Earnings Forecasts and the Predictability of Stock Returns: Evidence from Trading the S&P*

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Abstract

We develop a simple error-correction model, based on a well known theory espoused by Benjamin Graham and David Dodd, and others, which presumes stock returns tend to restore an equilibrium relationship between the forecasted earnings yield on common stocks and the yield on bonds. The estimation uses I/B/E/S analysts forecasts of S&P earnings. To evaluate the model, we use rolling regressions to obtain out-of-sample forecasts of excess returns. Tests of association show the implicit timing signals to be statistically significant. Further, a strategy of investing in cash when the excess return is forecasted to be negative and in the S&P otherwise outperforms the S&P, yielding higher returns with smaller volatility. Using the bootstrap methodology we demonstrate that the findings are statistically significant.

KEYWORDS: Asset allocation, earnings yield, analyst earnings forecasts, I/B/E/S, S&P 500, market timing, regression models.

JEL Classification System: G11, G14.

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Introduction

Among academic researchers, conventional wisdom regarding the predictability of stock prices has shifted dramatically over the past couple of decades. While early empirical evidence favored the random walk hypothesis for stock returns, accumulating empirical evidence now suggests that stock returns are, in fact, partly predictable. The initial trickle of evidence in favor of predictability, obtained by examining the univariate time series properties of stock prices (Lo and MacKinley, 1988; Poterba and Summers, 1988), has been supplemented by convincing evidence that financial and accounting variables appear to have predictive power for stock returns. (See Keim and Stambaugh, 1986; Fama and French, 1988, 1989; Campbell and Shiller, 1988; Jaffe, Keim, and Westerfield 1989; and Lakonishok, Shleifer and Vishny, 1994.)

Clearly, such evidence could have important implications for market timing or active asset allocation strategies. Whether stock returns are sufficiently predictable at horizons relevant for such strategies to be sensible once trading costs are considered, however, remains contentious. For example, Fuller and Kling (1994) suggest that, despite some predictive power, market timing strategies would likely not be useful to practitioners. Larsen and Wozniak (1995) present alternative elaborate specifications using logit models with a large number of parameters. However, market participants could have scarcely been expected to be aware of, let alone implement their complex approach. Yet, Brock, Lakonishok and LeBaron (1992) report that simple technical trading rules, fashioned around techniques championed by market practitioners over several decades, appear to provide useful market "buy" and "sell" signals even in the recent past. They do not, however, evaluate the performance of such rules, adjusting for trading costs.

In this paper, we provide new supporting evidence that simple trading strategies based on investment concepts long enunciated by market practitioners could indeed be useful to gauge the direction of future stock prices and to time the market. We investigate a well-known security valuation theory that presumes a simple relationship between earnings yields and yields on government and high-grade corporate bonds. We formalize this theory in a statistical framework and evaluate how trading rules based on this approach would fare under real trading conditions. To that end, we limit our attention to simple regression models and focus our evaluation on out-of-sample forecasts based only on real-time data.

In particular, our approach considers whether stocks are appropriately valued relative to analysts' perceptions of future earnings and yields on alternative investments. The documentation of the usefulness of earnings forecasts and price-to-earnings ratios in this regard has a long history. In the 1951 edition of *Security Analysis*, for instance, Graham and Dodd provide annual comparisons of the Dow-Jones Industrial and a "central value" obtained by comparing historical earnings yields and high-grade corporate bond yields. As explained in their 1962 edition,

> Theoretical analysis suggests also that both the dividend yield and the earnings yield on common stocks should be strongly affected by changes in long-term interest rates. It is assumed that many investors are constantly making a choice between stock and bond purchases; as the yield on bonds advances, they would be expected to demand a correspondingly higher return on stocks, and conversely as bond yields decline. (*Security Analysis*, 4th edition, 1962, p. 510.)

Exhibit 1 depicts the yield on constant maturity 30-year Treasury bonds and our construction of a forecasted earnings yield that aggregates analysts' forecasts. The strong visual correlation suggests continued validity to Graham and Dodd's observation.

Some other recent studies use model specifications that are close in spirit to the observations of Graham and Dodd. Campbell and Shiller (1988) show that averages of past earnings yields have some power to predict future equity returns. However, past earnings serve only as a proxy for forecasted earnings yields in this framework. Indeed, Graham and Dodd note that "[T]he proper *theoretical* basis for valuing the Dow-Jones Unit or an individual common stock is to estimate average *future* earnings and to capitalize that figure at an appropriate rate." (1951, p. 671, emphasis in the original). Reiterating this distinction, Molodovsky (1953) also carefully distinguishes between current earnings and "earnings power" (reflecting expected future earnings) in discussing stock valuation.

In practice over the last 18 years, market practitioners have had access to actual analyst earnings forecasts from which to compute a forecasted earnings yield. In this paper, we compute such a monthly forecasted earnings yield series for the S&P 500 index, use the resulting series in simple regressions to predict the return on the S&P, and evaluate the usefulness of the month-ahead forecasts with a simple trading rule. Specifically, we use a simple error-correction model that predicts the return of the S&P based on the deviations from a presumed equilibrium between forecasted earnings yields and yields on bonds. The trading rule uses out-of-sample forecasts from rolling samples such that a money manager could have implemented it in real time. The sole determination of the investment direction is whether the forecast of the excess return of the S&P is positive–in which case all funds are invested in the S&P–or negative–in which case all funds are invested in cash. We provide estimates and evaluations of the resulting trading rules using several alternatives for the maturity of the long-term bonds and the length of the sample period used in our rolling regression analysis and report all results. Statistically, the rule correctly identifies which months to be in and out of the market relative to the null hypothesis of no market timing ability. The rule also generates returns that are both higher on average even after deducting trading costs and less volatile than those of the alternative of buying and holding the S&P.

We examine the significance of the higher returns and lower volatility under our model-based rule using the bootstrap methodology. We find that under most specifications the model-based trading rule generates a cumulative return that exceeds that of random timing rules at statistical significance levels below 5%. We also find that the volatility of returns under our trading rule is significantly lower than expected under random market timing.

Thus, while the rule is designed to significantly outperform random market timing regarding the level of returns it also achieves the additional benefit of reduced volatility of returns. The relatively consistent results among trading rules suggests that the results are robust to alternative specifications of the model.

Methodology

Our forecasting model is best motivated by the principle that the expected earnings yield on stocks and the yield on bonds should be closely linked, on average. We express this as a simple linear equilibrium relationship between the equilibrium expected earnings yield, EP^*, and bond yield, R.

$$EP_t^* = a_0 + \rho R_t$$

Potentially, this equilibrium could be violated when, for instance, the current stock price overreacts or underreacts relative to shifts in fundamentals. Using the Graham and Dodd terminology, the equilibrium relationship is best identified for the "central value" of stock prices, while actual prices may deviate from this "... 'central value' or 'justified selling price.' " (1962, p. 511). We denote the deviation between the actual and equilibrium earning yields by e_t.

$$EP_t - EP_t^* = e_t$$

The theory predicts that investors reallocate assets in response to this disequilibrium causing stock prices to move in the direction that reduces the deviation. If so, and to the extent the full adjustment is not immediate, stock returns can be represented as:

$$SPRET_t = b_0 + \kappa e_{t-1} + \epsilon_t$$

where b_0 is the unconditional expected stock return, κ the speed of adjustment to the equilibrium expected earnings yield consistent with the bond yield, and ϵ_t is the unforecastable part of the period's return. Combining all three equations yields the following regression model:

$$SPRET_t = \alpha + \kappa(EP_{t-1} - \rho R_{t-1}) + \epsilon_t \tag{1}$$

where $\alpha = b_0 - \kappa a_0$.

Needless to say, partially predictable returns that owe to the temporary deviation of the earnings yield from its hypothesized equilibrium level need not indicate market inefficiency. Instead, a time-varying risk premium could, in principle, be the driving factor of this term.[1]

Data

Since the end of 1978, on the morning of the third Friday of each month, I/B/E/S has published consensus analyst forecasts of earnings-per-share that correspond to one unit of the S&P 500 index. The "Bottom-Up" forecasts we employ for the S&P are created by I/B/E/S as a weighted average of the earnings-per-share forecasts for all of the companies comprising the index. On each release date except in January, I/B/E/S reports an estimate of earnings-per-share for the previous calendar year and forecasts for the current and next calendar years. The January release includes estimates of earnings for the previous two calendar years and a forecast for the current calendar year.[2] Each month, we combine the latest I/B/E/S calendar year earnings estimates and forecasts to form $AEPS$, an estimate of the expected average monthly earnings for the 24-month period centered around that month.[3] We construct the earnings yield variable, EP_t, required for estimating equation 1 as the ratio $AEPS_t/P_t$, where P_t is the month-ending level of the S&P.

[1]Fama (1991) elaborates on this point. Here, such considerations could in principle be modeled by abandoning the constant unconditional expectation of expected stock returns, b_0, in favor of a more complicated time series process or relation to other variables.

[2]Individual companies report their actual earnings per share with varying lags. The estimates for the entire S&P 500 index only become finalized several months after the end of the year in question, after all companies have reported.

[3]For example, the March 1995 value for $AEPS$ is computed using data published by I/B/E/S on March 17, 1995 as 10/24 of the estimated 1994 earnings plus 12/24 of the forecasted 1995 earnings plus 2/24 of the forecasted 1996 earnings.

Our regression model also requires the effective yield to maturity on a long-term bond; in alternative specifications, we present results using month average yields of the 3-, 7-, 10-, and 30-year maturity Treasury bonds and Moodys' Aaa-rated long-term corporate bonds as the variable R_t. Most consistent with the theoretical framework are the longer maturities. From these, comparison of the results using the 10-, and 30-year Treasury benchmarks with those obtained by employing Moodys' Aaa-rated yield allows us to examine the sensitivity of the results to the implicit risk premium in non-Treasury debt. We included the 3-, and 7-year benchmark yields to examine the sensitivity of the results to using shorter maturities recognizing that the short duration of the 3-year Treasury yield makes it the least consistent with the theory.

For the dependent variable in the regression, $SPRET$, we use the total monthly return on the S&P, inclusive of dividend payments. For the regression analysis, we standardize all yield variables and the S&P return by converting them to a 30.5-day monthly effective basis. In our trading rule analysis, we employ the actual monthly return on the S&P as would be appropriate to evaluate actual performance. The trading rule also requires that we compare the forecasted S&P return to the risk-free yield for which we employ the effective return on the one-month Treasury bill, adjusting it for the correct number of days.

Exhibit 2 reports summary statistics of the variables used in our analysis. The sample period 1979-1996 in the top panel corresponds to all years for which complete data are available. The bottom panel reports statistics for the period 1984-1996 corresponding to the time frame over which our out-of-sample trading rule is in effect. (Our rolling regression models require the earlier years of data for estimation.) For most variables in the exhibit, we report statistics on their one-month lagged values to correspond to their use in our regression analysis.

The yield variables (S&P return, and earnings and bond yields) are reported on a 30.5

day monthly basis, in percent. As can be seen, the S&P return inclusive of dividends averaged 1.401 percent on a monthly basis during the 1979-1996 period. In the worst month, October 1987, the total return on the S&P was -21.877 percent. The average S&P return far exceeded that of the risk-free return, 0.592 percent as well as yields on Treasuries with maturities of 3-, 7-, 10-, and 30-years and Moodys' Aaa-rated corporate industrial bonds. The relatively small value of the risk-free return helps explain why random market timing is unlikely to be fruitful. The Aaa-rated bonds had the highest mean yield among the bonds examined, 0.816 percent. The average earnings yield over this period was 0.724 percent, similar in magnitude to the Treasury yields.

Estimation

As a first step for evaluating the predictability of stock returns using our model, we present estimation results based on the full sample and describe the associated in-sample properties of the predicted one-month returns.

Exhibit 3 presents results for the 1979-1996 sample period and also for the shorter 1984-1996 period. Each row presents estimates for a specification of equation 1 based on the alternative bond yield variables shown. As anticipated, higher bond yields lead to lower subsequent expected returns (for constant earnings yields) and higher earnings yields lead to higher subsequent expected stock returns (for constant bond yields). What is surprising, perhaps, is the strength of the statistical results for the smaller sample period. In all five regressions, the coefficient estimates of both κ and ρ are positive as expected, and their t-statistics exceed three. And as indicated by the summary statistics in the last columns of the exhibit, the implied predictability of stock returns in these specifications captures generally about 10 percent of the variance in stock returns. The regression results for the longer sample period are not as strong; the summary statistics indicate that the models explain only half as much of the variance. This result, however, is not unexpected as the parameters of the equilibrium relationship between expected earnings yields and bond yields in a model as simple as this could be expected to change slowly over time.[4]

We use these regressions to develop forecasts of S&P returns in order to implement a trading rule. Our trading rule is to invest all funds in either the S&P or cash, according to which one has the higher expected value. In addition to the in-sample forecasts obtained from the regressions shown in exhibit 3, we estimated rolling regressions to generate one-month-ahead out-of-sample forecasts of the S&P for the 1984-1996 test interval. Recursive use of rolling regressions for forecasting recognizes that money managers could not have had the data from which to estimate the fixed parameters used for our in-sample forecasts and also that the parameters of the model might be varying over time. An additional issue we investigate is whether the model's predictive power is sensitive to the sample length used in each of the rolling regressions. To that end, we present results using estimation horizons of 48 and 60 months to test the robustness of our approach.

Exhibit 4 depicts the risk-free return and in-sample and out-of-sample predicted returns for the S&P, generated using the 30-year Treasury specification. The depicted out-of-sample predictions use a 60-month estimation horizon. For either the in-sample or out-of-sample implementations, the intersections of predicted S&P and the risk-free return lines indicate recommended switches between cash and the S&P. As can be seen, although the in-sample and out-of-sample predictions are not identical, their overall pattern is similar suggesting that the timing recommendations from the two specifications would be predominantly in agreement.

[4] In describing their central tendency for stock prices in 1962 Graham and Dodd indeed argue that different multipliers (the equivalent of our parameter ρ) appear appropriate for the 1950s relative to the 1940s. (p. 745, 1962).

Market Timing

To assess the market timing ability of trading rules based on our model, we examine the frequency under which the rule correctly and incorrectly gives out-of-the-market and in-the-market signals. Exhibit 5 reports these contingency table results. The first two panels correspond to the in-sample regressions, and the last two panels correspond to the out-of-sample forecasts using 48-month and 60-month rolling regressions. Within each panel, each row corresponds to alternative specifications in which a different constant maturity Treasury yield or the Aaa-rated yield is used in the regression. The first column reports the number of months out of the market specified by the trading rule; recall that out-of-the-market months occur when the predicted excess return is negative.

The next two columns report for out-of-the-market months, the frequency that the actual excess return was positive and negative. Columns 4-6 report the same statistics for in-the-market months.

For example, in the case of the out-of-sample forecasts using 60-month rolling regressions and the 30-year Treasury yield specification, there were 27 out-of-market months. During 16 of those months the excess return on the S&P was negative (as predicted) and during 11 of those months it was positive. For this same specification, there were 129 in-the-market months. During 87 of those months, the excess return on the S&P was positive (as predicted) and during 47 of those months it was negative.

The last column reports the p-value from Fisher's exact one-tailed test of association. The null hypothesis is that the sign of the actual excess return on the S&P is not associated with the sign of the predicted excess return from our model. As can be seen, under each model specification for the in-sample regressions for the 1979-1996 period, the null hypothesis of no predictive ability is rejected at the 1 percent level of significance. For the out-of-sample models using either the 48-month or 60-month rolling samples, the null hypothesis is rejected at significance levels ranging from 1 to 10 percent as shown.

Another noteworthy feature of the out-of-sample results is that while the rules based on the Treasury yield specifications provide out-of-market signals with roughly similar frequency (about 25 percent of all months for the 48 month horizon and 20 percent for the 60 month horizon) the rules based on the Aaa yield provide about 30 percent fewer signals. Clearly, the implicit risk premium in non-Treasury debt introduces some differences in the performance of the trading rules. Such a difference could arise, for instance, if the difference between the equilibrium and the actual earnings yields (which determine the likelihood of out-of-market signals) are correlated with the spread between the Treasury and corporate yields.

Trading Rule Performance

Given the timing ability of our model demonstrated in Exhibit 5 our next step is to examine whether trading rules based on these timing recommendations would be superior to a buy-and-hold strategy. Exhibits 6 and 7 examine profitability measures from a trading rule that places all funds either in the S&P or in cash depending on which is the forecast with the highest return. The rule produces superior returns both relative to those earned under buying and holding the S&P and relative to random market timing implementations.

Exhibit 6 plots the geometric average of the monthly returns associated with the rule when out-of-sample forecasts are generated using rolling regressions, against the number of the months the rule recommends to stay out of the market. To assess the statistical significance of the timing rule returns, we used stochastic simulations to obtain a distribution of comparable returns from random timing rules specifying the number of months to be out of the market but picking these months at random. The solid line on exhibit 6 represents the median return from 10,000 random market timing implementations. The median return is a decreasing function of the number of out-of-market months because on average and for most months the risk-free return is less than the S&P return. The dashed lines correspond to the 5th and 95th percentiles of the distribution of returns from the simulations. As can be seen by comparing our model results to the upper dashed line, a test based on this bootstrapping technique rejects the hypothesis that random timing could achieve results comparable to those based on our timing rule at about the 5 percent or lower level under all model specifications.

Exhibit 7 presents the complete results for all our in-sample and out-of-sample tests. The left three columns pertain to the months that the rule specifies a cash position; the middle three columns to the months that the rule specifies being in the S&P; and the last four columns report principal ratios (P-ratios). The P-ratio is the accumulated value of a $1 initial investment following the rule divided by the principal that would have accumulated from buying-and-holding the S&P over the same time period; hence, a P-ratio exceeding one indicates superior performance. To ensure that our results would be representative of actual trading strategies, we also provide statistics adjusting for roundtrip trading costs of 0.5% whenever the trading strategies call for reallocating assets between cash and the S&P.[5] These are shown in the adjusted P-ratio column in the exhibit. The entries in the expected P-ratio column correspond to the median P-ratios from 10,000 stochastic simulations based on random timing. As such, they provide a benchmark for comparison adjusting for the fact that random timing should be expected to yield a P-ratio below 1. The corresponding p-values show the fraction of P-ratios of the random timing simulations which exceeded the P-ratios obtained from our rule. As a result, they correspond to p-values associated with a one-sided test of the hypothesis that the results obtained from our timing rule are merely due to chance.

[5]For investors facing taxes, our trading rule returns would be negatively impacted owing to higher turnover and superior gains. The results we report are exact for tax-exempt investors such as managers of pension plan assets.

The in-sample results suggest the rule is quite effective. For the 1979-1996 sample, depending on the model specification, the number of months out of the market range from 26 to 36 months (12 percent to 17 percent) of a total of 216 months. The geometric mean of the S&P total return during those months is negative for all specifications. For the Aaa-rated bond specification, the average S&P return is -1.23 percent during out-of-market months compared to 1.66 percent during in-market months. The P-ratio is 1.75 (the transaction-cost adjusted P-ratio is 1.67) compared to an expected value of .81 for a random market timing strategy that has an equal number of out-of-market months. The second to last column reports p-values indicating the likelihood that our results were merely due to chance. For the 1979-1996 in-sample regression and specification using the Aaa-rated corporate bonds, the p-value rejects this hypothesis at below the .0005 level.

The in-sample results over the shorter 1984-1996 sample are also impressive. For all specifications out-of-market months comprise about 25 percent of the total 156 months. Under all model specifications, mean returns of the S&P for those months are negative and the P-ratios range from 1.17 to 1.51 compared to expected P-ratios under .80. The associated p-values range from .002 to .034.

The bottom panels pertain to the results of the rule based on out-of-sample predictions from rolling regressions. The results remain much the same. For the 48-month rolling regression approach, out-of-market months range from 30 to 42 months out of 156 total months depending on the specification, and the mean S&P return is close to zero or negative for each specification. The P-ratios range from 1.05 to 1.37, and the associated p-values range from .004 to .071. For the 60-month rolling regression approach, there are fewer out-of-the-market months under each specification than when the 48-month rolling sample is used. Otherwise, the results are similar. The P-ratios ranging from 1.17 to 1.33 are well above unity and the p-values range from .011 to .039 indicating rejection of the null hypothesis that our rule is no more likely to produce high returns than any random market timing rule.

Exhibits 8 and 9 evaluate the riskiness of our trading rule as measured by the standard deviation of its returns compared to returns under the alternative of buying and holding the S&P and random market timing rules with an equal number of out-of-market months. As in exhibit 6, exhibit 8 pertains to the rule when out-of-sample forecasts are generated using rolling regressions. The solid and dashed lines correspond to the median and 5th and 95th percentiles from the distribution of standard deviations under 10,000 random market timing implementations. The drop off in the dashed line representing the 5th percentile reflects the fact that in a small number of months the returns were extremely large in absolute value, and the more out-of-market months there are, the more likely the 5th percentile will exclude all such months.

Under all model specifications, the standard deviation of returns is lower than 4.2 percent per month as it was for the S&P 500 over the entire sample period. Moreover, the standard deviation of returns were in all cases less than the median standard deviation of the random market timing implementations. The bootstrapping test for risk rejects the null hypothesis that the standard deviation of returns for our rule has the same expected value as a random market timing implementation at about the 5 percent confidence level. We show results for all such tests in exhibit 9. For both in-sample and out-of-sample tests and for all model specifications, the standard deviation of the returns under our rule are much lower than for the S&P. The standard deviations under our rule ranged from 3 to 3.7 percent per month, considerably lower than that of the S&P. The last two columns report the bootstrap results. The standard deviation for most specifications is significantly lower than expected under random market timing; the p-values range for the out-of-sample implementations of our trading rule range from .007 to .034.

The lower than expected standard deviation of returns obtained from our trading rule suggests that the superior performance in terms of return is not obtained at a cost of additional risk. Indeed, these results suggest that our trading rule recommends staying out of the market disproportionately more frequently when the return on the S&P exhibits large deviations from its average rather than when it exhibits small deviations. A likely explanation is that the conditional variance of stock returns may be increasing in the difference between the equilibrium and the actual earnings yield. Then, stock return volatility will tend to be larger in exactly those months when our model is more likely to trigger an out-of-the-market recommendation.

Summary

We formalize Graham and Dodd's observation that common stock and bond valuations are linked by an equilibrium relation between forecasted earnings yields and bond yields and that stock prices tend to move to restore deviations from this equilibrium. With the resulting model we obtain one-month-ahead forecasts of S&P 500 returns and implement a market timing trading rule that alternates between the S&P and cash. For the 1984-1996 sample period, the trading rule performed well compared to the alternative of buying and holding the S&P 500 and yielded significantly higher returns (in a statistical sense) than what would be expected by pure chance. Surprisingly, the rule also tended to produce returns with significantly lower variance.

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Exhibit 1

Expected Earnings Yield and 30-year Treasury Bond Yield

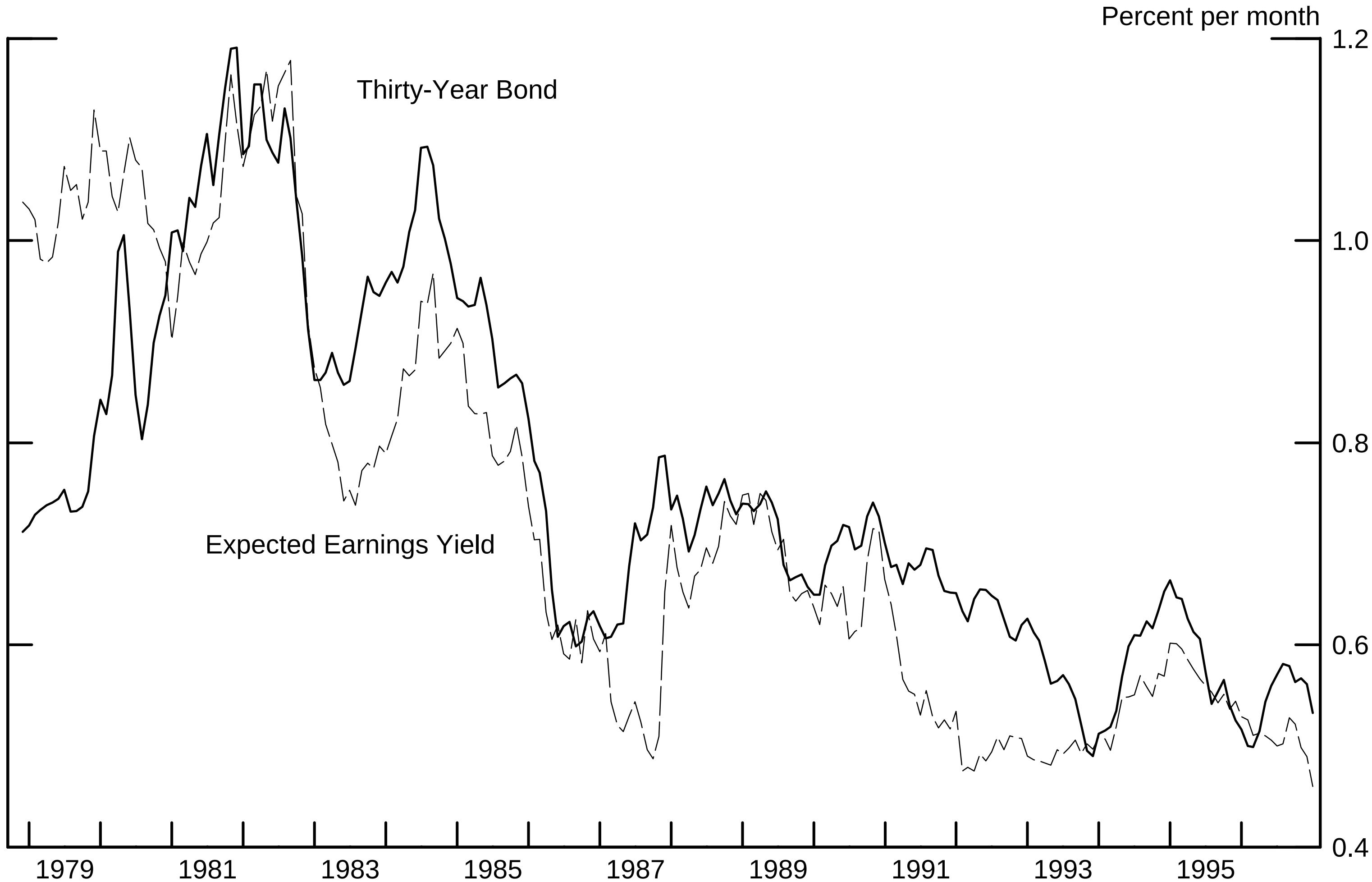


Exhibit 2
Summary Statistics

Variable	Mean	S.D.	Min	Q1	Median	Q3	Max
Sample: 1979-1996							
Expected Earnings (-1)	1.926	0.637	0.991	1.406	1.724	2.269	3.564
S&P Price (-1)	295.211	159.469	96.110	153.070	272.760	415.150	757.020
Expected earnings yield (-1)	0.724	0.208	0.460	0.540	0.662	0.887	1.178
Riskfree return	0.592	0.254	0.221	0.420	0.555	0.725	1.364
S&P 500 return	1.401	4.207	−21.877	−0.844	1.534	3.826	13.587
Treasury yields (-1)							
3-year (-1)	0.709	0.227	0.346	0.534	0.678	0.860	1.312
7-year(-1)	0.743	0.204	0.418	0.582	0.707	0.882	1.267
10-year (-1)	0.751	0.196	0.441	0.597	0.717	0.885	1.241
30-year (-1)	0.760	0.176	0.490	0.623	0.726	0.891	1.191
Aaa yield (-1)	0.816	0.176	0.549	0.685	0.769	0.960	1.255
Sample: 1984-1996							
Expected Earnings (-1)	2.172	0.582	1.387	1.569	2.161	2.355	3.564
S&P Price (-1)	360.596	140.082	150.550	252.360	344.960	450.720	757.020
Expected earnings yield (-1)	0.621	0.124	0.460	0.515	0.589	0.701	0.968
Riskfree return	0.477	0.156	0.221	0.381	0.458	0.595	0.901
S&P 500 return	1.349	4.172	−21.877	−0.754	1.494	3.714	13.587
Treasury yields (-1)							
3-year (-1)	0.612	0.163	0.346	0.498	0.606	0.693	1.072
7-year(-1)	0.660	0.153	0.418	0.553	0.644	0.726	1.102
10-year (-1)	0.672	0.148	0.441	0.568	0.648	0.734	1.102
30-year (-1)	0.690	0.135	0.490	0.606	0.659	0.739	1.093
Aaa yield (-1)	0.746	0.128	0.549	0.656	0.729	0.792	1.102

NOTES: All variables except the S&P price are in percent monthly rates. All variables except the risk-free rate and the S&P return are lagged one month to match the sample employed in the estimation and trading rule analysis. Bond yields are month average. Means are calculated on an arithmetic basis.

Exhibit 3
In-sample Model Estimates

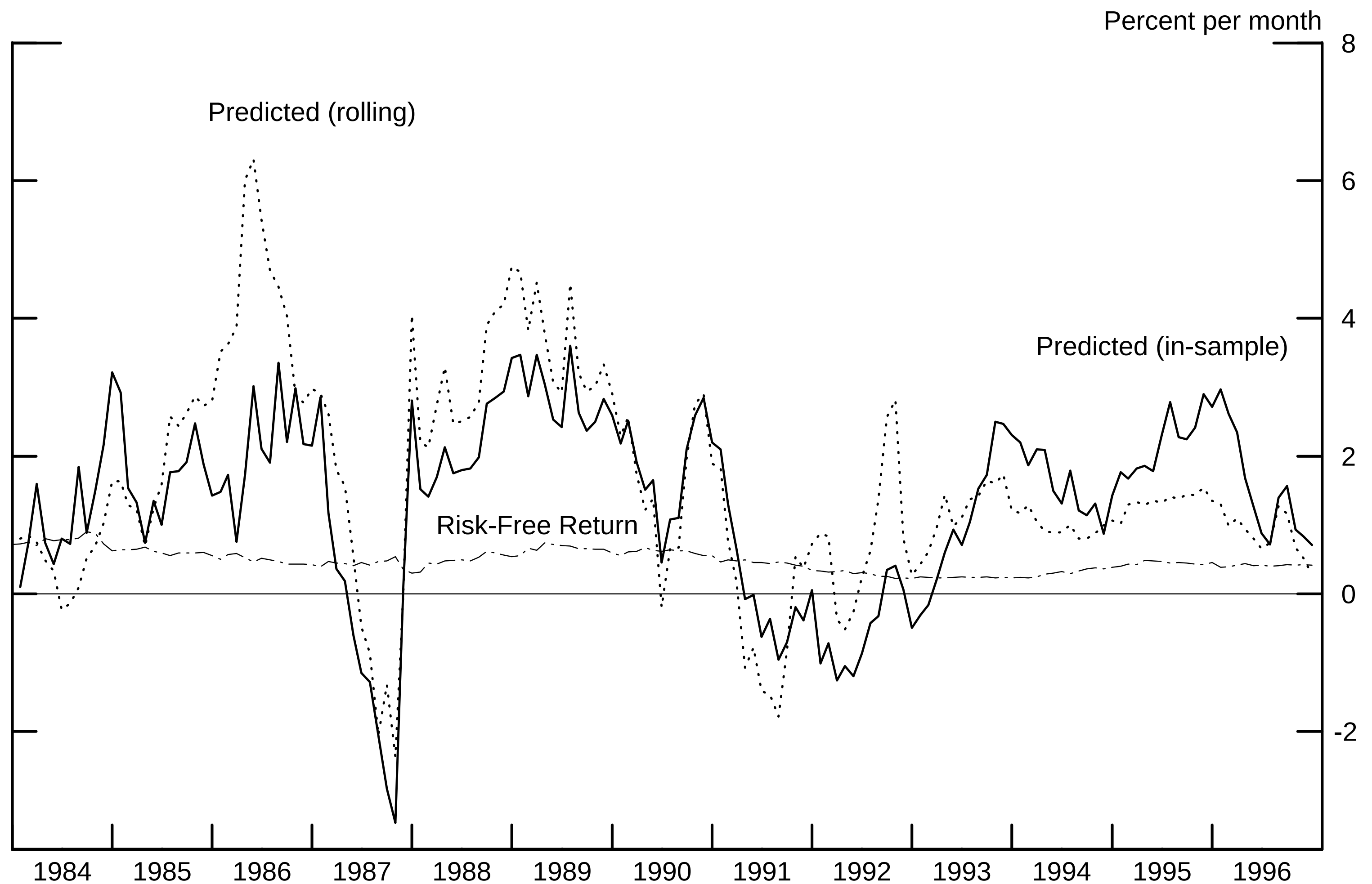
$$SPRET_t = \alpha + \kappa(EP_{t-1} - \rho R_{t-1}) + \epsilon_t$$

Model	Parameter Estimates			Summary Statistics		
	α	κ	ρ	R^2	$\bar{R}^2$	SEE
In sample: 1979-1996						
3 year	0.387	9.612	0.873	0.047	0.038	4.126
	(1.019)	(2.995)	(0.130)			
7 year	1.404	8.589	0.975	0.044	0.035	4.133
	(1.080)	(2.780)	(0.163)			
10 year	1.715	8.329	1.015	0.043	0.034	4.135
	(1.122)	(2.732)	(0.176)			
30 year	2.360	7.439	1.122	0.039	0.030	4.144
	(1.257)	(2.585)	(0.220)			
Aaa	2.542	6.549	1.101	0.032	0.022	4.160
	(1.366)	(2.519)	(0.250)			
In sample: 1984-1996						
3 year	−3.594	25.291	0.695	0.085	0.073	4.017
	(1.794)	(6.711)	(0.078)			
7 year	−2.130	28.864	0.758	0.108	0.097	3.965
	(1.644)	(6.702)	(0.072)			
10 year	−1.277	27.759	0.784	0.107	0.095	3.968
	(1.626)	(6.484)	(0.078)			
30 year	0.533	24.282	0.851	0.097	0.085	3.991
	(1.695)	(6.011)	(0.098)			
Aaa	2.605	26.523	0.896	0.101	0.089	3.981
	(1.899)	(6.393)	(0.094)			

NOTES: Least squares regression. All variables are measured in percent per month. Standard errors in parentheses.

Exhibit 4

Predicted S&P and Risk-Free Returns



NOTES: The predicted S&P returns correspond to regressions using the 30-year Treasury Bond yield. The in-sample predictions correspond to the fixed regression over the 1984-1996 sample period. The rolling predictions are out-of-sample predictions from 60-month rolling regressions.

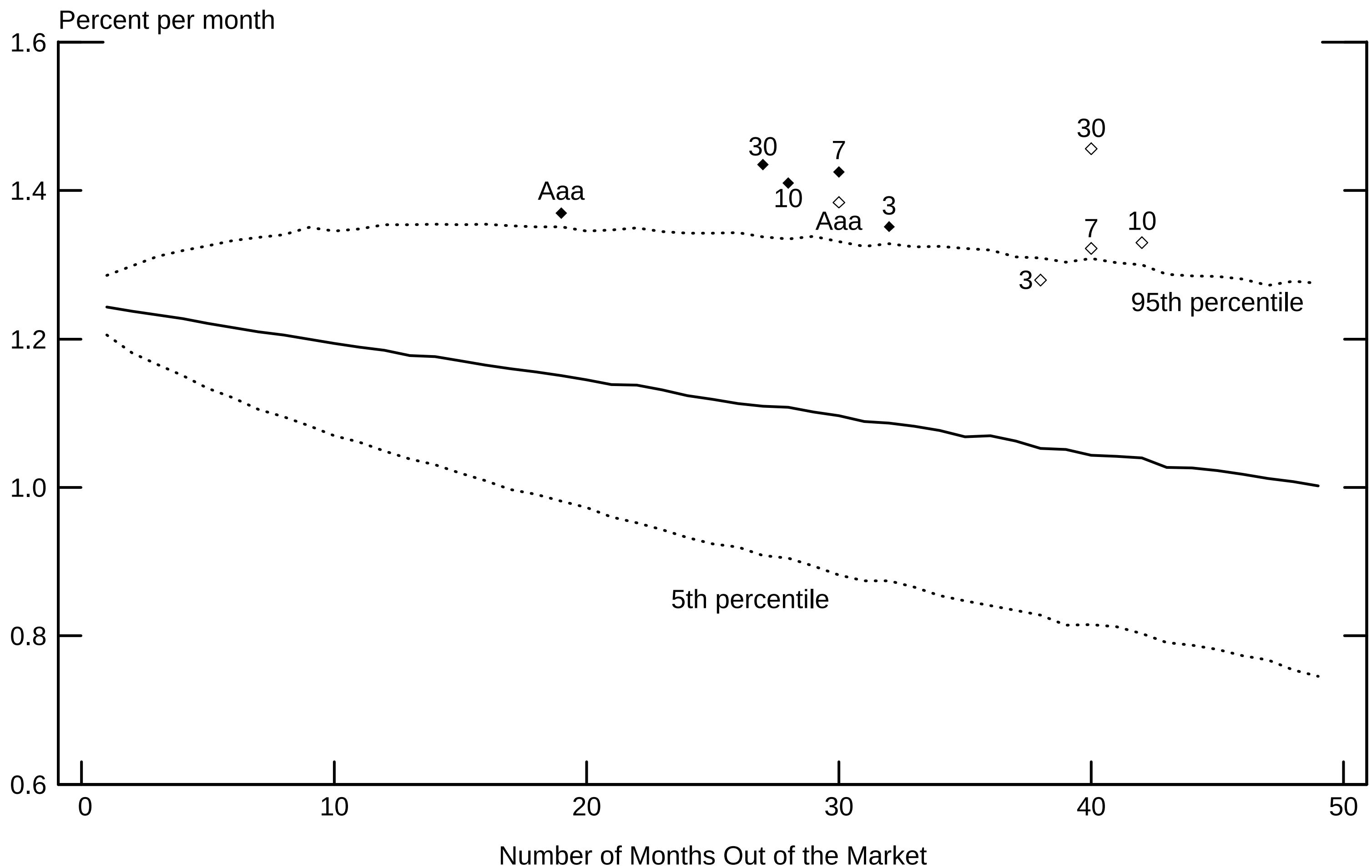
Exhibit 5
Trading Rule Market-Timing Ability Test Results

Model	Out-of-market months			In-market months			Association
	Number	Excess Return		Number	Excess Return		Exact Test
	of months	> 0	< 0	of months	> 0	< 0	p-value
In sample: 1979-1996 (216 months)							
3 year	36	15	21	180	118	62	0.007
7 year	34	13	21	182	120	62	0.002
10 year	33	13	20	183	120	63	0.004
30 year	32	12	20	184	121	63	0.003
Aaa	26	8	18	190	125	65	0.001
In sample: 1984-1996 (156 months)							
3 year	33	17	16	123	81	42	0.096
7 year	37	16	21	119	82	37	0.005
10 year	39	18	21	117	80	37	0.011
30 year	38	19	19	118	79	39	0.047
Aaa	35	19	16	121	79	42	0.162
48 month rolling: 1984-1996 (156 months)							
3 year	38	20	18	118	78	40	0.097
7 year	40	18	22	116	80	36	0.006
10 year	42	19	23	114	79	35	0.005
30 year	40	17	23	116	81	35	0.002
Aaa	30	13	17	126	85	41	0.013
60 month rolling: 1984-1996 (156 months)							
3 year	32	15	17	124	83	41	0.031
7 year	30	13	17	126	85	41	0.013
10 year	28	12	16	128	86	42	0.015
30 year	27	11	16	129	87	42	0.009
Aaa	19	8	11	137	90	47	0.043

NOTES: Out-of-market and in-market months correspond to the dictates of our trading rule. When the predicted S&P return is less than the risk-free return, the rule specifies being out of the market; otherwise, the rule specifies being in the market. The significance statistics are Fisher exact right-tailed test p-values.

Exhibit 6

Expected and Actual Geometric Mean of Trading Rule Returns



NOTES: The solid line indicates the average monthly return over the 1984-1996 period which would have been expected by randomly selecting to be out of the market for a specific number of months. The clear and solid diamonds denote the actual average return generated from the trading rules based on our 48-month and 60-month rolling regression models, respectively. The labels indicate the yield variable used.

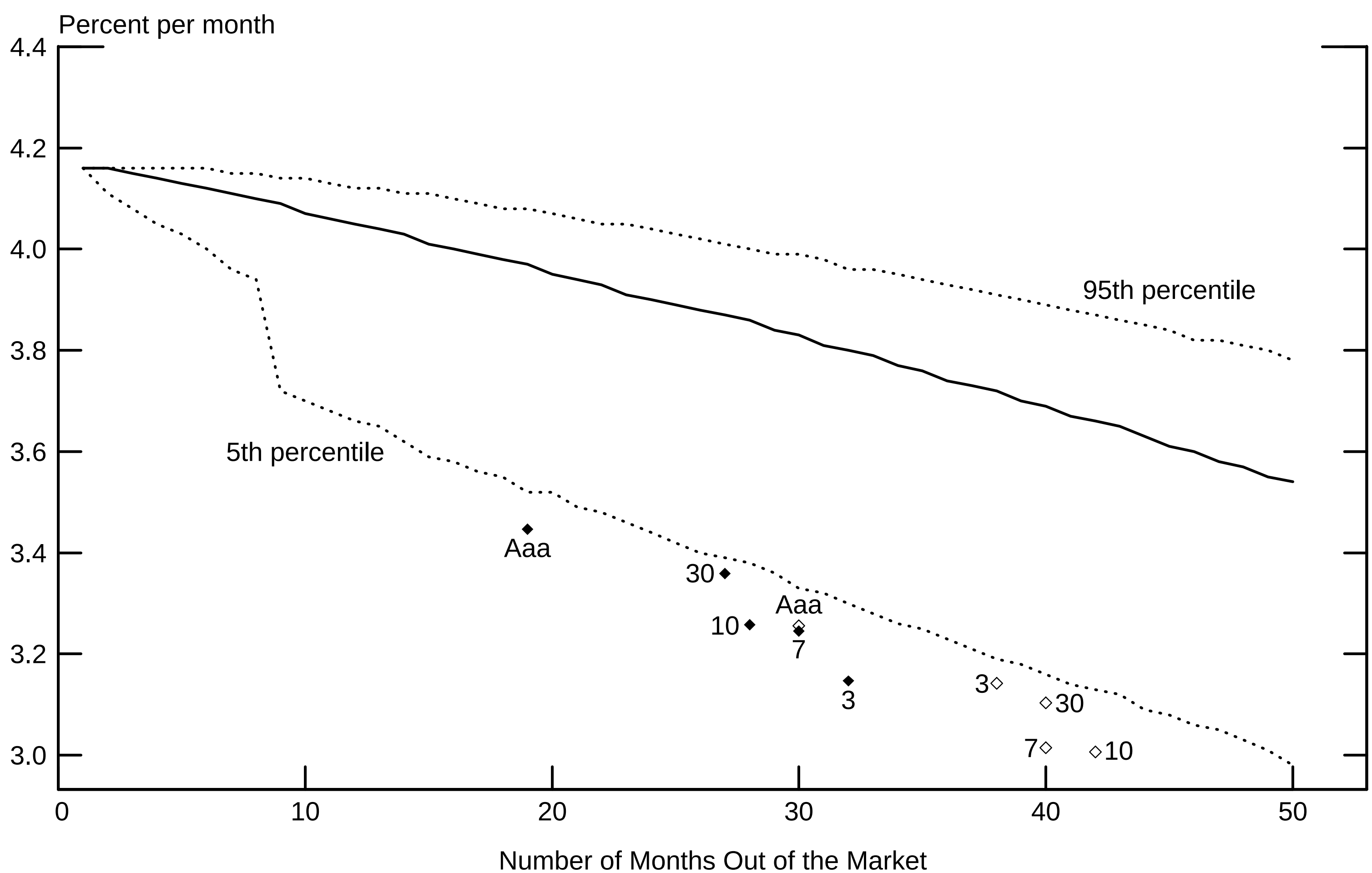
Exhibit 7
Trading Rule Profitability Results

Model	Out-of-market months			In-market months			Principal Ratio Statistics			
	Number of months	Mean S&P return	Mean risk-free return	Number of months	Mean S&P return	Mean risk-free return	Actual P-ratio	Expected P-ratio	p-value	Adjusted P-ratio
In sample: 1979-1996 (216 months)										
3 year	36	−0.08	0.87	180	1.58	0.54	1.41	0.75	0.006	1.35
7 year	34	−0.29	0.85	182	1.61	0.54	1.47	0.77	0.004	1.41
10 year	33	−0.28	0.86	183	1.59	0.54	1.45	0.78	0.004	1.40
30 year	32	−0.36	0.87	184	1.60	0.54	1.48	0.78	0.003	1.43
Aaa	26	−1.23	0.91	190	1.66	0.55	1.75	0.81	0.000	1.67
In sample: 1984-1996 (156 months)										
3 year	33	−0.06	0.47	123	1.60	0.48	1.19	0.77	0.028	1.15
7 year	37	−0.64	0.47	119	1.85	0.48	1.51	0.75	0.002	1.44
10 year	39	−0.32	0.45	117	1.78	0.49	1.36	0.74	0.005	1.28
30 year	38	−0.17	0.44	118	1.71	0.49	1.26	0.74	0.011	1.21
Aaa	35	−0.02	0.42	121	1.62	0.49	1.17	0.76	0.034	1.12
48 month rolling: 1984-1996 (156 months)										
3 year	38	0.44	0.56	118	1.51	0.45	1.05	0.74	0.071	0.99
7 year	40	0.26	0.53	116	1.60	0.46	1.12	0.73	0.043	1.07
10 year	42	0.23	0.53	114	1.63	0.46	1.13	0.72	0.032	1.09
30 year	40	−0.26	0.53	116	1.78	0.46	1.37	0.73	0.004	1.34
Aaa	30	−0.17	0.52	126	1.59	0.47	1.23	0.79	0.023	1.19
60 month rolling: 1984-1996 (156 months)										
3 year	32	0.08	0.57	124	1.56	0.45	1.17	0.78	0.036	1.13
7 year	30	−0.26	0.56	126	1.62	0.46	1.28	0.79	0.015	1.23
10 year	28	−0.31	0.57	128	1.60	0.46	1.28	0.80	0.014	1.24
30 year	27	−0.52	0.53	129	1.63	0.47	1.33	0.81	0.011	1.28
Aaa	19	−0.42	0.55	137	1.49	0.47	1.20	0.86	0.039	1.17

NOTES: Out-of-market and in-market months correspond to the dictates of our trading rule. When the predicted S&P return is less than the risk-free return, the rule specifies being out of the market; otherwise, the rule specifies being in the market. Mean returns are calculated on a geometric basis. The expected P-ratios and p-values are produced using the bootstrap methodology from 10,000 random market timing rules. The adjusted P-ratios assume .5 percent roundtrip trading costs.

Exhibit 8

Expected and Actual Standard Deviation of Trading Rule Returns



Notes: The solid line indicates the standard deviation of the monthly returns over the 1984-1996 period which would have been expected by randomly selecting to be out of the market for a specific number of months. The clear and solid diamonds denote the actual standard deviation generated from the trading rules based on our 48-month and 60-month rolling regression models, respectively. The labels indicate the yield variable used.

Exhibit 9
Trading Rule Volatility Results

Model	Months	Standard Deviation of Returns			
	Out	S&P	Actual	Expected	p-value
In sample: 1979-1996 (216 months)					
3 year	36	4.19	3.61	3.88	0.106
7 year	34	4.19	3.61	3.90	0.084
10 year	33	4.19	3.62	3.91	0.077
30 year	32	4.19	3.61	3.92	0.069
Aaa year	26	4.19	3.70	3.97	0.078
In sample: 1984-1996 (156 months)					
3 year	33	4.16	3.28	3.79	0.045
7 year	37	4.16	3.26	3.73	0.079
10 year	39	4.16	3.29	3.70	0.125
30 year	38	4.16	3.32	3.72	0.141
Aaa year	35	4.16	3.33	3.76	0.100
48 month rolling: 1984-1996 (156 months)					
3 year	38	4.16	3.14	3.72	0.029
7 year	40	4.16	3.02	3.69	0.008
10 year	42	4.16	3.01	3.66	0.011
30 year	40	4.16	3.10	3.69	0.025
Aaa year	30	4.16	3.26	3.83	0.019
60 month rolling: 1984-1996 (156 months)					
3 year	32	4.16	3.15	3.80	0.007
7 year	30	4.16	3.24	3.83	0.016
10 year	28	4.16	3.26	3.86	0.010
30 year	27	4.16	3.36	3.87	0.034
Aaa year	19	4.16	3.45	3.97	0.018

NOTES: Out-of-market and in-market months correspond to the dictates of our trading rule. When the predicted S&P return is less than the risk-free return, the rule specifies being out of the market; otherwise, the rule specifies being in the market. The expected standard deviations of returns and p-values are produced using the bootstrap methodology for 10,000 random market timing rules.