# Papers

# Equity-style timing: A multi-style rotation model for the Russell large-cap and small-cap growth and value style indexes

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**Abstract** Researchers and practitioners have devoted considerable attention to devising market-timing strategies as potential value-enhancement tools. The success of such active or tactical asset allocation strategies is dependent on their ability to capture either inefficiencies, to the extent that they exist, or disequilibria associated with changes in the investor opportunity set. Much of the equity-style timing literature focuses on the shifting between pairs of risky assets or between one risky and one riskless asset class, using a binomial approach. This paper develops a multinomial timing model based on macroeconomic and fundamental public information using Frank Russell large-cap and small-cap style indexes. We model four different market segments simultaneously. Out-of-sample tests demonstrate that active multi-style rotation strategies can be devised that outperform the best performing buy-and-hold portfolio. The profitability of such strategies is robust to reasonable levels of transaction costs.
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## Introduction

Previous research (eg Brinson *et al.*, 1986; Sharpe, 1992; Bauman and Miller, 1997; Ibbotson and Kaplan, 2000) suggests that asset allocation decisions, across different asset classes and within a particular asset class such as equities, account for a large part of a portfolio's return. Practitioners and researchers deem style allocation to be as important as asset allocation. Given the decline in transaction costs and the proliferation of style-based ETFs in recent years, being able to predict the direction of style indexes has deep implications for researchers and practitioners concerned with testing for market efficiency, as well as for devising value-enhancing tactical asset allocation strategies.

Different equity styles demonstrate disparate time-varying performance (see eg Arshanapalli *et al.*, 1998; Oertmann, 1999; Ahmed *et al.*, 2002; Amenc *et al.*, 2003). With accurate timing strategies, investors who rotate portfolios as a particular style goes in and out of favour will consistently add value in both up and down markets.

To our knowledge, none of the previous 'timing strategy' studies have sought to capture the determinants of time-varying returns of several style classes simultaneously to generate investment strategies to produce superior returns. In this paper, we investigate whether investors could have enhanced the performance of their style portfolios over the last two decades by implementing a style-based timing strategy, using fundamental and macroeconomic factors including those that have been widely cited in the literature as having a predictable influence on stock returns (eg Keim and Stambaugh, 1986; Campbell, 1987; Campbell and Shiller, 1988; Fama and French, 1989; Ferson and Harvey, 1991).

The remainder of the study is organised as follows. In the following section, we present a description of the data and the econometric approach used to predict the return spreads of the different Frank Russell indexes. The next section presents the buy-and-hold portfolios and an explanation of the different trading strategies used in the study. Then the fourth section analyses the performance results of our market-timing strategies. The fifth section applies a set of robustness checks to our results and the sixth section investigates the viability of our timing strategies in the presence of transaction costs. The penultimate section provides an analysis of an iteratively resample among the universe of underlying economic variables (fundamental, sentiment, and variable factors) to determine an updated model, using an in-sample period of 60 months, from January 1986 to December 1990, as a basis for a second out-of-sample forecast period that extends from January 1991 to December to April 2005. The paper concludes with a summary in the last section.

## Data and methodology

### Data

We obtained monthly data from January 1979[1] to April 2005 for this study from four different sources: Datastream, Ibbotson Associates, Bloomberg, and the Federal Reserve Board. In the initial analyses, the first 60 months of the sample, from January 1979 to December 1983, were used as the in-sample period to choose from a set of economic variables that attempt to measure fundamental factors, sentiment factors, and momentum factors to construct the econometric model aimed at predicting the best performing index, over an out-of-sample horizon of 204 months, from January 1984 to December 2000. We then iteratively resample among the universe of underlying economic variables (fundamental, sentiment, and variable factors) to determine an updated model, using an in-sample period of 60 months, from January 1986 to December 1990, as a basis for a second out-of-sample forecast period that extends from January 1991 to December to April 2005.

In order to implement our style-timing strategy, we have selected the Russell 1000 Value and Growth indexes and the Russell 2000 Value and Growth indexes. There are two reasons for the use of the Frank Russell Company style indexes throughout the study. First, these indexes tend to be widely followed by the investment community. In fact, according to Frank Russell Company's 2003 fact sheet, more than $250bn are invested in investment products that have the Russell US indexes qas benchmarks. Secondly, the availability of exchange-traded funds[2] on the Russell indexes and the availability of futures contracts on the Russell iShares products make practitioners' implementation of our style-timing model a more realisable and viable option.

The predicting variables investigated were based on those identified from the style-timing literature and the literature investigating the predictability of stock returns, as well as standard causality tests as will be discussed further.[3]

We also consider other variables that have also been asserted to influence stock returns, such as changes in consumer confidence and the unemployment rate, as well as lagged variables of the return of other style indexes (Wilshire indexes, S&P Barra indexes), and the S&P500 return.[4]

## Methodology

While there exists an extensive body of literature dealing with the predictability of stock market returns that attempts to predict the price level or the return of stock market indexes, this approach, which tries to minimise the deviations of the forecasted value from the actual value, may not be the optimal procedure to follow depending on the trading strategies implemented by the investors. In fact, a recent study by Leung *et al.* (2000), which compares the different types of econometric models used in the forecasting literature, has demonstrated that econometric models that attempt to predict the direction of stock market changes can result in a more significant out-of-sample performance than models predicting stock-indexes price levels.

Since the goal of our style-timing model is to select the best performing index among the four Frank Russell style indexes, a statistical technique that generates a probabilistic forecast of a group membership is most appropriate. This paper extends the previous literature that has examined the timing issue from a two asset choice model (eg Arshanapalli *et al.* (2004)) to a multi-asset approach, using the multinomial logit model. The multinomial logit model is specified as:

$$\text{Prob}\,(y=j) = \frac{e^{\sum_{k=1}^{K} \beta_{jk} X_k}}{1 + \sum_{j=1}^{J-1} e^{\sum_{k=1}^{K} \beta_{jk} X_k}}$$

The equation gives Prob $(y=j)$, defined as the probability that the $j$th asset class style outperforms the other asset classes for $j = 1, 2, \ldots, J-1$. Each asset class $j$ has a set of explanatory factors $X$, which need not be the same across asset classes. Since only $J-1$ equations are needed to identify the system, the last response category is selected as the base category from which the other response categories are evaluated. One can derive the probability of this reference category by taking $1-[\text{Prob}\ (y=1) + \ldots + \text{Prob}\ (y=J-1)]$.

In our study, we select the small-cap Russell 2000 Value index as the base index, and our estimation focuses on the Russell 1000 Value/Russell 2000 Value total return spread (ie return relative to the base index), the Russell 1000 Growth/Russell 2000 Value total return spread, and the Russell 2000 Growth/Russell 2000 Value total return spread.

The information set used to generate our models attempts to capture that available to a decision maker who makes conditional forecasts based on both fundamental and technical factors including: (i) valuation proxies; (ii) cyclical indicators; (iii) sentiment variables; and (iv) momentum/volatility variables.

We run pairwise Granger causality tests and the Akaike Information Criteria to choose potential variables among each of these four categories, and each asset return spread over the January 1979 to December 1983 period, and determine the optimal lags to consider for each variable. We then estimate a set of models in an in-sample framework using the statistically significant publicly available macroeconomic and fundamental variables and generate out-of-sample monthly forecasts in a rolling window framework for each potential model. In the second stage, we use the highest conditional probability estimate of the likelihood that one particular index will outperform the others as an investment signal (default model).

Based on the Granger causality tests, the probabilities for each asset class are estimated jointly as:

$$\begin{aligned}\mathrm{LKVal}_t =\ & \alpha + \beta_1 \mathrm{WILSHIRELV}_{t-1} \\ & + \beta_2 \mathrm{WILSHIRELV}_{t-2} \\ & + \beta_3 \mathrm{WILSHIRELV}_{t-3} \\ & + \beta_4 \Delta\mathrm{CONF}_{t-1} \\ & + \beta_5 \Delta\mathrm{CONF}_{t-2} \\ & + \beta_6 \Delta\mathrm{CONF}_{t-3} \\ & + \beta_7 \Delta\mathrm{CONF}_{t-4} \\ & + \beta_8 \Delta\mathrm{CPI}_{t-1} + \beta_9 \Delta\mathrm{CPI}_{t-2} \\ & + \beta_{10} \Delta\mathrm{CPI}_{t-3} \\ & + \beta_{11} \Delta\mathrm{CPI}_{t-4} + \beta_{12} \mathrm{TERM}_{t-1}\end{aligned}$$

$$\begin{aligned}LK\mathrm{Gro}_t =\ & \alpha + \beta_1 \mathrm{TERM}_{t-1} + \beta_2 \mathrm{TERM}_{t-2} \\ & + \beta_3 \mathrm{TERM}_{t-3} \\ & + \beta_4 \mathrm{EAYIELDGAP}_{t-1} \\ & + \beta_5 \mathrm{EAYIELDGAP}_{t-2} \\ & + \beta_6 \mathrm{EAYIELDGAP}_{t-3} \\ & + \beta_7 \mathrm{EAYIELDGAP}_{t-4} \\ & + \beta_8 \mathrm{SP500\,E/P}_{t-1} \\ & + \beta_9 SP500\,\mathrm{E/P}_{t-2} \\ & + \beta_{10} \mathrm{CURVESPREAD}_{t-1}\end{aligned}$$

$$\begin{aligned}\mathrm{SKGro}_t =\ & \alpha + \beta_1 \mathrm{USTB1MR}_{t-1} \\ & + \beta_2 \mathrm{USTB1MR}_{t-2} \\ & + \beta_3 \mathrm{USTB1MY}_{t-1} \\ & + \beta_4 \mathrm{USTB1MY}_{t-2} \\ & + \beta_5 \mathrm{USTB1MY}_{t-3} \\ & + \beta_6 \mathrm{CURVESPREAD}_{t-1} \\ & + \beta_7 \mathrm{CSPREAD}_{t-2} \\ & + \beta_8 \mathrm{CSPREAD}_{t-3} \\ & + \beta_9 \mathrm{EAYIELDGAP}_{t-1} \\ & + \beta_{10} \mathrm{EAYIELDGAP}_{t-2} \\ & + \beta_{11} \mathrm{LTGVTY}_{t-1} \\ & + \beta_{12} \mathrm{DEFPREM}_{t-1}\end{aligned}$$

where LKVVal, LKGro, and SKGro are the log-odds ratio for the large-cap value portfolio, the large-cap growth portfolio, and the small-cap growth portfolio, respectively. WILSHIRELV represents the total return of the Wilshire large value index, CONF represents the change in the consumer confidence index,[5] CPI represents the change in the consumer price index, TERM represents the US bond horizon premium,[6] EAYIELDGAP represents the earnings yield gap,[7] S&P500 E/P represents the earnings–price ratio of the S&P500, CSPREAD represents the yield spread of the long-term government bond over the three-month T-Bills, USTB1MR represents the US 1-month treasury bills total return, USTB1MY represents the US 1-month treasury bills yield, LTGVTY represents the long-term government bond yield, and

DEFPREM represents the US bond default premium.[8] It should be noted that all of the variables of the model are in the information set of the investor for month $t$ as a basis for forecasting returns in month $t+1$. Again, this ensures that the predictive model could be realistically implemented, and there is no look ahead bias in the estimation.

Using the specifications of the optimal predictive model based on the Granger causality tests, the regression coefficients of the first 60 months of the sample (our in-sample period from January 1979 to December 1983) are estimated and fitted into the above equations 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 the others in January 1984. As for the conditional probabilities thereafter, until the last prediction month of December 2000, a similar procedure is repeated monthly using a five-year rolling window (60 months rolling window), by dropping the first month of data included in the estimation of the preceding prediction month and adding the data corresponding to the month preceding the new prediction month.

The relative *economic importance* of the variables in the multinomial logit model cannot be determined from the fitted parameters, but rather from the model *elasticities*. Table 1 shows the computed out-of-sample elasticities of the estimated probabilities of the asset classes with respect to changes in the variables of the multinomial logit model.

They are computed as in Greene (2003, p. 723) according to

$$\frac{\partial \log P_i}{\partial \log x_{kr}} = x_{kr}[1(i=k) - P_k]\beta_r,$$

where $P_i$ is the log odds of the $i$th portfolio, $x_{kr}$ is the predictive variable $r$ in portfolio $k$, and $\beta_r$ is its estimated coefficient.

For the large-cap value portfolio, the negative elasticity of the previous period's

**Table 1 Estimated out-of-sample model elasticity estimates: January 1984–December 2000**

| Independent variables | LKVal | LKGro | SKGro | Independent variables | LKVal | LKGro | SKGro |
|---|---|---|---|---|---|---|---|
| $WILSHLV_{t-1}$ | −0.70066 | | | $WILSHLV_{t-1}$ | −2.039937071 | | |
| $\Delta CONF_{t-1}$ | −0.04134 | | | $\Delta CONF_{t-1}$ | 1.428381868 | | |
| $\Delta CPI_{t-1}$ | | −0.0101 | | $\Delta CPI_{t-1}$ | 0.718561951 | | |
| $TERM_{t-1}$ | | −0.0471 | −0.31217 | $TERM_{t-1}$ | −3.110242718 | −0.25188 | |
| $ERP_{t-1}$ | | 0.272081 | | $EAYIELDGAP_{t-1}$ | | −6.46057 | −1.36306 |
| $SCP_{t-1}$ | | −0.07676 | | $SP500E/P_{t-1}$ | | −14.1357 | |
| $EAYIELDGAP_{t-1}$ | | −4.67805 | −1.7955 | $CSPREAD_{t-1}$ | | −1.06307 | 3.704409 |
| $SP500E/P_{t-1}$ | | −13.1085 | | $USTB1MR_{t-1}$ | | | −0.4952 |
| $CSPREAD_{t-1}$ | | −2.2211 | 4.302951 | $USTB1MY_{t-1}$ | | | 1.286066 |
| $USTB1MR_{t-1}$ | | | 0.112076 | $LTGVTY_{t-1}$ | | | 2.137462 |
| $USTB1MY_{t-1}$ | | | 4.844036 | $DEFAULT_{t-1}$ | | | 0.028446 |
| $LTGVTY_{t-1}$ | | | 4.991791 | | | | |
| $DEFAULT_{t-1}$ | | | 0.00333 | | | | |

This table shows the average out-of-sample elasticities of the estimated probabilities of the asset classes in a given month with respect to changes in the variables of the multivariate logit model, where LKVVal, LKGro, and SKGro are the log-odds ratio for the large-cap value portfolio, the large-cap growth portfolio, and the small-cap growth portfolio, respectively. The other variables are defined as: WILSHIRELV — the total return of the Wilshire large value index; CONF — the Conference Board consumer confidence index; CPI — the consumer price index; TERM — the US bond horizon premium (computed as the geometric mean difference between the long-term government bond and the US 30-day treasury bills returns); EAYIELDGAP — the earnings yield gap (computed as the difference between the earnings to price ratio (E/P) of the S&P 500 and the long-term government bond yield); S&P500 E/P — the earnings–price ratio of the S&P 500; CSPREAD — the yield spread of the long-term government bond over the one-month T-Bill; USTB1MR — the US 1-month treasury bills total return; USTB1MY — the US 1-month treasury bills yield, LTGVTY — the long-term government bond yield DEFAULT — the US bond default premium. The coefficients are estimated in 60-month rolling windows, with the initial in-sample period from January 1979 to December 1983 used to generate the first out-of-sample projection for January 1984. Rolling out-of-sample projections extend to December 2000.They are computed as in Greene (2003, p. 723) according to $(\partial \log P_i)/(\partial \log x_{kr})=x_{kr}[1(i=k)-P_k]\beta_r$, where $P_i$ is the log odds of the $i$th portfolio, $x_{kr}$ is the predictive variable $r$ in portfolio $k$, and $\beta_r$ is its estimated coefficient.

return is suggestive of mean reversion. For the large-cap growth portfolio, sizable lagged earnings/price and earnings yield gap effects are observed: a 1 per cent increase in the lagged earnings price ratio of the S&P500 results in a 14 per cent decline in the log odds of the large-cap growth portfolio. Similarly, a 1 per cent increase in the earnings yield gap is associated with a 6 per cent decline in the log odds of this portfolio. Small-cap growth stocks are positively affected by increases in the term spreads and default risk spreads, although the effect of the latter is relatively small.

## Trading strategies

Starting with an initial wealth of $100 at the end of December 1983, our trading simulation assumes that, at the beginning of each month, an investor needs to take an asset allocation decision involving the four Russell indexes and some other major asset classes (eg T-bills, long-term government bonds). At the end of every month, we run our multinomial logit model and look at the conditional probabilities estimated by our model to allocate the funds according to our rules. It should be noted that our trading simulation is implemented at the start of January 1984, and is repeated until December 2000, a period corresponding to our out-of-sample period mentioned earlier in the paper.

We build our style-timing model according to the conditional probabilities generated by our model without applying a cutoff probability. We define the 'default' strategy as a strategy where all our portfolio's assets are invested in the Russell index, with the highest conditional probabilities at the start of each month.

In order to evaluate the profitability of our style-timing model, the trading strategies that implement the signals of our timing model are compared to ten buy-and-hold strategies selected for their relevance. From these ten strategies, four strategies follow a unique style-consistency strategy. Those control portfolios consist of a Russell 1000 Growth buy-and-hold strategy, a Russell 1000 Value buy-and-hold strategy, a Russell 2000 Growth buy-and-hold strategy, and a Russell 2000 Value buy-and-hold strategy. Three portfolios follow multi-style type buy-and-hold strategies. They are: a portfolio spreading its money equally among the four Frank Russell indexes (Russell — 25 per cent), a portfolio investing 50 per cent of its assets in each of the two large-cap Russell 1000 indexes (R1000 — 50 per cent), and a strategy investing 50 per cent of its assets in each of the two small-cap Russell 2000 indexes (R2000 — 50 per cent). The last three strategies, which do not invest assets in style indexes, invest 100 per cent of their funds in the one-month T-bills asset class, the long-term government bond asset class, and the S&P500 index, respectively. In addition, we also compared the performance of our timing model with two momentum strategies. First momentum strategy (Momentum 1) involves investing 100 per cent of the funds in the asset class that performed best over the prior year, while the second momentum strategy (Momentum 2) involves investing 100 per cent of the fund in the asset class that outperformed all other asset classes under consideration in the previous month.

## Model results

In this section, we analyse the results that the investor would have obtained if s/he had invested his/her portfolio by following the switching signals of the 'default' strategy. Figure 1 shows the portfolio wealth of the simple buy-and-hold equity strategies and the default switching strategy over the out-of-sample period. During the period from January 1984 to December 2000, the portfolio's value of our default style-timing strategy is generally

 

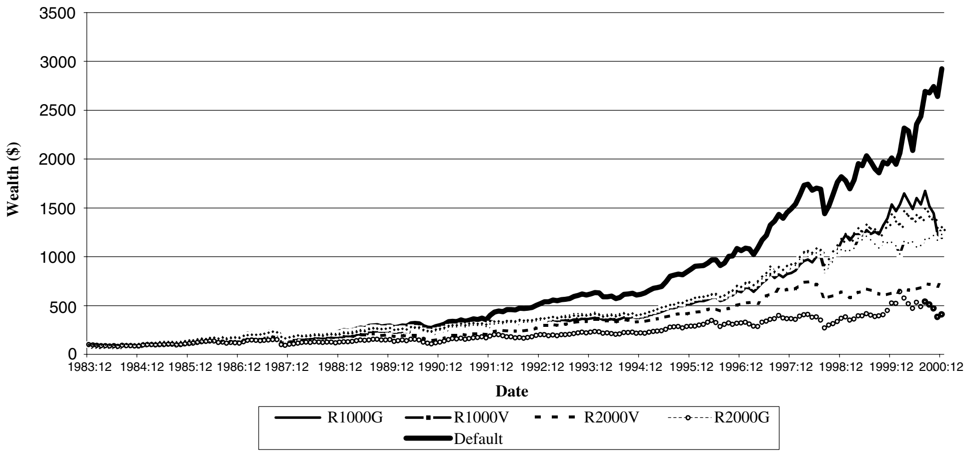


**Figure 1** Portfolio wealth over the out-of-sample period. This figure shows the portfolio wealth of the 'default' portfolio and the simple equity buy-and-hold strategies over the January 1984 to December 2000 period. Initial amount invested is $100

higher than the portfolios' values of the buy-and-hold strategies. While the 'default' strategy sometimes seems to outperform or underperform one or more of the Russell indexes or the S&P500 in the first four years (50 months to be precise) of the out-of-sample period (January 1984 to February 1988), our 'default' strategy consistently outperforms the Russell indexes during the remaining 12 years (154 months to be precise) of the out-of-sample period. This can be seen in Figure 1 as the widening of the gap between the cumulative portfolio values of the default rotation strategy and the cumulative portfolio values of the buy-and-hold strategies. In fact, during the first four years of the sample, the 'default' strategy underperformed one or more of the single-style buy-and-hold strategies in only 31 months of the 50 months. During those months, the default strategy's underperformance amounted to a mere $2.89 per month on average. On the whole, our switching strategy performed quite well during the entire period.[9]

Taking these perspectives together, our 'default' strategy appears to have the characteristics of an efficient market-timing model. As illustrated in Table 2, the 'default' strategy's portfolio value grows from $100 at the beginning of January 1984 to $2,926.42 at the end of December 2000, compared to a terminal value of $1,227.61 for the best performing single-style buy-and-hold strategy (Russell 1000 Value strategy). In other words, investors following our model would have earned more than twice[10] as much money as they would have, had they pursued a single-style buy-and-hold strategy. If we compare performances using the default strategy's annualised return (21.97 per cent) over the entire out-of-sample period, we see that it was considerably higher than the highest Russell single-index buy-and-hold strategy's annualised return (15.89 per cent). This means that an investor could have earned an excess return of at least 6.08 per cent per year by following the recommendations of our model.[11] In addition, default strategy has also outperformed the momentum strategies that invest $100 in the month *t* in the asset class that performed best in the previous year (Momentum 1) as well as in the previous month (Momentum 2). The annualised return for Momentum 1 strategy is 15.98 per cent, while the annualised return for Momentum 2 strategy is 17.90 per cent. This implies that an investor

**Table 2 Terminal wealth and out-of-sample performance of multinomial logit market timing strategy**

| | T-bills | LTGvtBond | S&P 500 | R1000G | R1000V | R2000G | R2000V | Russell-25% | R1000-50% | R2000-50% |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Buy-and-hold strategies:* | | | | | | | | | | |
| Term. wealth $ | 261.4682 | 669.0262 | 1301.4279 | 1192.3436 | 1227.6102 | 407.2078 | 773.1638 | 869.5628 | 1237.4995 | 580.8580 |
| Avg. monthly ret% | 0.4723 | 0.9360 | 1.2658 | 1.2224 | 1.2368 | 0.6907 | 1.0077 | 1.0658 | 1.2408 | 0.8661 |
| | | | | | | | | 13.5672 | 15.9491 | 10.9035 |
| | **Default** | **Momentum 1** | **Momentum 2** | | | | | | | |
| *Panel B: Market timing strategies:* | | | | | | | | | | |
| Term. wealth $ | 2926.4265 | 938.5385 | 1239.0472 | | | | | | | |
| Avg. monthly ret% | 1.6689 | 1.2427 | 1.3820 | | | | | | | |

This table features the terminal wealth, the average monthly return and the annualised return of the control portfolios, and all the portfolio switching strategies. Terminal wealth data are in $, and represent the portfolio value at the end of December 2000, of $100 invested at the beginning of January 1984. Monthly returns are in percentage terms.
Monthly mean return data and standard deviation data are in percentage terms.
R1000V (R1000G) is the Russell large-cap value (growth) index.
R2000V (R2000G) is the Russell small-cap value (growth) index.
Russell-25% is an equal-weighted portfolio of the four Russell Portfolios.
R-1000-50% is an equal-weighted portfolio of the two large-cap Russell portfolios.
R-2000-50% is an equal-weighted portfolio of the two small-cap Russell portfolios.
Momentum 1 is formed as the momentum portfolio in which the investor invests 100% in month $t$ in the asset class that performed best in the previous year (month $t-1$).
Momentum 2 is formed as the momentum portfolio in which the investor invests 100% in month $t$ in the asset class that performed best in the previous year (month $t-1$).

**Table 3 Sharpe and Sortino ratios**

| | T-bills | LTGvtBond | S&P 500 | R1000G | R1000V | R2000G | R2000V | Russell-25% | R1000-50% | R2000-50% |
|---|---|---|---|---|---|---|---|---|---|---|
| *Buy-and-hold strategies* | | | | | | | | | | |
| Monthly mean return (%) | 0.4724 | 0.9734 | 1.3616 | 1.3514 | 1.3228 | 0.9230 | 1.1160 | 1.1783 | 1.3371 | 1.0195 |
| Standard deviation (%) | 0.1469 | 2.7595 | 4.3507 | 5.0461 | 4.1243 | 6.7037 | 4.5561 | 4.6646 | 4.3583 | 5.4276 |
| Sharpe ratio | | 0.1816 | 0.2044 | 0.1742 | 0.2062 | 0.0672 | 0.1413 | 0.1513 | 0.1984 | 0.1008 |
| Sortino ratio | | 0.3857 | 0.3512 | 0.3004 | 0.3525 | 0.1088 | 0.2199 | 0.2424 | 0.3398 | 0.1605 |
| | **Default** | **Momentum 1** | **Momentum 2** | | | | | | | |
| *Portfolio switching strategies* | | | | | | | | | | |
| Monthly mean return (%) | 1.7848 | 1.2427 | 1.3820 | | | | | | | |
| Standard deviation (%) | 4.7994 | 5.2615 | 5.2738 | | | | | | | |
| Sharpe ratio | 0.2735 | 0.1464 | 0.1725 | | | | | | | |
| Sortino ratio | 0.4870 | 0.2480 | 0.3017 | | | | | | | |

This table presents the Sharpe and Sortino ratios, the mean monthly return and the monthly standard deviations of all the buy-and-hold strategies, and the portfolio switching strategies.
Monthly mean return data and standard deviation data are in percentage terms. R1000G is the Russel large-cap growth index, R1000V is the Russell large-cap value index, R2000G is the Russell small-cap growth index, and R2000V is the Russell small-cap value index. Momentum 1 (2) is formed as the momentum portfolio in which the investor invests 100% in month $t$ in the asset class that performed best in the previous year (month $t-1$).

could have earned an excess return of over 3 per cent per year over the momentum strategies if the investor had followed the default model predicted strategy.[12]

## Robustness checks

Having analysed our timing strategy results in the previous section, an important question needs to be answered at this time to further evaluate our model, and that is: 'Would the model's forecasts have been valuable for investors accounting for risk?'

### Sharpe ratios

We can run an initial check on the robustness of the investment recommendations of our model by computing the Sharpe ratios of our portfolio switching strategies and comparing them with the Sharpe ratios (calculated as the return of the portfolio minus the risk-free rate divided by the portfolio's standard deviation) of the buy-and-hold strategies to assess whether or not the superior return performance of our timing strategies is the result of higher risk.

Table 3 illustrates the computed Sharpe ratios of the buy-and-hold strategies and the three portfolio-switching strategies. The table also provides additional information, such as the risk and the mean return of each portfolio. Among all the buy-and-hold strategies, the buy-and-hold strategy with the highest Sharpe ratio corresponds to the Frank Russell 1000 Value index. With a Sharpe ratio of 0.2062, this strategy is closely followed by the S&P500 strategy (0.2044) and the strategy that spreads 50 per cent of the assets in the two Frank Russell 1000 indexes (0.1984). The Sharpe ratio of the remaining buy-and-hold strategies lagged far behind those mentioned above. It is interesting to note here that, while the S&P500 has a greater terminal wealth than the Russell 1000 Value index ($1,301.42 vs $1,227.61), the S&P500's Sharpe ratio is lower than the Russell 1000 Value index's Sharpe ratio (0.2044 vs 2062). This can be explained by the fact that the S&P500 portfolio is riskier than the Russell 1000 Value index, as illustrated by their respective standard deviations (4.35 per cent for the S&P500 vs 4.12 per cent for the R1000V). When we look at the set of equity buy-and-hold strategies, we note that the standard deviation range is from a low of 4.12 per cent per month to a high of 6.70 per cent per month. The table also shows that growth buy-and-hold strategies and small-cap buy-and-hold strategies are riskier than value buy-and-hold strategies and large-cap buy-and-hold strategies, respectively.

If we take the portfolio-switching strategies, we note that default strategy (0.2735) possesses a Sharpe ratio that is higher than the Sharpe ratio of the Russell 1000 Value index buy-and-hold strategy (0.2062). Sharpe ratios for both the momentum portfolios are, however, below the Sharpe ratio of the Russell 1000 Value index buy-and-hold strategy. Since there is no guarantee that the timing strategy produces symmetric returns, we check the performance of the strategy by examining the Sortino ratio. Instead of using standard deviation in the denominator, Sortino ratio uses downside deviation. The downside deviation is calculated for only those months where the returns are below the minimum acceptable rate. In this paper, we used the mean of the return as the minimum acceptable rate. The Sortino ratios presented in Table 3 show that the default timing strategy has the highest Sortino ratio (0.4870) implying, that it has the highest return per unit of downside risk.

### Fama–French three factor models

To further evaluate the risk-adjusted performance of all the models, we estimated Fama–French three factor model given by the following:

$$R_p R_f = \alpha + \beta_1(R_m - R_f) + \beta_2(\mathrm{SMB}) + \beta_3(\mathrm{HML}) + \varepsilon$$

In this model, $R_p - R_f$ is the excess return of the portfolio over the Treasury bill return, and $(R_m - R_f)$ is the market risk premium; SMB and HML are returns on zero-investment, factor mimicking portfolios for size and book to market equity, while $\varepsilon$ is the error term. If Fama–French factors completely account for risks associated with the returns, then alpha will be statistically insignificant. The results of these regressions are presented in Table 4. The results reveal that alpha is statistically not different from zero for all buy-and-hold and momentum strategies. Alpha is, however, statistically different from zero for default timing strategy. This implies that the Fama–French model does not explain all the returns of market-timing strategy. The alpha estimate of the Fama–French model indicates an abnormal performance of about 49 basis points per month (5.9 per cent per year) for the default timing strategy, which is quite impressive when compared with buy-and-hold and momentum strategies.

## Henriksson and Merton market-timing test

As an additional check to determine whether the predictions of our model are of value to investors, we apply Henriksson and Merton's (1981) non-parametric market-timing test.

The Henriksson and Merton (HM) test statistics is computed as:

$$p - \text{stat} = \frac{n_1}{N_1} + \frac{n_2}{N_2}$$

The $p$-value of the $p$-stat is calculated as in Park and Switzer (1996):

$$p - \text{value} = \sum_{x=n_1}^{\min(N_1,n)} \binom{N_1}{x} \binom{N_2}{n-x} \Big/ \binom{N}{n},$$

where $N = N_1 + N_2$ and $n = n_1 + n_3$

**Table 4 Regression results of Fama–French factors**

| | LTGvtBond | S&P 500 | R1000G | R1000V | R2000G | R2000V | Russell-25% | R1000-50% | R2000-50% |
|---|---|---|---|---|---|---|---|---|---|
| *Buy-and-hold strategies* | | | | | | | | | |
| $\alpha$ | 0.0028 | 0.0000 | 0.0002 | −0.0006 | −0.0030 | −0.0008 | −0.0010 | −0.0002 | −0.0019 |
| $t$-stat | 1.5279 | 1.6047 | 0.3453 | −0.9225 | −2.2181 | −0.6339 | −1.7979 | −0.7983 | −1.7895 |
| $p$-value | 0.1281 | 0.1101 | 0.7302 | 0.3574 | 0.0277 | 0.5269 | 0.0737 | 0.4256 | 0.0750 |
| | **Default** | **Momentum 1** | **Momentum 2** | | | | | | |
| *Portfolio switching strategies* | | | | | | | | | |
| $\alpha$ | 0.0049 | 0.0011 | 0.0020 | | | | | | |
| $t$-stat | 3.3741 | 0.6851 | 1.0360 | | | | | | |
| $p$-value | 0.0009 | 0.4940 | 0.3014 | | | | | | |

This table presents the alpha for Fama–French three-factor regression. The regression equation is $R_p - R_f = \alpha + \beta_1(R_m - R_f) + \beta_2(\text{SMB}) + \beta_3(\text{HML}) + \varepsilon$.

$R_p - R_f$ is the portfolio return over the treasury bill rate, $(R_m - R_f)$ is the market risk premium, SMB and HML are zero-investment factor mimicking portfolios for size and book-to-market equity.

The default model has the investor place 100% in the asset class with the highest *ex ante* probability.

Momentum 1 (2) is formed as the momentum portfolio in which the investor invests 100% in month $t$ in the asset class that performed best in the previous year (month $t-1$).

where $n_1$ is the number of times the model correctly prescribed investment strategy G; $N_1$ is the number of observations for which investment strategy G was the winning strategy; $n_2$ is the number of times the model correctly prescribed investment strategy V; $N_2$ is the number of observations for which investment strategy V was the winning strategy; $n_3$ is the number of incorrect predictions of strategy G. It should be noted, from the aforementioned specifications, that a prediction is classified as 'correct', whenever the model selects one of the two best performing indexes in a given month. The default strategy has an HM pstat of 1.2595, with a highly significant $p$-value of 0.0024, indicating superior market-timing performance.

## Transaction costs

Upto this point, we have analysed the performance of our style-switching strategies without taking into consideration the effect of transaction costs. In fact, in order for our style-switching strategies to be a viable investment option for practitioners, those strategies, despite the fact that they are subject to a much higher turnover, need to earn a higher return than the buy-and-hold equivalents.

To verify whether our timing model's strategies could have been profitable when implemented, accounting for realistic costs of trading, we assume a round-trip transaction cost amounting to 50 basis points (25 bps per sell or buy orders) of the transaction value. There are two reasons for the selection of this level of transaction cost. First, while this level may be high by current standards, it appears to be reasonable for the earlier period of the study. Secondly, while trading in small-cap stocks usually results in prohibitive transaction costs, this level seems to be appropriate in our study, since the Russell 2000 indexes encompass the largest small-cap stocks. As for our passive, buy-and-hold equity strategies, since the Russell indexes provider rebalances its indexes 30th each June, we employ a calendar-rebalancing strategy whereby the buy-and-hold portfolios are rebalanced annually at this date. Assuming that our buy-and-hold portfolios are subject to a 4 per cent turnover rate per year, 8 per cent of the portfolio value will be transacted each year (4 per cent for the sell order and 4 per cent for the buy order). With the exception of the first year,[13] annual trading costs in these portfolios will, therefore, amount to a negligible 4 bps[14] per year. With regard to the other asset classes, trading costs for long-term government bonds are assumed to be similar to the Russell indexes even though evidence suggests that trading in the bond market is more expensive than trading in the equity market. The transaction costs for T-bills are assumed to be zero.

Applying the trading costs of 4 bps for the buy-and-hold strategies generates a terminal value of $1,216.24, $1,181.30, $766, and $403.43 for the Russell 1000 Value, the Russell 1000 Growth, the Russell 2000 Value, and the Russell 2000 Growth, respectively. As for the S&P500, or the portfolios that spread their assets across the four Russell indexes, the two Russell 1000 indexes and the two Russell 2000 indexes, their terminal value drops to $1,289.63, $861.68, $1,226.28, and $575.59, respectively. On the whole, the portfolio value of each buy-and-hold equity strategy drops by less than 1 per cent when transaction costs are taken into consideration, an insignificant factor.

A different story, however, emerges when we look at the default strategy. Contrary to the buy-and-hold strategies that have only 17.5 round-trip transactions taking place in them during the entire period, the active portfolio strategies face a far greater number of round-trip transactions as a result of their higher turnover rates. Starting with the default strategy, one can note that the terminal value of the default-strategy portfolio goes from $2,926.43 to $1,990.33, a drop of $936.1 or 31.99 per cent. In contrast to the buy-and-hold strategies, where the transaction costs have a negligible effect of less than 1 per cent, the transaction costs in all the portfolio-switching strategies will have a detrimental effect. In fact, the percentage drop of the terminal wealth is 30 times bigger than for the buy-and-hold strategies.

Despite the fact that the transaction costs subtract almost one-third of the portfolios' value, pursuing a strategy following the signals of our model nonetheless remains a more profitable option than pursuing a buy-and-hold strategy. In fact, the terminal wealth net of transaction costs of the default strategy is \$1,990.33. On the other hand, the terminal wealth of the best performing Frank Russell index (the Russell 1000 Value index) is only \$1,216.24. Even though the performance gap is narrower than if transaction costs are ignored, the strategies still outperform the Russell 1000 Value index by at least 63.64 per cent. This translates to an annual excess return of at least 3.41 per cent per annum. Given the fact that such a level of annual excess return is not negligible, investors may want to consider a market-timing strategy such as the model presented in this paper.

In sum, the portfolio-switching strategy remained profitable in the presence of the level of transaction costs presented in the study. It is, however, important to note that the viability of these strategies is highly dependent on the level of transaction costs actually involved. In fact, a level of round-trip transaction costs greater than 100 bps would make our portfolio-switching strategy unprofitable. Taking into consideration that transaction costs will continue to decrease over time, one should expect the profitability of our timing model to grow accordingly.

## Iterative resampling of universe of underlying economic variables

Using historical data to identify a model for forecasting does not guarantee against model obsolescence. Although the moving coefficients of the model allow for some structural change to occur, it does not by itself permit changes among the variables that determine the returns of the alternative asset classes. Hence, we iteratively resample among the universe of underlying economic variables (fundamental, sentiment, and variable factors) to determine an updated model, using an in-sample period of 60 months from January 1986 to December 1990, as a basis for a second out-of-sample forecast period that extends from January 1991 to December to April 2005. Using similar rules for selecting variables and portfolio strategies, the updated model performance measures are provided in Table 5.[15] Since downside risk is of importance (as discussed previously regarding avoiding the worst performing months), we also report Sortino Ratios, which use the square root of the semi-variance in the denominator. To evaluate risk-adjusted performance, we also present Fama–French alphas. Our results show that the model is also robust with respect to the Sortino metric as well as the Fama–French Alpha. In sum, these results demonstrate that the investor can add substantial value to their portfolio by timing the Russell large-cap growth, large-cap value, small-cap growth, and small-cap value equity-style indexes with our model.[16]

## Conclusions

This study is, to the best of our knowledge, the first study in the style-timing 'arena' that attempts to time a family of style indexes using a multinomial logit model. We found that investors can add substantial value to their portfolio by timing the Russell large-cap growth, large-cap value, small-cap growth, and small-cap value equity-style indexes with our model. According to our results, investors who would have invested a \$100 in the best-performing buy-and-hold equity-style index (Russell 1000 Value index) in January 1984 would have obtained a terminal wealth of \$1,227.61 before transaction costs or \$1,216.24 after such costs

 

**Table 5 Updated model based on iterative resampling of universe of underlying economic variables**

| | T-bills | R1000G | R1000V | R2000G | R2000V |
|---|---|---|---|---|---|
| *Buy-and-hold strategies* | | | | | |
| Monthly mean return (%) | 0.318086 | 0.8913 | 1.1099 | 0.8995 | 1.3292 |
| Standard deviationD | 0.138211 | 5.0897 | 4.1327 | 6.8273 | 4.1959 |
| Sharpe Ratio | | 0.1751 | 0.2686 | 0.1318 | 0.3168 |
| Sortino Ratio | | 1.1836 | 1.6241 | 1.2336 | 2.0708 |
| Fama–French Alpha | | −0.0019 | 0.0015 | −0.0069 | 0.0019 |
| *t*-stat | | −1.9345 | 1.55 | −4.0537 | 1.2433 |
| | **Default model** | **Momentum 1** | **Momentum 2** | | |
| *Active/portfolio switching strategies* | | | | | |
| Monthly mean return (%) | 1.3317 | 1.1143 | 1.2405 | | |
| Standard deviation (%) | 4.3465 | 5.2741 | 5.3481 | | |
| Sharpe ratio | 0.3064 | 0.2113 | 0.232 | | |
| Sortino ratio | 2.2547 | 1.6470 | 1.9084 | | |
| Fama–French alpha | 0.0035 | 0.0005 | −0.0009 | | |
| *t*-stat | 1.8167 | 0.2494 | −0.3823 | | |

In-sample model: January 1986–December 1990.
Out-of-sample performance: January 1991–April 2005.
This table presents the mean out-of-sample monthly return, monthly standard deviation, the Sharpe Ratio, and the Sortino Ratio, of the Large-cap growth (R1000G), Large-cap value (R1000V), Small-cap growth (R2000G), and (R2000V) Small-cap value. We compare these to active strategies: the momentum portfolio switching strategies and the model portfolio switching strategy. Monthly mean return data and standard deviation data are in percentage terms. Momentum 1 (2) is formed as the momentum portfolio in which the investor invests 100% in month $t$ in the asset class that performed best in the previous year (month $t-1$); the default model has the investor place 100% in the asset class with the highest *ex ante* probability.

in December 2000, compared with a terminal wealth of $2,926.43 excluding transaction costs or $1,990.33 after accounting for transaction costs by following the default signals of our model. This represents a 138.38 per cent out performance of our model over the Russell 1000 Value index for the scenario ignoring transaction costs and a 63.64 per cent out performance for the scenario with 50 bps round-trip transaction costs, suggesting that significant opportunities for 'excess returns' can still be exploited regardless of transaction costs. In addition, we also updated the model by including the recent data to check how well the timing strategy will perform. The results show that the earlier results are robust, and timing strategy seem to do better than the buy-and-hold strategy irrespective of the time period used.

Lakonishok Shleifer, and Vishny (1994) (LSV) argue that the value anomaly exists in the markets because of suboptimal behaviour of a typical investor who consistently overestimates the future growth rates of glamour stocks while underestimating the growth rates of value stocks. The fact that the Russell large-cap and small-cap value portfolios do better on a risk-adjusted basis than their counterpart growth portfolios in both periods that we examine supports this hypothesis. Our style-based model does, however, outperform the value stock portfolios for both periods.

Barberis and Shleifer (2003) also introduce an inefficient market approach that may be more consistent with our results than with LSV. As in LSV, value strategies are shown to be potentially profitable. Barberis and Shleifer (2003), however, demonstrate that momentum strategies and style-level counterparts that are similar in spirit to those of our model may also be associated with superior returns.

To conclude, our style-based model results may be the consequence of the rational response of investors to changing macroeconomic and fundamental data, as reflected by changes in yields and yield spreads, which would change the investor opportunity set. We cannot, however, rule out the influence of behavioural factors, as introduced in Barberis and Shleifer (2003) as well, as we demonstrate that behavioural variables such as momentum and sentiment also have predictive power in enhancing the returns of the investor over the time period examined.

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### Notes

1. Inception date of the Frank Russell Company style indexes.
2. ETFs provided by Barclay Global Fund Advisors: iShares Russell 1000 Value (IWD), iShares Russell 1000 Growth (IWF), iShares Russell 2000 Value (IWN), and iShares 2000 Growth (IWO).
3. See, for example, Ferson and Harvey (1994), Solnick (1993), Jensen, Mercer, and Johnson (1996), Chan, Karceski and Lakonishok (1998), Copeland and Copeland (1999), Kao and Shumaker (1999), Levis and Liodakis (1999), Kao and Shumaker (1999), Copeland and Copeland (1999), Avramov (2002), Black (2002), and Resnick and Shoesmith (2002).
4. All of the variables are in the information set of the investor at time *t*, for projecting the probabilities of $t+1$. Hence, there is no look ahead bias in the model.
5. This variable is the Conference Board announcement of the change in the consumer confidence index. It is the announced estimate for month *t* less the estimate of month $t-1$ as reported at month *t*. For the CPI, the variable used for time *t* is the announced level at month *t*, which actually corresponds to the level of the CPI at $t-1$, less that of the previous month.
6. The geometric mean difference between the long-term government bond and US 30-day T-bills returns.
7. The difference between the earnings to price ratio (E/P) of the S&P500 and the long-term government bond yield.
8. The geometric mean difference between long-term corporate and government bond returns.
9. We have also performed the analyses for various alternative definitions of bull and bear markets, including the bull (bear) market definitions suggested: that is, when the market excess return (S&P500 return less the one-month *t*-bill rate) is positive (negative), the market is characterised as a bull(bear) market; the extreme bull (bear) market definition is also used: a market is an extreme bull (bear) market when the market excess return is greater (less than) than the mean plus (minus) 0.5 standard deviations. Using these definitions, the default model performs very well relative to the S&P and the momentum strategies during the up and extreme up market periods; its performance is similar to the S&P, and considerably better than the momentum strategies during down market periods, and better than the S&P and the momentum strategies during extreme down markets: these results are available from the authors on request.
10. Approximately 2.4 times more.
11. In order to test whether logit probabilities are different across the asset classes, we estimated several models imposing probability cutoffs. Results show that default strategy does as well as other cutoff strategies. The results of this exercise are available from authors upon request.
12. As a further check of the performance of the style investment strategies, we also looked at the simple small cap vs large cap and the value vs growth dichotomies. Based on the Russell 1000 (2000) index as the benchmark large-cap (small-cap) portfolios, the terminal wealth on a \$100 investment in January 1984 to December 2000 would have been \$1253.99 (\$579.76) corresponding to a monthly return of 1.022 per cent (0.86522 per cent). Using the Fama–French Value vs Growth benchmarks, we note that the terminal wealth on a \$100 investment in the Fama–French Value (Growth) in January 1984 to December 2000 would have been \$1,136.08 (\$1,172.253) corresponding to a monthly return of 1.19838 per cent (1.21392 per cent). It is interesting to note that none of these style portfolios performs as well as the S&P500, let alone the default strategy.
13. First-year trading costs amount to 27 bps (25 bps for buying a 100 per cent of the index selected by our model and 2 bps for selling 4 per cent of the portfolio at the end of June).
14. Computed as : $0.08*50\,\text{bps} = 4\,\text{bps}$.
15. The full specification of the updated model is available on request. The elasticity estimates are fairly similar to those of the earlier specification for the common variables that appear, although in the more recent period, both consumer confidence changes and inflation changes (as captured by changes in the CPI) now have negative elasticities on the log odds of the large-cap value portfolios. Also, a positive effect of the lagged equity risk premium for the large-cap value portfolio is indicative of a mild momentum effect for the more recent period.
16. We also compared the default strategy (of choosing the asset class with the highest *ex ante* probability) with two momentum strategies, consistent with Jegadeesh and Titman, Carhart, and others. Momentum 1(2) is formed as the portfolio in which the investor invests 100 per cent in month *t* in the asset class that performed best in the previous year (month $t-1$); the default model has the investor place 100 per cent in the asset class with the highest *ex ante* probability each month; cut-35-Lg-Sg is the trading rule: if (Prob $t+1>0.35$) for one or more of the indices, then invest 100 per cent in the index with the highest conditional probability; or else if (Prob $t+1\leqslant 0.35$), invest 50 per cent in both the Russell 1000 Growth index and the Russell 2000 Growth index.

 

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