03	y	
NCA_to_MV	1		EG24P_Dsp			y	ExRate			
Risk										
Beta	1 2 3	MA12	Mkt_stdDev6m			y	Optimism	11,12		
PVar12	1 2 3	MA12								
RetVar12	1 2 3	MA12	EY_Spread				DS_Index	01,10		
Momentum										
Crossover3_12	1 2 3	MA12	Mkt_stdDev6m	01,02		y	Optimism	10,11,12		
MOM1	1 2 3	MA12	Optimism	01,02,03,04,12	y					
MOM3	1 2 3 4	MA12	DLComposite			y	Mkt_StdDev6m	08,09,10,11,12		y
MOM6	1 2 3 4	MA12	Mkt_StdDev6m	1		y				
MOM12	1 2 3	MA12	Mkt_StdDev6m	08,09,10,11,12		y				
MOM18	1 2 3 4	MA12	Mkt_StdDev6m							

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Table 8.3.1.1. Consolidated Model Construction (continued)

Slopes	Factor3	Lags	MA6	MA12	Factor4	Lags	MA6	MA12	Factor5	Lags	MA6	MA12
Size												
LMV	DS_Index	2	y	y								
LPrice	Tbill_3Month	1										
Value												
BVTP												
CEY												
DY	Mkt_StdDev6m			y	Optimism	02,11,12						
EY												
Sales_to_MV												
Growth												
CEYG1	DLMkt_Earnings	03,05,08			Mkt_EY	01,02,03,04	y	y	Optimism	01,02,03,04	y	
CEYG12	Term_Structure											
DPSG12	ExRate	01,02,03,04	y		Tbill_3Month	01,02,03,04	y		Term_Structure	01,02,03,04	y	
DPSG24												
EG12_P	EY_Dsp				Mkt_EY	07,08,09			Optimism			
EG24_P												
Expectedgrowth												
Gearing												
POUT												
ROE												
SG12												
SG24												
Liquidity												
Current												
ICBT												
NCA_to_MV												
Risk												
Beta												
PVar12												
RetVar12	Optimism	01,12										
Momentum												
Crossover3_12												
MOM1												
MOM3	Optimism	02,03,04,012										
MOM6												
MOM12												
MOM18												

Diagnostics that show the appropriateness of the three regression models for each style in-sample are provided in *Appendices C.1. - C.3.* For each model, the F-statistic of virtually all style regressions is significant. The standard errors are generally very low with most styles having standard errors below 0.01. Most models therefore represent a good fit. The forecasting ability of each model is examined in conjunction with the five non-regression based models. The out-of-sample results for each model are displayed in *Appendices C.4. – C.11.* The three evaluation diagnostics held to be the most important, correlation between forecast and realised payoffs, Theil's Inequality Coefficient and the ratio of sign forecast correctly, are used to compare the models directly in-sample in *Section 8.3.2.* and out-of-sample in *Section 8.3.3.*

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8.3.2. In-sample Performance of Forecasting Models for Individual Styles

Table 8.3.2.1. compares the in-sample correlations between forecast and realised payoffs for each style across the six models. The mean and standard deviation at the bottom of *Table 8.3.2.1.* allow for a comparison of overall forecasting ability across all styles. Due to the fact that the coefficients of the three regression based models, AR12, 12M Reg and Consolidated, are estimated over the entire in-sample period there is a strong element of look-ahead bias in the in-sample results. The out-of-sample results, however, provide a completely non-biased comparison of model performance. For this reason only a brief in-sample comparison is made, aggregating performance across all styles. Out-of-sample, in *Section 8.3.3.*, a more detailed 'style by style' comparison is made.

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Table 8.3.2.1. In-sample Comparison of Model Forecasting Ability Using Mean Correlation Between Forecast And Realised Payoffs:

Displays the mean Pearson's product-moment coefficient between forecast and realised style payoffs over the 120 months in the in-sample period (1 Mar 1990 – 1 Feb 2000.) Probabilities significant at the 5% level are shaded and the model that performs best for each style is bolded. For each model, the mean and standard deviation of the mean correlation values across all styles is provided.

	1M Model	6M Model	12M Model	18M Model	12M Reg Model	Mean Model	AR12 Model	Consolidated Model
Size								
LMV	0.30	0.25	0.24	0.12	0.25	0.24	0.53	**0.69**
LPrice	0.30	0.15	-0.01	-0.10	0.02	0.00	**0.68**	0.62
Value								
BVTP	0.36	0.37	0.32	0.26	0.33	0.30	**0.58**	0.49
CEY	0.56	0.61	0.57	0.45	0.56	0.14	**0.77**	0.68
DY	0.65	0.59	0.59	0.53	0.57	0.25	0.77	**0.77**
EY	0.65	0.63	0.58	0.56	0.57	0.29	**0.73**	0.70
Sales_to_MV	0.51	0.33	0.27	0.17	0.26	-0.03	**0.70**	0.68
Growth								
CEYG1	0.28	0.40	0.25	0.03	0.23	0.04	0.71	**0.75**
CEYG12	0.01	0.05	0.07	-0.02	0.09	-0.10	**0.51**	0.01
DPSG12	0.14	0.19	0.19	0.12	0.21	-0.09	0.54	**0.59**
DPSG24	0.13	0.24	0.00	0.05	0.02	-0.04	**0.61**	0.49
EG12_P	0.11	-0.05	0.05	-0.04	0.07	-0.11	**0.49**	0.44
EG24_P	0.13	-0.15	0.08	-0.02	0.07	-0.15	**0.43**	0.38
Expectedgrowth	0.16	0.23	0.17	0.11	0.19	0.18	**0.53**	0.38
Gearing	0.19	0.24	0.24	0.04	0.22	0.18	**0.50**	0.33
POUT	0.51	0.55	0.58	0.50	0.56	0.45	**0.66**	0.60
ROE	0.23	0.41	0.34	0.12	0.36	0.22	**0.57**	0.54
SG12	0.52	0.55	0.58	0.61	0.60	0.31	**0.70**	0.67
SG24	0.43	0.48	0.49	0.46	0.48	0.36	**0.72**	0.65
Liquidity								
Current	0.48	0.41	0.38	0.33	0.36	-0.03	**0.64**	0.52
ICBT	0.16	0.17	0.11	0.09	0.13	0.06	**0.63**	0.53
NCA_to_MV	0.15	0.09	0.04	0.11	0.06	-0.01	**0.48**	0.27
Risk								
Beta	0.54	0.50	0.58	0.53	0.59	0.35	**0.77**	0.67
PVar12	0.42	0.51	0.47	0.41	0.45	0.37	**0.58**	0.56
RetVar12	0.49	0.47	0.46	0.36	0.48	0.32	**0.72**	0.65
Momentum								
Crossover3_12	0.79	0.81	0.82	0.84	0.83	0.39	**0.89**	0.88
MOM1	0.65	0.61	0.51	0.43	0.53	0.42	**0.80**	0.74
MOM3	0.74	0.72	0.63	0.53	0.61	0.50	0.83	**0.83**
MOM6	0.72	0.71	0.55	0.47	0.57	0.31	**0.85**	0.80
MOM12	0.69	0.65	0.54	0.44	0.52	0.48	**0.82**	0.78
MOM18	0.58	0.46	0.35	0.26	0.33	-0.01	**0.75**	0.67
Mean	**0.41**	**0.39**	**0.36**	**0.28**	**0.36**	**0.18**	**0.66**	**0.59**
Standard deviation	**0.22**	**0.24**	**0.22**	**0.24**	**0.22**	**0.20**	**0.12**	**0.19**

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Over the in-sample period the regression based models (AR12, 12M Reg and Consolidated) show extremely high correlations (the AR12 model mean correlation is 66%) however this should be tempered by the presence of look-ahead bias. According to all three main criteria, (correlation between forecast and realised payoffs, Theil's Inequality Coefficient and the ratio of sign forecast correctly) the AR12 model performs best, closely followed by the Consolidated model. The Consolidated model is slightly better at forecasting the payoff sign than other models. The strong performance of the AR12 model raises the question of whether the inclusion of macroeconomic factors adds forecasting value. Of the remaining four models, the 1M model performs best according to both the mean correlation between forecast and realised payoffs and the mean Theil Coefficient. It is only beaten by the 12M Reg model according to the mean ratio sign forecast correctly. The 1M model is followed by the 6M model, both 12M models and the 18M model. It is difficult to distinguish between the 12M Reg model and the 12M model as results are fairly similar for both models across all three criteria. Some styles are better forecast by the 12M model and others by the 12M Reg model. The Mean model performs worst by all three criteria. Of the trailing mean models, it appears that the shorter the history used to forecast, the more accurate the forecast.

8.3.3. Out-of-sample Performance of Forecasting Models for Individual Styles

Comprehensive out-of-sample diagnostics for each model separately are provided in *Appendices C.4. – C.11.* and comparative summaries are displayed in *Tables 8.3.3.1. – 8.3.3.3.* Out-of-sample correlation between forecast and realised payoffs, shown in *Table 8.3.3.1.*, is used primarily to evaluate the forecasting ability of each model for each style. Importantly, there is no look-ahead bias in these out-of-sample results.

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Table 8.3.3.1. Out-of-sample Comparison of Model Forecasting Ability Using Mean Correlation Between Forecast And Realised Payoffs:

Displays the mean Pearson's product-moment coefficient between forecast and realised style payoffs over the 47 months in the out-of-sample period (1 Mar 2000 – 1 Feb 2004.) Probabilities significant at the 5% level are shaded and the model that performs best for each style is bolded. For each model, the mean and standard deviation of the mean correlation values across all styles is provided.

	1M Model	6M Model	12M Model	18M Model	12M Reg Model	Mean Model	AR12 Model	Consolidated Model
Size								
LMV	0.16	0.24	0.17	0.09	0.13	-0.14	0.17	**0.27**
LPrice	**0.17**	0.14	0.02	0.00	-0.04	-0.13	0.02	0.02
Value								
BVTP	**0.22**	-0.02	-0.11	-0.22	-0.12	-0.24	-0.02	0.04
CEY	**0.28**	0.08	0.10	-0.08	0.02	-0.23	0.12	0.18
DY	0.30	0.04	0.01	-0.17	-0.02	-0.27	0.32	**0.36**
EY	**0.33**	0.08	0.04	-0.12	0.00	-0.26	0.22	0.27
Sales_to_MV	**0.23**	0.03	0.01	-0.10	-0.07	-0.20	-0.04	0.11
Growth								
CEYG1	-0.23	-0.10	-0.22	0.02	-0.25	-0.17	-0.08	**0.04**
CEYG12	0.04	-0.12	-0.15	0.08	-0.06	**0.09**	0.06	-0.10
DPSG12	0.11	**0.18**	-0.01	-0.06	-0.05	-0.17	0.09	0.13
DPSG24	0.09	0.11	-0.03	-0.03	-0.25	-0.18	**0.25**	-0.16
EG12_P	-0.16	-0.04	-0.08	-0.11	-0.16	-0.11	-0.26	**0.17**
EG24_P	-0.20	-0.06	0.09	-0.05	-0.02	-0.17	**0.18**	-0.22
Expectedgrowth	**0.04**	-0.03	-0.08	-0.05	-0.11	-0.29	-0.11	0.04
Gearing	-0.07	-0.04	-0.06	-0.16	-0.08	-0.28	**0.16**	-0.35
POUT	**0.22**	0.11	0.10	-0.02	0.05	-0.21	0.11	0.10
ROE	0.16	0.22	**0.26**	0.08	0.23	-0.10	0.03	0.03
SG12	**0.18**	0.04	0.03	-0.04	0.05	-0.16	0.08	0.13
SG24	**0.30**	0.23	0.13	-0.03	0.11	-0.23	0.23	0.15
Liquidity								
Current	**0.25**	0.24	0.20	0.04	0.12	-0.20	0.05	0.12
ICBT	0.07	**0.16**	0.09	0.05	-0.07	-0.13	0.10	-0.08
NCA_to_MV	0.10	0.03	-0.16	-0.17	-0.22	-0.23	**0.11**	0.08
Risk								
Beta	**0.13**	0.10	0.04	-0.05	0.02	-0.19	0.00	0.04
PVar12	0.02	-0.08	-0.05	0.03	-0.03	-0.16	**0.16**	-0.01
RetVar12	0.26	0.10	0.05	-0.04	-0.02	-0.24	0.17	**0.33**
Momentum								
Crossover3_12	**0.52**	0.33	0.13	0.20	0.31	-0.23	0.24	0.35
MOM1	-0.21	-0.02	-0.09	**0.04**	-0.13	-0.35	-0.16	-0.21
MOM3	0.10	-0.10	-0.28	-0.06	-0.08	-0.28	**0.17**	0.13
MOM6	**0.19**	-0.13	-0.25	-0.07	-0.14	-0.15	0.01	0.02
MOM12	**0.19**	-0.05	-0.16	-0.19	-0.16	-0.20	0.07	0.02
MOM18	**0.24**	0.00	-0.03	-0.31	-0.13	-0.25	0.05	0.10
Mean	**0.13**	**0.05**	**-0.02**	**-0.05**	**-0.04**	**-0.20**	**0.08**	**0.06**
Standard deviation	**0.17**	**0.12**	**0.13**	**0.10**	**0.13**	**0.08**	**0.13**	**0.16**

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Across all styles the 1M model performs best achieving a mean correlation between forecast and actual payoffs across styles of 0.13. In general, however, the models are unable to maintain their extremely strong in-sample forecasting power. For the regression models, this is explained by the fact that they no longer have any look-ahead bias. The mean model performs extremely badly showing a strongly negative mean correlation between forecast and realised returns. The reason could be that the historical mean looks too far back using past relationships that no longer hold. The 1M, 6M, AR12 and Consolidated models however perform fairly well showing some forecasting ability. Therefore, timing appears to be a prerequisite for expected return models to be able exploit anomalies.

Size, represented by log of market value, shows strong predictability based on a consolidated model employing two past lags, a twelve month moving average, business cycle indicators, the dispersion of the growth attribute, and returns on the market. The consolidated model does not perform well, however, for log of price, which is moderately predictable using its payoff in the previous month.

The value attributes all show strong predictability using the 1M model. Only dividend yield is better forecast by a consolidated model based on three lags, a twelve month moving average, business cycle indicators, and the standard deviation of the market performing best.

On average the growth attributes are considerably less predictable than the value attributes. One-month and one-year growth in cash earnings yield are not predictable using any model. Both these attributes also perform poorly in univariate and multivariate tests. These attributes can therefore be confidently discarded by expected return models. Two-year sales growth on the other hand shows strong predictability with the 1M model performing best. One-year sales growth shows moderate predictability with a 1M model also performing best. One-year dividend per share growth shows moderate predictability with the six-month trailing mean performing best. Two-year dividend per share growth shows strong predictability with the AR12 model performing best. Two-year earnings yield shows moderate predictability with the AR12 model performing best. One-year earnings growth is moderately predictable using a consolidated model incorporating two lags and macroeconomic

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variables including business optimism, the dispersion of the growth and earnings yield attributes and the market earnings yield. Gearing, payout and ROE are also moderately predictable using the AR12 and 1M and 12M models respectively. Expected growth is not predictable using any model.

Of the liquidity attributes, the current ratio shows the strongest predictability with the 1M model performing strongly. Interest cover before tax is moderately predictable with the six-month trailing mean providing the best forecast. Net current assets to market value shows a low, but positive, correlation with the AR12 and 1M models performing best.

Of the risk attributes, only returns variance shows strong predictability with a consolidated model based on three lags, a twelve month moving average, business optimism, returns on the market, and the spread in earnings yield performing best. Price-variance is moderately predictable with AR12 performing best while beta shows a low level of predictability with the 1M model performing best.

The momentum attributes with longer duration show more predictability. Crossover3_12 is the most predictable style overall with a correlation between forecast and realised payoffs of 0.52. The best forecasting model for Crossover3_12 is the 1M model. Six-month, one-year and eighteen month momentum show moderate predictability with the 1M model also performing best. Three-month momentum is only moderately predictable using the AR12 model and one-month momentum is not at all predictable.

On the whole, therefore, it appears that a few attributes are strongly predictable, a greater number are moderately predictable, and the 1M model performs best most frequently. For certain attributes the consolidated model performs best, however in many cases the addition of the extra variables appears to reduce forecasting accuracy.

Table 8.3.3.2. compares the frequency that each models is able to forecast each attribute's sign correctly and *Table 8.3.3.3.* shows the Theil's Inequality Coefficient for each model for each style. Theil's Inequality Coefficient provides a measure of

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forecast accuracy. All coefficients lie between zero and one where zero indicates the model was able to forecast the style without error.

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Table 8.3.3.2. Out-of-sample Comparison of Model Forecasting Ability Using the Ratio of Sign Forecast Correctly

Displays the Ratio of Sign Forecast Correctly for each forecasting model over the out-of-sample period 1 Mar 2000 – 1 Feb 2004. The probability associated with the null that the Ratio of Sign Forecast Correctly is less than 50% is calculated using the non-parametric Sign test based on the binomial distribution. The methodology is provided in *Section 8.2.1*. Ratios significant at the 5% level are shaded and the model that performs best for each style is bolded. For each model, the mean and standard deviation of the Ratio Sign Forecast Correctly values across all styles is provided.

	1M Model	6M Model	12M Model	18M Model	12M Reg Model	Mean Model	AR12 Model	Consolidated Model
Size								
LMV	0.58	**0.72**	0.65	0.60	0.65	0.52	0.46	0.67
LPrice	0.54	**0.60**	0.58	0.49	0.44	0.48	0.46	0.54
Value								
BVTP	0.67	0.70	0.69	0.68	0.71	**0.77**	0.67	0.71
CEY	0.60	**0.64**	0.60	0.45	0.54	0.56	0.56	0.56
DY	**0.65**	**0.64**	0.60	0.47	0.52	0.44	0.50	0.60
EY	0.54	**0.66**	0.60	0.51	0.54	0.60	0.54	0.52
Sales_to_MV	0.69	**0.79**	0.71	0.66	0.63	0.65	0.63	0.63
Growth								
CEYG1	0.52	0.53	0.58	**0.62**	0.54	0.60	0.46	0.42
CEYG12	0.56	0.38	0.52	**0.60**	0.46	0.54	0.50	0.50
DPSG12	**0.54**	**0.53**	**0.54**	**0.53**	0.46	**0.54**	**0.54**	0.42
DPSG24	0.60	0.60	0.58	0.53	0.54	0.54	**0.65**	0.42
EG12_P	0.63	0.57	0.56	**0.64**	0.63	0.63	0.50	0.63
EG24_P	0.44	0.51	0.58	**0.60**	**0.60**	**0.60**	0.58	0.54
Expectedgrowth	**0.54**	0.47	0.48	0.40	0.44	0.35	0.52	0.52
Gearing	0.48	**0.53**	0.46	0.45	0.46	0.52	0.46	0.35
POUT	0.67	**0.68**	0.56	0.51	0.52	0.33	0.50	0.60
ROE	0.56	**0.68**	0.63	0.57	0.63	0.60	0.60	0.54
SG12	0.65	**0.68**	0.67	0.60	0.67	0.50	0.56	0.65
SG24	0.65	**0.70**	0.63	0.51	0.60	0.60	0.54	0.63
Liquidity								
Current	0.58	0.62	0.58	0.57	0.60	0.58	**0.65**	0.63
ICBT	0.58	0.62	**0.67**	0.66	0.65	0.65	0.46	0.52
NCA_to_MV	0.52	0.49	0.52	0.45	0.48	0.52	0.54	0.48
Risk								
Beta	0.58	**0.68**	0.58	0.55	0.58	0.35	0.56	0.52
PVar12	0.52	0.68	0.63	0.62	0.65	**0.69**	0.58	0.63
RetVar12	0.63	**0.70**	0.60	0.53	0.58	0.52	0.54	0.65
Momentum								
Crossover3_12	0.40	0.47	0.46	0.51	0.50	0.50	0.56	0.38
MOM1	0.44	0.60	0.58	**0.62**	0.54	0.56	0.44	0.44
MOM3	0.52	0.51	0.50	**0.57**	0.56	0.56	0.60	0.56
MOM6	0.56	0.60	0.54	0.64	**0.65**	**0.65**	0.46	0.56
MOM12	0.63	**0.66**	0.60	0.57	0.58	0.58	0.54	0.56
MOM18	0.63	**0.68**	0.54	0.36	0.48	0.48	0.54	0.54
Mean	**0.57**	**0.61**	**0.58**	**0.55**	**0.56**	**0.55**	**0.54**	**0.54**
Standard deviation	**0.07**	**0.09**	**0.06**	**0.08**	**0.07**	**0.10**	**0.06**	**0.09**

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Table 8.3.3.3. Out-of-sample Comparison of Model Forecasting Ability Using Theil's Inequality Coefficient

Displays Theil's inequality coefficient over the out-of-sample period 1 Mar 2000 – 1 Feb 2004. Values lie between 0 and 1 where 0 implies a perfect fit. For each model, the mean and standard deviation of Theil's Coefficient across all styles is provided.

	1M Model	6M Model	12M Model	18M Model	12M Reg Model	Mean Model	AR12 Model	Consolidated Model
Size								
LMV	0.66	0.64	0.67	0.71	0.74	0.91	0.67	**0.61**
LPrice	**0.67**	0.70	0.78	0.80	0.83	0.84	0.74	0.75
Value								
BVTP	**0.57**	0.65	0.67	0.70	0.75	0.80	0.70	0.70
CEY	**0.57**	0.68	0.71	0.76	0.75	0.95	0.66	0.65
DY	**0.57**	0.69	0.72	0.79	0.76	0.97	0.59	0.59
EY	**0.55**	0.66	0.69	0.74	0.74	0.93	0.62	0.58
Sales_to_MV	**0.60**	0.62	0.67	0.67	0.78	0.94	0.70	0.68
Growth								
CEYG1	0.76	0.73	0.75	0.72	0.87	0.92	0.74	**0.72**
CEYG12	**0.68**	0.76	0.82	0.83	0.95	0.97	0.75	0.95
DPSG12	**0.67**	0.70	0.80	0.85	0.87	0.92	0.76	0.75
DPSG24	**0.68**	0.73	0.80	0.83	0.89	0.89	0.68	0.79
EG12_P	0.72	0.68	0.71	0.73	0.80	0.83	0.80	**0.60**
EG24_P	0.73	0.73	0.72	0.74	0.79	0.85	**0.68**	0.80
Expectedgrowth	**0.71**	0.78	0.83	0.85	0.91	0.99	0.81	0.75
Gearing	**0.72**	0.78	0.83	0.89	0.90	0.89	0.76	0.90
POUT	**0.61**	0.67	0.69	0.74	0.75	0.96	0.68	0.70
ROE	**0.64**	0.67	0.69	0.76	0.75	0.86	0.72	0.74
SG12	**0.64**	0.67	0.71	0.74	0.74	0.97	0.70	0.68
SG24	**0.60**	0.62	0.68	0.73	0.72	0.95	0.63	0.67
Liquidity								
Current	**0.56**	0.58	0.60	0.65	0.65	0.92	0.67	0.64
ICBT	0.62	**0.60**	0.62	0.63	0.70	0.76	0.65	0.74
NCA_to_MV	**0.64**	0.72	0.82	0.87	0.96	0.95	0.78	0.77
Risk								
Beta	**0.65**	0.69	0.74	0.78	0.77	0.97	0.71	0.74
PVar12	0.65	0.68	0.71	0.70	0.75	0.76	**0.63**	0.69
RetVar12	**0.60**	0.69	0.73	0.77	0.80	0.97	0.66	0.63
Momentum								
Crossover3_12	0.57	0.57	0.64	0.62	0.57	0.84	0.61	**0.55**
MOM1	0.78	**0.72**	0.75	0.74	0.76	0.94	0.75	0.78
MOM3	0.67	0.74	0.81	0.78	0.75	0.92	**0.64**	0.65
MOM6	**0.62**	0.74	0.77	0.74	0.78	0.89	0.69	0.68
MOM12	**0.63**	0.73	0.77	0.78	0.80	0.89	0.67	0.70
MOM18	**0.62**	0.74	0.78	0.87	0.86	0.90	0.70	0.69
Mean	**0.64**	**0.69**	**0.73**	**0.76**	**0.79**	**0.90**	**0.70**	**0.71**
Standard deviation	**0.06**	**0.05**	**0.06**	**0.07**	**0.08**	**0.06**	**0.06**	**0.09**

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Table 8.3.3.2. and *Table 8.3.3.3.* confirm the conclusions drawn from *Table 8.3.3.1.* The 1M model performs best taking into account all three criteria over all styles. The AR12 and Consolidated models are not far behind. All models are only able to predict the sign correctly approximately 56% of the time, while the 6M model is able to forecast the sign correctly 61% of the time. The trailing mean models show the same pattern of performance as during the in-sample period. After the 1M model, the 6M model performs best, followed by the 12M and 18M models. The mean model performs extremely poorly again finishing last overall. The 12M model outperforms the 12M Reg model. The constant term in the 12M Reg model appears to bring down the model's forecasting ability.

The bias, variance and co-variance proportions are shown for all styles for each model in *Appendices C.4. – C.11.* Each term lies between zero and one and together they sum to one. The bias proportion measures how far the mean forecast is from the mean payoff. The variance proportion measures how far the forecast variation is from the payoff variation. The covariance proportion measures remaining unsystematic forecasting errors. It is desirable for the co-variance term to equal one and the bias and variance terms to equal zero. All models across all styles show very low bias. The 1M, AR12, 12M Reg and Consolidated models all show very low variance proportions with covariance proportions close to one. The 6M and Mean models have variance proportions on average higher than the covariance proportion. The 12M models have lower but still considerable variance proportions. The main problem with forecasting models therefore appears to be that they produce forecasts with lower variance than the actual payoff series. This is a generic problem associated with forecasting an unknown time-series.

The out-of-sample results confirm that recent payoff values are better at forecasting future payoffs than long term average payoffs, as on average, the 1M model performs best. The Consolidated model performs well out-of-sample yet in most cases, does not seem to add additional value to the AR12 and 1M models. It therefore appears that the most important forecasting factors come from within the time-series of payoffs, with the first lag displaying the most forecasting ability.

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8.4. Results of Forecasting Models in a Multivariate Framework

The multivariate models constructed in *Section 6.5.* used a trailing twelve month mean payoff to forecast the style payoffs in the following month. In light of the finding in *Section 8.3.2.* that the trailing twelve month mean does not constitute the best forecast method available for all styles we adapt the Haugen and Baker (1996) multi-factor methodology to forecast payoffs based on the eight style payoff forecasting models tested in *Section 8.3.2.* The results will give an indication of which forecasting method is most appropriate in a multivariate environment.

For the comparison, the attributes in each model are fixed. Fixing the attributes provides for a more controlled environment to test the relative forecasting ability of each model. By allowing models to select their own attributes, differences that arise will more likely be due to differences in the composition of attributes than the forecasting ability of each model. In *Appendix C.16.* the three top models from this section are compared, allowing each to select its own attributes. In this section however, the comparison is performed using the eleven attributes selected by the ICM model stepwise procedure used in *Section 6.5.* The eleven attributes are: ICBT, LPrice, MOM18, MOM12, Crossover3_12, Beta, ROE, DY, SG12, BVTP and SG24. As the attributes are fixed, results will be dependent on the attributes used. Fortunately, the attributes selected by the ICM model span all of the style clusters and represent well known styles, similar to style factors discovered in other markets. The analysis therefore gives a good general overview of which forecasting procedure is most appropriate in a multivariate environment. The only downside of this approach is that attributes that payoff in a timable fashion not acknowledged by the twelve-month trailing mean forecast will not be included in the ICM model. Results will therefore be slightly biased toward the 12M model. However the bias only applies to the in-sample period over which attributes are selected.

Before running the analysis it is worth checking that our generic conclusions based on all attributes (equally weighted) hold for these "important" attributes identified by the ICM model. *Table 8.4.1.* confirms that conclusions drawn in *Section 8.3.* hold for these eleven attributes. The AR12 model performs best in-sample and the 1M model

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performs best out-of-sample. The strong contrast between in- and out-of-sample results confirms the overall conclusion.

Figure 8.4.1. Comparison of Forecasting Models for Individual Styles limited to ICM Attributes (In- and Out-of--sample)

For each of the six forecasting models displays the mean and standard deviation of the correlation between forecast and realised payoffs for styles in the Information coefficient model (ICM) developed in Section 8.2.1. The ICM model selects factors based on a stepwise procedure using the model's IC before and after inclusion of each factor. The comparison refers to the in-sample period, 1 Mar 1990 – 1 Feb 2000. Comparative model performance for each style is presented in *Tables 8.3.3.1. – 8.3.3.2.*

In-sample	1M Model	6M Model	12M Model	18M Model	12M Reg Model	Mean Model	AR12 Model	Consolidated Model
Size								
LPrice	0.30	0.15	-0.01	-0.10	0.02	0.00	**0.68**	0.62
Value								
BVTP	0.36	0.37	0.32	0.26	0.33	0.30	**0.58**	0.49
DY	0.65	0.59	0.59	0.53	0.57	0.25	0.77	**0.77**
Growth								
ROE	0.23	0.41	0.34	0.12	0.36	0.22	**0.57**	0.54
SG12	0.52	0.55	0.58	0.61	0.60	0.31	**0.70**	0.67
SG24	0.43	0.48	0.49	0.46	0.48	0.36	**0.72**	0.65
Liquidity								
ICBT	0.16	0.17	0.11	0.09	0.13	0.06	**0.63**	0.53
Risk								
Beta	0.54	0.50	0.58	0.53	0.59	0.35	**0.77**	0.67
Momentum								
Crossover3_12	0.79	0.81	0.82	0.84	0.83	0.39	**0.89**	0.88
MOM12	0.69	0.65	0.54	0.44	0.52	0.48	**0.82**	0.78
MOM18	0.58	0.46	0.35	0.26	0.33	-0.01	**0.75**	0.67
Mean	**0.48**	**0.47**	**0.43**	**0.37**	**0.43**	**0.25**	**0.72**	**0.66**
Standard deviation	**0.20**	**0.19**	**0.24**	**0.27**	**0.23**	**0.16**	**0.10**	**0.12**
Out-of-sample								
Size								
LPrice	**0.17**	0.14	0.02	0.00	-0.04	-0.13	0.02	0.02
Value								
BVTP	**0.22**	-0.02	-0.11	-0.22	-0.12	-0.24	-0.02	0.04
DY	0.30	0.04	0.01	-0.17	-0.02	-0.27	0.32	**0.36**
Growth								
ROE	0.16	0.22	**0.26**	0.08	0.23	-0.10	0.03	0.03
SG12	**0.18**	0.04	0.03	-0.04	0.05	-0.16	0.08	0.13
SG24	**0.30**	0.23	0.13	-0.03	0.11	-0.23	0.23	0.15
Liquidity								
ICBT	0.07	**0.16**	0.09	0.05	-0.07	-0.13	0.10	-0.08
Risk								
Beta	**0.13**	0.10	0.04	-0.05	0.02	-0.19	0.00	0.04
Momentum								
Crossover3_12	**0.52**	0.33	0.13	0.20	0.31	-0.23	0.24	0.35
MOM12	**0.19**	-0.05	-0.16	-0.19	-0.16	-0.20	0.07	0.02
MOM18	**0.24**	0.00	-0.03	-0.31	-0.13	-0.25	0.05	0.10
Mean	**0.23**	**0.11**	**0.04**	**-0.06**	**0.02**	**-0.19**	**0.10**	**0.10**
Standard deviation	**0.12**	**0.12**	**0.12**	**0.15**	**0.15**	**0.06**	**0.11**	**0.14**

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The eight forecasting models are now used to build separate multivariate expected return models. Note that over the in-sample period the regression based models use coefficients estimated over the whole period while over the out-of-sample period the regression based models use an expanding window to estimate coefficients. See *Section 8.2.1.* for a more detailed explanation of the expanding window. The comparative multifactor model results are displayed in *Table 8.4.1.*

Table 8.4.1. In-sample and Out-of-sample Evaluation of Multivariate Forecasting Procedures

Displays the performance of multivariate expected return models based on the eleven attributes selected by the Information Coefficient model (ICM) (See Section 6.3.2 for details on the stepwise construction of the ICM model) for each forecasting model during the in-sample (1 Mar 1990 – 1 Feb 2000) and out-of-sample (1 Mar 2000 – 1 Feb 2004) periods. Note that over the in-sample period the regression based models use coefficients estimated over the whole period while over the out-of-sample period the regression based models use an expanding window to estimate coefficients. See *Section 8.2.1.* for a more detailed explanation of the expanding window. The ICM model is used as a base model as it gives performs best of the models tested in *Section 6.5.* Mean slope is obtained by running monthly regressions of expected returns against realised returns over the sample period and taking the mean value of the monthly slope coefficient. T-statistic of slope is obtained by dividing the mean slope by its standard deviation over the sample period and multiplying by the number of observations in each month. IC is obtained by applying Pearson's correlation coefficient to expected and realised returns. Qian and Hua's (2003) Information Ratio is obtained by dividing IC by the standard deviation of IC and Grinold's (1989) Information Ratio is obtained by multiplying IC by the square root of the number of forecasts each month. Mean monthly values are displayed for both information ratio's The decile spread measures the difference between the average return earned by shares in the top decile of forecast returns and the average return earned by shares in the lowest decile. The standard deviation of the decile spread is displayed along with the T-statistic of spread which takes into account the mean and standard deviation of the spread along with the number of shares forecast each month. Earliest (latest) number of shares relates to the number of observations at the start (end) of the period. For each criterion the greatest (or in the case of standard deviation, the least) value is bolded for both the in-sample and out-of-sample periods.

	1M Model		6M Model		12M Model		18M Model	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Mean Slope	0.26	0.32	0.52	**0.73**	**0.72**	0.60	0.64	0.50
Standard Deviation of Slope	**0.43**	0.71	0.76	1.22	0.87	1.08	0.96	1.38
T-statistic of Slope	6.51	3.05	7.46	**4.04**	**9.04**	3.74	7.31	2.45
IC	0.09	0.11	0.10	**0.14**	**0.12**	0.11	0.09	0.09
Standard Deviation of IC	0.138	0.245	0.140	0.221	0.139	0.194	0.137	0.181
Mean IR (Qian and Hua)	0.63	0.43	0.74	**0.62**	**0.88**	0.56	0.68	0.50
Mean IR (Grinold)	1.75	2.60	2.00	**3.29**	**2.34**	2.67	1.89	2.22
Decile Spread	0.03	**0.10**	0.04	-0.01	0.05	0.04	0.04	0.02
T-statistic of Spread	4.67	**3.40**	5.90	-0.10	**7.28**	1.19	5.67	0.41
Standard Deviation of Spread	0.07	0.12	0.07	0.19	0.07	0.13	0.07	0.14
Earliest Number of Shares	132	559	132	576	132	559	132	576
Earliest Number of Shares	381	581	381	578	381	581	381	578
Latest Number of Shares	576	338	576	338	576	338	576	338

Continued	12M Reg Model		Mean model		AR12 Model		Consolidated model	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Mean Slope	0.44	0.29	0.62	0.09	0.34	0.18	0.28	0.18
Standard Deviation of Slope	0.70	0.55	0.95	**0.30**	0.49	0.89	0.49	0.49
T-statistic of Slope	6.92	3.58	7.20	2.07	7.52	1.36	6.32	2.44
IC	0.08	0.05	0.10	0.01	0.09	0.04	0.08	0.03
Standard Deviation of IC	0.12	0.08	0.13	0.10	0.12	0.18	0.12	0.10
Mean IR (Qian and Hua)	0.66	0.60	0.74	0.14	0.73	0.23	0.69	0.32
Mean IR (Grinold)	1.76	1.20	1.92	0.34	1.85	0.98	1.81	0.73
Decile Spread	0.03	0.01	0.04	0.01	0.05	-0.01	0.03	0.00
T-statistic of Spread	5.13	0.94	6.33	0.52	2.79	-0.55	3.08	-0.32
Standard Deviation of Spread	**0.06**	0.06	0.06	0.09	0.17	0.07	0.09	**0.05**
Earliest Number of Shares	132	559	132	559	132	559	132	559
Earliest Number of Shares	381	581	381	581	381	581	381	581
Latest Number of Shares	576	338	576	338	576	338	576	338

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In-sample, the 12M model performs best achieving an average spread between top and bottom deciles of 5% and an IC of 0,12.

Out-of-sample, the 1M model produces the greatest average decile spread of 10% and a fairly attractive IC of 0.9 confirming the model's high forecasting ability highlighted in *Section 8.3*. It is likely that the 12M model derives a considerable portion of its explanatory power from the first lag. The 6M model achieves the best out-of-sample IC of 0.14, however, strangely, its average decile spread is negative for the out-of-sample period. It appears therefore that the 6M model and (slightly less so) the 12M model are best at estimating style payoffs for the majority of shares while the 1M model is best at forecasting shares that achieve very high (low) returns.

The Mean model performs well in the in-sample period, however it performs extremely badly in the out-of-sample period confirming the very low out-of-sample forecasting ability demonstrated in *Section 8.3*. The change in the Mean models performance in- and out-of-sample is so dramatic that it may well be due to an event or structural change that took place between samples. The obvious change that took place around 1999/ 2000 is the IT bubble crash. Perhaps in the out-of-sample period the Mean model forecasts relied too heavily on pre-crash data when the other models were able to adapt to a structurally changed market.

The Consolidated model performs poorly in the out-of-sample period. This is disappointing considering the arduous construction process involved. The indication is that the most important source of forecasting power is from the time-series of payoffs itself. This confirms the similar finding in *Section 8.3.3*.

There is a slight but noticeable disparity between the 6M, 12M, and 18M models' good out-of-sample univariate forecasting ability and excellent out-of-sample multivariate model performance. This may be due to the fact that the former measure weights all attributes equally whereas the latter measure over-weights performing attributes. Based on this insight, the 6M model appears to be the best at forecasting the priced (performing) attributes.

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Based on in *Table 8.4.1.*, it is concluded that the 6M model provides the most accurate style payoff forecasts although it may be that the 1M model provides more exploitable forecasts.

In *Appendix C.16.*, it is attempted to build the best model possible by not only forecasting attribute payoffs, but also selecting attributes based on the different forecasting models. For simplification purposes, the analysis is limited to the 1M, 6M and 12M models, as these attributes perform best in the first analysis where the attributes are fixed. A similar attribute selection stepwise procedure is adopted to the one described in *Section 6.3.2.* using IC as the selection criteria and each forecasting model to generate monthly weights for each style. Results show that allowing forecasting models to select their own attributes does not improve the overall performance of the models. Out-of-sample the 6M model produces the best IC and t-statistic of slope followed closely by the 12M model, however neither the 1M model nor the 6M model is able to improve on the 12M model's decile spread either in- or out-of-sample. Surprisingly, the IC's of the models constructed in *Appendix C.16.* are generally below the IC's produced by the models in this section. The 1M and 6M select too few attributes resulting in models that are unable to convincingly beat the 12M model or, indeed, the 1M and 6M models in this section.

It appears that forecasting models are able to add significant value to the payoff forecasting process (as shown in this section) but not to the attribute selection process (as shown in *Appendix C.16.*). This evidence adds to earlier misgivings that the attribute selection procedures are too strict. Out-of-sample results appear to be strongly influenced by the number of attributes included.

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8.5. Summary and Conclusion

Using the eleven fixed ICM attributes, the 1M and 6M models show strong in- and out-of-sample performance. Out-of-sample, the 1M model produces the greatest average decile spread of 10% and an IC of 0.9 while the 6M model achieves the best out-of-sample IC of 0.14 however the 6M model has a negative average decile spread over the out-of-sample period. It appears therefore that the 6M model is best at estimating style payoffs for the majority of shares, while the 1M model is best at forecasting the shares that matter, i.e. the shares that achieve very high and very low returns. The Mean and Consolidated models both perform relatively badly in the out-of-sample period, although the consolidated model performs best for some styles. It is concluded that the most important source of forecasting power is derived from the time-series of style payoffs itself.

When the attributes are selected separately for each forecasting model, the results are disappointing. The 1M and 6M models select too few attributes resulting in expected return models that are unable to beat the 12M expected return model.

Throughout this analysis all attributes have been presented with the same forecasting treatment. Superior more complex multivariate models can potentially forecast each style individually based on its most appropriate forecasting model and then blend the forecasts into a multivariate model. In such multivariate models it becomes possible to incorporate individual attribute timing characteristics into attribute selection procedures to ensure that timbale attributes are not excluded. These models should be able to further enhance the return forecasting abilities of expected return models.

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9.

Discussion of results and Conclusion

9.1. Univariate Tests

Table 6.4.3.2. summarises univariate findings of in- and out-of-sample tests. Eleven attributes are found to be significant at the 5% level over the in-sample period: interest cover before tax, three-month, six-month, one-year and eighteen-month momentum, crossover3_12, beta, and return on equity are found to be significantly positively related to future returns while log of price, the payout ratio, and price variance are found to be significantly negatively related to future returns. Many studies performed on different markets have found similar attributes representing value, momentum, growth and risk that represent anomalous behaviour (the findings of Haugen and Baker (1996) in particular are very similar to those presented here). Only three of the in-sample attributes remain significant at the 5% level out-of-sample: interest cover before tax, the payout ratio and price variance. A number of new attributes become significant: dividend yield, one-year and two year sales growth, one-year earnings growth, book value to price, sales to market value, the current ratio and earnings yield. This finding provides support for research into style timing. Both APT and CAPM risk adjustments do not remove the anomalies. The adjustments decrease the significance of most attributes while increasing the significance of others.

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Cluster analysis is used to evaluate the relationships between attribute payoffs and group similar attributes. The time-series of attribute payoffs are displayed graphically in *Appendices A.7. – A.14.* grouped according to the observed clusters. Attributes within most clusters perform similarly throughout the period, with the exception of the growth and size clusters. Growth, in particular, appears to constitute a collection of disparate items. This could indicate that the growth style is less distinct than other styles, or that a number of attributes belonging to the growth cluster do not capture the "growth" effect. The diagrams show that some attributes, such as log of price and interest cover before tax, perform consistently well throughout the in-sample and out-of-sample periods while other attributes, such as beta, payout ratio and current ratio undergo major changes sign. Risk and growth attributes appear to be more variable and less consistent than other styles. Value attributes perform very negatively during the period July 1999 – March 2000 possibly because of the growth of the IT-bubble and resulting crash. However, they perform extremely positively from March 2000 onwards, possibly indicating the market's unrelenting re-rating of overpriced growth stocks. Risk measures, beta and price variance, perform very well during the period July 1999 – March 2000, they then change sign to perform negatively in the years following March 2000. It is likely that this dramatic change is linked to the IT bubble collapse. The evidence therefore supports the idea that after 2000, investors changed their preferences placing a higher premium on high yield value investments and a lower premium on growth opportunities and high risk investments. These observations support further research into style timing, and the underlying macroeconomic influences on style returns.

9.2. Multivariate Tests

The in-sample and out-of-sample performance of each model is presented in *Table 6.5.2.1.* The performance of each model is shown graphically in *Appendices A.21 – A.24.* The ICM model that selects factors based on their contribution to the overall model's IC, performs best overall achieving an IC over 0.1 and a monthly decile spread of 4% in- and out-of-sample. The reason for the ICM outperforming the other models by such a margin is likely to be linked to the greater number of attributes retained by the IC selection criteria. The IRM and TSM models select factors based on their contribution to the overall model's information ratio (IR) and t-statistic of the slope between expected and realised returns respectively. Both models therefore have more stringent selection criteria that take into account the number of monthly observations of potential factors. This results in the ICM model retaining eleven factors while the TSM and IRM models retain only six and seven factors respectively. This is likely to be a reason for the ICM model's outperformance.

Additionally, it appears that including too many factors has a negative impact on performance. The All Attribute model (AAM) espoused by Haugen and Baker (1996) comprised of all 27 factors performs well below the ICM model, particularly during the in-sample period. The AAM model does improve out-of sample beating both the IRM and TSM models. It appears therefore that model robustness hinges on the number of attributes included. Placing too many bets increases statistical interference within the forecast process lowering forecast accuracy and placing too few bets increases reliance on potentially spurious factors and raises the likelihood of missing a late performing factor. Out-of-sample results show that the latter is a far more serious problem. Future researchers are therefore encouraged to relax factor selection criteria somewhat.

9.3. Style Timing Exploratory Analysis

Robust relationships are discovered within the time-series of payoffs. There is strong low order autocorrelation, most powerful at one lag for the majority of styles. Trailing moving averages are also found to have strong forecasting power with six-month and one-year moving averages dominating eighteen-month and two-year moving averages. An AR12 model based on the first twelve lags performs particularly well in-sample with an R^2 between 0.4 and 0.7 for most styles. The model is not as successful out-of-sample, however it still achieves a root mean squared error of less than 0.05 for most styles. Style payoffs are found to have an element of seasonality with a small number of styles paying off greater in April. A number of Granger dynamic relationships are discovered between payoffs and stationary macroeconomic variables, mostly to do with the business cycle, confirming past literature. Styles perceived to be riskier, such as size, risk, and momentum, perform better when the economy is strong and styles perceived to be 'safer', such as value, perform better when the economy is weak.

9.4. Style Forecasting Models

The six models constructed to test predictability all perform extremely well in-sample with the AR12 model performing best followed by the Consolidated model. Only the 1M, AR12, and Consolidated models predict relatively well out-of-sample, however, all at a much lower level than in-sample. The 1M model performs best on average achieving a mean correlation between forecast and actual payoffs across styles of

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0.13. The mean model performs exceptionally poorly out-of-sample strengthening the motivation for incorporating timing into return forecasting models.

The multivariate results presented in *Table 8.4.1.* confirm most of these findings, however the 6M model is found to perform best according to IC. Interestingly, the 1M model performs best according to decile spread, however IC is held to be a more robust and accepted measure of performance due to its widespread use and the fact that IC takes all forecasts into account and not just the forecasts in the top and bottom deciles. The 6M model provides the most accurate style payoff forecasts although it may be that the 1M model provides more exploitable forecasts. The Consolidated model on the other hand performs poorly out-of-sample. Evidence therefore suggests that the most important source of forecasting power is from the time-series of payoffs itself. Perhaps macroeconomic relationships become more important over longer return horizons (e.g. using quarterly data) or over a greater total sample of returns (e.g. using a sample of 50 years.)

The 1M and 6M models are better than the 12M model at forecasting style payoffs, however when they are used to select attributes they select too few attributes and are unable to beat the 12M model.

9.4. Conclusion

In *Chapter 6* the presence of stock market anomalies on the LSE is clearly established. The anomalies, relating to risk, size, value, momentum and growth, persist after risk adjustment via both the CAPM and three factor APT risk models. Furthermore, results are robust in the out-of-sample period that is free of survivorship, look-ahead and data-snooping biases. Similar to Haugen and Baker (1996) multifactor strategies that exploit anomalies are found to earn strong returns in- and out-of-sample. A stepwise selection procedure based on IC is found to produce the best results. The ICM model achieves an IC over 0.1 and a monthly decile spread of 4% in- and out-of-sample.

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The multivariate results indicate that out-of-sample performance is largely dependent on the number of factors included in a model. Including too many factors lowers forecast accuracy while including too few factors raises the likelihood of missing a performing factor thereby lowering model robustness.

Style payoffs are found to be persistent in- and out-of-sample, with most styles exhibiting strong first order autocorrelation. Trailing moving averages, particularly six and twelve-month averages, show strong forecasting ability for most styles. Evidence of calendar seasonality in the time-series of style payoffs is discovered. A number of the styles perform better during the month of April when individuals submit their tax returns. Additionally, a number of robust dynamic relationships are observed between style payoffs and macroeconomic variables. Of the economic variables tested, those relating to the business cycle are found to be the most useful indicators of future style payoffs. Styles perceived to be riskier perform better when the economy is strong and styles perceived as 'safer' perform better when it is weak.

Payoff forecasting models developed for each style based on past lags, moving averages and macroeconomic indicators perform excellently in-sample but only moderately well out-of-sample. The 1M model forecasts best out-of-sample. Relative model performance reveals that the most important source of forecasting power is located in the time-series of payoffs itself. When the alternative forecasting models are used in a multivariate framework to forecast the payoffs of the eleven attributes from the ICM model, the six-month trailing mean is found to produce the best out-of-sample results. The Mean model is found to perform worst in- and out-of-sample. This is powerful evidence that style payoffs are time varying, yet exploitable.

Further research can determine whether return forecasting models that use separate models to forecast each attribute payoff and then blend the forecasts into a multivariate framework can enhance performance. In addition future research can take portfolio rebalancing costs into account to test the economic profitability of the models developed in this thesis. It will then be possible to optimise the level of

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monthly rebalancing and evaluate the returns possible to investors managing live portfolios.

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Appendices

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Appendix A (Chapter 6)

A.1. Ground Rules For The FTSE UK All Share Index
Displays liquidity requirements as of Jan 2004 for the FTSE UK All share index. Supplied on the FTSE website www.ftse.co.uk. (V9.2 Jan 2004)

The following criteria are used to ensure that illiquid securities are excluded from the FTSE All share index:

a) Price - The FTSE Europe/Middle East/Africa Regional Committee must be satisfied that an accurate and reliable price for the purposes of determining the market value of a company exists. The FTSE Europe/Middle East/Africa Regional Committee may exclude a security from the FTSE Actuaries UK Share Indexes should it consider that an 'accurate and reliable' price is not available. A sterling or euro denominated price on SETS or SETSmm or a firm quotation on SEAQ or SEATS must exist for a company to be included in the UK Series.

b) Size - All eligible listed companies will be included in the UK Series. The FTSE Europe/Middle East/Africa Regional Committee will determine which UK companies are included on an annual basis at its meeting held in December. The largest eligible companies ranked by full market capitalisation i.e. before the application of any investibility weightings, comprising at least 98% of all companies will be included in the All-Share. The decision will take effect on the next trading day following the third Friday in December. At the quarterly reviews in March, June and September, companies whose full market capitalisation (i.e. before the application of individual constituent investibility weightings) is greater than 0.2% of the full market capitalisation of the FTSE SmallCap will be added to the FTSE All-Share, providing they meet all the relevant FTSE eligibility criteria (see rules 4.2 – 4.10). Companies whose full market capitalisation is less than 0.05% of the full market capitalisation of the FTSE SmallCap will be deleted from the FTSE All-Share at the review and will be added to the FTSE Fledgling index. These market capitalisations will be calculated using data as at the close of business on the day before the review (see Rule 6.1.1).

c) Liquidity - Securities which do not turnover at least 0.5% of their shares in issue, after the application of any free float restrictions (see Rule 4.6), per month in at least ten of the twelve months prior to the annual review by the FTSE Europe/Middle East/Africa Regional Committee at its meeting held in December, will not be eligible for inclusion in the indexes (except FTSE Fledgling and FTSE AIM). An existing constituent failing to trade at least 0.5% of its shares in issue, after the application of any free float restrictions, per month for more than four of the twelve months prior to review will be removed on the next trading day following the third Friday in December. Any period when a share is suspended will be excluded from the above calculation (see Rule 7.4). FTSE Fledgling and FTSE AIM constituents must trade at least 0.5% of their shares in issue, after the application of any free float restrictions, per month for 10 or more of the twelve months prior to review to be eligible for the FTSE All-Share.

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A.2. Description Of Attributes

Definitions of firm-specific attribute values for the month beginning at time t

Code	Name and definition
Size	
LMV	Log of market value. The logarithmic transformed variable is normally distributed.
LPrice	Log of share price. The logarithmic transformed variable is normally distributed.
Value	
BVTP	Book value to price ratio Book value of equity/ Price
CEY	Cash flow to price (Cash earnings yield) (Cash earnings / Ordinary shares in issue)/ Price
DY	Dividend yield (Ordinary dividends/ Ordinary shares in issue)/ Price
EY	Earnings yield Earnings per share/ Price
Sales_to_MV	Sales to market value Total Sales/ Market value
Growth	
CEYG1	One-month growth in cash flow to price (Cash flow to price_t - cash flow to price_{t-1})/ cash flow to price_{t-1}
CEYG12	Twelve-month growth in cash flow to price (Cash flow to price_t - cash flow to price_{t-12})/ cash flow to price_{t-12}
DPSG12	Twelve-month growth in dividend per share (dividend per share_t - dividend per share_{t-12})/ dividend per share_{t-12}
DPSG24	Two-year growth in dividend per share (dividend per share_t - dividend per share_{t-24})/ dividend per share_{t-24}
EG12_P	Twelve-month growth in earnings (divided by price) (Earnings per share_t - Earnings per share_{t-12})/ P_{t-12}
EG24_P	Two-year growth in earnings (divided by price) (Earnings per share_t - Earnings per share_{t-24})/ P_{t-24}

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A.2. Description of attributes (continued)

Code	Name and definition
Growth (continued)	
ExpectedGrowth	Expected earnings growth rate Return on book value of equity * (1 – dividend payout ratio)
Gearing	Financial gearing ratio
POUT	Dividend payout ratio Ordinary dividend/Earnings per share
ROE	Return on book value of equity Profit after taxation/Total owners interest
SG12	Twelve-month growth in sales (Total $Sales_t$- Total $Sales_{t-12}$)/ Total $Sales_{t-12}$
SG24	Two-year growth in sales (Total $Sales_t$- Total $Sales_{t-24}$)/ Total $Sales_{t-24}$
Liquidity	
Current	Current ratio Currents assets/ Current liabilities
ICBT	Interest cover before tax Profit before interest and tax/Interest accrued
NCA_to_MV	Net current assets to market value (Currents assets - Current liabilities) / market value
Risk	
Beta	Beta The Sharpe-Lintner-Black (CAPM) beta coefficient as calculated by DataStream. Measures the exposure of a share to overall market movements.

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A.2. Description of attributes (continued)

Code	Name and definition
Risk (continued)	
PVar12	Twelve-month price variance Variance of monthly price level (measured at end point) over the last twelve months. Calculated as $$\sigma^2 = \frac{\sum_{t-12}^{t}(P_t - \bar{P}_t)^2}{11}$$ where P_t is the share price at time t and $\bar{P}_t$ is the twelve month trailing mean value of P_t (including P_t).
Retvar12	Twelve month Returns variance Variance of the last twelve monthly returns. Calculated as $$\sigma^2 = \frac{\sum_{t-12}^{t}(R_t - \bar{R}_t)^2}{11}$$ where R_t is the reinvested total return earned by a shareholder for holding the share over the calendar month ending at time t and $\bar{R}_t$ is the twelve month trailing mean value of R_t (including R_t).
Momentum	
Momentum calculations are based on the Datastream calculated return index (RI) which is the share price adjusted for dividends received by shareholders and capital events such as share splits.	
Crossover3_12	Crossover three/ twelve (Three month momentum-Twelve month momentum)/ Twelve month momentum
Mom1	One-month returns momentum The reinvested total return earned by a shareholder for holding the share over the calendar month ending at time t.

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A.2. Description of attributes (continued)

Code	Name and definition
Momentum (continued)	
Mom3	Three-month returns momentum The reinvested total return earned by a shareholder for holding the share for three calendar months ending at time t.
Mom6	Six month returns momentum The reinvested total return earned by a shareholder for holding the share for six calendar months ending at time t.
Mom12	Twelve-month returns momentum The reinvested total return earned by a shareholder for holding the share for one calendar year ending at time t.
Mom18	Eighteen-month returns momentum The reinvested total return earned by a shareholder for holding the share for eighteen calendar months ending at time t.

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A.3. Financial Ratios Used In Attribute Definitions

Book value of equity
The difference between total assets and total debt.

Cash earnings (cash flow)
The net cash flow to the business from operations, financing activities and investment activities.

Current assets
Consists of all stock on hand including raw materials, finished goods, merchandise, consumable stores, work in progress, cash and outstanding debtors net of provisions for bad debts and unearned finance charges.

Current liabilities
Liabilities with respect to trade creditors, shareholders for dividends, provisions for taxation, bank overdraft balances and short-term borrowings.

Earnings per share
Profit after taxation attributable to each outstanding ordinary share. The latest annualised rate either reflects the last financial year or is derived from an aggregating interim earnings.

Financial Gearing
Preference capital and total debt divided by total capital employed plus short term borrowings minus total intangibles minus future income tax benefits.

Market value
Total market capitalisation of ordinary shares. Calculated as the share price multiplied by the number of ordinary shares in issue. The amount in issue is updated whenever new shares are issued or after a capital change. For companies with more than one class of equity capital, the market value is expressed according to the individual issue. Market value is displayed in millions of Pounds.

Dividend per share
Calculated on a twelve-month rolling basis, including dividends declared, interim and final, in favour of the various classes of ordinary shareholders. Once-off dividends are generally excluded

Ordinary share capital
Represents the total value of issued (and fully paid up) ordinary share capital. No distinction is made between various classes of ordinary shares. For shares with a par value this figure represents the nominal amount of the shares fully paid up. Share premiums paid on such shares and non-distributable reserves are not included.

Ordinary Shares in issue

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Ordinary shares in issue represent the total number of ordinary shares issued. weighted for issues made in the course of the financial year. The weighted number of shares in issue is reduced with regards to bonus issues where the full value is not paid for the shares.

Price
The share price in Pounds available from the London stock exchange (LSE), adjusted for capital actions Prices are generally based on 'last trade' or an official price fixing.

Profit after taxation
The net profit for the year, including extraordinary profits and losses and providing for the year's taxation.

Total Sales
The amount of sales of goods and services to third parties relating to the normal industrial activities of the company. It is net of sales related taxes and excludes any royalty income, rental income, and other operating income.

Total assets
The sum of tangible fixed assets, intangible assets, investments (including associates), other assets, total stocks & work in progress, total debtors & equivalent and cash & cash equivalents.

Total debt
The total of all long and short term borrowings, including any subordinate debt and 'debt-like' hybrid finance instruments.

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A.4. Attribute Availability (Table)

Displays the number of observations per attribute available in the data set as at the 1st of March and 1st of September in each year of the sample period.

	DPSG12	ROE	MOM12	MOM18	POUT	Beta	BVTP	ICBT	EY	DY	SG12	Gearing
Mar-90	772	332	229	402	426	762	426	412	435	435	772	336
Sep-90	772	347	240	411	432	762	433	419	443	442	772	352
Mar-91	772	356	248	422	437	762	438	424	447	446	772	361
Sep-91	772	360	260	436	448	762	448	434	456	456	772	367
Mar-92	772	367	267	443	455	762	454	441	462	462	772	375
Sep-92	772	371	277	447	463	762	463	448	471	472	772	379
Mar-93	772	376	289	457	470	762	470	455	478	479	772	385
Sep-93	772	382	301	463	483	762	481	468	489	489	772	391
Mar-94	772	385	479	472	502	762	499	482	507	509	772	468
Sep-94	772	400	489	479	530	762	528	512	533	538	772	484
Mar-95	772	424	510	489	538	762	539	517	539	550	772	508
Sep-95	772	433	539	510	552	762	554	534	552	562	772	524
Mar-96	772	440	552	539	573	762	574	552	561	577	772	534
Sep-96	772	465	563	552	604	762	605	578	585	609	772	556
Mar-97	772	486	581	563	624	762	624	598	605	622	772	577
Sep-97	772	507	613	581	647	762	646	619	631	646	772	603
Mar-98	772	530	633	613	660	762	658	631	647	663	772	628
Sep-98	772	539	655	633	678	762	679	649	673	682	772	644
Mar-99	772	556	669	655	687	762	687	655	685	692	772	664
Sep-99	772	569	687	669	699	762	701	669	691	706	772	672
Mar-00	718	573	692	684	709	715	711	682	701	715	718	675
Sep-00	752	589	704	692	745	744	745	714	715	748	752	693
Mar-01	759	606	711	695	753	752	754	724	739	755	759	719
Sep-01	744	605	730	696	738	737	739	710	736	739	744	714
Mar-02	731	591	731	717	720	724	723	697	724	728	731	702
Sep-02	713	578	713	713	705	710	703	679	708	710	713	688
Mar-03	690	558	690	690	682	689	682	656	686	687	690	668
Sep-03	665	534	665	665	657	664	660	631	665	665	665	646

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A.4. Attribute Availability (Table) Continued

	MOM1	MOM6	MOM3	NCA_to_MV	CEYG1	DPSG24	EG24_P	SG24	LMV	Current	RetVar12	EG12_P
Mar-90	249	246	245	335	772	772	174	772	436	345	218	212
Sep-90	258	252	253	351	772	772	189	772	443	361	229	221
Mar-91	264	262	260	361	772	772	214	772	447	371	242	228
Sep-91	274	275	272	365	772	772	223	772	457	378	248	236
Mar-92	284	279	278	372	772	772	233	772	463	386	253	244
Sep-92	294	289	288	376	772	772	242	772	472	390	264	251
Mar-93	300	296	298	382	772	772	249	772	479	395	272	254
Sep-93	312	310	310	389	772	772	254	772	489	402	283	259
Mar-94	504	489	500	396	772	772	259	772	510	473	479	268
Sep-94	538	510	528	408	772	772	281	772	539	487	479	288
Mar-95	549	539	545	431	772	772	290	772	552	512	491	299
Sep-95	563	552	555	441	772	772	300	772	563	531	517	319
Mar-96	577	563	573	449	772	772	314	772	581	540	529	343
Sep-96	610	581	595	470	772	772	337	772	613	561	539	359
Mar-97	631	613	626	489	772	772	365	772	633	584	563	379
Sep-97	655	633	646	514	772	772	378	772	655	611	597	403
Mar-98	668	655	664	536	772	772	393	772	669	637	615	439
Sep-98	687	669	677	547	772	772	419	772	687	653	636	467
Mar-99	693	687	690	563	772	772	449	772	695	672	669	490
Sep-99	707	695	701	575	772	772	478	772	707	679	675	510
Mar-00	717	703	710	580	718	718	503	718	718	684	664	530
Sep-00	752	720	733	595	752	752	532	752	752	704	680	558
Mar-01	759	745	759	612	759	759	542	759	759	727	694	560
Sep-01	744	744	744	607	744	744	535	744	744	724	706	558
Mar-02	731	731	731	596	731	731	525	731	731	712	707	569
Sep-02	713	713	713	575	713	713	517	713	713	701	691	552
Mar-03	690	690	690	560	690	690	518	690	690	679	667	524
Sep-03	665	690	665	533	665	665	500	665	665	656	632	500

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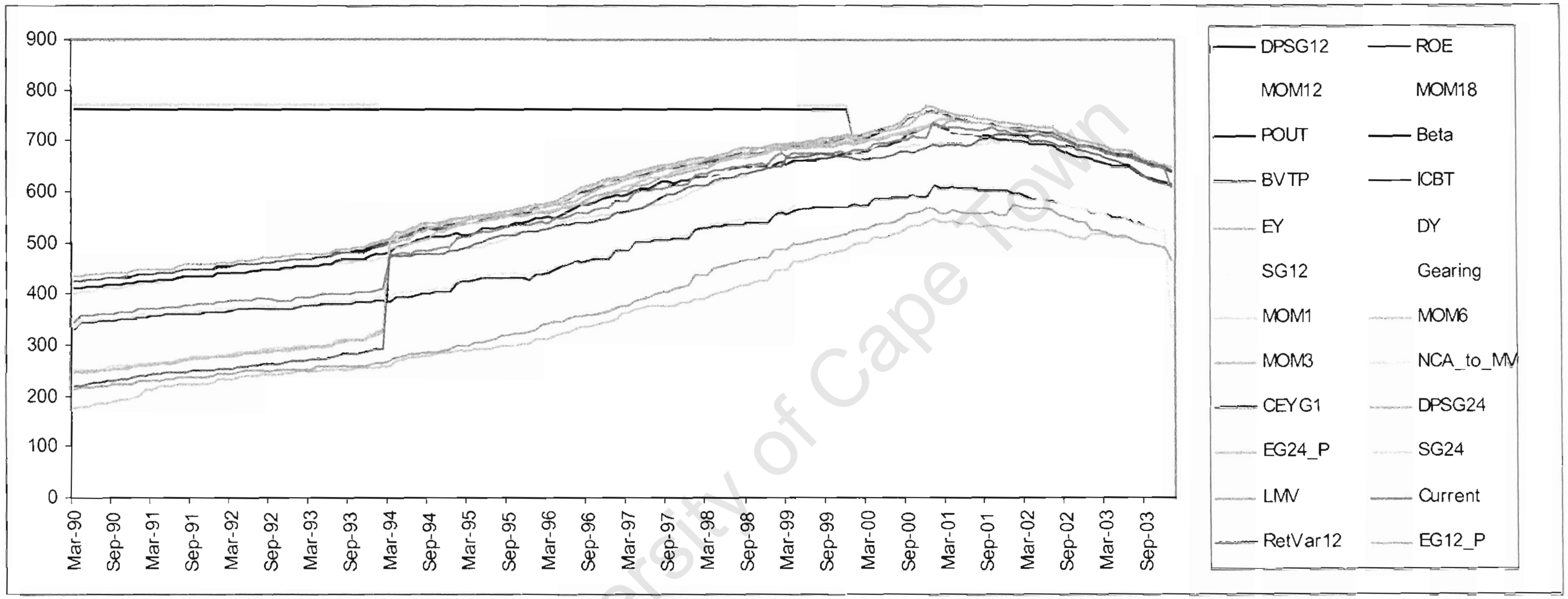
A.5. Attribute Availability (Figure)

Displays the number of observations per attribute available in the data set over the in-sample and out-of-sample periods (1 Mar 1990 – 1 Feb 2004 . The decline in the number of observations between 2000 and 2004 is due to shares delisting. This is a result of the out-of-sample data being free of survivorship bias.



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A.6. Standardisation Test Results

The monthly univariate regressions are repeated using non-standardised attribute data for the period 1 Mar 1990 - 1 Feb 2004. The T-statistic of the mean monthly slope coefficient is compared against the T-statistic calculated using standardised attribute data. In no case is the monthly coefficient mean significantly different (Using a comparison T-statistic) after the standardisation procedure.

	Insample		Out-of-sample	
	Non-standardised	Standardised	Non-standardised	Standardised
LPrice	-4.51	-4.51	-4.51	-4.51
LMV	-1.78	-1.61	-1.78	-1.61
DY	-2.07	-1.92	-2.07	-1.92
BVTP	1.30	1.61	1.30	1.61
POUT	-3.16	-3.06	-3.16	-3.06
ICBT	5.43	5.43	5.43	5.43
Sales_to_MV	-2.00	-1.51	-2.00	-1.51
Beta	2.70	2.70	2.70	2.70
CEY	-0.91	-0.96	-0.91	-0.96
NCA_to_MV	-1.10	0.21	-1.10	0.21
Gearing	-2.33	-1.88	-2.33	-1.88
ROE	2.97	2.28	2.97	2.28
EY	-1.03	-1.04	-1.03	-1.04
RetVar12	2.06	1.94	2.06	1.94
PVar12	-3.90	-2.88	-3.90	-2.88
MOM1	2.20	1.18	2.20	1.18
MOM3	3.38	2.13	3.38	2.13
MOM6	3.80	2.84	3.80	2.84
MOM12	4.74	3.25	4.74	3.25
MOM18	4.29	4.22	4.29	4.22
Crossover3_12	2.66	2.93	2.66	2.93
Current	1.27	1.37	1.27	1.37
EG12_P	1.38	1.35	1.38	1.35
EG24_P	0.38	1.54	0.38	1.54
SG12	1.02	1.77	1.02	1.77
SG24	0.76	2.04	0.76	2.04
DPSG12	1.43	1.52	1.43	1.52
DPSG24	-1.41	-1.89	-1.41	-1.89
CEYG12	1.26	0.50	1.26	0.50
CEYG1	-1.46	-1.21	-1.46	-1.21
Expectedgrowth	-0.26	0.06	-0.26	0.06

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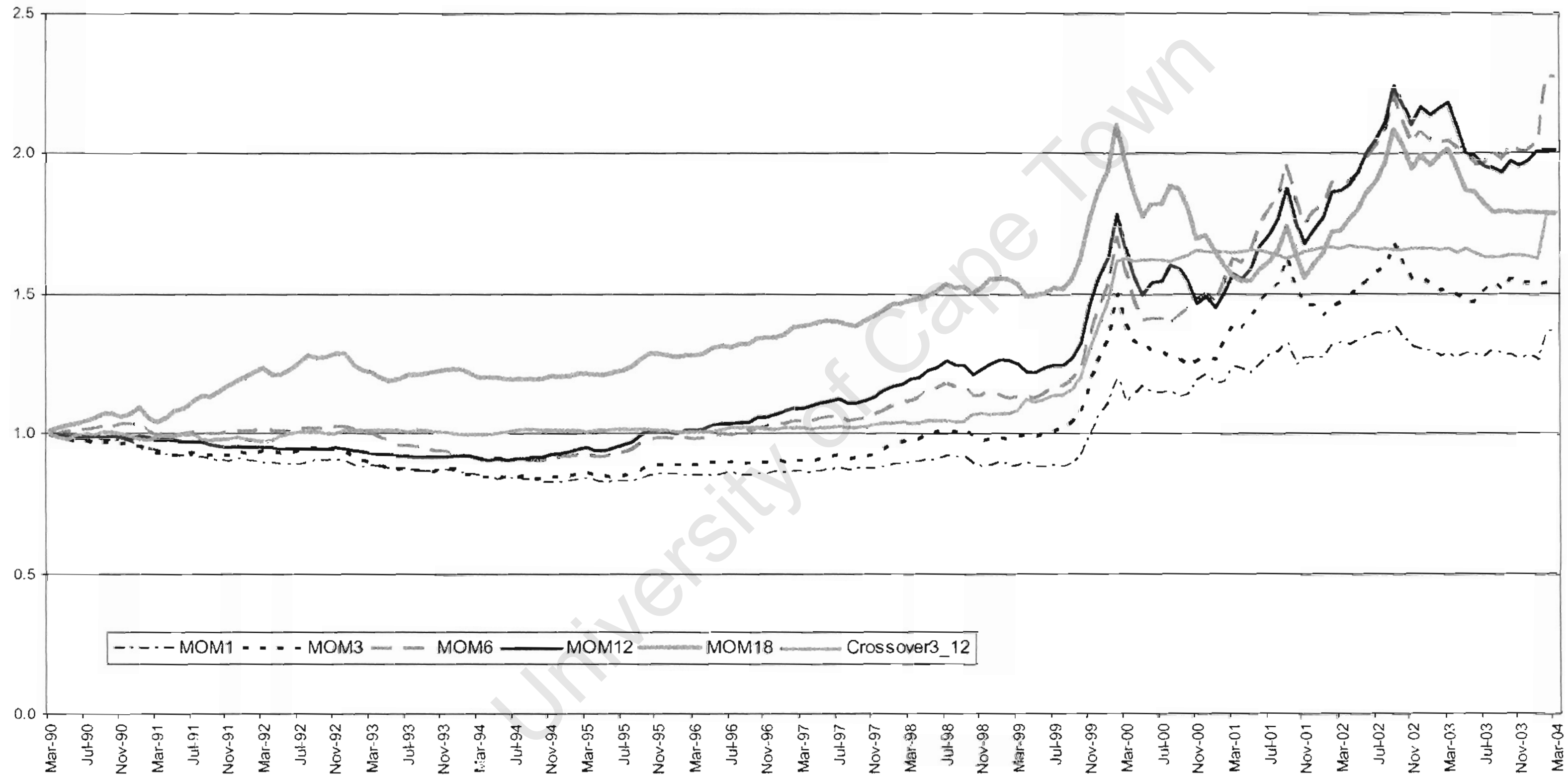
Charts of cumulative payoff to attributes

A.7. Momentum

A geometric cumulative graph of the payoff to momentum related attributes over the period Mar 1990 - Feb 2004. The dashed line separates in-sample and out-of-sample periods.



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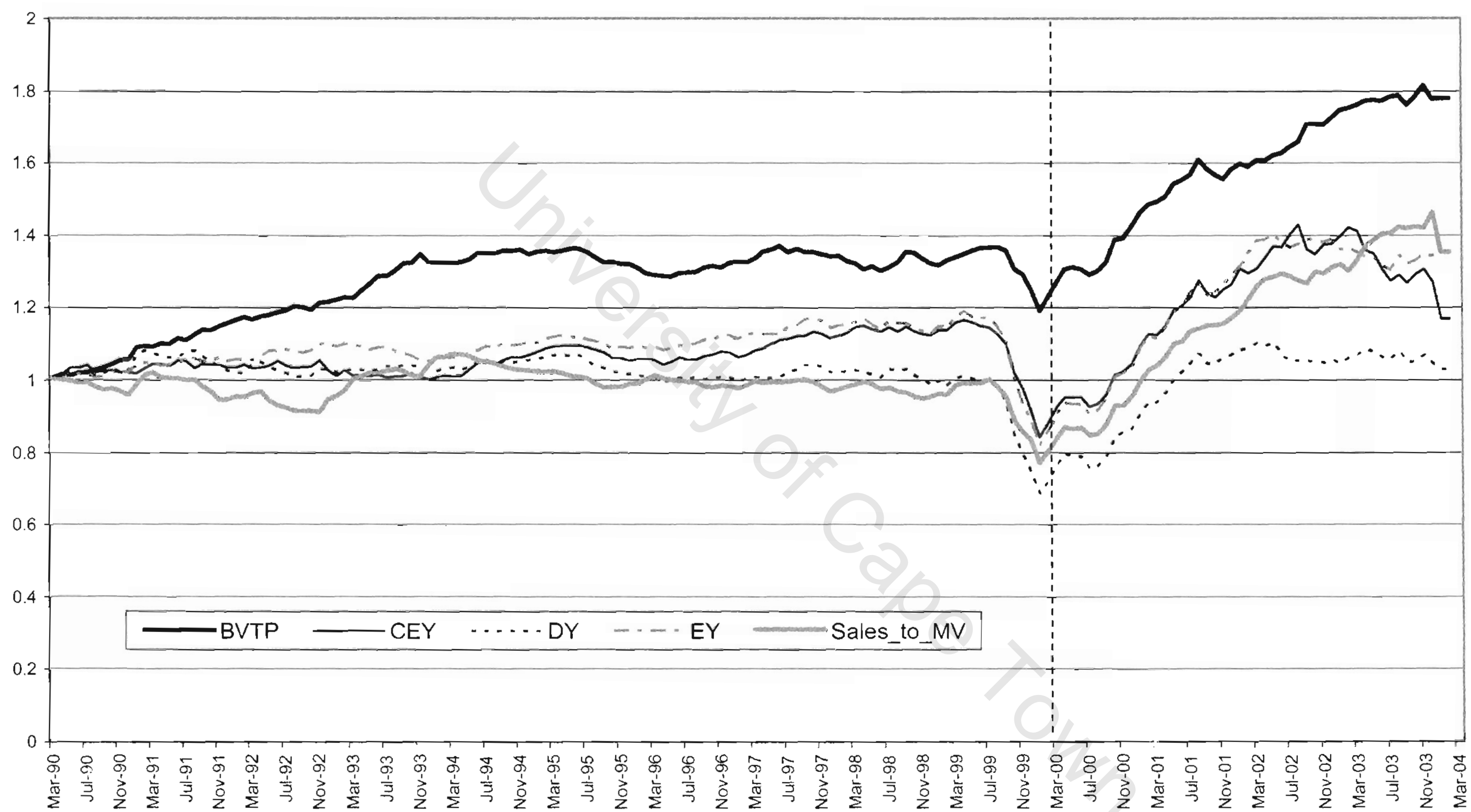
A.8. Value

A geometric cumulative graph of the payoff to value related attributes over the period Mar 1990 - Feb 2004. The dashed line separates in-sample and out-of-sample periods.



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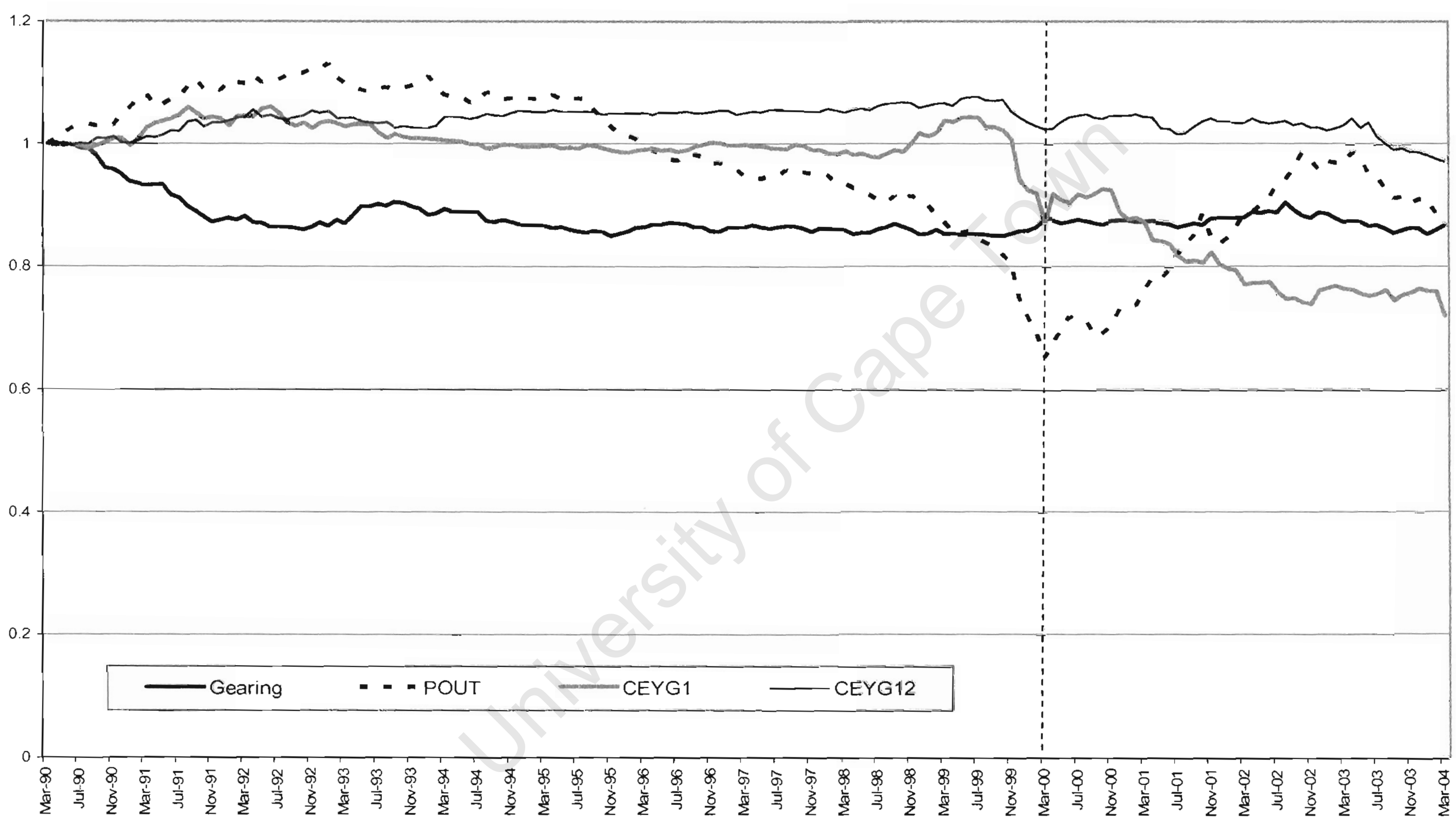
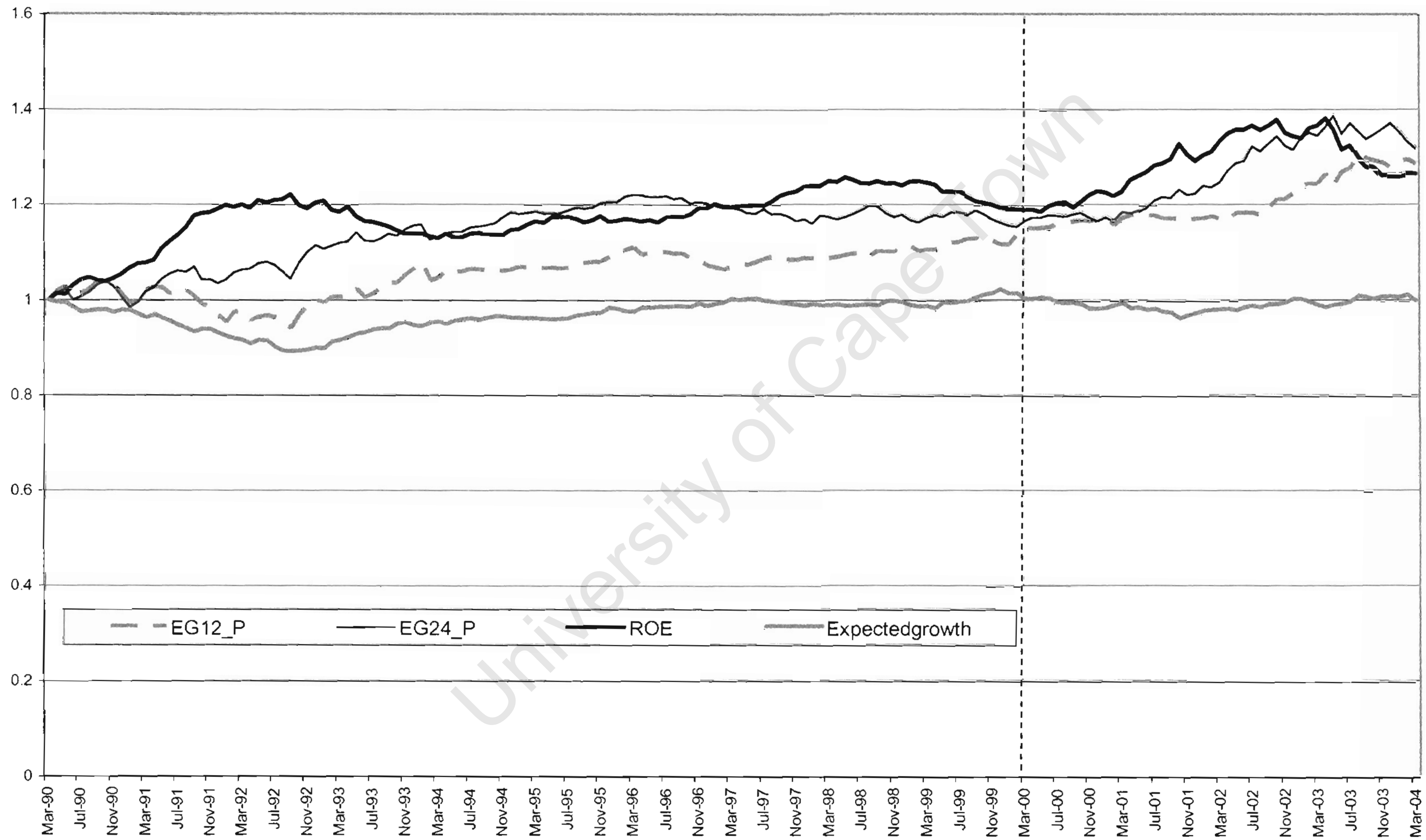
A.9. Growth

A geometric cumulative graph of the payoff to growth related attributes over the period Mar 1990 - Feb 2004. The dashed line separates in-sample and out-of-sample periods.



A.10. Growth (Continued)

A geometric cumulative graph of the payoff to growth related attributes over the period Mar 1990 - Feb 2004. The dashed line separates in-sample and out-of-sample periods.



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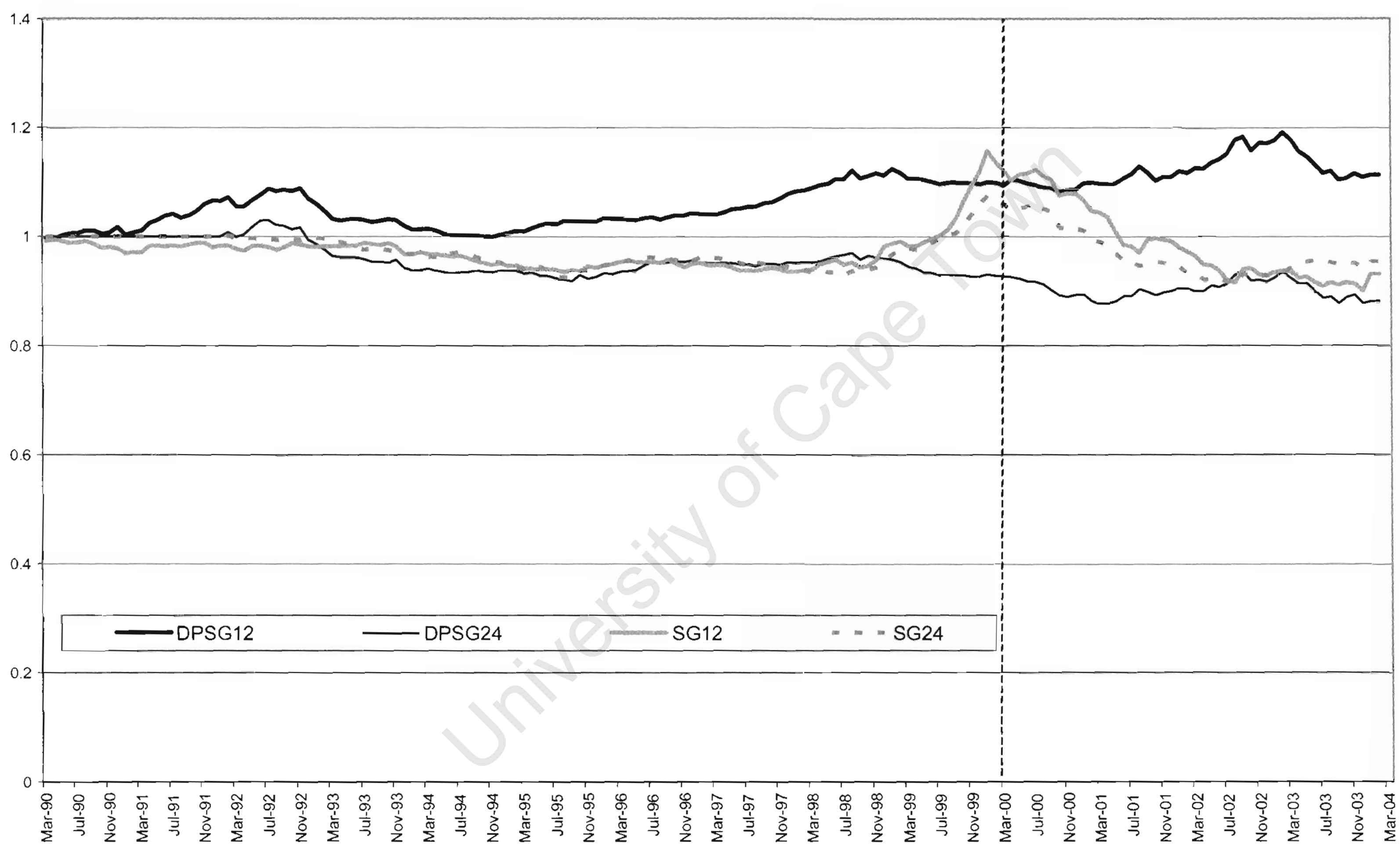
A.11. Growth (Continued)

A geometric cumulative graph of the payoff to growth related attributes over the period Mar 1990 - Feb 2004. The dashed line separates in-sample and out-of-sample periods.



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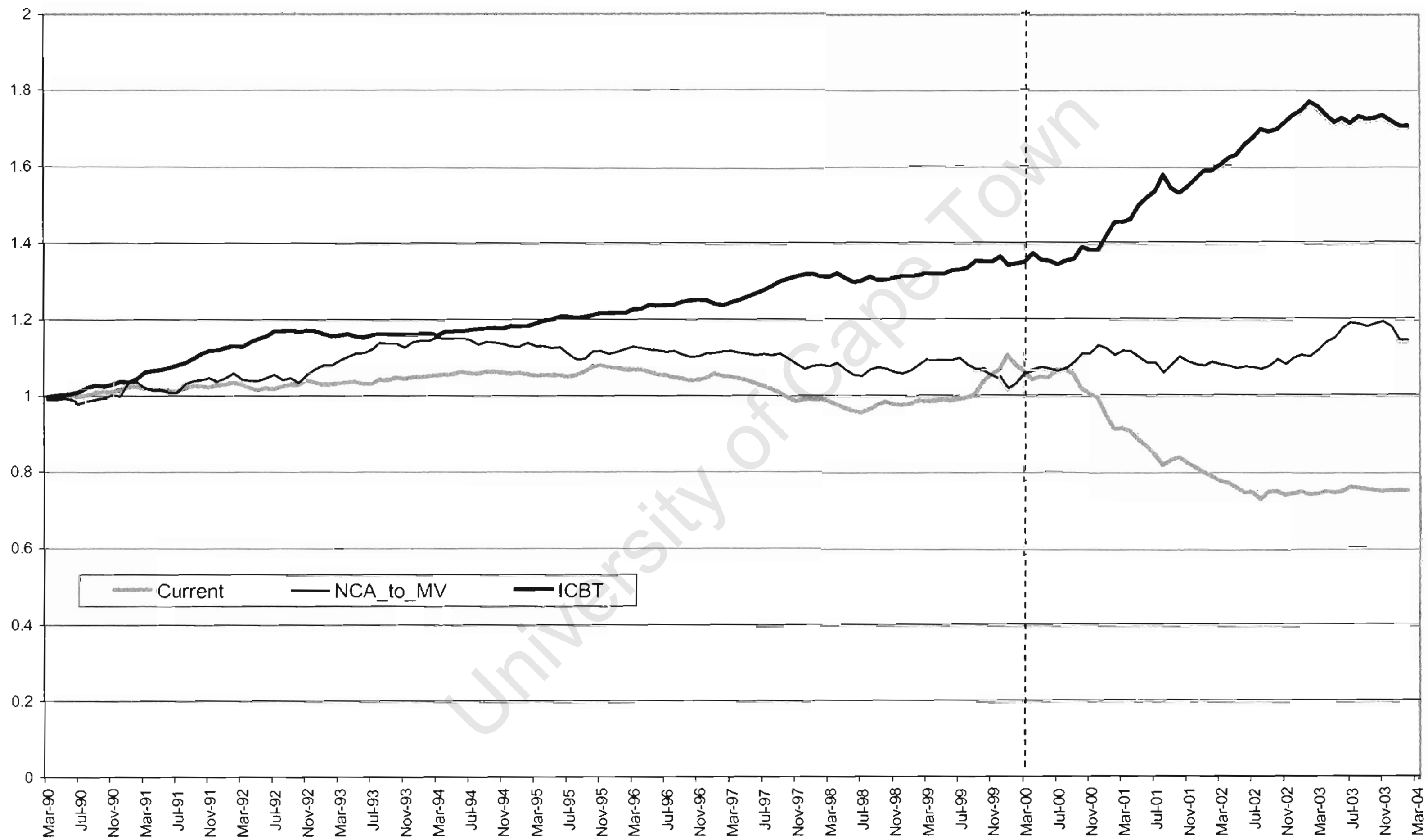
A.12. Liquidity

A geometric cumulative graph of the payoff to liquidity related attributes over the period Mar 1990 - Feb 2004. The dashed line separates in-sample and out-of-sample periods.



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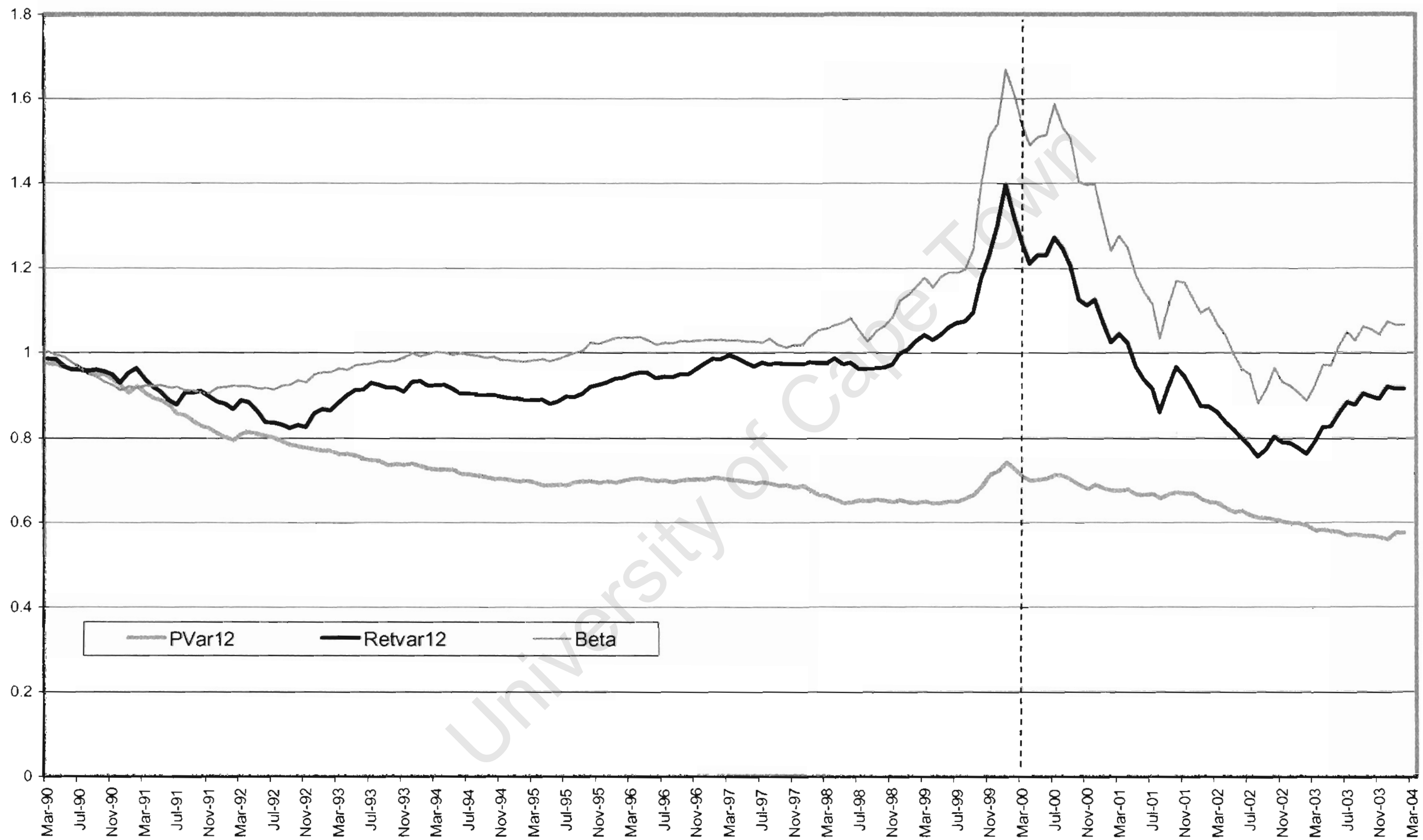
A.13. Risk

A geometric cumulative graph of the payoff to risk related attributes over the period Mar 1990 - Feb 2004. The dashed line separates in-sample and out-of-sample periods.



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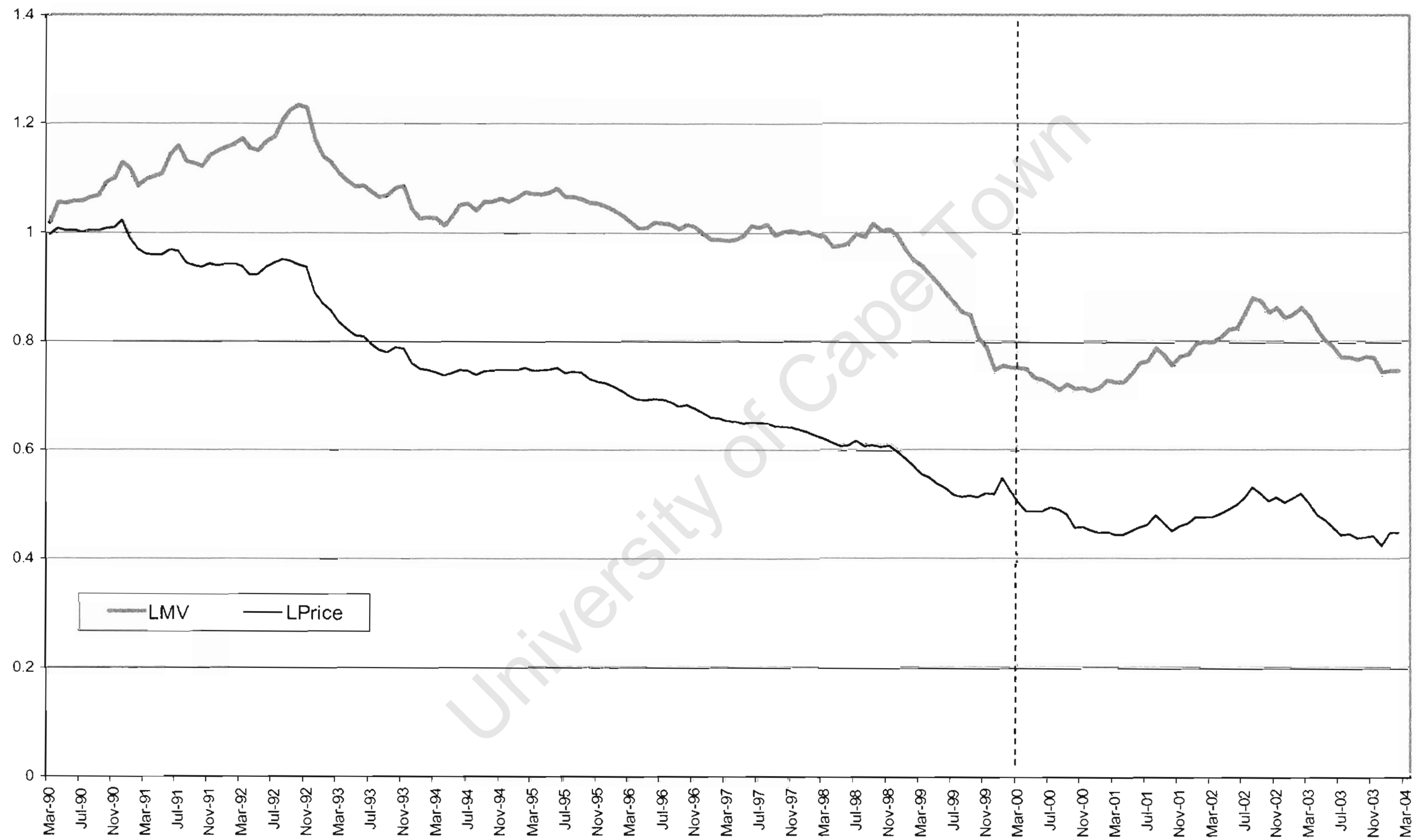
A.14. Size

A geometric cumulative graph of the payoff to size related attributes over the period Mar 1990 - Feb 2004. The dashed line separates in-sample and out-of-sample periods.



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A.15. Construction Of APT Model

An APT model was constructed using the factor analytic method. Monthly returns data for each FTSE level 6 index was obtained for the period 01 Mar 1990 -01 Feb 2000 (sample period corresponds to the in-sample period in the main analysis.) Appendix A.16. lists the FTSE level 6 indexes. After deleting 14 indexes with too few data points to perform meaningful analysis, 71 indexes are analysed. Eigenvalues and percentages are displayed for the first 10 factors. Although the scree plot *(Figure A.15.1)* indicates a significant flattening out after two factors, the individual eigenvalues of factors one to five are all greater than one. Factor one explains a very high 72% of variation, factors two and three individually explain 2.5% and 2.3%, and factor 4 explains 1,6% of variation. Whilst under the usual flattening curve cut-off rule, a one-factor model is most appropriate, a three factor model is decided upon. This is done to complement the CAPM one factor model constructed, conservatively erring on the side of an over-specified APT risk model. The three factors together account for 77% of the shared variation in the sample.

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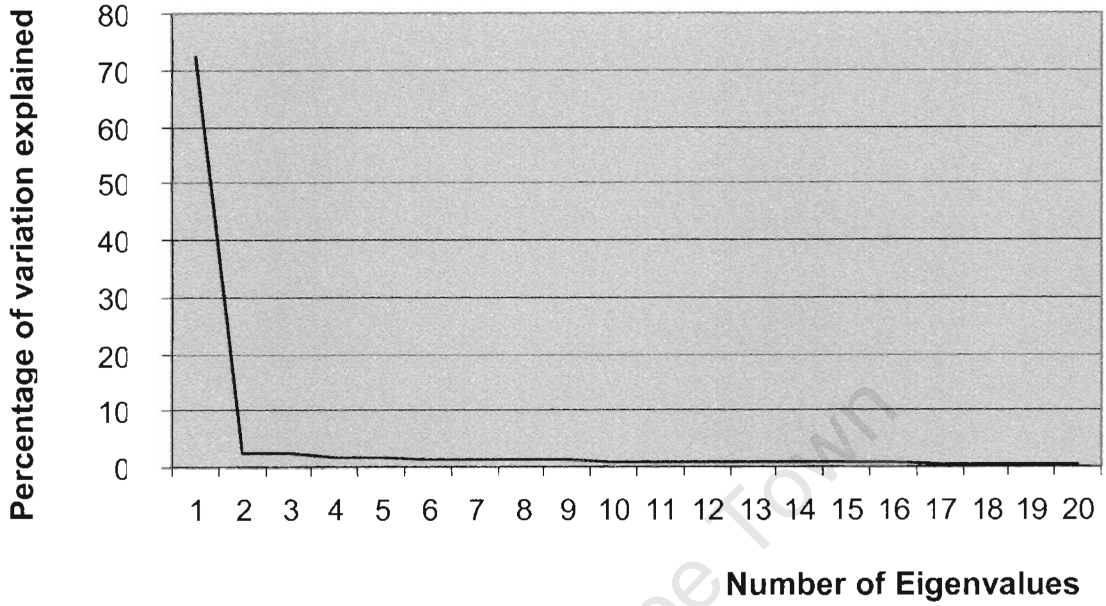
Figure A.15.1. Scree Plot of eigenvalues

Displays eigenvalues (as a percentage of total variation) explained by each factor cumulatively from the principal factor analysis performed over the period 01 Mar 1990 - 01 Feb 2000. The table below provides the exact eigenvalues for each factor.



	Eigenvalue	Cumulative	% Total	Cumulative
1	51.41	51.41	72.41	72.41
2	1.77	53.18	2.49	74.90
3	1.60	54.79	2.26	77.16
4	1.16	55.95	1.64	78.80
5	1.02	56.97	1.44	80.24
6	0.96	57.93	1.36	81.60
7	0.88	58.81	1.24	82.84
8	0.81	59.62	1.14	83.98
9	0.74	60.36	1.04	85.02
10	0.63	60.99	0.88	85.90

The indexes are then rotated using a three factor VARIMAX rotation, and the index loadings for each factor are obtained. Indexes are selected to represent each factor, based on the factor loadings. *Table A.15.1.* provides a summary of the three factors identified and *Table A.15.2.* presents the factor loadings. The final step is to calculate betas between each the excess return on share and the excess return on each factor (proxied by a share index.) This is done using ordinary least squares (OLS) regression over the entire in-sample and out-sample period. (01 Mar 1990 - 01 Feb 2004).

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Table A.15.1. Factors identified in Principal factor Analysis

Displays the FTSE UK level six indexes used as a proxy each of the three identified factors. Selection is based on the VARIMAX three factor rotated factor loadings for the period 01 Mar 1990 - 01 Feb 2000. A qualitative description for each is given based on the general loadings for each factor . In addition, closely associated sectors are provided.

Factor 1	Factor 2	Factor 3
Index chosen to proxy factor		
ENG. GENERAL	MULTI-UTILITIES	COMPUTER SERVICE
Factor description		
Engineering, Construction and Materials Industries	Basic Utilities	Technology industries
Closely associated sectors		
CHEMS.ADV.MATS. BUILDERS MERCH. BLDNG&CONS. MATS HOUSE BUILDING OTHER CONSTRUCTN PAPER STEEL	GAS DISTRIBUTION FOOD PROCESSORS PHARMACEUTICALS TOBACCO FOOD&DRUG RETLRS TELECOM FXD.LINE	SOFTWARE MEDIA AGENCIES EDUCATION & TRNG

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Table A.15.2. VARIMAX rotated Factor Loadings

Displays VARIMAX (normalised) rotated factor loadings for each FTSE UK level six index for the period 01 Mar 1990 - 01 Feb 2000. Values greater than 0.6 are bolded and indexes selected to represent a factor are shaded. 14 indexes were deleted as they contained too few data points for analysis.

Sector	Factor 1	Factor 2	Factor 3
OTHER MINING	**0.65**	0.50	0.28
OIL&GAS EXP&PROD	**0.70**	0.40	0.24
OIL SERVICES	0.54	0.18	0.30
OIL INTEGRATED	**0.64**	**0.61**	0.25
CHEMS. COMMODITY	**0.70**	0.54	0.26
CHEMS., SPECIAL	**0.78**	0.48	0.28
CHEMS.ADV.MATS.	**0.77**	0.47	0.28
BUILDERS MERCH.	**0.77**	0.45	0.23
BLDNG&CONS. MATS	**0.77**	0.49	0.29
HOUSE BUILDING	**0.77**	0.38	0.36
OTHER CONSTRUCTN	**0.72**	0.44	0.34
PAPER	**0.78**	0.30	0.16
STEEL	**0.64**	0.31	0.30
AEROSPACE	**0.72**	0.47	0.25
DEFENCE	**0.63**	0.51	0.38
ELECTRONIC EQUIP	0.50	0.50	0.50
ENG. CONTRACTORS	**0.75**	0.51	0.23
ENG. GENERAL	**0.81**	0.45	0.30
AUTO PARTS	**0.77**	0.43	0.26
VEHICLE DISTRIB.	**0.72**	0.46	0.26
FURN.& FLOORCOV.	0.45	0.36	0.51
CONS. ELECTRONIC	0.54	0.41	0.41
DISTIL.&VINTNERS	0.60	**0.67**	0.21
SOFT DRINKS	0.40	**0.64**	0.41
FOOD PROCESSORS	0.60	**0.72**	0.21
HOSPITAL MNGMNT.	0.45	0.13	0.34
MED. EQUIP&SUP.	0.58	**0.67**	0.32
HOUSEHOLD PRODS.	0.54	0.59	0.28
PERSONAL PRODUCT	0.41	**0.61**	0.47
PHARMACEUTICALS	0.36	**0.77**	0.25
TOBACCO	0.41	**0.76**	0.13
DSCT.&SPR.STORES	0.36	0.17	0.32
RETAIL HARDLINE	**0.63**	0.46	0.42
RETAILERS-DEPT.	**0.61**	**0.67**	0.17
RTLRS SOFT GOODS	0.59	0.56	0.32
GAMBLING	**0.65**	0.49	0.36
HOTELS	**0.67**	0.45	0.34
LEISURE FACILITY	**0.66**	0.51	0.37
RESTS. & PUBS.	**0.61**	**0.67**	0.29
TV, RADIO, FILM	0.57	0.48	0.55
SUB. ENTERTAIN	0.30	0.43	0.39
MEDIA AGENCIES	0.55	0.24	**0.65**
PHOTOGRAPHY	0.19	0.44	0.46
PUBLISH.&PRINT.	**0.61**	0.52	0.49
BUSINESS SUPPORT	0.58	**0.61**	0.44
EDUCATION & TRNG	0.28	0.20	**0.72**
ENVIRON. CONTROL	0.46	0.53	0.34
TRANS. + PAYROLL	0.39	0.53	0.50
SECURITY & ALARM	**0.69**	0.50	0.21
AIRLINES&A'PORTS	**0.67**	0.58	0.28
RAIL,RD,FREIGHT	0.55	**0.64**	0.28
SHIPPING & PORTS	**0.72**	0.50	0.31
FOOD&DRUG RETLRS	0.47	**0.74**	0.24
TELECOM FXD.LINE	0.39	**0.70**	0.43
TELECOM,WIRELESS	0.38	0.58	0.50
GAS DISTRIBUTION	0.37	**0.79**	0.20
MULTI-UTILITIES	0.39	**0.78**	0.28
WATER	0.41	**0.79**	0.20
COMPUTER SERVICE	0.31	0.53	**0.65**
SOFTWARE	0.40	0.43	**0.63**
BANKS	**0.63**	**0.63**	0.23
INSURANCE BROKRS	0.53	0.51	0.27
INSURANCE,NON-LF	**0.60**	**0.65**	0.25
LIFE ASSURANCE	0.49	**0.71**	0.31
UK INV. TRUSTS	**0.64**	**0.62**	0.41
REAL ESTATE DEV.	0.60	**0.64**	0.30
PROPERTY AGENCY	**0.62**	0.29	0.43
ASSET MANAGERS	**0.65**	0.43	0.46
CONSUMER FINANCE	**0.61**	**0.61**	0.33
INVESTMENT BANKS	**0.64**	0.45	0.43
OTHER FINANCIAL	0.51	**0.65**	0.42

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A.16. FTSE UK Level 6 Indexes

Displays the correspondence between FTSE level 6 indexes and FTSE level 4 indexes

FTSE Broad sectors (Level 4)	FTSE Sectors (Level 6)
Aerospace & Defence	Aerospace Defence
Automobiles & Parts	Automobiles Auto Parts Tyres & Rubber Vehicle Distribution
Banks	Banks
Beverages	Brewers Distillers & Vintners Soft Drinks
Chemicals	Chemicals,Commodity Chemicals,Speciality Chemicals,Advanced Materials
Construction & Building Materials	Builders Merchants Building & Construction Material House Building Other Construction
Diversified Industrials Electricity	Diversified Industrials Electricity
Electronic & Electrical Equipment	Electrical Equipment Electronic Equipment
Engineering & Machinery	Commercial Vehicles Engineering Contractors Fabricators Engineering General
Food & Drug Retailers	Food & Drug Retailers
Food Producers & Processors	Farming & Fishing Food Processors
Forestry & Paper	Forestry Paper
Health	Health Maintenance Organisations Hospital Management Medical Equipment & Supplies Other Health Care
Household Goods & Textiles	Clothing & Footwear Furnishings & Floor coverings Consumer Electronics Household Appliances & Housewares Leisure Equipment Textiles & Leather
Information Technology Hardware	Computer Hardware Semiconductors Telecom Equipment
Insurance	Insurance Brokers Insurance Non-Life Re-insurance Other Insurance
Investment Entities (Ineligible for indexes cont'd)	Unclassified Unquoted equities Other equities Equity warrants Other warrants Interest rate futures Fixed interest Futures
Leisure & Hotels	Gambling Hotels Leisure Facilities Restaurants & Pubs
Life Ass.	Life Assurance
Media & Entertainme	Television, Radio & Filmed Entertainment Subscription Entertainment Netwks Media Agencies Photography Publishing & Printing
Mining	Gold Mining Mining Finance Other Mineral Extractors
Oil & Gas	Oil & Gas Exploration & Production Oil Services Oil Integrated
Personal Care & Household Products	Household Products Personal Products
Pharmaceutica Biotechnology	Pharmaceuticals Biotechnology
Real Estate	Real Estate Development Property Agencies Real Estate Investment Trusts
Retailers, General	Discount & Super Stores & Warehses Retailers e-commerce Retailers, Hardlines Retailers Multi Department Retailers-Soft Goods
Software & Computer Services	Computer Services Internet Software
Speciality & Other Finance	Asset Managers Consumer Finance Investment Banks Mortgage Finance Other Financial
Steel & Other Metal	Non-Ferrous Metals Steel
Support Services	Business Support Services Delivery Services Education, Training Environmental Control Transaction & Payroll Services Security & Alarm

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A:2 FTSE UK Level 6 indexes (continued)

FTSE Broad sectors (Level 4)	FTSE Sectors (Level 6)
Investment Companies	Investment Companies Investment Trust International European Geographic Specialist Emerging Markets Venture & Developme
Investment Entities (Ineligible for indexes)	Exchange Traded Funds Housing income investment trusts Open Ended investment
Investment Entities (Ineligible for indexes cont'd)	Venture capital trusts Currency funds Other Investment Trusts Split capital investment trusts Authorised unit trusts Insurance and property bonds Mutual funds Money market funds

FTSE Broad sectors (Level 4)	FTSE Sectors (Level 6)
Telecom	Telecom Fixed Line
Services	Telecom Wireless
Tobacco	Tobacco
Transport	Airlines & Airports Rail, Road & Freight Shipping & Ports
Utilities, Other	Gas Distribution Multi-Utilities Water

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A.17. In- and Out-of-sample Style Beta's

Presents the slope coefficient (market beta) estimated when monthly excess market return is separately regressed against the monthly payoff for each style over the combined in- and out-of-sample periods (1Mar 1990 – 1 Feb 2004). The standard error and related t-statistic of the slope coefficient are presented. Styles are ordered by the t-statistic of the market beta.

	Market Beta	Standard Error	T-statistic
Beta	0.30	0.02	**14.1**
ICBT	-0.07	0.01	**-11.1**
RetVar12	0.21	0.02	**10.0**
DPSG12	-0.06	0.01	**-8.9**
Current	0.09	0.01	**8.6**
DPSG24	-0.04	0.01	**-6.6**
POUT	-0.10	0.01	**-6.5**
CEY	-0.10	0.02	**-5.5**
ROE	-0.04	0.01	**-5.2**
MOM18	-0.11	0.02	**-4.8**
EY	-0.08	0.02	**-4.5**
MOM3	-0.10	0.02	**-4.4**
CEYG12	-0.02	0.01	**-4.4**
LPrice	-0.07	0.02	**-4.3**
MOM6	-0.10	0.02	**-4.2**
MOM12	-0.09	0.02	**-4.0**
Expectedgrowth	0.02	0.01	**3.7**
SG24	0.02	0.01	**3.5**
PVar12	0.03	0.01	**3.4**
SG12	0.03	0.01	**3.2**
NCA_to_MV	0.03	0.01	**3.0**
CEYG1	0.03	0.01	**2.7**
Crossover3_12	0.04	0.02	**2.4**
BVTP	-0.02	0.01	-1.9
DY	-0.04	0.02	-1.9
MOM1	-0.03	0.02	-1.8
EG24_P	-0.02	0.01	-1.8
Sales_to_MV	-0.02	0.02	-1.1
LMV	-0.01	0.02	-0.4
EG12_P	0.00	0.01	0.4
Gearing	0.00	0.01	-0.1

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In-sample Stepwise Multifactor Model Construction

A.18. T-Statistic of Slope (TSM)

Displays the stepwise process by which attributes are either included (accepted) or rejected entry into the model using the t-statistic of the slope coefficient obtained from the regression of forecast returns on actual returns. Attributes are accepted if there is an improvement in the performance of the model now including the attribute (as measured by t-statistic of slope.) Attributes rejected in a pass are retested in the following pass. This process repeated until no new attributes are accepted in an entire pass. Statistics are calculated using the in-sample period (1 Mar 1990 – 1 Feb 2000) The inclusion of the final attribute is shaded.

Pass 1						Pass 2					
Step	t-stat	IC	IR	Accept	Reject	Step	t-stat	IC	IR	Accept	Reject
1	4.54	0.03	0.57	ICBT		28	9.68	0.11	2.35		MOM12
2	7.16	0.06	1.46	LPrice		29	10.92	0.11	2.59	POUT	
3	9.34	0.10	2.30	MOM18		30	9.57	0.11	2.26		Crossover3_12
4	8.57	0.10	2.20		MOM12	31	10.82	0.11	2.49		PVar12
5	8.86	0.10	2.29		POUT	32	10.26	0.12	2.40		MOM6
6	8.41	0.10	2.07		Crossover3_12	33	10.28	0.12	2.66		Beta
7	8.89	0.10	2.19		PVar12	34	10.83	0.12	2.41		ROE
8	8.30	0.10	2.09		MOM6	35	9.80	0.11	2.39		MOM3
9	8.51	0.10	2.34		Beta	36	9.58	0.11	2.24		RetVar12
10	9.20	0.10	2.10		ROE	37	10.75	0.11	2.48		Gearing
11	8.20	0.10	2.14		MOM3	38	10.69	0.11	2.48		SG12
12	8.17	0.10	2.06		RetVar12	39	10.03	0.11	2.54		LMV
13	9.56	0.10	2.34	DY		40	8.06	0.10	1.77		EG24_P
14	9.34	0.10	2.20		Gearing	41	10.95	0.11	2.57		DPSG12
15	9.60	0.10	2.26		SG12	42	10.77	0.12	2.32		Sales_to_MV
16	10.43	0.11	2.48	BVTP		43	10.86	0.12	2.54		Current
17	9.49	0.11	2.43		LMV	44	9.11	0.11	1.95		EG12_P
18	7.69	0.10	1.69		EG24_P	45	9.54	0.10	2.37		DPSG24
19	10.47	0.11	2.47		DPSG12	46	9.21	0.10	2.26		SG24
20	10.45	0.11	2.21		Sales_to_MV	47	10.14	0.10	2.33		CEYG1
21	10.39	0.11	2.42		Current	48	9.62	0.11	2.27		MOM1
22	8.75	0.11	1.87		EG12_P						
23	9.17	0.10	2.28		DPSG24						
24	8.74	0.09	2.15		SG24						
25	9.67	0.10	2.23		CEYG1						
26	9.23	0.10	2.18		MOM1						
27	10.35	0.11	2.47		EY						

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A.19. Information Coefficient (IC)

Displays the stepwise process by which attributes are either included (accepted) or rejected entry into the model using IC. Attributes are accepted if there is an improvement in the performance of the model now including the attribute (as measured by IC.) Attributes rejected in a pass are retested in the following pass. This process repeated until no new attributes are accepted in an entire pass. Statistics are calculated using the in-sample period (1 Mar 1990 – 1 Feb 2000) The inclusion of the final attribute is shaded. Note that all attributes in pass 2 are rejected.

Pass 1					
Step	t-stat	IC	IR	Accept	Reject
1	4.54	0.03	0.57	ICBT	
2	7.16	0.06	1.46	LPrice	
3	9.34	0.10	2.30	MOM18	
4	8.57	0.10	2.20	MOM12	
5	8.25	0.10	2.19		POUT
6	8.37	0.11	2.16	Crossover3_12	
7	8.18	0.10	1.99		PVar12
8	7.94	0.10	1.89		MOM6
9	7.97	0.11	2.19	Beta	
10	7.92	0.11	1.99	ROE	
11	7.80	0.11	1.92		MOM3
12	6.35	0.10	1.78		RetVar12
13	8.03	0.11	2.00	DY	
14	7.54	0.11	1.94		Gearing
15	8.77	0.11	2.05	SG12	
16	8.88	0.12	2.14	BVTP	
17	8.62	0.12	2.12		LMV
18	6.31	0.10	1.50		EG24_P
19	8.88	0.12	2.11		DPSG12
20	8.57	0.12	2.01		Sales_to_MV
21	8.97	0.12	2.12		Current
22	6.92	0.11	1.67		EG12_P
23	8.23	0.11	1.96		DPSG24
24	9.14	0.12	2.16	SG24	
25	8.60	0.11	1.91		CEYG1
26	7.57	0.11	1.85		MOM1
27	9.11	0.12	2.14		EY

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A.20. Information Ratio (Grinold, 1989)

Displays the stepwise process by which attributes are either included (accepted) or rejected entry into the model using Grinold's (1989) Information Ratio (IR). IR adapts the IC coefficient by taking the breadth of shares over which forecasts are made into account. $IR \approx IC\sqrt{N}$ Attributes are accepted if there is an improvement in the performance of the model now including the attribute (as measured by the performance criterion.) Attributes rejected in a pass are retested in the following pass. This process repeated until no new attributes are accepted in an entire pass. Statistics are calculated using the in-sample period (1 Mar 1990 – 1 Feb 2000) The inclusion of the final attribute is shaded.

Pass 1						Pass 2					
Step	t-stat	IC	IR	Accept	Reject	Step	t-stat	IC	IR	Accept	Reject
1	4.54	0.03	0.57	ICBT		28	9.09	0.11	2.53	POUT	
2	7.16	0.06	1.46	LPrice		29	8.43	0.11	2.22		Crossover3_12
3	9.34	0.10	2.30	MOM18		30	9.13	0.11	2.44		PVar12
4	8.57	0.10	2.20		MOM12	31	8.65	0.11	2.35		MOM6
5	8.86	0.10	2.29		POUT	32	9.68	0.12	2.38		ROE
6	8.41	0.10	2.07		Crossover3_12	33	8.52	0.11	2.33		MOM3
7	8.89	0.10	2.19		PVar12	34	8.34	0.10	2.16		RetVar12
8	8.30	0.10	2.09		MOM6	35	10.28	0.12	2.66	DY	
9	8.51	0.10	2.34	Beta		36	10.23	0.12	2.57		Gearing
10	8.54	0.10	2.13		ROE	37	10.03	0.11	2.55		SG12
11	7.84	0.10	2.19		MOM3	38	9.55	0.12	2.61		LMV
12	7.80	0.10	2.07		RetVar12	39	7.70	0.10	1.81		EG24_P
13	8.91	0.10	2.39		DY	40	10.31	0.12	2.65		DPSG12
14	8.72	0.10	2.26		Gearing	41	10.33	0.12	2.37		Sales_to_MV
15	8.90	0.10	2.31		SG12	42	10.34	0.12	2.62		Current
16	9.78	0.11	2.55	BVTP		43	8.79	0.11	2.01		EG12_P
17	9.04	0.11	2.50		LMV	44	8.99	0.11	2.44		DPSG24
18	7.33	0.10	1.73		EG24_P	45	8.72	0.10	2.32		SG24
19	9.82	0.11	2.53		DPSG12	46	9.48	0.11	2.41		CEYG1
20	10.06	0.12	2.26		Sales_to_MV	47	9.35	0.11	2.34		MOM1
21	9.83	0.11	2.50		Current	48	9.99	0.12	2.63		EY
22	8.43	0.11	1.93		EG12_P						
23	8.63	0.10	2.35		DPSG24						
24	8.32	0.10	2.21		SG24						
25	8.98	0.10	2.31		CEYG1						
26	8.96	0.11	2.24		MOM1						
27	9.83	0.11	2.53		EY						

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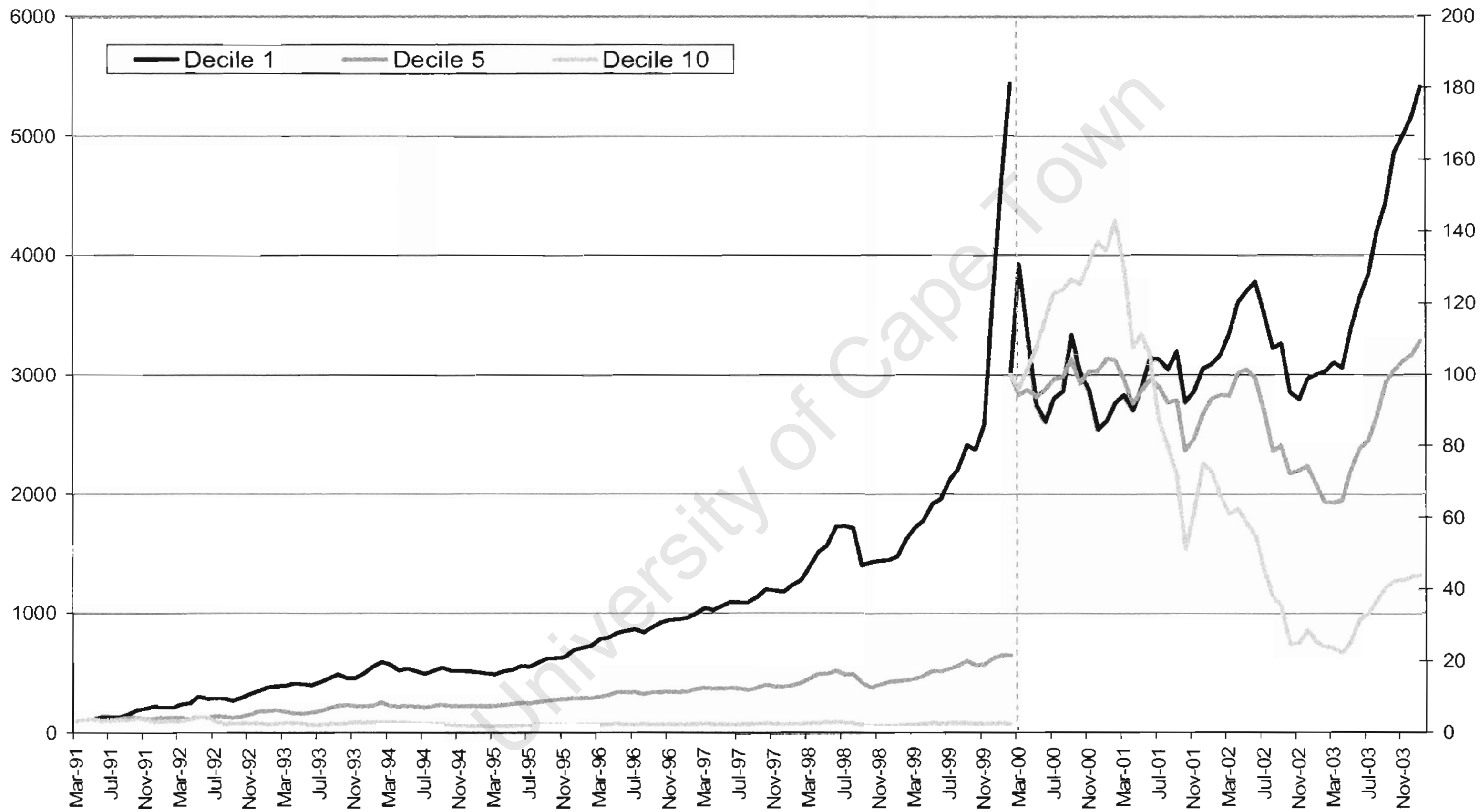
Expected Return Model Performance Graphs

A.21. All Attribute Model (AAM)

Cumulative (reinvested) return on £100 invested for the in-sample period 1 Mar 1990 – 1 Feb 2000, and £100 again invested for the out-of-sample period 1 Mar 2000 – 1 Feb 2004. The dashed line separates in-sample from out-of-sample. Decile 1 represents the top forecast decile's cumulative mean return, and Decile 10 represents the bottom decile's cumulative mean return.



A.22. T-Statistic Of Slope Model (TSM)

Cumulative (reinvested) return on £100 invested for the in-sample period 1 Mar 1990 – 1 Feb 2000, and £100 again invested for the out-of-sample period 1 Mar 2000 – 1 Feb 2004. The dashed line separates in-sample from out-of-sample. Decile 1 represents the top forecast decile's cumulative mean return, and Decile 10 represents the bottom decile's cumulative mean return.

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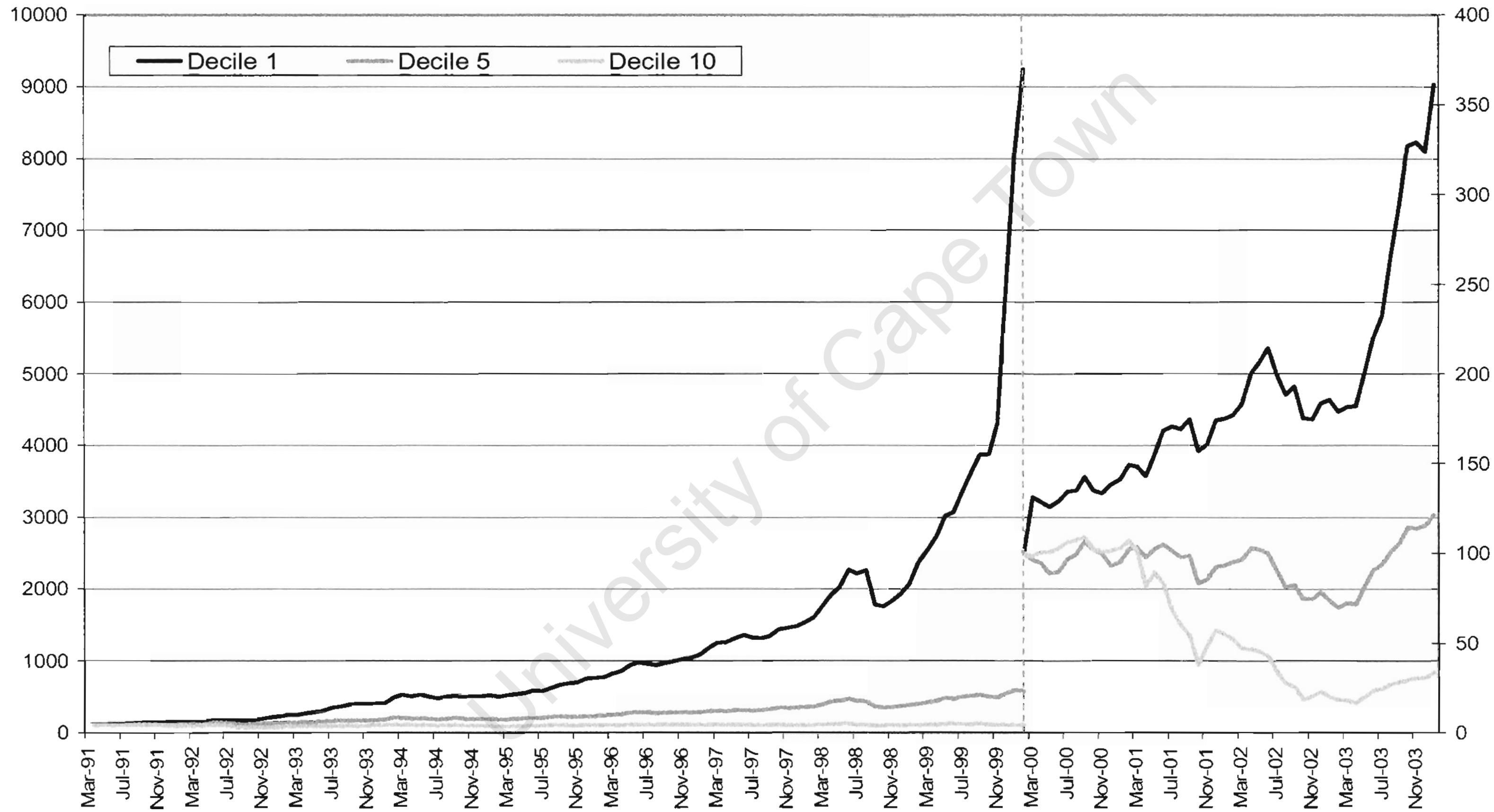
A.23. Information Coefficient (IC) Model (ICM)

Cumulative (reinvested) return on £100 invested for the in-sample period 1 Mar 1990 – 1 Feb 2000, and £100 again invested for the out-of-sample period 1 Mar 2000 – 1 Feb 2004. The dashed line separates in-sample from out-of-sample. Decile 1 represents the top forecast decile's cumulative mean return, and Decile 10 represents the bottom decile's cumulative mean return.



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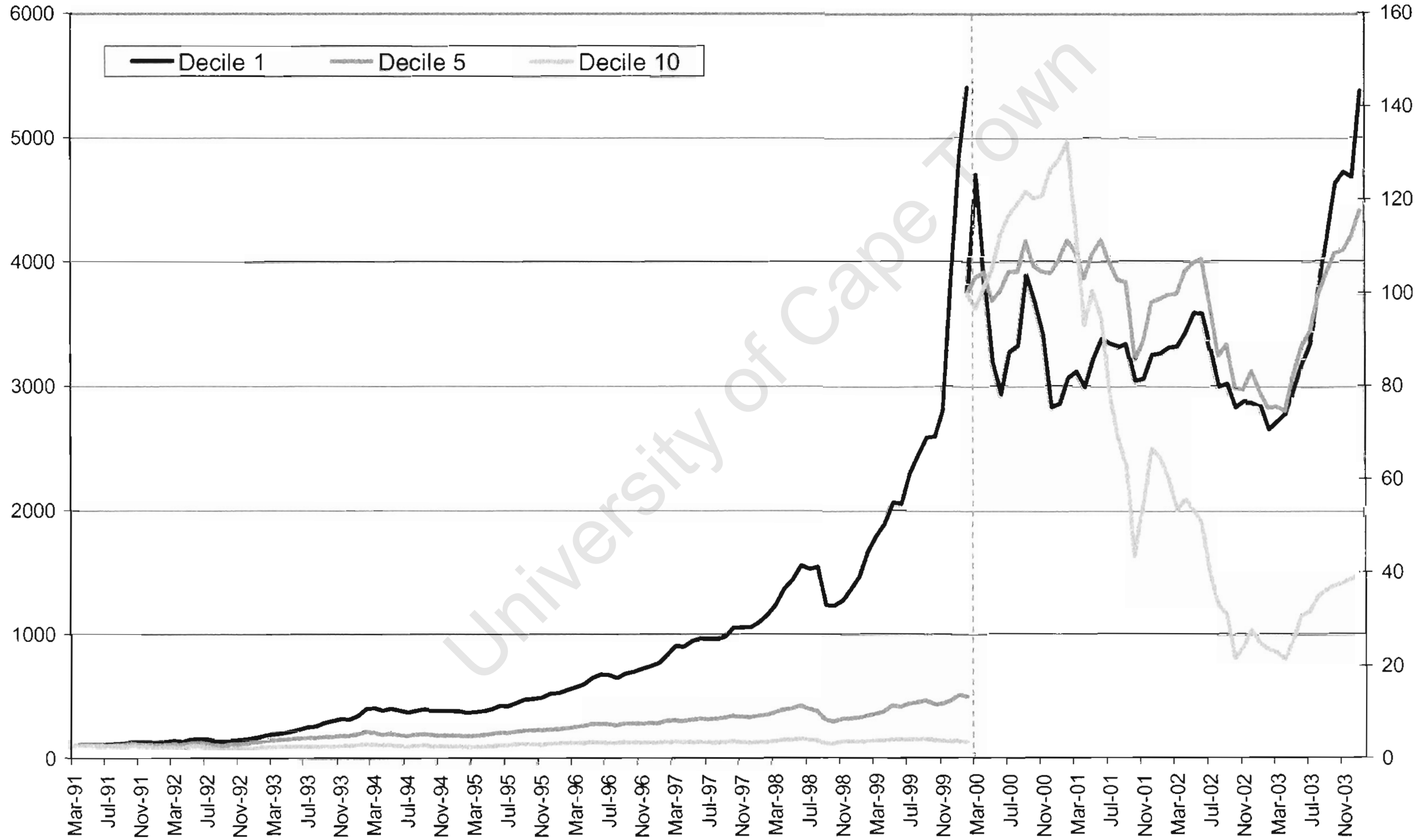
A.24. Information Ratio (IR) Model (IRM)

Cumulative (reinvested) return on £100 invested for the in-sample period 1 Mar 1990 – 1 Feb 2000, and £100 again invested for the out-of-sample period 1 Mar 2000 – 1 Feb 2004. The dashed line separates in-sample from out-of-sample. Decile 1 represents the top forecast decile's cumulative mean return, and Decile 10 represents the bottom decile's cumulative mean return.



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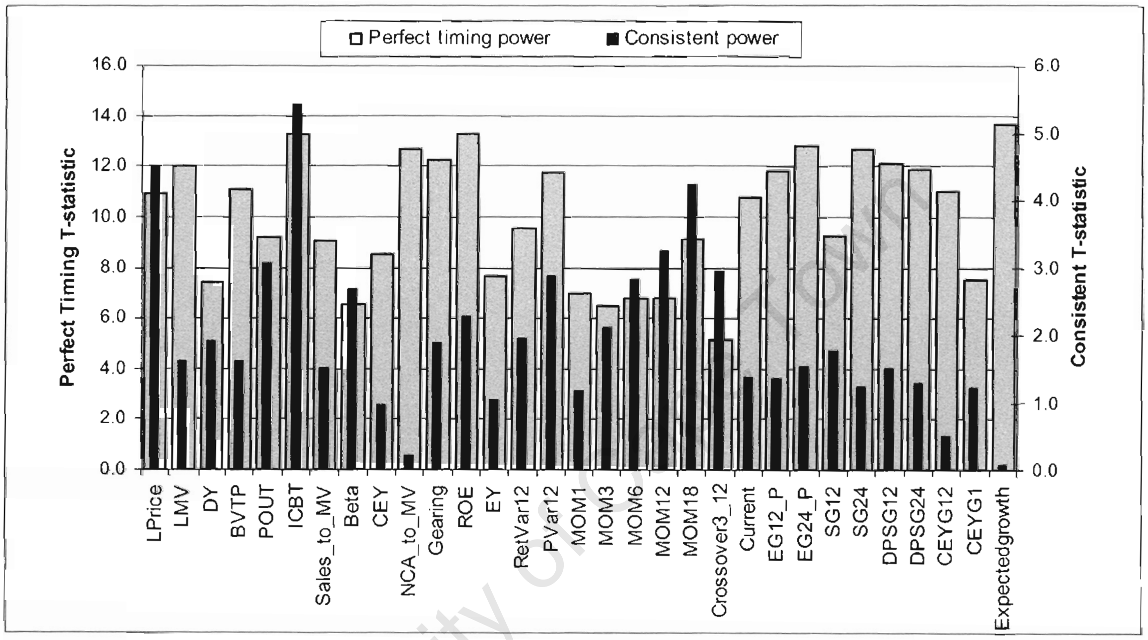
Appendix B (Chapter 7)

B.1 Consistent Performance versus Potential (Timed) Performance

Dark bars represent t-statistics of the absolute value of the mean monthly univariate slope coefficient over the in-sample period 1 Mar 1990 – 1 Feb 2000. Light bars represent t-statistics of the mean absolute value of monthly univariate slope coefficients over the in-sample period 1 Mar 1990 – 1 Feb 2000. Dark bars represent the absolute value of the conventional t-statistic discussed in *Section 6.4*. Light bars represent t-statistics possible if the sign of each monthly payoff is known in advance. In this case the direction of the payoff is not important as it can be forecast. The mean absolute value of monthly payoffs therefore gives an overall measure of magnitude ignoring sign. The related t-statistic gives a measure of potential t-statistic possible if payoff signs can be correctly forecast.



Style momentum results

B.2. Q-Statistic Test For Autocorrelation In Payoffs

Displays Ljung-Box Q-Statistics for each number of payoff lags cumulatively. The Q-statistic is used to test for autocorrelation in style payoffs for k = 1 to 12 lags. (H_0: There is no autocorrelation up to order k.) Values significant at the 95% significance level are bolded

Lags:	1	2	3	4	5	6	7	8	9	10	11	12
Size												
LMV	**11**	**17**	**18**	**19**	**19**	**20**	**23**	**31**	**32**	**33**	**34**	**34**
LPrice	**8**	**13**	**13**	**15**	**15**	**18**	**18**	**18**	**20**	**29**	**30**	**30**
Value												
BVTP	**13**	**24**	**32**	**32**	**33**	**34**	**34**	**34**	**35**	**35**	**36**	**39**
CEY	**29**	**45**	**59**	**63**	**64**	**64**	**64**	**64**	**65**	**66**	**66**	**66**
DY	**43**	**63**	**75**	**77**	**77**	**77**	**77**	**77**	**77**	**77**	**78**	**78**
EY	**43**	**68**	**83**	**85**	**85**	**85**	**86**	**87**	**88**	**88**	**88**	**89**
Sales_to_MV	**25**	**35**	**43**	**44**	**44**	**46**	**49**	**50**	**52**	**53**	**55**	**58**
Growth												
CEYG1	**8**	**9**	**28**	**31**	**31**	**31**	**31**	**32**	**34**	**34**	**34**	**38**
CEYG12	0	1	1	1	2	5	7	7	8	8	9	9
DPSG12	2	5	6	6	8	9	11	12	12	12	12	13
DPSG24	2	**9**	**12**	**14**	**15**	**16**	**21**	**24**	**26**	**29**	**35**	**35**
EG12_P	1	**7**	7	7	7	7	7	8	8	8	9	9
EG24_P	2	3	8	9	10	10	10	11	11	15	18	18
Expectedgrowth	3	6	7	**14**	**14**	**14**	**21**	**21**	**21**	**22**	**25**	**25**
Gearing	**4**	**9**	**12**	**13**	**16**	**16**	**17**	**19**	**20**	**23**	**25**	**25**
POUT	**26**	**48**	**60**	**63**	**65**	**66**	**68**	**72**	**73**	**75**	**79**	**83**
ROE	**7**	**10**	**22**	**42**	**44**	**47**	**51**	**58**	**58**	**59**	**61**	**63**
SG12	**28**	**44**	**51**	**57**	**58**	**60**	**61**	**63**	**66**	**69**	**71**	**73**
SG24	**21**	**36**	**37**	**42**	**46**	**54**	**55**	**61**	**61**	**68**	**71**	**71**
Liquidity												
Current	**23**	**31**	**37**	**37**	**38**	**39**	**39**	**40**	**41**	**41**	**42**	**43**
ICBT	3	3	**12**	**14**	**15**	**15**	**17**	**17**	**18**	18	18	19
NCA_to_MV	3	3	3	5	7	7	8	8	8	9	9	9
Risk												
Beta	**30**	**46**	**60**	**62**	**62**	**62**	**62**	**65**	**66**	**72**	**77**	**79**
PVar12	**20**	**37**	**53**	**57**	**58**	**61**	**63**	**64**	**65**	**67**	**68**	**68**
RetVar12	**25**	**36**	**45**	**47**	**48**	**48**	**51**	**51**	**52**	**52**	**53**	**55**
Momentum												
Crossover3_12	**53**	**82**	**101**	**105**	**106**	**107**	**110**	**112**	**113**	**115**	**115**	**115**
MOM1	**40**	**65**	**78**	**80**	**80**	**80**	**80**	**80**	**81**	**81**	**81**	**81**
MOM3	**46**	**79**	**100**	**105**	**106**	**106**	**107**	**108**	**108**	**108**	**108**	**108**
MOM6	**43**	**73**	**92**	**98**	**100**	**100**	**101**	**102**	**102**	**103**	**103**	**103**
MOM12	**45**	**71**	**85**	**89**	**90**	**90**	**90**	**90**	**91**	**91**	**91**	**92**
MOM18	**33**	**44**	**54**	**58**	**58**	**59**	**59**	**60**	**61**	**62**	**62**	**62**

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Seasonality

B.3. Results: Calendar Seasonality In Style Payoffs (all months)

Autocorrelations and partial autocorrelations between style payoffs and their twelve month lagged values. Significant correlations indicate an annual pattern to payoffs. Tests are conducted over the in-sample period (1 Mar 1990 – 1 Feb 2000). No values are significant at the 5% level..

	AC	(T-statistic)	PAC	(T-statistic)
Size				
LMV	0.08	(0.80)	0.10	(1.08)
LPrice	0.02	(0.18)	0.10	(1.06)
Value				
BVTP	0.15	(1.57)	0.09	(0.88)
CEY	0.06	(0.66)	0.05	(0.56)
DY	0.04	(0.45)	-0.02	-(0.20)
EY	0.05	(0.47)	0.04	(0.43)
Sales_to_MV	0.15	(1.51)	0.06	(0.64)
Growth				
CEYG1	-0.17	-(1.80)	-0.14	-(1.40)
CEYG12	0.02	(0.23)	-0.01	-(0.09)
DPSG12	0.08	(0.85)	0.02	(0.25)
DPSG24	-0.02	-(0.19)	0.15	(1.51)
EG12_P	0.00	(0.02)	-0.01	-(0.05)
EG24_P	0.01	(0.11)	0.02	(0.24)
Expectedgrowth	0.03	(0.31)	0.05	(0.49)
Gearing	-0.02	-(0.16)	-0.13	-(1.30)
POUT	0.17	(1.72)	0.10	(1.01)
ROE	0.11	(1.13)	-0.01	-(0.10)
SG12	0.12	(1.21)	0.02	(0.18)
SG24	0.05	(0.55)	-0.15	-(1.56)
Liquidity				
Current	0.10	(1.06)	0.12	(1.23)
ICBT	-0.08	-(0.86)	-0.05	-(0.46)
NCA_to_MV	0.00	-(0.04)	-0.02	-(0.21)
Risk				
Beta	0.13	(1.30)	-0.01	-(0.11)
PVar12	0.02	(0.20)	-0.07	-(0.72)
RetVar12	0.13	(1.33)	0.06	(0.63)
Momentum				
Crossover3_12	0.02	(0.24)	0.07	(0.67)
MOM1	-0.05	-(0.55)	-0.04	-(0.43)
MOM3	-0.03	-(0.33)	0.03	(0.35)
MOM6	-0.02	-(0.24)	0.05	(0.54)
MOM12	0.07	(0.69)	0.00	(0.00)
MOM18	0.03	(0.28)	0.04	(0.45)

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Economic Relationships

B.4. Description Of Macroeconomic Variables

All variables downloaded using Datastream International.

Interest Rates, Inflation and the Money Supply

Tbill_3Month
Three months treasury bills yield
Datastream code: UKGBILL3
Source: Office for National Statistics, United Kingdom
Updated: Monthly using endpoint
Unit: Percentage

Bond_20y
Gross redemption yield on 20 year gilts
Datastream code: UKGBOND
Source: Bank of England
Updated: Monthly using average
Unit: Percentage

Term_Structure
Difference between the gross redemption yield on 20 year gilts and the three months treasury bills yield
Datastream codes: UKGBOND - UKGBILL3
Unit: Percentage

Inflation
Inflation rate
Datastream code: UKRPANNL
Source: Office for National Statistics, United Kingdom
Updated: Monthly using average
Unit: Percentage

Moneysupply
UK money supply (M4) at current prices, seasonally adjusted
Datastream code: UKM4....B
Source: Office for National Statistics, United Kingdom
Updated: Monthly using endpoint
Units – £ million

ExRate
US:UK exchange rate. US dollars ($) to one pound.
Datastream code: UKXRUSD
Source: Bank of England
Updated: Monthly using average

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Cross-sectional Dispersion of Attributes

DY_Dsp
Monthly standard deviation of the attribute dividend yield (DY) for constituents of the FTSE UK Allshare index.

EG12P_ Dsp
Monthly standard deviation of the attribute EG12P for constituents of the FTSE UK Allshare index

EG24P_ Dsp
Monthly standard deviation of the attribute EG24P for constituents of the FTSE UK Allshare index

EY_ Dsp
Monthly standard deviation of the attribute Earnings yield (EY) for constituents of the FTSE UK Allshare index

Market Variables

Market variables are calculated using the overall UK index maintained by Datastream.
Datastream Code: TOTMKUK

The Following securities are excluded from the index: fixed interest shares, unit trusts, mutual funds, investment funds, warrants, temporary issues, foreign listings, including ADRs and foreign board shares. A full set of rules governing the maintenance of the index is available from Datastream.

Mkt_DY
Aggregate dividend yield (DY) of the market

Mkt_Earnings
Aggregate earnings (E) of the market

Mkt_EY
Aggregate earnings yield (EY) of the market

EY_Gap
Difference between the aggregate earnings yield (EY) of the market and the gross redemption yield on 20 year gilts

DS_ Index
Aggregate market capitalisation

Mkt_RP
Difference between monthly return on the market (percentage change in DS_Index) and the three months treasury bills yield

Mkt_StdDev6M
Standard deviation of the monthly market capitalisation (DS_Index) over the past six months.

Business Cycle indicators

Composite
UK Composite Leading Indicator (trend restored)
Datastream code: UKCYLEAD
Source: Main Economic Indicators (MEI), OECD
Measures quantitative and qualitative economic variables to predict the future short-run state of the economy. Detailed information on the OECD methodology can be found on the OECD website at http://www.oecd.org/std/cli
Updated: Monthly

Optimism
CBI enquiry: business optimism, not seasonally adjusted
Datastream code: UKCNFBUSR
Source: Confederation of British Industry
Updated: Quarterly
Unit: Percentage

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B.5. Granger Causality Results

Granger tests are performed on the monthly payoff and macroeconomic data over the in-sample period (1 Mar 1990 – 1 Feb 2000). F-statistics of the null that a macroeconomic variable (row) does not Granger cause a payoff series (column) are reported. The minimum Coefficients significant at the 5% level are displayed in bold.

	Interest Rates, Exchange Rates, Inflation and the Money Supply						Cross-sectional Dispersions of Attributes		
	Tbill_3Month	DBond_20y	Term_Structure	Inflation	DLMoneysupply	ExRate	EG12P_Dsp	EG24P_Dsp	EY_Dsp
Size									
LMV	0.19	0.29	0.30	0.44	0.87	0.43	**0.04**	0.29	0.57
LPrice	**0.04**	0.36	0.67	0.54	0.79	0.37	0.13	0.15	0.54
Value									
BVTP	0.78	0.88	0.86	0.10	0.48	0.84	1.00	0.62	0.43
CEY	0.34	0.21	0.38	0.87	0.69	0.89	0.43	0.54	0.54
DY	0.43	0.28	0.22	0.66	0.40	0.08	0.47	0.99	0.61
EY	0.24	0.29	0.11	0.87	0.06	0.26	0.63	1.00	0.97
Sales_to_MV	0.73	0.11	0.90	0.58	0.80	0.59	0.07	0.12	0.72
Growth									
CEYG1	0.06	0.25	0.76	0.90	0.93	**0.01**	0.31	0.59	0.09
CEYG12	0.18	0.19	**0.02**	0.12	0.72	0.28	0.11	0.46	0.07
DPSG12	**0.00**	0.06	**0.00**	0.09	0.96	**0.00**	**0.02**	**0.01**	0.70
DPSG24	0.39	0.19	0.32	0.28	0.84	0.13	0.06	**0.00**	0.49
EG12_P	0.45	0.15	0.30	0.35	0.70	0.17	0.11	**0.00**	**0.03**
EG24_P	0.45	0.34	0.11	0.14	0.89	0.63	0.29	**0.00**	0.18
Expectedgrowth	0.07	0.86	0.16	0.14	0.56	0.14	**0.04**	**0.05**	0.29
Gearing	0.38	0.16	0.40	0.06	0.40	0.95	0.05	**0.00**	0.50
POUT	0.53	0.66	0.48	0.92	0.69	0.50	0.31	0.51	0.05
ROE	0.34	0.40	0.17	0.37	0.64	0.11	0.71	0.07	0.97
SG12	0.45	0.85	0.21	**0.02**	0.57	0.68	0.97	0.40	0.39
SG24	0.15	0.54	0.16	0.74	0.80	0.77	0.97	0.79	0.30
Liquidity									
Current	0.39	0.92	0.58	0.69	0.70	0.91	0.12	0.30	0.07
ICBT	0.06	0.64	0.67	0.16	0.11	0.24	0.45	0.25	0.07
NCA_to_MV	0.11	0.66	0.53	0.42	0.40	**0.03**	0.23	**0.04**	0.09
Risk									
Beta	0.55	0.54	0.39	0.13	0.35	0.11	0.94	0.63	0.51
PVar12	0.45	0.75	0.45	0.66	0.58	0.53	0.71	0.98	0.08
RetVar12	0.48	0.45	0.56	0.56	0.52	0.27	0.39	0.15	**0.01**
Momentum									
Crossover3_12	0.43	0.62	0.69	0.08	0.81	0.87	0.89	0.96	0.27
MOM1	0.77	0.28	0.78	0.62	0.35	0.35	0.78	1.00	0.93
MOM3	0.76	0.35	0.65	0.41	0.48	0.91	0.91	0.94	0.54
MOM6	0.76	0.73	0.77	0.50	0.39	0.54	0.90	0.99	0.98
MOM12	0.80	0.68	0.85	0.70	0.23	0.70	0.99	1.00	0.98
MOM18	0.53	0.07	0.24	0.86	0.96	0.27	0.37	0.42	0.87
Minimum P value	**0.00**	**0.06**	**0.00**	**0.02**	**0.06**	**0.00**	**0.02**	**0.00**	**0.01**

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I.5. Granger Causality Results (Continued)

	Market Variables					Business Cycle Indicators	
	DLMkt_Earnings	Mkt_EY	EY_Gap	DLDS_Index	Mkt_StdDev6m	DLComposite	Optimism
Size							
LMV	0.74	0.43	0.38	**0.00**	0.09	**0.01**	0.12
LPrice	0.52	0.41	0.09	**0.00**	0.14	**0.04**	0.33
Value							
BVTP	0.08	0.76	0.21	0.41	**0.03**	0.07	0.20
CEY	0.06	0.31	**0.03**	0.78	0.17	0.55	0.22
DY	**0.02**	0.68	0.39	0.81	**0.03**	**0.04**	**0.03**
EY	0.09	0.49	0.58	0.39	0.05	0.06	0.14
Sales_to_MV	0.28	0.20	**0.01**	0.07	0.16	**0.02**	0.11
Growth							
CEYG1	**0.02**	**0.01**	**0.01**	0.18	0.80	0.15	**0.01**
CEYG12	0.98	0.24	**0.04**	0.57	0.51	0.06	**0.03**
DPSG12	0.87	0.65	0.30	0.76	0.86	0.05	0.74
DPSG24	0.92	0.99	0.55	0.62	0.73	0.16	0.16
EG12_P	0.09	**0.05**	**0.04**	0.18	0.64	0.27	**0.03**
EG24_P	0.49	0.20	0.38	0.21	0.12	0.89	0.32
Expectedgrowth	0.76	0.55	0.84	0.61	0.58	0.81	0.13
Gearing	0.29	0.37	0.09	0.45	0.30	0.21	0.15
POUT	**0.02**	0.37	0.27	0.18	0.49	0.40	0.07
ROE	0.81	0.22	0.50	0.68	0.94	0.07	0.29
SG12	0.58	0.91	0.36	0.33	0.22	0.43	0.75
SG24	0.82	0.35	**0.04**	0.48	**0.04**	0.20	0.75
Liquidity							
Current	0.21	0.06	0.15	0.35	0.13	**0.05**	0.44
ICBT	0.09	**0.04**	0.89	0.84	**0.01**	0.27	0.34
NCA_to_MV	0.17	0.55	0.27	0.86	0.11	0.27	0.90
Risk							
Beta	0.10	0.79	0.21	0.98	**0.03**	0.83	**0.02**
PVar12	0.71	0.49	0.24	0.50	0.31	0.15	0.09
RetVar12	0.21	0.18	0.12	**0.02**	0.26	0.58	**0.02**
Momentum							
Crossover3_12	0.80	0.32	0.35	0.34	**0.01**	0.16	**0.02**
MOM1	0.06	0.42	0.13	0.94	0.05	0.17	**0.00**
MOM3	0.41	0.44	0.09	0.25	**0.00**	**0.05**	**0.01**
MOM6	0.36	0.47	0.38	0.81	**0.00**	0.50	0.15
MOM12	0.12	0.72	0.40	0.91	**0.00**	0.29	0.12
MOM18	0.14	0.62	0.14	0.39	**0.02**	0.72	0.12
Minimum P value	**0.02**	**0.01**	**0.01**	**0.00**	**0.00**	**0.02**	**0.00**

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Appendix C (Chapter 8)

Regression Model diagnostics

C.1. Consolidated Model

Results from regressions with each style payoff as the independent variable and all useful forecasters including macroeconomic variables (for construction see Section 8.2.1) as dependent variable over the in-sample period 1 Mar 1990 – 1 Feb 2000. T-statistics of individual factor coefficients are not shown due to space constraints. Constant coefficient t-statistics and F-statistic probabilities significant at the 5% level are bolded.

	R^2	R^2adj	Akaike	Schwartz	Stnd Error of Regression	F-statistic	prob(F)	DW-statistic	Log Likelihood	Mean of Dependent Var.	Stnd dev. of Dependent Var.	T:constant
Size												
LMV	0.47	0.47	-5.91	-5.49	0.01	5.03	**0.00**	1.91	336	0.00	0.01	-0.6
LPrice	0.38	0.38	-6.32	-6.07	0.01	6.74	**0.00**	1.79	351	-0.01	0.01	**-2.6**
Value												
BVTP	0.24	0.24	-6.49	-6.34	0.01	6.34	**0.00**	1.84	356	0.00	0.01	0.6
CEY	0.47	0.47	-6.00	-5.83	0.01	14.86	**0.00**	2.05	331	0.00	0.02	**-2.3**
DY	0.60	0.60	-6.00	-5.70	0.01	13.07	**0.00**	1.95	336	0.00	0.02	0.4
EY	0.49	0.49	-5.95	-5.83	0.01	24.73	**0.00**	1.98	327	0.00	0.02	-1.0
Sales_to_MV	0.46	0.46	-5.85	-5.45	0.01	5.20	**0.00**	1.91	332	0.00	0.02	**-2.5**
Growth												
CEYG1	0.56	0.56	-6.82	-6.35	0.01	6.28	**0.00**	2.16	387	0.00	0.01	**-2.5**
CEYG12	0.00	0.00	-7.81	-7.76	0.00	0.01	0.92	1.99	467	0.00	0.00	0.5
DPSG12	0.35	0.35	-7.56	-7.06	0.01	2.49	**0.00**	1.99	428	0.00	0.01	-0.7
DPSG24	0.24	0.24	-7.62	-7.35	0.01	3.01	**0.00**	2.06	426	0.00	0.01	-0.2
EG12_P	0.19	0.19	-6.54	-6.34	0.01	3.48	**0.00**	1.98	374	0.00	0.01	**3.0**
EG24_P	0.14	0.14	-6.53	-6.34	0.01	2.52	**0.02**	2.11	384	0.00	0.01	-0.2
Expectedgrowth	0.14	0.14	-7.66	-7.47	0.01	2.38	**0.03**	1.89	422	0.00	0.01	-1.3
Gearing	0.11	0.11	-7.40	-7.25	0.01	2.44	**0.04**	1.93	405	0.00	0.01	-0.7
POUT	0.36	0.36	-6.30	-6.17	0.01	14.19	**0.00**	1.91	345	0.00	0.01	-0.9
ROE	0.30	0.30	-7.36	-7.21	0.01	8.60	**0.00**	2.00	403	0.00	0.01	0.3
SG12	0.45	0.45	-7.24	-6.94	0.01	7.24	**0.00**	1.97	403	0.00	0.01	-0.8
SG24	0.43	0.43	-7.62	-7.10	0.00	3.23	**0.00**	2.04	433	0.00	0.01	-0.1
Liquidity												
Current	0.27	0.27	-7.21	-7.06	0.01	7.55	**0.00**	1.91	395	0.00	0.01	0.0
ICBT	0.28	0.28	-7.94	-7.74	0.00	5.61	**0.00**	1.85	441	0.00	0.01	-1.6
NCA_to_MV	0.07	0.07	-6.51	-6.43	0.01	4.22	**0.02**	1.75	358	0.00	0.01	-1.5
Risk												
Beta	0.45	0.45	-5.61	-5.41	0.01	11.49	**0.00**	2.01	311	0.01	0.02	-0.5
PVar12	0.31	0.31	-6.78	-6.65	0.01	11.56	**0.00**	1.76	371	0.00	0.01	0.6
RetVar12	0.42	0.42	-5.72	-5.49	0.01	9.01	**0.00**	1.97	318	0.00	0.02	0.0
Momentum												
Crossover3_12	0.78	0.78	-6.75	-6.48	0.01	34.01	**0.00**	2.01	376	0.00	0.02	0.5
MOM1	0.55	0.55	-6.06	-5.78	0.01	11.86	**0.00**	1.95	338	0.00	0.02	1.1
MOM3	0.69	0.69	-5.97	-5.55	0.01	12.81	**0.00**	1.91	339	0.00	0.02	-1.2
MOM6	0.64	0.64	-6.02	-5.82	0.01	25.26	**0.00**	1.91	333	0.01	0.02	-0.7
MOM12	0.62	0.62	-6.03	-5.75	0.01	15.55	**0.00**	2.03	336	0.01	0.02	-0.4
MOM18	0.45	0.45	-5.85	-5.70	0.01	16.86	**0.00**	1.82	322	0.01	0.02	1.6
Mean	**0.38**	**0.38**	**-6.63**	**-6.38**	**0.01**	**9.60**	**0.03**	**1.95**	**370.42**	**0.00**	**0.01**	**-0.44**
Standard deviation	**0.19**	**0.19**	**0.72**	**0.73**	**0.00**	**7.71**	**0.16**	**0.10**	**42.28**	**0.00**	**0.00**	**1.24**

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C.2. 12M Reg Model

Results from regressions with each style payoff as the independent variable and its trailing twelve month moving average as dependent variable over the in-sample period 1 Mar 1990 – 1 Feb 2000. T-statistics of individual factor coefficients are not shown due to space constraints. Constant coefficient t-statistics and F-statistic probabilities significant at the 5% level are bolded.

	R^2	R^2adj	Akaike	Schwartz	Stnd Error of Regression	F-statistic	prob(F)	DW-statistic	Log Likelihood	Mean of Dependent Var.	Stnd dev. of Dependent Var.	T:constant
Size												
LMV	0.06	0.06	-5.62	-5.57	0.01	7.20	**0.01**	1.55	305	0.00	0.01	-1.7
LPrice	0.00	0.00	-5.99	-5.94	0.01	0.06	0.81	1.19	325	-0.01	0.01	**-2.9**
Value												
BVTP	0.11	0.11	-6.41	-6.36	0.01	13.11	**0.00**	1.29	348	0.00	0.01	-1.2
CEY	0.31	0.31	-5.83	-5.78	0.01	47.62	**0.00**	1.20	317	0.00	0.02	**-2.7**
DY	0.33	0.33	-5.66	-5.61	0.01	51.30	**0.00**	0.99	308	0.00	0.02	-1.7
EY	0.32	0.32	-5.72	-5.67	0.01	50.03	**0.00**	1.06	311	0.00	0.02	-3.1
Sales_to_MV	0.07	0.07	-5.56	-5.51	0.01	7.40	**0.01**	0.94	302	0.00	0.02	-1.3
Growth												
CEYG1	0.05	0.05	-6.37	-6.32	0.01	5.98	**0.02**	1.43	346	0.00	0.01	-1.6
CEYG12	0.01	0.01	-7.84	-7.79	0.00	0.86	0.36	1.97	426	0.00	0.00	-0.1
DPSG12	0.04	0.04	-7.51	-7.46	0.01	4.85	**0.03**	1.71	407	0.00	0.01	0.7
DPSG24	0.00	0.00	-7.51	-7.46	0.01	0.04	0.84	1.76	408	0.00	0.01	-2.0
EG12_P	0.00	0.00	-6.54	-6.49	0.01	0.52	0.47	1.93	355	0.00	0.01	1.0
EG24_P	0.00	0.00	-6.65	-6.60	0.01	0.48	0.49	1.90	361	0.00	0.01	0.9
Expectedgrowth	0.04	0.04	-7.66	-7.61	0.01	3.98	**0.05**	1.76	416	0.00	0.01	0.6
Gearing	0.05	0.05	-7.41	-7.36	0.01	5.63	**0.02**	1.85	402	0.00	0.01	0.1
POUT	0.32	0.32	-6.29	-6.24	0.01	48.77	**0.00**	1.52	342	0.00	0.01	-1.0
ROE	0.13	0.13	-7.22	-7.17	0.01	15.58	**0.00**	1.91	392	0.00	0.01	-0.1
SG12	0.36	0.36	-7.26	-7.21	0.01	59.05	**0.00**	1.58	394	0.00	0.01	1.8
SG24	0.23	0.23	-7.67	-7.62	0.01	31.22	**0.00**	1.60	416	0.00	0.01	1.6
Liquidity												
Current	0.13	0.13	-7.11	-7.06	0.01	16.03	**0.00**	1.19	386	0.00	0.01	1.1
ICBT	0.02	0.02	-7.74	-7.69	0.00	1.86	0.18	1.58	420	0.00	0.01	**2.1**
NCA_to_MV	0.00	0.00	-6.58	-6.53	0.01	0.38	0.54	1.60	357	0.00	0.01	-0.3
Risk												
Beta	0.35	0.35	-5.56	-5.51	0.01	57.24	**0.00**	1.58	302	0.01	0.02	0.6
PVar12	0.21	0.21	-6.69	-6.64	0.01	27.59	**0.00**	1.45	363	0.00	0.01	1.9
RetVar12	0.23	0.23	-5.56	-5.51	0.01	31.41	**0.00**	1.29	302	0.00	0.02	1.3
Momentum												
Crossover3_12	0.70	0.70	-6.60	-6.55	0.01	241.98	**0.00**	1.33	358	0.00	0.02	-0.8
MOM1	0.28	0.28	-5.75	-5.70	0.01	40.89	**0.00**	1.00	313	0.00	0.02	**2.6**
MOM3	0.38	0.38	-5.54	-5.49	0.02	64.09	**0.00**	0.80	301	0.00	0.02	1.7
MOM6	0.33	0.33	-5.50	-5.45	0.02	51.41	**0.00**	0.73	299	0.01	0.02	0.9
MOM12	0.28	0.28	-5.56	-5.51	0.01	40.29	**0.00**	0.82	302	0.01	0.02	0.3
MOM18	0.11	0.11	-5.44	-5.39	0.02	13.29	**0.00**	0.80	296	0.01	0.02	0.7
Mean	**0.18**	**0.18**	**-6.46**	**-6.41**	**0.01**	**30.33**	**0.12**	**1.40**	**351.00**	**0.00**	**0.01**	**-0.02**
Standard deviation	**0.16**	**0.16**	**0.83**	**0.83**	**0.00**	**44.88**	**0.25**	**0.37**	**44.56**	**0.00**	**0.00**	**1.56**

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C.3. AR12 Model

Results from vector autoregressions with each style payoff as the independent variable and twelve lags as dependent variable over the in-sample period 1 Mar 1990 – 1 Feb 2000. (see *Section 8.2.1* for details on the construction of the AR12 models) T-statistics of individual factor coefficients are not shown due to space constraints. T-statistics of individual factor coefficients are not shown due to space constraints. Constant coefficient t-statistics and F-statistic probabilities significant at the 5% level are bolded.

	R^2	R^2adj	Akaike	Schwartz	Stnd Error of Regression	F-statistic	prob(F)	DW-statistic	Log Likelihood	Mean of Dependent Var.	Stnd dev. of Dependent Var.	T:constant
Size												
LMV	0.28	0.28	-5.53	-5.01	0.01	1.72	**0.04**	1.88	320	0.00	0.01	-1.9
LPrice	0.46	0.46	-6.25	-5.73	0.01	3.66	**0.00**	1.79	358	-0.01	0.01	-1.5
Value												
BVTP	0.34	0.34	-6.41	-5.96	0.01	2.74	**0.00**	1.86	364	0.00	0.01	0.5
CEY	0.59	0.59	-6.06	-5.61	0.01	7.67	**0.00**	2.00	345	0.00	0.02	**-2.7**
DY	0.60	0.60	-5.82	-5.30	0.01	6.43	**0.00**	1.97	336	0.00	0.02	-1.0
EY	0.54	0.54	-5.91	-5.59	0.01	9.29	**0.00**	1.96	332	0.00	0.02	-0.9
Sales_to_MV	0.49	0.49	-5.82	-5.30	0.01	4.21	**0.00**	1.85	335	0.00	0.02	-1.6
Growth												
CEYG1	0.50	0.50	-6.66	-6.14	0.01	4.42	**0.00**	2.01	381	0.00	0.01	-0.5
CEYG12	0.26	0.26	-7.79	-7.27	0.00	1.56	0.08	1.92	442	0.00	0.00	**-2.2**
DPSG12	0.29	0.29	-7.45	-6.93	0.01	1.78	**0.04**	1.93	423	0.00	0.01	**2.2**
DPSG24	0.37	0.37	-7.71	-7.32	0.00	3.60	**0.00**	2.09	433	0.00	0.01	0.2
EG12_P	0.24	0.24	-6.45	-5.93	0.01	1.34	0.17	2.04	369	0.00	0.01	0.8
EG24_P	0.19	0.19	-6.57	-6.15	0.01	1.32	0.20	1.99	372	0.00	0.01	0.1
Expectedgrowth	0.28	0.28	-7.60	-7.08	0.00	1.71	**0.05**	1.86	431	0.00	0.01	-0.1
Gearing	0.25	0.25	-7.37	-6.95	0.01	1.94	**0.03**	1.83	415	0.00	0.01	-0.5
POUT	0.43	0.43	-6.18	-5.73	0.01	4.03	**0.00**	1.94	352	0.00	0.01	-1.5
ROE	0.33	0.33	-7.27	-6.95	0.01	3.84	**0.00**	2.00	406	0.00	0.01	0.2
SG12	0.49	0.49	-7.17	-6.70	0.01	4.69	**0.00**	1.97	406	0.00	0.01	-0.3
SG24	0.52	0.52	-7.80	-7.28	0.00	4.75	**0.00**	2.00	442	0.00	0.01	0.2
Liquidity												
Current	0.40	0.40	-7.19	-6.74	0.01	3.59	**0.00**	1.93	406	0.00	0.01	0.1
ICBT	0.40	0.40	-7.89	-7.37	0.00	2.92	**0.00**	1.96	447	0.00	0.01	**-2.6**
NCA_to_MV	0.23	0.23	-6.49	-5.96	0.01	1.32	0.19	1.93	371	0.00	0.01	-0.9
Risk												
Beta	0.59	0.59	-5.67	-5.15	0.01	6.23	**0.00**	1.91	327	0.01	0.02	-1.2
PVar12	0.33	0.33	-6.66	-6.34	0.01	3.95	**0.00**	1.73	373	0.00	0.01	0.6
RetVar12	0.52	0.52	-5.69	-5.17	0.01	4.80	**0.00**	1.99	328	0.00	0.02	-1.2
Momentum												
Crossover3_12	0.79	0.79	-6.61	-6.09	0.01	16.17	**0.00**	1.91	378	0.00	0.02	-0.2
MOM1	0.64	0.64	-6.16	-5.71	0.01	9.54	**0.00**	2.07	351	0.00	0.02	1.1
MOM3	0.69	0.69	-5.88	-5.36	0.01	9.62	**0.00**	1.90	339	0.00	0.02	-0.5
MOM6	0.73	0.73	-6.10	-5.63	0.01	13.26	**0.00**	1.87	348	0.01	0.02	-0.6
MOM12	0.67	0.67	-6.06	-5.61	0.01	10.94	**0.00**	1.99	345	0.01	0.02	-0.6
MOM18	0.57	0.57	-5.85	-5.37	0.01	6.55	**0.00**	1.85	335	0.01	0.02	-0.3
Mean	**0.45**	**0.45**	**-6.58**	**-6.11**	**0.01**	**5.15**	**0.03**	**1.93**	**374.54**	**0.00**	**0.01**	**-0.54**
Standard deviation	**0.16**	**0.16**	**0.74**	**0.74**	**0.00**	**3.72**	**0.06**	**0.08**	**39.60**	**0.00**	**0.00**	**1.08**

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Out-of-sample Model Forecasting Ability for Individual Styles

C.4. 1M Models

Evaluation of the 1M models over the out-of-sample period 1 Mar 2000 – 1 Feb 2004. 1M models forecast the slope coefficient one-month ahead based on the current slope coefficient. Descriptions of each diagnostic can be obtained from 7.3.3. Proportions of bias, variance and covariance are displayed. T-statistics of individual factor coefficients are not shown due to space constraints. Probabilities significant at the 5% level are bolded.

	Correlation of Forecasted and Realised Payoffs	Ratio Sign right	Probability of Ratio Sign right	Root Mean Squared Error	Mean Absolute Percentage Error	Theil Inequality Coefficient	Bias	Variance	Covariance
Size									
LMV	0.16	0.60	0.07	0.02	19531.52	0.65	0.00	0.00	1.00
LPrice	0.17	0.55	0.19	0.03	340.10	0.64	0.00	0.00	1.00
Value									
BVTP	0.22	0.68	**0.00**	0.02	408.89	0.57	0.00	0.00	1.00
CEY	0.28	0.60	0.07	0.03	334.89	0.58	0.00	0.00	1.00
DY	0.30	0.64	**0.02**	0.03	495.93	0.57	0.00	0.00	1.00
EY	0.33	0.55	0.19	0.03	341.54	0.55	0.00	0.00	1.00
Sales_to_MV	0.23	0.70	**0.00**	0.03	268.49	0.55	0.00	0.00	1.00
Growth									
CEYG1	-0.23	0.53	0.28	0.03	442.92	0.76	0.00	0.00	1.00
CEYG12	0.04	0.55	0.19	0.01	384.58	0.68	0.00	0.00	1.00
DPSG12	0.11	0.55	0.19	0.01	322.66	0.67	0.00	0.00	1.00
DPSG24	0.09	0.62	**0.04**	0.01	290.65	0.67	0.00	0.00	1.00
EG12_P	-0.16	0.64	**0.02**	0.01	419.04	0.72	0.00	0.00	1.00
EG24_P	-0.20	0.43	0.81	0.02	194.14	0.74	0.00	0.00	1.00
Expectedgrowth	0.04	0.55	0.19	0.01	1655.74	0.69	0.00	0.00	1.00
Gearing	-0.07	0.47	0.61	0.01	256.85	0.73	0.00	0.00	1.00
POUT	0.22	0.68	**0.00**	0.03	212.78	0.61	0.00	0.00	1.00
ROE	0.16	0.57	0.12	0.01	184.98	0.64	0.00	0.00	1.00
SG12	0.18	0.66	**0.01**	0.02	271.27	0.61	0.00	0.00	1.00
SG24	0.30	0.66	**0.01**	0.01	199.67	0.57	0.00	0.00	0.99
Liquidity									
Current	0.25	0.60	0.07	0.02	415.82	0.56	0.00	0.00	1.00
ICBT	0.07	0.57	0.12	0.02	506.78	0.63	0.00	0.00	1.00
NCA_to_MV	0.10	0.51	0.39	0.02	337.39	0.66	0.00	0.00	1.00
Risk									
Beta	0.13	0.60	0.07	0.05	289.18	0.65	0.00	0.00	1.00
PVar12	0.02	0.53	0.28	0.02	1503.40	0.63	0.00	0.00	1.00
RetVar12	0.26	0.64	**0.02**	0.04	399.14	0.60	0.00	0.00	1.00
Momentum									
Crossover3_12	0.52	0.40	0.88	0.02	11348.52	0.49	0.01	0.02	0.97
MOM1	-0.21	0.45	0.72	0.04	1384.90	0.77	0.00	0.00	1.00
MOM3	0.10	0.53	0.28	0.05	313.87	0.67	0.00	0.00	1.00
MOM6	0.19	0.55	0.19	0.05	255.48	0.62	0.00	0.00	1.00
MOM12	0.19	0.64	**0.02**	0.05	223.84	0.63	0.00	0.00	1.00
MOM18	0.24	0.62	**0.04**	0.04	404.26	0.62	0.00	0.00	1.00
Mean	**0.13**	**0.58**	**0.20**	**0.02**	**1417.39**	**0.64**	**0.00**	**0.00**	**1.00**
Standard deviation	**0.17**	**0.07**	**0.24**	**0.01**	**3906.87**	**0.07**	**0.00**	**0.00**	**0.01**

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C.5. 6M Models

Evaluation of the 6M models over the out-of-sample period 1 Mar 2000 – 1 Feb 2004. 6M models forecast the slope coefficient one-month ahead based on the six-month trailing moving-average of the slope coefficient. Descriptions of each diagnostic can be obtained from 7.3.3. Proportions of bias, variance and covariance are displayed. T-statistics of individual factor coefficients are not shown due to space constraints. Probabilities significant at the 5% level are bolded.

	Correlation of Forecasted and Realised Payoffs	Ratio Sign right	Probability of Ratio Sign right	Root Mean Squared Error	Mean Absolute Percentage Error	Theil Inequality Coefficient	Bias	Variance	Covariance
Size									
LMV	0.24	0.72	**0.00**	0.02	3626.64	0.64	0.01	0.11	0.88
LPrice	0.14	0.60	0.07	0.03	220.46	0.70	0.00	0.28	0.71
Value									
BVTP	-0.02	0.70	**0.00**	0.02	193.08	0.65	0.01	0.15	0.85
CEY	0.08	0.64	**0.02**	0.03	190.10	0.68	0.01	0.09	0.89
DY	0.04	0.64	**0.02**	0.03	347.85	0.69	0.01	0.05	0.93
EY	0.08	0.66	**0.01**	0.03	163.07	0.66	0.02	0.03	0.95
Sales_to_MV	0.03	0.79	**0.00**	0.03	191.85	0.62	0.02	0.07	0.92
Growth									
CEYG1	-0.10	0.53	0.28	0.02	242.64	0.73	0.01	0.27	0.72
CEYG12	-0.12	0.38	0.93	0.01	261.97	0.76	0.00	0.22	0.78
DPSG12	0.18	0.53	0.28	0.01	146.56	0.70	0.00	0.28	0.72
DPSG24	0.11	0.60	0.07	0.01	151.89	0.73	0.00	0.33	0.67
EG12_P	-0.04	0.57	0.12	0.01	386.94	0.68	0.00	0.38	0.62
EG24_P	-0.06	0.51	0.39	0.01	125.53	0.73	0.00	0.37	0.63
Expectedgrowth	-0.03	0.47	0.61	0.01	4997.20	0.78	0.00	0.30	0.70
Gearing	-0.04	0.53	0.28	0.01	172.43	0.78	0.00	0.32	0.68
POUT	0.11	0.68	**0.00**	0.02	125.37	0.67	0.01	0.10	0.89
ROE	0.22	0.68	**0.00**	0.01	154.98	0.67	0.00	0.25	0.75
SG12	0.04	0.68	**0.00**	0.01	161.55	0.67	0.02	0.08	0.90
SG24	0.23	0.70	**0.00**	0.01	161.04	0.62	0.02	0.08	0.90
Liquidity									
Current	0.24	0.62	**0.04**	0.02	197.19	0.58	0.01	0.13	0.87
ICBT	0.16	0.62	**0.04**	0.01	267.21	0.60	0.00	0.32	0.68
NCA_to_MV	0.03	0.49	0.50	0.01	192.24	0.72	0.00	0.25	0.74
Risk									
Beta	0.10	0.68	**0.00**	0.04	172.74	0.69	0.01	0.15	0.85
PVar12	-0.08	0.68	**0.00**	0.01	629.33	0.68	0.02	0.08	0.90
RetVar12	0.10	0.70	**0.00**	0.04	133.56	0.69	0.00	0.17	0.82
Momentum									
Crossover3_12	0.33	0.47	0.61	0.02	12177.24	0.57	0.05	0.00	0.94
MOM1	-0.02	0.60	0.07	0.03	614.28	0.72	0.02	0.17	0.81
MOM3	-0.10	0.51	0.39	0.04	182.75	0.74	0.01	0.13	0.86
MOM6	-0.13	0.60	0.07	0.04	125.87	0.74	0.01	0.18	0.82
MOM12	-0.05	0.66	**0.01**	0.04	106.71	0.73	0.01	0.18	0.81
MOM18	0.00	0.68	**0.00**	0.04	232.95	0.74	0.01	0.15	0.84
Mean	**0.05**	**0.61**	**0.16**	**0.02**	**872.69**	**0.69**	**0.01**	**0.18**	**0.81**
Standard deviation	**0.12**	**0.09**	**0.24**	**0.01**	**2342.72**	**0.05**	**0.01**	**0.10**	**0.10**

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C.6. 12M Models

Evaluation of the 12M models over the out-of-sample period 1 Mar 2000 – 1 Feb 2004. 12M models forecast the slope coefficient one-month ahead based on the on-year trailing moving-average of the slope coefficient. Descriptions of each diagnostic can be obtained from 7.3.3. Proportions of bias, variance and covariance are displayed. T-statistics of individual factor coefficients are not shown due to space constraints. Probabilities significant at the 5% level are bolded.

	Correlation of Forecasted and Realised Payoffs	Ratio Sign right	Probability of Ratio Sign right	Root Mean Squared Error	Mean Absolute Percentage Error	Theil Inequality Coefficient	Bias	Variance	Covariance
Size									
LMV	0.18	0.66	**0.01**	0.02	11888.94	0.67	0.01	0.14	0.85
LPrice	0.10	0.60	0.07	0.02	200.85	0.76	0.00	0.44	0.56
Value									
BVTP	-0.11	0.68	**0.00**	0.02	225.94	0.67	0.01	0.27	0.72
CEY	0.06	0.60	0.07	0.03	285.96	0.70	0.01	0.20	0.79
DY	0.01	0.60	0.07	0.03	366.32	0.72	0.02	0.14	0.84
EY	0.04	0.62	**0.04**	0.03	343.79	0.69	0.03	0.10	0.87
Sales_to_MV	0.02	0.72	**0.00**	0.02	184.89	0.63	0.03	0.16	0.81
Growth									
CEYG1	-0.17	0.57	0.12	0.02	196.50	0.74	0.01	0.50	0.49
CEYG12	-0.18	0.51	0.39	0.01	152.61	0.83	0.00	0.53	0.47
DPSG12	0.01	0.55	0.19	0.01	157.51	0.80	0.00	0.48	0.52
DPSG24	-0.02	0.60	0.07	0.01	162.85	0.80	0.00	0.47	0.53
EG12_P	-0.08	0.57	0.12	0.01	250.84	0.70	0.00	0.48	0.52
EG24_P	0.05	0.57	0.12	0.01	105.67	0.72	0.00	0.54	0.46
Expectedgrowth	-0.05	0.49	0.50	0.01	798.16	0.82	0.00	0.47	0.53
Gearing	-0.03	0.47	0.61	0.01	136.73	0.82	0.00	0.49	0.51
POUT	0.09	0.57	0.12	0.02	158.15	0.69	0.01	0.18	0.81
ROE	0.26	0.62	**0.04**	0.01	142.12	0.70	0.00	0.43	0.57
SG12	0.04	0.68	**0.00**	0.01	134.83	0.70	0.04	0.16	0.81
SG24	0.12	0.62	**0.04**	0.01	157.87	0.67	0.03	0.12	0.85
Liquidity									
Current	0.19	0.60	0.07	0.02	206.26	0.60	0.01	0.19	0.80
ICBT	0.05	0.66	**0.01**	0.01	202.98	0.62	0.00	0.46	0.53
NCA_to_MV	-0.10	0.53	0.28	0.01	130.83	0.81	0.01	0.43	0.56
Risk									
Beta	0.04	0.60	0.07	0.04	152.06	0.74	0.01	0.26	0.73
PVar12	-0.02	0.64	**0.02**	0.01	828.58	0.69	0.04	0.16	0.80
RetVar12	0.05	0.62	**0.04**	0.04	198.72	0.73	0.00	0.28	0.72
Momentum									
Crossover3_12	0.27	0.47	0.61	0.02	42223.17	0.59	0.09	0.02	0.89
MOM1	-0.03	0.60	0.07	0.03	487.18	0.74	0.03	0.35	0.62
MOM3	-0.28	0.51	0.39	0.04	165.14	0.81	0.02	0.36	0.62
MOM6	-0.20	0.53	0.28	0.04	215.44	0.76	0.02	0.43	0.55
MOM12	-0.17	0.60	0.07	0.04	132.27	0.77	0.02	0.40	0.58
MOM18	-0.03	0.53	0.28	0.04	272.70	0.78	0.02	0.33	0.65
Mean	**0.00**	**0.59**	**0.15**	**0.02**	**1976.32**	**0.72**	**0.02**	**0.32**	**0.66**
Standard deviation	**0.13**	**0.06**	**0.18**	**0.01**	**7758.23**	**0.07**	**0.02**	**0.15**	**0.14**

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C.7. 18M Models

Evaluation of the 18M models over the out-of-sample period 1 Mar 2000 – 1 Feb 2004. 18M models forecast the slope coefficient one-month ahead based on the eighteen-month trailing moving-average of the slope coefficient. Descriptions of each diagnostic can be obtained from 7.3.3. Proportions of bias, variance and covariance are displayed. T-statistics of individual factor coefficients are not shown due to space constraints. Probabilities significant at the 5% level are bolded.

	Correlation of Forecasted and Realised Payoffs	Ratio Sign right	Probability of Ratio Sign right	Root Mean Squared Error	Mean Absolute Percentage Error	Theil Inequality Coefficient	Bias	Variance	Covariance
Size									
LMV	0.09	0.60	0.07	0.02	34029.78	0.71	0.02	0.18	0.81
LPrice	0.00	0.49	0.50	0.03	169.66	0.80	0.00	0.52	0.48
Value									
BVTP	-0.22	0.68	**0.00**	0.02	288.69	0.70	0.01	0.38	0.61
CEY	-0.08	0.45	0.72	0.03	212.90	0.76	0.01	0.29	0.70
DY	-0.17	0.47	0.61	0.03	317.31	0.79	0.03	0.21	0.76
EY	-0.12	0.51	0.39	0.03	260.44	0.74	0.03	0.18	0.79
Sales_to_MV	-0.10	0.66	**0.01**	0.02	178.03	0.67	0.04	0.22	0.74
Growth									
CEYG1	0.02	0.62	**0.04**	0.02	198.95	0.72	0.01	0.68	0.30
CEYG12	0.08	0.60	0.07	0.01	140.72	0.83	0.00	0.76	0.24
DPSG12	-0.06	0.53	0.28	0.01	119.11	0.85	0.00	0.63	0.36
DPSG24	-0.03	0.53	0.28	0.01	148.51	0.83	0.00	0.57	0.42
EG12_P	-0.11	0.64	**0.02**	0.01	222.05	0.73	0.00	0.60	0.39
EG24_P	-0.05	0.60	0.07	0.01	102.58	0.74	0.00	0.53	0.47
Expectedgrowth	-0.05	0.40	0.88	0.01	624.97	0.85	0.00	0.58	0.42
Gearing	-0.16	0.45	0.72	0.01	121.18	0.89	0.01	0.66	0.34
POUT	-0.02	0.51	0.39	0.02	158.25	0.74	0.01	0.22	0.77
ROE	0.08	0.57	0.12	0.01	131.90	0.76	0.00	0.47	0.53
SG12	-0.04	0.60	0.07	0.01	153.53	0.74	0.05	0.18	0.77
SG24	-0.03	0.51	0.39	0.01	164.16	0.73	0.03	0.14	0.82
Liquidity									
Current	0.04	0.57	0.12	0.02	204.89	0.65	0.01	0.24	0.75
ICBT	0.05	0.66	**0.01**	0.01	188.71	0.63	0.00	0.56	0.44
NCA_to_MV	-0.17	0.45	0.72	0.01	123.14	0.87	0.01	0.62	0.36
Risk									
Beta	-0.05	0.55	0.19	0.04	176.16	0.78	0.01	0.32	0.67
PVar12	0.03	0.62	**0.04**	0.01	1126.29	0.70	0.06	0.24	0.69
RetVar12	-0.04	0.53	0.28	0.04	210.70	0.77	0.00	0.35	0.65
Momentum									
Crossover3_12	0.20	0.51	0.39	0.02	90068.30	0.62	0.12	0.07	0.81
MOM1	0.04	0.62	**0.04**	0.03	435.16	0.74	0.04	0.50	0.46
MOM3	-0.06	0.57	0.12	0.03	136.66	0.78	0.03	0.60	0.37
MOM6	-0.07	0.64	**0.02**	0.04	188.83	0.74	0.02	0.68	0.29
MOM12	-0.19	0.57	0.12	0.04	121.07	0.78	0.02	0.65	0.33
MOM18	-0.31	0.36	0.96	0.04	179.79	0.87	0.02	0.48	0.50
Mean	**-0.05**	**0.55**	**0.28**	**0.02**	**4222.66**	**0.76**	**0.02**	**0.43**	**0.55**
Standard deviation	**0.10**	**0.08**	**0.28**	**0.01**	**17049.25**	**0.07**	**0.02**	**0.20**	**0.19**

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C.8. 12M Reg Models

Evaluation of the 12M Reg models over the out-of-sample period 1 Mar 2000 – 1 Feb 2004. 12M Reg models forecast the slope coefficient one-month ahead based on the regression equation of the one-year trailing moving-average on the slope coefficient estimated historically using an expanding window for the out-of-sample period. Descriptions of each diagnostic can be obtained from 7.3.3. Proportions of bias, variance and covariance are displayed. T-statistics of individual factor coefficients are not shown due to space constraints. Probabilities significant at the 5% level are bolded.

	Correlation of Forecasted and Realised Payoffs	Ratio Sign right	Probability of Ratio Sign right	Root Mean Squared Error	Mean Absolute Percentage Error	Theil Inequality Coefficient	Bias	Variance	Covariance
Size									
LMV	0.13	0.65	**0.02**	0.02	13417.11	0.74	0.03	0.38	0.60
LPrice	-0.04	0.44	0.72	0.03	168.93	0.83	0.00	0.76	0.24
Value									
BVTP	-0.12	0.71	**0.00**	0.02	164.18	0.75	0.05	0.50	0.45
CEY	0.02	0.54	0.28	0.03	135.09	0.75	0.03	0.25	0.72
DY	-0.02	0.52	0.39	0.03	172.07	0.76	0.08	0.14	0.78
EY	0.00	0.54	0.28	0.03	129.06	0.74	0.11	0.09	0.80
Sales_to_MV	-0.07	0.63	**0.04**	0.03	127.39	0.78	0.06	0.49	0.46
Growth									
CEYG1	-0.25	0.54	0.28	0.02	173.47	0.87	0.02	0.66	0.32
CEYG12	-0.06	0.46	0.61	0.01	125.64	0.95	0.04	0.84	0.12
DPSG12	-0.05	0.46	0.61	0.01	123.62	0.87	0.00	0.72	0.28
DPSG24	-0.25	0.54	0.28	0.01	118.64	0.89	0.00	0.91	0.09
EG12_P	-0.16	0.63	**0.04**	0.01	191.69	0.80	0.01	0.80	0.19
EG24_P	-0.02	0.60	0.07	0.01	106.98	0.79	0.00	0.75	0.25
Expectedgrowth	-0.11	0.44	0.72	0.01	138.85	0.91	0.01	0.74	0.26
Gearing	-0.08	0.46	0.61	0.01	116.18	0.90	0.00	0.73	0.27
POUT	0.05	0.52	0.39	0.02	143.45	0.75	0.05	0.23	0.71
ROE	0.23	0.63	**0.04**	0.01	132.11	0.75	0.00	0.56	0.44
SG12	0.05	0.67	**0.01**	0.02	109.55	0.74	0.07	0.20	0.74
SG24	0.11	0.60	0.07	0.01	124.74	0.72	0.04	0.25	0.71
Liquidity									
Current	0.12	0.60	0.07	0.02	160.29	0.65	0.02	0.29	0.69
ICBT	-0.07	0.65	**0.02**	0.01	159.22	0.70	0.00	0.69	0.31
NCA_to_MV	-0.22	0.48	0.50	0.01	106.34	0.96	0.01	0.91	0.08
Risk									
Beta	0.02	0.58	0.12	0.04	114.67	0.77	0.04	0.28	0.68
PVar12	-0.03	0.65	**0.02**	0.01	773.01	0.75	0.05	0.32	0.64
RetVar12	-0.02	0.58	0.12	0.04	149.09	0.80	0.03	0.40	0.58
Momentum									
Crossover3_12	0.31	0.50	0.39	0.03	31632.26	0.57	0.08	0.01	0.90
MOM1	-0.13	0.54	0.28	0.03	323.56	0.76	0.00	0.30	0.70
MOM3	-0.08	0.56	0.19	0.04	128.72	0.75	0.01	0.25	0.73
MOM6	-0.14	0.65	**0.02**	0.04	146.62	0.78	0.00	0.39	0.61
MOM12	-0.16	0.58	0.12	0.04	146.26	0.80	0.00	0.46	0.53
MOM18	-0.13	0.48	0.50	0.04	144.84	0.86	0.03	0.63	0.34
Mean	**-0.04**	**0.56**	**0.25**	**0.02**	**1609.79**	**0.79**	**0.03**	**0.48**	**0.49**
Standard deviation	**0.13**	**0.07**	**0.23**	**0.01**	**6059.49**	**0.08**	**0.03**	**0.26**	**0.24**

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C.9. Mean Models

Evaluation of the Mean models over the out-of-sample period 1 Mar 2000 – 1 Feb 2004. Mean Reg models forecast the slope coefficient one-month ahead based on the mean of the slope coefficient estimated historically using an expanding window for the out-of-sample period. Descriptions of each diagnostic can be obtained from 7.3.3. Proportions of bias, variance and covariance are displayed. T-statistics of individual factor coefficients are not shown due to space constraints. Probabilities significant at the 5% level are bolded.

	Correlation of Forecasted and Realised Payoffs	Ratio Sign right	Probability of Ratio Sign right	Root Mean Squared Error	Mean Absolute Percentage Error	Theil Inequality Coefficient	Bias	Variance	Covariance
Size									
LMV	-0.14	0.53	0.28	0.02	9190.77	0.91	0.01	0.91	0.08
LPrice	-0.14	0.49	0.50	0.02	167.27	0.82	0.00	0.94	0.06
Value									
BVTP	-0.24	0.77	**0.00**	0.02	149.30	0.80	0.07	0.84	0.09
CEY	-0.23	0.57	0.12	0.03	105.53	0.94	0.04	0.86	0.09
DY	-0.27	0.45	0.72	0.03	106.62	0.97	0.07	0.83	0.10
EY	-0.26	0.60	0.07	0.03	111.31	0.93	0.09	0.80	0.11
Sales_to_MV	-0.13	0.66	**0.01**	0.02	101.56	0.93	0.21	0.68	0.11
Growth									
CEYG1	-0.22	0.60	0.07	0.02	157.48	0.92	0.02	0.92	0.06
CEYG12	0.06	0.53	0.28	0.01	110.59	0.97	0.03	0.93	0.03
DPSG12	-0.17	0.53	0.28	0.01	117.92	0.92	0.00	0.96	0.04
DPSG24	-0.18	0.55	0.19	0.01	114.30	0.89	0.00	0.96	0.04
EG12_P	-0.07	0.64	**0.02**	0.01	177.65	0.83	0.03	0.93	0.04
EG24_P	-0.16	0.62	**0.04**	0.01	107.90	0.85	0.02	0.92	0.06
Expectedgrowth	-0.24	0.36	0.96	0.01	172.04	0.98	0.00	0.96	0.04
Gearing	-0.29	0.53	0.28	0.01	119.57	0.89	0.02	0.94	0.05
POUT	-0.21	0.34	0.98	0.02	109.85	0.96	0.08	0.81	0.11
ROE	-0.11	0.62	**0.04**	0.01	106.63	0.86	0.00	0.95	0.05
SG12	-0.11	0.51	0.39	0.01	104.66	0.97	0.12	0.79	0.09
SG24	-0.22	0.62	**0.04**	0.01	105.16	0.95	0.06	0.84	0.10
Liquidity									
Current	-0.19	0.57	0.12	0.02	105.86	0.92	0.12	0.75	0.12
ICBT	-0.12	0.66	**0.01**	0.01	145.09	0.75	0.02	0.90	0.08
NCA_to_MV	-0.17	0.53	0.28	0.01	109.09	0.94	0.02	0.94	0.04
Risk									
Beta	-0.19	0.36	0.96	0.04	114.04	0.97	0.04	0.87	0.08
PVar12	-0.08	0.70	**0.00**	0.01	953.52	0.73	0.04	0.91	0.05
RetVar12	-0.24	0.51	0.39	0.04	108.55	0.97	0.04	0.88	0.09
Momentum									
Crossover3_12	-0.07	0.49	0.50	0.02	16840.98	0.80	0.01	0.95	0.04
MOM1	-0.36	0.55	0.19	0.03	212.98	0.93	0.00	0.96	0.04
MOM3	-0.28	0.55	0.19	0.03	107.39	0.92	0.00	0.97	0.03
MOM6	-0.19	0.64	**0.02**	0.04	140.37	0.88	0.00	0.95	0.05
MOM12	-0.20	0.60	0.07	0.04	103.59	0.89	0.00	0.96	0.04
MOM18	-0.25	0.49	0.50	0.04	158.93	0.90	0.02	0.93	0.05
Mean	**-0.18**	**0.55**	**0.27**	**0.02**	**985.05**	**0.90**	**0.04**	**0.89**	**0.07**
Standard deviation	**0.08**	**0.10**	**0.29**	**0.01**	**3363.49**	**0.07**	**0.05**	**0.07**	**0.03**

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C.10. AR12 Models

Evaluation of the AR12 models over the out-of-sample period 1 Mar 2000 – 1 Feb 2004. AR12 models forecast the slope coefficient one-month ahead based on the regression equation of the first twelve trailing lags on the slope coefficient estimated historically using an expanding window for the out-of-sample period. Descriptions of each diagnostic can be obtained from 7.3.3. Proportions of bias, variance and covariance are displayed. T-statistics of individual factor coefficients are not shown due to space constraints. Probabilities significant at the 5% level are bolded.

	Correlation of Forecasted and Realised Payoffs	Ratio Sign right	Probability of Ratio Sign right	Root Mean Squared Error	Mean Absolute Percentage Error	Theil Inequality Coefficient	Bias	Variance	Covariance
Size									
LMV	0.17	0.46	0.61	0.02	2148.30	0.67	0.02	0.14	0.84
LPrice	0.02	0.46	0.61	0.03	243.41	0.74	0.00	0.26	0.74
Value									
BVTP	-0.02	0.67	**0.01**	0.02	227.95	0.70	0.06	0.08	0.86
CEY	0.12	0.56	0.19	0.04	460.70	0.66	0.02	0.01	0.97
DY	0.32	0.50	0.39	0.03	638.77	0.59	0.04	0.02	0.94
EY	0.22	0.54	0.28	0.03	349.60	0.62	0.03	0.02	0.95
Sales_to_MV	-0.04	0.63	**0.04**	0.03	234.58	0.70	0.04	0.05	0.91
Growth									
CEYG1	-0.08	0.46	0.61	0.02	241.63	0.74	0.03	0.04	0.93
CEYG12	0.06	0.50	0.39	0.01	219.71	0.75	0.04	0.29	0.67
DPSG12	0.09	0.54	0.28	0.01	124.40	0.76	0.00	0.41	0.58
DPSG24	0.25	0.65	**0.02**	0.01	122.97	0.68	0.00	0.37	0.63
EG12_P	-0.26	0.50	0.39	0.01	192.49	0.80	0.01	0.50	0.49
EG24_P	0.18	0.58	0.12	0.01	104.45	0.68	0.00	0.40	0.59
Expectedgrowth	-0.11	0.52	0.39	0.01	1475.25	0.81	0.00	0.33	0.67
Gearing	0.16	0.46	0.61	0.01	146.99	0.76	0.00	0.48	0.52
POUT	0.11	0.50	0.39	0.03	263.13	0.68	0.07	0.02	0.91
ROE	0.03	0.60	0.07	0.01	168.78	0.72	0.00	0.19	0.80
SG12	0.08	0.56	0.19	0.02	187.61	0.70	0.07	0.06	0.87
SG24	0.23	0.54	0.28	0.01	216.73	0.63	0.02	0.08	0.90
Liquidity									
Current	0.05	0.65	**0.02**	0.02	172.54	0.67	0.04	0.05	0.91
ICBT	0.10	0.46	0.61	0.01	140.02	0.65	0.01	0.14	0.85
NCA_to_MV	0.11	0.54	0.28	0.01	137.45	0.78	0.01	0.46	0.53
Risk									
Beta	0.00	0.56	0.19	0.06	350.07	0.71	0.05	0.00	0.95
PVar12	0.16	0.58	0.12	0.01	1464.33	0.63	0.02	0.06	0.92
RetVar12	0.17	0.54	0.28	0.04	342.27	0.66	0.04	0.06	0.90
Momentum									
Crossover3_12	0.24	0.56	0.19	0.03	59824.89	0.61	0.02	0.04	0.94
MOM1	-0.16	0.44	0.72	0.04	675.44	0.75	0.00	0.00	1.00
MOM3	0.17	0.60	0.07	0.05	292.08	0.64	0.00	0.02	0.98
MOM6	0.01	0.46	0.61	0.06	357.72	0.69	0.00	0.00	1.00
MOM12	0.07	0.54	0.28	0.05	363.68	0.67	0.00	0.00	0.99
MOM18	0.05	0.54	0.28	0.04	407.26	0.70	0.02	0.03	0.95
Mean	**0.08**	**0.54**	**0.31**	**0.03**	**2332.10**	**0.70**	**0.02**	**0.15**	**0.83**
Standard deviation	**0.13**	**0.06**	**0.21**	**0.02**	**10680.08**	**0.06**	**0.02**	**0.17**	**0.16**

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C.11. Consolidated Models

Evaluation of the Consolidated models over the out-of-sample period 1 Mar 2000 – 1 Feb 2004. Consolidated models forecast the slope coefficient one-month ahead based on the regression equation of a parsimonious group of explanatory variables (including macroeconomic variables) on the slope coefficient estimated historically using an expanding window for the out-of-sample period. A complete description of the construction of the consolidated model is provided in *Section 8.2.1*. Descriptions of each diagnostic can be obtained from *Section 8.2.3*. Proportions of bias, variance and covariance are displayed. T-statistics of individual factor coefficients are not shown due to space constraints. Probabilities significant at the 5% level are bolded.

	Correlation of Forecasted and Realised Payoffs	Ratio Sign right	Probability of Ratio Sign right	Root Mean Squared Error	Mean Absolute Percentage Error	Theil Inequality Coefficient	Bias	Variance	Covariance
Size									
LMV	0.27	0.67	**0.01**	0.02	20900.58	0.61	0.00	0.02	0.98
LPrice	0.02	0.54	0.28	0.03	208.44	0.75	0.00	0.32	0.68
Value									
BVTP	0.04	0.71	**0.00**	0.02	209.81	0.70	0.06	0.24	0.70
CEY	0.18	0.56	0.19	0.03	356.16	0.65	0.01	0.09	0.90
DY	0.36	0.60	0.07	0.03	457.69	0.59	0.08	0.04	0.87
EY	0.27	0.52	0.39	0.03	220.98	0.58	0.02	0.00	0.98
Sales_to_MV	0.11	0.63	**0.04**	0.03	143.62	0.68	0.05	0.20	0.75
Growth									
CEYG1	0.04	0.42	0.81	0.02	325.49	0.72	0.06	0.09	0.84
CEYG12	-0.10	0.50	0.39	0.01	107.19	0.95	0.04	0.85	0.11
DPSG12	0.13	0.42	0.81	0.01	168.25	0.75	0.05	0.41	0.54
DPSG24	-0.16	0.42	0.81	0.01	155.68	0.79	0.00	0.31	0.69
EG12_P	0.17	0.63	**0.04**	0.01	321.12	0.60	0.05	0.38	0.58
EG24_P	-0.22	0.54	0.28	0.01	106.76	0.80	0.00	0.39	0.61
Expectedgrowth	0.04	0.52	0.39	0.01	1118.44	0.75	0.02	0.27	0.71
Gearing	-0.35	0.35	0.96	0.01	121.81	0.90	0.00	0.53	0.47
POUT	0.10	0.60	0.07	0.02	167.04	0.70	0.04	0.15	0.81
ROE	0.03	0.54	0.28	0.01	142.78	0.74	0.00	0.30	0.69
SG12	0.13	0.65	**0.02**	0.02	185.17	0.68	0.04	0.10	0.86
SG24	0.15	0.63	**0.04**	0.01	190.09	0.67	0.03	0.10	0.87
Liquidity									
Current	0.12	0.63	**0.04**	0.02	186.38	0.64	0.02	0.22	0.76
ICBT	-0.08	0.52	0.39	0.01	159.75	0.74	0.02	0.36	0.61
NCA_to_MV	0.08	0.48	0.50	0.01	132.37	0.77	0.00	0.52	0.48
Risk									
Beta	0.04	0.52	0.39	0.04	176.74	0.74	0.05	0.19	0.76
PVar12	-0.01	0.63	**0.04**	0.01	537.06	0.69	0.02	0.16	0.82
RetVar12	0.33	0.65	**0.02**	0.03	208.46	0.63	0.02	0.22	0.75
Momentum									
Crossover3_12	0.35	0.38	0.93	0.02	10664.93	0.55	0.01	0.00	0.99
MOM1	-0.21	0.44	0.72	0.03	263.90	0.78	0.00	0.11	0.89
MOM3	0.13	0.56	0.19	0.04	256.52	0.65	0.01	0.00	0.99
MOM6	0.02	0.56	0.19	0.05	333.99	0.68	0.00	0.02	0.98
MOM12	0.02	0.56	0.19	0.04	274.32	0.70	0.00	0.06	0.94
MOM18	0.10	0.54	0.28	0.04	281.68	0.69	0.02	0.11	0.87
Mean	**0.07**	**0.55**	**0.31**	**0.02**	**1260.75**	**0.71**	**0.02**	**0.22**	**0.76**
Standard deviation	**0.16**	**0.09**	**0.30**	**0.01**	**4100.02**	**0.09**	**0.02**	**0.19**	**0.19**

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C.12. In-sample Comparison of Model Forecasting Ability Using Theil's Inequality Coefficient In-sample:

Displays Theil's inequality coefficient over the in-sample period 1 Mar 1990 – 1 Feb 2000. Values lie between 0 and 1 where 0 implies a perfect fit. The model that performs best for each style is bolded. For each model, the mean and standard deviation of the coefficients across all styles is provided.

	1M Model	6M Model	12M Model	18M Model	12M Reg Model	Mean Model	AR12 Model	Consolidated Model
Size								
LMV	0.59	0.64	0.66	0.75	0.70	0.78	0.53	**0.42**
LPrice	0.54	0.59	0.62	0.65	0.65	0.70	**0.39**	0.42
Value								
BVTP	0.56	0.62	0.64	0.71	0.70	0.69	**0.51**	0.58
CEY	0.47	0.59	0.73	0.81	0.53	0.87	**0.36**	0.43
DY	0.42	0.58	0.69	0.79	0.50	0.90	0.35	**0.34**
EY	0.42	0.57	0.74	0.81	0.52	0.90	**0.39**	0.42
Sales_to_MV	0.49	0.66	0.75	0.81	0.74	0.92	**0.41**	0.43
Growth								
CEYG1	0.60	0.65	0.77	0.87	0.76	0.91	0.41	**0.37**
CEYG12	0.70	0.76	0.76	0.84	0.91	0.85	**0.57**	0.95
DPSG12	0.65	0.67	0.66	0.73	0.77	0.84	0.54	**0.50**
DPSG24	0.65	0.64	0.73	0.76	0.82	0.80	**0.48**	0.56
EG12_P	0.66	0.78	0.70	0.82	0.86	0.82	**0.58**	0.62
EG24_P	0.65	0.79	0.68	0.80	0.85	0.79	**0.61**	0.66
Expectedgrowth	0.65	0.66	0.67	0.73	0.81	0.74	**0.55**	0.67
Gearing	0.63	0.64	0.63	0.74	0.78	0.67	**0.57**	0.70
POUT	0.48	0.54	0.59	0.65	0.48	0.79	**0.41**	0.45
ROE	0.60	0.56	0.56	0.69	0.67	0.62	**0.51**	0.53
SG12	0.49	0.57	0.63	0.71	0.48	0.89	**0.41**	0.43
SG24	0.53	0.58	0.62	0.71	0.59	0.85	**0.40**	0.45
Liquidity								
Current	0.51	0.63	0.70	0.75	0.67	0.88	**0.47**	0.56
ICBT	0.57	0.56	0.57	0.60	0.62	0.57	**0.41**	0.47
NCA_to_MV	0.65	0.74	0.74	0.79	0.94	0.84	**0.59**	0.76
Risk								
Beta	0.47	0.58	0.63	0.72	0.47	0.85	**0.34**	0.42
PVar12	0.52	0.53	0.56	0.61	0.59	0.60	**0.50**	0.52
RetVar12	0.50	0.60	0.65	0.74	0.57	0.83	**0.39**	0.45
Momentum								
Crossover3_12	0.32	0.50	0.62	0.70	0.29	0.91	**0.23**	0.24
MOM1	0.42	0.59	0.72	0.80	0.54	0.84	**0.33**	0.38
MOM3	0.37	0.52	0.67	0.75	0.47	0.86	0.29	**0.29**
MOM6	0.37	0.51	0.66	0.73	0.49	0.90	**0.27**	0.32
MOM12	0.38	0.52	0.66	0.70	0.51	0.88	**0.30**	0.33
MOM18	0.43	0.56	0.65	0.70	0.59	0.72	**0.34**	0.40
Mean	**0.53**	**0.61**	**0.67**	**0.74**	**0.64**	**0.81**	**0.43**	**0.49**
Standard deviation	**0.10**	**0.08**	**0.06**	**0.06**	**0.16**	**0.10**	**0.10**	**0.15**

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C.13. In-sample Comparison of Model Forecasting Ability using the Ratio of Sign Forecast Correctly

Displays the Ratio of Sign Forecast Correctly for each forecasting model over the in-sample period 1 Mar 1990 – 1 Feb 2000. The probability associated with the null that the Ratio of Sign Forecast Correctly is less than 50% is calculated using the non-parametric Sign test based on the binomial distribution. The methodology is provided in *Section 8.2.1*. Ratios significant at the 5% level are shaded and the model that performs best for each style is bolded. For each model, the mean and standard deviation of the Ratio Sign Forecast Correctly values across all styles is provided.

	1M Model	6M Model	12M Model	18M Model	12M Reg Model	Mean Model	AR12 Model	Consolidated Model
Size								
LMV	0.60	0.61	0.54	0.54	0.58	0.50	0.66	**0.73**
LPrice	0.61	0.70	0.62	0.73	0.74	0.71	0.74	**0.81**
Value								
BVTP	0.55	0.61	0.56	0.55	0.64	0.61	0.61	**0.67**
CEY	0.59	0.53	0.52	0.50	0.49	0.55	**0.60**	0.55
DY	0.55	0.56	0.51	0.52	0.57	0.50	**0.58**	**0.58**
EY	0.52	**0.60**	0.51	0.50	**0.60**	0.56	0.45	0.52
Sales_to_MV	0.62	0.55	0.45	0.49	0.59	0.41	0.60	**0.69**
Growth								
CEYG1	0.53	0.59	0.48	0.52	0.60	0.46	0.61	**0.69**
CEYG12	0.45	0.50	0.50	0.50	0.52	0.51	**0.55**	**0.55**
DPSG12	0.53	0.64	0.59	0.59	0.65	0.59	0.62	**0.70**
DPSG24	0.57	**0.68**	0.53	0.55	0.63	0.58	0.67	0.66
EG12_P	0.53	0.59	0.58	0.57	0.58	0.58	**0.61**	0.54
EG24_P	0.53	0.51	0.55	**0.58**	0.58	0.55	0.55	0.47
Expectedgrowth	0.60	0.63	0.57	0.58	0.62	0.47	0.61	**0.69**
Gearing	0.53	0.55	0.42	0.50	0.48	0.55	**0.56**	0.56
POUT	0.64	0.69	0.61	0.66	**0.71**	0.64	0.58	0.67
ROE	0.55	0.65	0.61	0.62	**0.67**	0.54	0.61	**0.67**
SG12	0.47	0.58	0.49	0.51	0.56	0.52	0.58	**0.62**
SG24	0.59	0.58	0.57	0.57	0.55	0.56	0.61	**0.64**
Liquidity								
Current	0.62	0.58	0.49	0.60	0.57	0.50	0.61	**0.69**
ICBT	0.62	0.66	0.60	0.70	0.72	0.70	0.69	**0.76**
NCA_to_MV	0.51	0.50	0.47	0.58	0.56	0.50	**0.61**	0.57
Risk								
Beta	0.50	**0.61**	0.52	0.60	0.58	0.56	0.50	0.57
PVar12	0.64	**0.71**	0.66	0.62	0.69	0.68	0.61	0.70
RetVar12	0.57	0.61	0.55	0.58	**0.67**	0.57	**0.66**	0.66
Momentum								
Crossover3_12	0.55	0.52	0.49	0.54	0.50	0.55	0.50	**0.63**
MOM1	0.59	0.63	0.58	**0.64**	0.62	0.54	0.58	0.63
MOM3	0.64	0.66	0.58	0.64	**0.69**	0.52	0.64	0.64
MOM6	0.63	**0.70**	0.57	0.65	0.67	0.60	0.63	0.69
MOM12	0.66	0.68	0.66	0.72	**0.74**	0.63	0.66	0.71
MOM18	0.68	0.62	0.56	0.63	0.60	0.71	0.69	**0.74**
Mean	**0.57**	**0.61**	**0.55**	**0.59**	**0.61**	**0.56**	**0.60**	**0.64**
Standard deviation	**0.06**	**0.06**	**0.06**	**0.07**	**0.07**	**0.07**	**0.06**	**0.08**

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In-sample Stepwise Multifactor Model Construction for Style timing Models

C.14. 1M Model

Displays the stepwise process by which attributes are either included (accepted) or rejected entry into the model using the IC performance criteria and the 1M model to forecast style payoffs. Attributes are accepted if there is an improvement in the performance of the model now including the attribute (as measured by IC.) Attributes rejected in a pass are retested in the next pass. This process is repeated until no new attributes are accepted in an entire pass. Statistics are calculated using the in-sample period (1 Mar 1990 – 1 Feb 2000) The inclusion of the final attribute is shaded. Note that all attributes in pass 2 are rejected.

Pass 1					
Step	**t-stat**	**IC**	**IR**	**Accept**	**Reject**
1	4.17	0.02	0.53	ICBT	
2	6.70	0.06	1.41	LPrice	
3	8.58	0.10	2.21	MOM18	
4	7.64	0.09	1.98		MOM12
5	8.17	0.10	2.16		POUT
6	7.49	0.09	1.85		Crossover3_12
7	8.06	0.10	2.15		PVar12
8	7.32	0.09	1.95		MOM6
9	7.64	0.10	2.18		Beta
10	7.37	0.09	1.86		ROE
11	6.55	0.09	1.86		MOM3
12	6.14	0.08	1.67		RetVar12
13	9.04	0.10	2.34	DY	
14	8.76	0.10	2.15		Gearing
15	8.75	0.10	2.27		SG12
16	8.59	0.10	2.27		BVTP
17	8.18	0.10	2.27		LMV
18	6.88	0.09	1.56		EG24_P
19	9.02	0.10	2.33		DPSG12
20	8.59	0.10	2.03		Sales_to_MV
21	9.13	0.10	2.30	Current	
22	6.42	0.09	1.58		EG12_P
23	7.46	0.09	2.07		DPSG24
24	9.69	0.11	2.35	SG24	
25	8.78	0.10	2.10		CEYG1
26	7.58	0.09	1.93		MOM1
27	9.03	0.10	2.22		EY

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C.15. 6M Model

Displays the stepwise process by which attributes are either included (accepted) or rejected entry into the model using the IC performance criteria and the 6M model to forecast style payoffs. Attributes are accepted if there is an improvement in the performance of the model now including the attribute (as measured by IC.) Attributes rejected in a pass are retested in the next pass. This process is repeated until no new attributes are accepted in an entire pass. Statistics are calculated using the in-sample period (1 Mar 1990 – 1 Feb 2000) The inclusion of the final attribute is shaded.

Pass 1						Pass 2					
Step	t-stat	IC	IR	Accept	Reject	Step	t-stat	IC	IR	Accept	Reject
1	4.17	0.02	0.53	ICBT		28	8.84	0.11	2.15	POUT	
2	7.16	0.06	1.46	LPrice		29	8.45	0.11	2.01		Crossover3_12
3	8.43	0.09	2.15	MOM18		30	8.80	0.11	2.05		PVar12
4	8.29	0.10	2.09	MOM12		31	8.06	0.11	1.96		MOM6
5	7.85	0.10	2.10		POUT	32	8.23	0.11	1.97		MOM3
6	7.76	0.10	1.98		Crossover3_12	33	7.23	0.10	1.82		RetVar12
7	7.60	0.09	1.94		PVar12	34	9.00	0.12	2.21	DY	
8	7.68	0.10	1.88		MOM6	35	8.64	0.11	2.14		Gearing
9	7.94	0.10	2.11	Beta		36	9.39	0.11	2.16		SG12
10	7.99	0.10	1.92	ROE		37	8.40	0.11	2.15		LMV
11	7.37	0.10	1.78		MOM3	38	6.43	0.10	1.56		EG24_P
12	6.58	0.09	1.65		RetVar12	39	8.97	0.12	2.19		DPSG12
13	7.79	0.10	1.91		DY	40	9.17	0.12	2.13	Sales_to_MV	
14	7.60	0.10	1.85		Gearing	41	7.09	0.11	1.68		EG12_P
15	8.37	0.10	1.89		SG12	42	8.62	0.11	2.11		DPSG24
16	8.70	0.11	2.09	BVTP		43	9.20	0.12	2.12		SG24
17	7.93	0.11	2.02		LMV	44	9.22	0.11	1.98		CEYG1
18	5.77	0.09	1.40		EG24_P	45	8.84	0.11	1.96		MOM1
19	8.75	0.11	2.09		DPSG12						
20	8.52	0.11	1.99		Sales_to_MV						
21	8.82	0.11	2.10	Current							
22	6.90	0.10	1.62		EG12_P						
23	7.84	0.10	2.03		DPSG24						
24	8.89	0.11	2.09		SG24						
25	8.74	0.10	1.91		CEYG1						
26	8.04	0.11	1.92		MOM1						
27	8.73	0.11	2.09		EY						

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C.16. A Comparison of the 1M, 6M and 12M Models Allowing Each to Select its own Attributes

Based on the eleven ICM attributes used in *Section 8.4.1.*, the 1M and 6M models perform best out-of-sample (depending on whether you use the decile spread or the IC criterion to evaluate performance). Fixing the attributes allowed for the best comparison of relative forecasting ability, however it did not necessarily produce the best model possible as performing attributes under each forecasting criteria may have been excluded. An attempt is now made to build the best possible model by not only forecasting attribute payoffs, but also selecting attributes based on the different forecasting models. For comparative purposes, the 12M model is included in the analysis. A similar attribute selection stepwise procedure is adopted to the one described in *Section 6.3.2.* using IC as the selection criteria and each forecasting model to generate monthly weights for each style. The output of the stepwise process is provided in *Appendix A.19.* for the 12M model and in *Appendices C.14.* and *C.15.* for the 1M and 6M models respectively. The attributes selected using each forecasting model are displayed in *Table C.16.1* .

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Table C.16.1. Model Composition

Lists the attributes included in each model using the stepwise procedure outlined in *Section 6.3.2.* based on the criteria IC and the forecasting model named in the leftmost column. Results of the stepwise selection procedure are displayed in *Appendix A.19.* for the 12M model and in *Appendices C.19.* and *C.20.* for the 1M and 6M models respectively.

Model	Attributes	Constituent attributes
1M model	6	ICBT, LPrice, MOM18, DY, Current, SG24
6M model	11	ICBT, LPrice, MOM18, MOM12, Beta, ROE, BVTP, Current, POUT, DY, Sales_to_MV
12M model	11	ICBT, LPrice, MOM18, MOM12, Crossover3_12, Beta, ROE, DY, SG12, BVTP, SG24

It is striking that neither the 1M nor 6M models accept a greater number of attributes than the 12M model. This is disappointing as it is unlikely that the new models formed will be able to significantly outperform the models in *Section 8.4.1.* where the attributes were selected using the 12M forecasting model. The in-sample and out-of-sample performance of each of the three models is presented in Table C.16.2.

Table C.16.2. In-sample and Out-of-sample Evaluation of Multivariate Forecasting Procedures (Self-selection of Attributes)

Displays the performance of multivariate expected return models based on the attributes selected by the Information Coefficient criteria and each forecasting model (See *Section 6.3.2* for details on the stepwise construction of the ICM model) each forecasting model during the in-sample (1 Mar 1990 – 1 Feb 2000) and out-of-sample (1 Mar 2000 – 1 Feb 2004) periods. Note that over the in-sample period the regression based models use coefficients estimated over the whole period while over the out-of-sample period the regression based models use an expanding window to estimate coefficients. See *Section 8.2.1.* for a more detailed explanation of the expanding window. Mean slope is obtained by running monthly regressions of expected returns against realised returns over the sample period and taking the mean value of the monthly slope coefficient. T-statistic of slope is obtained by dividing the mean slope by its standard deviation over the sample period and multiplying by the number of observations in each month. IC is obtained by applying Pearson's correlation coefficient to expected and realised returns. Qian and Hua's (2003) Information Ratio is obtained by dividing IC by the standard deviation of IC and Grinold's (1989) Information Ratio is obtained by multiplying IC by the square root of the number of forecasts each month. Mean monthly values are displayed for both information ratio's The decile spread measures the difference between the average return earned by shares in the top decile of forecast returns and the average return earned by shares in the lowest decile. The standard deviation of the decile spread is displayed along with the T-statistic of spread which takes into account the mean and standard deviation of the spread along with the number of shares forecast each month. Earliest (latest) number of shares relates to the number of observations at the start (end) of the period. For each criterion the greatest (or in the case of standard deviation, the least) value is bolded for both the in-sample and out-of-sample periods.

	1M model		6M model		12M model	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Mean Slope	**5.87**	**3.60**	1.20	1.43	0.72	0.60
Standard Deviation of Slope	9.14	8.95	1.54	2.25	**0.87**	**1.08**
T-statistic of Slope	7.04	2.73	8.58	**4.30**	**9.04**	3.74
IC	0.107	0.086	0.118	**0.112**	**0.122**	0.110
Standard Deviation of IC	0.115	0.223	0.133	0.250	0.139	0.194
Mean IR (Qian and Hua)	**0.93**	0.39	0.88	0.45	0.88	**0.56**
Mean IR (Grinold)	**2.43**	2.30	2.32	2.58	2.34	**2.67**
Decile Spread	0.04	0.03	0.04	0.04	**0.05**	**0.04**
T-statistic of Spread	6.71	0.73	7.25	1.06	**7.28**	**1.19**
Standard Deviation of Spread	**0.06**	0.13	0.06	0.16	0.07	**0.13**
Earliest Number of Shares	345	655	229	501	132	559
Earliest Number of Shares	511	720	383	524	381	581
Latest Number of Shares	686	708	511	309	576	338

In-sample the 12M model produces the greatest IC and t-statistic of slope, followed closely by the 6M and 1M models. Out-of-sample the 6M model produces the best IC and t-statistic of slope followed closely by the 12M model. Neither the 1M model nor the 6M model is able to improve on the 12M model's decile spread both in- and out-of-sample. The 1M model performs well below the 1M and 12M models, almost surely because of the lesser number of attributes it includes.

While the 1M and 6M models appear to be better at forecasting style payoffs (*Section 8.4.*), when they are used to select attributes, they select too few attributes resulting in models that are unable to convincingly beat the 12M model.

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Table C.16.2. In-sample and Out-of-sample Evaluation of Multivariate Forecasting Procedures (Self-selection of Attributes)

Displays the performance of multivariate expected return models based on the attributes selected by the Information Coefficient criteria and each forecasting model (See *Section 6.3.2* for details on the stepwise construction of the ICM model) each forecasting model during the in-sample (1 Mar 1990 – 1 Feb 2000) and out-of-sample (1 Mar 2000 – 1 Feb 2004) periods. Note that over the in-sample period the regression based models use coefficients estimated over the whole period while over the out-of-sample period the regression based models use an expanding window to estimate coefficients. See *Section 8.2.1.* for a more detailed explanation of the expanding window. Mean slope is obtained by running monthly regressions of expected returns against realised returns over the sample period and taking the mean value of the monthly slope coefficient. T-statistic of slope is obtained by dividing the mean slope by its standard deviation over the sample period and multiplying by the number of observations in each month. IC is obtained by applying Pearson's correlation coefficient to expected and realised returns. Qian and Hua's (2003) Information Ratio is obtained by dividing IC by the standard deviation of IC and Grinold's (1989) Information Ratio is obtained by multiplying IC by the square root of the number of forecasts each month. Mean monthly values are displayed for both information ratio's The decile spread measures the difference between the average return earned by shares in the top decile of forecast returns and the average return earned by shares in the lowest decile. The standard deviation of the decile spread is displayed along with the T-statistic of spread which takes into account the mean and standard deviation of the spread along with the number of shares forecast each month. Earliest (latest) number of shares relates to the number of observations at the start (end) of the period. For each criterion the greatest (or in the case of standard deviation, the least) value is bolded for both the in-sample and out-of-sample periods.

	1M model		6M model		12M model	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Mean Slope	**5.87**	**3.60**	1.20	1.43	0.72	0.60
Standard Deviation of Slope	9.14	8.95	1.54	2.25	**0.87**	**1.08**
T-statistic of Slope	7.04	2.73	8.58	**4.30**	**9.04**	3.74
IC	0.107	0.086	0.118	**0.112**	**0.122**	0.110
Standard Deviation of IC	0.115	0.223	0.133	0.250	0.139	0.194
Mean IR (Qian and Hua)	**0.93**	0.39	0.88	0.45	0.88	**0.56**
Mean IR (Grinold)	**2.43**	2.30	2.32	2.58	2.34	**2.67**
Decile Spread	0.04	0.03	0.04	0.04	**0.05**	**0.04**
T-statistic of Spread	6.71	0.73	7.25	1.06	**7.28**	**1.19**
Standard Deviation of Spread	**0.06**	0.13	0.06	0.16	0.07	**0.13**
Earliest Number of Shares	345	655	229	501	132	559
Earliest Number of Shares	511	720	383	524	381	581
Latest Number of Shares	686	708	511	309	576	338

In-sample the 12M model produces the greatest IC and t-statistic of slope, followed closely by the 6M and 1M models. Out-of-sample the 6M model produces the best IC and t-statistic of slope followed closely by the 12M model. Neither the 1M model nor the 6M model is able to improve on the 12M model's decile spread both in- and out-of-sample. The 1M model performs well below the 1M and 12M models, almost surely because of the lesser number of attributes it includes.

While the 1M and 6M models appear to be better at forecasting style payoffs (*Section 8.4.*), when they are used to select attributes, they select too few attributes resulting in models that are unable to convincingly beat the 12M model.

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