Evidence of Predictability in Hedge Fund Returns and Multi-Style Multi-Class Tactical Style Allocation Decisions

Noël Amenc (*), Sina El Bied (**) and Lionel Martellini (***)

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Abstract: While there has been a significant amount of research on the predictability of traditional asset classes, very little is known about the predictability of returns emanating from alternative vehicles such as hedge funds. This paper attempts to fill this gap by documenting evidence of predictability in hedge fund returns. Using multi-factor models for the return on nine hedge fund indexes, where the factors are chosen to measure the many dimensions of financial risks (market, volatility, credit and liquidity risks), we find strong evidence of very significant predictability in hedge fund returns. We also find that the benefits in terms of tactical style allocation portfolios are potentially very large. Even more spectacular results are obtained both for an equity-oriented portfolio mixing traditional and alternative investment vehicles, and for a fixed-income oriented portfolio mixing traditional and alternative investment vehicles. These results do not seem to be significantly affected by the presence of reasonably high transaction costs.

(*) Noël Amenc is a professor in finance at EDHEC Graduate School of Business and head of research at Misys Asset Management Systems. (**) Sina El Bied is a graduate student at the Ecole Nationale de la Statistique et de l'Administration Economique. (***) Lionel Martellini is an assistant professor in finance at the Marshall School of Business at the University of Southern California. The author for correspondence is Lionel Martellini. He can be reached at University of Southern California, Marshall School of Business, Business and Economics, Hoffman Hall 710, Los Angeles, CA 90089-1427. Phone: (213) 740 5796. Fax: (213) 740 5796. Email address: martelli@usc.edu. Research for this paper received the support of the EDHEC/MISYS multi-style/multi-class program. We would like to express our gratitude to Sébastien Bonnet and an anonymous referee for very useful comments and suggestions. All errors are, of course, the authors' sole responsibility.

Abstract

While there has been a significant amount of research on the predictability of traditional asset classes, very little is known about the predictability of returns emanating from alternative vehicles such as hedge funds. This paper attempts to fill this gap by documenting evidence of predictability in hedge fund returns. Using multi-factor models for the return on nine hedge fund indexes, where the factors are chosen to measure the many dimensions of financial risks (market, volatility, credit and liquidity risks), we find strong evidence of very significant predictability in hedge fund returns. We also find that the benefits in terms of tactical style allocation portfolios are potentially very large. Even more spectacular results are obtained both for an equity-oriented portfolio mixing traditional and alternative investment vehicles, and for a fixed-income oriented portfolio mixing traditional and alternative investment vehicles. These results do not seem to be significantly affected by the presence of reasonably high transaction costs.

1 Introduction

There is now a consensus in empirical finance that expected asset returns, and also variances and covariances, 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 (1999), 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.[1] 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.

While there has been a significant amount of research on the predictability of traditional asset classes, and the implications in terms of tactical asset allocation strategies, very little is known about the predictability of returns emanating from alternative vehicles such as hedge funds. Also, and not surprisingly given the absence of academic evidence on the predictability of hedge fund returns, very little is known about the performance of tactical asset allocation strategies involving hedge funds. In particular, while the out-of-sample performance of optimal strategic asset allocation decisions based on alternative investment vehicles has recently been documented by Amenc and Martellini (2002), there is no such available evidence of the ability to generate superior risk-adjusted returns based on timing among various hedge fund styles.

This is perhaps surprising, given that interest in alternative investment strategies is undoubtedly gathering pace. The value of the hedge fund industry

[1] .Wells Fargo is considered to be the first firm to have introduced a tactical asset allocation product, in the 1970s.

worldwide is estimated at more than 500 billion dollars distributed among over 5,000 hedge funds[2] and the majority of institutional investors seem to be moving towards holding hedge funds in their portfolios.[3] As a result, it currently seems highly desirable to try to test whether there is as much evidence of predictability in hedge fund indexes as was found in traditional domestic and international equity and bond markets. This paper attempts to fill this gap by documenting evidence of predictability in hedge fund index returns. More specifically, we examine (lagged) multi-factor models for the return on nine hedge fund indexes. The factors are chosen to measure the many dimensions of financial risks: market risks (proxied by stock prices, interest rates, commodity prices), volatility risks (proxied by implicit volatilities from option prices), default risks (proxied by default spreads) and liquidity risks (proxied by trading volume). We show that a parsimonious set of models captures a very significant amount of predictability for most hedge fund styles. We also find that the benefits in terms of tactical style allocation portfolios are potentially very large. Even more spectacular results are obtained both for an equity-oriented portfolio mixing traditional and alternative investment vehicles, and for a fixed-income oriented portfolio mixing traditional and alternative investment vehicles. These results do not seem to be significantly affected by the presence of reasonably high transaction costs.

The rest of the paper is organized as follows. In section 2, we provide evidence of predictability in hedge fund returns. In section 3, we discuss the implications in terms of dynamic style allocation decisions. In section 4, we consider a multi-style multi-class setup, with an equity-oriented portfolio and a fixed-income oriented portfolio mixing traditional and alternative investment vehicles. In section 5, we discuss the impact of transaction costs on the performance of tactical style allocation models. We present our conclusion and suggestions for future research in section 6, while some information on hedge fund strategies are delegated to an Appendix.

2 Evidence of Predictability in Hedge Fund Returns

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

2.1 Data

To represent the alternative investment universe, we chose to use data from Credit Swiss First Boston/Tremont (CSFB/Tremont). The CSFB/Tremont Hedge Fund indexes have been used in a variety of studies on hedge fund performance (e.g., Lhabitant (2001)) and offer several advantages with respect to their competitors:

- They are transparent both in their calculation and composition, and constructed in a disciplined and objective manner. Starting from the TASS+

[2] Frank Russell-Goldman Sachs survey (1999).

[3] According to the Gollin, Harris, Ludgate (2001) survey, 64% of the European institutions included in the study invest in hedge funds. This is up from 56% in 2000.

database, which tracks over 2,600 US and offshore hedge funds, the indexes only retain hedge funds that have at least US $10 million under management and provide audited financial statements. Only about 300 funds pass the screening process.

- They are computed on a monthly basis and are currently the industry's only asset-weighted hedge fund indexes.[4] Funds are re-selected quarterly, as necessary, and in order to minimize the survivorship bias, they are not excluded until they liquidate or fail to meet the financial reporting requirements. This makes these indexes representative of the various hedge fund investment styles and useful for tracking and comparing hedge fund performance against other major asset classes.

The CSFB/Tremont sub-indexes were launched in 1999 with data going back to 1994. They cover nine strategies: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed-income arbitrage, global macro, long/short equity and managed futures (see the Appendix for descriptive information on these nine strategies). To ensure that the results we obtain are sufficiently robust, we have also tested a couple of other hedge fund index providers (HFR and Zurich) and find very similar evidence of predictability that we do not report here.[5]

Table 1 reports correlations, means and standard deviations for the nine Tremont hedge fund sub-indexes based on monthly data over the period 1994-2000.

Table 1: Descriptive statistics for the Tremont hedge fund indexes. This table reports correlations, means and standard deviations for the nine Tremont hedge fund indexes and the Tremont global index based on monthly data over the period 1994-2000.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Convertible Artibrage (1)	1.00								
Dedicated Short Bias (2)	-0.26	1.00							
Emerging Markets (3)	0.38	-0.56	1.00						
Equity Market Neutral (4)	0.35	-0.43	0.25	1.00					
Event Driven (5)	0.60	-0.65	0.70	0.43	1.00				
Fixed-Income Artitrage (6)	0.65	-0.08	0.33	0.06	0.44	1.00			
Global macro (7)	0.31	-0.14	0.42	0.23	0.40	0.47	1.00		
Long-Short Equity (8)	0.28	-0.77	0.60	0.37	0.67	0.23	0.45	1.00	
Managed Futures (9)	-0.35	0.23	-0.11	0.19	-0.23	-0.22	0.26	-0.05	1.00
Mean	0.85	0.08	0.54	0.94	0.96	0.54	1.14	1.31	0.49
Standard Deviation	1.46	5.52	5.92	0.99	1.91	1.26	4.14	3.65	3.31

[4] It should be noted that, as a result of capitalization weighting and the bull market, the CSFB/Tremont indexes tend to be overweighted towards equity and equity exposure.
[5] They are available from the authors upon request.

We confirm that the hedge fund universe is very heterogeneous: some hedge fund strategies have relatively high volatility (e.g., dedicated short bias, emerging markets, global macro, long/short equity and managed futures); they act as return enhancers and can be used as a substitute for some fraction of the equity holdings in an investor's portfolio. On the other hand, some other hedge fund strategies have lower volatility (e.g., convertible arbitrage, equity market neutral, fixed-income arbitrage and event driven); they can be regarded as a substitute for some fraction of the fixed-income holdings in an investor's portfolio.

2.2 Methodology

Given that we are searching for evidence of predictability in hedge fund 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. With a focus on attempting to avoid the pitfalls of data snooping, we use the following methodology.

- Step 1: 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 a short list of 10 meaningful variables. These variables are selected on the basis on previous evidence of their ability to predict asset returns, or their natural influence on asset returns.
    - Yield on T-Bill 3-month 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.
    - Dividend yield (proxied by the dividend yield on S\&P stocks). It has been shown to be 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.
    - Default spread (proxied by changes in the monthly observations of the difference between the yield on long term Baa bonds and the yield on long term AAA bonds). This captures the effect of default premium. Default premiums track long-term business cycle conditions: higher during recessions, lower during expansions (Fama and French (1998)).
    - Term spread (proxied by monthly observations of the difference between the yield on 3-month Treasuries and 10-year Treasuries).
    - Implicit volatility (proxied by changes in the average of intra-month values of the VIX).[6]
    - Market volume (proxied by changes in the monthly market volume on then NYSE). The last three variables have been identified by Amenc, Curtis and

[6] VIX, introduced by CBOE in 1993, measures the volatility of the U.S. equity market. It provides investors with up-to-the-minute market estimates of expected volatility by using real-time OEX index option bid/ask quotes. This index is calculated by taking a weighted average of the implied volatilities of eight OEX calls and puts. The chosen options have an average time to maturity of 30 days.

Martellini (2001) and Schneeweis and Spurgin (1999) as important factors explaining hedge fund returns.
  - Oil price (closely related to short-term business cycles).[7]
  - US equity factor (proxied by the return on the S&P 500 index).
  - World equity factor (proxied by the return on the MSCI World Index ex US).
  - Currency factor (proxied by changes in the level of a volume-weighted exchange index of currencies versus US dollar).

- Step 2: we test for the sub-set of variables that allows for a good trade-off between quality of fit and robustness. Our methodology is as follows. We select the sub-set of variables that allows for at least 5% in-sample explanation power (quality of fit). We have tested not only for the explanation power of the raw variables Z_i, for *i=1,...,10*, but also for changes in the variables $Z_{i,t-1} - Z_{i,t-2}$, one-month lag $Z_{i,t-1}$, two-month lag $Z_{i,t-2}$, three-month lag $Z_{i,t-3}$, moving average $\frac{1}{3}Z_{i,t-1} + \frac{1}{3}Z_{i,t-2} + \frac{1}{3}Z_{i,t-3}$, as well as combinations of the above. The explanation power at this stage is simply measured in terms of in-sample R-squared of regressions of the nine CSFB/Tremont hedge fund indexes on a sub-set of permutations (1-month lag, 2-month lag, 3-month lag, changes in the variable, moving average) on one of the 10 aforementioned variables. We also test for (in-sample) robustness by dividing the calibration period into two sub-samples of equal duration, and using a Chow test to test for stability of regression coefficients between two periods (see table 5 below).[8]

As a result of this two-step process, we select, for each index, a very limited number of factors (2 or 3) that predict the return on that index most closely. It actually turns out that the same sub-set of a small number of variables (6 in this instance; see table 2) is used for all indexes.

Table 2. Correlation matrix for the predictive factors. This table reports pair wise correlations for the 6 factors used as predictors of hedge fund returns. These correlations were computed using monthly data for the period January 1994 to December 2000.

	$MA(S\&P)_{t-1}$	Oil_{t-1}	$\Delta 3m_{t-1}$	ΔVIX_{t-1}	Vol_{t-1}	$MA(MSCI)_{t-1}$
$MA(S\&P)_{t-1}$	1.00					
Oil_{t-1}	-0.2259	1.00				
$D3m_{t-1}$	-0.4545	0.1315	1.00			
$DVIX_{t-1}$	-0.2677	0.0107	-0.1797	1.00		
Vol_{t-1}	-0.0980	0.3863	-0.06267	-0.0012	1.00	
$MA(MSCI)_{t-1}$	-0.0988	0.5117	0.0652	-0.0184	0.9478	1.00

[7] Data on crude oil price can be found at www.eia.doe.gov/emeu/cabs/chron.html.
[8] A Chow test consists of dividing the sample into two groups, estimating the model separately for each of the two sample groups and computing the error sum of squared residuals for each sample group. Then assume that the regression coefficients are the same over the entire period by estimating the model again but with the pooled sample. A Chow statistic is then obtained based on the restricted error sum of squares to test the null hypothesis that there is no structural change using the F-distribution tables (Chow (1960)).

From table 2, we find that the only variables that may involve a multicollinearity problem are the market volume and the moving average of the return on the MSCI World Index ex US. Therefore, we shall never use both of them simultaneously to predict hedge fund index return. For all other variables, pair wise correlations are considered low enough.

In addition to these variables, we also add the lagged return on each index as a potential regressor. If there is some evidence of positive or negative serial-correlation in the time-series of the index returns, then the lagged value of the index may indeed help in predicting current values. There are various ways of testing for the presence of serial correlation in a given time-series. In particular, serial correlation can be measured in terms of the *Hurst exponent*. The Hurst exponent is a convenient summary of statistics of persistence in time-series data that has been applied in broad areas of economics, finance and natural sciences. Here, we use the R/S method for estimating the Hurst Index of the time-series of returns on hedge fund indexes (see Peters (1991)).

Formally, first define R_t as the normalized rate of return (subtract the mean) and compute *H* as

$$H = \frac{\ln\left(\frac{Y_2 - Y_1}{s}\right)}{\ln T}$$

where $Y_1 = \max(Y_t, 0 \le t \le T)$, $Y_2 = \min(Y_t, 0 \le t \le T)$ and $Y_t = \sum_{s=0}^{t} R_s$.

If the Hurst exponent is less than 0.5, the process displays “anti-persistence”. This means that positive excess return is more likely to be reversed and therefore the next period's performance is likely to be below average. If the Hurst exponent is greater than 0.5, the process displays “persistence”. This means that positive excess return is more likely to be continued and therefore the next period's performance is likely to remain above average. Finally, if the Hurst Index is equal to 0.5, the returns do not display any memory and thus positive excess return is equally likely to be followed by above or below average performance.

Table 3: Persistence in Hedge Fund Returns. This table displays the Hurst Exponent for each of the nine CSFB/Tremont hedge fund indexes as a measure of serial correlation in hedge fund returns on the period 1994-2000. A Hurst exponent larger than .5 is evidence of persistence while a Hurst exponent lower than .5 is evidence of anti-persistence.

	Hurst Exponent
Convertible Arbitrage (HF1)	0.609
Dedicated Short Bias (HF2)	0.522
Emerging Markets (HF3)	0.539
Equity Market Neutral	0.621
Event Driven (HF5)	0.591
Fixed-Income Arbitrage (HF6)	0.618
Global Macro (HF7)	0.600
Long-Short Equity (HF8)	0.578
Managed Futures (HF9)	0.465

The results of our estimations are presented in table 3. As we can see, for all investment styles but one (managed futures), hedge fund indexes have Hurst indexes that were well above 0.5. We therefore expect past hedge fund returns to have potential explanatory power in predicting future hedge fund returns.[9]

We have run the following generalized least squares regressions

$$R_{i,t} = a_i + b_{i1}d_{i1}R_{i,t-1} + b_{i2}d_{i2}MA(S\,\&\,P)_{t-1} + b_{i3}d_{i3}Oil_{t-1} + b_{i4}d_{i4}\Delta 3m_{t-1}$$
$$+ b_{i5}d_{i5}\Delta VIX_{t-1} + b_{i6}d_{i6}Vol_{t-1} + b_{i7}d_{i7}MA(MSCI)_{t-1} + e_{i,t}$$

where the coefficients d_{ik} , *i=1,...,9* and *k=1,...,7* take the value *0* when the variable *k* is not used in the model for index *i*, or *1* otherwise. The following table (table 4) provides the information on which exact model is used for each hedge fund index. The numbers in the table are the sample values of the betas of each hedge fund index with respect to all possible factors. In parenthesis, we also show the probability that the T-statistics exceeds the observed sample value under the null hypothesis of a zero population value.[10] When a variable is not used in the model, we display “NA" in the table.

Table 4: Predictive Model for the Tremont Hedge Fund Indexes. This table provides the information on which exact model is used for each hedge fund index, with beta parameter values and associated probabilities (in parenthesis). When a variable is not used in the model, we display the mention "NA".

	$Ri_{,t-1}$	$MA(S\&P)_{t-1}$	Oil_{t-1}	$\Delta 3m_{t-1}$	ΔVIX_{t-1}	Vol_{t-1}	$MA(MSCI)_{t-1}$
HF1	0.1768 (0.24)	0.2917 (0.006)	0.0015 (0.008)	-0.0174 (0.04)	NA	NA	NA
HF2	NA	NA	NA	NA	NA	NA	NA
HF3	0.1893 (0.14)	NA	0.0064 (0.002)	NA	NA	NA	-0.0001 (0.003)
HF4	NA	0.1980 (0.38)	0.0003 (2.10^{-5})	-0.0037 (0.012)	NA	NA	NA
HF5	0.3193 (0.015)	NA	0.0004 (0.017)	NA	NA	NA	NA
HF6	NA	0.2566 (6.10^{-4})	0.0008 (3.10^{-5})	NA	-0.0008 (0.004)	-3.10^{-8} (3.10^{-5})	NA
HF7	-02651 (0.06)	0.9590 (0.002)	0.0014 (0.044)	NA	NA	-6.10^{-8} (0.05)	NA
HF8	NA	NA	NA	NA	NA	NA	NA
HF9	NA	NA	NA	NA	NA	NA	NA

[9] It is possible that this type of predictability is induced by infrequent trading.
[10] For example, a variable is significant in the model at the 10% level when the number in parenthesis is lower than .1.

A number of remarks can be spelled out. First, there are three out of nine indexes for which it has not appeared feasible to have a robust predictor model using the shortlist of variables defined above. In other words, we have not been able to identify a single set of variables that yields sufficient explanation power (R-squared greater than 5%), while allowing for significant robustness (see below). These indexes are dedicated short bias, long-short equity and managed futures. On the other hand, for the other six remaining indexes, a significant explanation power can be obtained. This can be seen from the fact that most coefficients are significant at the 95% level.

As discussed in the previous section, we have performed Chow tests of stability of the model by dividing the sample into two groups, one from early 1994 to mid-1997, the other from mid-1997 to the end of 2000. Table 5 provides the value of the Chow statistic and the associated value of the Fisher statistics.

Table 5: Chow tests of stability of the model. This table provides the value of the Chow statistic and the associated F value. The null hypothesis that there is no structural change over the period 1994-2000 is rejected when the Chow statistics is greater than the associated F-value.

	Chow Statistic	F Value
Convertible Arbitrage (HF1)	0.890701499	2.37
Dedicated Short Bias (HF2)	NA	NA
Emerging Markets (HF3)	1.08538381	2.76
Equity Market Neutral (HF4)	0.259448053	2.76
Event Driven (HF5)	0.915964781	3.15
Fixed-Income Arbitrage (HF6)	2.580389357	2.52
Global Macro (HF7)	3.372136115	2.76
Long-Short Equity (HF8)	NA	NA
Managed Futures (HF9)	NA	NA

We find that the null hypothesis that there is no structural change is clearly accepted for the models applied to convertible arbitrage, emerging markets, equity market neutral and event driven. In the case of fixed-income arbitrage and global macro indexes, the Chow statistics is slightly lower than the associated F-value, suggesting the possibility of a structural change in the model over the period. From table 6, we find however a sufficiently good stability of the model, as can be seen from hit ratios greater than 50%, and therefore we choose to include these models in our analysis. On the other hand, we have not been able to identify a single set of variables that yields sufficient explanation power (R-squared greater than 5%), while allowing for significant robustness (Chow statistic lower than twice the F-value) for dedicated short bias, long-short equity and managed futures. As a result, we have not calibrated any forecast model for these indexes, and we simply use the unconditional expected return as a forecast of the expected return in the style timing portfolio (section 4).

We also perform out-of-sample testing of the model. The methodology is as follows. We calibrate the models displayed above using a rolling window of the previous 60 months, that is, we dynamically re-estimate the coefficients each month using the past 60 months of observation. The calibration period is January 1994 to December 1998, and the back-testing period is January 1999 to December 2000. Table 6 provides information on the performance of the predictive models for the Tremont hedge fund indexes. The first column contains the in-sample R-squared of the regression. The second column contains the hit ratios of the model, that is the percentage of time the predicted direction is valid, i.e., the index goes up (resp. down) when the model predicts it will go up (resp. down).

Table 6: In-Sample and Out-of-Sample Performance of the Predictive Models for the Tremont Hedge Fund Indexes. The first column contains the in-sample R-squared of the regression. The second column contains hit ratios for the models, that is the percentage of time predicted direction is valid, i.e., the index goes up (resp. down) when the model predicts it will go up (resp. down).

	R^2	*HR(1)*
Convertible Arbitrage	51.8%	87.5%
Dedicated Short Bias	NA	NA
Emerging Markets	25.1%	50.0%
Equity Market Neutral	14.8%	95.8%
Event Driven	15.7%	79.2%
Fixed-Income Arbitrage	53.4%	62.5%
Global Macro	22.0%	54.2%
Long-Short Equity	NA	NA
Managed Futures	NA	NA

As we can see from table 6, hit ratios are very high, all above 50% and one at 95.8%. We have found clear statistical evidence of predictability in hedge fund returns. We now attempt to test whether there is also economic significance in the predictability of hedge fund return by investigating the implications in terms of a tactical asset allocation model.

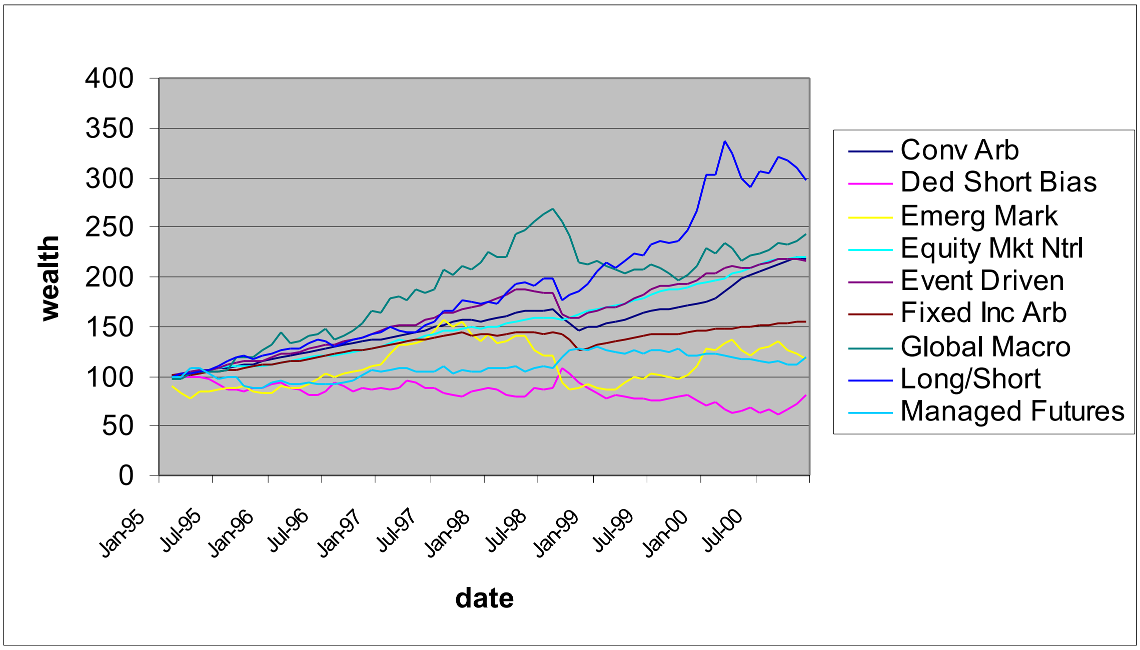
3 Implications for Tactical Style Allocation

Tactical asset allocation is a form of conditional asset allocation, which consists of re-balancing portfolios around long run asset weights depending on conditional information. We first provide some evidence of the economic significance of the performance of hedge fund style timing models by comparing the performance of a market timer with perfect forecast ability in the alternative investment universe versus the traditional universe. We then present the performance of a realistic style timing model.

3.1 Performance of a Style Timer with Perfect Forecast Ability

As can be seen from figure 1 below, different hedge fund styles perform somewhat differently.

Figure 1: Performance of Hedge Fund Investment Styles. This figure displays the evolution of $100 invested from January 1995 to December 2000 in each of the nine CSFB/Tremont hedge fund indexes.



In an attempt to assess the performance of a style timer with perfect forecast ability in the hedge fund universe, we compute the annual return on each of the nine CSFB/Tremont hedge fund indexes from 1995-2000, as well as the annual average return, volatility and Sharpe ratio (with a 4% annual risk-free rate) over the period, and compare it with the performance of a style timer with perfect forecast ability who invests 100% of a portfolio at the beginning of the year in the best performing style for the year. As in the previous section, HF 1 stands for convertible arbitrage, HF 2 for dedicated short bias, HF 3 for emerging markets, HF 4 for equity market neutral, HF 5 for event driven, HF 6 for fixed-income arbitrage, HF 7 for global macro, HF 8 for long/short equity and HF 9 for managed futures. TGI stands for Tremont Global Index, a value-weighted portfolio of the nine sub-indexes. The results appear in table 7.

From table 7, the benefits of style timing are very apparent. A perfect style timer has an average return of 29.44% with 10.82% volatility, and no losses during the period, for an annual Sharpe ratio of 2.35. This compares very favorably with the performance of the Tremont Global Index (last column in table 7), which shows a 14.34% average return and 9.56% volatility for a 1.08 Sharpe ratio (assuming a 4% risk-free rate). To get a better understanding of the economic significance of the performance of style timing models, we now perform the same exercise for the traditional equity universe. More specifically, we compute the annual return on S&P 500 Growth, S&P 500 Value, S&P 400 Mid Cap and S&P 600 Small Cap 1995-2000, and also the annual average return, volatility and Sharpe ratio (with a 4% annual risk-free rate) over the period, as well as similar performance measures for a style timer with perfect forecast ability who invests the totality of a portfolio at the beginning of the year in the best performing style for the year. The results appear in table 8.

Table 7: Performance of a Style Timer with Perfect Forecast Ability in the Hedge Fund Universe. This table features the annual return on each of the nine CSFB/Tremont hedge fund indexes from 1995-2000, and also the annual average return, volatility and Sharpe ratio (with a 4 percent annual risk-free rate) over the period, as well as similar performance measures for a style timer with perfect forecast ability who invests the totality of a portfolio at the beginning of the year in the best performing style for the year. HF 1 stands for convertible arbitrage, HF 2 for dedicated short bias, HF 3 for emerging markets, HF 4 for equity market neutral, HF 5 for event driven, HF 6 for fixed-income arbitrage, HF 7 for global macro, HF 8 for long/short equity and HF 9 for managed futures. TGI stands for Tremont Global Index, a value-weighted portfolio of the nine sub-indexes. The return on the best performing style for each year appears boldfaced.

	HF 1	HF 2	HF 3	HF 4	HF 5	HF 6	HF 7	HF 8	HF 9	Perfect Timer	TGI
1995	17.29	-8.56	-7.69	10.52	17.75	12.20	**33.99**	23.94	-7.03	33.99	24.13
1996	15.48	-6.07	**24.69**	14.20	18.92	14.30	13.69	14.86	8.90	24.69	14.26
1997	13.31	2.32	15.65	11.30	17.27	7.75	**26.71**	17.37	0.12	26.71	19.39
1998	-5.21	-5.00	-33.75	12.29	-6.49	-7.38	-1.50	18.27	**19.61**	19.61	0.86
1999	13.46	-7.59	**49.17**	14.54	20.01	10.02	8.95	40.26	-1.60	49.17	22.44
2000	**22.47**	11.58	-4.06	13.37	6.71	5.73	14.44	1.55	4.24	22.47	4.95
Average	12.80	-2.22	7.34	12.70	12.36	7.10	16.05	19.37	4.04	29.44	14.34
St. Dev.	9.44	7.78	28.86	1.61	10.41	7.73	12.66	12.65	9.34	10.82	9.56
Sharpe Ratio	0.93	-0.80	0.12	5.40	0.80	0.40	0.95	1.22	0.00	2.35	1.08

Table 8: Performance of a Style Timer with Perfect Forecast Ability in the Equity Universe. This table features the annual return on S&P 500 Growth, S&P 500 Value, S&P 400 Mid Cap and S&P 600 Small Cap 1995-2000, and also the annual average return, volatility and Sharpe ratio (with a 4 percent annual risk-free rate) over the period, as well as similar performance measures for a style timer with perfect forecast ability who invests the totality of a portfolio at the beginning of the year in the best performing style for the year. The return on the best performing style for each year appears boldfaced.

	S&P Growth	S&P Value	S&P Mid Cap	S&P Small Cap	Perfect Timer
1995	**34.79**	33.38	29.59	31.82	34.79
1996	19.41	18.46	17.50	**21.06**	21.06
1997	26.61	24.25	**27.47**	23.53	27.47
1998	**37.54**	16.11	21.43	0.66	37.54
1999	**20.87**	10.49	19.37	13.83	20.87
2000	-16.52	9.57	**20.91**	15.38	20.91
Average	20.45	18.71	22.71	17.71	27.10
St. Dev.	19.51	8.99	4.76	10.54	7.51
Sharpe Ratio	0.84	1.64	3.93	1.30	3.08

Comparing the results from tables 7 and 8, we find that style timing in the alternative investment universe rivals style timing in the traditional universe as it generates comparable levels of average return (29.44% versus 27.10%) and volatility (10.82% versus 7.5%). On the other hand, perfect timing ability applied to standard tactical asset allocation between stocks and bonds only returns 20.88% over the period, as can be seen from table 9.

Table 9: Performance of a Market Timer with Perfect Forecast Ability. This table features the annual return on the S&P 500 and the Lehman Brother Global Bond Index (LBGBI) from 1995-2000, and also the annual average return, volatility and Sharpe ratio (with a 4 percent annual risk-free rate) over the period, as well as similar performance measures for a style timer with perfect forecast ability who invests the totality of a portfolio at the beginning of the year in the best performing style for the year. The return on the best performing style for each year appears boldfaced.

	S&P 500	LBGBI	Perfect Timer
1995	**34.10**	10.07	34.10
1996	**18.91**	-2.29	18.91
1997	**25.52**	2.07	25.52
1998	**27.17**	1.29	27.17
1999	**16.19**	-6.91	16.19
2000	-4.30	**3.38**	3.38
Average	19.60	1.27	20.88
St. Dev.	13.31	5.70	10.66
Sharpe Ratio	1.17	-0.48	1.58

We therefore conclude that tactical style allocation in the hedge fund universe potentially generates as much reward as tactical style allocation in the traditional equity universe and standard stocks/bonds tactical asset allocation.

Despite their illustrative power, these experiments obviously do not provide a fair understanding of what the performance of a realistic style timing model could be. On the one hand, we assume perfect forecast ability and no transaction costs, which, of course, is not achievable in practice. On the other hand, we only consider annual data, while further benefits of timing can be achieved by working with monthly returns. In an attempt to test the economic significance of predictability in hedge fund index returns through their use for tactical style allocation decisions, we now turn to a realistic style timing model in the alternative investment area which is based on monthly returns and forecast ability generated by the econometric models presented in section 2.

3.2 Performance of a Realistic Style Timing Model

Given that optimal dynamic portfolio decision rules in the presence of predictable returns can be solved explicitly only under somewhat restrictive assumptions (see in particular Brennan, Schwartz and Lagnado (1997), Campbell and Viceira (1998) or Barberis (2000)), we choose instead to test the economic significance of return predictability in terms of over-performance of style allocation models in a static mean-variance framework.[11] We base our tactical style allocation strategies on the conditional expected returns obtained from the predictive models presented in the previous section. In the case of the 3 indexes for which no forecasting model could be calibrated, we simply use the unconditional expected return as a forecast of the expected return. This amounts to regressing the return on these indexes on a constant variable (which leads to a 0 R-squared). In principle, it would also be desirable to allow for the possibility that the state variables predict changes in risk. By limiting ourselves in ruling out the use of lagged variables to forecast covariances, portfolio choice can only be affected by improved conditional forecasts of changes in expected returns. The loss of generality involved, might, however, be limited. Campbell (1987), Harvey (1989, 1991) and Glosten, Jagannathan and Runkle (1993) have tested the ability of the state variables to predict risk, and have found only limited effects that are dominated by the impact of forecasts on expected returns. Besides, we expect covariance to be more stable in the case of hedge funds compared to unmanaged assets because managed funds typically have a target level of volatility (enforced via VaR or other limits).

In the same vein, correlations also tend to be more stable because dynamic hedge fund strategies adapt to changes in the market environment. For example, fixed income arbitrage managers will reduce leverage when equity index volatility goes up, since equity index volatility is usually associated with spread widening in credit markets.[12]

We consider the following two optimization programs

$$\text{P1}: \ \underset{w_1,\ldots,w_9}{\text{Max}} \ IR = \frac{E\left(R_p - R_{Bench} \mid F_{t-1}\right)}{\text{Var}\left(R_p - R_{Bench}\right)}$$

$$\text{P2}: \ \underset{w_1,\ldots,w_9}{\text{Max}} \ E\left(R_p - R_{Bench} \mid F_{t-1}\right) \text{s.t} \sqrt{\text{Var}\left(R_p - R_{Bench}\right)} \leq \overline{TE}$$

where $R_p = \sum_{i=1}^{9} w_i R_i$, *i=1,...,9*, is a portfolio invested in each of the nine hedge fund indexes, R_{Bench} is the return on a benchmark portfolio defined as an equally-weighted portfolio invested in the 9 Tremont indexes[13] and F_{t-1} is the conditioning information, i.e., an information set containing the past values of the predictive factors. Given the multi-dimensional regression $R_{i,t} = Z'_{i,t-1} b_i + e_{i,t}$ fully described in section 2.3, the conditional expected return prediction is given by $Z'_{i,t-1} b_i$, and is used for implementing dynamic style allocation.

The first problem P1 consists of a simple maximization of the information ratio *IR*, defined as the ratio of the conditional expected excess return of the portfolio over the benchmark divided by the tracking error (i.e., the volatility of the difference between the portfolio and the benchmark) (see Grinold and Kahn (2000) for more on

[11] A promising avenue for future research would be to use the non-parametric approach recently introduced by Brandt (1999) and Ait-Sahalia and Brandt (2001)).
[12] We are indebted to George Martin for this comment.
[13] We have also tested using the value-weighted Tremont Global Index as a benchmark and obtained similar results.

the information ratio). It is well known that maximizing the information ratio is often likely to generate strategies with very low tracking error (simply because the tracking error appears in the denominator of the information ratio, so that minimizing that quantity allows the information ratio to be increased significantly). We have therefore also considered another problem (P2), which consists of the maximization of the conditional excess return subject to a tracking error constraint. This allows us to test different tracking error targets. Note also that we impose the usual portfolio ($\sum_{i=1}^{9} w_i = 1$ and positivity *(* $w_i \geq 0$ *, for i=1,...,9*) constraints.

The testing of a tactical style allocation model is of predictive nature in essence: we perform out-of-sample testing of the performance of the model by using estimates for the hedge fund index returns obtained from the predictive models, the coefficients of which are dynamically re-estimated on a monthly basis using a 57-month rolling window. The calibration period is again January 1994 to December 1998, while the back-testing period is January 1999 to December 2000.

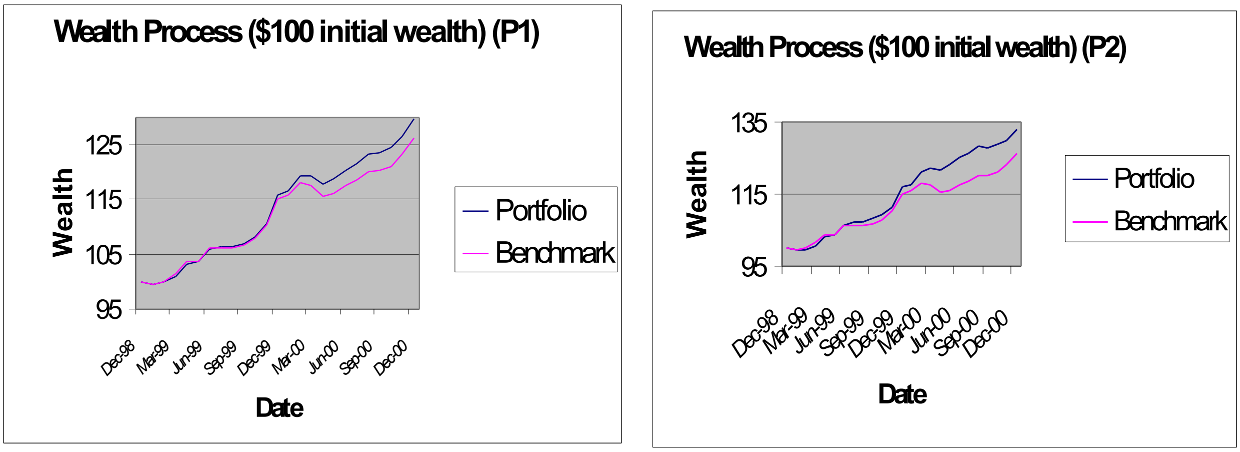
Table 10 provides a summary of the performance of both tactical style allocation models (P1 and P2). A hit ratio that is different from the one we computed before appears in line 5. This one is the percentage of time that the return on the tactical style allocation portfolio is greater than the return on the benchmark (we denote it as HR(2) to distinguish it from HR(1) which is the percentage of time that the predicted direction is valid). Mean and standard deviation are expressed in percentage per year, and obtained from monthly data through a multiplicative factor of 12 and square-root of twelve, respectively.

Table 10: Performance of the TSA Model for the Tremont Hedge Fund Indexes. This table provides a summary of the performance of both tactical style allocation models (P1 and P2). The Hit Ratio HR(2) is the percentage of time that the return on the tactical style allocation portfolio is greater than the return on the benchmark. Mean and standard deviation are expressed in percentage per year, and obtained from monthly data through a multiplicative factor of 12 and square-root of twelve, respectively.

	$P1$	$P2\left(\overline{TE} = 2\%\right)$
Annualized Return on Benchmark	11.78%	11.78%
Annualized Volatility on Benchmark	4.32%	4.32%
Annualized Return on TSA Portfolio	13.2%	14.48%
Annualized Volatility on TSA Portfolio	4.24%	4.12%
Hit Ratio *HR (2)*	83.3%	66.7%
Annualized Excess Return	1.4%	2.7%
Annualized Tracking Error	0.58%	1.8%
Information Ratio	2.44	1.5

In both cases, the ex-post information ratio obtained is very high (see Grinold and Kahn (2000), chapter 5, for a heuristic empirical distribution of information ratios among active portfolio managers). The two graphs below (see figure 2) display the evolution of $100 invested in the benchmark and the TSA portfolio (P1 and P2, respectively), from January 1998 to December 2000.

Figure 2: Performance of TSA Portfolios. The picture on the left-hand side displays the evolution of $100 invested in the benchmark and the TSA portfolio (problem P1) from January 1998 to December 2000. The picture on the right-hand side displays the evolution of $100 invested in the benchmark and the TSA portfolio (problem P2) from January 1998 to December 2000.



4 Multi-Style Multi-Class Tactical Style Allocation

The benefits of alternative investments can be better understood when hedge funds are combined with traditional assets in a diversified portfolio. To test whether superior tactical style allocation can be achieved by considering a global investment universe mixing alternative and traditional style indexes, we perform the following experiments.[14]

- Style timing in an equity-oriented universe: we consider a style timing portfolio invested in S&P 500 growth, S&P 500 value and S&P 400 mid-cap for the traditional part, and in Tremont dedicated short bias, Tremont market neutral and Tremont long/short.
- Style timing in a fixed-income oriented universe: we consider a style timing portfolio invested in the Lehman Brother Treasury bond index, Lehman Brother investment grade corporate bond index, and Lehman Brother high yield corporate bond index for the traditional part, and in Tremont convertible arbitrage and Tremont fixed-income arbitrage for the alternative part.

4.1 Equity-Oriented Universe

[14] Because hedge funds may be regarded as new investment styles as much as new investment classes, we prefer to use the term "tactical style allocation" rather than "tactical asset allocation".

We first consider style timing in an equity-oriented universe, i.e., we try to implement a style timing portfolio invested in S&P 500 growth, S&P 500 value, and S&P 400 mid-cap for the traditional part, and in Tremont market neutral and Tremont long/short. We consider two benchmarks, one being the value-weighted portfolio (S&P 500), the other being an arbitrary strategic asset allocation (SAA) benchmark: 25% S&P growth, 25% S&P value, 20% S&P 400 mid-cap, 15% equity market neutral and 15% event driven.

We use the same methodology as above to come up with predictive models for traditional investment styles. The results are summarized in table 11.

Table 11: Performance of the Predictive Models for Traditional Equity Indexes. The first column contains the in-sample R-squared of the regression. The second column contains the hit ratios of the model, that is the percentage of time the predicted direction is valid, i.e., the index goes up (resp. down) when the model predicts it will go up (resp. down).

	R^2	*HR* (1)
S&P 500 Growth	17.7%	58.3%
S&P 500 Value	9.7%	54.2%
S&P 400 Mid Cap	7.8%	58.3%

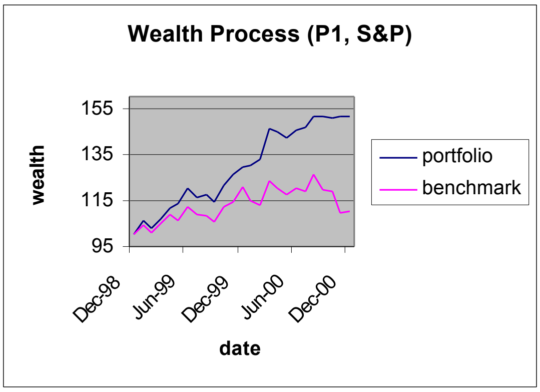
We then compute optimal portfolios using both maximization of the information ratio (program P1) and maximization of the excess expected return under tracking error constraint (program P2), and we test both the S&P benchmark and the strategic asset allocation benchmark. Table 12 summarizes the results.

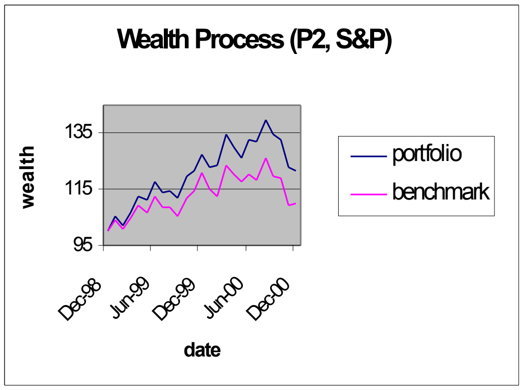
Table 12: Performance of the TSA Model for the Equity Oriented Universe. This table provides a summary of the performance of both tactical style allocation models. The Hit Ratio HR(2) is the percentage of time that the return on the tactical style allocation portfolio is greater than the return on the benchmark. Mean and standard deviation are expressed in percentage per year, and obtained from monthly data through a multiplicative factor of 12 and square-root of twelve, respectively. IR in column 5 stands for information ratio; it is the ratio of the annual excess return (column 30 over the annual tracking error (column 4). One benchmark is the S&P 500, the other is an arbitrary strategic asset allocation (SAA) benchmark: 25% S&P growth, 25% S&P value, 20% S&P 400 mid-cap, 15% equity market neutral and 15% event driven.

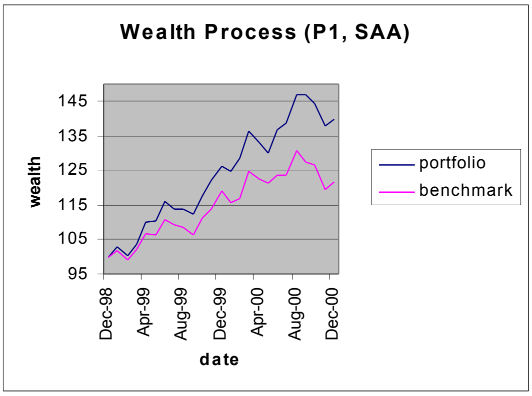
	HR (2)	Annual Excess Return	Annual TE	*IR*
S & P 500; Max *IR*	66.7%	15.6%	9.3%	1.68
S & P 500; Max $E\left(R_p - R_{Bench} \mid F_{t-1}\right)$ s.t $TE \leq 2\%$	62.5%	4.9%	3.8%	1.3
SAA; Max *IR*	62.5	7.0%	4.2%	1.66
SAA; Max $E\left(R_p - R_{Bench} \mid F_{t-1}\right)$ s.t $TE \leq 2\%$	66.7%	4.7%	3.4%	1.41

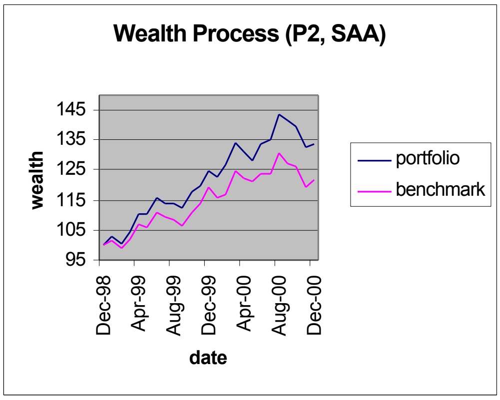
The four graphs below (see figure 3) display the evolution of $100 invested in the benchmark and the TSA portfolio (P1 and P2, respectively), from January 1998 to December 2000.

Figure 3: Performance of TSA Portfolios in an Equity-Oriented Universe. The picture on the top left-hand side displays the evolution of $100 invested in the S&P 500 and the TSA portfolio (program P1) from January 1998 to December 2000. The picture on the top right-hand side displays the evolution of $100 invested in the S&P 500 and the TSA portfolio (program P2) from January 1998 to December 2000. The picture on the bottom left-hand side displays the evolution of $100 invested in the SAA benchmark and the TSA portfolio (program P1) from January 1998 to December 2000. The picture on the bottom right-hand side displays the evolution of $100 invested in the SAA benchmark and the TSA portfolio (program P2) from January 1998 to December 2000.









4.2 Fixed-Income Oriented Universe

We now consider a style timing portfolio invested in the Lehman Brother Treasury bond index, Lehman Brother investment grade corporate bond index, and Lehman Brother high yield corporate bond index for the traditional part, and in Tremont convertible arbitrage and Tremont fixed-income arbitrage for the alternative part. We consider two benchmarks, one being the Lehman Brother Global Bond Index (LBGBI), the other being an arbitrary strategic asset allocation benchmark: 25% Lehman Brother Treasury bond index, 25% Lehman Brother investment grade corporate bond index, 25% Lehman Brother high yield corporate bond index, 12.5% convertible arbitrage and 12.5% fixed-income arbitrage.

We use the same methodology as above to come up with predictive models for traditional investment styles. The results are summarized in table 13.

Table 13: Performance of the Predictive Models for Traditional Fixed-Income Indexes. The first column contains the in-sample R-squared of the regression. The second column contains the hit ratios of the model, that is the percentage of time the predicted direction is valid, i.e., the index goes up (resp. down) when the model predicts it will go up (resp. down).

	R^2	HR (1)
Lehman Brother Treasury Bond Index	28.1%	58.3%
Lehman Brother Investment Grade Corporate Bond Index	35.4%	54.2%
Lehman Brother High Yield Corporate Bond Index	45.2%	66.7%

We then compute optimal portfolios using both maximization of the information ratio (program P1) and maximization of the excess expected return under tracking error constraint (program P2), and we test both the Lehman Brother Global Bond Index (LBGBI) benchmark and the strategic asset allocation benchmark. Table 14 summarizes the results.

Table 14: Performance of the TSA Model for the Fixed-Income Oriented Universe. This table provides a summary of the performance of both tactical style allocation models. The Hit Ratio HR(2) is the percentage of time that the return on the tactical style allocation portfolio is greater than the return on the benchmark. Mean and standard deviation are expressed in percentage per year, and obtained from monthly data through a multiplicative factor of 12 and square-root of twelve, respectively. IR in column 5 stands for information ratio; it is the ratio of the annual excess return (column 30 over the annual tracking error (column 4). One benchmark is the Lehman Brother Global Bond Index (LBGBI), the other is an arbitrary strategic asset allocation (SAA) benchmark: 25% Lehman Brother Treasury bond index, 25% Lehman Brother investment grade corporate bond index, 25% Lehman Brother high yield corporate bond index, 12.5% convertible arbitrage and 12.5 fixed-income arbitrage.

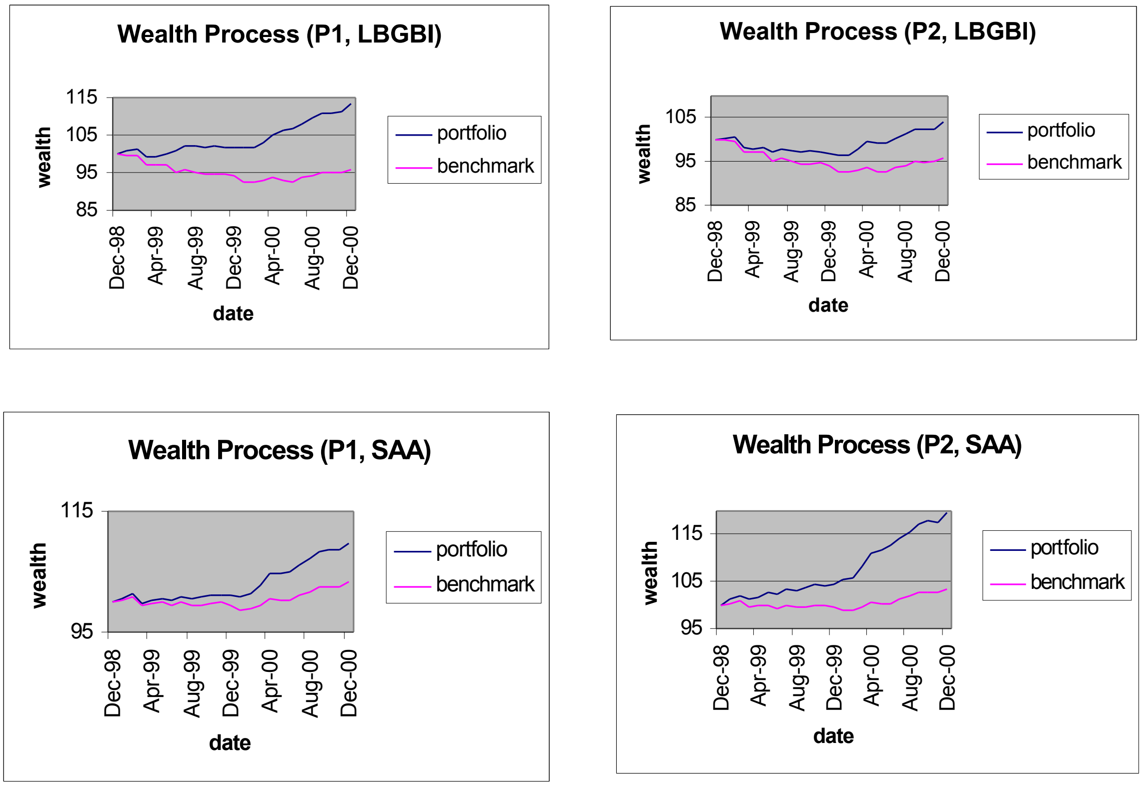
	HR (2)	Annual Excess Return	Annual TE	IR
LBGBI; Max IR	91.7%	8.4%	2.8%	3
LBGBI; Max $E\left(R_p - R_{Bench} \mid F_{t-1}\right)$s.t $TE \leq 2\%$	83.8%	4.2%	1.6%	2.7
SAA; Max IR	87.5%	3.0%	0.7%	4.1
SAA; Max $E\left(R_p - R_{Bench} \mid F_{t-1}\right)$s.t $TE \leq 2\%$	87.5%	7.4%	2.0%	3.8

The four graphs below (see figure 4) display the evolution of \$100 invested in the benchmark and the TSA portfolio (P1 and P2, respectively), from January 1998 to December 2000.

5 Transaction costs

It is well-known that the presence of all sorts of frictions and transaction costs may transform a theoretically derived optimal tactical asset allocation strategy into a very costly sub-optimal dynamic trading strategy. Seminal contributions to optimal multi-period investment decisions in the presence of transaction costs have been made by Constantinides (1979, 1984, 1986) and Dumas and Luciano (1991) (see also Davis and Norman (1990), Dixit (1991), Dumas (1991), Shreve and Soner (1997)). More recently, Leland (1999) extends this work in a slightly different setting to account for the effects of capital gains taxes.[15]

Figure 4: Performance of TSA Portfolios in a Fixed-Income Oriented Universe. The picture on the top left-hand side displays the evolution of $100 invested in the LBGBI and the TSA portfolio (problem P1) from January 1998 to December 2000. The picture on the top right-hand side displays the evolution of $100 invested in the LBGBI and the TSA portfolio (problem P2) from January 1998 to December 2000. The picture on the bottom left-hand side displays the evolution of $100 invested in the SAA benchmark and the TSA portfolio (problem P1) from January 1998 to December 2000. The picture on the bottom right-hand side displays the evolution of $100 invested in the SAA benchmark and the TSA portfolio (problem P2) from January 1998 to December 2000.



In this paper, we attempt to identify the impact of transaction costs on the benefits of multi-style multi-class by implementing a simple strategy whereby re-balancing occurs at fixed intervals of time, i.e., every month. For simplicity, we model transaction costs as an affine function of the volume of transactions, i.e., they include both fixed and proportional components. Therefore, the transaction costs incurred at date *t+1* are

$$TC_{t+1} = a + b\sum_{i=1}^{I} W_{i,t}\left|w_{i,t+1} - w_{i,t}\right|$$

[15] Other contributions to the subject borrow from the literature on option replication in the presence of transaction costs (see in particular Leland (1985), Hodges and Neuberger (1989), Constantinides (1993), Davis, Panas and Zariphopoulou (1993), Henrotte (1993), Hoggard et al. (1994), Grannan and Swindle (1996), Toft (1996), Martellini (2000), El Bied, Martellini and Priaulet (2001a,b) or Martellini and Priaulet (2002)).

where *a* is the fixed cost component, *b* is the proportional cost component, $W_{i,t}$ is the wealth invested in asset *i* at date *t*, and $w_{i,t}$ is the proportion of wealth invested in asset *i* at date *t*. As an illustration, we have tested implementing this strategy in the equity-oriented universe (S&P 500 used as a benchmark, program P1) by taking *a=0* and *b=5%,* a rather high level of transaction costs. The results we obtain are summarized in table 15.

Table 15: Performance of TSA in the Presence of Transaction Costs. This table provides a summary of the performance of the tactical style allocation model in the equity-oriented universe (S&P 500 used as a benchmark, program P1). The Hit Ratio HR(2) is the percentage of time that the return on the tactical style allocation portfolio is greater than the return on the benchmark. Mean and standard deviation are expressed in percentage per year, and obtained from monthly data through a multiplicative factor of 12 and square-root of twelve, respectively.

	$HR(2)$	Annual Excess Return	Annual TE	IR
S&P 500; Max IR ; no transaction costs	67%	15.6%	9.3%	1.68
S&P 500; Max IR ; 5% transaction costs	54.2%	15.3%	9.4%	1.63

We conclude that the presence of even large transaction costs does not, significantly affect the performance of the tactical style allocation models, at least when some optimal trading strategy is implemented.

6 Conclusion

This paper is, to the best of our knowledge, the first to document the existence of predictability in hedge fund index returns, focusing on its implications use for tactical style allocation decisions. Using data from nine CSFB-Tremont hedge fund indexes, we find that there is strong evidence of very significant predictability in hedge fund returns. We also find that the benefits in terms of tactical style allocation portfolios are potentially very large. Even more spectacular results are obtained both for an equity-oriented portfolio mixing traditional and alternative investment vehicles, and for a fixed-income oriented portfolio mixing traditional and alternative investment vehicles. These results do not seem to be significantly affected by the presence of transaction costs.

Our analysis can be further improved in a number of ways. First, on the econometric front, more sophisticated techniques could be used to forecast asset returns. An interesting avenue for future research would be to use the non-parametric approach recently introduced by Brandt (1999) and Ait-Sahalia and Brandt (2001) which directly focuses on the dependence of the optimal portfolio weights on the predictive variables rather than first model the return distribution and subsequently characterize the portfolio choice. Also, on the portfolio front, further constraints may be added to the simple mean-variance analysis. In particular, there is clear evidence that hedge fund returns may not be normally distributed (see for example Amen and Kat (2001) or Lo (2001)). Hedge funds typically exhibit non-linear option-like exposures to standard asset classes (Fung and Hsieh (1997, 2000), Agarwal and

Naik (2000)) because they can use derivatives and they follow dynamic trading strategies, and also because of the explicit sharing of the upside profits (post-fee returns have option-like element even if pre-fee returns do not). Therefore, hedge fund returns may not be normally distributed even if traditional asset returns are. In that context, it would be interesting to expand the portfolio analysis so as to encompass further constraints, such as Value-at-Risk constraints, in an attempt to improve the risk-management of the dynamic style allocation portfolios (see for example Alexander and Baptist (2001) or Sentana (2001)).[16]

We believe that the performance of tactical allocation in the alternative universe can be explained at the intuitive level by the fact that hedge fund returns are exposed to a large number of rewarded risk factors, not only market related sources risk, but also credit or liquidity risks (see Schneeweis and Spurgin (1999)). This induces more opportunities to search for predictability in hedge fund returns, as argued by Ferson and Harvey (1991) who find that most of the predictability in returns can be attributed to predictable shifts in risks and the market wide reward for risks.

One might have wondered in the past whether documenting the predictability of hedge fund returns could be regarded as anything but a purely academic exercise. Obviously, some specific features of hedge fund investing do not facilitate the implementation of tactical allocation strategies. In particular, the absence of liquidity and the presence of lockup periods typical to investments in hedge funds are likely to prevent investors from implementing any kind of dynamic allocation among funds. In an attempt to estimate the actual percentage of funds applying strict investment constraints, we have decided to analyze the current conditions of access to funds by investors. The results of this analysis are striking: we have listed a relatively high total of 714 out of 2000 hedge funds covered by Altvest[17] that claim to offer monthly liquidity and no lockup period as of July 2002.[18] It should be noted, however, that drastic conditions of minimum assets under management apply to individual funds or funds of funds, which still impose binding constraints to investors willing to re-allocate a large fraction of their wealth among various alternative investment vehicles. In that context, the results presented in this paper can perhaps be regarded as most relevant for multi-strategy managers, who can freely dynamically allocate funds among various accounts of funds.

We actually have reasons to believe that the future of hedge fund style timing is even brighter than its past or present. The hedge fund industry is still relatively new, and market conditions are evolving at a frightening pace. While in its infancy the world of alternative investment strategies consisted of a disparate set of managers following very specific strategies, significant attempts at structuring the markets have occurred over the last decade. Following an early lead by CSFB/Tremont, we have

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[16] When returns are jointly normally distributed, the injection of a VaR constraint in mean-variance analysis is redundant, because asset return distributions are fully specified once the means and asset return covariance-matrix are specified.

[17] Altvest is one of the main hedge fund databases for managers with at least 1 year track record and $2 million of assets under management).

[18] There is evidence that the trend is towards more, and not less, hedge funds imposing lockup periods, as more and more investors seek to invest in a small number of funds. In this context, it is generally new funds that offer accommodating conditions to investors, while the most successful ones can afford to impose strict redemption rules and lockup periods.

also witnessed the creation of investment products designed to track the performance of hedge fund indexes (see Amenc and Martellini (2001) for an overview of existing hedge fund indexes and evidence of the contrasted view they offer). In particular, Zurich Capital Markets has launched in 2001 a series of hedge fund indexes that consist of equally weighted portfolios of funds that satisfy a number of qualitative criteria for institutional investment as well as a statistical classification procedure for style classification, under the supervision of an independent advisory board.[19] Investable portfolios, i.e., replicating portfolios with an approximate 2.5% tracking error, are available for each of these 5 indexes with monthly liquidity provided by Zurich Capital Markets, and no lockup period imposed to investors. In a similar spirit, S&P, MSCI and HSBC Republic Investments expect to launch index funds of funds with a high level of liquidity in the very near future.

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[19] The five hedge fund strategies currently covered are Convertible Arbitrage, Merger Arbitrage, Distressed Securities, Event Driven and Hedged Equity. These indexes differ from existing hedge fund indexes by focusing only on those funds/managers that are 1) strategy pure in their style 2) have a two-year minimum performance track record and 3) sufficient assets under management to demonstrate organizational and managerial infrastructure, scalable strategies and the ability to raise funds from sophisticated investors.

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Appendix: Information on Hedge Fund Strategies

- **Convertible Arbitrage.** Attempts to exploit anomalies in prices of corporate securities that are convertible into common stocks (convertible bonds, warrants, convertible preferred stocks). Convertible bonds tends to be under-priced because of market segmentation; investors discount securities that are likely to change types: if issuer does well, convertible bond behaves like a stock; if issuer does poorly, convertible bond behaves like distressed debt. Managers typically buy (or sometimes sell) these securities and then hedge part of or all of associated risks by shorting the stock. Delta neutrality is often targeted. Over-hedging is appropriate when there is concern about default as the excess short position may partially hedge against a reduction in credit quality.

- **Dedicated Short Bias.** Sells securities short in anticipation of being able to re-buy them at a future date at a lower price due to the manager's assessment of the overvaluation of the securities, or the market, or in anticipation of earnings disappointments often due to accounting irregularities, new competition, change of management, etc. Often used as a hedge to offset long-only portfolios and by those who feel the market is approaching a bearish cycle.

- **Emerging Markets.** Invests in equity or debt of emerging (less mature) markets that tend to have higher inflation and volatile growth. Short selling is not permitted in many emerging markets, and, therefore, effective hedging is often not available, although Brady debt can be partially hedged via U.S. Treasury futures and currency markets.

- **Long/Short Equity.** Invests both in long and short equity portfolios generally in the same sectors of the market. Market risk is greatly reduced, but effective stock analysis and stock picking is essential to obtaining meaningful results. Leverage may be used to enhance returns. Usually low or no correlation to the market. Sometimes uses market index futures to hedge out systematic (market) risk. Relative benchmark index is usually T-bills.

- **Equity Market Neutral.** Hedge strategies that take long and short positions in such a way that the impact of the overall market is minimized. Many practitioners of market-neutral long/short equity trading balance their longs and shorts in the same sector or industry. By being sector neutral, they avoid the risk of market swings affecting some industries or sectors differently than others. Market neutral can imply dollar neutral, beta neutral or both.
    - Dollar neutral strategy has zero net investment (i.e., equal dollar amounts in long and short positions).
    - Beta neutral strategy targets a zero total portfolio beta (i.e., the beta of the long side equals the beta of the short side). While dollar neutrality has the virtue of simplicity, beta neutrality better defines a strategy uncorrelated with the market return.

- **Event Driven :** corporate transactions and special situations
    - Deal Arbitrage (long/short equity securities of companies involved in corporate transactions)
    - Bankruptcy/Distressed (long undervalued securities of companies usually in financial distress)
    - Multi-strategy (deals in both deal arbitrage and bankruptcy)

- **Fixed-Income Arbitrage.** Attempts to hedge out most interest rate risk by taking offsetting positions. May also use futures to hedge out interest rate risk.

- **Global Macro.** Aims to profit from changes in global economies, typically brought about by shifts in government policy that impact interest rates, in turn affecting currency, stock, and bond markets. Participates in all major markets -- equities, bonds, currencies and commodities -- though not always at the same time. Uses leverage and derivatives to accentuate the impact of market moves. Utilizes hedging, but the leveraged directional investments tend to make the largest impact on performance.

- **Managed Futures.** Opportunistically long and short multiple financial and/or non financial assets. Sub-indexes include Systematic (long or short markets based on trend-following or other quantitative analysis) and Discretionary (long or short markets based on qualitative/fundamental analysis often with technical input).