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# Tactical Style Allocation – A New Form of Market Neutral Strategy

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### Abstract:

Even though there is little evidence of predictability in stock specific risk, most equity market neutral managers still rely on stock picking as the preferred way to generate abnormal returns. In this paper, we document the benefits of a new form of market-neutral portfolio strategy that aims at delivering absolute return over the full business cycle through systematic equity style timing decisions. Using a robust multi-factor recursive modeling approach, we find strong evidence of predictability in value and size style differentials. We use these econometric forecasts to generate systematic style timing allocation decisions. These portfolio decisions can be implemented using Exchange Traded Funds on US style indexes.

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# 1 Introduction

There is now a consensus in empirical finance that security returns are, to some extent, predictable. Pioneering work on the predictability of asset class returns in the U.S. market was carried out by Keim and Stambaugh [1986], Campbell [1987], Campbell and Shiller [1988], Fama and French [1989], and Ferson and Harvey [1991]. More recently, some authors started to investigate this phenomenon on an international basis by studying the predictability of asset class returns in various national markets (see, for example, Bekaert and Hodrick [1992], Ferson and Harvey [1993, 1995], Harvey [1995], and Harasty and Roulet [2000]). The use of predetermined variables to predict asset returns has produced new insights into asset pricing models, and the literature on optimal portfolio selection has recognized that these insights can be exploited to improve on existing policies based upon unconditional estimates. For example, Kandel and Stambaugh [1996] argue that even a low level of statistical predictability can generate economic significance and abnormal returns may be attained even if the market is successfully timed only 1 out of 100 times. While Samuelson [1969] and Merton [1969, 1971, 1973] have paved the way by showing that optimal portfolio strategies are significantly affected by the presence of a stochastic opportunity set, optimal portfolio decision rules have subsequently been extended to account for the presence of predictable returns (see in particular Barberis [2000], Campbell and Viceira [1998], Campbell et al. [2000], Brennan, Schwartz and Lagnado [1997], Lynch and Balduzzi [2000], Lynch [2000], for a parametric approach in a simple setting or Brandt [1999] and Ait-Sahalia and Brandt [2001] for a non-parametric approach in a more general setting). Practitioners also recognized the potential significance of return predictability and started to engage in “tactical asset allocation strategies as early as the 1970s.<sup>1</sup> The exact amount of investment currently engaged in tactical asset allocation (TAA) is not clear, but it is certainly growing very rapidly. For example, Philip, Rogers and Capaldi [1996] estimated that around \$48 billion was allocated to domestic TAA in 1994; while Lee [2000] estimates that more than \$100 billion dollars was dedicated to domestic TAA at the end of 1999.

TAA strategies were traditionally concerned with allocating wealth between two asset classes, typically shifting between stocks and bonds. More recently, more complex *style* timing strategies have been successfully tested and implemented. These strategies are based on the recognition that Sharpe’s CAPM [1964] needs to be extended to account for the presence of other pervasive risk factors, i.e., size and book-to-market factors [Fama and French [1992]]:

$$R_{i,t} - r_{f,t} = \underbrace{b_{i,M} [R_{M,t} - r_{f,t}]}_{\text{systematic market}} + \underbrace{b_{i,B/M} [R_{B/M,t} - r_{f,t}] + b_{i,size} [R_{size,t} - r_{f,t}]}_{\text{systematic style}} + \underbrace{e_{i,t}}_{\text{specific}}$$

Such a decomposition of returns allows for a natural extended classification of active portfolio strategies (see Exhibit 1). *Market Timing or Tactical Asset Allocation Strategies* aim at exploiting evidence of predictability in market factor; *Style Timing or Tactical Style Allocation (TSA) Strategies* aim at exploiting evidence of predictability in style factors; *Stock picking strategies* aim at exploiting evidence of predictability in individual stock specific risk.

**Exhibit 1: Classification of Active Portfolio Strategies**

	<u>Systematic - market</u>	<u>Systematic - style</u>	<u>Specific</u>
<b>Form of active strategy</b>	<b>Tactical Asset Allocation</b>	<b>Tactical Style Allocation</b>	<b>Stock picking</b>
Mutual fund – stock picking	X (discretionary)	X (discretionary)	X
Hedge fund – stock picking	0	X (discretionary)	X
Mutual fund – market timing	X (discretionary or systematic)	0	0
<b>TSA – long only</b>	X (systematic)	X (systematic)	0
<b>TSA – market neutral</b>	0	X (systematic)	0

It is perhaps surprising that, on the one hand, most long/short equity managers still favor stock picking as a way to generate abnormal return, while, on the other hand, thirty years of academic studies have shown that there is little evidence of predictability in the specific component of stock returns in the absence of private information. It should be noted that TSA is not a new concept. Most mutual fund managers actually make discretionary, and sometimes unintended, bets on styles as much as they make bets on stocks. In other words, they perform TAA, TSA and stock picking at the same time in a somewhat confusing ‘mélange des genres’. As in many other contexts, we have evidence that specialization pays. In particular, Daniel, Grinblatt, Titman and Wermers [1997] find that evidence that mutual funds showed some stock selection ability, but no discernable ability to time the different stock characteristics in terms of book-to-market or size.

More recently, several authors have emphasized the benefits of focusing on style timing exclusively. In particular, Fan [1995], Sorensen and Lazzara [1995], Kao and Shumaker [1999], Avramov [2002] or Bauer and Molenaar [2002] report strong evidence of predictability in equity style returns and underline the performance of strategies that involves dynamic trading in various equity styles. Related papers also include Gerber [1994], Case and Cusimano [1995], Fisher, Toms and Blount [1995], Mott and Condon [1995], Levis and Liodakis [1999], Oertmann [1999], Reiganum [1999], Amenc and Martellini [2001], Cooper et al. [2001], Ahmed, Lockwood and Nanda [2002], or Amenc, El Bied and Martellini [2003].

In this paper, we complement existing research by considering the performance of portfolios aiming at delivering absolute return over the full business cycle ensured though systematic style timing and market neutrality. We believe that focusing on market neutral funds allows us to better isolate the benefits of the style timing approach. We use a robust dynamic multi-factor modeling approach and we confirm the presence of predictability in growth/value

and size style differentials. We then turn econometric bets into portfolio decisions that can be implemented by trading ETFs on S&P style indexes. These portfolio decisions have generated a spectacular out-of-sample performance over the period 06/2000-12/2002.

The rest of the paper is organized as follows. In section 2, we report the results of a contemporaneous as well as a lagged factor analysis of style index returns. In section 3, we present the econometric model used to forecast equity style returns. In section 4, we present the performance of a dynamic style allocation strategy. We discuss various implementation problems in section 5, and present our conclusions in section 6.

## 2 Factor Analysis of Style Index Returns

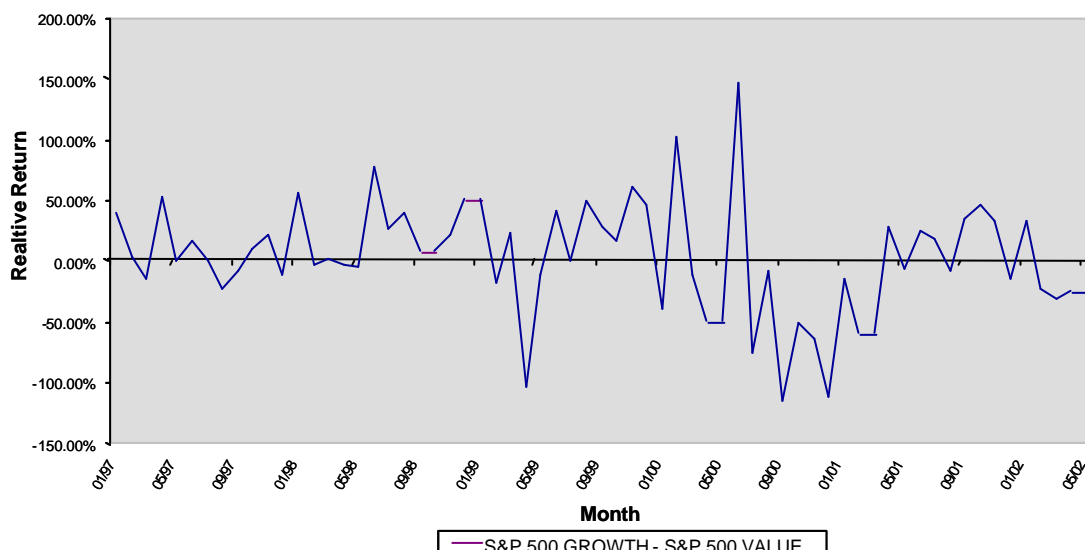
In this section, we provide evidence that different equity styles perform better at different points in time. We also present a series of examples of economic and financial factors driving style index returns.

### 2.1 Analyzing the Growth/Value and Small/Large Differentials

The stock market can be divided into two types of stocks, value and growth. Roughly speaking, value stocks are "bargain" or out-of-favor stocks that are inexpensive relative to company earnings or assets. Growth stocks represent companies with rapidly expanding earnings growth.

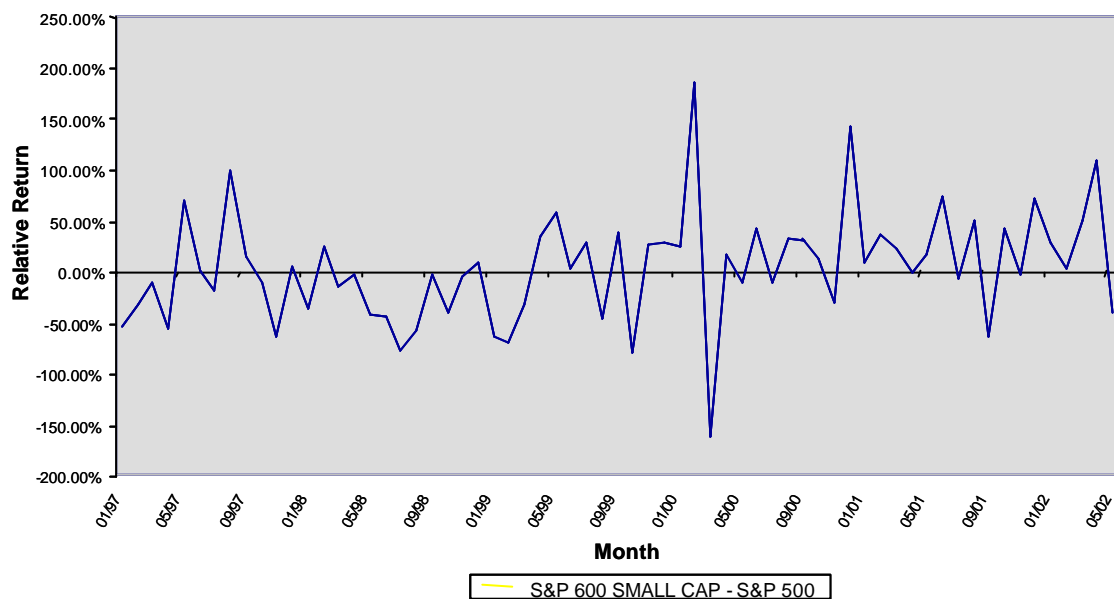
Investors have an intuitive understanding that equity indexes have contrasted performance at different points of the business cycle. To confirm and test the validity of such an intuition, we have used monthly data on the period January 1997-June 2002 and plot in Exhibit 2 the time series of the growth/value differential (S&P 500 Growth – S&P500 Value). Exhibit 2 shows that historically, growth and value stocks have moved in and out of favor at different times.

**Exhibit 2: Dynamics of the Growth/Value Differential.** This Exhibit shows the annualised returns on a portfolio strategy going 100% long the S&P 500 Growth and 100% short the S&P500 Value, based on monthly data over the period 01/1997-06/2002.



Another dimension has been found to be relevant, which emphasizes the distinction between small and large cap stocks. We have also used monthly data on the period January 1997-June 2002 to plot in Exhibit 3 the time series of the small cap/large cap differential (S&P 600 Small Cap – S&P500).

**Exhibit 3: Dynamics of the Size Differential.** This Exhibit shows the annualised returns on a portfolio strategy going 100% long the S&P 600 Small Cap and 100% short the S&P500, based on monthly data over the period 01/1997-06/2002.



## 2.2 Understanding the Growth/Value and Small/Large Differentials

Style indexes perform differently in different points in time because they are exposed to different economic and financial risk factors. In what follows, we provide some examples of stylized facts on why and when growth should outperform value, and small cap stocks should outperform large cap stocks. We do not provide in this section a formal econometric analysis of style differentials (we leave it for next section); we merely provide the reader with a couple of illustrating examples.

One first example is as follows. A common characteristic of most growth stocks is a very low dividend payout to shareholders. Value stocks tend to pay out much more of their net income in the form of a current dividend. Therefore growth stocks can be said to have a longer "duration" than value stocks. Thus, we would expect growth stocks to underperform in an environment of steeper yield curves, which imply expectations of rising interest rates in the future. To confirm this intuition, we perform the following experiment. We use the difference in return between the S&P500 Value index and the S&P500 Growth index as a proxy for the value differential and differences between a 10Y T-Bond and a 3 month T-Bill rates as a proxy for the term spread. We collect monthly data on the period ranging from September 1991 to May 2002.

Exhibit 4 presents the performance of the value/growth differential under 3 different economic conditions: low, medium and high values of changes in the slope of the yield curve. For example, low values of changes in the slope of the yield curve are any value that is less than -6.59%, which indicates a flattening scenario for the yield curve. Under this condition S&P growth outperforms S&P value by an annualized 6.39% on average above its annualized mean, 0.89%. At the same time, volatility of the growth-value differential is 2.33% higher than the (annualized) unconditional value, 10.74%. On the other hand, when changes in the term spread are high (i.e., when the yield curve is steepening), S&P growth underperforms S&P value by an annualized 7.46% on average below the annualized mean.

**Exhibit 4 : Growth versus Value and Changes in the Term Spread.** Exhibit 4 presents the performance, expressed in term of the difference between conditional and unconditional value mean and standard deviation estimates, of the value/growth differential under 3 different economic conditions: low, medium and high values of changes in the slope of the yield curve. Yellow signals difference between conditional and unconditional average returns greater than 5% or lower than -5% annualized. Pale blue signals difference between conditional and unconditional average returns between 2 and 5% or between -5 and -2% annualized.

Percentage Change in Term Spread  Difference between Conditionnal Values and Unconditionnal Values	Low		Medium		High		Unconditionnal Values		
	Minimum	Maximum	Minimum	Maximum	Minimum	Maximum			
	-4100.00%	-6.59%	-6.38%	5.98%	6.36%	284.21%			
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Correlation
S&P 500	7.04%	3.09%	-0.32%	-3.94%	-6.72%	0.03%	10.28%	14.22%	-0.13
S&P 500 GROWTH	10.08%	3.46%	0.30%	-4.79%	-10.39%	0.11%	10.64%	16.41%	-0.11
S&P 500 VALUE	3.70%	3.12%	-0.78%	-3.08%	-2.93%	-0.48%	9.75%	13.81%	-0.13
S&P 600 SMALL CAP	-5.23%	1.56%	4.08%	-4.95%	1.15%	2.71%	13.75%	17.47%	-0.14
S&P 500 - S&P 600 SMALL CAP	12.27%	1.60%	-4.40%	-3.77%	-7.87%	1.06%	-3.47%	13.23%	0.05
S&P 500 GROWTH - S&P 500 VALUE	6.39%	2.33%	1.08%	-1.92%	-7.46%	-1.01%	0.89%	10.74%	0.01

In this example, we have discussed the performance of the value/growth differential under different contemporaneous economic conditions. It is also useful, especially in the context of tactical timing strategies, to study the performance of style differentials using a one-month lag between the economic factors and performance of various strategies. The goal is to see if lagged values of economic factors affect the subsequent performance of style differentials.

For that purpose, we now consider an example related to the differential between small versus large cap and the lagged return on large cap stocks. Research by Lo and Mackinlay [1990] on the momentum effect in portfolio returns showed there was a correlation between one weeks return and the next, where about four percent of the price change of next weeks return could be predicted from this weeks return. When the constituents of the portfolio were altered to contain small capitalization companies, rather than an equal amount invested in each stock of the New York Stock Exchange, the effect was enhanced to around ten percent. This is known as a lead-lag pattern, which means that *big stocks lead little stocks*. For example, if Microsoft goes up dramatically and a few days later one may expect a price jump in other computer software manufacturers.

To confirm this intuition, we perform the following experiment. We use the difference in return between the S&P600 Small Cap index and the S&P500 index as a proxy for the small versus large cap differential, and the return on the S&P500 index as a proxy for the return on large cap stocks. Using monthly data on the period ranging from September 1991 to May 2002,

Exhibit 5 presents the performance of the small/large differential under 3 different economic conditions: low, medium and high one-month lagged values of S&P500 returns. For example, low values of monthly S&P500 returns range between –14.58% and –0.03% on the period. Under this condition S&P 600 SC underperforms S&P 500 one month later by an annualized 6.30% on average *below* the annualized mean of the large-small differential (-3.11%). On the other hand, when S&P4500 returns are high, S&P 600 SC outperforms S&P 500 one month later by an annualized 10.15% on average in excess of the annualized mean.

**Exhibit 5: Small Cap versus Large Cap and the Lead-Lag Effect.** Exhibit 5 presents the performance, expressed in term of the difference between conditional and unconditional value mean and standard deviation estimates, of the large/small differential under 3 different economic conditions: low, medium and high values of the return on the S&P500. Dark blue signals difference between conditional and unconditional average returns greater than 5% or lower than -5% annualized. Pale blue signals difference between conditional and unconditional average returns between 2 and 5% or between –5 and –2% annualized.

S&P 500 Index Return  Difference between Conditionnal Values and Unconditionnal Values	Low		Medium		High		Unconditionnal Values		
	Minimum	Maximum	Minimum	Maximum	Minimum	Maximum			
	-14.58%	-0.03%	-0.53%	2.79%	2.80%	11.16%			
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Correlation
S&P 500	6.50%	2.55%	0.77%	-2.44%	-7.27%	-0.50%	11.01%	14.27%	-0.10
S&P 500 GROWTH	10.75%	2.38%	-0.86%	-2.77%	-9.89%	-0.17%	11.28%	16.53%	-0.12
S&P 500 VALUE	1.77%	3.42%	2.48%	-2.73%	-4.25%	-1.18%	10.57%	13.80%	-0.06
S&P 600 SMALL CAP	0.20%	3.74%	-3.08%	-1.50%	2.88%	-2.49%	14.12%	17.57%	0.00
S&P 500 - S&P 600 SMALL CAP	6.30%	3.42%	3.85%	-4.15%	-10.15%	-0.54%	-3.11%	13.35%	-0.10
S&P 500 GROWTH - S&P 500 VALUE	8.98%	2.24%	-3.34%	-2.41%	-5.64%	-0.56%	0.71%	10.82%	-0.11

We have discussed a couple of examples illustrating that both contemporaneous and lagged economic and financial variables had an impact on style differentials (growth - value, large - small cap). Such casual contemporaneous and lagged factor analysis provides a very useful tool for helping an asset allocator in his/her *discretionary* decision making process. On the other hand, the objective of a *systematic* tactical allocator is to set up an econometric model able to predict when a given style is going to outperform other styles. This is what we turn to in the next section.

Forecasting economic variables is a difficult art, with the failures often leading to all systematic tactical allocation processes being abandoned. There are actually two ways of considering tactical style allocation decisions. One approach consists in forecasting returns by first forecasting the values of economic variables (scenarios on the contemporaneous variables). The other approach to forecasting returns is based on anticipating market reactions to known economic variables (econometric model with lagged variables). A number of academic studies (e.g., de Bondt and Thaler [1985], Thomas and Bernard [1989]) suggest that the reaction of market participants to known variables is easier to predict than financial and economic factors. The performance of timing decisions based on an econometric model with lagged variables results from a better ability to process available information, as opposed to privileged access to private information.



### 3 Evidence of Predictability in Style Index Returns

In this section, we describe the econometric approach that we have used in an attempt to search for evidence of predictability in style index returns.

Previous research (e.g., Leung, Daouk and Chen [2000]) has show that forecasts based on the direction of stock market movements can lead to more robust outperformance than forecasts based on price levels. In this paper, we therefore focus on calibrating direction forecasting models for the following two style differentials:

- S&P Growth – S&P Value
- S&P 600 (Small Cap) – S&P500

Given that we are searching for evidence of predictability in equity style returns with the goal of implementing a style allocation strategy, we attempt to find the best possible trade-off between quality of fit and robustness. For a forecast starting in June 2000, we first decompose the period June 1994 to May 1999 (6 years) into 2 sub-periods, a calibration period and a training period. In the *calibration period*, we use a 4-year rolling window of data (starting in June 94) to calibrate the model, i.e., estimate the coefficients. For the *training period*, we use a 2-year rolling window of data (starting in June 98) to backtest the model, i.e., generate forecasts and compute hit ratios. Hit ratios are the percentage of times the predicted sign equals the actual sign of the style return. We test whether hit ratios are significantly greater than  $\frac{1}{2}$  (benchmark case of no model): in the case of 24 observations, a hit ratio of at least 63% (respectively, 67%) is significantly greater than  $\frac{1}{2}$  at the 10% (respectively, 5%) level. We also compute the associated t-statistics to check whether the variable had a statistically significant explanatory power. Finally, we select the model at the end of the training period and use subsequently in the *trading period* (June 2000 to December 2002).

#### 3.1 Selecting the Variables

Rather than trying to screen hundreds of variables through stepwise regression techniques, which usually leads to high in-sample R-squared but low out-of-sample R-squared (robustness problem), we instead choose to select, for each style differential, a short list of economically meaningful variables, which are known to have a natural impact on stock returns.

Most of these variables can be found within the following three broad categories.

##### 3.1.1 Variables related to interest rates

- a. Level of the term structure of interest rates, proxied by the short-term rate: Fama [1981] and Fama and Schwert [1977] show that this variable is negatively correlated with future stock market returns; it serves as a proxy for expectations of future economic activity.
- b. Slope of the term structure of interest rates, proxied by the term spread: An upward sloping yield curve signals expectations of an increase in the short-term rate, usually associated with an economic recovery.

### 3.1.2 Variables related to risk

- c. Quantity of risk, proxied by historical volatility (intra-month volatility of stock or bond returns) or expected volatility (implied volatility from option prices).
- d. Price of risk, proxied by credit spreads (on high yield and/or emerging markets debt): it captures the effect of default premiums [Fama and French [1998]], which track long-term business cycle conditions (higher during recessions, lower during expansions).

3.1.3 Variables related to relative cheapness of stock prices, proxied by B/M, but also P/E ratios, dividend payout ratios, etc.: It has been shown that the dividend yield is associated with slow mean reversion in stock returns across several economic cycles (Keim and Stambaugh [1986], Campbell and Shiller [1998], Fama and French [1998]). It serves as a proxy for time variation in the unobservable risk premium since a high dividend yield indicates that dividends have been discounted at a higher rate.

Other variables which are known to have a natural impact on style returns include returns on stock and bond indexes, liquidity indicators (in particular measures of market volume on the NYSE and bid-ask spreads), commodity prices (in particular oil prices, and global commodity index), currency rates (in particular dollar-yen, dollar-pond, dollar euro), etc. We also consider a limited number of economic variables while controlling for the risk of back-filling and posterior adjustment. These economic variables include in particular traditional measures of inflation, economic growth, unemployment, monetary mass indicators, consumer confidence, etc.

We have not only tested the explanation power of the one-month lag  $Z_{i,t-1}$ , but also of the two-month lag  $Z_{i,t-2}$ , three-month lag  $Z_{i,t-3}$ , moving average  $\frac{1}{3}Z_{i,t-1} + \frac{1}{3}Z_{i,t-2} + \frac{1}{3}Z_{i,t-3}$ , absolute changes  $Z_{i,t-1} - Z_{i,t-2}$  and  $Z_{i,t-2} - Z_{i,t-3}$ , relative changes  $\ln Z_{i,t-1} - \ln Z_{i,t-2}$  and  $\ln Z_{i,t-2} - \ln Z_{i,t-3}$ , stochastic detrending  $Z_{i,t-1} - \frac{1}{12}(Z_{i,t-2} + Z_{i,t-3} + Z_{i,t-13})$ , as well as combinations of the above.

To avoid spurious regression problems, we first check whether the independent and dependent variables are stationary, and/or integrated of order one (or I(1)), which means that the series become stationary (I(0)) after differencing once, using standard unit root test (Dickey-Fuller [1981] and Phillips and Perron [1987]).

For each index, we select a shortlist of variables (around 30) according to two types of indicators. Indicators of type 1 are meant to represent the in-sample performance of the forecasting variable, measured in terms of t-stats and R-squared. Indicators of type 2 are meant to represent the out-of-sample forecasting power, measured in terms of hit ratio (accuracy of the direction) and mean-squared prediction error (accuracy of the magnitude). We then normalize (i.e., subtract the mean and divide by standard deviation) these indicators and aggregate (i.e., average) them into a single number that we call a “preference number”.<sup>ii</sup> For example, we find on the period June 1994 – May 1999 a preference number equal to 2.21 for the variable “term spread” when used as a predictive variable for the value premium. This is telling us that the “term

spread” variable performs unusually well, since it is more than two standard deviations above the mean performance of all variables in the database, on average over the 4 afore-mentioned dimensions (t-stats R-squared, hit ratio and mean-squared prediction error).

Within the shortlist of variables can typically be found two types of variables. Type 1 variables (typically about 10) score high both on economic analysis (i.e., they belong to the set of variables listed in section 3.1.1 to 3.1.3), and econometric performance (i.e., they have a high preference number). Type 2 variables (typically about 20) score high either on economic analysis or econometric performance.

### 3.2 Selecting the Models

The process for model selection is similar to the one used for variable selection. From the selected short-list of variables for a given index, we form multi-variate linear models based on at most 5 variables, where we systematically seek to avoid multi-collinearity.<sup>iii</sup> It is indeed well-known that in the presence of multi-collinearity, it becomes very difficult to determine the relative influences of the independent variables and the coefficient estimates could be sensitive to the block of data used (robustness problem).

For each index, we then select a model on the basis of a preference number that aggregates three criteria, as in the case of variable selection. The only difference is that we use the Schwartz Information Criterion (SIC), as opposed to the R-squared, as an indicator of in-sample quality-of-fit. The SIC allows one to penalize the different models for the number of degrees of freedom more harshly than the adjusted R-squared. It is computed as:

$$SIC = T^{k/T} \frac{\sum_{t=1}^T e_t^2}{T}$$

where  $T$  is the number of observations (48 monthly observations for a rolling window of 4 months),  $k$  the number of variables and  $e_t$  the error term at date  $t$ .

As a result of this process, we select, for each style differential, one model that predicts the return on that differential most closely.<sup>iv</sup>

Given the wide range of filters applied to select factors and models, there is of course a potential concern over the pitfalls of data snooping. We try to mitigate this problem by using the 3 stages approach (calibration, training and trading periods). This procedure, similar to the recursive modeling approach as proposed by Pesaran and Timmerman [1995], 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.<sup>v</sup>

### 3.3 Improving the Models

We apply standard econometric theory to test for the presence of heteroskedasticity and autocorrelation, and adjust the models accordingly when needed.<sup>vi</sup> In particular, we perform a regression analysis with ARMA (autoregressive moving average) modeling of the serial correlation in the disturbance (see Hamilton [1994] for more details on ARMA models).

We also perform several robustness checks. First, we check the robustness of the model through time by using a Chow [1960] test to test for stability of regression coefficients between two periods.<sup>vii</sup> When we find significant evidence of parameter instability, we use a [Kalman filter](#) analysis, which is a general form of a linear model with dynamic parameters, where priors on model parameters are recursively updated in reaction to new information (again see Hamilton [1994]). Also, we perform a Jarque-Bera [1980] test for [evidence of non-normality](#) in the residuals. Finally, we check the robustness of the linear specification by also estimating the probability of a positive sign differential through a [logit regression](#). We actually find that linear and logit models agree in most cases. When they do not, we decrease the level of confidence in the model, an input that we use in the portfolio process (see section 4).

### 3.4 Updating the Models

On the trading period extending from June 2000 to December 2002, we allow for a dynamic updating procedure of the models. A model is regarded as satisfactory as long as the coefficients remain significant (t-statistics for all coefficients remain higher than two in absolute value) and hit ratios are good. Decisions of updating the model are triggered by two (one) consecutive months with (strongly) decreasing t-stats and/or t-stat below a 5% confidence level, and/or three consecutive errors on predicted sign of style differential.<sup>viii</sup>

When one of these events happens, we take this an indication of a paradigm shift. We then re-do the whole analysis from sections 3.1 to 3.3, and select the new best performing models in these new market conditions.<sup>ix</sup>

## 4 Implications for Tactical Style Allocation

We use the econometric procedure presented in section 3 to generate predictions on expected return differentials for the four equity style indexes, S&P 500 Large Cap, S&P 500 Large Cap Growth, S&P 500 Large Cap Value, and S&P 600 Small Cap.

More specifically, we have implemented a beta-neutral strategy that generates abnormal return from timing between these 4 indexes, while maintaining a zero exposure with respect to the S&P500.<sup>x</sup> The goal is to deliver absolute return over the full business cycle ensured through systematic style timing and market neutrality.

We implement an optimal allocation in these four styles and the risk-free asset (0<sup>th</sup> style) so as to satisfy also a portfolio constraint (sum of weights should be 1), and a leverage constraint (sum of absolute values of weights should be equal to the target leverage  $l$ ).

$$\begin{cases} p_1 b_1 + p_2 b_2 + p_3 b_3 + p_4 b_4 = 0 & (\text{beta - neutrality constraint}) \\ p_0 + p_1 + p_2 + p_3 + p_4 = 1 & (\text{portfolio constraint}) \\ |p_0| + |p_1| + |p_2| + |p_3| + |p_4| = l & (\text{leverage constraint}) \end{cases}$$

Because we believe there is more robustness in forecasting signs than absolute values, our portfolio process focuses on pairs of returns differentials. We actually make two types of econometric bets. Bet 1 is a bet on the Growth versus Value differential, while Bet 2 is a bet on the Small Cap versus Large Cap differential.

2. Exhibit 6 summarizes the trading decisions that are consistent with econometric bets 1 and 2.

**Exhibit 6: Trading Decisions based on Econometric Bets 1 and 2**

	Bet 2 : $S C - L C > 0$	Bet 2 : $S C - L C < 0$
Bet 1 : Growth - Value $> 0$	Long SC / Short LC Short V / Long G	Short SC / Long LC Short V / Long G
Bet 1 : Growth - Value $< 0$	Long SC / Short LC Short G / Long V	Short SC / Long LC Short G / Long V

As explained below, we implement an optimal decision rule that makes the relative weighting of two bets a function of *relative* confidence in 2 models, and the level of leverage a function of *absolute* level of confidence in 2 models.

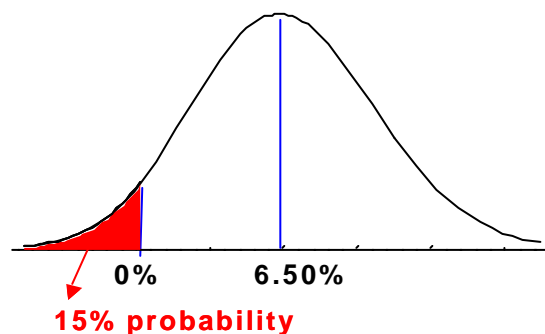
#### 4.1 Confidence in the Models

There are two aspects in the level of confidence: one is the confidence in the model; the other is the confidence in the model's prediction. These are clearly two different items: for example, a good trusted model can generate a prediction with low confidence if the predicted sign differential close to zero.

The computation of the confidence in the model's prediction is actually straightforward, under the assumption of normally distributed forecast errors. For each model, we assume that the actual value is normally distributed with a mean equal to forecast value and standard deviation given by model's standard error. We then use the Gaussian distribution function to compute the estimated probability that actual value has a sign different from forecast value. By construction, that number is less than 50%.

In Exhibit 7, we present an illustration of the method, where the forecast value is 6.50%, and where the uncertainty around that estimate is such that there is only 15% chances (assuming a Gaussian distribution) that the true value of the style differential will be negative when the model forecasts a value as high as 6.50%. In this case, the confidence level in the model prediction would be 85%.

**Exhibit 7: Confidence in a Model's Prediction on the Sign of the Style Differential.** This Exhibit shows the probability that the true value of the style differential can be negative when the predicted value is as high as 6.50%.



The confidence in the model, on the other hand, is harder to measure. We use a mix of economic analysis and econometric analysis (in particular, level and persistence of t-stats, agreement between linear model and competing models -Kalman, logit regression-, etc.) to generate a confidence level that can take on the following values: 0%, 25%, 50%, 75% and 100%.

We then build an indicator of total confidence, which is calculated as the confidence in model multiplied by the confidence in prediction.<sup>xi</sup> We call that number  $x\%$  for bet 1 and  $y\%$  for bet 2.

#### 4.2 Relative and Absolute Weighting Schemes

We use the relative confidence in the models to obtain a relative weighting of bet 1 and bet 2. To that end, we introduce  $w = x\% / (x\% + y\%)$ . The relative weighting rule is as follows:

- If  $0\% < w < 12.5\%$ , we take  $w = 0\%$  (100% weight in bet 2)
- If  $12.5\% < w < 37.5\%$ , we take  $w = 25\%$  (75% weight in bet 2)
- If  $37.5\% < w < 62.5\%$ , we take  $w = 50\%$  (50% weight in bet 2)
- If  $62.5\% < w < 87.5\%$ , we take  $w = 75\%$  (25% weight in bet 2)
- If  $87.5\% < w < 100\%$ , we take  $w = 100\%$  (0% weight in bet 2)

As a result, we obtain three different types of weighting schemes:

- Weighting scheme 1: 50% -50%
  - This corresponds to an equal-weighting of bets 1 and 2 since we have the same level of confidence in both models
  - Example (with a leverage  $l=2$ ): -25% LC, 25% SC, -25% V, 25% G
- Weighting scheme 2: 75% -25%
  - This corresponds to an over-weighting of the bet for which we have higher confidence in predictive model
  - Example (with a leverage  $l=2$ ): -37.5% LC, 37.5% SC, -12.5% V, 12.5% G
- Weighting scheme 3: 100% -0%
  - 100% of the portfolio invested in single bet with higher confidence
  - Example (with a leverage  $l=2$ ): -50% LC, 50% SC

We then use the absolute confidence in the models to optimally adjust the level of leverage. The target leverage is 2 but the actual leverage can be lower (or higher) than 2. In particular, 100% of the portfolio invested in cash if there is no satisfying model available for any of the two bets. More generally, we make the leverage a function of the absolute level of

confidence in both models by taking  $l=a(x\%+y\%)$ , where we choose  $a$  so as to reach level  $l=2$  on average

The resulting portfolio weights are shown in Exhibit 8.

**Exhibit 8: Portfolio Weights of the TSA Portfolio.** This Exhibit features the portfolio recommendations from June 2000 to December 2002 for a TSA portfolio based on the econometric models presented in section 3, and beta neutrality with a level of leverage equal to 2. As explained in Section 5, the Russell 2000 is used as a proxy for the return on small cap stocks because of the presence of high liquidity for the underlying investible product (Russell 2000 ETF - IWM).

Recommendations	S&P 500 Growth	S&P 500 Value	S&P 500	Russell 2000
June 2000	-23.43%	24.86%	21.72%	-26.57%
July 2000	-23.40%	24.62%	21.42%	-26.60%
August 2000	25.20%	-26.77%	-23.23%	28.75%
September 2000	-36.29%	38.35%	11.17%	-13.71%
October 2000	22.20%	-24.56%	21.31%	-25.44%
November 2000	-37.85%	41.85%	-12.15%	14.41%
December 2000	-25.21%	28.78%	-24.79%	29.20%
January 2001	-25.05%	30.02%	-24.95%	30.12%
February 2001	-24.91%	29.70%	-25.09%	29.53%
March 2001	-22.65%	27.87%	23.18%	-27.35%
April 2001	-24.60%	30.46%	-25.40%	29.66%
May 2001	-24.43%	30.53%	-25.57%	29.38%
June 2001	-24.47%	30.71%	-25.53%	29.65%
July 2001	-24.47%	30.63%	-25.53%	29.57%
August 2001	-24.50%	30.79%	-25.50%	29.80%
September 2001	-12.30%	15.15%	44.66%	-37.70%
October 2001	-12.28%	15.16%	-37.72%	44.62%
November 2001	-24.60%	30.80%	-25.40%	29.99%
December 2001	-24.35%	30.52%	-25.65%	29.22%
January 2002	-12.01%	15.08%	-37.99%	43.27%
February 2002	-50.00%	60.63%	0.00%	0.00%
March 2002	-36.08%	42.69%	12.33%	-13.92%
April 2002	0.00%	0.00%	0.00%	0.00%
May 2002	-50.00%	60.09%	0.00%	0.00%
June 2002	31.43%	-37.69%	10.73%	-12.31%
July 2002	37.25%	-44.31%	-12.75%	14.44%
August 2002	-11.38%	13.00%	34.52%	-38.62%
September 2002	-11.02%	12.90%	32.77%	-38.98%
October 2002	-23.34%	26.27%	22.96%	-26.66%
November 2002	-13.62%	14.70%	-36.38%	48.56%
December 2002	-35.91%	38.42%	10.69%	-14.09%

Note that no trading decision was implemented in April, as it proved impossible on that month to calibrate a valid model based on the econometric protocol presented in section 3. In such situation, 100% is invested in risk-free asset until a satisfactory model is found.

## 5 Implementation

In theory, a market neutral style timing strategy can be implemented by trading two instrument types: index futures (Chicago Mercantile Exchange) or Exchange Traded Funds, or ETFs (American Stock Exchange).

However, we have found that the index futures market is not liquid enough, especially for the large cap growth and value indexes. This is the reason why we have chosen to implement our portfolio recommendations by using ETFs. The ETF market also offers a larger range of investible products. Note also that new shares of EFTs can be created readily to meet demand if necessary, so the specialist and market makers are actually able to provide greater liquidity than the volume in the ETF would indicate.

It actually turns out that the correlation between ETFs and style indexes is higher than the correlation between futures and style indexes, signalling the presence of a large basis risk in style index markets. This holds whatever the equity style index used. Furthermore, the correlation between Russell 2000 and S&P 600 is sufficiently high for us to feel comfortable in calibrating our models indifferently using S&P 600 or Russell 2000 as a proxy for the return on small cap stocks. (For the sake of brevity, we do not report the results of that correlation analysis here but they can be obtained from the authors upon request).

Moreover, ETFs make the management process easier. When index futures mature every quarter, investors eventually have to roll futures positions forward and incur associated trading costs. This does not happen with ETFs. Furthermore, ETFs allow us to implement the TSA strategy by applying the exact allocations recommended by the model (with ETFs, there is no approximation, one share being priced at less than \$150 while one futures contract accounts for \$120,000 to \$300,000). Finally, ETFs can also be traded on margin and sold short.



In Exhibit 9, we present the performance of the model implemented using ETFs, and also the performance based on style index returns.

**Exhibit 9: Performance of the TSA strategy implemented with AMEX ETFs from June 2000 to December 2002.** These returns are net of (i) transaction cost: 1.8 cents/share (pair trades); (ii) stock loan fee: 40 bps; (iii) fund administration: about 100 bps of the net asset; (iv) debit interest: Libor + 60 bps (charged on a net basis).

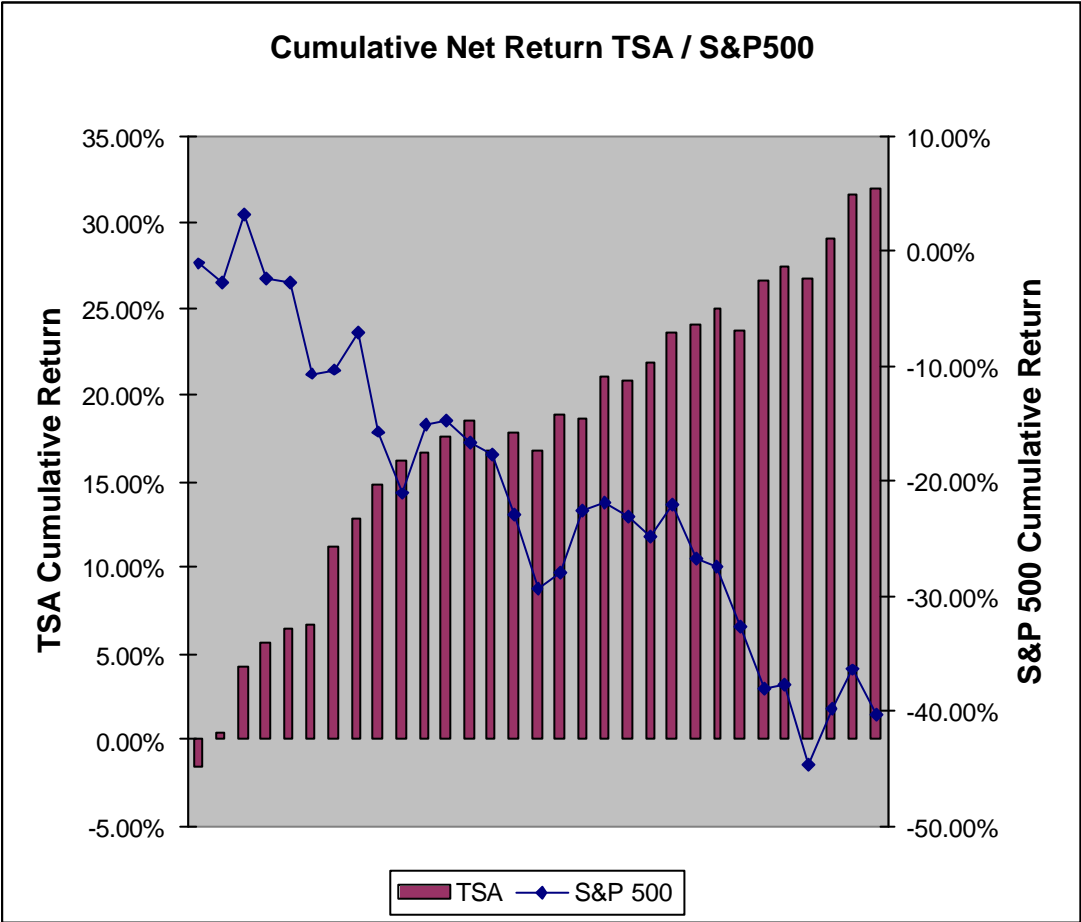
	January	February	March	April	May	June	July	August	September	October	November	December
2000						-1.56%	1.93%	3.97%	1.30%	0.72%	0.22%	4.32%
2001	1.32%	1.84%	1.20%	0.33%	0.74%	0.95%	-1.54%	0.90%	-0.90%	1.83%	-0.25%	1.99%
2002	-0.16%	0.90%	1.38%	0.41%	0.80%	-1.08%	2.40%	0.59%	-0.56%	1.87%	1.99%	0.30%

	TSA	S&P 500
Cumulative Return	32.00%	-40.20%
Annualized Return	10.90%	-18.03%
Annualized Std Deviation	4.71%	18.72%
Downside Deviation (3.0%)	2.26%	11.49%
Sortino (3.0%)	3.50	-1.83
Sharpe	1.84	-1.10
1st Centile	-1.55%	-10.47%
% Negative Returns	22.58%	61.29%
Worst Monthly Drawdown	-1.56%	-11.00%
Peak to Valley	-1.56%	-46.28%
Months in Max Drawdown	1	25
Months to recover	1	no recovery
Beta	0.075	

The performance of the tactical allocation models is spectacular. The average net performance is 10.90% with a 4.71% volatility, an attractive risk-return tradeoff that can be read in terms of a high 1.84 Sharpe ratio. It should be noted that downside risk, as measured by downside deviation or Sortino ratio, is extremely low.

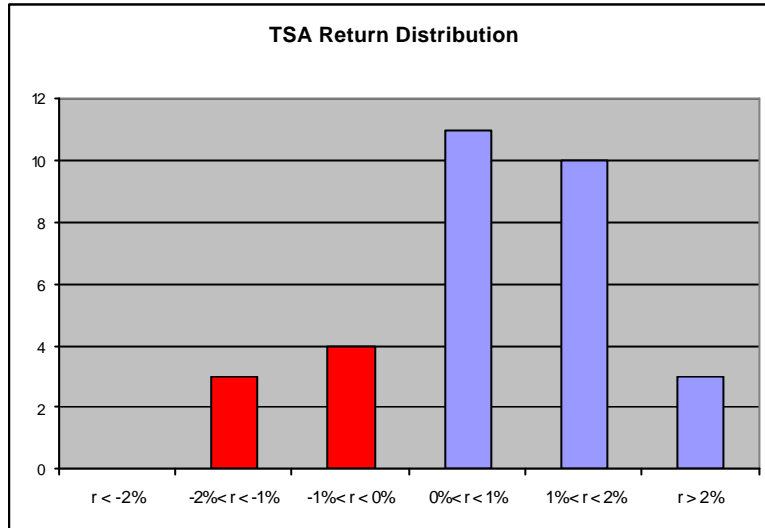
Exhibit 10 shows the cumulative net return on the strategy.

**Exhibit 10: Cumulative net returns of the TSA strategy and the S&P500.**



The distribution of returns shows that a positive performance is achieved in 77.42% of the cases (see Exhibit 11).

**Exhibit 11: Distribution of returns**



## 6 Conclusion

This paper documents the benefits of a new form of market neutral strategy based upon systematic timing decisions on US equity style indexes.

Using dynamic multi-factor models for the return on style indexes, where the factors are chosen to measure the many dimensions of financial risks (in particular, market, volatility, credit and liquidity risks), we first document strong evidence of very significant predictability in equity style returns. We also emphasize the benefits of a market neutral strategy that generates abnormal return from timing between Large Cap Growth, Large Cap Value, and Small Cap equity indexes, while maintaining a zero exposure with respect to the S&P500. These portfolio decisions can be implemented using Exchange Traded Funds on US equity style indexes.

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<sup>i</sup> Wells Fargo is considered to be the first firm to have introduced a tactical asset allocation product, in the 1970s.

<sup>ii</sup> We use an exponentially-weighted average of values taken at different points in time on the period January 1998 to December 1999 so as to put more weight to more recent observations. We use an exponential decay factor equal to 0.81, a value that was calibrated to achieve a relevant trade-off between stationary risk and sample risk.

<sup>iii</sup> In case of highly correlated variables, we either use a simple find-and-drop procedure, or an orthogonalization procedure, where we keep in the model both the first variable and the residuals of a regression of the second variable onto the first one.

<sup>iv</sup> We actually maintain a set of 3 models for each style differential. Models number 2 and 3 are tested as candidates in case a model switch is needed (see section 3.4).

<sup>v</sup> In a recent paper, White [2000] proposes a “reality check” method for testing the null hypothesis that the best model encountered during a specification search has no predictive superiority over a benchmark.

<sup>vi</sup> We perform these improvements only for the few selected models. In principle, it would be better to consider all possible models after improvement, and then select the ones we like best, as opposed to select the ones we like best, and then improve only these. This, however, would not be practically feasible.

<sup>vii</sup> One limitation of the Chow test is that the structural break points have to be specified before estimation. Other tests can be used to check for the presence of structural changes (see in particular Chow [1960], Brown, Durbin, and Evans [1975], Andrews [1993], Andrews and Ploberger [1994] or Chu, Stinchcombe and White [1996]).

<sup>viii</sup> It should be noted that there is a strong interconnection between these events: more often than not, decrease in t-stats precedes a decrease in hit ratio. This is fortunate as the dynamics of t-stats provide us with useful advanced signals of a model’s failure.

<sup>ix</sup> .We first check whether models 2 and 3 can be a valid alternative.

<sup>x</sup> Market neutral strategies represent almost one-third of the amount invested in equity hedge strategies in 2001 according to Hedge Fund Research.

<sup>xi</sup> Note that this is based upon an implicit assumption of independence between “model” confidence and “forecast” confidence.