Evidence of Predictability in Bond Indices and Implications for Fixed-Income Tactical Style Allocation Decisions

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Abstract
This paper presents strong evidence of predictability in various fixed-income style portfolio returns using a robust recursive modelling approach based on multi-factor models for the return on bond indices. We also emphasise the benefits of an optimal market neutral strategy that generates abnormal return from timing between traditional Treasury, Corporate and High Yield bond indices, while maintaining a zero exposure with respect to a global bond index.

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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 recognised 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 recognised the potential significance of return predictability and started to engage in “tactical asset allocation strategies as early as the 1970s. 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 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))

\[
R_{i,t} - r_{f,t} = \beta_{i,M} \left[ R_{M,t} - r_{f,t} \right]_{\text{systematic-market}} + \beta_{i,B/M} \left[ R_{B/M,t} - r_{f,t} \right]_{\text{systematic style}} + \beta_{i,\text{size}} \left[ R_{\text{size},t} - r_{f,t} \right]_{\text{specific}} + \epsilon_{i,t}
\]

Such a decomposition of returns allows for a natural extended classification of active portfolio strategies (see Table 1). Market Timing or Tactical Asset Allocation Strategies aim to exploit 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 specific risk.

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1 - Wells Fargo is considered to be the first firm to have introduced a tactical asset allocation product, in the 1970s.
It should be noted that TSA is not a new concept. Most mutual fund managers actually make 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”. Furthermore, there is little evidence of predictability in the specific component of stock returns in the absence of private information. On the other hand, several authors have recently shown that various equity style returns were at least as much predictable as a broad market index, and emphasised the benefits of active strategies that focus on tactical style timing only. In particular, Kao and Shumaker (1999), Amenc et al. (2003) and Bauer and Molenaar (2002) have underlined the performance of strategies that involves dynamic trading in various equity styles (see also Fan (1995), Sorensen and Lazzara (1995), and Avramov (2000)).

While the performance of tactical style allocation models is well documented in equity markets, very little evidence is available on the performance of systematic dynamic allocation decisions among various bond indices. Most of the existing literature on predictability in bond returns has actually focused on timing bonds versus stocks or bonds versus cash, with no emphasis on the timing of the different classes of credit ratings. These papers include Shiller (1979), Shiller, Campbell, and Schoenholtz (1983), Fama (1984), Keim and Stambaugh (1986), Fama and Bliss (1987), Campbell (1987), Fama and French (1989), Campbell and Shiller (1991), Bakaert, Hodrick and Marshall (1997), Ilmanen (1995, 1997), Lekkos and Milas (2001), Baker et al. (2002), Ilmanen and Sayood (2002), among others. One exception is Keim and Stambaugh (1986) who find that several ex ante observable variables based on asset price levels predict ex post risk premiums on common stocks of NYSE firms of various sizes, long-term bonds of various default risks, and U.S. Government bonds of various maturities.

This paper is an attempt to fill in this gap. Our contribution is to investigate the predictability of fixed-income style portfolio returns using a robust recursive modelling approach based on multi-factor models for the return on bond indices. We also emphasize the benefits of an optimal market neutral strategy that generates abnormal return from timing between traditional Treasury, Corporate and High Yield bond indices, while maintaining a zero exposure with respect to a global bond index.

The rest of the paper is organised as follows. In Section 2, we report the results of a contemporaneous as well as a lagged factor analysis of bond index returns. In Section 3, we provide strong evidence of predictability in fixed-income portfolio returns. In Section 4, we discuss the implications in terms of dynamic style allocation decisions. We present our conclusions in Section 5.

\[ \text{Table 1: Classification of Active Portfolio Strategies} \]

<table>
<thead>
<tr>
<th>Form of active strategy</th>
<th>Systematic - market</th>
<th>Systematic - style</th>
<th>Specific</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mutual fund – stock picking</td>
<td>Tactical Asset Allocation</td>
<td>X (discretionary)</td>
<td>X (discretionary)</td>
</tr>
<tr>
<td>Hedge fund – stock picking</td>
<td>0</td>
<td>X (discretionary)</td>
<td>X</td>
</tr>
<tr>
<td>Mutual fund – market timing</td>
<td>X (discretionary or systematic)</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>TSA – long only</td>
<td>X (systematic)</td>
<td>X (systematic)</td>
<td>0</td>
</tr>
<tr>
<td>TSA – market neutral</td>
<td>0</td>
<td>X</td>
<td>0</td>
</tr>
</tbody>
</table>


3 - See also Walden (2000) for a model of optimal dynamic allocation to Treasury and corporate bonds, as well as Berardi, Crast and Trivo (2000) for evidence of predictability in implicit probabilities of default on high yield emerging market debts.

4 - Also related are recent attempts by Dolan (1999), Diebold and Li (2002) or Fabozzi, Martellini and Priaulet (2003), who calibrate forecasting models not on bond index returns but on the shape of the term structure itself, by focusing on time-varying estimates level, slope and curvature parameters obtained from traditional term structure fitting models.
2. Factor Analysis of Bond Index Returns

Investors have an intuitive understanding that different bond indices 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 1991-2001 for three broad-based bond indices by Lehman Brothers, the Lehman T-Bond index, the Lehman investment grade corporate bond index (which in this paper we also refer to as the "credit bond index"), and the Lehman high-yield bond index. The following table reports correlations, means and standard deviations for the fixed-income indices based on monthly data over the period 1991-2001.

Table 2: Descriptive Statistics for the Fixed-Income Indices. This table reports correlations, annual means and standard deviations for the Lehman Brothers bond indices based on monthly data over the period 1991-2001.

<table>
<thead>
<tr>
<th></th>
<th>T-Bond</th>
<th>Investment Grade</th>
<th>High Yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>T-Bond</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investment Grade</td>
<td>0.77</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>High Yield</td>
<td>0.12</td>
<td>0.24</td>
<td>1.00</td>
</tr>
<tr>
<td>Mean</td>
<td>0.37%</td>
<td>0.40%</td>
<td>0.22%</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>4.92%</td>
<td>5.60%</td>
<td>6.64%</td>
</tr>
</tbody>
</table>

The relatively low correlations between T-Bond and Investment Grade indices and the high yield index reported in Table 2 suggest that different fixed-income strategies perform better at different points in time. While unconditional correlations suggest potential economic value in timing bond indices, conditional correlations are perhaps more indicative.

From an intuitive standpoint, the notion of flight-to-quality suggests for example that during times of increased stock uncertainty, the price of U.S. Treasury bonds tends to increase relative to stocks and also corporate bonds. This strongly suggests that using a predictive variable such as a proxy for stock market volatility can help in the appreciation of the future relative performance of various bond indices. Before providing formal evidence of predictability in bond indices, we first document how bond indices perform under various economic conditions. Economic conditions are described in terms of the values of a shortlist of financial and macroeconomic factors. Some of these factors have been shown to be useful in predicting the performance of traditional asset classes and/or explaining a significant fraction of the cross-sectional differences in various stock and bond index returns.

The financial factors are:
- 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).\(^5\)
- Market volume (proxied by changes in the monthly market volume on the NYSE).
- US equity factor (proxied by the return on the S&P 500 index).

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\(^5\) 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.
The economic factors are:
- Inflation (proxied by Consumer Price Index);
- Money supply (proxied by M1 monetary aggregate);
- Economic growth (proxied by real quarterly Gross Domestic Product).

Two general sets of results are discussed below. First, we discuss the performance of these strategies under different contemporaneous levels as well as changes in each of the factors. Next, we discuss the performance of the same strategies using a 3-month lag between the observing the economic factors and performance of various strategies. The goal is to see if lagged values of economic factors affect the subsequent performance of various strategies. We study the performance of bond indices under various levels of these factors as well as changes in them.

We first report the results on a contemporaneous analysis for the example of changes in implicit volatility based on monthly data over the period 1991-2001 (see Table 3).

Table 3: Performance of Bond Indices under Different Contemporaneous Economic Conditions – the Example of Changes in Implicit Volatility

<table>
<thead>
<tr>
<th>Change in Implicit Volatility</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Unconditional Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference between Conditional Values and Unconditional Values</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>Minimum</td>
<td>Maximum</td>
<td>Mean</td>
<td>Minimum</td>
</tr>
</tbody>
</table>

These results allow for interesting interpretations. For example, the largest 1/3 of decreases in implicit volatility on equity corresponds to drops ranging from −33.15% to −4.39%. Under these conditions, the Lehman high yield index performs rather well, since on an annual basis it over performs the Lehman Investment grade index by 6.53% more than the unconditional annualised mean, a small negative −0.18%. On the other hand, when implicit volatility on equity is decreasing significantly (from +4.46% to +59.22%), on average the Lehman high yield index under performs the Lehman Investment grade index by 7.64% more than the unconditional mean. This is consistent with the intuition that high yield bonds are a good investment in periods of low uncertainty, but are dominated by higher quality bonds in periods of higher uncertainty.

Table 4 provides a summary of such an analysis for all variables.

Table 4: Performance of Bond Indices under Different Contemporaneous Economic Conditions – Synthesis. H corresponds to value greater than 3%; L corresponds to values lower than 3%

From such an analysis, we conclude for example that high yield bonds tend to over perform investment grade bonds when
- Short-term rates are low and do not change much;
- The dividend yield is decreasing or remaining stable.
The yield curve is very upward slopping and steepening;
• Implicit volatility is decreasing significantly and the S&P is increasing;
• Inflation is low and economic growth is high.

We next report the results of a one-month lagged analysis, in the example of the term spread (Table 5).

Table 5: Performance of Bond Indices under Different Contemporaneous Economic Conditions – the Example of the Term Spread

<table>
<thead>
<tr>
<th>Term spread</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Unconditional Values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Minimum</td>
<td>Maximum</td>
<td>Minimum</td>
<td>Maximum</td>
</tr>
<tr>
<td>CREDIT BOND INDEX - LEHMAN AGGREGATE</td>
<td>-0.6%</td>
<td>-0.2%</td>
<td>-0.2%</td>
<td>-0.4%</td>
</tr>
<tr>
<td>HIGH YIELD BOND INDEX - LEHMAN AGGREGATE</td>
<td>-3.9%</td>
<td>-1.3%</td>
<td>-0.7%</td>
<td>-0.8%</td>
</tr>
<tr>
<td>TREASURY BOND INDEX - LEHMAN AGGREGATE</td>
<td>0.3%</td>
<td>-1.4%</td>
<td>-0.4%</td>
<td>-0.4%</td>
</tr>
<tr>
<td>HIGH YIELD BOND INDEX - CREDIT BOND INDEX</td>
<td>-2.2%</td>
<td>-1.0%</td>
<td>-1.0%</td>
<td>-0.2%</td>
</tr>
</tbody>
</table>

For example, the lowest 1/3 of values for the term spread range from –0.61% to 0.99%. Under these conditions, the Lehman high yield index performs rather poorly, since on an annual basis it underperforms the Lehman Aggregate bond index – 3.17% below the unconditional annualised mean, a small positive 0.05%. On the other hand, when the yield curve is very upward slopping implicit (term spread ranging from 2.48% to 3.01%), on average the Lehman high yield index overperforms the Lehman Aggregate bond index by 3.90% more than the unconditional mean. This is consistent with the intuition that an upward slopping yield curve signals expectations of increasing short term rates, typically associated with scenarios of economic recovery, conditions under which high yield bond tend to over perform safer bonds.

Table 6 provides a summary of such an analysis for all variables.

Table 6: Performance of Bond Indices under Different One-Month Lagged Economic Conditions – Synthesis. H corresponds to value greater than 3%; L corresponds to values lower than 3%.

From such an analysis, we conclude for example that high yield bonds tend to over perform investment grade bonds with a one month lag when:

• Short-term rates are low and decreasing;
• Dividend yield is decreasing;
• Default spread is high;
• The yield curve is very upward slopping and steepening;
• Market volume is significantly increasing;
• S&P return is high.

Contemporaneous and lagged factor analysis provide 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 fixed-income strategy is going to outperform other strategies. We now turn to formal econometric evidence of predictability in bond index returns.
3. Evidence of Predictability in Bond Index Returns

In this section, we describe the econometric approach that we have used in an attempt to search for evidence of predictability in bond index returns. 6 We calibrate forecasting models on differentials
- Treasury Bond index – Lehman Aggregate bond index
- Credit Bond index – Lehman Aggregate bond index
- High Yield Bond index – Lehman Aggregate bond index

Given that we are searching for evidence of predictability in fixed-income portfolio 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.

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 a short list of economically meaningful variables. These variables are the ones used in the factor analysis from Section 2, to which we add the lagged return on each index as a potential regressor.

We have tested not only for the explanation power of the raw variables $Z_t$ but also for changes in the variables $Z_{t-1} - Z_{t-2}$, one-month lag $Z_{t-1}$, two-month lag $Z_{t-2}$, three-month lag $Z_{t-3}$, moving average 
$$\frac{1}{3}Z_{t-1} + \frac{1}{3}Z_{t-2} + \frac{1}{3}Z_{t-3},$$
as well as combinations of the above.

To select a shortlist of useful variables for each index, we decompose the period ranging from January 1992 to December 1997 (6 years) into 2 sub-periods.
- Calibration period (January 1992 to December 1995): for each index and each predictive variable, we use a 4-year rolling window of data (starting in January 1994) to calibrate the model, i.e. estimate the coefficients.
- Training period (January 1995 to December 1997): for each index and each predictive variable, we use a 2-year rolling window of data (starting in January 1998) to 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 ½ (benchmark case of no model): in the case of 24 observations, a hit ratio of at least 63% (respectively, 67%) is significantly greater than ½ at the 10% (respectively, 5%) level. We also compute the associated t-statistics to check whether the variable had a statistically significant explanatory power.

For each index, we select a shortlist of variables according to the following three criteria (hit ratio, R-square and t-stat) that we normalise and aggregate into a single number that we call a “preference number”. 7 We select the variables and their permutations on the basis of their preference number.

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 multivariate linear models based on at most 5 variables, where we systematically seek to avoid multi-collinearity. It is indeed well-known that in the presence of multicollinearity, 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).

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6 - See Amenc, El Bied and Martellini (2003) for some evidence of predictability in alternative fixed income strategies such as fixed-income arbitrage and convertible arbitrage.
7 - 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.
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 penalise the different models for the number of degrees of freedom more harshly than the adjusted R-squared. It is computed as

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

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, we select, for each index, one model that predicts the return on that index most closely.

Given the wide range of filters applied to select factors and models, a first potential concern over the pitfalls of data snooping. We have tried to mitigate this problem by using the 3 stages approach (calibration, training and trading periods) presented in Section 3.1. This procedure, similar to the recursive modelling 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.

Another potential concern at this stage is the presence of auto-correlation and/or heteroscedasticity in the time-series of the model’s residuals. It is indeed well-known that in the presence of auto-correlation and/or heteroscedasticity, the variance of the regression coefficients will by underestimated leading one to falsely believe some parameters are statistically significant (see Hamilton (1994) for more details). 8

In this context, we use the Newey and West (1987) covariance estimator that is consistent in the presence of both heteroscedasticity and auto-correlation of unknown form.

### 3.3 Using the Models

We then perform out-of-sample testing of the models. The methodology is as follows. We calibrate the models displayed above using a rolling window of the previous 48 months, that is, we dynamically re-estimate the coefficients each month using the past 48 months of observation. The calibration period is January 1992 to December 1998, and the back-testing period is January 1999 to December 2001. Table 7 provides information on the performance of the predictive models for the Tremont hedge fund indices. 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). In parenthesis, the $p$-value associated with the test of the hit ratio being significantly greater than $1/2$.

Table 7: In-Sample and Out-of-Sample Performance of the Predictive Models for Bond Portfolio Returns. 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). In parenthesis, the $p$-value associated with the test of the hit ratio being significantly greater than $1/2$.

<table>
<thead>
<tr>
<th></th>
<th>$R^2$</th>
<th>HR (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lehman Brother Treasury Bond Index</td>
<td>22%</td>
<td>69.4% (1%)</td>
</tr>
<tr>
<td>Lehman Brother Investment Grade Corporate Bond Index</td>
<td>28%</td>
<td>61.1% (9%)</td>
</tr>
<tr>
<td>Lehman Brother High Yield Corporate Bond Index</td>
<td>21%</td>
<td>58.3% (16%)</td>
</tr>
</tbody>
</table>

8 - When a model with auto-correlated residuals is used to forecast, the predictions will also suffer from unnecessarily large sampling variances. Intuitively, the performance of the model could be improved by including lagged residuals as additional predictive variables. More generally, one can perform a regression analysis with ARMA (autoregressive moving average) modeling of the serial correlation in the disturbance. In other words, using suitably designed standard econometric refinements could further magnify the evidence of predictability reported in this paper.
As we can see from Table 7, hit ratios are relatively high, all above 50% and one at 69.4%. These hit ratios are statistically greater than $\frac{1}{2}$ (case of no predictive power of the models) with a significance level equal to 1% for the Treasury bond index, 9% for the investment grade bond index and 16% for the high yield index.

We have found clear in-sample and out-of-sample statistical evidence of predictability in bond index returns. We now attempt to test whether there is also economic significance in the predictability of bond index return by investigating the implications in terms of a tactical asset allocation model.

4. 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.

4.1 Performance of a Style Timer with Perfect Forecast Ability

Different fixed-income investment strategies perform somewhat differently in different times. In an attempt to assess the performance of a style timer with perfect forecast ability in the fixed-income universe, we compute the annual return on fixed-income indices such as Lehman Brothers T-Bond, corporate, high yield and global bond indices. We also display 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. The results appear in Table 8.

Table 8: Performance of a Style Timer with Perfect Forecast Ability in the Fixed-Income Universe. This table features the annual return on various traditional and alternative fixed-income indices from 1995-2001, and also the annual average return and volatility 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 in italic.

<table>
<thead>
<tr>
<th>Year</th>
<th>T-Bond</th>
<th>Corporate</th>
<th>High Yield</th>
<th>LGBI</th>
<th>Perfect Timer</th>
</tr>
</thead>
<tbody>
<tr>
<td>1994</td>
<td>-10.22%</td>
<td>-12.42%</td>
<td>-11.39%</td>
<td>-10.86%</td>
<td>-10.22%</td>
</tr>
<tr>
<td>1995</td>
<td>10.00%</td>
<td>13.06%</td>
<td>9.46%</td>
<td>10.24%</td>
<td>13.08%</td>
</tr>
<tr>
<td>1996</td>
<td>-4.61%</td>
<td>-5.14%</td>
<td>0.20%</td>
<td>-4.03%</td>
<td>0.20%</td>
</tr>
<tr>
<td>1997</td>
<td>3.72%</td>
<td>4.51%</td>
<td>2.63%</td>
<td>3.49%</td>
<td>4.51%</td>
</tr>
<tr>
<td>1998</td>
<td>2.31%</td>
<td>-1.41%</td>
<td>-9.00%</td>
<td>0.37%</td>
<td>2.31%</td>
</tr>
<tr>
<td>1999</td>
<td>-8.07%</td>
<td>-8.68%</td>
<td>-8.60%</td>
<td>-7.70%</td>
<td>-8.80%</td>
</tr>
<tr>
<td>2000</td>
<td>8.32%</td>
<td>5.19%</td>
<td>-7.46%</td>
<td>5.95%</td>
<td>8.32%</td>
</tr>
<tr>
<td>2001</td>
<td>-1.34%</td>
<td>2.07%</td>
<td>5.89%</td>
<td>0.09%</td>
<td>5.89%</td>
</tr>
<tr>
<td>Average</td>
<td>0.12%</td>
<td>-0.35%</td>
<td>-2.06%</td>
<td>-0.31%</td>
<td>2.16%</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>7.07%</td>
<td>7.74%</td>
<td>7.15%</td>
<td>6.57%</td>
<td>7.19%</td>
</tr>
</tbody>
</table>

From Table 8, the benefits of timing are very obvious. A perfect style timer has an average return of 2.16% with 7.19% volatility. This compares very favorably with the performance of each of the traditional and alternative fixed-income indices. Furthermore, a perfect style timer would generate a return very significantly higher than the one on the Global Bond Index with a slightly higher volatility.

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, 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 bond 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.

4.2 Performance of a Realistic Style Timing Model

We use the econometric model introduced in Section 1 to generate predictions on expected returns for the three traditional bond indices by Lehman Brothers, a Lehman T-Bond index, a Lehman investment grade corporate bond index, a Lehman high-yield bond index.9

To turn econometric bets into market-neutral portfolio decisions, we use an approach introduced by Cvitanic et al. (2002) who extend a seminal paper by Treynor and Black (1973) by relaxing a set of simplifying assumptions that was made there. In particular, they allow for dynamic (versus static) optimisation, power (versus mean-variance) preferences, uncertain and potentially correlated (versus certain) priors, the presence of learning and also the presence of dollar or beta-neutrality constraints.10 Focusing on market-neutral strategies allows us to better assess the economic significance of the presence of predictability in bond index returns.

More specifically, we have implemented a market neutral strategy that generates abnormal return from timing between these three indexes, while maintaining a zero exposure with respect to Lehman global bond index.11 The goal is to deliver absolute return over the full business cycle ensured through systematic style timing and market neutrality.

Market neutral can imply dollar neutral, beta neutral or both.12 The dollar-neutral optimal allocation in n styles is shown to be (see Cvitanic et al. (2002))

\[
\pi_i = \frac{1}{a \sum_{j=1}^{n} \sigma_{e_j}^2} \left( \alpha_i - \frac{1}{n-1} \sum_{j \neq i} \alpha_j \right) \Rightarrow \sum_{i=1}^{n} \pi_i = 0
\]  

(1)

\(\alpha_i\) is the bet on index \(i\), \(\sigma_{e_j}\) is the residual risk on index \(i\) in a regression on the relevant benchmark, in this case the Lehman Brothers Global Bond index, and \(a\) is measure of risk-aversion. Here \(n=3\) since we invest only in the Lehman Treasury, Lehman Corporate and Lehman High Yield indices. Besides, 100% is invested in cash at a rate that we took equal to the corresponding LIBOR rate for the period. The intuition behind the formula in equation (1) is that weights are positive (respectively, negative) when expected differential for the class is higher (respectively, lower) than with other classes. On the other hand, residual (non-rewarded risk) decreases the allocation. The risk-aversion \(a\) allows investors to control for how aggressive the strategy is. We have chosen here a pragmatic implementation of the method and select the value for the risk-aversion coefficient \(a\) that allows an investor to achieve a target leverage \(l=2\), as can be seen in equation (2).

\[
\sum_{i=1}^{n} |\pi_i| = l \Rightarrow a = \frac{\sum_{i=1}^{n} |\alpha_i - \frac{1}{n-1} \sum_{j \neq i} \alpha_j|}{l \sum_{j=1}^{n} \sigma_{e_j}^2}
\]  

(2)

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 bond index returns obtained from the predictive models, the coefficients of which are dynamically re-estimated on a monthly basis using a 48-month rolling window. The calibration period is January 1994 to December 1998, while the backtesting period is January 1999 to December 2001.

9 - 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 Eliston, 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.


11 - Market neutral strategies represent almost one-third of the amount invested in equity hedge strategies in 2001 according to Hedge Fund Research.

12 - In Cvitanic et al. (2002), the alpha term is actually understood as a bet on the abnormal return with respect to the benchmark, here the Lehman Brothers Global Bond Index.
The performance of the portfolio is detailed in Table 9. We note that, as a result of dollar neutrality, 100% of the wealth is always invested in the risk-free asset, here proxied by an investment at LIBOR rate.

Table 9: Performance of TSA portfolio. This table features the monthly return from January 1999 to December 2001 for a TSA portfolio based on the econometric models presented in Section 3, and dollar neutrality with a level of leverage equal to 2.

<table>
<thead>
<tr>
<th>Year</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999</td>
<td>0.27%</td>
<td>1.20%</td>
<td>0.26%</td>
<td>-0.40%</td>
<td>0.53%</td>
<td>0.39%</td>
<td>0.89%</td>
<td>0.40%</td>
<td>-0.53%</td>
<td>0.03%</td>
<td>1.19%</td>
<td>1.14%</td>
</tr>
<tr>
<td>2000</td>
<td>0.50%</td>
<td>0.97%</td>
<td>1.11%</td>
<td>0.77%</td>
<td>0.64%</td>
<td>0.73%</td>
<td>0.47%</td>
<td>0.59%</td>
<td>-0.06%</td>
<td>2.18%</td>
<td>2.28%</td>
<td>0.59%</td>
</tr>
<tr>
<td>2001</td>
<td>-4.95%</td>
<td>-0.57%</td>
<td>-1.50%</td>
<td>0.26%</td>
<td>-1.51%</td>
<td>0.64%</td>
<td>0.73%</td>
<td>-0.11%</td>
<td>4.18%</td>
<td>0.06%</td>
<td>2.08%</td>
<td>1.51%</td>
</tr>
</tbody>
</table>

We also provide in Table 10 a summary of risk/return analysis.

Table 10: Risk/Return Analysis of TSA Portfolio. This table features the monthly return from January 1999 to December 2001 for a TSA portfolio based on the econometric models presented in section 3, and dollar neutrality with a level of leverage equal to 2.

<table>
<thead>
<tr>
<th>Risk Return Analysis</th>
<th>TSA Fund</th>
<th>Lehman Brothers Global</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative Return</td>
<td>36.31%</td>
<td>-2.65%</td>
</tr>
<tr>
<td>Annualised Return</td>
<td>10.45%</td>
<td>-9.34%</td>
</tr>
<tr>
<td>Annualised Std Deviation</td>
<td>4.16%</td>
<td>3.46%</td>
</tr>
<tr>
<td>Downside Deviation (3.0%)</td>
<td>2.66%</td>
<td>3.46%</td>
</tr>
<tr>
<td>Sortino (3.0%)</td>
<td>2.91</td>
<td>-1.11</td>
</tr>
<tr>
<td>Sharpe (Risk Free Rate = 3.0%)</td>
<td>1.79</td>
<td>-1.11</td>
</tr>
<tr>
<td>1st Quartile</td>
<td>-1.54%</td>
<td>-2.30%</td>
</tr>
<tr>
<td>% Negative Returns</td>
<td>11.11%</td>
<td>52.76%</td>
</tr>
<tr>
<td>Up Months in Up Market</td>
<td>88.24%</td>
<td></td>
</tr>
<tr>
<td>Down Months in Down Market</td>
<td>10.53%</td>
<td></td>
</tr>
<tr>
<td>Up Market Outperformance</td>
<td>52.94%</td>
<td></td>
</tr>
<tr>
<td>Down Market Outperformance</td>
<td>89.47%</td>
<td></td>
</tr>
<tr>
<td>Worst Monthly Drawdown</td>
<td>-2.08%</td>
<td>-2.48%</td>
</tr>
<tr>
<td>Maximum Drawdown</td>
<td>-2.08%</td>
<td>-8.75%</td>
</tr>
<tr>
<td>Months in Max Drawdown</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>Months to recover</td>
<td>in progress</td>
<td>26</td>
</tr>
</tbody>
</table>

The performance of the tactical allocation models is spectacular. The average performance is 10.45% with a low 4.16% volatility, a spectacular risk-return trade-off.

It should be noted that downside risk, as measured by downside deviation or Sortino ratio, are extremely low in both cases. In the case of beta-neutral allocation, the optimal strategy is

\[
\pi_j = \frac{1}{\alpha} \left( \alpha - \beta_j \frac{\sum_{i=1}^{n} \alpha_i \beta_i}{\sum_{j=1}^{n} \beta_j^2} \right) = \frac{1}{\alpha} \left( \sum_{j=1}^{n} \beta_j^2 \right) = \sum_{j=1}^{n} \pi_j \beta_j = 0
\]

Again, we select the value for the risk-aversion coefficient \(a\) that allows an investor to achieve a target leverage \(l=2\). We also invest in cash (LIBOR) so as to ensure that the sum of portfolio weights is equal to one.

The performance of the portfolio is detailed in Table 11.

Table 11: Performance of TSA portfolio. This table features the monthly return from January 1999 to December 2001 for a TSA portfolio based on the econometric models presented in Section 3, and beta neutrality with a level of leverage equal to 2.

<table>
<thead>
<tr>
<th>Year</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999</td>
<td>0.30%</td>
<td>0.99%</td>
<td>0.26%</td>
<td>0.27%</td>
<td>0.59%</td>
<td>0.60%</td>
<td>1.00%</td>
<td>0.47%</td>
<td>-0.22%</td>
<td>0.43%</td>
<td>0.79%</td>
<td>0.61%</td>
</tr>
<tr>
<td>2000</td>
<td>0.72%</td>
<td>0.86%</td>
<td>1.12%</td>
<td>0.73%</td>
<td>0.59%</td>
<td>0.33%</td>
<td>0.48%</td>
<td>0.38%</td>
<td>-0.37%</td>
<td>0.18%</td>
<td>0.56%</td>
<td>0.52%</td>
</tr>
<tr>
<td>2001</td>
<td>1.95%</td>
<td>0.63%</td>
<td>0.83%</td>
<td>0.92%</td>
<td>0.71%</td>
<td>0.33%</td>
<td>0.29%</td>
<td>0.26%</td>
<td>1.16%</td>
<td>0.79%</td>
<td>-0.15%</td>
<td>0.17%</td>
</tr>
</tbody>
</table>
We also provide in Table 12 a summary of risk/return analysis.

Table 12: Risk/Return Analysis of TSA Portfolio. This table features the monthly return from January 1999 to December 2001 for a TSA portfolio based on the econometric models presented in Section 3, and beta neutrality with a level of leverage equal to 2.

<table>
<thead>
<tr>
<th>Risk Return Analysis</th>
<th>TSA Fund</th>
<th>Lehman Brothers Global</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative Return</td>
<td>21.00%</td>
<td>-3.85%</td>
</tr>
<tr>
<td>Annualised Return</td>
<td>6.33%</td>
<td>-9.94%</td>
</tr>
<tr>
<td>Annualised Std Deviation</td>
<td>1.46%</td>
<td>3.40%</td>
</tr>
<tr>
<td>Downside Deviation (1.0%)</td>
<td>1.12%</td>
<td>2.88%</td>
</tr>
<tr>
<td>Sortino (1.0%)</td>
<td>4.60%</td>
<td>-0.84%</td>
</tr>
<tr>
<td>Sharpe (Risk Free Rate = 3.0%)</td>
<td>2.31%</td>
<td>-1.11%</td>
</tr>
<tr>
<td>1st Centile</td>
<td>-0.31%</td>
<td>-2.30%</td>
</tr>
<tr>
<td>% Negative Returns</td>
<td>8.33%</td>
<td>52.76%</td>
</tr>
<tr>
<td>Up Months in Up Market</td>
<td>82.35%</td>
<td></td>
</tr>
<tr>
<td>Down Months in Down Market</td>
<td>5.26%</td>
<td></td>
</tr>
<tr>
<td>Up Market Outperformance</td>
<td>47.06%</td>
<td></td>
</tr>
<tr>
<td>Down Market Outperformance</td>
<td>100.00%</td>
<td></td>
</tr>
<tr>
<td>Worst Monthly Drawdown</td>
<td>-0.37%</td>
<td>-2.48%</td>
</tr>
<tr>
<td>Maximum Drawdown</td>
<td>-0.37%</td>
<td>-8.75%</td>
</tr>
<tr>
<td>Months in Max Drawdown</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>Months to recover</td>
<td>&lt; 2</td>
<td>26</td>
</tr>
</tbody>
</table>

The performance of the TSA portfolio is even more impressive with a 2.31 Sharpe ratio, resulting from a sharp decrease in volatility (1.46%) and a lower decrease in average annualised return (6.38%). Downside deviation is even more limited. These results confirm that beta neutrality allows for better risk control than dollar neutrality.

5. Conclusion

This paper documents the existence of predictability in bond indices, focusing on its implications for tactical style allocation decisions. Using multi-factor models for the return on bond indices, 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 bond index returns.

We also emphasise the benefits of a market neutral strategy that generates abnormal return from timing between traditional Treasury, Corporate and High Yield bond indices, while maintaining a zero exposure with respect to a global bond index.

References


Bauer, R., and R. Molenaar, 2002, Is the value premium predictable in real time?, working paper, Maastricht University.


• Fan, S., 1995, Equity style timing and allocation, chapter 14 from Equity Style Management, Irwin Publishing.


• Fisher, K., J., Toms, and K., Blount, 1995, Driving factors behind style-based investing, chapter 22 from Equity Style Management, Irwin Publishing.


• Lee, W., 2000, Advanced theory and methodology of tactical asset allocation, Fabozzi and Associates Publications.

• Lekkos, I., and C. Milas, 2001, The predictability of excess return on UK bonds, a non linear approach, working paper, Brunel University.

• Lynch, A., 2000, Portfolio choice and equity characteristics: characterizing the hedging demands induced by return predictability, working paper, NYU.


• Mott, C., and K., Condon, 1995, Exploring the cycles of small-cap style performance,


• Walder, R., Dynamic allocation of Treasury and corporate bonds, working paper, University of Lausanne.
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