Is the Value Premium Predictable in Real Time?

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ABSTRACT

In this paper we develop a trading strategy in which the difference in observed returns of value and growth stocks in the US stock market is exploited. In the literature this return spread is often called the "value premium". In our modeling process we use a procedure similar to the recursive modeling approach as proposed by Pesaran and Timmerman (1995). We first estimate a universe of parsimonious models in an in-sample setting using a base set of technical and economic forecasting variables. Subsequently, we generate out-of-sample forecasts in a rolling window framework for all models and evaluate the performance in a so-called *model training* period. This adjustment directly relates to the critique of Bossaerts and Hillion (1999), who showed the insufficiency of in-sample criteria to forecast out-of-sample information ratios. Model selection is based on three well-known selection criteria: hit ratio (% correct sign), the mean return of the strategy and the realized information ratio. Finally, we start implementing our investment strategy in a second stage out-of-sample period: the *trading period*. This model estimation and selection procedure enables us to address the issue whether we could have historically exploited the value/growth rotation strategy in a practical context. In the empirical section we show that it is possible to successfully forecast the time-varying value premium based on this strategy. Moreover, we observe that the set of relevant forecasting variables varies considerably through time.

1. INTRODUCTION

A large body of empirical literature documents a strong value premium in average stock returns. Fama and French (1992, 1996) and Lakonishok, Shleifer and Vishny (1994) provide evidence for the U.S. stock market. Fama and French (1998) among many others display similar results for international stock markets. A large number of money managers translate these empirical findings into portfolios with a clear tilt towards value characteristics like book-to-market (BM), earnings-to-price (EP) and cash flow-to-price (CP). Value-based strategies in a long term setting have produced years with significant outperformance, but also experienced periods with persistent, negative relative returns, see e.g. Chan, Karceski and Lakonishok (1999). A good, recent example of this phenomenon is the poor performance of value tilted portfolios in the last few years of the previous decade. Despite these positive long term features, portfolio managers are generally cautious to implement a pure value-based investment strategy as they are often facing short-term judgment periods.

The long-term value premium has been explained in the finance literature by several parallel lines of reasoning. Fama and French (1993) argue that value features of a company are a proxy for financial distress. The observed higher returns for these companies should therefore mainly be interpreted as a compensation for risk. Jensen, Johnson and Mercer (1997) extend this view by claiming that value companies are quite sensitive to the same macroeconomic conditions, e.g. interest rate risk or the business cycle. Lakonishok, Shleifer and Vishny (1994) give an alternative and competing view on the observed value premium. In their opinion, value characteristics provide useful information about the inefficient pricing of securities in stock markets. A possible third explanation suggested by Lo and Mackinlay (1990) is that the observed return patterns are mainly due to data snooping. They claim that almost all financial asset pricing studies suffer from conditioning on previous studies and therefore we should expect them to corroborate earlier findings.

There is substantial evidence that the value premium is not constant through time, nor that it has the same (positive) sign consistently. The main objective of this paper is to provide a framework for selecting a multifactor forecast model to predict the sign of the value premium in the U.S. stock market. In our analysis we build on previous work in this area by Arnott, Kelso, Kiscadden and Macedo (1989), who explored the added value of a factor strategy in the US stock market based on calendar effects, market conditions and macroeconomic indicators. Jacobs and Levy (1996) use the same set of market and economic factors in order to predict style returns and find evidence of a successful style timing strategy. Satchell and Yoon (1994) present a procedure of style rotation using a Markov switching model. The portfolios based on their methodology are able to produce excess return net of transaction costs in the UK. Levis and Liodakis (1999) investigate the potential profitability of style rotation strategies in the UK stock market using both OLS and Logit models. Kao and Shumaker (1999) show the benefits of style rotation in the US stock market using a number of macro-economic indicators. Lucas, van Dijk and Kloek (2001) develop a framework for capturing the time-varying impact of firm characteristics like size and book-to-market on excess returns of individual stocks. They show that both magnitude and direction of the impact displayed considerable time-variation. In their approach incorporating macro-economic conditions into the analysis substantially increased prediction results. Recently, Ahmed, Lockwood and Nanda (2002) demonstrated the benefits of multi-style rotation strategies in the U.S. stock market.

It is questionable whether these strategies can be implemented in practice to the full extent, as most of these rotation strategies suffer from a high turnover. This explains our choice of two well-known indices to calculate the value premium in the US stock market: the S&P Barra Value and Growth indices. Using futures on these indices we are able to exploit a trading strategy with a high turnover and acceptable trading costs. A second reason why we should be cautious in using the results of these studies in a practical context is the possible impact of data snooping. As pointed out by Cooper and Gulen (2001) there is a considerable gap between real-time reported results of trading strategies and the performance of (rotation) strategies in academic research papers. Most of these studies forecast style spreads using a fixed subset of forecasting variables and present regression results based on the entire sample or on substantial sub-samples of the data. This seems rather inappropriate as no investor could have obtained these results based on the entire sample. Throughout the analysis we would like to ensure that a “real-time” trading strategy could be implemented in a practical context without the benefit of hindsight. Forecasting variables are selected with the information set available at the time the decision is made and not “implicitly” conditioned on the observed relevance of these variables in later time periods. This is in line with the work of Pesaran and Timmerman (1995) and Cooper and Gulen (2001) who claim that endogenizing the choice of the forecasting variables is one of the crucial measures to avoid the data snooping critique[1].

In our modeling process we use a procedure similar to the recursive modeling approach as proposed by Pesaran and Timmerman (1995). We first estimate a universe of parsimonious models in an in-sample setting using a base set of publicly available technical and economic forecasting variables. Following this, we generate out-of-sample forecasts in a rolling window framework for all models and evaluate the performance in a first-stage out-of-sample period we define as the *training period*. Based on practical model selection criteria we start implementing our trading strategy in a second stage out-of-sample period we define as the *trading period*. The intermediate out-of-sample model selection phase contributes to the procedure of Pesaran and Timmerman (1995) and relates to the critique of Bossaerts and Hillion (1999), who showed the insufficiency of in-sample criteria to forecast out-of-sample information ratios. We briefly address the issue of model uncertainty by averaging across a set of highly ranked models instead of choosing just the optimal model[2]. In the empirical section, we will estimate and select models and subsequently evaluate trading strategies for different forecast horizons and various levels of transaction costs.

The remainder of this paper is organized as follows: in section 2 we will give more detailed information on the data used in the empirical section. In particular, we describe how the value-spread series the set of forecasting variables are constructed. The forecasting and model selection methodologies as well as the portfolio construction procedure are presented in section 3. In section 4 we will present our main empirical results and section 5 concludes.

2. CONSTRUCTION OF THE SPREAD SERIES AND THE CHOICE OF THE FORECASTING VARIABLES

The choice of an appropriate measure to determine the value premium is crucial. Our main goal is to come up with a trading strategy, which can be easily implemented in a practical context[3]. We expect these rotation strategies to have a considerable turnover. For this reason, we will conduct our analysis on the S&P Barra Growth and Value indices. Transaction costs are expected to be relatively low as we are able to buy and sell futures on these indices[4]. Both indices are constructed by dividing the stocks in the S&P 500 index according to just one single attribute: the book-to-market ratio. This procedure splits the S&P 500 index into two, mutually exclusive groups of stocks and is designed to track these accepted investment styles in the U.S. stock market. The Value index contains firms with high book-to-market ratios and conversely the Growth index firms with lower book-to-market ratios. The combination of both (market cap weighted) indices adds up to the (market cap weighted) S&P500[5].

It can be questioned whether these indices are the best representation of "value" and "growth". First of all, the S&P 500 index is clearly biased towards large capitalization stocks. Therefore our results will only hold for this particular universe of stocks. Secondly, the Barra Value and Growth indices have significantly different sector weights. Relative to the regular S&P 500 index, the S&P Barra Growth index has more exposure to Health Care (12%) and Technology (8%). The S&P Barra Value index on the other hand has more exposure to Financial Services (21%) and Energy (12%) than the benchmark[6]. This implies that a considerable part of the variance of the value spread will possibly be due to sector movements. Finally, we feel that "value" and "growth" stocks can best be captured by a combination of attributes, like for instance earnings-to-price, cash-flow-to-price and sales-to-price. Nonetheless, we will use the S&P 500 Barra value and growth series to calculate the value premium as they are commonly used in practice and therefore perfectly suitable for our trading strategy.

[insert Figure 1: graphical presentation of value spread series]

Figure 1 shows that a strategy purely based on the value premium would have witnessed some highly volatile periods. These series are the returns of a long position in the Value index and a short position in the Growth index throughout the entire sample period ranging from January 1984 to December 2001[7]. Monthly minimum and maximum returns of this strategy are extraordinary high: -23.18% and 10.27%. Summary statistics reveal that the spread series exhibits considerable leptokurtosis. We can also see that the number of negative performance months of this "buy-and-hold value strategy" is approximately 50.0%. The average return on an annualized basis is –0.89% with a standard deviation of 10.93%. We therefore conclude that pure and unconditional value investing in this particular sample period was not a very attractive trading strategy. Furthermore, we observe a time-varying pattern in the behavior of the premium. In some periods, like for instance in the last years of the previous decade, growth stocks outperformed value stocks considerably and in other periods value stocks clearly outperformed growth stocks. A good example of the latter is the crisis in Technology (and hence “growth”) stocks in the beginning of this century. A possible explanation for this phenomenon could be that the sign of the value premium is strongly connected with the business cycle and the economic regime. It is for instance likely that value stocks - relative to growth stocks - gain from a surge of economic activity and a sharp upward revision of sentiment, see e.g. Schwob (2000). As profit expectations turn sharply and broadly positive at the bottom of the economic cycle, profitability and earnings growth become a less scarce resource. Portfolio managers then start looking for stocks with typical value features. This largely explains why value stocks generally belong to cyclical industries.

We will introduce two classes of forecasting variables in this section. First, we give a brief overview of potential technical or market-based variables. It is likely that the value spread series are subject to the same statistical or behavioral patterns as the majority of financial series. Subsequently, we will address several macro-economic variables, which might shed some light on the behavior of the spread series. We aim to provide a wide range of relevant forecasting variables, but we restrict ourselves to those claimed to be economically interpretable in the literature on this subject. Good examples of a technical factor are the lagged value and small cap spreads used by Levis and Liodakis (1999). Asness, Friedman, Krail and Liew (2000) propose two other variables of this class: the spread in valuation multiples and expected earnings growth between value portfolios and growth portfolios. Other candidates are changes in the implied volatility of the market, see Copeland and Copeland (1999), and price and earnings momentum in the market, see for instance Miller, Li and Cox (2001) and Bernstein (2001).

The class of economic variables is mainly related to economic fundamentals, the business cycle and trends in corporate earnings. Value companies belong to mature sectors in the economy. These sectors generally grow and shrink with the economy. Growth sectors on the other hand can offer protection during weaker periods in the economy. Examples of macro-economic series can be found in a variety of papers on style rotation. Kao and Shumaker (1999) document the influence of GDP growth, industrial production, the yield-curve spread, inflation (CPI) and the corporate credit spread on the value premium. In their view, GDP growth reflects the corporate earnings cycle. In periods of high corporate earnings growth, the often highly leveraged value companies profit disproportionately. Industrial production and composite leading indicators (CLI) can serve as an alternative to measure the same relationship. The interest rate environment can also have a substantial impact on the sign of the value premium. A yield spread widening between long government bonds and short term T-bills will probably hurt growth companies more than value companies as their profits are based further into the future. Growth stocks have longer durations than value stocks and are therefore more interest rate sensitive. These companies will underperform most likely in a setting with steep yield curves, which implies rising interest rates in the future. In the study of Levis and Liodakis (1999) the spread series are explained by the level of inflation, changes in the short-term interest rate and the equity risk premium respectively[8]. We present a table of the set of forecasting variables used in the regression in Appendix A:

Figure 2 displays the 60-month rolling correlations between each factor and the subsequent three-monthly value spread. The relationship between the forecasting factors and the value premium does not seem to be constant through time. Some factors appear to be relevant in a particular time frame, but loose their power completely in a different period. This is a clear indication that we should use a dynamic modeling framework. Nonetheless, in the vast majority of literature on style (rotation) strategies a fixed and predefined subset of forecasting variables is used, see for instance Levis and Liodakis (1999) and Kao and Shumaker (1999).

[insert Figure 2: 60-months rolling correlations of forecasting variables with value spread series]

The observed time variation in the correlations however motivates our choice of a dynamic model selection procedure in the spirit of Pesaran and Timmerman (1995). We use the whole set of forecasting variables as a starting point for the empirical analysis. At every point in time our methodology will select a limited set of forecasting variables in order to come up with a robust and parsimonious forecasting model. The relevance of the forecasting variables is then based on dynamic model selection criteria. This implies a procedure in which forecasting variables can be part of the model in some periods and skipped in others. In section 3 we will elaborate on our estimation method.

3. METHODOLOGY

In our analysis we adopt the recursive modeling approach of Pesaran and Timmermann (1995) (*from hereon PT95*), who applied this method on an equity timing strategy. In line with their setup, we assume that economic agents (i.e. portfolio managers) establish a base set of forecasting variables and search for a reasonable model specification capable of predicting the value premium. PT95 (pp. 1202) state: "…, *at each point in time, investors use only historically available information to select a model according to a predefined model selection criterion and then use the chosen model to make one-period ahead predictions of excess returns. The recursive forecasts are then employed in a portfolio switching strategy according to which shares or bonds are held depending on whether excess returns on stocks are predicted to be positive or negative*." Using this procedure we assess the economic significance of the predictability of the value premium in the U.S. stock market, explicitly accounting for the forecasting uncertainty faced by investors who only have access to historical information.

In order to successfully apply a style rotation strategy we first need a forecast model to predict the value premium. The observed leptokurtosis of the spread series in the previous section is a clear indication of the existence of a non-normal distribution of spread returns. This points into the direction of more robust estimation methods than simple OLS. This motivates our choice of a Logit modeling approach – in line with Levis and Liodakis (1999) - which implies that we will exclusively focus on predicting the sign of the value premium[9]. In detail the steps in our procedure are as follows:

1. We first define a base set of 17 forecasting variables (x_t), described in the previous paragraph and Appendix A. In order to have a more robust and parsimonious model specification, we limit the set of forecasting variables in the model to a maximum of 4. This results in 3,213 (out of 2^{17}) variable combinations, i.e. models. A model is defined here as a combination of forecasting variables with a minimum of 1 and a maximum of 4.

2. Using a standard Logit modeling approach of the form,

$$p_{t+1} = P(y_{t+1} = 1) = \frac{\exp(\alpha + \beta x_t)}{1 + \exp(\alpha + \beta x_t)} \qquad (1)$$

   with:

   $y_{t+1} = 1 \;\; if \;\; Value_{t+1} \geq Growth_{t+1}, \; 0 \;\; otherwise$

   we estimate all possible variable combinations in a rolling window (60 months) framework in order to capture the dynamics in the parameters[10].

3. Subsequently, we select the best model(s) by statistics based on the performance of the strategy in a 24-month out-of-sample *training* period. We explicitly include transaction costs and out-of-sample model performance in the model selection. This last adjustment is due to the critique of Bossaerts and Hillion (1999) who showed the insufficiency of in-sample criteria to forecast out-of-sample information ratios. We estimate and select models for three forecast horizons (1, 3 and 6 months) and various levels of transaction costs (0, 25 and 50 basis points). The selection criteria used are here either hit ratio (equal to the sign criterion, the percentage of correctly forecasted signs), mean (excess) return and the realized information ratio[11].

4. We additionally employ a simple model averaging procedure: instead of selecting only the highest ranked model, we allow the selection of the best *n* models in order to reduce the effect of possible outlier models. It should be noted that we take transaction costs into account in the model selection *stage*, whereas most other studies merely correct for transaction costs in the back testing of strategies by imposing a fixed penalty on the return series.

5. In order to explain the portfolio construction procedure, let us first define a default strategy in which the forecast horizon is 3 months, the model selection criterion is *mean return* and the number of optimal models *n* = 1. Each forecast is then generated for a 3-month holding period. We combine monthly forecasts as follows: each month *t+2,* we build an

equally weighted portfolio consisting of three portfolios: one created per ultimo *t*, one per ultimo *t+1* and one per ultimo month *t+2* respectively[12].

6. The monthly portfolios are long-short portfolios based on the net aggregated signals of the *n* optimal models. In the default case where *n* = 1 this simply means that we monthly have a new signal. In the case of for instance *n* = 10 we monthly have 10 signals. The exposure we then assign to the style indices is dependent on the strength of the monthly signal[13].

7. The signals are generated as follows: if the forecasted probability of a particular model is $\hat{p}_{t+1} \geq 0.55$, this implies a "Value" signal. If on the other hand $\hat{p}_{t+1} \leq 0.45$, we assign a "Growth" signal. In the case of $0.45 < \hat{p}_{t+1} < 0.55$ we will assume there is no signal and hence we will have no exposure to the style indices. The range is introduced here to reduce the sensitivity of the model outcome. In the Logit modeling context forecasted probabilities of both 0.5001 and 0.9999 both indicate a preference for "Value" versus "Growth" respectively.

In our sample this results in the following procedure: starting 1987/09 we estimate the Logit model mentioned above based on a *in-sample period* of 60 months. As the default strategy is based on the 3-month value spread, the first out-of-sample forecasts can be generated as per 1987/12. This procedure is repeated until the last forecast is made in 2001/11. Starting 1989/12 - at the end of the *model-training period* - we are able to calculate model selection criteria taking into account transaction costs. This procedure is then repeated for each model. Starting 1989/12 we monthly rank all models on the predefined selection criterion and select the *n* best models. In the *trading period* we then invest according to the signals of these models taking transaction costs into account. We repeat this procedure for the whole sample period. Figure 3 gives a graphical presentation of the methodology used.

[insert Figure 3: Methodology]

4. RESULTS OF THE ROTATION STRATEGY

In this section we present empirical results for the style timing strategies explained in the previous section. We show the performance of trading strategies based on recursive forecasts generated by the selected Logit models. In our analysis we use a 1-, 3- and 6-month forecast horizon with and without including a penalty for transaction costs. Transaction costs are assumed to be 0 or 25 basis points single trip[14]. Results are displayed for the three model selection criteria. Most of the tables and graphs in this section are based on the before mentioned default strategy[15].

[insert Table 1: Results style timing strategy using a 1-month forecast horizon]

[insert Table 2: Results style timing strategy using a 3-month forecast horizon]

[insert Table 3: Results style timing strategy using a 6-month forecast horizon]

The out-of-sample period used for the evaluation of the timing strategy starts January 1990 and ends December 2001. Tables 1 through 3 give results for the three forecast horizons. In every table we include the results of the so-called buy-and-hold strategy (BH): Long Value and Short Growth. We can clearly see that this strategy was not very successful in the *trading* period. The mean annual return of this strategy was in fact negative: –1.89% associated with a huge amount of risk: 12.56%. Portfolio managers using this strategy faced devastating 12-month losses up to 28%. Looking through the tables we see that the 1-month forecast horizon does not seem to be able to forecast the changing spread correctly. Realized information ratios are negative in every single case. For the 3- and 6-month horizon, we find much better realized information ratios for the trading strategies, especially when using the "mean return" selection criterion. In the remainder of this section we will focus on the default strategy.

The realized information ratio of the default strategy is highest in the case of using "mean return" as the discriminating selection criterion: 0.81. This is a result of both a higher return (6.86%) and a lower risk (8.51%) of the rotation strategy versus the buy-and-hold strategy. In our opinion, it is quite surprising that the realized information ratio is insignificantly low when using the information ratio as an ex ante selection criterion[16]. Nonetheless, the results based on the other two criteria are positive too: information ratios of 0.68 and 0.29 respectively. Relative to the buy-and-hold portfolio, the default style timing strategy suffers much less from monthly extreme returns. Skewness and excess kurtosis measures confirm these findings. Moreover, portfolio managers face less dramatic "worst years": the largest 12-month loss is only –5.58% and the percentage of negative months is 43.75%. Another interesting finding is that these strategies generate Growth signals in most time periods (59.03%), whereas the buy-and-hold strategy implicitly chooses a long position in Value and a short position in Growth in every time period (i.e. 100% Value).

[insert Figure 4: excess returns and positions buy-and-hold and style timing strategy]

Figure 4 shows monthly excess returns for the buy-and-hold strategy (upper left panel) and the default rotation strategy (upper right panel). These graphs show that most action can be found in the first two and in the last four years of the sample. Furthermore, we show the monthly signals of our style rotation strategy (lower left panel) and the aggregate positions it builds up to (lower right panel). In the first two years of the sample we see that the strategy consistently produces growth signals. This results in aggregate growth positions of the strategy. Value signals are less common than growth signals. Value signals are mainly forecasted in the years 1992, 1993 and 1995 and furthermore in 2000 and 2001. In all other years of the sample Growth was forecasted by our analysis.

[insert Table 4: % inclusion of forecasting variables through out-of-sample period]

[insert Figure 5: % inclusion of forecasting variables through time]

Figure 5 gives information on the inclusion of forecasting variables in the models. It is clear from these graphs that some variables are included regularly throughout the whole sample period (e.g. yield spread) and some are entering the model only in specific time periods (e.g. 12 month forward PE). Table 4 lists the forecasting variables and the average % inclusion throughout the period under investigation. From this it shows that the lagged spread variables, the yield spread, the real bond yield and industrial production are included in most cases, but none of these forecasting variables are incorporated in more than 50% of the models.

[insert Figure 6: cumulative performance of trading strategy]

The cumulative performance of the rotation strategy and the buy-and-hold strategy is displayed in Figure 6. The rotation strategy is moderately successful in the first years of the sample. But at the start of the TMT bubble the growth signals pay off heavily. Especially in 1998 and 1999, when the static buy-and-hold strategy suffers dramatically, the dynamic rotation strategy almost consistently adds value. Even more astonishing, it seems to be able to forecast the shift in sentiment in the beginning of 2000 as it starts producing value signals in these months.

[insert Figure 7: information for default strategy for varying number of optimal models]

The results so far are based on the default strategy in which we assumed to purely invest in the signals of the optimal model (n = 1). Figure 7 shows the impact of equally weighted averaging across a larger set of optimal models. For n = 1 to 250 we display realized information ratios of the trading strategies. It shows that information ratios are still acceptably high (0.40), even after averaging across the 250 best models. The relationship is not completely linear: after averaging the first 25 models the decrease in information ratio is approximately the same as the decrease from n = 25 to 250.

5. CONCLUDING COMMENTS

In this paper we developed a trading strategy in which the difference in observed returns of value and growth stocks in the US stock market is exploited. In the literature this return spread is often called the “value premium”. We use an approach in which the choice of the relevant forecasting variables is endogenized in the estimation procedure. This procedure enables us to evaluate style rotation strategies in a real time context without the benefit of hindsight most previous studies on this subject suffered from. The selection of optimal models is not based on statistical criteria, but on simple and straightforward evaluation measures, frequently used in the money management profession. Furthermore, model selection takes place in a separate model training period, which overcomes the problems often encountered with in-sample based model selection. Trading strategies based on this methodology are able to provide information ratios above 0.50. These results are dependent on the choice of the model selection criterion and do not hold consistently for very short return horizons. A simple model averaging exercise shows that these results are quite robust for the choice of the number of optimal models.

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TABLES

Table 1 Results rotation strategy using a one-month forecast horizon

S&P Barra	BH	HR	MR	IR
1-month horizon (costs 0 basis points)				
Mean	-1.89	-1.47	-0.75	-0.69
Standard deviation	12.56	9.44	12.33	12.30
Information ratio	-0.15	-0.16	-0.06	-0.06
Median	0.06	0.00	0.00	0.00
Minimum (monthly)	-23.18	-23.18	-23.18	-23.18
Maximum (monthly)	10.27	9.48	12.02	12.02
Skewness	-1.50	-4.26	-1.75	-1.75
Excess kurtosis	11.27	35.99	12.49	12.65
% negative months	48.61	16.67	43.75	42.36
Largest 3 months loss	-14.51	-27.46	-36.93	-37.73
Largest 12 months loss	-28.60	-32.84	-27.67	-32.41
% months in Growth	0.00	20.14	54.86	54.17
% months in Value	100.00	10.42	32.64	28.47
% months no position	0.00	69.44	12.50	17.36
1-month horizon (costs 25 basis points)				
Mean	-1.89	-2.29	-1.41	-1.44
Standard deviation	12.56	10.50	12.21	12.17
Information ratio	-0.15	-0.22	-0.12	-0.11
Median	0.06	0.00	-0.25	-0.25
Minimum (monthly)	-23.18	-23.43	-23.68	-23.68
Maximum (monthly)	10.27	9.48	11.77	11.77
Skewness	-1.50	-3.48	-1.92	-1.93
Excess kurtosis	11.27	25.17	13.95	14.17
% negative months	48.61	34.72	54.86	54.17
Largest 3 months loss	-14.51	-27.16	-37.43	-37.43
Largest 12 months loss	-28.60	-30.84	-28.26	-28.26
% months in Growth	0.00	26.39	53.47	52.78
% months in Value	100.00	12.50	31.94	25.69
% months no position	0.00	61.11	14.58	21.53

BH denotes Buy-and-Hold strategy. HR, MR and IR denote timing strategies based on hit ratio, mean return and information ratio respectively. All strategies are long/short portfolios based on the optimal model (n = 1). All numbers are annual data unless stated otherwise. The out-of-sample period under investigation is 1990/01 – 2001/12.

Table 2 Results rotation strategy using a three-month forecast horizon

S&P Barra	BH	HR	MR	IR
3-month horizon (costs 0 basis points)				
Mean	-1.89	2.88	7.01	2.03
Standard deviation	12.56	8.40	8.36	7.97
Information ratio	-0.15	0.34	0.84	0.25
Median	0.06	0.00	0.19	0.00
Minimum (monthly)	-23.18	-10.27	-10.27	-8.82
Maximum (monthly)	10.27	12.02	9.48	15.46
Skewness	-1.50	-0.37	-0.12	1.61
Excess kurtosis	11.27	8.33	4.66	13.96
% negative months	48.61	40.28	39.58	44.44
Largest 3 months loss	-14.51	-17.13	-10.10	-8.77
Largest 12 months loss	-28.60	-11.57	-4.29	-12.98
% months in Growth	0.00	49.31	56.94	53.47
% months in Value	100.00	27.08	29.86	25.00
% months no position	0.00	23.61	13.19	21.53
3-month horizon (costs 25 basis points)				
Mean	-1.89	5.27	6.86	2.32
Standard deviation	12.56	7.79	8.51	7.95
Information ratio	-0.15	0.68	0.81	0.29
Median	0.06	-0.00	0.13	-0.08
Minimum (monthly)	-23.18	-10.27	-10.27	-8.82
Maximum (monthly)	10.27	9.48	9.48	15.46
Skewness	-1.50	0.50	-0.12	1.58
Excess kurtosis	11.27	5.37	4.13	13.98
% negative months	48.61	45.83	43.75	54.86
Largest 3 months loss	-14.51	-10.10	-10.10	-8.77
Largest 12 months loss	-28.60	-4.56	-5.58	-9.11
% months in Growth	0.00	60.42	59.03	57.64
% months in Value	100.00	27.08	30.56	25.00
% months no position	0.00	12.50	10.42	17.36

BH denotes Buy-and-Hold strategy. HR, MR and IR denote timing strategies based on hit ratio, mean return and information ratio respectively. All strategies are long/short portfolios based on the optimal model (n = 1). All numbers are annual data unless stated otherwise. The out-of-sample period under investigation is 1990/01 – 2001/12.

Table 3 Results rotation strategy using a six-month forecast horizon

S&P Barra	BH	HR	MR	IR
6-month horizon (costs 0 basis points)				
Mean	-1.89	2.47	2.28	0.29
Standard deviation	12.56	6.16	6.42	6.33
Information ratio	-0.15	0.40	0.36	0.05
Median	0.06	0.00	0.00	0.00
Minimum (monthly)	-23.18	-8.01	-8.82	-8.82
Maximum (monthly)	10.27	8.00	6.67	6.67
Skewness	-1.50	-0.44	-0.39	-0.61
Excess kurtosis	11.27	7.19	4.91	4.64
% negative months	48.61	44.44	45.14	47.22
Largest 3 months loss	-14.51	-8.89	-10.04	-12.96
Largest 12 months loss	-28.60	-15.82	-12.74	-26.59
% months in Growth	0.00	55.56	57.64	55.56
% months in Value	100.00	32.64	34.03	33.33
% months no position	0.00	11.81	8.33	11.11
6-month horizon (costs 25 basis points)				
Mean	-1.89	2.79	3.29	0.16
Standard deviation	12.56	6.59	6.78	6.20
Information ratio	-0.15	0.42	0.48	0.03
Median	0.06	-0.04	-0.03	-0.08
Minimum (monthly)	-23.18	-8.90	-8.90	-7.35
Maximum (monthly)	10.27	8.00	6.67	6.67
Skewness	-1.50	0.15	-0.16	-0.19
Excess kurtosis	11.27	5.31	3.82	3.26
% negative months	48.61	52.78	51.39	56.25
Largest 3 months loss	-14.51	-8.92	-8.87	-13.04
Largest 12 months loss	-28.60	-10.11	-8.45	-27.17
% months in Growth	0.00	54.86	59.03	56.25
% months in Value	100.00	34.72	32.64	33.33
% months no position	0.00	10.42	8.33	10.42

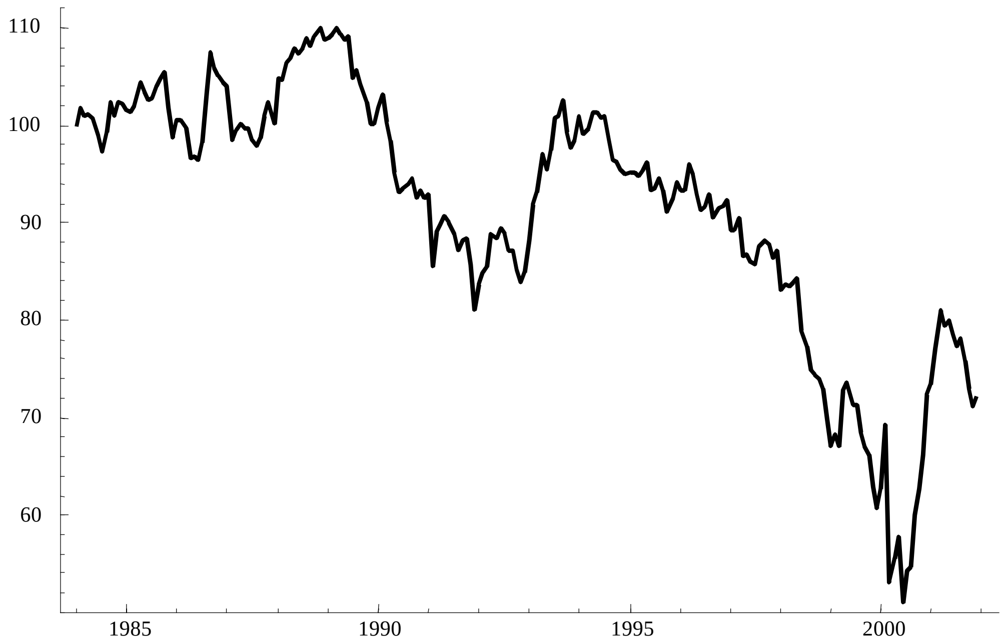
BH denotes Buy-and-Hold strategy. HR, MR and IR denote timing strategies based on hit ratio, mean return and information ratio respectively. All strategies are long/short portfolios based on the optimal model (n = 1). All numbers are annual data unless stated otherwise. The out-of-sample period under investigation is 1990/01 – 2001/12.

Table 4 % Inclusion of variables in model in the out-of-sample period

Forecasting Variable	Description	% Inclusion
L-V	Lagged value spread	28.47
L-SC	Lagged small cap spread	33.33
Corp.S	Corporate Spread	11.11
CPI	CPI	16.67
EY	Earnings Yield	25.00
Y-Spread	Yield Spread	42.36
Real BY	Real Bond Yield	28.47
IP	Industrial Production	31.94
Oil Price	Oil Price change	12.50
NAPM	NAPM	23.61
CLI	Composite Leading Indicator	15.97
VIX	3-month change in the VIX	15.28
PE(FW)	12-month forward PE	16.67
3-MOM	3-month price momentum	26.39
Profit cycle	Profit cycle	10.42
PE(dif)	Difference in PE (V-G)	8.33
DY(dif)	Difference in DY (V-G)	8.33

For a further description of these variables see Appendix A

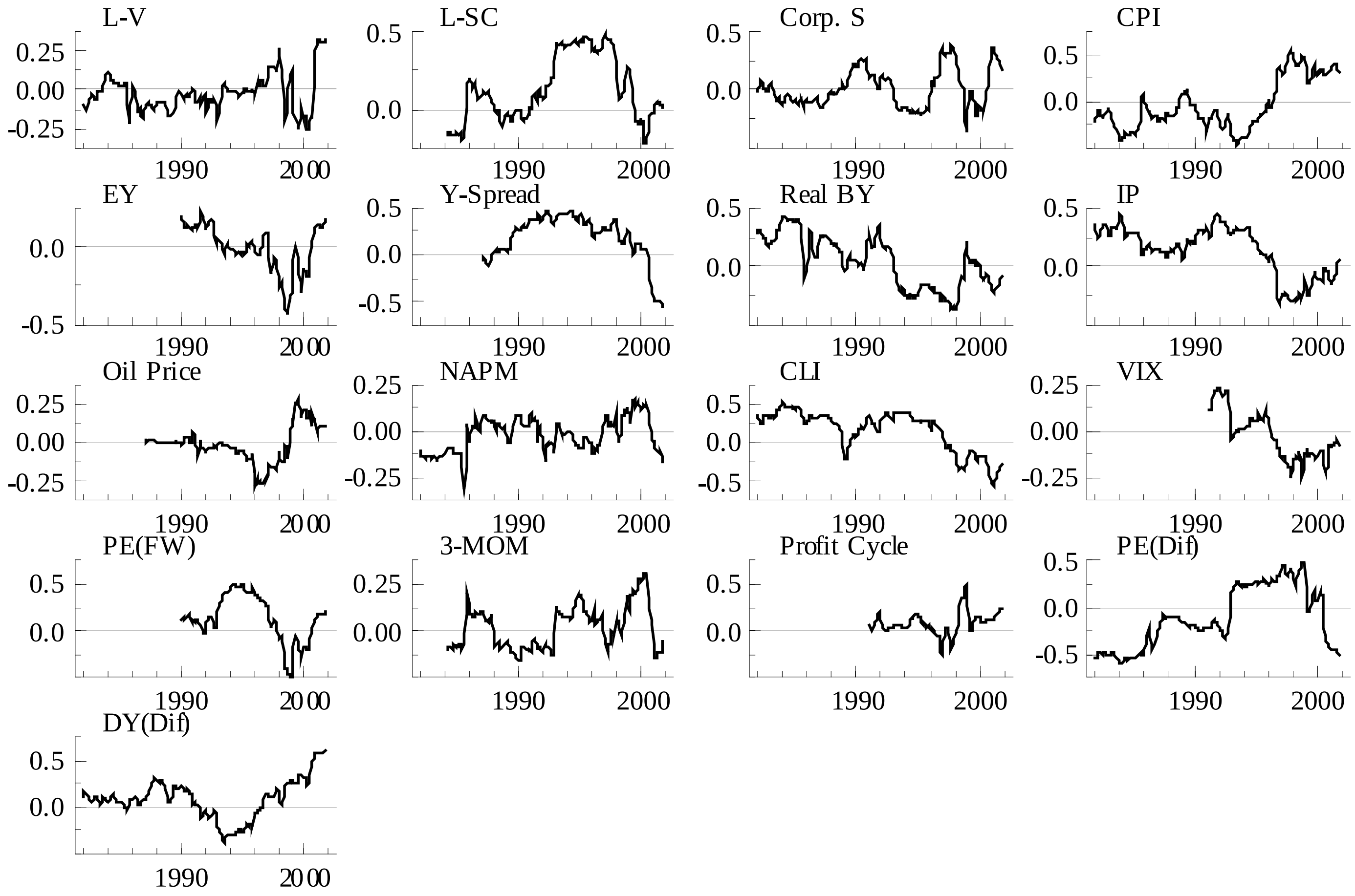
Figure 1 Cumulative performance of the Value Premium (1984/01 – 2001/12).



Summary Statistics Value Premium	
Mean	-0.89
Std. Deviation	10.93
Information Ratio	-0.08
Min (monthly)	-23.18
Max (monthly)	10.27
Skewness	-1.55
Excess Kurtosis	13.94
% Negative Months	49.07

All numbers are annual data (in %) unless stated otherwise. The spread series are computed as returns of a long/short portfolio (long S&P Barra Value Index and short S&P Barra Growth Index).

Figure 2. 60-month rolling correlations of forecasting variables with the Value Premium (3-month horizon)



For a description of variables see Table 4 and Appendix A

Figure 3 Estimation Procedure (rolling window)

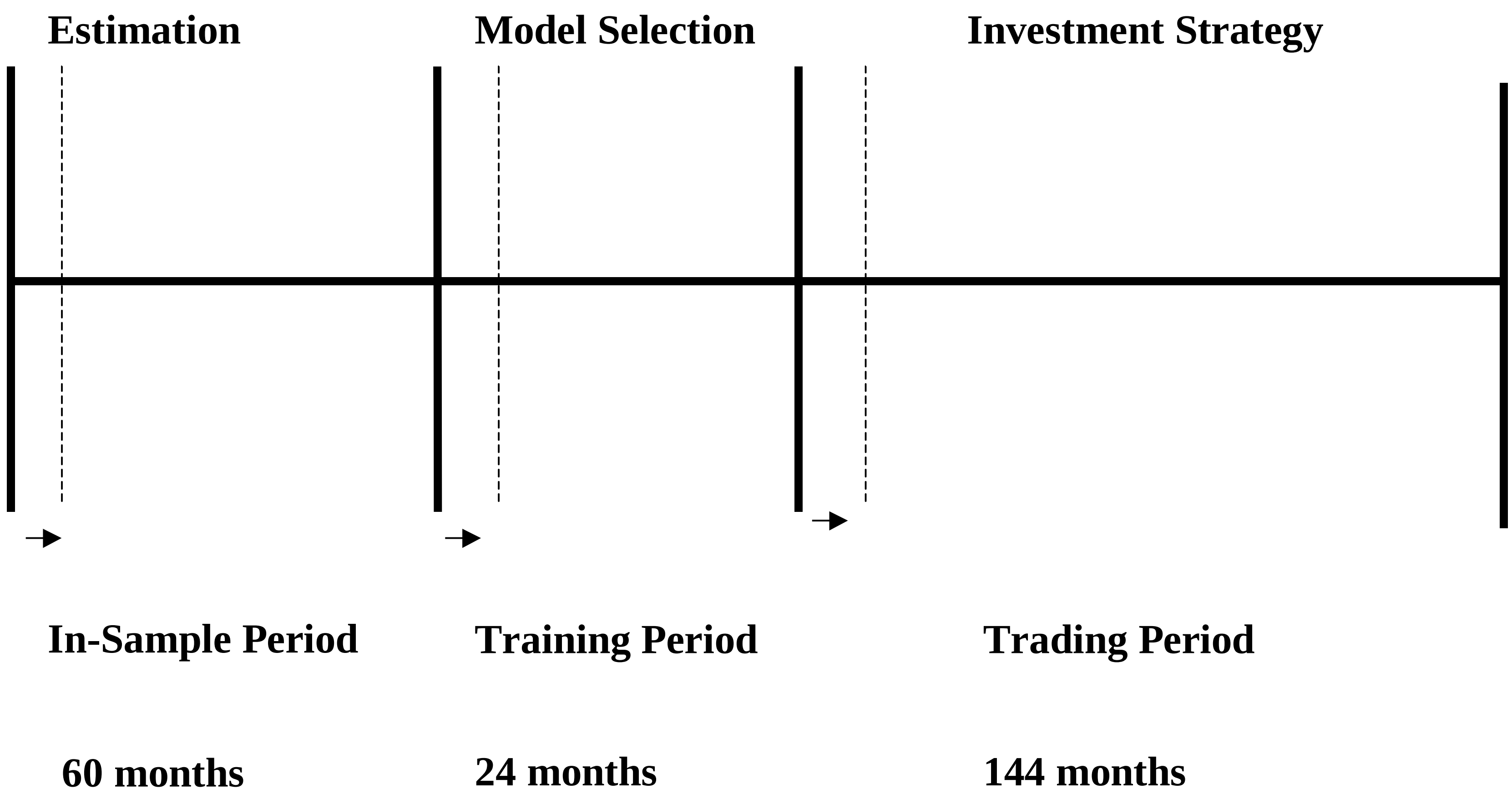


Figure 4. Excess buy-and-hold returns, style rotation returns, signals style rotation (1 = value, 0 = no position and –1 = growth) and aggregate positions style rotation for a 3-month horizon (*default strategy*) with 25 basis points transaction costs.

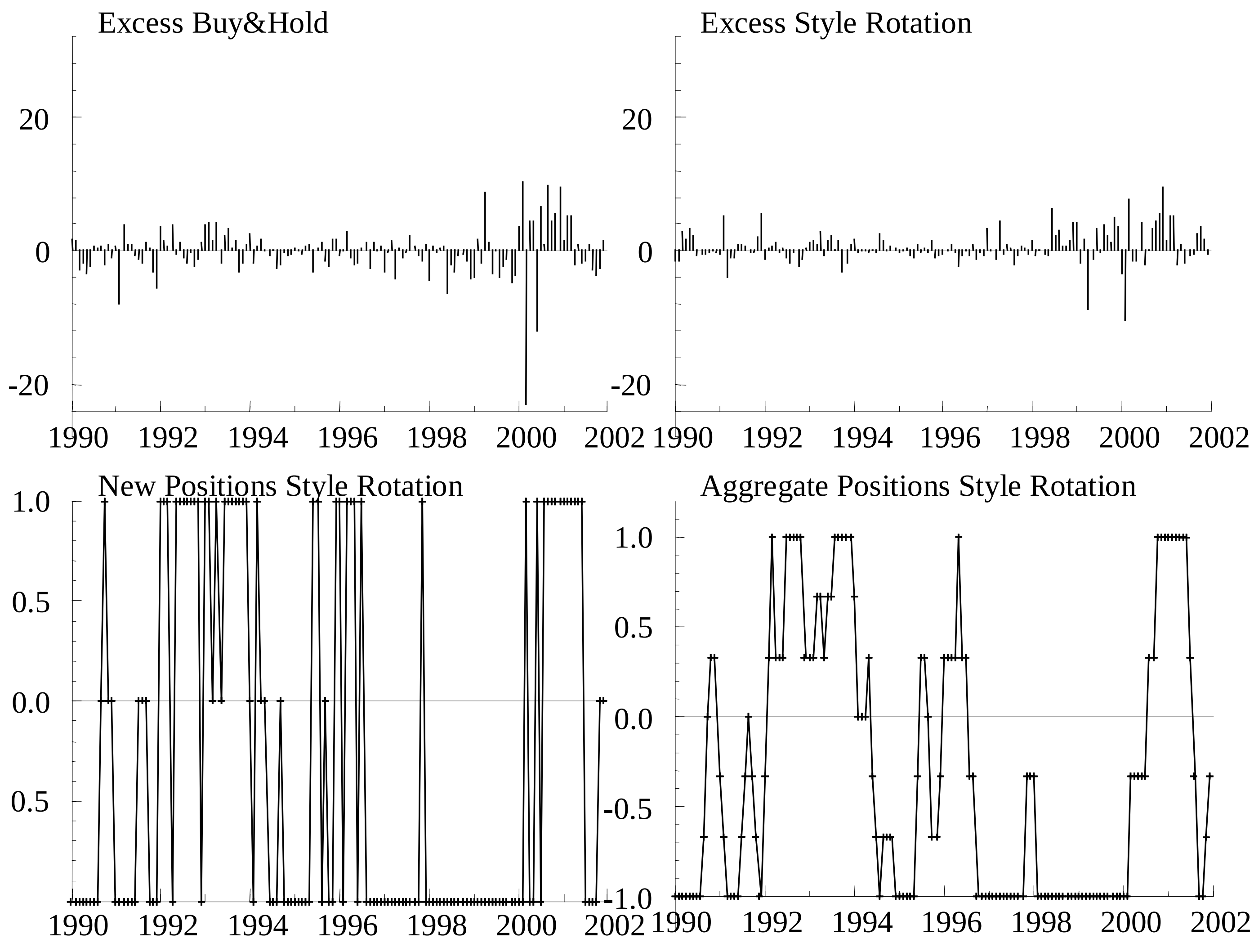
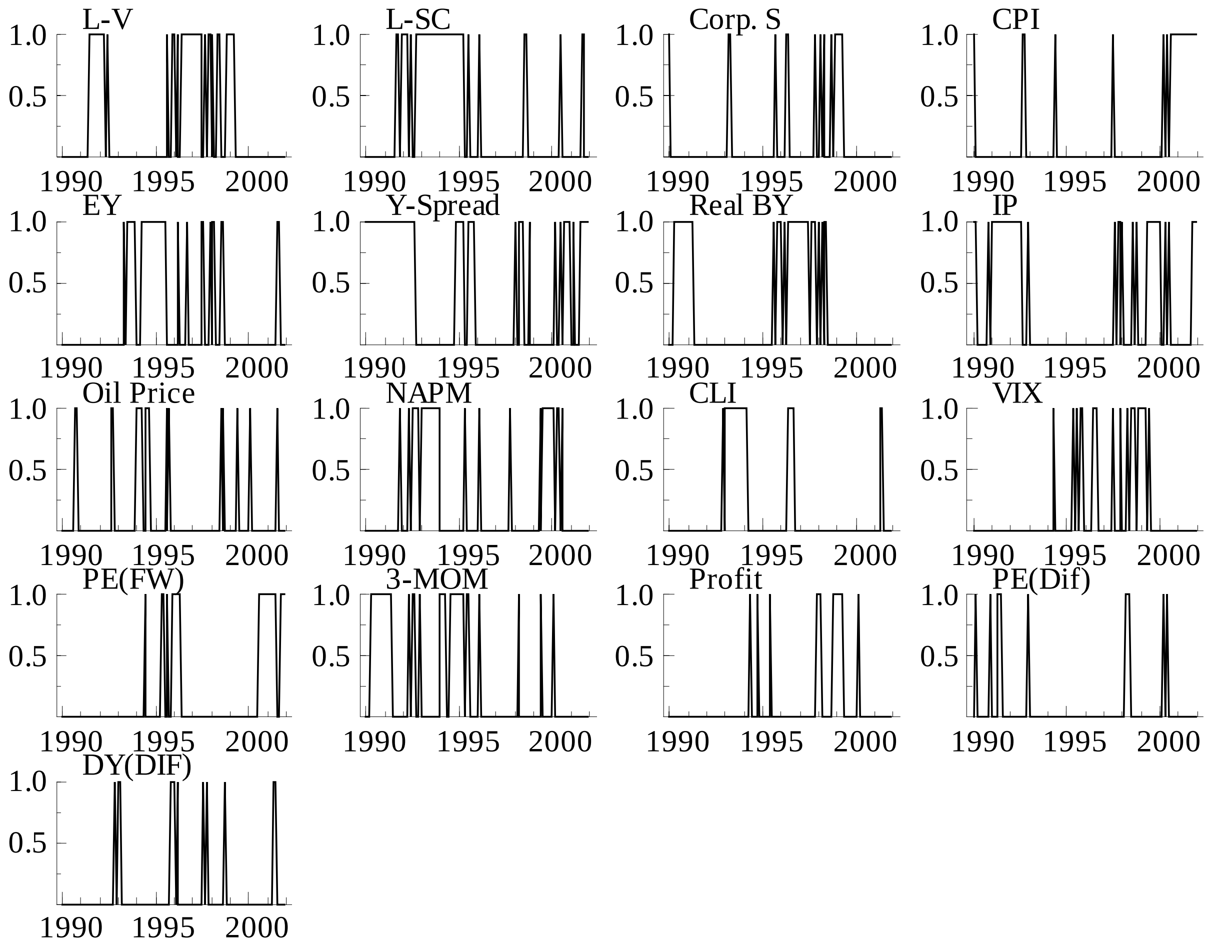


Figure 5. Inclusion of forecasting variables through time (*default strategy*).



For a description of variables see Table 4 and Appendix A

Figure 6 Cumulative performance of rotation strategy versus buy-and-hold strategy

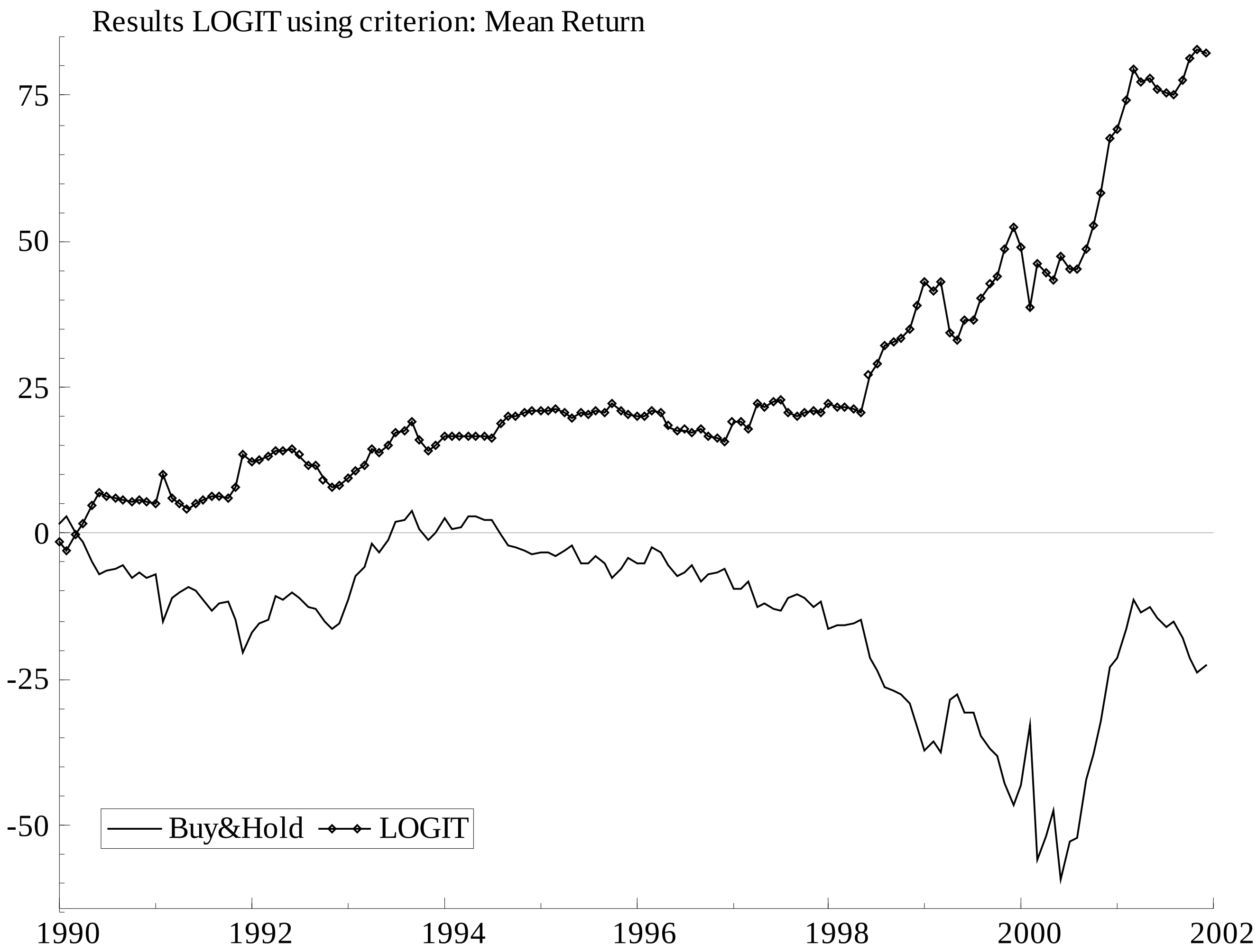
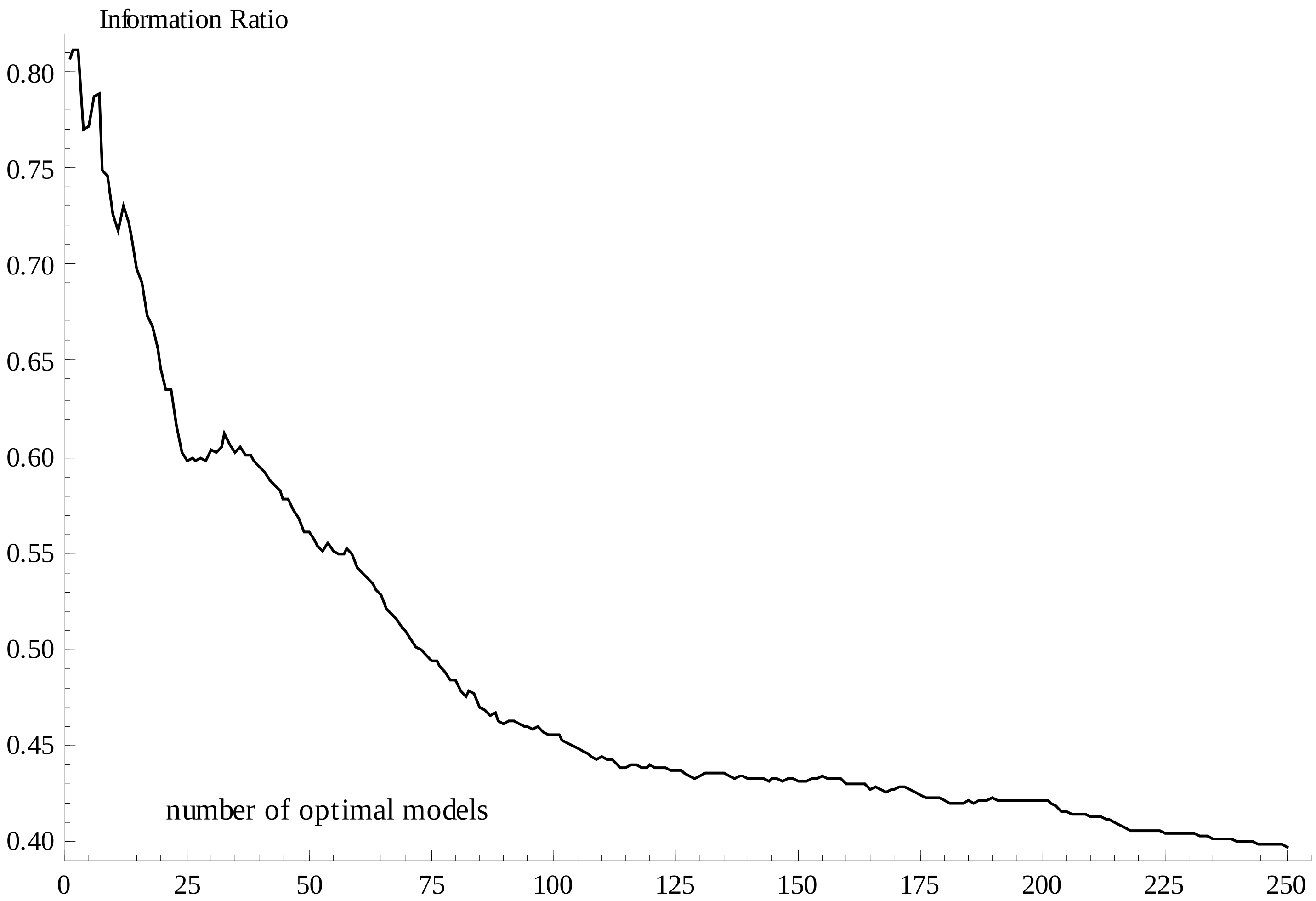


Figure 7 Information ratio for default strategy with varying number of optimal models



APPENDIX A

Technical variables are:

- Lagged Value/Growth spread
- Lagged Small/Large spread
- VIX: the 3-month change in the VIX indicator
- 12 month Forward P/E (S&P500)
- 3 month return momentum (S&P500)
- Profit cycle: Year on Year change in earnings per share of the S&P 500
- PE dif
- DY dif

Economic variables are:

- Corporate Credit Spread: the yield spread of (Lehman Aggregate) Baa over Aaa
- Core inflation: the 12-month trailing change in the U.S. Consumer Price Index
- Earnings-yield gap: the difference between forward E/P ratio (S&P500) and the 10-year T-bond yield
- Yield Curve Spread: the yield spread of 10-year T-bonds over 3-month T-bills
- Real Bond Yield: the 10-year T-bond yield adjusted for the 12-month trailing inflation rate
- Ind. Prod: U.S. Industrial Production Seasonally Adjusted
- Oil Price: the 1-month price change
- NAPM: the 1-month change in the National Association of Purchase Management indicator
- Leading Indicator: the 12-month change in the Conference Board Leading Indicator

Endnotes

[1] Cooper and Gulen (2001) mention two other important data snooping possibilities: the choice of the assets under consideration and the length of the in-sample window length.
[2] A full treatment of model uncertainty implies the use of Bayesian analysis, which is beyond the scope of this paper.
[3] In the case of for instance the High book-to-market minus Low book-to-market (HML) series of Fama and French (1993), we can expect relatively high transaction costs as portfolios generally exhibit unacceptable liquidity features, particularly in a long/short setting.
[4] In practice the maximum exposure of the trading strategy is still bound by the liquidity features of this future. Even in situations where the futures are not traded in large amounts, we can offer our baskets of (large cap) value and (large cap) growth stocks to the broker community.
[5] The S&P Barra Growth and Value indices are rebalanced semi-annually around January 1st and July 1st. The exact rebalance date is selected and announced by Standard & Poor's well in advance. The sole criterion for the S&P Barra Growth/Value split is the book value divided by the market capitalization of a firm. The values used at the time of rebalancing are the equity's position at the close of trading one month prior (i.e. November 30th and May 31st). This one month lag makes it possible to invest in the indices as of the rebalancing dates because the new constituent lists are known well in advance.
[6] Source: www.barra.com.
[7] The choice of this sample period is dependent on the availability of the macro-economic data.
[8] Recently, Liew and Vassalou (2001) claim that past style performance can actually function as *a forecast* for economic growth, which brings a new dimension to this literature.
[9] Kao and Shumaker (1999) use a regression tree.
[10] Another possible way of dealing with time-varying parameters is applying Kalman filter techniques.
[11] Note that PT95 use model selection criteria (AIC, BIC, R^2 or sign) based on in-sample characteristics.
[12] This procedure is similar to the one used by Jegadeesh and Titman (1993).
[13] The net average signal should then be interpreted as follows: suppose there are 7 Value signals and 3 Growth signals in a particular month. This would imply a net of 4 Value signals. In this period we would invest 40% of our (maximum) exposure in a long value and short growth strategy.
[14] Results for 50 basis points transaction costs are available upon request.
[15] Results for other forecast horizons and other values for *n* are available upon request.
[16] A good explanation for this could be that the length of the training period is too short to calculate useful information ratios.