S&P FUTURES RETURNS AND CONTRARY SENTIMENT INDICATORS

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This article investigates the predictive power of popular market-based sentiment measures for subsequent returns on the Standard & Poor's (S&P) 500 futures contract over 10-day, 20-day, and 30-day horizons from January 1989 through June 1999. These measures include the volatility index, the put–call ratio, and the trading index. The empirical results show that these variables over a variety of specifications frequently have statistically and economically significant forecasting power. The results indicate that these variables are contrarian indicators, consistent with the view that periods of extreme fear in the stock market have provided excellent buying opportunities. Finally, out-of-sample trading simulations performed over the second half of the sample period demonstrate that profits and risk-adjusted profits would have been enhanced by buying S&P futures when the fear indicators were high rather than low. © 2001 John Wiley & Sons, Inc. Jrl Fut Mark 21:447–462, 2001

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INTRODUCTION

Technical indicators have captured the attention of academics and practitioners in recent years. Some technical indicators provide supporting evidence concerning the existence and strength of price trends, whereas others capture the sentiment of market participants. *Investment Business Daily* publishes a variety of sentiment indicators, some of which are culled from options on stocks and stock indexes. The underlying premise of these indicators is that when market participants are excessively bearish, institutional investors have large cash positions and favorable news can generate large cash inflows into the market. By contrast, if market participants are excessively bullish, institutional investors are more fully invested, and, as a result, good news cannot bring as much buying power into the market. A cornerstone of the contrarian paradigm is that cash on the sidelines is the financial tinder that fuels subsequent strong rallies.[1]

This article examines the predictive power of popular market-based sentiment indicators, including the volatility index (VIX), the put–call ratio, and the trading index (TRIN) for Standard & Poor's (S&P) 500 futures returns over the sample period January 1989 through June 1999. The article then presents out-of-sample trading simulations that involve buying S&P futures when the fear indicators are high.

With the recent interest in technical analysis, the efficient markets paradigm has been challenged by a series of articles that have chiseled away at its foundation. One line of research demonstrates the profitability of momentum trading strategies that involve buying stocks on strength (e.g., Chan, Jegadeesh, & Lakonishok, 1996; Rouwenhorst, 1998). A second and more extensive body of work focuses on contrarian trading strategies that involve buying weakness (e.g., Dechow & Sloan, 1997; Jegadeesh & Titman, 1995; Lakonishok, Shleifer, & Vishny, 1994). A third line of research analyzes the profitability of simple technical trading rules in the U.S. equity market (e.g., Bessembinder & Chan, 1998; Brock, Lakonishok, & LeBaron, 1992; Knez & Ready, 1996).

Although sentiment indicators appear to be used widely by market participants, relatively little research has focused on their efficacy. This research has examined whether market sentiment, as measured by survey data, provides clues for future stock returns. Clarke and Statman (1998) found that the Bullish Sentiment Index, a survey measure of the bullishness of newsletter writers, did not have significant forecasting power, contrarian or otherwise, for subsequent S&P returns over the subsequent 4,

[1]This general view has been expressed as "the market needs to climb a wall of worry."

26, and 52 weeks from 1963 to 1995.[2] The authors also found that extreme levels of the Bullish Sentiment Index did not have predictive power for subsequent returns. One interesting finding from their study is that sentiment is endogenous. Recent strong (weak) stock market performance is associated with newsletter writers becoming more (less) bullish, which is consistent with positive feedback trading.

More recently, Brown and Cliff (1999) examined whether a variety of technical indicators are correlated with survey measures of sentiment and whether a composite sentiment measure that they created on the basis of the principal components of several indicators drives both future stock returns and deviations of stock prices from measures of intrinsic value. In agreement with Clarke and Statman (1998), the authors found that survey measures of sentiment are driven largely by lagged returns in a manner consistent with positive feedback trading and to a lesser extent by some of the technical indicators.[3] Brown and Cliff also found that their sentiment measure had predictive power for subsequent returns at 2-year and 3-year horizons and for deviations of stock prices from fair value measures.

The approach of this article differs from the previous literature in a few ways. First, the predictive power of indicators is examined directly rather than via a created index as in Brown and Cliff (1999). The motivation is that the specific indicators have predictive power at specific points in the market cycle and aggregating them into an overall index could dilute or obscure their individual information content. Second, the market-based sentiment indicators are examined in light of their values in different market environments rather than how well they correlate with survey-based measures of sentiment (e.g., Brown & Cliff, 1999). In doing so, several of the problems inherent in survey data are avoided. One problem arises from the possibility that the surveys may be out of date by the time that they are published, particularly when markets are volatile.[4] Other potential problems with survey data are that the responses are weighted equally regardless of the amount of funds managed by respondents and that no distinction is made between the degrees of bullishness

[2]Solt and Statman (1988) found essentially the same results for the bullish consensus over an earlier sample.

[3]Brown and Cliff (1999) categorized these technical variables into one of three groups: (a) variables based on recent market performance, (b) those related to short selling, and (c) those related to derivative trading activity. Specific indicators that proved significant in their analysis include the TRIN, the advance–decline line, the ratio of new highs to new lows, the ratio of specialists to short sales, the percentage change in margin borrowing, the ratio of odd lot sales to total sales, and the net trading position in S&P futures by trader type (institutional versus individual investors).

[4]Brown and Cliff (1999) lagged the survey responses by 1 week to accommodate the potential staleness of survey responses.

or bearishness. By contrast, market-based measures of sentiment are observed in real time and reflect both the market power of market participants and the intensity of bullishness or bearishness.

A final consideration has to do with the risk–return paradigm. The intertemporal Capital Asset Pricing Model (CAPM) model developed by Merton (1973) suggests a positive relation between expected market returns and the volatility of market returns. Empirical research with Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models also has shown a positive relation between excess returns for the S&P 500 Index and conditional variance (French, Schwert, & Stambaugh, 1987) and for value-weighted New York Stock Exchange (NYSE) returns (Chou, 1988), although others, including Nelson (1991), have found a negative relation between Center for Research in Security Prices (CRSP) value-weighted returns and conditional volatility. In view of the possibility that market participants are rewarded for accepting greater volatility, it is important to examine whether the returns from buying S&P futures when fear and volatility are high are attractive on a risk-adjusted basis. This issue is addressed when trading-rule simulations are performed.

The article proceeds as follows. The section Sentiment Indicators and Preliminary Data Analysis discusses the indicators and provides background information. The section Forecasting Properties of the Sentiment Indicators examines the forecasting power of the indicators for subsequent returns on the S&P 500 futures contract. The section Out-of-Sample Trading-Rule Simulations provides trading-rule simulations, and the last section summarizes the findings.

SENTIMENT INDICATORS AND PRELIMINARY DATA ANALYSIS

This section describes the sentiment indicators that are investigated and provides information about their statistical properties, the market environments in which they reach extreme levels, their correlations, and their central tendencies when other indicator variables are at extremes. The indicators include the VIX, the put–call ratio, and the TRIN. The data are daily closing observations from January 1989 through June 1999 and were collected from The Bloomberg professional database.

The VIX is constructed from Black–Scholes implied volatilities of S&P 100 index options, which are traded at the Chicago Board Options Exchange. The options used in the calculation of the VIX are the closest in-the-money and out-of-the-money calls and puts of the two front month contracts. These eight implied volatilities are weighted so that the VIX represents the average implied volatility of an at-the-money call and put 30 days before expiration. The VIX has a tendency to surge during sharp sell-offs as investors hedge their equity portfolios by buying S&P 100 index puts.[5] For example, the VIX surged to around 80% during the stock market crash in October 1987, compared with a mean level of 18.5% over the sample period examined in this article. Because of this tendency to spike during pronounced market weakness, the VIX is viewed as a fear index. Conversely, the VIX typically registers low levels during smoothly upward trending markets because of increased complacency and a lower demand for insurance against market declines. The VIX is reported from 9:45 Eastern Standard Time (EST), 15 minutes after S&P 100 index options begin trading, to 4:15 EST, when the S&P 100 index options stop trading.

The put–call ratio is another measure of market sentiment derived from options. The put–call ratio equals the total trading volume of puts divided by the total trading volume of calls. This study uses the put–call ratio constructed from S&P 100 index options. The put–call ratio is reported from 9:45 EST until 4:15 EST. Like the VIX, market participants view the put–call ratio as a fear indicator, with higher levels reflecting bearish sentiment. The conventional interpretation of the put–call ratio is that as market participants become bearish, they buy puts either to hedge their portfolios or to make bearish bets. By contrast, a low level of the put–call ratio is associated with a lower demand for puts, which would reflect bullish sentiment. Thus, the consensus view is that the put–call ratio is driven by demand rather than supply.

The final sentiment indicator examined is the trading index on the NYSE, which is typically called the TRIN.[6] The TRIN is equal to the number of advancing stocks scaled by the trading volume of advancing stocks divided by the number of declining stocks scaled by the trading volume of declining issues. The TRIN is reported from the opening of trading on the NYSE at 9:30 EST until 4:00 EST, when stocks stop trading on the NYSE. A high level of the TRIN can be achieved mathematically in a variety of ways. Evidence (not shown) indicates that over the sample period, the TRIN tends to be high when the number of advancing stocks is low relative to the number of declining stocks. Although this by itself lowers the TRIN, the impact is more than offset by a much lower trading volume of advancing issues relative to the trading volume of de-

[5]The VIX could also rise because the demand for calls increases because investors prefer the limited downside risk of call options to outright long positions.
[6]This index is often called the ARMS index after Richard Arms, who popularized the index.

clining issues.[7] High levels of the TRIN are viewed by technical analysts as indicative of market bottoms because the relatively low number of advancing issues on low volume compared with the high number of declining issues on high volume may indicate that sellers are finished selling. This empirical issue is examined in the next section of the article.

Table I presents descriptive information about the sentiment data and the percentage change (i.e., return) of the S&P 500 futures contract data over the most recent 10 (business) days for the sample period January 1989 through June 1999. The latter is included to provide information about the market environment in which the indicator variables reach extreme values and is calculated from the front contract. The return series are adjusted for rollovers between contracts on the 1st day of contract months, when it is assumed that traders roll to the next contract. Panel A of the table shows the means, the standard errors of the means, the top and bottom deciles, and the correlations of the variables at the close of trading. Panel B provides the means and standard errors of the means of the other variables when the variable along the top of Panel B is in its top and bottom deciles. The mean 10-day return of the S&P 500 futures contract over the sample period is 0.57%, whereas the corresponding mean returns for the top and bottom deciles are 3.82% and −2.84%, respectively. The mean of the VIX is 18.50, whereas the mean of the put–call ratio is 1.15, which demonstrates that on average more S&P 100 puts are traded than calls. The mean for the TRIN is 0.968, which indicates that on average the number of advancing issues scaled by the trading volume of advancing issues is slightly less than the number of declining issues scaled by the trading volume on declining issues. The top and bottom deciles of the put–call ratio and the TRIN indicate that the distribution of these variables is fairly tight, whereas the VIX varies over a fairly wide range.

The VIX has a significantly negative correlation with lagged S&P returns, and when S&P returns over the previous 10 days are in their lowest rather than highest deciles, the VIX tends to be a statistically significant 4% higher. This finding is consistent with the leverage effect explored by Nelson (1991), in which large negative stock market returns lead to higher subsequent volatility than equal magnitude positive stock market returns. By contrast, the put–call ratio does not have a significantly negative correlation with lagged S&P returns or with the VIX and varies little across extremely strong and weak market environments and extremely high and low levels of the VIX. This evidence indicates that

[7]For example, when the TRIN is in its highest and lowest deciles over the sample period, the advance decline lines on the NYSE are −602 and 487, respectively.

TABLE I

Data Analysis (Daily Data From January 1989 to June 1999)

Panel A: Summary Characteristics

Variable	*M*	*SE of M*	*Top Decile*	*Bottom Decile*	*Correlations* Returns	*Correlations* VIX	*Correlations* Put–Call Ratio
S&P futures returns	0.57	0.057	3.82	−2.84			
VIX	18.50	0.116	26.55	12.12	−0.196*		
Put–call ratio	1.15	0.005	1.48	0.86	−0.033	0.016	
TRIN	0.968	0.0075	1.36	0.61	−0.260*	0.166*	0.127*

Panel B: Mean Values (Standard Errors of the Means) of Other Variables When the Variable Across the Top Is in the Top/Bottom Decile

Variable	*10-Day Lagged S&P Futures Return* Top	*10-Day Lagged S&P Futures Return* Bottom	*VIX* Top	*VIX* Bottom	*Put–Call Ratio* Top	*Put–Call Ratio* Bottom	*TRIN* Top	*TRIN* Bottom
10-day lagged S&P futures return	—	—	−1.36 (0.21)	1.31 (0.07)	0.620 (0.16)	1.03 (0.17)	−1.45 (0.21)	1.08 (0.21)
VIX	20.92 (0.31)	25.13 (0.48)	—	—	18.18 (0.34)	18.21 (0.34)	22.21 (0.47)	19.81 (0.40)
Put–call ratio	1.14 (0.017)	1.16 (0.014)	1.15 (0.017)	1.13 (0.015)	—	—	1.21 (0.016)	1.03 (0.015)
TRIN	0.86 (0.016)	1.20 (0.048)	1.14 (0.048)	0.909 (0.013)	1.01 (0.020)	0.844 (0.019)	—	—

*Significance at the 1% level.

weakness in S&P futures translates into subsequent higher implied volatilities more so than a greater trading volume in puts relative to calls. The TRIN has a significantly negative correlation with lagged S&P returns and a significantly positive correlation with the VIX and the put–call ratio.

Overall, a preliminary investigation of the data suggests that with the possible exception of the put–call ratio, the indicator variables respond as expected to market environments. The issue investigated in the next section is whether the indicators have forecasting power for subsequent S&P futures returns.

FORECASTING PROPERTIES OF THE SENTIMENT INDICATORS

This section examines whether general movements as well as extremely high levels of the sentiment indicators have predictive power for subsequent S&P 500 futures returns. Technical analysts differ on the relevant investment horizon over which the indicators work and whether moving averages of the indicators should be used to purge noise. To consider a range of possibilities and to examine robustness, we examined both unsmoothed and smoothed indicators, where the latter are constructed as 5-day moving averages of the indicators, and the predictive power of the indicators was examined for S&P futures returns over 10-day, 20-day, and 30-(business) day horizons.

Table II shows the results of regressing S&P 500 futures returns over the three investment horizons on a constant (which is not reported) and the levels of the three sentiment variables. Because the models are estimated with daily data and the investment horizons are 10, 20, and 30 days, moving average errors are built into the residuals of the estimated models. As a result, reported T statistics are corrected for moving average errors and for heteroscedasticity with the Newey–West method.[8]

The results indicate that increases in the VIX are associated with statistically significant higher subsequent returns at the 10 to 5% level for all specifications, except for the 10-day ahead returns with smoothing. The significant positive coefficients on the VIX support the view that it

[8]Again, S&P futures returns, the VIX, and the put–call ratio are measured at 4:15 EST when the S&P 500 futures and S&P 100 index options stop trading, whereas the TRIN is measured at the close of trading on the NYSE at 4:00 EST. Because the underlying stocks stop trading at 4:00 EST, the sentiment measures typically do not change much from 4:00 to 4:15 EST. Thus, it is assumed that traders buying the S&P futures at the close of futures trading have the sentiment indicators in their information sets.

TABLE II

Predictive Power of the Indicator Variables for S&P Futures Returns
(Daily Data From January 1989 to June 1999)

	10-Day Horizons		*20-Day Horizons*		*30-Day Horizons*	
Variable	*Not Smoothed*	*5-Day Average*	*Not Smoothed*	*5-Day Average*	*Not Smoothed*	*5-Day Average*
VIX	0.001 (1.72)*	0.000 (1.29)	0.001 (1.87)*	0.001 (1.76)*	0.002 (2.19)**	0.002 (2.17)**
Put–call	0.007 (1.67)*	0.011 (1.44)	0.010 (1.75)*	0.024 (2.24)**	0.015 (2.27)**	0.029 (2.12)**
TRIN	0.004 (2.35)**	0.011 (1.81)*	0.005 (1.89)**	0.020 (2.48)**	0.006 (2.18)**	0.025 (2.48)**
Adjusted R^2	0.020	0.019	0.036	0.049	0.058	0.072

Note: The table shows the results of regressing the percentage change of the S&P 500 futures contract over the next 10, 20, and 30 days on the unsmoothed and 5-day lagged moving averages of the indicator variables. t statistics with the Newey–West correction for heteroscedasticity and autocorrelation are shown in parentheses. The estimated constant term is not shown.
*Significance at the 10% level. **Significance at the 5% level.

is a contrary indicator. As shown in Table I, the VIX typically rises after the market has sold off sharply, which induces fear of further weakness. The greater level of fear causes market participants to bid up implied volatilities. In this environment, investors raise cash, which creates the fuel for a subsequent rally. A 1% point increase in the VIX is associated with a 0.2% increase in returns over the next 30 days, whereas a shift in the VIX from its average level to its average when in the highest decile (from 18.5 to 26.55) is associated with roughly 1.6% higher returns over the next 30 days.

Like the VIX, the parameter estimates on the put–call ratio are significantly positive at the 10 to 5% levels for all specifications, expect for the 10-day horizon with smoothing. As the trading volume of puts rises relative to the trading volume of calls, subsequent returns on the S&P futures tend to be significantly higher. These findings are also consistent with the contrarian investment hypothesis. A 0.1 increase in the smoothed put–call ratio is associated with subsequent 30-day S&P returns that are higher by roughly 0.3%, whereas an increase from the overall mean of the smoothed put–call ratio of 1.15 to its mean for the highest decile of 1.48 is associated with an increase in S&P futures returns of 0.6% over the next 30 days.

The coefficient on the TRIN is statistically significantly positive at the 10 to 5% level for all specifications, consistent with the TRIN being a contrary indicator. As mentioned in the previous section, the TRIN tends to be high when the ratio of the number of advancing to declining stocks is low and the ratio of the trading volume of advancing to declining

TABLE III

Predictive Power of the Indicator Variables When They Are in the Top Decile for S&P 500 Futures Returns (Daily Data From January 1989 to June 1999)

	10-Day Horizons		*20-Day Horizons*		*30-Day Horizons*	
Variable	*Not Smoothed*	*5-Day Average*	*Not Smoothed*	*5-Day Average*	*Not Smoothed*	*5-Day Average*
VIX	0.008 (1.19)	0.005 (.74)	0.016 (1.29)	0.016 (1.27)	0.027 (1.65)*	0.028 (1.71)*
Put–call	0.0032 (1.32)	0.0087 (2.39)**	0.006 (1.65)*	0.017 (3.82)***	0.009 (2.04)**	0.015 (2.57)**
TRIN	0.0011 (.43)	0.0052 (1.33)	0.004 (1.26)	0.011 (1.91)**	0.009 (2.03)**	0.015 (2.13)**
Adjusted R^2	0.007	0.013	0.017	0.036	0.033	0.047

Note: The table shows the results of regressing the percentage change of the S&P 500 futures contract over the next 10, 20, and 30 days on a dummy variable equal to 1 when the unsmoothed and 5-day lagged moving averages of the independent variables are in the top decile. *t* statistics with the Newey–West correction for heteroscedasticity and autocorrelation are shown in parentheses. The estimated constant term is not shown.
*Significance at the 10% level. **Significance at the 5% level. ***Significance at the 1% level.

issues is even lower. As the TRIN rises, the market action is weaker. The weaker market action leads to a tendency for stronger subsequent stock market activity. A 0.1 increase in the unsmoothed TRIN is associated with a 0.1% increase in returns over the next 30 days, whereas an increase in the unsmoothed TRIN from its overall mean of 0.97 to its mean of 1.36 when it is in its highest decile is associated with a 0.4% increase in returns over the next 30 days. Overall, the levels of the sentiment indicators explain roughly 2 to 7% of the overall variation of S&P futures returns over the three horizons.

Table III shows the predictive power of the sentiment variables when they are at extremely high levels.[9] The table shows the results of regressing the S&P futures return over 10-day, 20-day, and 30-day horizons on a constant and on dummy variables for each of the indicator variables. The dummy variables are set equal to one when sentiment variables or their lagged 5-day moving averages are in their top deciles, and zero otherwise. Again, the estimated constant term is not reported, and the *T* statistics incorporate the Newey–West adjustment for moving average errors and for heteroskedasticity.

The results generally indicate that the dummy variables become more significantly positive for longer investment horizons. The VIX enters the models with significantly positive coefficients at the 10% level only

[9] It is also possible that extremely low indicator levels indicate complacency and could be associated with subsequent market weakness. However, results not shown indicate that dummy variables that take on the value of one when the indicator variables are in their lowest deciles, and zero otherwise, seldom have significant forecasting power.

for 30-day horizons. Nonetheless, the coefficient estimates indicate that the impact on S&P futures returns is substantial: when the VIX is in its highest decile, the S&P futures rises an additional 2.7% over the next 30 days. The dummy variable for the put–call ratio enters the model with significantly positive coefficients at the 10 to 1% level for each specification, except for the 10-day unsmoothed specification. The coefficient estimates also indicate that when the put–call ratio is in its highest decile, S&P futures returns over the next 30 days tend to be higher by about 1%. The dummy variables for high levels of the TRIN enter the model with significantly positive coefficients at the 5% levels for 30-day horizons with and without smoothing and for 20-day horizons with smoothing. When the unsmoothed TRIN is in its highest decile, S&P futures returns are about 1% higher over the next 30 days. These models explain between 1 and 5% of the total variation in S&P futures returns.

Overall, the empirical results are consistent with the view that the sentiment variables examined are contrary indicators that frequently have statistically and economically significant predictive value.[10] For investors or traders whose decisions largely are based on fundamentals, the evidence suggests that the sentiment indicators would be useful secondary information. The question remains whether the sentiment indicators alone could have been used to identify attractive trades. In the next section, this question is addressed.

OUT-OF-SAMPLE TRADING-RULE SIMULATIONS

This section simulates out-of-sample trading rules from January 1994 through June 1999. The goal of the simulations is to determine whether buying S&P futures when the sentiment indicators are flashing high levels of fear provides favorable trading opportunities. The forecasts are constructed from regressions of S&P futures returns for 10-day, 20-day, and 30-day horizons on the levels of the VIX, the put–call ratio, and the TRIN. The out-of-sample return forecasts for each year beginning in 1994 are constructed from the parameter estimates from data up to the end of the previous year.[11] For example, to obtain predicted returns for 1994, the

[10]To check for the influence of any collinearity effects among the independent variables, the technical indicators were tested individually. These results were qualitatively the same as the results presented here. Also, to examine whether the indicator variables might be merely proxying lagged S&P futures returns, we estimated models with lagged S&P returns as an additional explanatory variable. This term did not enter significantly.

[11]The models are estimated in deviations from means form with the mean of each variable over the estimation period subtracted from each variable. This is done to mitigate the impact of the estimated

parameters are estimated with data through the end of 1993. Out-of-sample predicted S&P returns are obtained with the parameters derived from the earlier estimation period and from the observed values of the sentiment indicators during the forecast period. Only those sentiment variables that enter the models at the 10% level or better during the estimation period are retained.[12]

The out-of-sample predicted S&P returns over 10-day, 20-day, and 30-day horizons are the basis of the trading-rule simulations. When the fear indicators are high, predicted returns will be high, and when the fear indicators are low, predicted returns will be low. Purchases of S&P futures are triggered by predicted returns that are greater than 1, 2, or 3%.[13] Purchases are made at the market close on the basis of readings of the sentiment variables at the close.[14] Because of the strong upward trend in the S&P futures over the sample period, control or benchmark simulations are desirable to determine whether these rules truly identify favorable trades or merely reflect the strong performance of stocks. Control simulations are performed in which S&P futures purchases are triggered by predicted returns that are less than zero, which occurs when the fear indicators are low. All of the simulations assume that long positions are exited at the end of their respective 10-day, 20-day, or 30-day periods. In addition, once a long trade is entered, no further long trades are entered until the open trade is exited, and thus the simulations assume nonoverlapping trades.

Finally, transaction costs are incorporated into the simulations. Specifically, the simulations assume that the bid–ask spread in the S&P futures contract, which is typically one tenth of a point, is paid on both

constant term on the out-of-sample return forecasts and to prevent the unconditional return from previous periods from affecting decisions to enter the market in subsequent periods. A strategy of buying S&P futures partly because the unconditional returns were high during the estimation period would be more akin to a momentum strategy than the contrarian strategies that we want to examine. Out-of-sample predicted returns are constructed from the sentiment variables, expressed in deviations from the means form based on the mean of the estimation period.

[12]For the 10-day simulations, the VIX and the put–call ratio are in the model for 1994, only the VIX is in the model for 1995, the VIX and the put–call ratio are in the model for 1996 and 1997, and all three variables are in the model for 1998 and 1999. For the 20-day simulations, only the VIX is in the model for 1994 and 1995, the VIX and the put–call ratio are in the model for 1996 and 1997, and all three variables are in the model for 1998 and 1999. For 30-day simulations, the VIX and the TRIN are in the model for 1994 and 1995, and all three variables are in the model from 1996–1999.

[13]Finer increments for the trigger rules were also examined such as 0.5, 1.5, 2.5, and 3.5% predicted returns. The simulation results with these finer increments were qualitatively similar to those reported. Also, when trading strategies triggered by predicted returns higher than 3% were simulated, there were few trades, and these results are not reported.

[14]As mentioned in an earlier section of the article, these indicators can be assumed to be in the information set of market participants. Nevertheless, the results are qualitatively similar if we assume that trades are entered at the close on the next day.

position entry and exit. In addition, a brokerage fee of $25 per round trip is paid on each trade.[15] An additional brokerage fee and a bid–ask spread are assumed to be paid if a trade is open on the 1st day of a settlement month because the position is rolled to the next contract.

The simulations cover the period from January 1994 through June 1999. The results of these simulations are shown in Table IV. Panels A, B, and C show the results for the 10-day, 20-day, and 30-holding periods, respectively. Each panel shows the mean percentage return, the associated standard deviation, the number of profitable or unprofitable trades, the p value for the hypothesis that the mean percentage return is greater than zero, and a quasi-Sharpe ratio. The Sharpe ratio in this article is defined as the mean return divided by the standard deviation of returns.[16] The Sharpe ratio sheds light on whether significantly profitable trading strategies truly represent attractive opportunities or merely represent requisite compensation for accepting risk. This assessment is particularly important because the simulations involve buying S&P futures when fear levels and volatility are high.

The simulations demonstrate that the trading results are more favorable when long positions are triggered by high rather than low levels of fear. For the control simulations for 10-day horizons, the mean return is a statistically insignificant 31 basis points, the number of profitable trades is only about 20% higher than the number of unprofitable trades, and the Sharpe ratio is 0.14. When high levels of fear cause predicted returns to be greater than 1, 2, and 3%, mean returns rise to 1.1, 2.2, and 3.9%, respectively, and the mean returns on trades triggered by 1 and 3% predicted returns are significantly greater than zero. The ratio of the number of profitable to unprofitable trades rises substantially, and the Sharpe ratios rise to 0.34, 0.35 and 1.44, respectively.

The simulation results are more favorable to the contrarian hypothesis for 20-day horizons. The mean returns are a statistically insignificant 0.84% for the control simulations, whereas the mean returns for the simulations triggered by expected returns greater than 1, 2, and 3% are 2.0, 2.7, and 3.6%, respectively, and are all statistically significant at the 1% level. Again, the ratio of profitable to unprofitable trades rises relative to

[15]These assumptions are probably conservative as the closing price is as likely to be at the bid as it is at the ask, so that the bid–ask spread likely would be paid only once. Also, discount futures brokers charge as little as $12 per round trip. However, a large trader could move the market, resulting in higher transactions costs. Thus, the simulations should be viewed as reflecting the opportunity set of a small trader who does not move the market.

[16]Because Treasury bills can be used to meet margin requirements, it is assumed that there is no opportunity cost to buying the S&P futures. As a result, the return-to-risk ratio that we examine does not subtract a risk-free rate from the returns on the S&P futures.

TABLE IV

Out-of-Sample Trading-Rule Simulations (January 1994 to June 1999)

	Predicted Returns from the Simulation Model			
	Predicted Returns < 0	*Predicted Returns > 0.01*	*Predicted Returns > 0.02*	*Predicted Returns > 0.03*
		Panel A: 10 Days		
M return	0.0031	0.0114	0.0218	0.0387
SD	0.0122	0.0338	0.0632	0.0268
Number of winners/losers	29/24	39/22	14/6	6/0
p value	0.30	0.01	0.14	0.02
Sharpe ratio	0.143	0.337	0.345	1.44
		Panel B: 20 Days		
M return	0.0084	0.0204	0.0274	0.0356
SD	0.0374	0.0454	0.0470	0.0411
Number of winners/losers	21/9	26/14	23/7	13/3
p value	0.19	0.01	0.01	0.01
Sharpe ratio	0.244	0.449	0.580	0.867
		Panel C: 30 Days		
M return	0.0090	0.0277	0.0285	0.0405
SD	0.0419	0.0706	0.0542	0.0531
Number of winners/losers	12/8	20/9	17/7	16/3
p value	0.35	0.04	0.02	0.01
Sharpe ratio	0.214	0.392	0.526	0.762

Note: The simulations are based on rolling regressions of the returns of S&P futures on the levels of the VIX, the put-call ratio, and the TRIN over the sample period prior to the year to be forecasted. Out-of-sample predicted returns are constructed from these parameter estimates and from current levels of the sentiment indicators. Purchases of S&P futures are executed when predicted returns are greater than 1, 2, or 3% (and, for control purposes, when predicted returns are less that 0%). All of the simulations assume that long positions are exited at the end of 10-, 20-, or 30-day holding periods. Assumed transaction costs consist of the bid–ask spread in the S&P futures contract of one tenth of a point paid both on entry and exit and a round-trip brokerage fee of $25. The Sharpe ratio equals the mean return divided by the standard deviation of returns.

the control simulations. Moreover, the Sharpe ratios rise from 0.24 for the control simulations to 0.45, 0.58, and 0.87 for the simulations triggered by high levels of fear.

The results for 30-day horizons are fairly similar to those for 20-day horizons. The mean return for the control simulations is a statistically insignificant 0.9%, and the Sharpe ratio is 0.21. For the simulations triggered by 1, 2, and 3% expected returns, the mean returns rise to statistically significant 2.8, 2.9, and 4.1%, and the Sharpe ratios rise to 0.39, 0.53 and 0.76. Again, the number of profitable to unprofitable trades rises beyond that of the control simulations. Overall, the simulations demonstrate an improvement in returns on both absolute and risk-adjusted bases when the sentiment indicators are flashing high versus low levels of fear.[17]

CONCLUSION

Sentiment indicators such as the VIX, the put–call ratio, and the TRIN frequently are mentioned in the financial press and are widely used by technical analysts as contrary market indicators. This article investigates whether these indicators had significant forecasting power for S&P futures returns and whether they could have been used to identify favorable return-to-risk trades. Our results demonstrate that these indicators generally had both statistically and economically significant predictive power for subsequent S&P futures over the sample period January 1989 through June 1999. The VIX, the put–call ratio, and the TRIN are useful contrarian indicators, consistent with the view that periods of rising or extreme fear in the stock market have provided excellent buying opportunities over the last decade. We then simulated trading rules where traders buy S&P futures on the basis of out-of-sample return forecasts based on the sentiment indicators. The simulations demonstrate that greater returns and risk-adjusted returns would have been earned from buying the S&P futures when the sentiment indicators were flashing a high versus low level of fear. Overall, the findings are consistent with the contrarian paradigm that maintains that a high degree of market fear and skepticism leads to subsequent strong stock market performance.

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[17]The finding that mean returns are higher than their corresponding predicted return thresholds reflects the fact that the thresholds are minimum predicted returns for entering long trades.

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