

**DO THE SPREADS BETWEEN THE E/P RATIO
AND INTEREST RATES CONTAIN INFORMATION ON
FUTURE EQUITY MARKET MOVEMENTS?**

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Abstract

We examine the usefulness of the spreads between the e/p ratio of the S&P 500 index and the yields on 3-month and 10-year Treasury securities as indicators of future market conditions. We find that while spreads are not particularly useful in a regression framework, the extreme values of the spreads do contain information on the market outlook. Specifically, for the period of 1967 to 1997, portfolios that only invested in the stock index when the spreads were above their historical tenth percentile levels produced higher average returns (not statistically significant) and lower variances (statistically significant) than the stock index.

Do the Spreads between the E/P Ratio and Interest
Rates Contain Information on Future Equity
Market Movements?

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1 Introduction

In recent years, spreads between the earning/price ratios of some stock market indices (e.g. S&P 500 index) and interest rates have been widely used as indicators for future equity market movements by market practitioners. For example, a number of investment banks have used the spreads in the past few years to justify their bullish outlook for the stock market. Various business publications (Wall Street Journal, Barrons, Business Week are a

few examples) use the spreads in their discussions of the overall market conditions and outlooks as well. Value Line Investment Survey in its market monitor section regularly publishes the current spread, its changes since last week, last quarter, last year, and the level of the spread at last market top, last market bottom, etc.

Academics, on the other hand, tend to be suspicious to any claim that a model can consistently predict future market movements beyond a long-term trend because they generally believe stock prices are on average efficient. E/P ratios and interest rates also appear to be unlikely candidates since they contain only widely publicly available information. While e/p ratios of individual stocks or portfolios are regularly used to explain the stock or portfolio returns,¹ there are only a few papers using e/p ratios or interest rates to forecast the overall market performance. Campbell and Shiller (1998) show that the e/p ratio at the beginning of a 10-year period is negatively correlated to the stock returns for the 10-year period. Lander,

¹A number of studies document the ability of e/p ratios to predict future returns of individual stocks or portfolios. These include Basu (1977), Basu (1983), Chan et al (1991), Cole et al (1996), Dreman and Berry (1995), Fairfield (1994), Fama and French (1992), Fuller et al (1993), Jaffe et al (1989), Kakonishok et al (1994), and Roll (1994).

Orphanides, and Douvogiannis (1997) use linear combinations of e/p ratio and bond yields to predict returns on the S&P 500 index in a regression framework.² Finally, both interest rates and e/p ratios are among the possible explanatory variables in Pesaran and Timmermann's attempt to explain stock market movements (1995). None of these papers, however, have used spreads between the e/p ratio and interest rates or directly evaluated the usefulness of the spreads as indicators for the overall market outlook

The purpose of this paper is two-fold. Our main goal is to examine directly the usefulness of the spreads between the e/p ratio and interest rates as indicators for overall stock market conditions. We will first examine the predictive power of the spread variable in the in-sample regression analysis and out-of-sample forecast comparisons. As known to people familiar with financial market data, regressions with market returns as the dependent variable tend to be characterized by very low R-squares, which makes it difficult to assess the economic significance of such regressions. Further,

²They propose that there is a linear relationship between e/p ratio and bond yields, and when such equilibrium is violated, market prices move SLOWLY back towards the equilibrium level. This slow adjustment of market prices allows the predictive power of their model.

neither approach captures the essence of how spreads are used by practitioners or in the business press. This is because in-sample regression is an exercise to find the correlations between the explanatory variables and the dependent variable which minimize the variance of the residuals, while the out-of-sample forecasting provides some indication whether such regression analysis actually helps reduce forecast errors. In reality, few people consider the spread between the e/p ratio and interest rate the most important variable in forecasting stock returns. Spreads only become prominent in the press when they are in relatively extreme ranges. For these reasons, in the rest of the paper, we focus on “horse races” between the benchmark strategy, which is a buy-and-hold strategy that invests in the stock market index all the time, versus alternative strategies, which can be described as staying invested in the market index most of the time, only switching out occasionally when the spreads between the e/p ratio and some interest rates are below certain thresholds. The “horse races” provide some interesting results.

The second goal of this paper is to compare the predictive power of the spreads when different interest rates are used. Many practitioners have focused on the spreads between the e/p ratio and long-term interest rates.

The most commonly used interest rates are the yields on 10-year or 30-year Treasury securities. Two reasons are typically cited for using long rates: one is that stocks are in general perpetual assets, thus their returns are more likely to be related to yields on long-term bonds; the other is that stock prices are the discounted sum of their future earnings, most of which will only be realized in the distant future; therefore the long-term interest rates are more likely to be related to the discount rate used in valuing stock prices. While these arguments are appealing, neither of them is convincing. For example, one can counter the first reason by arguing that while stocks may be perpetual, the way spreads are often used by practitioners is for short-term decisions, i.e., as indicators for near term (3 to 12 months) market movements. Thus, it is the short rate that matters. Similarly, one can counter the second reason by pointing out that in the discounted earnings model, the proper discount rate to use is the risk-free rate plus the risk premium. There is little reason to expect that the rate on a long-term Treasury security is a good proxy for the discount rate for the future earnings on stocks because the risk premium for the Treasury bond is likely to be very different from the risk premium for stocks. On the other hand, the short rate is, at least, a good proxy for the risk-free rate in the near term. For both of these reasons, short-term interest rates may

be more appropriate to use in evaluating the usefulness of spreads. Because both long rates and short rates may be useful (or useless) from a theoretical standpoint, we try to address the issue empirically. In particular, we provide the portfolio “horse race” results based on using different interest rates in the spread variables.

The rest of the paper is organized as follows. The second section provides regression based results. The third section describes the three portfolios in the “horse race”: the benchmark buy-and-hold portfolio, the switching portfolio using the spread between the e/p ratio and short-term interest rate for the switching signal, and the switching portfolio using the spread between the e/p ratio and long-term interest rate for the switching signal. It then shows the results of the horse race. The fourth section provides some more detailed discussions of the horse race, in particular, the comparison of the market conditions when the switching strategies call for staying in the stock market versus when switching strategies call for staying out of the stock market. It also discusses the possible impact of transaction costs. The fifth section views the switching strategies as following the signals of the spreads – when the spreads are below the switching thresholds, they are interpreted as giving signals that market downturns are likely to happen in

the following month – and examines the quality of the signals. The last section concludes the paper.

2 Regression Analysis

In this section, we use the standard regression analysis to examine whether the spreads between e/p ratios and interest rates can explain some of the variations in the market returns.³ The in-sample regressions subsection uses the entire sample of data for the regression analysis, while the out-of-sample

³An intuitive explanation why spreads may be useful in predicting future returns of stock market indexes goes as follows: Mathematically, let E_t represents the expectation at time t , g_t the growth rate from time t to $t + 1$; then we have the following identity:

$$E_t R_{t+1} = E_t g_t^{p/e} + E_t g_t^e.$$

If the expected future growth rate of the p/e ratio is positively related to the current spread $(e/p)_t - r_t$, then a higher spread leads to higher expected growth for the p/e ratio, thus higher expected market returns. The intuition is that, relative to the interest rate, there is an equilibrium level of the spread, and when the spread is higher than its equilibrium level, the p/e ratio is more likely to grow fast, thus reducing the e/p ratio and the spread towards the equilibrium level, and vice versa.

forecast subsection uses the rolling regression method to generate forecast errors, which provide an indication as how useful the regression models are with real time data.

2.1 In-sample regressions

Our sample covers the time period from January 1962 to December 1997. The dependent variable of the regression is the monthly total returns of the CRSP value-weighted index. We choose the CRSP index (instead of the S&P 500 index) because we need a total return series that includes dividend payouts, which will be important for the horse race in the next section. The total return series of the CRSP index satisfies this criterion, while we have not been able to find a total return series including dividends based on the S&P 500 index. The CRSP index covers more stocks than the S&P 500 index, yet the two indexes are highly correlated: the statistical correlation of the two indexes is in the range of 99 percent. Thus it is reasonable to think the two indexes behave very similarly. The independent variable is the spread lagged by one month. The spreads are calculated as follows: we use the reciprocal of the S&P 500 index p/e ratio reported by Standard

and Poor's as the e/p ratio, in which the earnings are the total earnings of the S&P 500 index companies for the previous four-quarters (earnings for the most recent quarter are typically monthly updated estimation with the end of quarter market capitalizations as the weights), and the price is the latest end of the month price.⁴ Two interest rates are used: one is the short rate, which is the yield on 3-month Treasury bills; and the other is the long rate, which is the yield on 10-year Treasury notes. Both are the most recent weekly averages as of the last Monday of the current month.⁵ For simplicity, when the spreads are calculated using the yields on 3-month Treasury-bills, we call them the short spreads; and when they are calculated using the yields on 10-year Treasury-notes, we call them the long spreads.

A typical regression is in the form of:

⁴For example, the p/e ratio for December 1997 is calculated as follows: the numerator is weighted average of the stock prices in the index at December 31 1997, with the weights updated to the same day; the denominator is the total weighted average earnings of the companies in the index for the fourth quarter of 1996, and the first, second, and third quarter of 1997, with the weights updated to the end of September, 1997.

⁵The reason that yields on 10-year Treasury notes are chosen as the long rates instead of the yields on 30-year Treasury bonds is that in the most convenient data series available to us, the 30-year series did not start until late 1970s, while the 10-year series started at early 1960s.

$$R_{t+1} = a + b\left[\left(\frac{e}{p}\right)_t - r_t\right] + error_{t+1}. \quad (1)$$

As explained in the introduction, the goal of this exercise is not to find a model that best predicts future movements of the market index, but to examine the usefulness of the spread variables in the context they are regularly cited, i.e., the indicative property of the spreads to the general outlook of the overall stock market. For this reason, we purposely restrict our explanatory variables to the spreads only and leave out many other possible explanatory variables in the regression.⁶ Similarly, we restrict the spreads to include only past information, and no attempts to forecast either future interest rates or future earnings are incorporated. This way, the explanatory power of the spreads (if there is any) will not be confused as the consequence of superior forecasts of future interest rates or earnings.

(Insert Table 1 here)

⁶We sometimes allow the lag of the dependent variable to be used in some auxiliary regressions in order that the errors are not serial correlated. The standard tests (AIC, Schwarz) suggest that at most one lag is sufficient for all regression models studied in this paper.

Table 1 summarizes the regression results.⁷ The coefficients on the spread variable in both models are positive, which are consistent with the assertion that higher spreads imply a more favorable outlook for the overall stock market. Nevertheless, only the coefficient on the short spreads (when the 3-month Treasury-bill yields are used as r_t) is statistically significant, while the coefficient on the long spreads (when the 10-year Treasury-note yields are used as r_t) is not. This is in sharp contrast with the fact that usually only the long spreads are cited by practitioners or discussed in the business press.⁸

In a sense, the surprising news here is not that the long spreads are not statistically significant, but that the short spreads are significant. Recall that not only are the spreads public information, but also the earning data consist only of observations from the past. Therefore, the fact that short spreads are significant seems to suggest that some public information is not entirely incorporated in the stock market prices instantaneously. A different interpretation is that while the coefficient for the short spreads is

⁷The standard errors are heteroscedasticity robust estimates.

⁸For simplicity, only results in monthly frequency are reported in the text. We have repeated all the analysis with quarterly data, and the results are qualitatively identical.

statistically significant, it may not be significant economically, in the sense that a regression-based trading strategy may not generate excess returns. The very small R-squares for both regressions provide some support to this interpretation.⁹

2.2 Out-of-sample forecasts

One problem with in-sample regression is that an independent variable can be highly significant in the regression but actually has very little predictive power in out-of-sample forecasts. Given our interest is to assess the usefulness of the spreads as indicators for future stock market movements,

⁹While it is common in regression analysis of financial market data to have the R-square be lower than 10%, an R-square of under 2% is still exceptionally low. The low R-squares are also in sharp contrast to the regressions in the Lander et al, which tend to have R-squares in the range of 6% to 10%. Some possible explanations are: (a) we use a much longer sample of data; (b) we use the spreads between the e/p ratio and interest rates while they estimate the linear combinations of the e/p ratio and interest rates to maximize the R-square; and (c) we purposely do not use a sophisticated model of earnings because we do not want to confuse the explanatory power of the spreads with the explanatory power of estimated earning growth, whereas their earnings data are forecasts for the future.

in-sample regression analysis is not a particularly meaningful exercise. A more informative exercise is to see whether regression-based models provide better out-of-sample forecasts. In this subsection, we provide results based on one-step forecast errors generated by rolling regressions.

(Insert Table 2 here)

The out-of-sample forecast errors are generated as follows: We start with the first five years of data, from January 1962 to December 1966. We run the regression in equation (1) with the five-year data and use the estimated model to forecast expected total returns for the next month, January 1967. The difference between the forecast returns and the realized returns is the one-step ahead forecast error. We then include the data from January 1967 and re-estimate the model, using the updated model to forecast total returns for February 1967, and so on. Table 2 reports the mean errors, the root-mean-square errors, and the mean absolute errors of the one-step ahead out-of-sample forecasts for both the short-spread model and the long-spread model. There is little difference between the performances of the two spreads in out-of-sample forecasts. The model using short spreads is slightly better

than the model using long spreads in terms of mean errors or the root-mean-square errors, but is slightly worse in terms of mean absolute errors. The root-mean-square errors of both models are actually worse than the standard deviation of the dependent variable, 0.4327, which is equivalent to the root-mean-square errors of always using the full sample mean as the one-step ahead forecast. While mathematically it is possible that regression based models can be outperformed by always predicting the full sample mean because the knowledge of full sample mean is not available in real time, this still highlights the poor performances of both models. The poor out-of-sample forecasts are also consistent with the extremely low R-squares in the in-sample regressions.

In summary, the regression analysis suggests that while the spreads between e/p ratios and short interest rates may have better explanatory power than the spreads between e/p ratios and long interest rates, the usefulness of either is dubious.

3 Portfolio Switching Strategies (1)

The results in the second section suggest that while spreads may be statistically significant in regression analysis, their economic significance is fairly marginal. This is somewhat puzzling given the prominence of spreads in the discussions of various practitioners and the press. A more careful look at the way spreads are cited suggests that the regression analysis may miss the point. Practitioners typically do not claim that spreads are highly correlated with future market returns. Instead, they are more likely to use the extreme values of spreads, relative to their historical ranges, as an indication that overall market conditions are unusually vulnerable. In this section, we construct portfolio switching strategies which use extreme values of the spreads as signals to exit the stock market temporarily. We use the historical data to compare the performances of the switching strategy portfolios with a benchmark strategy, which is simply investing in the CRSP index all the time. This way, our evaluation of the usefulness of the spreads can be based on the relative performances the switching strategies to the benchmark strategy.

The switching strategy using the short spread as the switching signal goes as follows. The portfolio starts with \$1 in the CRSP index at the end of January, 1967. At the end of every month, we look at the value of the short spread. If the spread is above the threshold level, to be defined shortly, the portfolio is invested in the CRSP index for the next whole month. If the spread is under the threshold level, the entire portfolio is liquidated at the end of month market price and invested in the 30-day Treasury-bills for the next whole month. Then at the end of the next month, if the spread is still under the threshold level, the portfolio will again be 100% invested in the 30-day Treasury-bills for the following month. If the spread is above the threshold level, the entire portfolio will be moved to the stock market and invested in the CRSP index for the following month. We repeat this process at the end of every month until the end of the sample, which is the end of December 1997.¹⁰ All dividends and interest are reinvested in the portfolio.

We also change the timing of the spread variable slightly by increasing the lag of the earning variable one more month to ensure that the switching

¹⁰Our “horse race” ended at the end of 1997 since the data for 1998 will only be provided by CRSP in April 1999. Nevertheless, we used some crude data and did the “back-of-the-envelope” calculations with 1998 data. We are fairly confident that including data in 1998 will not change any of our results qualitatively.

strategy is implementable in real time.¹¹

The threshold level of the spread is defined in the following way: We use the first five years of data (January 1962 - December 1966) to calculate the value of the spread that was at the 10th percentile point for the first five years and use this value as the threshold. Every month, we add the new observation and update the threshold. The choice of the 10th percentile is arbitrary. We want to choose a number that represents an “extreme range” of the spreads, and the 10th percentile seems pretty extreme. We also repeated the exercise with the 20th percentile. The results are qualitatively

¹¹The current month S&P 500 index p/e ratio is typically reported in the middle of next month. For example, the p/e ratio for May is reported at the middle of June. To make the switching strategy implementable in real time, one possibility is to simply lag the whole p/e ratio for a month. This is equivalent to investors making the portfolio allocation decision at the end of June using the market price of the end of May. We think this is too long a lag. Because market price data are more readily available, we assume when investors making portfolio allocation decision at the end of June, they use the end of May earnings data, which is reported in the middle of June, and the current market prices to calculate the spreads. As a robustness check, we have also simulated the switching portfolios with the entire p/e ratio lagged for a month. Surprisingly, qualitatively nothing changes. That is, the switching portfolios still outperformed the benchmark “buy-and-hold” portfolio.

identical.¹²

The switching strategy using the long spread is similar except the switching signal is based on the long spread. That is, the portfolio stays in the stock market unless the long spread is under the threshold level, which is the updated 10th percentile level for the long spread.

(Insert Table 3 here)

Table 3 shows some statistics of the benchmark portfolio and the two switching portfolios. Both switching portfolios did slightly better than the benchmark portfolio. The mean monthly return for investing in the market all the time for the entire 31 year period was close to 1.1 percent, while the mean monthly return for the switching portfolio with short spreads was almost 1.3 percent and the return for the switching portfolio with long spreads was a bit over 1.2 percent. Nevertheless, the differences are not statistically

¹²We did not, however, repeat the exercise with the 5th percentile. With 5-year of monthly data to start, there are only six observations to define the value of 10th percentile at the beginning of the sample. If we repeat the exercise with the 5th percentile, that will leave us with only three observations to start with.

significant. On the other hand, the sample mean standard deviations of the switching portfolios are much smaller than the sample mean standard deviation of the benchmark portfolio, and statistical tests reject the null hypotheses that the sample variances of either strategies are the same as the sample variance of the benchmark. Furthermore, even though the return differences of the switching portfolios and the benchmark are not statistically significant, they are quite large in an economic sense. One dollar invested in the beginning of 1967 became roughly \$36 at the end of 1997 if kept in the CRSP index all the time; the \$1 would become \$69 by following the switching strategy based on long spreads; and the same dollar would become \$82 by following the switching strategy based on short spreads. The last row of the table shows that the Sharpe ratios of both switching portfolios are higher than the Sharpe ratio of the benchmark portfolio. There are, however, no statistically significant differences between the two switching portfolios either in the means or the sample variances.

(Insert Figure 1 here)

Figure 1 shows the actual dollar values for the benchmark portfolio and

the two switching portfolios from January 1962 to December 1997.

In summary, the horse races between the benchmark portfolio and switching portfolios suggest the following: (1) The switching strategies produce higher returns than the buy-and-hold benchmark index in the historical data. Nevertheless, the differences in the mean monthly returns are not statistically significant. (2) The switching strategies produce lower sample variances than the benchmark index and the differences are statistically significant. (3) Consequently, after adjusting for risk, the switching strategies produce better performances than the benchmark portfolio, which are reflected in the higher Sharpe ratios for the switching portfolios. (4) Finally, while the switching strategy using the short spread appears to produce slightly better risk adjusted returns (a higher Sharpe ratio), the difference is not statistically significant. In this context, spreads using either long rates or short rates clearly contain useful information regarding future market movements.¹³

¹³One natural question to ask is whether the usefulness of the spreads are mainly from their components or from the whole. To find out, we have also conducted horse races using the e/p ratio alone as the switching signal, and using interest rates alone as the switching signals. The portfolio using the e/p ratio alone has slightly lower mean returns and slightly lower sample variance than the benchmark portfolio, and the portfolio using

4 Portfolio Switching Strategies (2)

In this section, we provide some more details about the switching portfolios. We also discuss the issues of transaction costs, and whether there are any differences between the periods when the switching portfolios are out of the market and the periods they are in the market.

(Insert Figure 2 here)

Figure 2 shows the actual log-values of the benchmark portfolio and the switching portfolio using short spreads as the signal, as well as the positions of the switching portfolio. Figure 3 shows the actual log-values of the long rate alone has slightly higher mean returns and slightly lower sample variance than the benchmark portfolio. They both are dominated by switching strategies using either spreads. The portfolio using the short rate alone, on the other hand, performs as well as the portfolio using the short spreads, though a more detailed examination reveals some subtle differences.

the benchmark portfolio and the switching portfolio following long spreads, and the positions of the switching portfolio. The periods that switching portfolios are out of the stock market are marked by bars. As the figures show, the switching strategies did not involve much trading: the switching strategy using short spreads only made 11 “round-trip” trades, or 22 actual trades, for the entire sample period of 31 years. Since we use monthly data, which is equivalent to restricting the switching strategy to making decisions only at the end of each month, the total number of possible trades is the same as the number of months in the sample: 372. The switching strategy using long spreads involved a bit more trading: it made 18 “round-trip” trades, or 36 total, for the 372-month sample period.

(Insert Figure 3 here)

One issue that has not been addressed in the earlier comparison is transaction costs. Transaction costs, however, are unlikely to have a serious impact on our results given that the switching strategies did not involve much trading. For example, if we assume that each trade costs one percent of the total portfolio value at the time, then for the switching port-

folio using short spreads, its end value would be reduced by roughly 20% ($0.99^{22} = 0.8016$), which would be about \$66 instead of \$82 when transaction costs were ignored.¹⁴ Comparing this to Table 3, it is obvious that this portfolio would still produce higher, but statistically insignificant, average returns and statistically lower variance, as transaction costs have a negligible effect on the sample variance of the portfolio. The impact on the switching portfolio using long spreads would be bigger because the signal produced by the long spreads induces more trades. The same assumption of one percent transaction costs would lower the end value of the switching portfolio with long spreads by about 30% ($0.99^{36} = 0.6964$), to about \$48, still higher than the benchmark. Similarly, its sample variance would still be significantly lower than that of the benchmark. In sum, the main conclusions in the last section are not affected by incorporating transaction costs.

(Insert Table 4 here)

¹⁴One percent seems a reasonable average. While it is fairly easy to buy or sell no load S&P 500 index funds nowadays, it was more costly during the earlier years of our sample period.

Because both switching strategies produce portfolios with lower sample variances, one might suspect that instead of predicting lower mean returns, the extreme values of the spreads may be better at predicting periods with higher volatilities of the stock market. Table 4 provides some summary statistics of the benchmark stock index on the time periods when the switching strategies were out of the stock market versus when they were in the market. Surprisingly, even though the sample variances for the benchmark index tended to be higher during the periods that switching portfolios were out of the market, the differences are not statistically significant. The mean return of the benchmark index, on the other hand, on average was negative when the switching portfolio using short spreads was out of the stock market and the mean return differences are statistically significant at 0.6% level. Even though the benchmark index on average did not post negative returns when the switching portfolio using long spreads was out of the market, the benchmark return differences between the two kinds of periods were also highly significant at the same probability level. Table 4 suggests that both switching strategies are successful in avoiding periods with low mean returns in the overall market index. They are, however, not particularly useful in predicting the higher volatility periods.¹⁵ Then how do we reconcile this

¹⁵In contrast, Kane et al (1996) find a strong relationship between p/e ratios and the

with the fact that both portfolios have significantly lower sample variances? The explanation is that both portfolios achieve the lower sample variances by staying out of the market a non-trivial percentage of the time.¹⁶

5 Portfolio Switching Strategies (3)

(Insert Table 5 here)

A natural question to ask is whether the switching strategies outperform the benchmark by luck. As Table 4 shows, on average the market index

level of stock market volatility.

¹⁶Careful readers may notice that the actual months of either switching portfolios were not in the market were more than 10%. This is mainly due to the factor that the ten percentile values of the spreads were real time. We do not want to use the entire sample ten percentile point because that would make the switching strategies non-implementable in real time framework. During our sample period, both ten percentile values for long spreads and short spreads declined noticeably which caused the actual switching out time higher than 10 percent. If we had used the whole sample ten percentile values for the entire sample, then some of the earlier switching out would not have happened and the months either portfolio were out of the market would have been exactly 10 percent.

declined when the short spreads were below the 10th percentile level. An interesting test is to view the spreads as signaling devices: when they are lower than their historical tenth percentile levels, they produce signals that market downturns are imminent. In this context, we can evaluate their signaling properties by comparing the percentage of times the spreads give the “correct signal” versus the percentage of times the spreads do not give the correct signal. Tables 5 and 6 tabulate the actual market downturns versus the predicted market downturns. When the monthly return (including dividends) was negative, it is considered an actual market downturn. When a spread was below its historic 10th percentile level, we consider the spread to predict a market downturn in the following month. By this definition, the market downturn occurred roughly 38% of the months in the data period ($N_2 = 142$). By contrast, when the spreads “predicted” a market downturn, about 50% of the time the prediction was correct. Therefore, it appears that signals produced by the spreads contain useful information.

(Insert Table 6 here)

We can also formally test the statistical significance of the signals. The null hypothesis is that the spreads produced the correct signals by mere luck. Under this null hypothesis, the number of times that the “prediction” of the spreads coincided with the actual market downturns is distributed as a hypergeometric distribution.¹⁷ Table 7 shows the test results. The first row shows the sum of the ratios that the spread “predictions” were correct. $\frac{n_1}{N_1}$ is the ratio when the spread “predicted” that the next monthly return of the market index would be positive and the return was actually positive. $\frac{N_2-n_2}{N_2}$ is the ratio when the spread “predicted” the next monthly return of the market would be negative and it was negative. Under the null hypothesis that the spreads only got it right by luck, this sum is expected to be 1. As shown in Table 7, both sums for short spreads and long spreads are bigger than 1. Further, the p-value shows the probability that this performance is achieved by mere luck is under 1% for the short spreads, and under 2% for the long spreads.¹⁸ In other words, we can reject the null hypotheses that the signals produced by the spreads were correct by chance at the 2% level.

¹⁷For details of the test, see Henriksson and Merton (1981), and Cumby and Modest (1987). Merton (1981) provides some excellent theoretical background discussions.

¹⁸ $probability(n_1 \geq 195 | N = 372, N_1 = 230, M = 300) = \sum_{k=0}^{194} \frac{230k142300-k}{372300} = 0.0079$,
and $probability(n_1 \geq 177 | N = 372, N_1 = 230, M = 271) = \sum_{k=0}^{194} \frac{230k142271-k}{372271} = 0.0164$.

(Insert Table 7 here)

6 Conclusion

We examine the usefulness of the spreads between the e/p ratio of the stock market index and the interest rates of 3-month and 10-year Treasury securities. We find that while spreads do not appear to be particularly useful in a regression framework, the extreme values of the spreads, relative to their historical ranges, do contain useful information on future overall equity market movements. In particular, for the time period of 1967 to 1997, when the spreads were below their historical 10th percentile levels, roughly 50% of the time they were followed by a market downturn. Further, switching strategies based on the signals of the spreads outperformed the benchmark buy-and-hold strategy. Finally, even though many practitioners and the business press have focused on the spreads calculated with long-term interest rates, spreads calculated with short-term interest rates actually

perform marginally better, though the differences between the two are not significant statistically.

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Figure 1
Portfolio Value for the Benchmark, Short Spread
Switching and Long Spread Switching

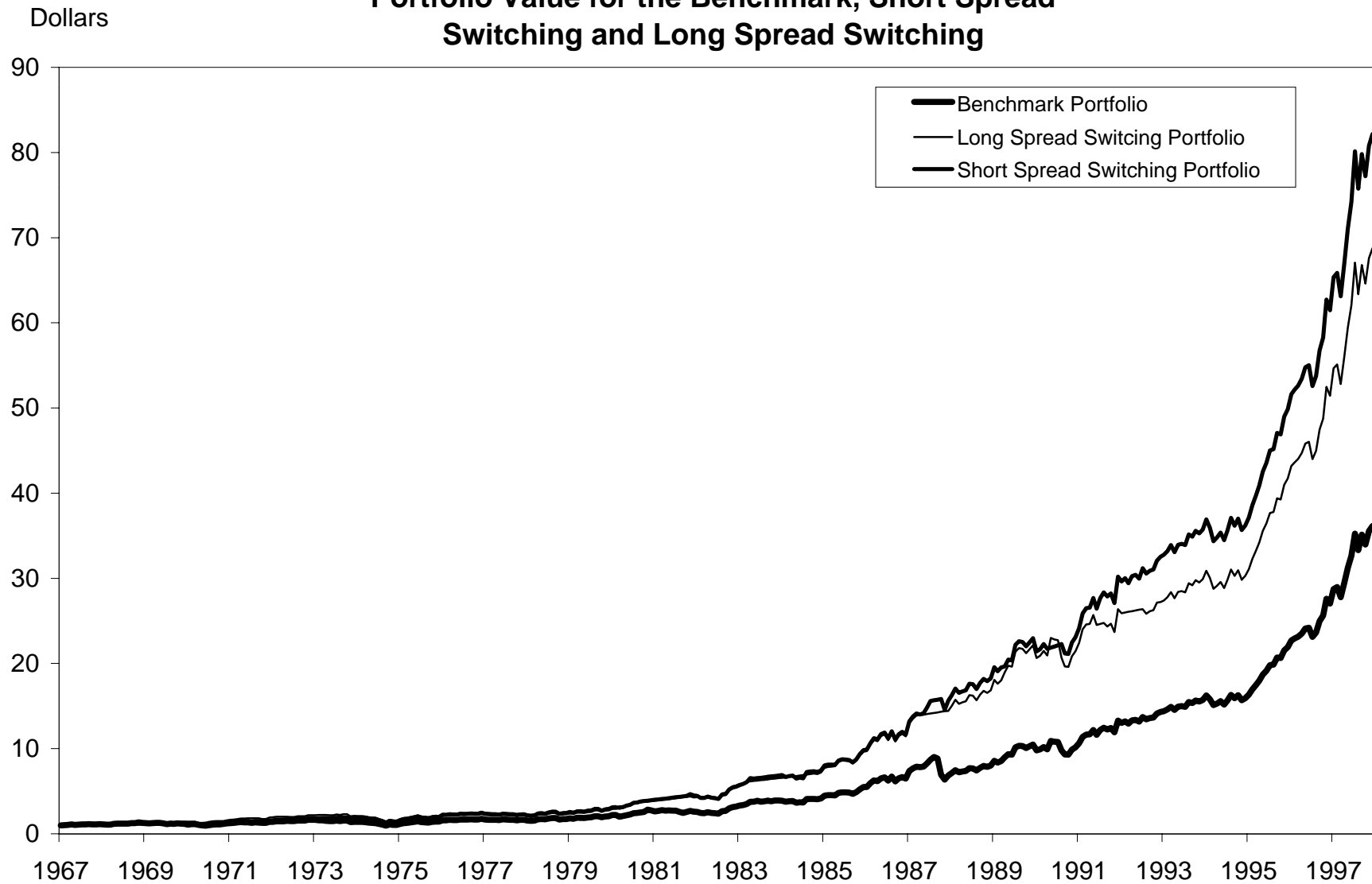


Figure 2
Benchmark Portfolio & Switching Portfolio using Short Spread

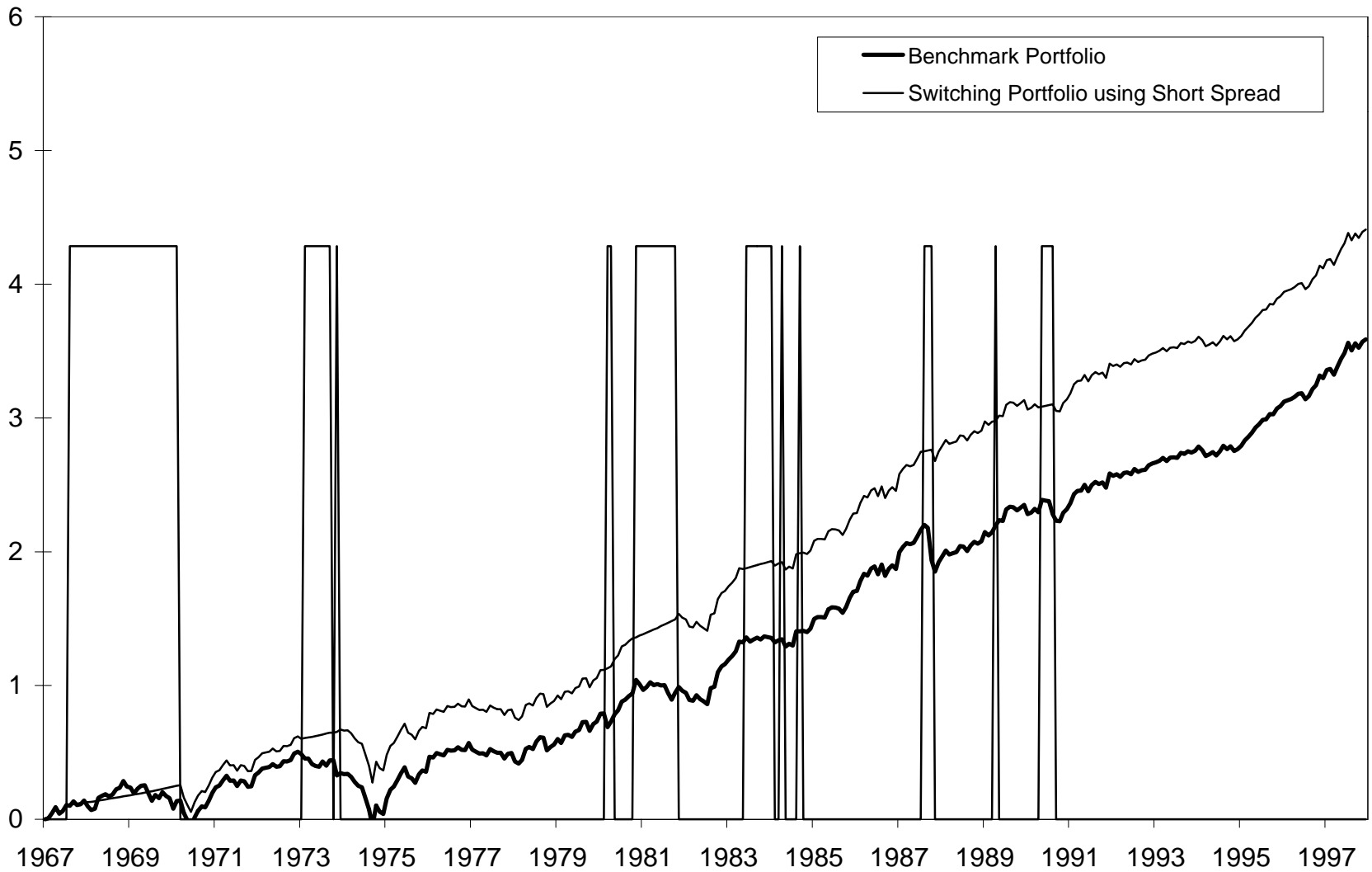


Figure 3
Benchmark Portfolio & Switching Portfolio using Long Spreads

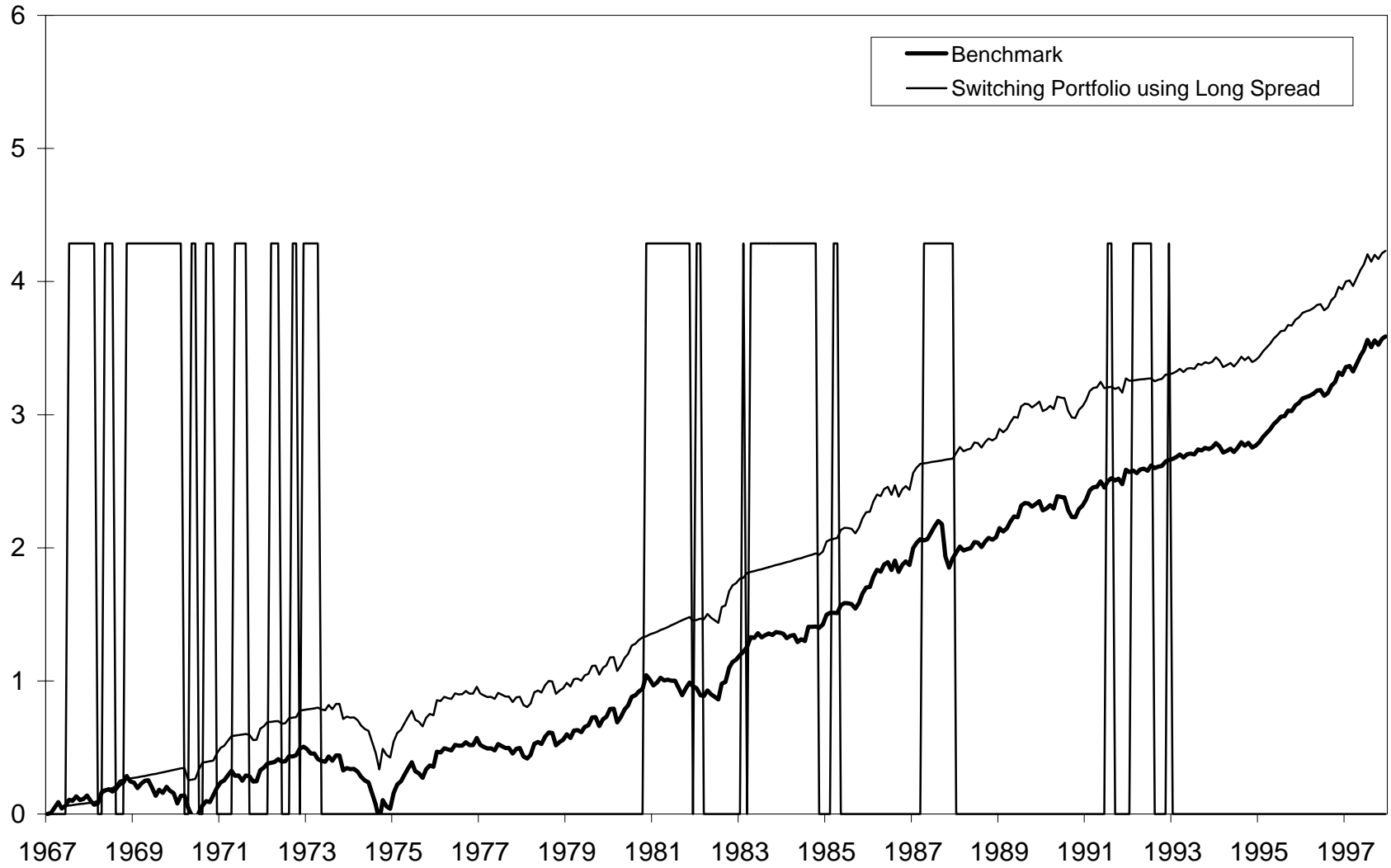


Table 1. In-Sample Regressions

	Coefficient of the explanatory variable	DW test	R ²
Short spread model	0.00315** (0.00125)	2.00	0.019
Long spread model	0.00155 (0.00128)	1.98	0.006

Table 2. Out-of-Sample One-Step ahead Forecast Errors Based on Regression Models

	Mean Error (ME)	Root-Mean-Square Error (RMSE)	Mean Absolute Error (MAE)
Short spread model	-0.00476	0.04385	0.03304
Long spread model	-0.00589	0.04404	0.03290

Table 3. Switching Strategies versus Benchmark (CRSP)

	Benchmark (CRSP)	Switching strategy using short spreads	Switching strategy using long spreads
Mean monthly returns	0.01083	0.01280	0.01231
Test against benchmark (p-values)	n.a.	0.5051	0.6162
Sample standard deviations	0.00224	0.00192	0.00191
Test against benchmark (p-values)	n.a.	0.0027	0.0017
End values of portfolios	36.1512	82.1824	68.7583
Sharpe ratios	0.125	0.200	0.188

Table 4. Performances of the Benchmark (CRSP) Portfolios in Different Periods

	Entire sample period	When switching portfolio using short spreads in the market	When switching portfolio using short spreads out of the market	When switching portfolio using long spreads in the market	When switching portfolio using long spreads out of the market
Mean monthly returns	0.01083	0.01426	-0.00343	0.01464	0.00062
Test of same mean for in and out of the market periods (p-values)			0.0058		0.0057
Monthly standard deviations	0.04327	0.04108	0.04922	0.04280	0.04307
Test of same sample standard deviation for in and out of the market periods (p-values)			0.0545		0.9397
Total number of months	372	300	72	271	101

Table 5. Comparison of realized monthly stock market returns and signals produced by the short spreads

	Positive realized returns	Negative realized returns	Total number of occurrences
Signal to stay in the stock market	$n_1 = 195$	$n_2 = 105$	$M = n_1 + n_2 = 300$
Signal to stay out of the stock market	35	37	72
Total number of occurrences	$N_1 = 230$	$N_2 = 142$	$N = 372$

Table 6. Comparison of realized monthly stock market returns and signals produced by the long spreads

	Positive realized returns	Negative realized returns	Total number of occurrences
Signal to stay in the stock market	$n_1 = 177$	94	$M = 271$
Signal to stay out of the stock market	53	$n_2 = 48$	101
Total number of occurrences	$N_1 = 230$	$N_2 = 142$	$N = 372$

Table 7. Henriksson and Merton tests on the significance of the spread signals

	Short spreads	Long spreads
$\frac{n_1}{N_1} + \frac{N_2 - n_2}{N_2}$	1.1084	1.1076
p-values	0.0079	0.0164