Salomon Brothers

Forecasting U.S. Bond Returns

Understanding the Yield Curve: Part 4

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INTRODUCTION

It is extremely difficult to forecast bond market fluctuations. However, recent research shows that these fluctuations are not fully unpredictable: **It is possible to identify in advance periods when the reward for duration extension is likely to be abnormally high or abnormally low.** In this report, we first describe a few variables that have the ability to predict near-term bond market performance. We then show how to combine the information that these predictors contain into a single forecast and, further, into implementable investment strategies. Finally, we backtest the historical performance of these strategies in a realistic "out-of-sample" setting.

This report is the fourth part of a series titled *Understanding the Yield Curve*. Historical analysis included in Part 3, *Does Duration Extension Enhance Long-Term Expected Returns?*, showed that intermediate- and long-term bonds earn higher average returns than short-term bonds. This evidence suggests that the long-run bond risk premium is positive.[1] If the risk premium is constant over time, the long-run average risk premium is also our best forecast for the near-term bond market performance. However, we showed in Part 3 that steeply upward-sloping yield curves tend to precede high excess bond returns and inverted yield curves tend to precede negative excess bond returns. It follows then that **the risk premium is not constant** and that **the current shape of the yield curve provides valuable information about the time-varying bond risk premium**. In this report, we show that **other variables can enhance the yield curve's ability to forecast the near-term excess bond return**. The predictability of the excess bond return has important implications for investors who are willing to use so-called tactical asset allocation strategies. Based on our extensive historical analysis, **strategies that adjust the portfolio duration dynamically using the signals from the predictor variables would have earned substantially higher long-run returns than did static strategies** that do not actively adjust the portfolio duration.

REASON FOR THE CHANGING RISK PREMIUM: A CYCLE OF FEAR AND GREED

Earlier empirical research shows that the expected excess returns of stocks and long-term bonds vary over the business cycle; they tend to be high at the end of the recession and low at the end of the expansion. Are there any intuitive reasons that expected excess returns should vary with economic conditions?

If the expected returns reflect rational risk premia, they change over time as the amount of risk in assets or the market price of risk varies over time. The risk premium that bond market participants expect should increase if the risk increases (because of higher interest rate volatility, higher covariance between bonds and stocks, greater inflation uncertainty, etc.). In addition, the required risk premium should increase if the market participants' aggregate risk aversion level increases. **We propose that investors are more risk averse (afraid) when their current wealth is**

[1] We define the *bond risk premium* as the near-term (say, one-month) expected return of a long-term government bond in excess of the return of the near-term riskless asset (say, the one-month Treasury bill). The *long-run* bond risk premium is the long-run average expected return of a long-duration strategy in excess of the long-run average expected return of a short-duration strategy. It may differ from the (near-term) bond risk premium if the latter is abnormally high or low. Our definition of bond risk premium encompasses any expected return differential between a long-term bond and the near-term riskless bond, whether it is actually related to risk or to some technical factor. For this reason, we often call the bond risk premium, more neutrally, the "expected excess bond return."

low relative to their past wealth. The higher risk aversion makes them demand higher risk premia (larger compensation for holding risky assets) near business cycle troughs. Conversely, higher wealth near business cycle peaks makes investors less risk averse (more complacent and greedy); therefore, they bid down the required risk premia (by bidding up the asset prices). Thus, **the observed time-variation in risk premia may be explained by the old Wall Street adage about the cycle of fear and greed**.

ARE EXCESS BOND RETURNS PREDICTABLE?

Which Variables Forecast the Excess Bond Return?

As mentioned above, measures of yield curve steepness have some ability to predict the subsequent excess bond return. In the appendix to Part 2 of this series, *Market's Rate Expectations and Forward Rates*, we showed that a steep yield curve may reflect a high required risk premium or the market's expectations of rising rates. If the second term is assumed to be zero (the current yield curve is the market's best forecast for future yield curves), then the curve steepness is a good proxy for the bond risk premium. We measure the curve steepness by the term spread (the difference between a long-term rate and a short-term rate).

Conveniently, we can use the **term spread as an overall proxy for the bond risk premium** even if we do not know what causes the expected return differentials across bonds. For this reason, the term spread will be our first predictor variable. Yet, if we are trying to forecast bond returns, why restrict ourselves to just one predictor? It is likely that the term spread is sometimes influenced by the market's rate expectations, making the previous assumption unrealistic. Because the rate expectations are unobservable, we cannot know how much "noise" they introduce to our risk premium proxy. Thus, we do not know to what extent a given shape of the curve reflects the required bond risk premium and to what extent it reflects the market's rate expectations. Using other predictor variables together with the term spread should help us *filter out* the noise and give us a better signal about the future risk premium.

The filter variables should be correlated with the risk premium. Based on our hypothesis of wealth-dependent risk aversion, we **combine the information in the term spread and in the stock market's recent performance**. The inverse of the recent stock market performance is our proxy for the (unobservable) aggregate level of risk aversion. If a high term spread coincides with a depressed stock market, the curve steepness is less likely to reflect rising rate expectations (because monetary policy tightening and inflation threat are less likely in this environment) and more likely to reflect high required risk premia (because low stock prices may reflect high required returns on risky assets, or even cause them via wealth-dependent risk aversion). We measure the recent stock market performance by "inverse wealth," a weighted average of past returns, where more distant observations have lower weights.

As a third predictor, we will examine the **real bond yield**, which is sometimes used as the overall proxy for the bond risk premium instead of the term spread. This measure incorporates the inflation rate into the forecasting model. Our final predictor, **momentum**, is a dummy variable that simulates a simple moving average trading rule to exploit the persistence (positive autocorrelation) in bond returns.[2] This strategy tries to capture large trending moves in the bond market. To reduce trading when the yields are oscillating within a narrow trading range and, thereby, to avoid "whipsaw" losses from buying at low yields and selling at high yields, we impose a neutral trading range in which no position is held. Somewhat arbitrarily, we use a six-month moving average window and a ten-basis-point neutral trading range. Thus, the rule is to take a long (short) position in the bond market when the long-term bond yield declines (increases) to more than five basis points below (above) its six-month moving average; such a break-out from a trading range is attributed to positive (negative) momentum in the bond market. If the bond yield returns to (stays within) the ten-basis-point range around its six-month average, the rule is to take (retain) a neutral position. The dummy variable takes value 1, -1 or 0 if the strategy is long, short or neutral, respectively.

Our empirical analysis will confirm that the term spread can forecast future excess bond returns, but combining the information contained in several predictor variables improves these forecasts further. Linear regression is the most common way to combine the information in several variables.[3] We will run a multiple regression of the realized excess bond return on the term spread, the real bond yield and measures of recent stock and bond market performance, and we will use the fitted value from this regression as an estimate of the (expected) bond risk premium.

Correlations Between Predictor Variables and Subsequent Excess Bond Return

We will examine **the predictability of the monthly excess return of a 20-year Treasury bond over the one-month bill rate between January 1965 and July 1995.**[4] We focus on the four predictor variables described in Figure 1: the term spread; the real bond yield; inverse wealth; and momentum.

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[2] Moving average trading rules are perhaps the most popular trend-following strategies among traders. Such strategies are profitable if the market moves more in trends than sideways within a trading range. Even though academic research in the 1960s and 1970s found that common technical trading rules do not consistently outperform buy-and-hold strategies, more recent studies have shown that some trend-following strategies are profitable, especially in the foreign exchange market. See, for example, "Technical Trading: When It Works and When It Doesn't," William Silber, *Journal of Derivatives*, Spring 1994. Momentum indicators are often viewed as indicators of the market sentiment. An alternative interpretation, which is consistent with economic theories with rational behavior, is that the trends in bond markets reflect slow declines (increases) in the bond risk premium that coincide with bull (bear) markets.

[3] The Equity Portfolio Analysis Group at Salomon Brothers has developed more sophisticated ways to combine the information in several predictive variables. See, for example, *Salomon Brothers Global Quantitative Strategy: Anatomy of the Global Allocation Model*, Eric Sorensen et al., Salomon Brothers Inc, September 1991, and "When Is a Tree a Hedge?," Joe Mezrich, *Financial Analysts Journal*, November-December 1994.

[4] We forecast the *excess* return rather than the return for three reasons: (1) The former is a proxy for the realized risk premium of a long-term bond (because any asset's return can be viewed as the sum of the riskless return and a realized risk premium); (2) it corresponds to a return on a self-financed position; and (3) it is harder to predict (because we subtract the riskless return which is known at the time of forecasting). Anyway, this choice hardly affects the predictability findings because the correlation between returns and excess returns is 0.997. (We also could forecast the long-term rate changes, whose correlation with excess bond returns is -0.97.) Finally, we examine a *20-year* bond because it has a long historical return series; however, the main findings of this report are similar if we examine a shorter history of a ten-year or a 30-year bond instead. This similarity is not surprising because the returns of all long-term government bonds are highly correlated.

Figure 1. Description of the Predictor Variables and the Predicted Variable

Variable	Definition	Data Source
Term Spread	Difference between the estimated five-year spot rate and the three-month spot rate.	Center of Research for Security Prices at the University of Chicago. Salomon Brothers since 1994.
Real Yield	Difference between the estimated five-year spot rate and the most recently published yearly consumer price inflation rate.	Center of Research for Security Prices at the University of Chicago. Salomon Brothers since 1994.
Inverse Wealth	Ratio of the exponentially weighted past stock market level to the current stock market level (W_t). Formally, = $(W_{t-1} + 0.9^*W_{t-2} + 0.9^2{}^*W_{t-3} + \ldots)^*0.1/W_t$.	Ibbotson Associates — Standard and Poor's 500 total return index.
Momentum	A dummy variable which takes value 1 if the bond yield is more than five basis points below its six-month average, -1 if the bond yield is more than five basis points above its six-month average, and 0 otherwise.	Ibbotson Associates — yield of a long-term government bond with an approximate maturity of 20 years.
Excess Bond Return	Monthly return of a long-term Treasury bond in excess of the nominally riskless return of a one-month Treasury bill. Also called Realized Bond Risk Premium.	Ibbotson Associates — total return index of a long-term government bond with an approximate maturity of 20 years.

Note: All rates and returns are compounded continuously.

Figure 2 shows the correlations between the excess bond return and various predictor variables.[5] The conventional view that risk premia cannot be forecast using available information implies that all these correlations should be very close to zero. This conventional view is partly based on the finding that some obvious predictor candidates have limited forecasting ability. For example, the first three columns in Figure 2 show that a bond's yield level, its lagged monthly return, and its past volatility (measured by the 12-month rolling standard deviation of monthly excess returns) all have low correlations with next month's excess bond return (0.03-0.11). In contrast, **the predictors that we have identified above — the term spread, the real yield, inverse wealth, and momentum — have correlations with the subsequent excess bond return between 0.09 and 0.21**. Note that our momentum variable, which is based on a moving average strategy, has somewhat better forecasting ability than a simple lagged return (which could be used as an alternative proxy for the market's momentum). Finally, **combining the information in these four predictors gives even more accurate return predictions, with a correlation of 0.32.**[6] Steep yield curves, high real yields, depressed stock markets, and rallying bond markets are all positive indicators of subsequent bond market performance.

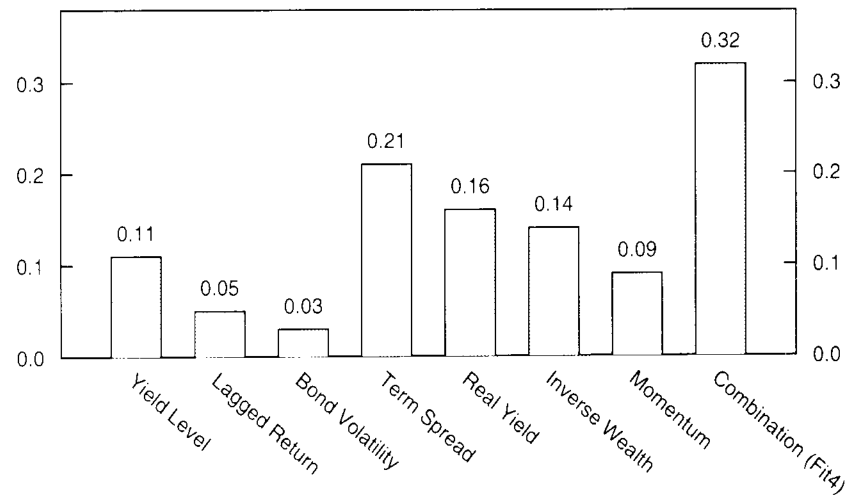
Our predictor variables are financial market data. Many bond market participants are more used to forecasting market movements based on available "fundamental" macroeconomic data. Previous empirical research (see the Literature Guide) suggests, however, that **financial market variables are better predictors of asset returns than macroeconomic variables** such as production growth rates, perhaps because the latter are less accurately measured and less timely. While market-based variables are forward looking (partly reflecting the market's expectations about future

[5] A correlation coefficient measures how closely two series move together. Its possible values range from -1 to 1, where 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation and 0 indicates the lack of any correlation. The square of the correlation coefficient, so-called R^2, measures what part of the variability in a regression's dependent variable (say, excess bond return) the variation in the independent variables explains (or predicts).

[6] The correlations may appear low to those readers that are used to examining contemporaneous relations between bond returns and other variables. It is easy to *explain* a large part of the fluctuations in monthly excess bond returns, but it is very difficult to *forecast* those returns. Because most of the realized monthly excess returns are unexpected, even the optimal predictor will have a low correlation with the realized return. In fact, if the bond risk premium is constant over time, we should expect to see zero correlations between the excess bond return and its predictors, which are known at the beginning of the forecasting month.

economic developments), contemporaneous macroeconomic data describe past events, and with a publication lag. Another finding worth noting from previous studies is the low correlation between various risk measures (such as volatility in Figure 2) and future bond returns; periods of high risk do not seem to provide bondholders with high near-term expected returns.

Figure 2. Correlation of Various Predictors with Subsequent Monthly Excess Bond Return, 1965-95



Correlations are not the only way to show that our predictors can discriminate between good and bad times to hold long-term bonds. In Figure 3, we examine the average monthly returns in subsamples that are based on the beginning-of-month values of the term spread and inverse wealth. **The annualized average excess return is -12.4% in months that begin with an inverted curve and 2.6% in months that begin with an upward-sloping curve** (87% of the time). This finding is consistent with the hypothesis of wealth-dependent risk aversion above. Periods of steep yield curves and high risk premia tend to coincide with cyclical troughs (high risk aversion), while periods of flat or inverted yield curves and low risk premia tend to coincide with cyclical peaks (low risk aversion). **Future bond returns also tend to be higher when inverse wealth is high (the stock market is depressed) than when it is low. Combining the information in these two predictors sharpens our return predictions further. The average excess bond return is higher when an upward-sloping yield curve coincides with a depressed stock market (12%) than when it coincides with a strong stock market (1%).** In the latter case, the curve steepness is more likely to reflect the market's expectations about rising rates than about the required bond risk premium.

Figure 3. Excess Bond Return in Subsamples, 1965-95

Months Begin With	Term Spread > 0	Term Spread < 0
Average	2.63%	-12.40%
No. of Months of Total (%)	87	13

Months Begin With	Inverse Wealth > 1	Inverse Wealth < 1
Average	6.24%	-0.36%
No. of Months of Total (%)	16	84

Months Begin With	Term Sp. > 0 and Inv. Wealth > 1	Term Sp. > 0 and Inv. Wealth < 1	Term Sp. < 0 and Inv. Wealth > 1	Term Sp. < 0 and Inv. Wealth < 1
Average	11.95%	1.23%	-9.76%	-13.60%
No. of Months of Total (%)	12	75	4	9

Note: **Average** is the annualized average of a 20-year bond's monthly excess return in each subsample.

The inverse relation between stock market level and subsequent bond returns may be interpreted in many ways. We proposed earlier that declining wealth level makes investors more risk averse and increases the risk premium that they require for holding risky assets. Alternatively, the relation may be caused by lagged portfolio flows. Poor recent stock market performance can make investors shift money to bonds, either because these are less risky or because investors extrapolate and expect the poor stock market performance to continue. More generally, the time-variation in expected returns may reflect rational factors (time-varying risk or risk aversion level) or irrational factors (such as swings in market sentiment or an underreaction of long-term rate expectations to current inflation shocks).

Another way to think about the patterns on the next-to-last row in Figure 3 is that when *both* bond and stock markets appear to be "cheap" (the term spread is high and inverse wealth is high), investors can rely more on these cheapness indicators and expect high future returns for risky assets. Conversely, when *both* bond and stock market indicators signal "richness" (the term spread is negative and inverse wealth is low), investors can more confidently expect low future returns. In this light, our three first predictors may be viewed as "value" indicators that tend to give buysignals when asset markets are weak. These predictors are complemented by the fourth, momentum, which gives a buysignal when bond prices are trending higher.

Figure 4 shows the regression results for our whole sample period. All four predictors are statistically significantly related to subsequent excess bond returns. The regression coefficients show that the expected excess bond returns are high when the yield curve is steeply upward sloping, the real yield is high, the stock market is depressed, and the bond market has positive momentum. Together, the four predictors capture 10% of the monthly variation in excess bond returns. The fact that 90% of the return variation is unpredictable tells us that even if strategies that exploit these patterns are profitable, they certainly will not be riskless.

Figure 4. Results from Regressing Excess Bond Return on Four Predictors, 1965-95

	Coefficient	T-Statistic
Constant	-10.15	-4.98
Term Spread	0.37	2.24
Real Yield	0.20	2.89
Inverse Wealth	9.85	4.81
Momentum	0.34	2.02
R^2		10.3%

Out-of-Sample Estimation of Return Predictions

The regression splits each month's excess bond return to a fitted part and a residual. The fitted part can be viewed as the expected excess bond return and the residual as the unexpected excess bond return. Because the current value of each predictor is known, we can compute the current forecast for the near-term excess bond return by using the following equation:

Expected Excess Bond Return =
-10.15 + 0.37 * Term Spread + 0.20 * Real Yield + 9.85 * Inverse Wealth + 0.34 * Momentum

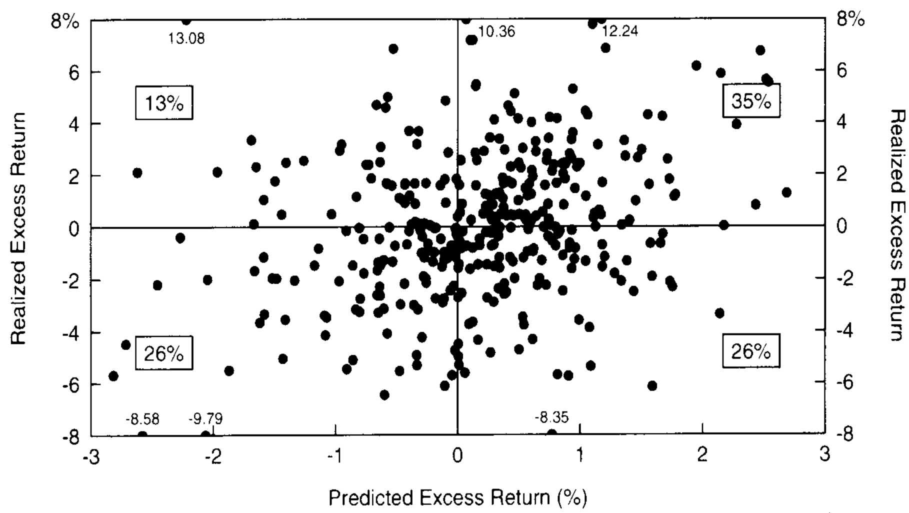
We are only using available information to make this forecast; we combine current values of the predictors with the historical estimates of the regression coefficients. For this reason, we can call this an *out-of-sample* forecast, as opposed to an *in-sample* forecast. As an example of an in-sample forecast, we could combine the predictor values at the beginning of January 1965 with the above regression coefficients and treat the fitted value as the expected excess bond return for January 1965. In doing so, we would be peeking into the future and assuming that investors already knew the above regression coefficients in 1965. In reality, these coefficients were estimated in 1995 using data from 1965 to 1995. The use of in-sample forecasts adds an element of hindsight to the analysis, which leads, at best, to an exaggerated view of return predictability and, at worst, to totally spurious findings. Many investors find the use of in-sample forecasts unrealistic and unappealing.

In general, investors are well advised to be concerned about the potential impact of data-snooping bias when faced with any "exciting" new empirical findings. Data snooping refers to the fact that many investors and researchers are intensively searching for profitable regularities in the financial market data. The bias means that some apparently significant findings are likely to be period-specific and spurious. **We try to guard against such data-snooping bias by conducting out-of-sample analysis, in which the return predictions are made each month using only data that are available at the time of forecasting.** When we make the forecast of the monthly U.S. excess bond return for January 1965, we run a regression using all historical data from January 1955 to December 1964. The forecast (the fitted part of the regression) combines the estimated regression coefficients with the values of the predictors at the end of December 1964. To make the forecast for February 1965, we run another regression which uses data from January 1955 to January 1965. We run these monthly rolling regressions with an expanding historical sample until July 1995. This process gives us a series of monthly out-of-sample excess bond return forecasts.[7]

[7] This approach still leaves one element of hindsight to the analysis: The predictors may have been chosen based on their historical fit. It may be unrealistic to assume that bond analysts chose to focus on this particular set of predictors (out of many alternative sets) a long time ago. We have three answers to such criticism: (1) We can motivate our predictors with economic reasoning; (2) the relation between the predictors and future bond returns is reasonably stable. Data analysis could have alerted investors of these relations a long time ago; and (3) the ultimate test is the predictors' performance with "new" data. We will present some evidence from the 1990s, after the predictive relations were identified.

We begin the evaluation of the out-of-sample forecasts' predictive ability by showing in Figure 5 a scatter plot of realized monthly excess bond returns on the out-of-sample predictions. To enhance visual clarity, we have trimmed the range of the y-axis to (-8%, +8%) and marked six exceptional observations on the borders. If the forecasts tend to have correct signs (realized excess returns are positive when they were predicted to be positive and negative when they were predicted to be negative), most observations will lie in the upper-right quadrant or in the lower-left quadrant. Without any forecasting ability, all quadrants should contain 25% of the observations. Figure 5 shows that the forecasts have the correct sign in 61% (= 35 + 26) of the months. These odds are better than 50-50, but clearly the forecasts are not infallible.

Figure 5. Realized Excess Return versus Predicted Excess Return, 1965-95



The relation between the predicted and the realized excess returns in Figure 5 may not appear very impressive, reflecting the fact that most of the short-term fluctuations in excess bond returns are unpredictable. Perhaps the long-term fluctuations are more predictable; averaging many monthly returns will smooth the return series and may increase the share of the predictable returns. Our unpublished analysis shows that in a scatter plot of the subsequent 12-month realized excess bond returns on the predicted excess returns, 84% of the observations are in the upper-right quadrant or in the lower-left quadrant. Moreover, the correlation between the out-of-sample predictions and the subsequent 12-month excess returns is 0.57, much larger than the 0.26 correlation between these predictions and the subsequent monthly excess returns.

Figure 6 displays a time series plot of the monthly predicted excess returns and the subsequent 12-month average excess returns. We also plot the time series of each predictor variable in Figure 7, to better identify the sources of fluctuations in expected excess bond returns. **Figure 6 shows that the predictions track the movements in the realized bond returns reasonably well.** Both series in Figure 6 were low in the 1960s and 1970s and exceptionally high in the 1982-85 period, reflecting slow-moving changes in the real yield and in the term spread. Aside from these broad movements, both series exhibit apparent business cycle patterns: **The predicted returns tend to increase during cyclical contractions such as those in 1970, 1974 and 1982.** Figure 7 shows that these increases in expected returns as well as those in the aftermath of the 1987 stock market crash (when a recession was widely expected) and in the most recent recession (1990 Gulf War) coincide with inverse wealth spikes, that is, with poor stock market performance. These patterns are consistent with our hypothesis that wealth-dependent risk aversion causes the required bond risk premium to vary over time with economic conditions. However, the negative excess return forecasts in the 1960s, 1973-74, 1979-80, and 1989 are difficult to interpret; most bond market participants think that the bond risk premium is always positive. Finally, **it is worth noting that the forecasting model is currently quite bearish. The excess bond return predictions have been negative since the end of May 1995**, mainly because of the strong stock market (low inverse wealth) and the relatively flat yield curve (low term spread).[8]

Figure 6. Predicted Excess Bond Return and Subsequent Realized 12-Month Excess Bond Return, 1965-95

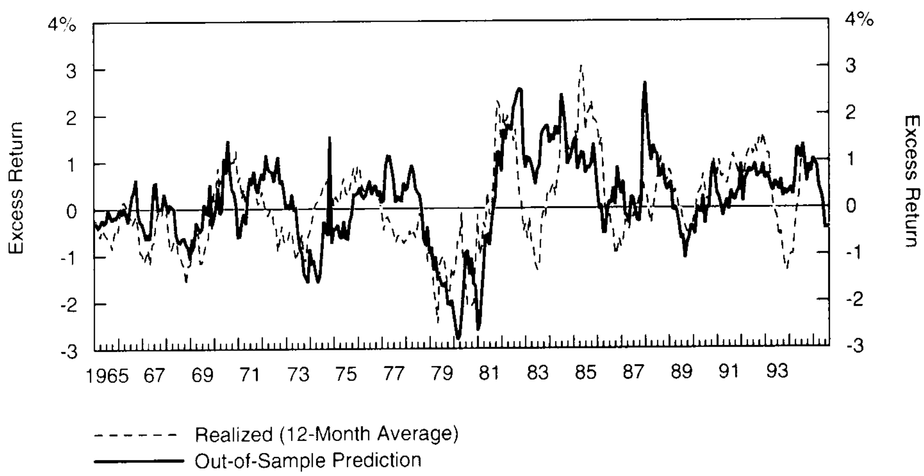
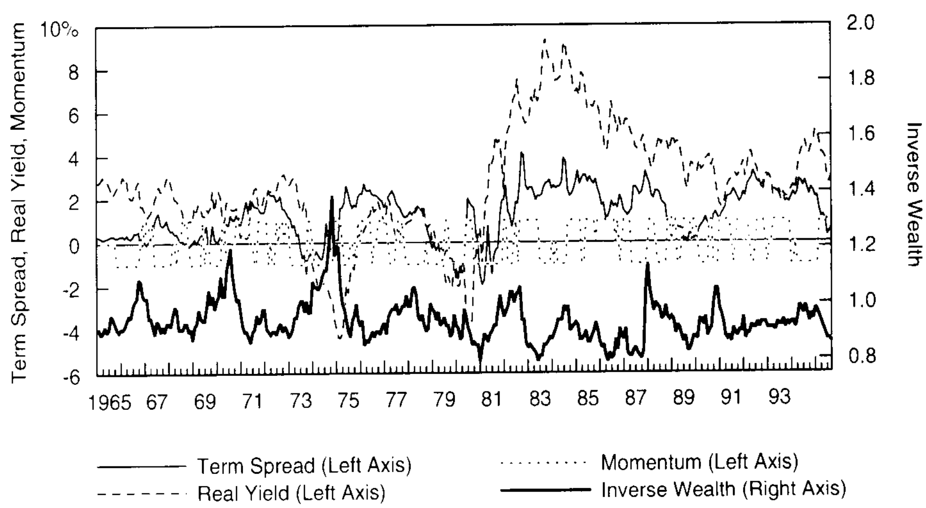


Figure 7. Historical Levels of the Predictor Variables, 1965-95



[8] We reemphasize that the model only produces estimates and that these estimates capture, at best, 10% of the future variation in excess bond returns. Thus, if the *unexpected* economic news in the coming months lowers the market's rate expectations, the bond market may perform well in spite of the low risk premium. The model just signals that the expected return cushion in favor of the long-term bonds now is abnormally low, making these bonds vulnerable to bad news and to a rising risk premium.

Exploiting Return Predictability by Using Dynamic Investment Strategies

Even if the predictor variables appear to have some ability to forecast excess bond returns in an out-of-sample setting, should investors care about these findings? **For portfolio managers, the key question is whether investment strategies that exploit the return predictability produce economically significant profits.** In this section, we first describe the implementation of such dynamic investment strategies and then present extensive analysis of their historical performance. In particular, we compare their historical returns to the returns of static strategies that have a constant portfolio composition regardless of economic conditions. One goal is to show that the information in the yield curve and in other predictors could have been used to enhance long-run returns. Another goal is to provide a tool kit to evaluate the future profitability of any forecasting strategy and a set of critical questions (economic reason for success, stability of success, sensitivity to transaction costs and to risk adjustment) that an investor should ask when faced with backtest evidence of an apparently attractive investment strategy.

The static strategies are called "always-bond" and "bond-cash combination." The former strategy involves always holding a 20-year Treasury bond, while the latter involves always holding 50% of the portfolio in cash (one-month Treasury bill) and 50% in the 20-year Treasury bond, with monthly rebalancing. The dynamic strategies adjust the allocation of the portfolio between cash and the 20-year Treasury bond each month, based on the predicted value of next month's excess bond return. The two dynamic strategies are called "scaled" and "1/0." The 1/0 strategy is simpler: It involves holding one unit of the 20-year bond when its predicted excess return is positive and zero when it is negative (thus, holding cash). This approach ignores information about the magnitude of the predicted excess return. In contrast, the scaled strategy involves buying more long-term bonds the larger the predicted excess return is. Specifically, investors should buy or short-sell the long-term bond in proportion to the size of the predicted excess return.[9]

Strategy returns are expressed in excess of the one-month bill return. For investors who have investable funds, each strategy's total return would be approximately equal to its excess return plus the one-month bill's return (which is the same number for all of the strategies). For arbitrage traders who only hold self-financed positions, the reported excess return can be interpreted as the total return of their "zero-net-investment" position — to the extent that they can finance their positions using the one-month bill rate.

Figure 8 shows, for each strategy, the annualized average excess return, the volatility of excess returns as well as the Sharpe ratio. Note that a cash portfolio earns zero excess return by definition; it is equivalent to holding cash financed with cash. Therefore, the 50-50 bond-cash combination has exactly half of the excess return and volatility of the always-bond strategy. **The static strategies yielded only insignificant excess returns over the sample period. In other words, long-term bonds and short-term bonds earned quite similar average returns. The dynamic strategies**

[9] An example illustrates how the scaled strategy works. If the predicted bond risk premium (BRP) over the next month is 0, the scaled strategy involves buying no long-term bonds, just cash. If the BRP is 1%, the strategy involves buying one unit of the long-term bond, no cash. If the BRP is 2%, the strategy involves buying two units of the long-term bond by using leverage (borrowing cash). If the BRP is -1%, the strategy involves short-selling one unit of the long-term bond and investing the sale proceeds in cash. Because the scaled strategy often involves either leveraging or short-selling, it is much riskier than the 1/0 strategy.

performed much better. The scaled strategy earned almost a 9% average annual excess return while the 1/0 strategy earned about half of that. Also the rewards to volatility (Sharpe ratios) of the dynamic strategies are much larger than those of the static strategies.[10]

Figure 8. Performance of Self-Financed Dynamic and Static Investment Strategies, 1965-95

Dynamic Strategies	
Scaled Strategy	
Average Excess Return	**8.64%**
Volatility	12.80
Sharpe Ratio	0.68
1/0 Strategy	
Average Excess Return	**4.16%**
Volatility	7.92
Sharpe Ratio	0.53
Static Strategies	
Always-Bond	
Average Excess Return	**0.67%**
Volatility	10.42
Sharpe Ratio	0.06
Bond-Cash Combination	
Average Excess Return	**0.33%**
Volatility	5.21
Sharpe Ratio	0.06

Note: **Average excess return** is the annualized average excess return of each strategy over the one-month bill. **Volatility** is the annualized standard deviation of the excess return series. The **Sharpe ratio** is the ratio of the (annualized) average excess return to volatility.

We can compare the performance of the dynamic strategies in Figure 8 with the performance of a dynamic strategy that uses only the information in the term spread. The scaled strategy would have earned 3.87% per annum and the 1/0 strategy 2.96% per annum if the out-of-sample forecasts had been based on the term spread alone. Comparison with the average returns in Figure 8 (8.64% and 4.16%) indicates that the marginal value of the other predictors has been substantial. It is also worth noting that the scaled strategy would have earned 11.15% per annum and the 1/0 strategy 4.94% per annum if the predictions had been based on the in-sample estimates from the regression of excess bond returns on the four predictors. The difference between the performance of the in-sample and the out-of-sample forecasts may reflect the data-snooping bias.

Stability of the Predictive Relations

The analysis above shows, first, that over the past 30 years, our predictors have been able to forecast near-term bond returns and, second, that strategies that exploit such predictability have earned economically meaningful profits. In this section, we examine the stability of these findings over time. If the predictive ability and exceptional performance arise from a couple of extreme observations, we become skeptical about the reliability of these findings. However, if the observed relations are consistent across subperiods, we think that they are less likely to be spurious. Thus, we become more comfortable in expecting that the historical experience (good predictive ability and the dynamic strategies' exceptional performance) will be repeated in the future. We will study three types of evidence: Rolling correlations; subperiod analysis of average returns; and cumulative performance of various investment strategies.

[10] Note that the scaling intensity used in the scaled strategy is arbitrary. More aggressive scaling factors would lead to higher average returns and higher volatilities. Fortunately, the Sharpe ratios do not depend on the scaling factor. Figure 8 shows that the scaled strategy has the highest Sharpe ratios.

Figure 9 shows that estimated rolling 60-month correlations between the predictors and the subsequent bond return are not constant, but they are positive in most subperiods. In the 1990s, the real yield and momentum have had little forecasting ability, but both the term spread and inverse wealth have had predictive correlations near 20%. The combined predictor tends to have better forecasting ability than any of the individual predictors. Similar subperiod analysis shows that the frequency of correctly predicting the sign (+/-) of the next month's excess bond return is reasonably stable and near 60%.

Figure 9. Rolling 60-Month Correlation of Various Predictors with Subsequent Excess Bond Return, 1965-95

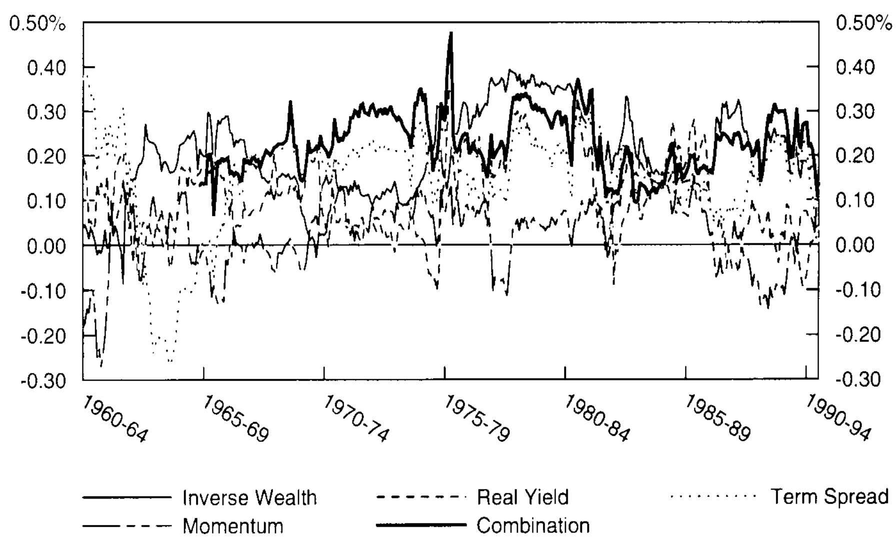


Figure 10 reports the statistics from Figure 8 for three decade-long subsamples and for the 1990s subperiod. It is encouraging to see that the observed patterns are stable across decade-long subsamples. In particular, both dynamic strategies outperform the bond-cash combination strategy by at least 200 basis points in all subperiods.

Figure 10. Subperiod Performance of Various Investment Strategies, 1965-95

	1965-74	1975-84	1985-94	1990-95
Dynamic Strategies				
Scaled Strategy				
Average Excess Return	**4.09%**	**15.29%**	**6.40%**	**5.30%**
Volatility	5.65	20.30	7.32	4.80
Sharpe Ratio	0.72	0.75	0.87	1.10
1/0 Strategy				
Average Excess Return	**0.89%**	**3.20%**	**7.27%**	**6.73%**
Volatility	5.56	8.92	8.66	7.79
Sharpe Ratio	0.16	0.36	0.84	0.86
Static Strategies				
Always-Bond				
Average Excess Return	**-3.13%**	**-1.68%**	**5.62%**	**5.25%**
Volatility	8.35	12.36	10.05	8.28
Sharpe Ratio	-0.38	-0.14	0.56	0.63
Bond-Cash Combination				
Average Excess Return	**-1.57%**	**-0.84%**	**2.81%**	**2.72%**
Volatility	4.18	6.18	5.03	4.14
Sharpe Ratio	-0.38	-0.14	0.56	0.63

The most informative way to display the stability of a predictive relation is to plot the cumulative wealth of an investment strategy that exploits the predictive relation. Such a graph shows how the profits from the strategy grow over time. Note that the cumulative wealth of an ideal perfect-foresight strategy would never decline; moreover, it should also be rising faster than the cumulative wealth of any competing strategies. Alternatively, we can plot the relative performance of two investment strategies, and again, the line representing a perfect-foresight strategy should always be rising (or flat if it matches the performance of the other strategies).

Figure 11 shows the cumulative wealth growth of both dynamic strategies and the always-bond strategy (plotted on a log-scale where constant percentage growth produces a straight line). Because the lines cumulate each strategy's monthly returns in excess of cash (the one-month bill), we also can interpret these lines as relative performance versus cash. Figure 12 measures the relative performance of the two dynamic strategies versus a more realistic benchmark, a 50-50 combination of cash and the long-term bond. These graphs show that **the dynamic strategies have had a consistent ability to outperform the static strategies.** The scaled strategy earned very high returns in the late 1970s and early 1980s by short-selling the long-term bond during the bear market. During the subsequent bull market, the dynamic strategies have earned similar returns as the static bondholding strategy. This result must be viewed as satisfactory, because this bull market has been exceptionally strong and long, making long-term bond returns a difficult target to beat. Figures 11 and 12 show that the dynamic strategies never underperformed the benchmark static strategies for an extended period. And what about the recent experience? The dynamic strategies have outperformed the static strategies in the 1990-95 period — see Figure 10 — but last year (1994) both dynamic strategies underperformed the cash-bond combination because they remained in long-term bonds throughout a period of rising rates.

Figure 11. Cumulative Wealth Growth from Three Self-Financed Strategies, 1965-95

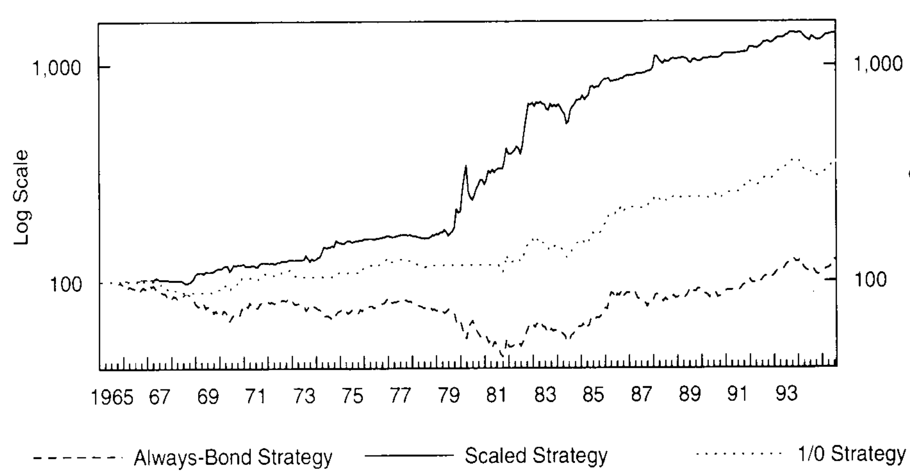
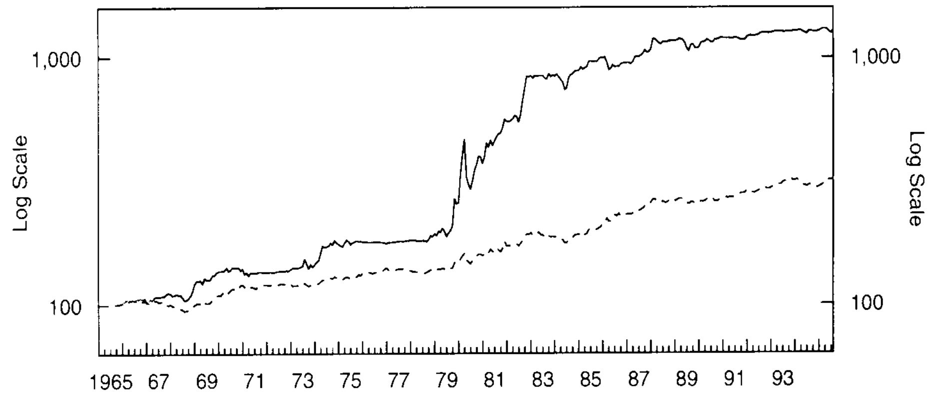


Figure 12. Dynamic Strategies' Relative Performance versus Bond-Cash Combination, 1965-95



Other Critical Considerations

The backtest results suggest that bond investors could enhance their performance substantially by exploiting the forecasting ability of the term spread, the real yield, inverse wealth, and momentum. However, historical success does not guarantee future success. We stress that any reported findings of apparently profitable investment strategies should be subjected to a set of critical questions. We already addressed the important **concern about data-snooping bias** — we used out-of-sample forecasts, we restricted the predictors to economically well-motivated variables, and we ensured that the observed findings are relatively stable across subperiods. Other reservations include **the sensitivity of the findings to transaction costs and to risk adjustment.**

Transaction costs will reduce the profitability of any investment strategy. However, government bonds have such small transaction costs for institutional investors that their impact on the reported returns should be small. In particular, the results of the 1/0 strategy are hardly affected because this strategy involves very infrequent trading — on average 1.5 trades per year. The scaled strategy is more transaction intensive, and it also involves short-selling. Thus, the reported results are somewhat exaggerated.

The dynamic strategies offer higher returns than the static strategies, but they excel even more when the comparison is made between risk-adjusted returns. First, if risk is measured by the volatility of returns, the Sharpe ratios in Figure 8 provide a risk-adjusted comparison. **The volatility of the scaled strategy is higher than that of the static bond strategy, but its reward-to-volatility ratio is more than ten times higher. The volatility of the 1/0 strategy is lower and the average return higher than that of the static always-bond strategy.** Second, if investors are concerned with downside risk, the dynamic strategies will look even better. The historical success of these strategies partly reflects their ability to avoid long-term bonds during bear markets. For example, we can infer from Figure 5 that the 1/0 strategy underperformed cash in only 26% of the months in the sample (outperforming it 35% of the time and matching its performance 39% of the time when the predicted excess return was negative and the strategy involved holding cash). However, if the return predictability reflects a time-varying risk premium, it is possible that the abnormally high returns of the dynamic strategies reflect only a fair compensation for taking up additional risk at times when either the amount of risk or risk aversion is abnormally high.

In spite of the apparent attractiveness of the dynamic strategies, few investors have tried to systematically exploit the predictability of bond returns. For those investors who venture to do that, this fact is good news. The profit opportunities are not likely to be "arbitraged away" any time soon. One major reason is that these strategies are not riskless arbitrages — they involve a lot of short-term risk because the forecasts are wrong 40% of the time. Nonetheless, 60-40 odds are attractive in competitive financial markets. **Therefore, what could make investors forego the exceptionally favorable odds that the dynamic strategies offer?** Here are some possible explanations:

- Many investors prefer the more subjective interest rate forecasting approach even if its track record is rarely good. Other investors believe that market fluctuations cannot be predicted; thus, they do not want to take any market-directional positions. Such investors would attribute our predictability findings to data snooping or to events that the market was expecting but that were not realized during the sample period.

- The potential losses from such strategies may loom larger than the potential gains. The short-term risk in the dynamic strategies may expose portfolio managers to substantial career risk[11] even if the strategies are likely to outperform in the long run. Moreover, the losses may have a tendency to occur at especially unpleasant times.[12] The dynamic strategies' high expected return may be a reward for such discomforts.

Even if some investors find the strategy too mechanical or too risky to be used systematically, they may want to use it *selectively*. For example, they may want to use the strategy only when the signal is very strong. What do historical data say about such an approach? The fact that the scaled strategy outperforms the 1/0 strategy suggests that the magnitude of the predicted excess return contains valuable information beyond the sign. Figure 13 studies whether the return predictions become more reliable when the forecast deviates much from zero. It also reports the average returns at different levels of predicted excess returns. We can see that the frequency of correct-sign forecasts is only weakly related to the absolute value of the forecast. The average excess returns show clearer patterns: large negative values when the predictions are very negative and large positive values when the predictions are very positive.

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[11] First, the dynamic strategy can make the portfolio differ significantly from most peer portfolios. Given the frequent performance evaluations, short-term underperformance relative to a peer group often implies serious career risk. Therefore, portfolio managers may avoid the dynamic strategies because "it is better to lose conventionally than to gain unconventionally." Second, the dynamic strategy works quite slowly. Many traders prefer making many trades with fast outcomes to making one trade with a slow outcome. The former approach allows better diversification (across a large number of trades within a given period) — and smaller career risk — than the latter approach.

[12] For example, the dynamic strategies might systematically underperform during recessions when many investors find it particularly difficult to tolerate losses. However, our empirical analysis shows that the dynamic strategies tend to perform particularly well in "bad times." During cyclical recessions, as defined by the National Bureau of Economic Research, the always-bond strategy earned an annualized average excess return of 6.55%, while the scaled strategy earned 19.75% and the 1/0 strategy earned 9.08%. Similarly, both dynamic strategies tended to outperform the static strategies near business cycle troughs, in months when excess bond returns were negative and following years of exceptionally poor bond market performance.

Figure 13. Impact of the Forecast Signal's Strength on the Return Predictability, 1965-95

	f < -1	-1 < f < -0.5	-0.5 < f < 0	0 < f < 0.5	0.5 < f < 1	f > 1
Frequency of Correct-Sign Predictions	65%	63%	65%	53%	57%	67%
Average Excess Return	-15.68	-3.80	-8.57	3.92	4.15	15.66
No. of Months of Total (%)	9	11	19	25	21	15

Note: **f** is the beginning-of-month out-of-sample forecast of the 20-year bond's monthly excess return, expressed in percent per month. **Average excess return** is the annualized average of the 20-year bond's monthly excess returns within each subsample, in percent.

Impact of Investment Horizon

We suggested above that the dynamic strategies may involve an unacceptably high risk of short-term underperformance (see footnote 11). However, the long-run performance of these strategies should make them very appealing for investors who can afford to take a long investment horizon. In this section, we focus on the impact of investment horizon on the attractiveness of the dynamic strategies. The crucial question we address is: **How long a horizon is long enough for investors to be confident that these strategies outperform cash and/or bonds?** Recall that the out-of-sample forecasts of next *month's* excess bond return have a correct sign in 61% of the months in the sample (see Figure 5). Increasing the investment horizon from one month makes the dynamic strategies look better and better. For example, Figure 14 shows that the scaled strategy outperformed the always-bond strategy in 23 calendar years out of 30 in this sample, and the 1/0 strategy underperformed the always-bond strategy in only two calendar years (and matched it in ten other years when it kept holding the long-term bond).

Figure 14. Annual Excess Returns of Three Self-Financed Strategies, 1965-94

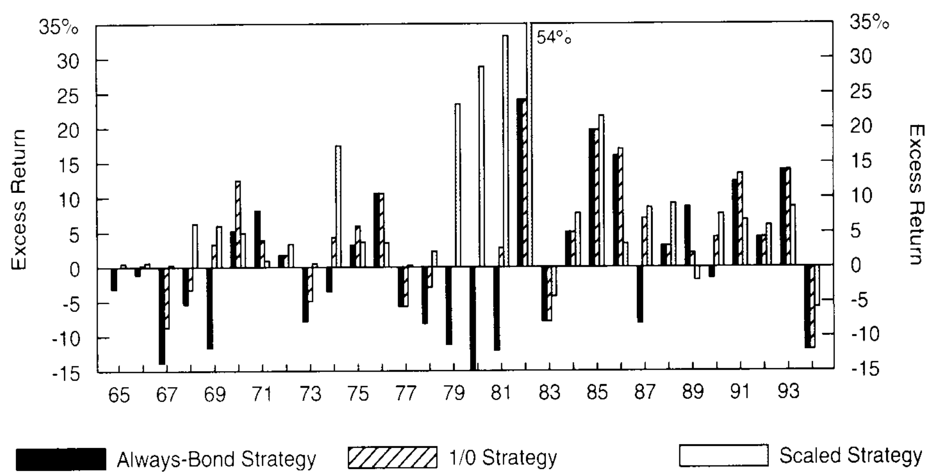


Figure 15 shows — for various horizons — the frequency at which the dynamic strategies outperformed or matched cash, the long-term bond or both. The longer horizon numbers are based on overlapping monthly data.[13]

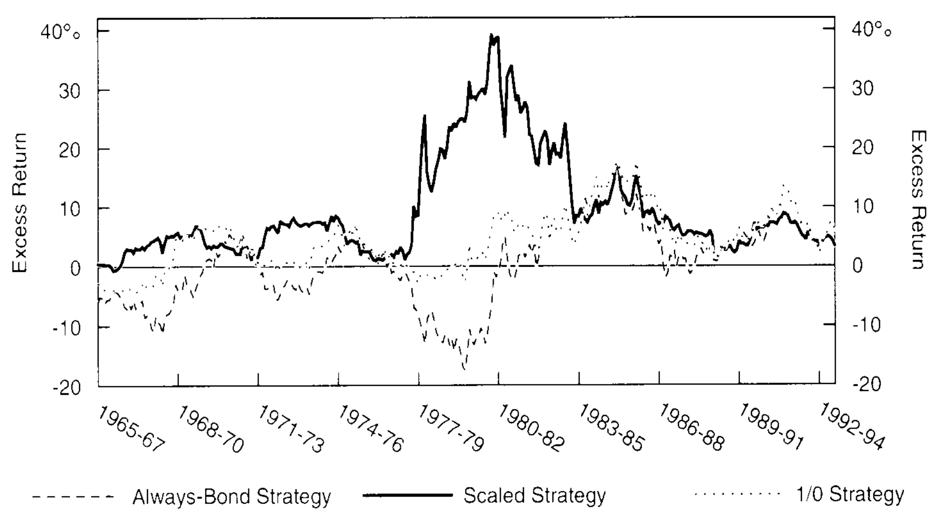
[13] For example, the evaluation at the five-year horizon compares the holding-period returns of various investment strategies between January 1965 and December 1969, February 1965 and January 1970, March 1965 and February 1970, ... until August 1990 and July 1995. There are a total of 307 overlapping five-year periods. (Recall that each strategy may involve monthly rebalancing: the dynamic strategies use the predictions to adjust the portfolio, the bond-cash combination is rebalanced to 50/50 shares and even the always-bond strategy requires occasional rebalancing so that the portfolio maturity does not deviate too much from 20 years.) The last row in Figure 15 reports how frequently — that is, in what part of the 307 five-year periods — the dynamic strategies beat or matched the performance of cash, bond or both.

Focusing on the toughest comparison, the dynamic strategies outperformed **both** bonds and cash in roughly 60% of the one-year periods in the sample. For the three-year horizon, the frequency increases to about 80% of the sample, and for the five-year horizon to 92%. In a way, the dynamic strategies would have provided a free outperformance option for long-term investors. Figure 16 illustrates this point by showing the rolling 36-month excess return for each strategy. If the dynamic strategies outperform both cash and bonds, their excess returns should lie above the excess returns of cash (zero line) and the always-bond strategy. This is roughly what we see in the graph. We conclude that although historical analysis provides no guarantee about the future and although backtest results are rarely achieved in real-world investments, the odds in favor of the dynamic strategies appear excellent for three- to five-year investment horizons.

Figure 15. Impact of the Horizon Length to the Strategy's Success Rate, 1965-95

	Scaled Strategy			1/0 Strategy		
Horizon	Beat/ Match Cash	Beat/ Match Bond	Beat/ Match Both	Beat/ Match Cash	Beat/ Match Bond	Beat/ Match Both
Month	61%	56%	35%	74%	86%	61%
Quarter	68	61	46	71	85	58
Year	84	69	58	73	87	64
Three Years	99	86	85	82	91	73
Five Years	100	92	92	94	97	92

Figure 16. Rolling 36-Month Excess Returns of Three Self-Financed Strategies, 1968-95



In this report, we have shown that long-term bond returns are predictable. A set of four predictors — yield curve steepness, real bond yield, recent stock market performance, and bond market momentum — is able to forecast 10% of the monthly variation in long-term bonds' excess returns. Thus, when making inferences about the yield curve behavior, bond market analysts should not assume that the bond risk premium is constant over time. **The bond risk premium may be small, on average, but we can identify in advance periods when it is abnormally large or small. A forecasting model gives us an estimate of the near-term bond risk premium — but even the best models' estimates are subject to various errors. Nevertheless, such models can be valuable tools for long-term investors.** We find that dynamic investment strategies that exploit the bond return predictability have consistently outperformed static investment strategies over long investment horizons.

There are **many ways to implement** investment strategies that exploit return predictability. This report presents two dynamic strategies (scaled and 1/0) that shift funds between cash and a long-term bond based on the sign and the magnitude of the return prediction. One alternative way to implement the strategy is through active duration management using on-the-run Treasury bonds or bond futures. An investor could modify his portfolio duration dynamically based on the magnitude of the return prediction. The range of durations would depend on the investor's risk aversion level and on his confidence in the proposed strategy. Figure 17 gives an example of how various investor types (aggressive, moderate, conservative) with a neutral benchmark duration of four years could vary their portfolio's target duration with economic conditions. Of course, more conservative implementation would reduce the potential for return enhancement.

Figure 17. Implementing the Strategy: From Return Predictions to Target Portfolio Durations

Predicted Excess Bond Return	Target Duration for an Aggressive Investor	Target Duration for a Moderate Investor	Target Duration for a Conservative Investor
Negative	-2	0	3.0
Low	1	2	3.5
Average	4	4	4.0
High	7	6	4.5
Very High	10	8	5.0

The analysis in this report focuses on the predictability of the excess return of a 20-year U.S. Treasury bond using four predictor variables. Obviously, **the analysis could be extended in various directions:**

- One might improve the forecasts by using **a broader set of predictors** or by combining their information in a more sophisticated way than a simple linear regression. However, our small set of predictors may have more robust forecasting ability in an out-of-sample setting than a broad predictor set would. We have not found other predictors that consistently and significantly improve the forecasting ability of our four-predictor model.

- One can examine the return predictability over **a shorter investment horizon** than one month. The predictors we use above may be too slow-moving for short-term traders. They often prefer to trade either on their fundamental views or on momentum and overreaction effects (price trends and reversals) or on other technical factors (supply effects and portfolio flows). It might be a good idea to subject even these trading approaches to the performance evaluation proposed in this report.

- One can examine the return predictability of **other government bonds**. We show elsewhere that our predictors can also forecast the excess returns of shorter-maturity bills and bonds in the United States and that similar variables forecast international bond returns (see the Literature Guide).

- One can examine **the predictability of the relative performance of various bond market sectors** and markets (changes in the yield spreads across maturities, across market sectors and across countries). In this report, we combine the information in the term spread and other predictors to improve our forecasts of excess bond returns. In a similar way, we could combine the information in mean-reverting yield spreads and in other predictors to develop better relative value indicators. **The tools presented in this report also can be used to evaluate the forecasting performance of various relative value indicators.**

Extensive literature exists discussing the predictability of bond, stock, and currency returns and the dynamic (or "tactical asset allocation") strategies that try to exploit the return predictability. We focus here on studies about bond return predictability.

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