Profitability of Quantitative vs. Momentum Size and Style Rotation Strategies in the UK Equity Market

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Abstract

This paper examines whether short-term variation in the spreads of the UK size and value/growth style indices is better predictable and exploitable by means of quantitative or momentum style rotation strategy. Applying different long-only and long-short strategies, we find that the value/growth rotation is not profitable regardless of the method used for choosing a style. Alternatively, both quantitative and momentum based small/large rotation is profitable at easily feasible levels of transaction costs for both ETFs and institutional traders, with quantitative rotation having an edge over the momentum one, in terms of generated end of period wealth and Sharpe ratios.

JEL classification: G11

Keywords: size and style rotation, logit model, momentum, ETF application

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1. INTRODUCTION

The concept of equity investment styles is nowadays widely accepted in the investment community. This can be seen both from the large number of funds following style investing strategies and from the proliferation of style indices published by several companies. Although most of those funds focus on one style at a time, where for example we can identify value or growth and small capitalisation funds, there is extensive evidence which suggests that each of those styles does not persistently outperform the market or the remaining styles. Therefore, there is a scope for generating higher returns when switching from one style to another, for example, growth stocks to value, when we have an outlook that value stocks will outperform or from large capitalisation stocks to small, when the forecast shows that the latter will perform better and vice versa.

With focus on UK equity style management, we apply a forecasting model which we believe is feasible by practitioners. We assess the potential profitability of equity style rotation strategies using a set of variables chosen for their ability to predict the direction of the style spread. These variables are market related, macroeconomic and fundamental factors. Additionally, we apply widely accepted momentum strategies in the relative past returns of value/growth and small/large styles separately, to investigate if such simple strategies could yield a more profitable result of style rotation. Our style rotation strategies are based on small-capitalisation, large-capitalisation, value and growth segments of the market, using the appropriate style benchmark indices as proxies for styles. We believe that there are two relatively simple and cheap ways in which the suggested rotation strategies can be applied in reality. Firstly, the increased popularity of exchange traded funds (ETFs) is enabling investors to buy and sell indices at a very low comparable cost. Secondly, the recent availability of futures contracts on style indices enables investors to apply the suggested strategies more cost effectively, due to low transaction costs, low tracking error and high liquidity of the futures contract. Furthermore, we should mention that our study specifically focuses on the UK equity market. The reasons for this are two-fold: Firstly, a host of empirical work on this topic is usually concentrated on the well-documented US equity market; and secondly, although institutional and individual investors are aware of the opportunities offered by international investing; in practice the home-country bias dominates investor portfolios.

2. REVIEW OF THE LITERATURE

There is a large body of evidence in the literature on style investing which suggests that consistently investing in value and/or small-cap stocks outperforms their counterparts, particularly over medium to long-horizons. Such evidence can be found in Capual et al. (1993), Arshanapalli et al. (1998), Fama and French (1998), Bauman et al. (1998) and Reinganum (1999). In practice, style consistency may not be the optimal strategy. This is due to the existence of style drift, whereby a value (growth) stock may evolve into a growth (value) stock over time or a small (large) cap stock into a large (small) cap stock. This style drift creates a need for active style rotation in order to maintain consistency.

In order to implement style rotation strategies, we must examine the evidence on the efficacy of market-timing i.e. whether one can predict movements in financial markets as the basis for short-term shifts into and out of a common stock, with the primary objective of maximising returns. Early studies by Sharpe (1975) and Jeffrey (1984) find that while the potential benefits of market-timing are attractive, the required forecasting skill needed to time the market successfully is probably unattainable for most portfolio managers. A more recent study by Bauer and Dahlquist (2001) shows that the buy-and-hold large cap stocks strategy slightly beats the switching strategy between small-cap and large-cap stocks.

Although many studies illustrate the difficulties in market-timing for successful style rotation, a number of researchers have tested whether the variability in returns of small-cap and large-cap stocks, and value and growth stocks is predictable. For example, Coggin (1998) finds that style indices cannot be predicted using only the time series of returns as information variables but that forecasts should be based on macroeconomic variables and the business cycle for example. Copeland and Copeland (1999) find that when the estimated volatility in the VIX increased, futures on the large-cap portfolio outperformed futures on the small-cap portfolio during the following time period. Furthermore, when estimated volatility decreased, futures on the small-cap portfolio outperformed futures on the large-cap portfolio. The advantage of this style timing strategy is that it can easily be implemented for short-term rotations because the futures market is highly liquid.

In terms of which factors are giving best signals for switching, Kao and Schumaker (1999) use the yield-curve, real bond yield, corporate credit spread, high yield spread, estimated GDP growth and the earnings-yield gap as signals for style switching. Asness *et al*. (2000) advocated that forecasting models utilising the difference between the spreads of growth in earnings for value stocks and growth stocks provided a statistically significant approach for style rotation techniques. Sorrensen and Lazzara (1995) argue that industrial production and interest rates influence value/growth return spread in the positive way while Anderson (1997) finds a positive relationship between the yield curve and small/large spread. Lucas *et al.* (2001) apply a variety of statistical approaches including models based on business cycle variables, time series models, pooling and cross sectional coefficients to explain variations in returns generated by style and size effects through macroeconomic conditions. Their findings suggested that models forecasting style drift for the use of profitable style rotation opportunities provided statistically robust excess returns once they were corrected for risk. Their results, in similar fashion to Coggin (1998), and Kao and Schumaker (1999), confirm the efficacy of models founded on macroeconomic factors to signal style changes.

Levis and Liodakis (1999) illustrate that an investor who could perfectly predict the direction of the size spread in the UK market would have earned an average annual return of 34%, 17% above the return of the FTSE 100 forecasting accuracy of 60%-70% would be sufficient to outperform the small-cap-only buy-and-hold portfolio. In the case of value/growth rotation, perfect foresight would have provided a return of 29% and a value-only buy-and-hold portfolio would have returned 24%. At least an 80% forecasting accuracy of the direction of the spread each month would be required to beat the value-index portfolio, which is quite difficult to sustain in reality.

Furthermore, Levis and Tessaromatis (2004) assess the power of a macroeconomic model to generate forecasts both about the direction and the magnitudes of the value/growth spread and find that style rotation strategies are profitable for investors with different benchmarks and various risk constraints.

Although the studies discussed above indicate that profitable opportunities exist by using methods of quantitative active long-only style rotation, the implementation of a suitable model and variables to predict the direction of the stocks to generate superior returns needs to be explored further. Additionally, with the availability of short-selling with ETFs, implementation of index based long/short style rotation strategies can be exploited, which hasn't been documented in the existing empirical evidence.

On the other hand, while the evidence noted above indicates the profitability of style rotation strategies based on quantitative models, we believe that a simpler approach that does not require complex (and often subjective) model specification can be used to achieve similar performance. Therefore, we use momentum strategies to show this. One of the reasons that make momentum strategies interesting is that the contribution of lagged macro, fundamental and market signals used in quantitative forecasting approaches such as logit or probit is almost fully captured by momentum.

Momentum studies are based on the idea of a) strong autocorrelation of equity returns, b) cross-serial correlation across crocks (lead-lag relationships) or c) the difference in cross-sectional means, as documented in Lo and McKinley (1990). There is vast evidence on profitability of momentum strategies that started from Jegadeesh and Titman (1993) study, which suggests that mid-term holding periods lead to high momentum returns. The studies usually relate momentum to firm-specific returns, suggesting that investors underreact or overreact to firm-specific news and events (Jagadeesh and Titman (2001)).

Our study will investigate if momentum is pronounced in style index portfolio based trading. Levellen (2002) assesses the profitability of momentum strategies based on Size and Book to Market based portfolios in the US and finds that momentum in these portfolios is in some instances even stronger than the momentum in individual stocks.

Although the majority of evidence on momentum is based on the US market data, Rouwenhorst (1998) has identified that momentum effects are present internationally. He documents momentum for 12 European countries and US over the period of 1978-1995.

The literature also provides a number of explanations for the momentum effect. For example, Hong, Lim, and Stein (2000) and Lesmond, Schill, and Zhou (2003) suggest that momentum returns are solely the result of overlapping holding periods of momentum portfolios and short positions in illiquid market segments. Our study will be based on style index portfolios widely used and traded in the UK market; hence we believe that they are not illiquid. Furthermore, concepts such as overconfidence of private over public information (see Daniel, Hirshleifer and Subrahmanyam, (1998, 2001)), or optimism and wishful thinking, as well as representativeness and conservatism, in terms of underweighting new information relative to prior (see Barberis, Shieifer and Vishny, (1998)) are causing investors to underreact or overreact to firm-specific news, therefore causing momentum.

The key to profitability of momentum trading is to spot trends early and to react quickly, providing that transaction costs are relatively low. For example, Carhart (1997) finds evidence that after transaction costs are taken into account, momentum strategies are no longer profitable. We will take this into consideration when presenting and interpreting our results.

3. THE CHOICE OF DATA

3.1 Defining the size and style indices

To represent our size indices, we use the FTSE 100 Index and the FTSE Small-Cap Index as proxies for our large-cap stocks and small-cap stocks respectively. To represent our style indices, we use the FTSE 350 Growth Index and the FTSE 350 Value Index as proxies for our growth stocks and value stocks respectively.

The sample period starts from January 1987 when the UK style indices became available and ends in May 2005. This provides us with a sample size of 220 observations. The size and style return spreads are then calculated to identify whether the size and style effects vary over time.[3]

Figures 1 and 2 in Appendix 1 show the size and style return spreads for our chosen indices. There are different patterns in the return spreads over our time-horizon, where one index seems to outperform another for short-term horizons. This suggests that an active rotation

[3] The benchmark small / large relative return spread is estimated on a monthly basis as the difference in the return between the FTSE Small-Cap Index minus the FTSE Large-cap Index. Likewise, the benchmark value / growth relative return spread is estimated on a monthly basis as the difference in the return between the FTSE 350 Value Index minus the FTSE 350 Growth Index.

strategy based on a robust forecasting model or a simple momentum model may have the ability to exploit these short-term shifts in out-performance of one index over another. Furthermore, long/short strategies, involving a purchase of an index whose style is expected to outperform and a sale of an index whose style is expected to be out of favour, may prove even more profitable.

3.2 Selecting the forecasting variables for quantitative model

Financial theory suggests that in markets with risk averse agents, stock returns would vary with the state of the business cycle, where a plausible analysis of investors' predictions of stock returns and subsequently index returns in 'real time' should be made on these business cycle variables. We initially consider a host of "potentially relevant" variables, with the smaller number of variables being chosen using the principal components analysis (PCA) technique. The variables chosen are based on macroeconomic, fundamental and market related factors, as used by some of the studies discussed below.

There is a long tradition for including some measure of inflation in the forecasting relation. Fama (1981) argues that expected inflation is negatively correlated with shocks to future economic growth. Anderson (1997) reports that during high levels of inflation, growth stocks and large-cap stocks tend to become unfavourable, where the inverse occurs for value and small-cap stocks. Small-cap stocks benefit from inflation, perhaps because small companies find it relatively easier to pass along price increases in inflationary times.

The predictive power of interest rate related variables and the term structure in relation to the size and the style premium is derivable from various lines of reasoning, as in Anderson (1997) and Sorensen and Lazzara (1995). Additionally, Kao and Schumaker (1999) propose that since growth stocks, whose valuations rely on expected earnings growth further into the future than value stock valuations, are said to have longer "duration" than value stocks; and, similarly to longer-duration bonds, rising or high future interest rates will disproportionately hurt the discounted value of a growth stock's future earnings stream. Therefore in a steep yield curve environment, growth stocks tend to underperform.

Currency exchange rates lie at the core of macroeconomics, hence given the degree of global integration and its impact on business activity, foreign exchange plays an important role in domestic equity investment, as used in Levis and Liodakis (1999). The inclusion of this variable is more likely to be pronounced in the case of size rather than style. For example, a depreciation of the UK Pound against the US Dollar would benefit domestic large-cap stocks as it would make exports relatively cheaper than imports.

The estimated growth domestic product (GDP) rate has been included as it is the standard measure of the health of the economy. When the economy is growing, GDP is rising. Consequently, GDP reflects the corporate profit cycles. During these expansionary periods when corporate profit is high, evidence shows that operating leverage contributes disproportionately to the profitability of value and small-cap stocks (see Kao and Schumaker, 1999). Hence, during these periods, value and small-cap stocks are likely to outperform large-cap and growth stocks.

To account for the impact of liquidity on stock prices, we include a rate of change in the industrial production index as another possible forecasting variable. The industrial production index is linked with company earnings, another variable mentioned in several early studies as being an important determinant of stock returns; see for example Sorenson and Lazzara (1995). This has the further advantage that observations on it are available on a monthly basis, whereas company earnings are typically reported on a half yearly basis in the UK.

The changes in the money supply, due to monetary policy actions, may affect market liquidity or economic activity and therefore future-cash flow expectations. Mercer (1998) found that size- and book-to-market ratios depend on monetary environment.

The final macroeconomic variable which we include is the rate of change in the spot price of Brent oil. This commodity is included to allow for the possible effect of oil price volatility on the stock market and is another proxy for other macroeconomic factors.

Regarding fundamental factors, there is extensive literature that uses the dividend yield as a proxy for the time variation in expected future returns for stocks. Fama and French (1998) propose that the market dividend yield is known to vary in response to changes in the business conditions and is able to forecast stock returns. Additionally, the growth index has a higher price-to-earnings (P/E) ratio than the value index where the value index is expected to perform better when the forecast P/E spread is low, and vice versa (Fabozzi, 1998).

Finally, we discuss the market variables which we consider including in our model. We include the one month lagged index spreads for small minus large index and for the value minus growth index, where the past trend is used as an indicator of the future trend. Evidence has shown that there is some serial correlation where the historical price is correlated to the current price in style rotation models (Fabozzi, 1998). We also include the annualised change in the variance of the FTSE 100 and FTSE Small-Cap index returns. Finally, evidence from Pesaran and Timmerman (1995) shows correlations between the FTSE All Share Price Index and the size and style indices. As a result, we include the FTSE All Share Price Index return, as one of our explanatory variables.

On a similar note, we include risk premium related variables such as Equity Risk Premium as suggested by Levis and Liodakis (1999) and Earnings Yield Gap similar to Arshanapalli et.al (2005). Earnings yield gap in our case represents the difference between FTSE All share dividend yield and yield on a 10 year UK Government benchmark bond. As the value stocks are those that pay high dividends whereas growth stocks are known for paying very small or no dividends, we take this earnings yield spread as a proxy for risk premium of value stocks and expect a positive relationship between the earnings yield gap and value/growth spread.

Specifically, our set of explanatory variables consists of the following nineteen variables with potential predictive ability, as shown in Table 1:

- Insert Table 1-

3.2.1 Determinants of the size and style spreads for quantitative model

We could use all of the explanatory variables to predict the change in the size and style spreads. However, as our primary concern is to successfully predict whether to invest in one particular size or style index, in reality it would be preferable for an investor to predict the direction of the index spreads by using the most appropriate minimum number of variables.

Unlike Levis and Liodakis (1999) who use univariate OLS to remove insignificant variables, we employ PCA. This is used because it is more appropriate when the primary concern is about prediction or the minimum number of factors needed to account for the maximum portion of the variance represented in the original set of variables (Hair *et al*., 2003). Also, since our data is multivariate, we have a large number of different explanatory variables; which may be highly correlated. Therefore, including all the variables in our model may not be statistically sensible, as it creates some redundancy in the information provided by the variables (Brooks, 2002).

The PCA technique finds the most parsimonious set of variables to include in the analysis as well as to identify the inter-relationships among the variables. Specifically, PCA computes a new set of orthogonal values from a unit length linear combination of the explanatory variables (Solberg, 1988). PCA can be defined as:

$$L_i = \alpha_1 X_1 + \ldots\ldots + \alpha_n X_n \tag{1}$$

where $\sum_{n-1}^{n} \alpha = 1$ and the variance of the equation is maximized, and L_i the explanatory variable is orthogonal. Therefore, the sum of squares of distances of plots along each component is the informational content of the components expressed as a percentage of the sample variance, which ultimately measures the relative importance of the component.[4]

PCA takes into account the total variance and derives factors that contain small proportions of unique variance and error variance. The procedure transforms a number of (possibly) correlated variables into a (smaller) number of variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

Using all explanatory variables relevant for the market-cap and style indices, Table 2 and Table 3 present the results for the extraction of component factors for each of our spreads. As we are extracting factors that account for less and less variance, using the criterion proposed by Kaiser (1960), we retain only the factors with eigenvalues greater than one; in other words, unless the factor extracts at least as much as the equivalent of one original variable, we drop it. Seven factors (components) have eigenvalues greater than one for small/large spread and eight factors (components) have eigenvalues greater than one, for value/growth spread.

- Insert Table 2 –

- Insert Table 3 -

Tables 4 and 5 report the factor matrices for all of the explanatory variables considered relevant to predict the market-cap indices and the style indices respectively. They are

[4] PCA differs from regression analysis as regression analysis minimises the sum of squares in a particular direction, whereas PCA minimises the sum of squares of the distance between the components and the original plot.

computed to assist us in obtaining the number of variables to be extracted. The matrices contain factor loadings for each variable and each factor.[5] In determining which factor loadings are significant we have used a cut-off point of ± 0.382. This is directly calculated from our sample size of 218 observations.[6] From all of the significant variables we chose the ones which have the highest absolute value and best fit the forecasting model in each of the component groups.

In tables 4 and 5, the numbers in the columns represent the factor loadings for each variable on each factor (principal component). We analyse each table in turn. The columns in Table 4 represent the seven principal components and the rows represent the 16 variables contributing to each dimension. The extracted eight components are separate factors that explain the variability of the total set of variables.

- Insert Table 4 -

The columns in Table 5 corresponding to value/growth analysis represent the eight principal components and the rows represent the 19 variables contributing to each dimension for our style spreads. The extracted eight components are separate factors that explain the variability of the total set of variables.

- Insert Table 5 -

The above results are beneficial for determining which variables should be included in our econometric model. We have reduced the number of variables in our models by setting a

[5] Each factor loading enables one to interpret the role that each variable plays in defining each factor. Simply, it is the correlation of each variable with each factor. Thus higher loadings make the variable more representative of the factor.

[6] See table 11 in the Appendix 2 for guidelines in identifying the significant factor loadings based on the sample size.

cut-off point of ± 0.382. To avoid multicollinearity and over-fitting the model, we select no more than one, two, in one instance three variables from each component to include in our size/style forecasting model.

From the highlighted significant explanatory variables in Table 4 and Table 5, we have chosen nine variables in our forecasting model relating to the small/large spread and eleven variables to be used in the forecasting model for value/growth spread. Table 6 lists these variables. It can be seen that the variables chosen are macroeconomic, fundamental and market related.

- Insert Table 6 –

4. METHODOLOGY

4.1. Methodology of the forecasting model

Implementation of a market-timing model can pose problems associated with devising a truly viable forecasting model. Since the goal of our market-timing model is to select the best performing index among the four FTSE indices, a statistical technique able to generate a probabilistic forecast of a group membership is more appropriate.

We employ a recursive dynamic modelling approach where we specifically opt to use the logistic approach to forecast our index return spreads. This econometric model is suitable to predict the sign (direction) of the index return spread, where predictions generated by such binary choice models indicate an estimated probability that one index will outperform the other. This approach exists in an extensive body of literature (see for example, Pesaran and

Timmerman (1995) and Levis and Liodakis (1999)). The procedure for our model is explained below.

Using the chosen explanatory variables (x_t) described in the previous section, we forecast the sign of the size and style spreads, which should be sufficient for a successful size and style rotation strategy. We employ a standard logit modelling approach of the form:[7]

$$\hat{P}_{t+1} = \hat{P}\,(y_{t+1} = 1) = \frac{\exp(\hat{\alpha} + \hat{\beta}\,x_t)}{1 + \exp(\hat{\alpha} + \hat{\beta}\,x_t)} \tag{2}$$

where $\hat{\alpha}$ is a constant term, $\hat{\beta}$ is the parameter estimate(s) and x is the explanatory variable(s).

It suffices to forecast the sign of the size or style index spread rather than the magnitude. Therefore, we classify each month as 1 or 0 based on the size/style spread. If in a particular month small-cap (value stocks) perform better than large-cap (growth stocks), we classify this month as 1, otherwise we set it to 0, where, the conditional probability $\hat{P}_{t+1}$ gives the likelihood that the next month will be a small-cap (value) month or a large-cap (growth) month, i.e.:

$\hat{P}_{t+1}$ = 1 if Small-Cap$_{t+1}$ $\geq$ Large-Cap$_{t+1}$, 0 otherwise;

and

$\hat{P}_{t+1}$ = 1 if Value$_{t+1}$ $\geq$ Growth$_{t+1}$, 0 otherwise.

[7] The full derivation of dynamic modelling approach that we utilise is presented in Pesaran and Timmerman (1995).

To ensure a forward-looking nature of the variables, all explanatory variables are lagged one month to make them predictive in nature. An intercept term is also included in all the regressions considered in our forecasting model. Our regressors remain in effect over the whole sample period.

Using the set of regressors, we make one-month-ahead forecasts of index return spreads.[8] The recursive model selection and estimation strategy is based on the monthly observations over the time-horizon January 1987 to May 2005. The out-of-sample evaluation (trading period) in the two size and style indices for the one-period-ahead forecasts begin at January 1997 and ends at May 2005. The regression coefficients of the first 119 months of the sample (our in-sample period from January 1987 to December 1996) are estimated and fitted into our logit equation along with the actual lagged values of the respective independent variables to obtain the conditional probability estimates of the likelihood that one particular Index will outperform its counterpart in January 1997. This presents us with a hold-out sample of 101 months for evaluation. At the end of January 1997, the regression coefficients are re-estimated using data from the 120 months preceding the forecasted month, and are fitted into the equations with the new lagged values of the independent variables to obtain the conditional probability estimates of the likelihood that one particular index will outperform the others in February 1997. The procedure is repeated, increasing the in-sample size by one month for each forecast. We generate probability estimates for all

[8] These are the 9 (11) explanatory variables for small/large (value/growth) model chosen by the PCA, as discussed in the previous section. In reality the investor would use this information as this is publicly available at the time. However, in principle, one can also consider the possibility of revising the regressors once clear indications of "regime switches" are established.

months in our out-of-sample period, and a time-series of logit probabilities for both size and style spreads are generated.

The forecasted probability estimates obtained for each individual month in our out-of-sample forecast ranges between 0 and 1. Based on these values, we design our implementation strategies.

4.1.1. Implementation strategies based on forecasting model: Long-Only and Long Short

In reality, fund managers in traditional asset management companies can have short-selling constraints; therefore we firstly devise strategies which only allow the fund manager to alter his investment by only taking long positions. Since our strategies are directional style rotation strategies, the manager invests the same absolute weight in the index invested in, i.e. 100% of the funds in the index. Therefore, the long-only style rotation strategies we implement are the following:

Strategy 1 is concerned with the direction of the probability value forecasted by the logit model rather than the magnitude. Whenever the logit model signals a small-cap (value) month, i.e. $\hat{P}_{t+1} \geq 0.5$, the investor will place 100% of the funds in the small-cap (value) index. Whenever the logit model signals an upcoming large-cap (growth) month i.e. $\hat{P}_{t+1} < 0.5$, the investor will invest 100% of the funds in the large-cap (growth) index.[9]

Strategy 2 takes into account the empirical distributions of value/growth and small/large spread in-sample which are then used to determine the cut-off point of p-value in each month. The empirical distributions are suggesting cut-off points very close to 0.5 (as used in strategy 1), in particular ranging from 0.448 to 0.522 for value/growth rotation and 0.459 to 0.51 for small/large rotation.

Long/short strategies are enabling investors to short-sell the index that is forecasted to be out of favour in a particular month. Investors investing in ETFs or style-index futures can apply long/short strategies at a relatively low cost. Therefore, to investigate the benefits of shorting, we construct Strategies 3 and 4:

Strategy 3 is identical to Strategy 2, except that the investor will be long in the style expected to outperform and short in the style expected to underperform, as indicated by the value of $\hat{P}_{t+1}$.

Strategy 4 is beta-neutral Strategy 3, i.e. we adjust the weights of long and short portfolio to obtain a portfolio which is free of systematic risk. As the betas of value and growth indices

[9] For example, if the p_{t+1} value signalled 0.6 in month 1, the investor places 100% of the funds in the small-cap index. If in the following month the p_{t+1} signalled 0.47, the investor would shift 100% of the funds from the small-cap index to the large-cap index.

or small and large indices are not very different at any point in time, we would expect that this strategy produces similar performance to Strategy 3.

4.2. Methodology of Momentum Strategies

We calculate cumulative compound returns for each of the four style indices for compounding periods based on 2-12 historical months:

$$r_t = \prod_{n=-2}^{k} ((1 + r_{t-1}) \ldots (1 + r_{t-n})) - 1 \qquad (3)$$

where, k = -3, -4, -5, -6, -9, -12 months

Momentum strategies are applied in the same sample period as in our quantitative analysis for comparative purposes (Jan 1997 – May 2005). We construct long only and long/short momentum strategies for value/growth rotation and small/large rotation separately. At the end of each month, we evaluate the style indices (value or growth on one hand and small or large on the other hand) based on their past cumulative return. Our formation and holding periods are presented in Table 7:

- Insert Table 7 -

Therefore, we analyse 13 long-only and 13 long-short momentum strategies. The long-only value/growth (small/large) momentum strategies utilise the following idea: buy an index generating greater positive momentum. If both indices exhibit negative momentum in a particular month, no investment is made in that month. The long/short value/growth (small/large) momentum strategies imply that investor should buy an index with greater positive momentum and short-sell the index in which the negative momentum is observed.

Note that a) if both indices, i.e. value/growth (small/large) exhibit negative momentum, one should short sell the one with lower negative cumulative return and b) if there is no negative momentum in either of the indices in a particular month, there should be no short-selling.

4.3. Transaction Costs

We calculate break-even transaction costs for each of our quantitative and momentum strategies. As benchmarks for this calculation we use buy-and-hold FTSE 350 Value index for value/growth rotation and FTSE Small Cap index for small/large rotation, as they have outperformed their counterparts. The average level of transaction costs for ETFs is 12-20bps, with maximum expense ratio for UK ETFs being 0.5% (50bps)[10], whereas the average for equities is around 140-150bps. Some mutual funds can have transaction costs of 200bps (or even more) when the rate of turnover for institutional trading is factored in. Having this in mind, we will comment on whether our trading strategies are profitable at a reasonable level of transaction costs.

5. ANALYSIS OF RESULTS

5.1 Profitability of quantitatively-based value/growth and small/large rotation

Table 8 provides the summary results our long-only and long/short trading strategies that we have employed based on the estimated logit probabilities. Panel A of the table reports value/growth rotation results, Panel B reports small/large rotation and panel C shows the results for the benchmarks.

- Insert Table 8 –

[10] www.trustnet.com

We will compare the performance of each rotation strategy over the trading period with the perfect foresight strategy (showing what one would have achieved if forecasting accuracy was 100%) and buy-and-hold benchmark index strategy. In the case of value/growth rotation, we use FTSE 350 Value Index as a benchmark while for small/large rotation our benchmark is FTSE Small-Cap buy-and-hold, as there is overwhelming evidence that value stocks outperform growth and that small stocks outperform large in the long run. This is also confirmed with our findings in panel C: FTSE 350 Value and FTSE Small cap indices produce higher end of period values and better Sharpe ratios than their style counterparts.

Results in Panel A suggest that although all four of our strategies produce better end of period wealth than the FTSE 350 Growth index, they do not outperform the benchmark index. The end of period value of the investment that could be achieved from any of the four strategies is below the value index buy-and-hold end of period value of £1,486,418.42. Additionally, if we compare the Sharpe ratios, as the risk-adjusted measures of performance, it can be seen that higher Sharpe ratios are achieved with long-only rather than long/short rotation strategies, but they are not high enough to exceed the Sharpe ratio of the benchmark value index (0.065). Our perfect foresight strategies which assume 100% forecasting accuracy indicate that investors would have achieved ten times higher than the benchmark's Sharpe ratio of 0.675 in long only rotation and the Sharpe ratio of 3.166% in long/short rotation. Although the forecasting accuracy of our models is 56% for Strategy 1 and 57% for all other strategies, which is considered to be a good level of forecasting accuracy in reality, it proves not to be enough to be successful. The reason for that may be in the fact that our model is value-biased. It can be seen from panel A that percentage of correct predictions for value style is 73.68% for Strategy 1 and 75.44% for all other Strategies, whereas the percentage of correct predictions of ‘growth months’ is only 32.56% for all models. These results obtained in panel A are consistent with results reported by Levis and Liodakis (1999), as they find that value/growth rotation in the UK is only profitable at a very low, unrealistic level of transaction costs. Overall, two main conclusions can be drawn form this part of the analysis of Panel A: 1) investors in value or growth stocks are better off following the style consistency rather than the style rotation strategy in the UK and 2) there is scope for improving the forecasting accuracy of the model, as it appears that a much higher accuracy rate is needed for a market timer to outperform the buy-and-hold FTSE 350 Value index.

Results in Panel B suggest that both long-only and long-short small/large rotation strategies easily outperform the passive buy-and-hold strategy at the reasonable level of transaction costs. Strategy 1 based on cut-off rate of 0.5 and Strategy 2 based on empirical distribution of small-large spread cut-off rates are generating identical end of period wealth and Sharpe ratios (0.419) with break-even transaction cost level of 141bps. Long-short Strategies 3 and 4 are performing better than all the other quantitatively-based rotation strategies reported in Table 8, with the end of period wealth exceeding £ 3,800,000 and Sharpe ratios of 0.955. Furthermore, Strategy 3 and Strategy 4 can make profits relative to the buy-and-hold small cap benchmark up to the level of 235bps and 252bps transaction costs per trade respectively. The break-even transaction costs for all four strategies in panel B are much above the average transaction costs for ETFs (50bps). Given that our strategies assumes trading indexes (portfolios) rather than individual equities, the turnover rates will be considerably lower than for individual equities, which implies that transaction costs up to about 140bps for long-only and up to about 235bps for long-short strategies are reasonable to assume. The level of forecasting accuracy of the small/large rotation model is 63%, however the percentage of correct small cap and correct large cap month predictions is more balanced (66.67% for small cap vs. 56.52% for large cap) than in the value/growth rotation case. Overall, the following conclusions arise from the analysis of Panel B: 1) investors in small or large cap stocks can achieve better profits after transaction costs when applying long-only or long-short style rotation strategies than if they are passively investing in small or large cap style and 2) the scope for improvement of the forecasting accuracy model still exists, as the perfect foresight strategies imply that there is a lot more profit to be earned (e.g. beta adjusted long-short strategy with perfect foresight would earn in excess of £28,000,000 during our out of sample period).

5.2 Profitability of Momentum-based strategies for value/growth and small/large rotation

We show the annualised returns, standard deviations, Sharpe ratios, end of period wealth and break-even transaction costs for value/growth rotation momentum strategies in Table 9 and for small/large rotation momentum strategies in Table 10.

- Insert Table 9 –

- Insert Table 10 –

The results in Table 9 are showing that the only strategies generating marginal profits are strategies based on short-term formation periods of 2, 3, and 4 months and one month holding period. However, the level of transaction costs that would make profits from these strategies at least equal to the profit from buy-and-hold FTSE 350 Value index is too low for some institutional investors and even ETFs traders (10bps and 2bps). Therefore, the value/growth momentum rotation strategy is not robust across different formation and rebalancing periods and the real advantage of this strategy, regardless of weather it is long-only or long-short, is non-existent. This is consistent with our findings from quantitative value/growth style rotation in section 5.1.

One the other hand, small/large momentum rotation strategies seem to be much more profitable. Specifically, the results from long-only small/large rotation strategies based on positive momentum, reported in Table 10, are indicating that portfolio formation periods of 5 months and longer are generating profits and higher Sharpe ratios than the benchmark small-cap index at very high levels of transaction costs. However, it can be seen that short formation/short rebalancing periods imply greater number of switches, allowing smaller transaction costs per switch which makes them less realistic for some institutional investors, but still possible for investors in ETFs. The best end of period value and Sharpe ratios are obtained with 6 months formation periods and those results are very similar to the ones generated with our quantitative model. Alternatively, long/short small/large rotation strategy based on buying a style that exhibits positive momentum and shorting the style that exhibits negative momentum generates much less favourable end of period wealth and Sharpe ratios than our quantitative model. However, it still outperforms buy-and-hold small cap index strategy in across all formation and holding periods at marginal level of transaction costs per switch, except in the case of 5 month formation – 1 month rebalancing case, where break-even transaction costs are higher.

This analysis for both long only and long-short momentum rotation implies that the real profitability of the strategy, when transaction costs are taken into account, is dependant on the choice of parameters for portfolio formation and rebalancing.

5.3. Quantitative or Momentum-based style rotation?

When comparing momentum-based rotation strategies and quantitative-based strategies, the following conclusions can be made:

a) It is very difficult to capture the variations in value and growth indices and to successfully apply style rotation strategy in the UK regardless of the method we use. Both quantitative and momentum based style rotation does not appear to show robust profitability at realistic level of transaction costs or realistic level of forecasting accuracy.
b) Small/large long-only and particularly long-short style rotation based on our quantitative model produces better end of period wealth at a reasonable level of transaction costs than momentum strategies. The Sharpe ratios are in most of the cases also larger.
c) The profitability of the quantitative rotation depends of the model specification, which is subjective.
d) Although momentum strategies are much simpler to apply, their profitability depends the choice of parameters chosen for portfolio formation and rebalancing, which is also subjective.

Overall, although both types of strategies have their advantages and disadvantages, our results show that beating the long-term buy-and-hold value index strategy is very difficult in the UK market while beating the small-cap long term buy-and-hold strategy is somewhat more profitable with quantitative small/large rotation strategies.

6. CONCLUSION

This study examined whether monthly directional variations in the size and style index spreads for the UK equity market are sufficiently predictable to be exploited by means of a market-timing strategy and produce better profits than a simple momentum strategy. Using a logistic dynamic forecasting model, we tested for the profitability of UK style index based long-only and long/short quantitative style rotation trading strategies. Additionally, using a variety of momentum strategy formation and holding periods, we assess if better profitability of style rotation can be achieved with simple momentum strategies.

To generalise our findings, forecasting the small/large size spreads using macroeconomic, fundamental and market variables with accuracy rates of 63%, was found to be sufficient to outperform the FTSE Small Cap buy-and-hold strategy both in the case of long-only and long/short investing. For value/growth rotation, similar level of forecasting accuracy is not sufficient for beating the buy-and-hold FTSE 350 Value strategy both in the case of long-only and long/short investing. Trading rules based on momentum strategies generate the same general findings, but the profitability of strategies is smaller than the one obtained with our forecasting model, particularly when long/short strategies are examined. This leads us to conclude that although quantitative model specification can be quite subjective it can lead to more profitable performance of size based style rotation strategies.

APPENDICES

Appendix 1:

Figure 1: Monthly return spread for Small-Cap minus Large-Cap index

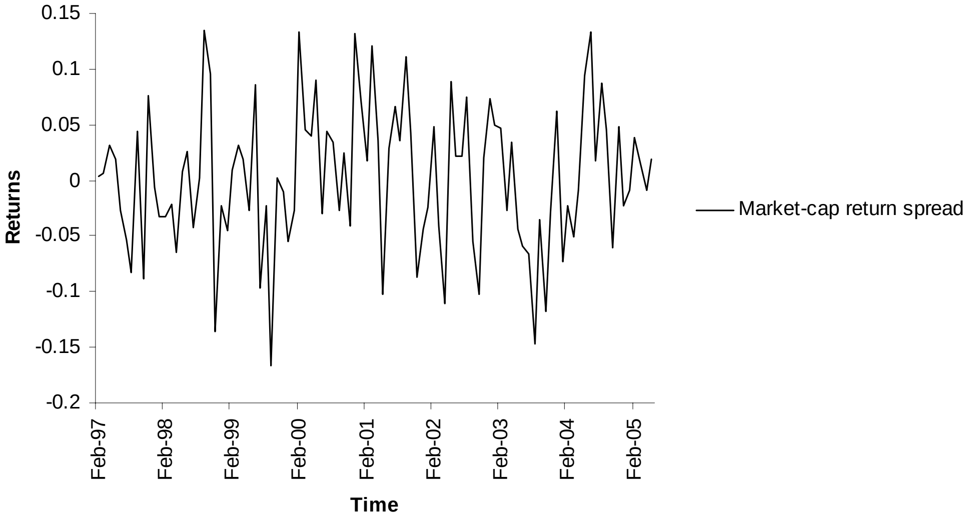
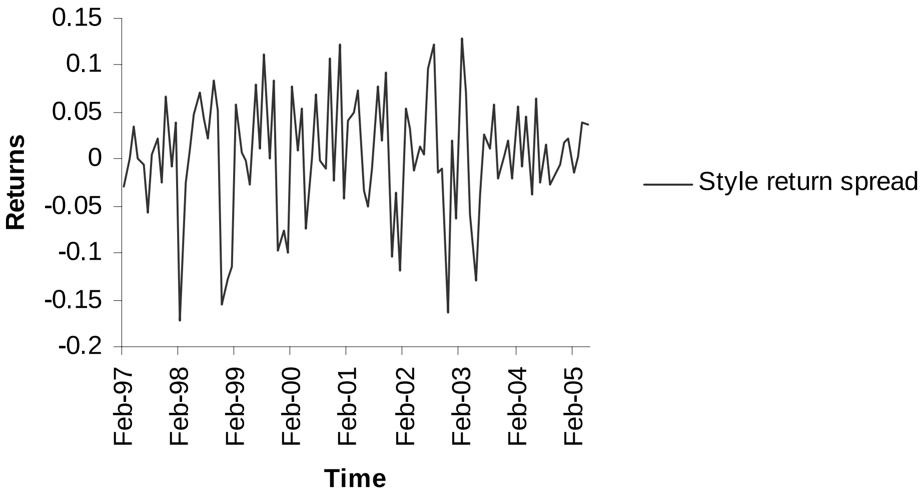


Figure 2: Monthly return spread for Value minus Growth index



Appendix 2:

Table 11: Guidelines for identifying significant factor loadings based on sample size

Factor Loading required for significance	Sample size
±0.20	>500
±0.25	450
±0.30	350
±0.35	250
±0.40	200
±0.45	150
±0.50	120
±0.55	100
±0.60	85
±0.65	70
±0.70	60
±0.75	50

Source: Hair, Anderson, Tatham and Black (2003), Multivariate Data Analysis, 5^{th} Edition

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Table 1: Variables considered as potential predictors for size and style spreads

Measure	Code	Description
Lagged Dependant Variable	VALUE_GROWTH(-1) **	1 month lagged FTSE350 Value minus FTSE 350 Growth returns
Lagged Dependant Variable	SMALL_LARGE(-1) *	1 month lagged FTSE Small Cap minus FTSE 100 returns
Exchange rate	C_ER	Monthly Change in GBP/USD exchange rate
FTSE All Share	C_FTA	FTSE All Share return
Risk Premium	C_RPR	Difference between FTAll Share return and 3month T-bill
Earnings Yield Gap	C_FTDY_LTBONDSPREAD**	Difference between FTAll Share Dividend Yield and Yield on10 Yr UK benchmark bond
Term Structure	C_TS	Term structure: 10 year UK Benchmark bond yield minus the 3 month T-bill
Interest rates	MC3MTB	Monthly change in 3 month T-bill
Inflation	CINFL	Monthly change in the UK CPI
Consumer Confidence	C_CNFDENCE	Consumer Confidence Indicator
Commodity	PER_C_OIL	Monthly % change in the price of Brent oil
GDP	PER_C_GDP	Monthly chagne in forecast GDP
Money Supply	C_M4MS	Monthly change in broad money M4
Money Supply	C_M0MS	Monthly change in narrow money M0
Liquidity	C_PM	Monthly change in the industrial production of the manufacturing sector
Liquidity	C_UKINDPRO	Monthly change in the UK production Index
P/E ratios	C_SPPER **	FTSE 350 Value minus FTSE 350 Growth P/E ratio
Dividend Yield	DYSMALL_LARGE *	FTSE Small Cap Dividend Yield minus FTSE 100 Dividend Yield
Variability in Style Indices	C_VARVAL **	Monthly change in FTSE 350 Value standard deviation
Variability in Style Indices	C_VARGR **	Monthly change in FTSE 350 Growth standard deviation
Difference in variability: Size	C_VARSML*	Standard deviation of FTSESmall minus standard deviation of FTSE 100
Difference in variability: Style	C_VARVMG**	Standard deviation of FTSE 350 Value minus standard deviation of FTSE 350 Growth

* Measure is only applicable for size models
**Measure is only applicable for style model

Table 2: Extraction of component factors with eigenvalues greater than 1 for small/large spread

Factor	Eigenvalue	Variance Prop.	Cumulative Prop.
1	2.45263	0.153289	0.153289
2	2.271625	0.141977	0.295266
3	2.130879	0.13318	0.428446
4	1.753601	0.1096	0.538046
5	1.156863	0.072304	0.61035
6	1.047162	0.065448	0.675797
7	1.015595	0.063475	0.739272

Table 3: Extraction of component factors with eigenvalues greater than 1 for value/growth spread

Factors	Eigenvalue	Variance Prop.	Cumulative Prop.
1	2.972388	0.156441	0.156441
2	2.313777	0.121778	0.278219
3	1.975464	0.103972	0.382191
4	1.861567	0.097977	0.480168
5	1.729944	0.09105	0.571218
6	1.1802	0.062116	0.633334
7	1.117574	0.05882	0.692153
8	1.002965	0.052788	0.744941

Table 4: Factor matrix for small/large spread

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
C_FTA	-0.19212	0.352785	0.505189	-0.09222	0.086003	0.183274	0.002322
SMALL_LARGE	0.180784	0.112827	-0.02743	-0.00198	-0.33911	0.061062	0.532513
C_ER	-0.16794	0.230334	0.158154	-0.04124	-0.3724	-0.35959	-0.24637
C_M0MS	0.024258	0.097117	-0.05816	-0.34095	0.261764	-0.41205	-0.41872
C_TS	0.433722	0.347135	-0.08576	0.004859	0.00449	0.186293	-0.14849
DYSMALL_LARGE	-0.3645	0.127525	-0.14702	0.176747	0.222774	-0.51579	0.226101
CINFL	-0.41443	-0.38612	0.102586	0.043065	-0.14266	0.255531	-0.07002
C_VARSML	0.190551	0.296712	-0.25842	0.036114	-0.12213	0.204282	-0.33256
MC3MTB	0.198059	-0.27992	0.087268	-0.19185	-0.24449	-0.10595	-0.26854
PER_C_GDP	-0.31483	0.146077	-0.22932	0.207104	0.009109	0.125662	-0.24464
PER_C_OIL	-0.05672	0.10037	0.086819	0.116663	-0.6927	-0.25131	-0.04273
C_UKINDPRO	0.224065	-0.10411	0.288739	0.528392	0.149116	-0.14301	-0.16696
C_M4MS	0.006873	-0.3884	0.26994	-0.26986	-0.03299	0.094508	-0.19758
C_PM	0.241149	-0.11968	0.292251	0.5365	0.067284	-0.11353	-0.08655
C_RPR	-0.17032	0.373186	0.499382	-0.09592	0.090221	0.17287	0.005354
C_CNFDENCE	0.30595	-0.03724	0.22493	-0.31106	0.099045	-0.30575	0.288994

significant factor loadings are highlighted

: Guidelines for identifying significant factor loadings are provided in Table 11, Appendix 2

Table 5: Factor matrix for value/growth spread

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8
VALUE_GROWTH	-0.079886	-0.009353	-0.022319	0.041302	0.174127	-0.667201	0.150668	0.225783
C_CNFDENCE	-0.275315	0.090513	0.083315	0.472619	0.027398	0.060998	-0.02842	0.049531
C_ER	0.054667	-0.291481	0.093523	0.076957	0.085758	0.382621	0.308763	0.015294
C_FTA	-0.027305	-0.554243	0.272584	0.151767	-0.131655	-0.05159	-0.156822	0.070992
C_FTDY_LTBONDSPREAD	-0.427545	-0.016203	-0.068109	0.060346	0.26591	0.021911	0.031223	-0.080997
C_M0MS	-0.081047	-0.09611	-0.188743	0.257755	0.131076	0.126694	-0.220754	-0.329603
C_M4MS	0.195896	0.16651	0.073899	0.403246	-0.218574	0.073708	-0.18449	0.132335
C_PM	-0.042852	0.225793	0.572317	-0.177594	0.071771	0.126027	-0.096731	-0.038236
C_RPR	-0.058925	-0.554671	0.270409	0.152875	-0.115107	-0.047904	-0.155327	0.069741
C_SPPER	0.033608	-0.062189	-0.262535	0.039028	0.153399	0.425599	-0.141817	0.388431
C_TS	-0.403746	-0.024346	-0.006086	-0.175582	0.169975	0.085207	-0.091536	0.15878
C_UKINDPRO	-0.047559	0.209754	0.569768	-0.177318	0.066529	0.104121	-0.130394	-0.108275
C_VARGR	0.348037	-0.039315	0.084769	0.138682	0.566627	-0.03807	-0.012317	-0.038346
C_VARVAL	0.340634	-0.055123	0.064566	0.016643	0.561083	-0.031965	-0.131193	0.165681
C_VARVMG	-0.058302	-0.041287	-0.067123	-0.365763	-0.076202	0.021609	-0.340607	0.590913
CINFL	0.498555	0.007996	0.021127	-0.009747	-0.293227	-0.098389	-0.002782	0.055724
MC3MTB	0.024342	0.344338	0.025238	0.334216	-0.074179	0.221425	-0.027467	0.246483
PER_C_GDP	0.157541	-0.156525	-0.186764	-0.35714	-0.009291	0.261373	-0.086184	-0.325114
PER_C_OIL	0.010374	-0.076335	0.133043	-0.044069	-0.008399	0.180888	0.743154	0.258435

significant factor loadings are highlighted

Note: Guidelines for identifying significant factor loadings are provided in Table 11, Appendix 2.

Table 6: The explanatory variables chosen to predict the small/large and value/growth spreads

Explanatory Variables selected predicting small-large spread	Explanatory Variables selected predicting value-growth spread
FTSE All Share Return	Lagged Value-Growth spread
Lagged Small-Large spread	Consumer Confidence Indicator
Narrow Money M0	Earnings Yield Gap
Term Structure	Risk premium
Difference in Dividend Yield Small-Large	Term Structure
Change in Inflation (UK CPI index)	Change in the UK Production Index
Percentage change in price of oil	Variability in Growth Index
Change in the UK Production Index	Variability in Value Index
Risk premium	Broad Money M4
	Change in Inflation (UK CPI index)
	Percentage change in price of oil

Table 7: Formation and Holding periods for Momentum strategies

Formation period – based on historical cumulative returns	**Holding period**
1 month	1 month
2 months	1 month
3 months	1 month
4 months	1 month
5 months	1 month
6 months	1, 2, 3, 4, 5, 6 months
9 months	1 month
12 months	1 month

Table 8: Style rotation results based on the quantitative model

PANEL A: VALUE/GROWTH rotation results

	Strategy 1: p>0.5	Strategy 2: Empirical distribution cut-off	Strategy 3: Long/Short Strategy 2	Strategy 4: Beta-neutral Strategy 3	Perfect Foresight Long-only	Perfect Foresight Long-Short	Perfect Foresight Beta-neutral Long-Short
Average Annual Returns	5.55%	5.73%	3.15%	3.50%	16.10%	24.34%	24.86%
Standard Deviation	16.33%	16.28%	8.74%	9.05%	16.17%	6.05%	6.31%
Sharpe Ratio	0.022	0.033	-0.233	-0.187	0.675	3.166	3.119
End of Period Wealth	£1,403,018.66	£1,425,048.26	£1,258,733.84	£1,288,027.00	£3,118,634.55	£6,055,208.41	£6,263,809.59
Recommended Switches	35	33	33	33	47	47	47
Break-Even Transaction Costs (Benchmark: Value Index)	-	-	-	-	156bps	295bps	301bps
Total Correct Predictions	56.00%	57.00%	57.00%	57.00%			
Correct Value Predictions	73.68%	75.44%	75.44%	75.44%			
Correct Growth Predictions	32.56%	32.56%	32.56%	32.56%			

PANEL B: SMALL/LARGE rotation results

	Strategy 1: p>0.5	Strategy 2: Empirical distribution cut-off	Strategy 3: Long/Short Strategy 2	Strategy 4: Beta-neutral Strategy 3	Perfect Foresight Long-only	Perfect Foresight Long-Short	Perfect Foresight Beta-neutral Long-Short
Average Annual Returns	12.75%	12.75%	17.44%	18.71%	25.59%	45.48%	49.96%
Standard Deviation	18.04%	18.04%	12.83%	14.16%	16.55%	8.04%	8.87%
Sharpe Ratio	0.419	0.419	0.955	0.955	2.644	5.012	5.045
End of Period Wealth	£2,377,784.46	£2,377,784.46	£3,573,571.15	£3,854,296.13	£5,980,448.31	£22,178,471.16	£28,416,379.23
Number of Switches	43	43	43	43	49	49	49
Break-Even Transaction Costs (Benchmark: Small Cap Index)	141bps	141bps	235bps	252bps	309bps	564bps	612bps
Total Correct Predictions	63.00%	63.00%	63.00%	63.00%			
Correct Small Cap Predictions	66.67%	66.67%	66.67%	66.67%			
Correct Large Cap Predictions	56.52%	56.52%	56.52%	56.52%			

PANEL C: Benchmarks results

	FTSE 350 Value	FTSE 350 Growth	FTSE Small Cap	FTSE 100
Average Annual Returns	6.22%	2.03%	4.97%	3.12%
Standard Deviation	15.97%	16.21%	19.11%	15.65%
Sharpe Ratio	0.065	-0.195	-0.012	-0.133
End of Period Wealth	£1,486,418.42	£1,060,010.05	£1,283,856.52	£1,165,880.78

Table 9: Value/Growth Style rotation results based on Momentum Strategies

	Annualised return	Annualised St. Deviation Standard Deviation	T-bill	Sharpe ratio	No. of switches	Berak-even Transaction costs (bps)	End of period wealth (£)
Long-only strategy: Positive Momentum							
1m formation -1m rebalancing	2.88%	12.58%	5.19%	-0.184	70	negative	1186852.494
2m formation - 1m rebalancing	10.79%	11.23%	5.19%	0.498	38	109	2231557.007
3m formation - 1m rebalancing	5.89%	10.65%	5.19%	0.065	36	10	1537844.853
4m formation - 1m rebalancing	5.42%	9.75%	5.19%	0.024	25	2	1493729.054
5m formation - 1m rebalancing	4.79%	10.58%	5.19%	-0.038	24	negative	1409957.824
6m formation - 1m rebalancing	5.03%	10.68%	5.19%	-0.015	15	negative	1435935.422
6m formation - 2m rebalancing	5.01%	10.44%	5.19%	-0.017	14	negative	1437129.063
6m formation - 3m rebalancing	4.89%	10.45%	5.19%	-0.029	15	negative	1423296.829
6m formation - 4m rebalancing	4.35%	10.28%	5.19%	-0.082	16	negative	1364888.715
6m formation - 5m rebalancing	3.80%	10.71%	5.19%	-0.130	16	negative	1300631.339
6m formation - 6m rebalancing	5.24%	10.35%	5.19%	0.005	15	negative	1464694.582
9m formation - 1m rebalancing	4.22%	10.82%	5.19%	-0.090	18	negative	1345146.347
12m formation - 1m rebalancing	3.69%	11.95%	5.19%	-0.126	20	negative	1274510.686
Long/Short strategy: Positive/Negative Momentum							
1m formation -1m rebalancing	1.49%	15.37%	5.19%	-0.241	134	negative	1025470.88
2m formation - 1m rebalancing	9.80%	15.52%	5.19%	0.297	82	35	1975886.113
3m formation - 1m rebalancing	8.24%	15.08%	5.19%	0.202	62	28	1764426.631
4m formation - 1m rebalancing	7.53%	15.37%	5.19%	0.152	54	21	1664926.443
5m formation - 1m rebalancing	3.87%	15.02%	5.19%	-0.088	50	negative	1250557.566
6m formation - 1m rebalancing	5.03%	15.12%	5.19%	-0.011	35	negative	1370636.934
6m formation - 2m rebalancing	5.01%	14.95%	5.19%	-0.012	35	negative	1371727.283
6m formation - 3m rebalancing	4.89%	14.96%	5.19%	-0.020	34	negative	1358524.535
6m formation - 4m rebalancing	4.35%	15.15%	5.19%	-0.056	32	negative	1297661.164
6m formation - 5m rebalancing	3.80%	15.45%	5.19%	-0.090	32	negative	1236568.783
6m formation - 6m rebalancing	5.24%	14.88%	5.19%	0.003	33	negative	1398038.332
9m formation - 1m rebalancing	5.13%	15.48%	5.19%	-0.004	31	negative	1376069.07
12m formation - 1m rebalancing	4.53%	15.40%	5.19%	-0.043	31	negative	1312205.499
Benchmark: FTSE 350 Value Index	6.22%	15.97%	5.19%	0.065	-	-	1486418.423

Table 10: Small/Large Style rotation results based on Momentum Strategies

	Annualised return	Annualised St. Deviation Standard Deviation	T-bill	Sharpe ratio	No. of switches	Berak-even Transaction costs (bps)	End of period wealth (£)
Long-only strategy: Positive Momentum							
1m formation -1m rebalancing	11.22%	13.51%	5.19%	0.446	57	98	2252587.076
2m formation - 1m rebalancing	8.97%	12.69%	5.19%	0.298	39	102	1917108.456
3m formation - 1m rebalancing	5.41%	12.67%	5.19%	0.017	35	35	1452735.784
4m formation - 1m rebalancing	5.77%	12.75%	5.19%	0.045	28	54	1493574.243
5m formation - 1m rebalancing	9.34%	11.81%	5.19%	0.351	22	197	1987881.552
6m formation - 1m rebalancing	11.12%	12.52%	5.19%	0.474	15	370	2260410.533
6m formation - 2m rebalancing	11.70%	12.28%	5.19%	0.530	11	541	2366216.017
6m formation - 3m rebalancing	11.01%	12.41%	5.19%	0.469	11	495	2244319.762
6m formation - 4m rebalancing	11.32%	12.31%	5.19%	0.498	11	408	2299176.011
6m formation - 5m rebalancing	9.58%	12.16%	5.19%	0.360	10	442	2017819.663
6m formation - 6m rebalancing	10.50%	12.45%	5.19%	0.426	12	461	2158143.775
9m formation - 1m rebalancing	6.31%	13.00%	5.19%	0.086	15	126	1552590.293
12m formation - 1m rebalancing	9.27%	12.25%	5.19%	0.333	9	464	1968534.826
Long/Short strategy: Positive/Negative Momentum							
1m formation -1m rebalancing	13.29%	16.36%	5.19%	0.495	117	57	2540482.309
2m formation - 1m rebalancing	9.04%	18.41%	5.19%	0.209	83	39	1795451.734
3m formation - 1m rebalancing	6.41%	19.08%	5.19%	0.064	69	17	1449009.297
4m formation - 1m rebalancing	9.01%	18.10%	5.19%	0.211	57	57	1799964.089
5m formation - 1m rebalancing	15.19%	17.53%	5.19%	0.570	44	174	2875200.14
6m formation - 1m rebalancing	8.76%	17.49%	5.19%	0.204	45	70	1777323.629
6m formation - 2m rebalancing	9.32%	17.33%	5.19%	0.238	37	97	1860536.165
6m formation - 3m rebalancing	8.65%	17.42%	5.19%	0.198	36	86	1764690.143
6m formation - 4m rebalancing	8.95%	17.34%	5.19%	0.217	37	90	1807823.161
6m formation - 5m rebalancing	7.24%	17.25%	5.19%	0.119	33	62	1585852.012
6m formation - 6m rebalancing	8.14%	17.47%	5.19%	0.169	35	79	1696136.037
9m formation - 1m rebalancing	5.95%	17.84%	5.19%	0.042	37	26	1421778.969
12m formation - 1m rebalancing	8.32%	18.21%	5.19%	0.172	24	108	1701145.888
Benchmark: FTSE Small Cap Index	4.97%	19.11%	5.19%	-0.012	-	-	1283856.517